UNIVERSITY OF TECHNOLOGY SYDNEY

The Impact of High Penetration of Variable Renewable Energy in Australia's National Electricity Market

by Muthe Mathias Mwampashi

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Doctor of Philosophy

under the supervision of Assoc. Prof. Christina Sklibosios Nikitopoulos, Prof. Erik Schlögl, Dr. Otto Konstandatos, and Dr. Alan Rai

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Certificate of original authorship

I, Muthe Mathias Mwampashi declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Business (Finance Discipline Group) at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Preface

A list of peer-reviewed journal publications, corresponding conference presentations, and selected media publications produced during the course of the doctoral candidature is provided below.

- ❑ **Journal Publication 1** (based on Chapter 2 of the thesis)

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  Conference Presentations:

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  Media publications:

  - Wind lowers energy prices, but adds to volatility without firming. Renew Economy, 7th December 2020.
  - Wind energy's impact on electricity prices: the good and the bad. Energy, 7th December 2020.
  - Gone with the wind: how wind power has affected electricity prices and volatility. Energy Magazine, 16th March 2021.

- ❑ **Journal Publication 2** (based on Chapter 3 of the thesis)

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Conference Presentations:

- The 4th Australasian Commodity Markets Conference (ACMC), Sydney, Australia, 7th–8th April 2022.
- The 8th International Symposium on Environment and Energy Finance Issues (ISEFI), Paris, France, 23rd–24th May 2022.
- The Commodity and Energy Markets (CEMA) 2022 Annual Meeting, Chicago, Illinois, US, 21st–22nd June 2022.

Media publications:

- 4 ways to stop Australia's surge in rooftop solar from destabilising electricity prices. The Conversation, 19th January 2022.
- Four ways to stop Australia's surge in rooftop solar from destabilising electricity prices. Energy Source & Distribution, 20th January 2022.

❑ **Working Paper—Under Review** (based on Chapter 4 of the thesis)

Mwampashi, M.M., Sklibosios Nikitopoulos, C. and Rai, A., 2022. From 30-to 5-Minute Settlement Rule in the NEM: An Early Evaluation. Available at SSRN.

Conference Presentations

- The Commodity and Energy Markets (CEMA) 2023 Annual Meeting, University of Technology and Economics, Budapest, Hungary, 20st–21nd June 2023.

Media publications:

- First look at the new settlement rule of Australia's electricity market, has it worked? The Conversation, 08th March 2023.
- Australia's five minute settlement rule for electricity markets: Has it worked? RenewEconomy, 08th March 2023.

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Acronyms and Abbreviations

ABS	Australian Bureau of Statistics
ACCC	Australian Competition and Consumer Commission
ACT	Australian Capital Territory
ADF	Augmented Dickey-Fuller
ADP	Administered Price Cap
AEMC	Australian Energy Market Commission
AEMO	Australian Energy Market Operator
AER	Australian Energy Regulator
AIC	Akaike Information Criterion
apARCH	Asymmetric Power Autoregressive Conditional Heteroscedasticity
ARCH	Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARMA	Autoregressive Moving Average
AUD	Australian Dollar
BIC	Bayesian information criterion
CCGT	Combined Cycle Gas Turbine
COVID-19	Coronavirus Disease of 2019
CO_2-e	Carbon Dioxide Equivalent
CPI	Consumer Price Index
CPM	Carbon Pricing Mechanism
CPT	Cumulative Price Threshold
DWGM	Declared Wholesale Gas Market
DWP	Dispatch Weighted Price

eGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
EPEX	European Power Exchange
ESB	Energy Security Board
FCAS	Frequency Control Ancillary Services
FiTs	Feed-in Tariffs
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GJ	Gigajoule
GW	Gigawatt
GWh	Gigawatt Hour
IRES	Intermittent Renewable Energy Sources
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
kW	Kilowatt
kWh	Kilowatt Hour
LCOE	Levelised Cost of Electricity
LM	Lagrange Multiplier
LNG	Liquefied Natural Gas
LRET	Large-scale Renewable Energy Target
LRMC	Long Run Marginal Cost
mcsGARCH	Multiplicative Component Generalized Autoregressive Conditional Heteroscedasticity
MAD	Median Absolute Deviation
MAD	Mean Absolute Deviation
MPC	Market Price Cap
MPF	Market Price Floor
MRET	Mandatory Renewable Energy Target
MW	Megawatt
MWh	Megawatt Hour
NEM	National Electricity Market

NEO	National Electricity Objective
NER	National Electricity Rules
NSW	New South Wales
OCGT	Open-Cycle Gas Turbine
OLS	Ordinary Least Squares
pARCH	Power Autoregressive Conditional Heteroscedasticity
PPA	Power Purchase Agreement
PV	Photovoltaic
QLD	Queensland
RET	Renewable Energy Target
SA	South Australia
SRES	Small-scale Renewable Energy Scheme
SRMC	Short Run Marginal Cost
STTM	Short Term Trading Market
tARCH	Threshold Autoregressive Conditional Heteroscedasticity
TAS	Tasmania
ToU	Time-of-Use
TWh	Terawatt Hour
VIF	Variance Inflation Factor
VIC	Victoria
VRE	Variable Renewable Energy
WEM	Wholesale Energy Market
5MS	Five-Minute Settlement
30MS	Thirty-Minute Settlement

Abstract

Australia's National Electricity Market (NEM) is in the midst of an unprecedented transition. The energy mix is rapidly shifting from large, centralized coal-fired power generation towards variable renewable energy (VRE). In fact, the NEM is experiencing one of the world's fastest and most marked transitions towards VRE generation, with rates 10 times higher than the global average. This transformation poses challenges to system security and reliability and has triggered increased variability and uncertainty in electricity prices. This thesis set out to investigate how rapid VRE penetration and the associated regulatory changes over the last decade have impacted electricity spot pricing and revenue dynamics in the NEM. The ultimate goal is to propose courses of action to effectively integrate high VRE shares into the grid.

The first study gauges the effects of wind power generation on the dynamics of electricity prices. Wind generation has attained the highest global penetration rates and is, thus far, the dominant VRE in the NEM. By employing an exponential generalized autoregressive conditional heteroscedasticity model, we demonstrate that wind generation reduces wholesale electricity prices and typically increases price volatility. These impacts vary across the NEM, reflecting the differences in regional market generation mixes. While wind generation exhibits an inconsistent impact on spot price volatility, the merit order effect has increased over time. We also show that interconnectors play a significant role in determining price levels and volatility dynamics. This underscores the critical role of greater interconnectivity within the NEM in minimizing the impacts on system reliability and price volatility from greater renewable energy generation. Regulatory interventions, such as the carbon pricing mechanism and nationwide lockdown restrictions due to the COVID-19 pandemic, had a measurable impact on electricity price dynamics.

The second study examines the impact of solar power generation on intraday electricity price dynamics. Unlike wind, solar generation challenges electricity price stability via out-

put variability coupled with the impact of rooftop solar on demand as a behind-the-meter resource. We demonstrate that, on average, large-scale and rooftop solar generation depresses the level of spot prices and positively impacts volatility. Further, solar generation increases electricity prices in the early morning and in the evening due to the high cost of fossil fuel generators used during off-peak solar generation periods. While large-scale solar generation typically smooths volatility, rooftop solar tends to increase it, reflecting the dominance of axis-tracking systems in the former and north-facing systems in the latter. Solar generation's impact on electricity prices differs substantially across seasons. These findings stress the need for policy adjustment to increase the correlation between solar output and electricity demand through small-scale renewable energy schemes and state-based policies, rooftop solar curtailment, dynamic feed-in tariffs, and two-sided market reform.

The third study investigates the impact of the recent transition from a 30- to a 5-minute settlement (5MS) rule on spot price dynamics and generators' spot market revenues in the NEM. The 5MS rule aims to eliminate inefficiency in pricing and artificial volatility while incentivising the entry of flexible generation sources and demand-side response. Using a Bayesian structural time-series model, we demonstrate that despite having no immediate impact on price dynamics, the rule change eventually exerts upward pressure on spot prices over time, depending on the region's generation mix and how generators adjust their bidding techniques. Spot price volatility remains essentially unchanged after the new rule comes into force. Moreover, dispatch-weighted prices (DWPs) for variable renewable energy and flexible generators, especially batteries, increase significantly. DWPs for aggregated gas generators barely change, while DWPs for inflexible and incumbent black coal-fired generators unexpectedly increase. These findings support the notion that the market is gradually adapting to the 5MS. For efficient market and consumer outcomes, stable energy policies must be in place to lower entry barriers to flexible, dispatchable generation capacity and to reduce market concentrations.

Chapter 1

Introduction

"Even if we didn't have greenhouse gases, were going to have to move away from fossil fuels, as we're going to run out. They're finite, whereas solar and wind are infinite."

-Ted Turner

1.1 Background and Motivation

Electricity sectors worldwide have undergone major reforms over the past three decades. Microeconomic reform of the electricity industry, which had its origins in Chile in 1982, is considered one of the most impactful power system reforms in the 20$^{\text{th}}$ century. The reform sought to promote power market liberalisation by unbundling vertically integrated monopolistic institutions and introducing a wholesale power trading mechanism (Weron, 2007). This reform shaped electricity industries across the globe, including in Australia. As part of the Hilmer reforms, also known as Australia's power "restructuring", several key energy policy initiatives were implemented in the mid-1990s. These reforms led to the corporatisation of electricity networks, the establishment of Australia's National Electricity Market (NEM) in 1998, and the emergence of a retail bundling market (Marshall et al., 2022). The NEM aimed to ensure appropriate risk allocation, promote competition, allow flexibility and resilience in regulatory and market frameworks, and reduce the cost of production (Rai and Nelson, 2020). Several benefits came from restructuring the Australian electricity industry. From the time of its inception to at least the period ending in 2016, the NEM managed to meet the reliability standard of no more than 0.002% lost load with only a few exceptions; prices decreased to efficient levels, oversupply was cleared, plant availability rates attained world-class levels, new investment entered the market when required, and investment risks shifted from captive franchise customers to capital markets (Rai and Nelson, 2020; Simshauser and Gilmore, 2022).

While the Australian electricity industry reforms over two to three decades centred around the deregularization of the electricity sector, recent reforms have been driven by climate change, technological advancements, and the ageing of coal-fired generators. Heavy reliance on fossil fuels for electricity generation has made the electricity sector a primary contributor to Australia's greenhouse gas emissions. In 2010, the electricity sectors accounted for around a third (35%) of Australia's total emissions (AER, 2010). Australia has pledged to achieve net-zero emissions by 2050 and has committed under the Paris Agreement (2016) to reduce its carbon emissions by 26-28% below 2005 levels by 2030. To meet this target, successive federal governments have formulated several policies to increase the uptake of renewable energy, such as the 2001 Mandatory Renewable Energy Target (MRET), which was replaced by the 2009 Renewable Energy Target (RET). The RET sought to generate 23.5% of Australia's electricity generation capacity from large-scale renewable projects by 2020 (Forrest and MacGill, 2013). Furthermore, the then Australian Labour government (2007–13) put in place a carbon pricing mechanism (CPM; 2012–2014) to encourage the largest carbon emitters to increase energy efficiency and invest in sustainable energy. Despite these measures, the reduction in power sector carbon emissions has been very gradual, with the 2019–20 emissions level being lower than the 2010 level by only 5% (AER, 2021a).

From its start, the NEM inherited a high-quality and abundant fleet of monopoly-built utility-scale coal-fired plants (Rai and Nelson, 2021). However, the generation landscape is rapidly changing. Most coal-fired generation fleets are nearing the end of their economic life, with a remaining median age of 35 years (AER, 2021a). Rising maintenance costs and increasing competition from other energy sources coupled with low spot prices are rendering coal-fired plants unprofitable to operate. A disorderly exit of sorts had occurred over the last decade, as a significant number of coal-fired plants withdrew their capacity with most exiting suddenly and unexpectedly.[1] It is expected that 60% of coal-fired capacity will be withdrawn by 2030 (AEMO, 2022a). Furthermore, the input cost of coal-fired

[1] A total of ten major coal-fired plants have withdrawn their considerable capacity since 2012: Swanbank B (500 megawatts (MW)), giving 23.6 months' notice; Munmorah (600 MW), giving no notice; Collinsville (180 MW), giving only 5.9 months' notice; Morwell (195 MW), giving only one month's notice; Redbank (151 MW), giving no notice; Wallerawang (1000 MW), giving no notice; Anglesea (150 MW), giving only 3.6 months' notice; Playford (240 MW), giving only 6.9 months' notice; Northern (546 MW), giving only 6.9 months' notice; and Hazelwood (1,600 MW), giving only 4.8 months' notice (Simshauser, 2022).

and gas-powered generation has also increased significantly over recent years, increasing the costs of electricity production in the NEM. Gas prices in Australia's domestic market have moved to more closely mirror those on the international market due to increasing competition between domestic and international consumers. Australia is the world's top exporter of coal and liquefied natural gas (LNG).[2] The development of three LNG export terminals, arguably where only two should have been developed, created an export-driven deficit from 2014 to 2017 (Simshauser and Gilmore, 2022).

The reduction in supply caused by substantial exits of coal-fired plants, the absence of sufficient entry of new "dispatchable" plants to replace retiring ones, and high input costs for coal and gas generation have accounted for much of the spot price increase in the NEM over the last decade (Rai and Nelson, 2020). Uncertainty around climate change policy, emissions reduction targets and trajectories also created barriers for new dispatchable generators to enter the market (Simshauser, 2022). Spot prices rose roughly fourfold from $30/MWh to $111/MWh between 2012 and 2019 (Rai and Nunn, 2020b). Electricity prices typically swing between short-run marginal cost (SRMC) and long-run marginal cost (LRMC) of new generation. Arguably, the NEM has reached a point in the capacity cycle where prices reflect the LRMC of new-build generation (Wood et al., 2018). High prices encourage new investments which increase supply and put downward pressure on prices. Indeed, spikes in prices between 2016 to 2021 attracted significant investment in the NEM, described by Simshauser and Gilmore (2022) as an "investment supercycle". More than half of the investment commitments made over the NEM's entire history (31,487 MW) were made solely during the period of 2016 to 2021 (15,939 MW, approx. 51%). A significant proportion of this capacity came from variable renewable energy (VRE) projects.

Australia is currently deploying VRE more quickly than in any other period in its history. More than 90% of proposed new generation investments, around 12.5 GW of large-scale wind and solar capacity and 8.5 GW of residential solar PV, have entered the NEM since 2014. The new capacity filled the more than 4 GW gap created by phased-out coal and gas generation during this period (AER, 2021a). The NEM is expected to have

[2]Eastern Australia exported more than 60% of the gas it produced in 2018 (AER, 2021a).

a total installed capacity of 8 GW for utility-scale solar, 12 GW for wind, and 22 GW for rooftop solar by 2025. At this rate, VRE would account for 50% of Australia's total generation in 2024 and 100% in 2032 (Blakers et al., 2019; Edis and Bowyer, 2021). This tide of VRE investment met the revised RET of 33,000 GWh of generation per year from eligible renewable generators ahead of schedule. The installed capacity was even sufficient to meet the original target of 41,000 GWh per year before the Abbott government reduced the target in 2015. These aggressive investments in VRE have created a path for Australia to become a renewable superpower. With 2.5 times the next-best (Germany) per capita rates, Australia currently leads the way globally in the installation of renewable electricity capacity (Stocks et al., 2019).

Although increased VRE generation contributes to the reduction of both prices and carbon emissions, at least in the short run, it also creates problems. The rates at which VRE enters the system are unprecedented and far from what the market expected. Accommodating the high rates of VRE entry is challenging as the NEM's market mechanism was designed for fossil-fuel energy sources at a time when intermittent renewable energy was neither existent nor expected. VRE has distinctive qualities that set it apart from the fossil fuel generation for which the market mechanism was designed. These qualities include near-zero marginal cost, variable and stochastic supply, the inability to trade across inter-temporal linkages, and widespread third-party power purchase agreement (PPA) contracting (Marshall et al., 2022). The existing conventional coal-fired fleets were not designed to operate flexibly to support intermittent wind and solar generation. In addition, the NEM design placed greater emphasis on the supply side, with electricity flowing in one direction: from large, centralized generators to consumers (Rai et al., 2021). Penetration of behind-the-meter resources is challenging for such a design. The demand side is increasingly active due to the rapid and significant uptake of rooftop solar PV. The inflexibility of coal-fired plants means they cannot follow the net load (at low levels of output), especially during high VRE generation periods, which in turn affects their financial viability and increases the probability of earlier than expected closure (Mountain and Percy, 2019a; Edis and Bowyer, 2021). Coal and gas generation, however, provide the market with the strength needed to stabilise the system, whereas VRE lacks these technical properties at present. On the whole, the transition towards low-cost sustainable energy has disrupted the traditional operations of the NEM and places the system's security and reliability at stake.

Typically, electricity markets exhibit higher price volatility than other types of markets as demand and supply must be matched instantaneously in real time due to the lack of cost-effective electricity storage.[3] The changing supply and demand dynamics in the NEM due to the ongoing transition exacerbate the challenge. Large-scale wind and solar generation drive variability on the supply side, whereas the demand side is driven by rooftop solar PV. As a result, prices are likely to be more volatile than otherwise in the absence of VRE. With insufficient firming capacity and interconnector capacities, volatility may rise as scarcity pricing increases. Although price movements may appear economically efficient from the standpoint of market theorists, such volatility may not appeal to various stakeholders (Marshall et al., 2022). Incidences of negative prices have also increased dramatically and are becoming a typical feature of the NEM. Furthermore, the difference in the dispatch and settlement prices, in conjunction with high VRE generation, have created a good environment for generators to "game" the NEM. When the sun shines and the wind blows, the market is flooded with supply from solar and wind generation. However, unfavourable weather conditions and the constraints of interconnectors mean less spare supply and more room for generators to create artificial scarcity and force prices up (Sheehan et al., 2017; Mountain and Carstairs, 2018; Wood et al., 2018). This gaming behaviour becomes possible because the NEM remains a highly concentrated market.

Over the past two decades, researchers have focused on demonstrating the negative effect of VRE generation on electricity prices (Cutler et al., 2011; Forrest and MacGill, 2013; McConnell et al., 2013; Cludius et al., 2014a; Bell et al., 2017; Csereklyei et al., 2019). While the findings of most studies point in this direction, some have noted the potential for a system with a large proportion of VRE generation to experience higher

[3]For perspective: treasury bills and notes tend to have the lowest volatility of daily prices (less than 0.5%), stock indices (roughly 1–1.5%), commodities like crude oil or natural gas (1.5–4%) and very volatile stocks (not exceeding 4%). However, electricity tends to exhibit extreme volatility of up to 50% (Weron, 2007).

prices than they would be without the renewables (Gullì and Balbo, 2015; Ciarreta et al., 2014; Luňáčková et al., 2017; Bushnell and Novan, 2021; Simshauser, 2022). Few previous authors have extensively investigated the effect of VRE on NEM price dynamics to clarify this contradiction. Most studies also remain narrow in focus, investigating only the impact of wind generation. Historically, large-scale wind generation has been higher than large-scale solar generation, with the latter beginning to peak in 2018. To this end, the impact of solar generation on NEM price dynamics, especially rooftop solar PV, has not been investigated previously. It is worth mentioning that despite wind and solar PV generation having low SRMC of generation, they possess different characteristics and thus tend to affect prices differently. As stated in the preceding paragraph, the recent increase in VRE penetration is most likely to trigger a rise in price volatility. Price volatility has important implications for end consumers in the NEM. Typically, retailers use hedging contracts (derivatives) to reduce the risk of volatile prices in the wholesale market. Thus, high price volatility translates into high prices for these contracts and ultimately high electricity costs for the end consumer. Despite price fluctuation being one of the critical issues in the NEM, no empirical analysis has attempted to investigate whether price volatility is affected by the increasing uptake of VRE. Furthermore, the NEM has experienced major regulatory changes and restrictions over the past decade, including the CPM, the COVID-19 pandemic, and the introduction of the 5-minute settlement (5MS) rule. None of the existing studies have investigated how these changes shaped and are shaping the NEM in relation to its price dynamics and the uptake of VRE. This research aims to thoroughly examine and establish these effects in Australia's NEM.

The scientific evidence indicates with ever greater clarity that it is urgent for policy-makers to act decisively to mitigate the worst aspects of climate change. The electricity sector has an important role to play in contributing to Australia's emissions reduction commitments. VRE is a necessary part of the mix of policies and initiatives that are important starting points towards this end. This research aims to inform the discussion regarding electricity generation, greenhouse gas emissions, and climate change as Australia transitions towards low-carbon economies. Bearing in mind that the current market mechanism was designed without intermittent renewables in mind, this study contributes to an understanding of how conventional electricity markets and price dynamics are affected by high penetrations of VRE and how the challenges can be mitigated going forward. We aim to inform policymakers, market operators, and participants so that they are well aware of the potential impact of high VRE penetration as well as regulatory changes and restrictions. By doing so, appropriate policies can be implemented to ensure a smooth transition with minimal capacity disruption. Overall, this study is particularly important in providing insights on how to resolve the "energy trilemma"—reducing emissions without undermining affordability and power system reliability and security, and, in turn, achieving Australia's National Electricity Objective (NEO).[4]

1.1.1 The National Electricity Market (NEM)

Prior to 1998, electricity in Australia was supplied by vertically integrated publicly owned state utilities, with limited grid connections and trade (Marshall et al., 2022). The NEM commenced its operations as a wholesale spot market for electricity on December 13, 1998. It was established to provide consumers with reliable and secure electricity at the best possible price through designing and enabling competitive markets and robust and resilient regulatory frameworks (Rai and Nelson, 2020). The NEM represents over 90% of Australian electricity demand and is among the world's longest interconnected power systems, covering five states on the eastern and south-eastern coasts of Australia—a distance of approximately 5,000 kilometres (km) and about 40,000 km of transmission lines and cables (AEMO, 2021a). The five states are New South Wales (NSW), Queensland (QLD), Victoria (VIC), South Australia (SA), and Tasmania (TAS).[5,6] The market consists of several participants, including market generators, transmission network service providers, distribution network service providers, and market customers—making a total

[4]The NEO states that: "the objective of this Law is to promote efficient investment in, and efficient operation and use of, electricity services for the long term interests of consumers of electricity with respect to: (1) price, quality, safety, reliability, and security of supply of electricity; and (2) the reliability, safety and security of the national electricity system."(AEMC, 2019a).

[5]The NEM formerly consisted of NSW, QLD, VIC, SA, and Snowy. Snowy was dissolved as a region in 2008 and divided between VIC and NSW. TAS joined the NEM in 2005 and became fully operational when the undersea Basslink became fully activated on 29$^{\text{th}}$ April 2006 (AER, 2011). Western Australia and the Northern Territory are not currently physically connected to the eastern electricity network due to the large distance separating these states and the eastern seaboard Australian states.

[6]The Australian Capital Territory (ACT) is considered part of NSW.

of more than 504 registered participants. Distribution network operators in each market are responsible for planning network links and developing constraint equations for network flows and network service tariffs. In the financial year 2020-21, the market traded a total of around $11.5 billion and met the demand from around 10.7 million customers (AEMO, 2021a).

The NEM involves wholesale generation, which is transported from generation centres to direct large industrial electricity users and retailers in each state and across states via high voltage transmission lines.[7] Transmission lines that allow the flow of electricity from one state to another are called interconnectors. Currently, a total of six interconnectors flow in both to and from directions, namely Victoria to New South Wales, Basslink (TAS-VIC), Heywood (VIC-SA), Murraylink (VIC-SA), Terranora (NSW-QLD), and Queensland to New South Wales. Except for the Basslink, all the other interconnectors are regulated, meaning that they have passed the national electricity regulatory test and are considered to add net value to the NEM. The revenues for these interconnectors are set annually by the Australian Energy Regulator (AER) based on the asset's value rather than on the usage of the interconnector. The Basslink interconnector is unregulated and generates revenue by trading electricity on the spot market (PC, 2017).

The Australian Energy Market Operator (AEMO) is responsible for ensuring the "reliability" of the power system, that is, sufficient capacity to generate and transport electricity to meet demand.[8] The current reliability standard stipulates that the unserved energy (USE), or the proportion of the end-consumer demand (measured in megawatt hours (MWh)) that cannot be met due to insufficient generation or interconnector capacity, must not exceed 0.002% in a region.[9] The national electricity rules also stipulate the price mechanisms in the NEM to ensure its efficient functioning, also known as reliabil-

[7]The retailers are local electricity distributors that deliver electricity to homes and businesses.

[8]A central federal system oversees and regulates the NEM. The governing market institutions are the AEMO, the Australian Energy Market Commission (AEMC), and the AER. The AEMO is responsible for administering and managing the operations of the NEM, including coordinating the dispatch of generated electricity, setting spot prices and financial settlement of the market, and ensuring sufficient electricity is in reserve. The AEMC is responsible for making and maintaining the National Electricity Rules (NER) and market development. The AER is responsible for economic regulation and rule enforcement (Christoph et al., 2020).

[9]In other words, enough generation and transmission capacity should be in place to meet 99.998% of the estimated yearly regional demand.

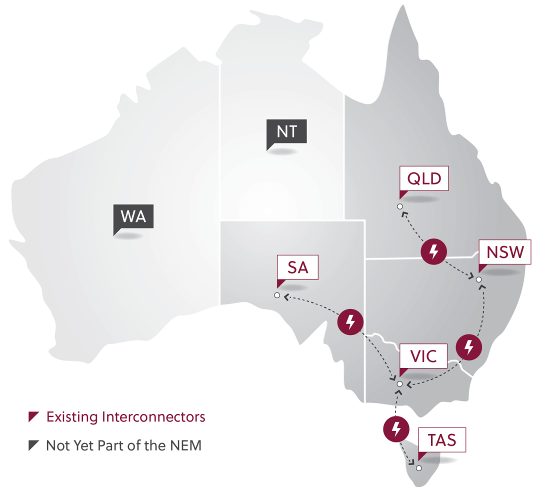


Figure 1.1 : **Regional market jurisdictions in the National Electricity Market (NEM)**, namely New South Wales (NSW), Queensland (QLD), South Australia (SA), Victoria (VC), and Tasmania (TAS). Source: ElectraNet (2022).

ity settings. They include the market price cap (MPC), the market price floor (MPF), the cumulative price threshold (CPT), and the administered price cap (ADP). The MPC and MPF are the maximum and minimum prices a generator may bid during a dispatch interval. These prices are set at $15,500/MWh and -$1,000/MWh, respectively, for the financial year 2022-23.[10] The MPC helps protect market participants from exposure to temporary high prices, and the MPF is the lowest allowable limit for the spot price, designed to limit the amount of money a generator can lose in a single trading interval (AEMC, 2017g). The CPT is intended to safeguard market participants from prolonged exposure to persistently high prices over a specific period. The current market rules require that within a seven-day rolling period, the sum of spot prices must not exceed the cumulative price threshold of $1,398,100. If this happens, the AEMO steps in to implement an ADP, effectively capping the price at $300/MWh (AEMC, 2017d).

The NEM is particularly interesting because it runs an "energy only" market; neither a capacity market nor a technical forwards market exists (Forrest and MacGill, 2013; Sheehan et al., 2017). Energy-only markets provide compensation for energy produced

[10]Changing the reliability standard changes the reliability settings. The reliability settings are reviewed periodically every four years to align them with the reliability standard.

instead of mere readiness or capacity for power generation (NKG, 2022b). The NEM operates as a pool or spot market and is compulsory for all generators with more than 30 MW of capacity.[11] Output from all generators is aggregated and scheduled at 5-minute intervals to meet demand. Trading involves real-time matching of demand and supply using a centrally coordinated dispatch process. Generators bid their price-quantity offers every five minutes, and the operator schedules these generators to meet demand in a cost-efficient manner. The marginal generator sets the dispatch price at each 5-minute interval.[12] Before 1st October 2021, dispatch prices differed from trading prices. The trading or spot price for financial settlement purposes was an average of six dispatch prices.[13] The introduction of the 5-minute settlement on 1st October 2021, aimed to align the dispatch and trading prices to better reflect real-time market conditions and price signals for investment in faster response technologies. Depending on demand and supply conditions, spot prices may reach the MPC and MPF thresholds.

1.1.1.1 The NEM generation mix

Coal-fired generation has historically dominated the Australian electrical industry. Currently, 18 coal-fired plants (black and brown coal) remain operational in the NEM, with an installed capacity of 22,418 MW (approx. 34% of total capacity). Figure 1.2 shows generation capacity and output by fuel source in the NEM. Coal generation accounted for

[11] The AEMO classifies generators as scheduled, semi-scheduled, and non-scheduled generators. Generating units above 30 MW are classified as scheduled. These generators must submit offers indicating their generation intentions and comply with AEMO dispatch instructions. Batteries with greater than 5 MW are also classified as scheduled generators. Generating units greater than 30 MW, but with varying generation, such as wind and solar, are classified as semi-scheduled. The operators forecast their generations, and generators specify prices for their output. The operators may force these generators to withdraw their output from the system if deemed necessary. Non-scheduled generators include intermittent or non-intermittent generating units with a capacity between 5 MW and 30 MW. The operators forecast their output, but they are not required to submit their generation intentions, nor do they generally restrict their output (AEMC, 2018).

[12] We present further clarification on the price setting process in electricity markets in subsection 1.1.2.

[13] The wholesale or spot electricity price is the value of energy traded between participants in the NEM. The retailers' wholesale costs of buying electricity in spot and hedge markets is one component of consumers' retail energy bills and accounted for roughly 34% of a bill in 2020–21. Other components include costs that retailers incur to supply electricity to consumers, that is, transmission and distribution network charges, which account for roughly 46% of a bill; environmental scheme costs for promoting renewable generation and energy efficiency and reducing carbon emissions, accounting for about 9% of a bill; and retail operating expenses, accounting for about 11% of a bill (AER, 2021a).

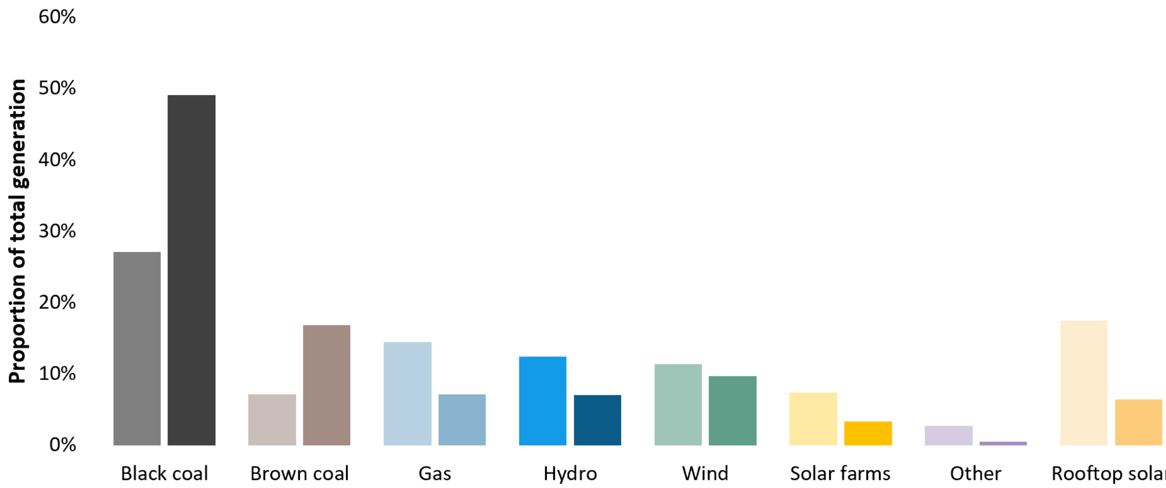


Figure 1.2 : **Generation capacity as of January 2021 (left column) and output for 2020 (right column) in the NEM by fuel source.** "Other" generation output and capacity include biomass, waste gas, and liquid fuels. Data source: AER (2021a).

about 65% of the total electricity generated in 2020, a significant drop from more than 80% in 2010 (AER, 2010). Black coal generation operates in QLD and NSW, whereas brown coal operates in VIC. Gas-fired generation is another fossil fuel generation source that operates in the NEM. More than 6,000 MW of gas-fired power plants (peaking and intermediate) entered the NEM in the 10 years leading up to 2009.[14] More than half (over 3,600 MW) were added in 2008 and 2009 alone in response to policy signals and the price spikes brought on by the drought in 2007–2008 (Rai and Nelson, 2020). As of 2020, the installed capacity of gas generation in the NEM was 9,493 MW (approx. 14% of total capacity), a decrease of around 7% from registered capacity in 2010 (AER, 2010, 2021a).

Hydropower is the oldest and largest renewable source of electricity developed in Australia. Mountainous and high-rainfall areas like NSW and TAS have been the initial focus of hydro development since the 19th century. The total installed capacity of hydro

[14]Generators that supply most of the electricity demand are called baseload generators. Baseloads tend to have high start-up costs but relatively low operating costs, making it cost-effective to run them continually. Coal-fired generation is the predominant baseload generation in the NEM. Peaking generators are those that operate occasionally and are used to supplement base load at times when prices are high. The operating costs of these generators are higher, but they possess reasonably quick and economical start-ups as they may need to operate at short notice. Intermediate generators run more regularly than peaking plants but not continuously (AER, 2010).

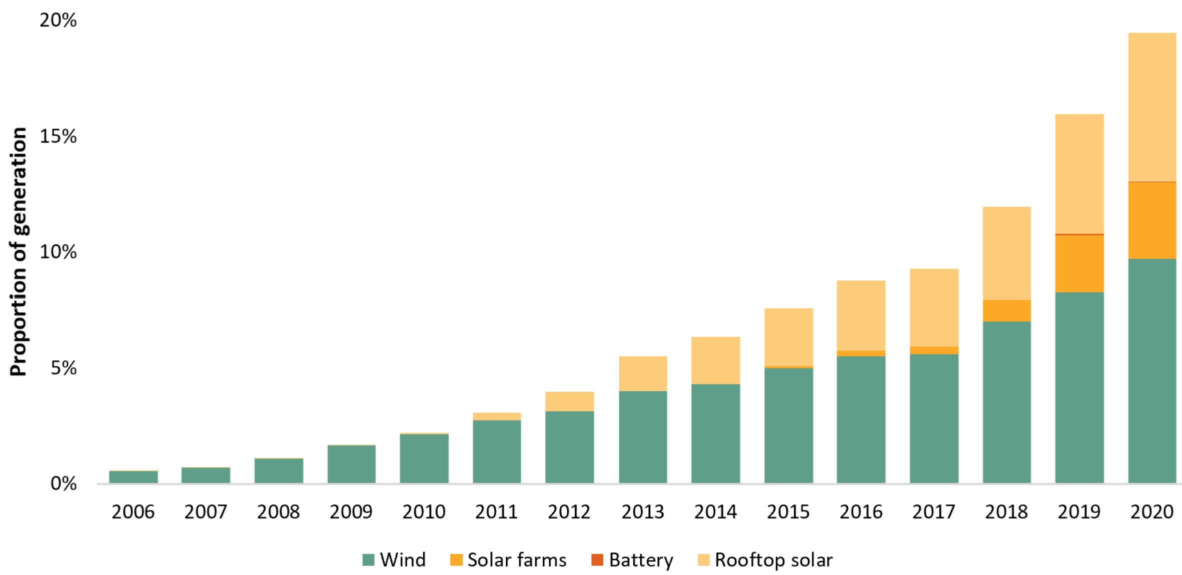


Figure 1.3 : **Large-scale wind and solar, rooftop solar, and battery generation per total generation in the NEM from 2006 to 2020**. Data source: AER (2021a).

in Australia is 8,790 MW, positioning the country as the world's fourth largest hydropower producer (Li et al., 2020). Hydro generation accounted for around 12% of registered capacity in the NEM and supplied 7% of output in 2020. Hydro generation is dominant in TAS, producing around 83% of total electricity in 2020 (AER, 2021a). Output from hydro tends to vary from time to time due to drought conditions affecting TAS and eastern Australia. In addition, hydro in the form of pumped hydroelectric technology is utilized in the NEM for large-scale storage by pumping water into an elevated reservoir when electricity is cheap and releasing it to generate electricity when prices are high. Although the installed capacity of pumped hydro is currently still marginal, it will account for a significant proportion of NEM storage capacity after the completion of the proposed Battery of the Nation (2,500 MW) and Snowy 2.0 (2,000 MW) hydro projects (AER, 2021a).

Apart from hydro, other forms of renewables in the form of VRE generation are increasingly penetrating the electricity generation mix in the NEM.[15] Figure 1.3 shows the growth of the share of large-scale wind and solar, rooftop solar, and battery generation

[15]VRE or intermittent renewable energy sources (IRES) include all forms of energy with varying outputs due to their dependence on weather conditions and thus are not dispatchable. VRE generation includes wind and solar generations, which produce electricity only when the wind blows and the sun shines.

in the NEM from 2006 to 2020. The installed capacity of wind generation rose to 11% of total installed capacity, accounting for 10% of output in 2020, up from installed capacity of about 3% and only 2% of output in 2010 (AER, 2010, 2021a). Installation of rooftop solar generation also increased dramatically over the last decade. Australia has by far the largest per capita rooftop solar deployment in the world (Stocks et al., 2019). Rooftop solar accounted for more than one-third of renewable capacity and met about 6.4% of the NEM's electricity requirements in 2020. Large-scale solar generation also increased markedly in recent years, from zero capacity over the last decade to an installed capacity of 4,832 MW, equivalent to 7% of total NEM capacity in 2020. Flexible technologies, in the form of batteries, are also entering the market to mitigate fluctuating VRE generation. However, their contribution to the NEM generating mix is still marginal, accounting for less than 1% of output (AER, 2021a).

As presented in this section, the NEM is particularly suitable for understanding how high VRE penetration impacts price dynamics due to its appealing features, some of which are not shared with other electricity markets across the globe. The NEM operates an energy-only market consisting of interconnected states; each has a diverse generation mix and has world-leading VRE penetration rates. The NEM is also highly concentrated with the potential for generators to game the market. In the next subsection, we introduce the economics of electricity markets and renewable energy generation.

1.1.2 Economics of electricity markets and renewable energy generation

The merit order model is one potential functional design for creating a typical electricity market.[16] The term "merit order" refers to the sequence in which power plants are scheduled to deliver power to economically optimize electricity supply (NKG, 2022a). The merit order is based on the lowest marginal cost: the cost of producing a single megawatt-hour (MWh) of electricity under current market conditions. As such, power plants with the lowest marginal cost and that can generate at low price are the first to be dispatched to supply electricity. If demand is not met, higher marginal cost plants

[16]The merit order model is a static description model for representing short-term electricity price formation. It does not account for long-term effects or fixed costs associated with power generation technologies.

are called upon until enough supply is available to meet demand. Figure 1.4 plots a stylized merit order according to the costs and capacities of each generator, from the least expensive to the most expensive units. Generators' costs depend on the technology employed for generation and fuel prices. Renewables have marginal costs close to zero (zero fuel costs), followed by nuclear energy, coal, gas, and peak unit plants.[17] The marginal generator needed to satisfy electricity demand sets the spot market price.

The demand curve represents demand by participants who buy electricity directly from the spot market, typically electricity retailers and large direct consumers. Electricity demand by end consumers is almost independent of spot price in the short run. For this reason, the demand curve is typically assumed to be vertical (inelastic) or very steep (Forrest and MacGill, 2013). The supply curve, also called the merit order curve, represents offers (MW) that each generator is willing to supply to the market at or above a particular price depending on its marginal costs of generation. The market clearing price, commonly known as the spot price, is set at the intersection of the electricity supply and demand curves. Several factors, such as time of day, are likely to influence prices. During high/peak demand and tight supply periods, generators tend to set high prices above their marginal cost of generation due to the lack of competition. Furthermore, the near inelastic demand and steep supply curves account for extreme spot price volatility in electricity spot markets.

To illustrate the merit order effect (MOE) of renewables, consider stylized demand and supply curves for an electricity spot market with and without renewables in Figure 1.5. Renewables have a low marginal cost of generation and therefore enter near the bottom of the supply curve, pushing conventional power plants towards the end of the merit order. The shifts of the supply curve to the right cause prices to move from P_1 to P_2, where $P_2 < P_1$, depending on the price elasticity of demand. Thus, prices are expected to be lower during high VRE generation periods compared to low generation periods. This effect is referred to as the merit order effect as it shifts market prices along the merit order of power plants.[18] Furthermore, VRE is typically associated with an increase in

[17]Different markets have different generation mixes. For instance, to date, no nuclear generation technology is in the NEM.

[18]Renewable generation may also be recorded as negative demand depending on how it is incorporated

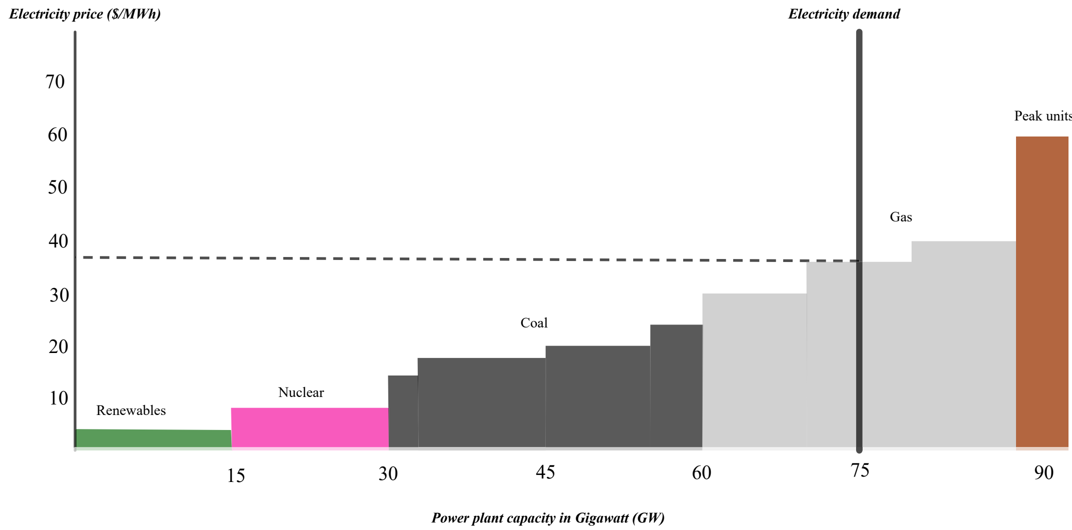


Figure 1.4 : **Stylized merit order.** Price is set by the marginal plant, that is, gas plant required to meet demand.

price variance due to fluctuation in electricity prices as VRE output varies (Forrest and MacGill, 2013). It is worth mentioning that price level is likely to be affected by other factors, such as strategic bidding, transmission constraints, and potential demand-side participation, which, for the purpose of this illustration, are assumed to be constant.

In the next section, we review empirical works that have studied the MOE in the NEM, among other studies.

1.2 Literature Review

The growth and increased investment in renewable energy have attracted both theoretical and empirical studies. A large and growing body of literature has concentrated on countries that pioneered and led in the promotion of renewable energy, such as Germany. We first review the literature focusing on the relationship between VRE generation and electricity price behaviour in Australia and provide summaries of the findings from other markets. The review goes beyond the VRE-prices relationship and includes studies that examined volatility dynamics, the interdependence of regional electricity markets,

into the electrical market. If the renewables are always dispatched under this treatment, the overall effect in this stylized model is the same (Forrest and MacGill, 2013).

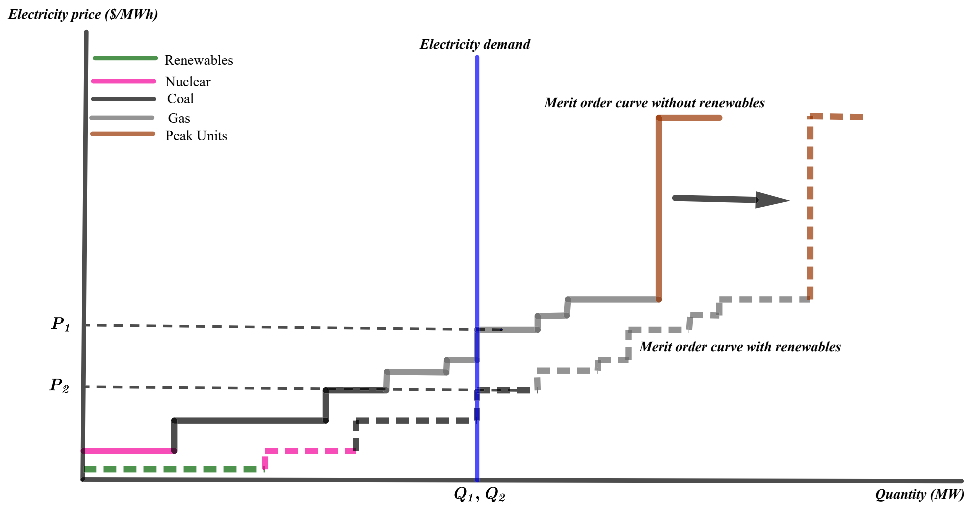


Figure 1.5 : **Stylized demand and supply curves for the electricity spot market with an inelastic demand curve without and with renewables generation.** Before introducing renewable energy, price is set by the high marginal cost gas plant at P_1 and moves to P_2 after introducing the renewables, where $P_2 < P_1$.

and the impact of regulatory changes in the Australian context. Each of these aspects is investigated at different points in this thesis.

1.2.1 The effect of wind and solar PV generation on electricity prices

In Australia, studies examining the effect of VRE on electricity spot price dynamics have only started peaking in recent years. The earliest piece of research in Australia appears to have started in 2011—a work by Cutler et al. (2011).[19] This indicates the immaturity of the Australian renewable industry, at least in comparison to the European and North American markets. We provide detailed reviews of Cutler et al. (2011) and other studies below.

SA has been the focus of most previous studies investigating the impact of VRE on electricity prices, as it was the first state to start operating wind farms at a significant scale

[19] To get a sense of when researchers commenced conducting research in this space, we examined two of the earlier studies in the area of non-hydro renewable energy generation often cited in the literature and their corresponding references. These two papers are by Forrest and MacGill (2013) and McConnell et al. (2013). We built a graph of similar papers using the Connected Papers application, a visual tool to help explore papers relevant to one's area of interest. This platform can be accessed here: https://www.connectedpapers.com/

and with high wind penetration rates. One of the earliest studies is that of Cutler et al. (2011), which investigated the effect of increasing wind generation in SA from 2008 to 2010.[20] The findings from this study demonstrated a decrease in electricity prices and an increase in extreme negative price events during high wind generation periods. Similarly, Forrest and MacGill (2013) investigated the impact of wind generation on spot prices as well as gas and coal-fired generation in SA and VIC.[21] Using 30-minute intraday data for two years from 2009 to 2011, the study demonstrated that the increase in wind generation reduced the level of electricity prices by approximately A$8.05/MWh and A$2.73/MWh in SA and VIC, respectively. The authors also showed that wind generation displaced both peaking and intermediate generation, especially gas and brown coal generation. Cludius et al. (2014a) extended this study by estimating the MOE of wind generation for the NEM as a whole for the two-year period 2011/12 and 2012/13. The application of time-series regression to the 30-minute intraday day data demonstrated the negative effect of wind generation on volume-weighted prices of approximately A$2.30/MWh and A$3.29/MWh for the years 2011/12 and 2012/13, respectively. The authors further showed that customers pay higher retail electricity prices as a result of the RET costs passed onto them. Furthermore, Bell et al. (2017) applied the Australian NEM (ANEM) model to examine how spot prices would change from 2014 to 2025 as wind penetration rates increased under the NEM transmission grid capacity that existed at the time of the study. They discovered that increasing wind penetration from a scenario with no wind to a scenario sufficient to meet Australia's original 2020 41TWh large-scale RET decreased wholesale electricity prices. However, they found that retail prices rose in three states: SA, QLD, and VIC. Their findings also suggested that congestion of interconnectors in the NEM limits the potential of wind generation to lower wholesale electricity prices.

Studies investigating the impact of solar or both solar and wind generation on electricity spot prices in Australia are relatively scarce. One early study on solar PV generation often cited in the Australian context is that of McConnell et al. (2013). In this study, the

[20]During this period, the total electricity produced by wind generation in SA was equivalent to roughly 16%, the highest wind penetration in the NEM at the time.

[21]At the time of the study, these two regional markets had the highest penetration rates of wind generation in the NEM at roughly 19% and 1.9%, respectively.

researchers applied PV generation and price-demand models to demonstrate the MOE of solar PV generation from 2009 and 2010 on the four largest NEM capitals: Brisbane (QLD), Sydney (NSW), Melbourne (VIC), and Adelaide (SA). The first study to investigate the impact of large-scale wind and solar PV generation on NEM electricity prices over a longer period of time is that of Csereklyei et al. (2019) in which the authors demonstrated the MOE of wind and solar PV generation by applying econometric models to 30-minute and daily data from 2010 to 2018. Solar PV generation exhibited a much stronger impact than wind generation. Furthermore, the study found the marginal impact of solar PV and wind generation on spot prices when studied in smaller (daily) windows.

Another stream of literature, such as Riesz et al. (2016), investigated the potential for the NEM to operate with 100% renewables. The authors created an adjusted price profile to represent potential price patterns in a market with 100% renewable energy sources by manipulating historical pricing data under a number of market assumptions. The study found that for the NEM to achieve 100% renewables, the MPC would need to increase from $13,500/MWh (in 2014–15) to the range of $60,000 to $80,000/MWh. Their findings also underscored the need for a liquid and efficient derivative contracts market to enable generators and retailers to hedge the growing market risks. In a subsequent study, Rai and Nunn (2020b) attempted to address some of the key issues highlighted by Riesz et al. (2016). In particular, the authors examined whether an increase in VRE resulted in an increase in extreme spot prices and whether an increase in reliability price settings accompanied such an increase. Although they did find an increase in price volatility, this effect was observed across the NEM, rather than just in SA, where wind penetration was the highest. This increase in volatility was driven by an increase in frequency of extremely low prices rather than extremely high prices. Moreover, the MPC remained constant in real terms despite the increased VRE.[22]

The maturity of wind and solar PV generation industries in Europe and North America has been reflected in more MOE studies compared to other countries, in particular Aus-

[22] The authors accounted for low instances of extremely high spot prices and almost unchanged reliability outcomes in real terms to the increased role of interconnectors, utility- and small-scale storage capacity, contract cover to limit exposure to the risk of spot price volatility, price-responsive demand, and additional ancillary service revenue streams.

tralia. Some of these studies include Germany (Tveten et al., 2013; Paraschiv et al., 2014; Cludius et al., 2014b; Ketterer, 2014; Kyritsis et al., 2017; Rintamäki et al., 2017; Maciejowska, 2020), Denmark (Jónsson et al., 2010; Rintamäki et al., 2017), Spain (De Miera et al., 2008; Gelabert et al., 2011; Gil et al., 2012; Ballester and Furió, 2015), Italy (Clò et al., 2015), Ireland (Denny et al., 2017), and the United States (Woo et al., 2011, 2013, 2016; Gil and Lin, 2013; Kaufmann and Vaid, 2016; Wiser et al., 2017; Haratyk, 2017; Jenkins, 2017; Westgaard et al., 2021). These studies applied either simulation-based modelling approaches by analysing a simulated electricity price with and without VRE or by using econometric approaches.[23] Overall, it is notable that all these authors reached to the same conclusions regarding the impact of wind and solar PV on electricity prices. In particular, the increase in the share of intermittent renewable energy leads to a decrease in the average electricity prices, namely the MOE.[24]

Apart from demonstrating the MOE of VRE generation, experience from other countries suggests several issues related to the increase in wind and solar PV generation in electricity markets worth investigating. Such issues can be summarized as follows: First, conflicting accounts exist of the decline in electricity prices aside from an increase wind and solar PV generation (Ciarreta et al., 2014; Gullì and Balbo, 2015; Bublitz et al., 2017). Indeed, some studies have demonstrated an inverse MOE, that is, VRE generation can exert positive effects on electricity prices (Luňáčková et al., 2017; Jha and Leslie, 2020; Bushnell and Novan, 2021). Second, the effect of VRE on both electricity prices and volatility depends on the time horizon over which the study is conducted and whether the analysis employs low- or high-frequency data (Mauritzen, 2010; Martinez-Anido et al., 2016; Kyritsis et al., 2017; Rintamäki et al., 2017; Maciejowska, 2020). Third, the effect of VRE on price volatility varies across markets and depends on the generation mixes, among other factors. For instance, while Woo et al. (2011), Tveten et al. (2013), Ketterer (2014), Pereira and Rodrigues (2015), Clò et al. (2015), Ballester and Furió (2015), Martinez-Anido et al. (2016), and Pereira and Rodrigues (2015) demonstrated the poten-

[23]Most of the earlier studies applied the former method due to the limited data availability. However, actual price and renewable generation time series data are becoming more and more readily available, paving the way for empirical studies and the dominance of research applying the latter approach.

[24]See Würzburg et al. (2013), Wiser et al. (2017), and Mountain et al. (2018) for comparison of the merit order effect across countries.

tial for VRE to increase price volatility, Jónsson et al. (2010), Mauritzen (2010), Kyritsis et al. (2017), Rintamäki et al. (2017), and Maciejowska (2020) showed that VRE can reduce price volatility or exhibit both positive and negative effects. Furthermore, the increase in VRE can potentially reduce maximum prices and the probability of price jumps (Ballester and Furió, 2015). Fourth, the impact of wind generation on electricity prices is likely to be lower than solar generation depending on the correlation between solar generation and electricity demand (Maciejowska, 2020). Fifth, VRE curtailment has the potential to increase prices and reduce volatility (Martinez-Anido et al., 2016). Sixth, VRE affects the distribution of electricity prices differently, and this impact differs between wind and solar PV generation. For instance, Maciejowska (2020) and Westgaard et al. (2021) showed that while wind generation tends to exhibit a strong MOE on the lower tail of the price distribution, solar PV tends to do so on the upper tail. Finally, electricity prices are affected by VRE forecasting errors: over-forecasting has the potential to increase electricity prices, whereas under-forecasting has the potential to dampen prices (Martinez-Anido et al., 2016).

The findings from the Australian literature regarding the impact of VRE on the level of electricity prices are consistent with those observed in other electricity markets. However, the extent to which high VRE penetration challenges the NEM remains largely unknown. Much of the literature has paid particular attention to wind generation, which historically appears to have a low levelized cost of generation compared to solar PV generation. The few studies that have investigated the impact of solar generation focused on large-scale solar and applied only the scant observations that existed at the time of study. No empirical studies have investigated the impact of small-scale (rooftop) solar generation in a similar context. Most importantly, there is little empirical analyses investigating how the increase in VRE affects the volatility of electricity prices, which is one of the major challenges facing the NEM. Those that do exist are merely descriptive analyses, and no econometric assessment of VRE impact on price volatility has been documented thus far. Therefore, apart from adding to the earlier studies on the MOE, this thesis aims to shed new light on the impact of VRE on price volatility by employing both low- and high-frequency data and demonstrating how these effects vary across time periods and states.

Experience from other countries suggests the potential for large-scale wind and solar generation to impact pricing dynamics differently; this thesis seeks to understand these effects and assess for the first time the impact of small-scale (rooftop) solar generation on price dynamics in the NEM.

1.2.2 Volatility dynamics and interdependence between regional electricity markets

Although the deregulation and restructuring of the NEM in the late 1990s promoted competition in the electricity industry, it has also been linked to the increase in volatility of electricity prices. In this light, many studies in the 2000s focused on examining volatility of electricity prices in the NEM. Two prominent studies in this space are those of Higgs and Worthington (2005) and Thomas and Mitchell (2005). Higgs and Worthington (2005) were among the first to investigate the intraday price volatility process in the NEM. Using 30-minute electricity prices and demand volumes from 2002 to 2003, the authors modelled time-varying volatility using standard generalised autoregressive conditional heteroscedasticity (GARCH), RiskMetrics, normal asymmetric power ARCH (apARCH), Student apARCH, and skewed Student apARCH models. Their findings suggested that the apARCH specification best accounts for the right-skewed and fat-tailed characteristics of electricity prices in the NEM compared to other specifications. Using a much longer time series, Thomas and Mitchell (2005) investigated volatility of electricity prices in the NEM using 30-minute prices from 1998 to 2005. In their analysis, various GARCH specifications were tested and compared, namely, the standard GARCH, threshold ARCH (tARCH), exponential GARCH (eGARCH), and power ARCH (pARCH) specifications. Their empirical findings suggest that volatility in the NEM could be effectively captured by the eGARCH specification.

The intra- and inter-relationships of wholesale electricity prices and price volatility across regional electricity markets in the NEM have been the subject of numerous studies. Worthington et al. (2005) studied price transmission and price volatility between Australia's regional electricity markets using daily spot electricity prices from 1998 to 2001. Four states—NSW, QLD, SA, VIC and one non-state (Snowy Mountains)—were considered. The study applied the multivariate GARCH models and found significant own-mean spillovers from own-lagged electricity prices for only QLD and Snowy Mountains. Although all five markets were connected at the time of the study, on average no evidence suggested that short-run electricity prices in one spot market affected another. On the other hand, the researchers showed that a shock in one market affected price volatility of the same and other markets. In a similar context, Higgs (2009) applied a family of constant and dynamic conditional correlation MGARCH models to capture the effects of cross-correlation volatility spillovers between four regional markets in the NEM, namely NSW, QLD, SA, and VIC. The analysis found little evidence of mean spillovers from other lagged markets and positive own-mean spillovers in all four markets using 30-minute electricity prices from 1999 to 2007. The findings from the dynamic conditional correlation equation suggested that well-connected markets had higher conditional correlations than less connected markets.

The interdependence of regional electricity pricing dynamics and markets has also been examined in a number of studies. Ignatieva (2011) examined the dependence structure of spot electricity prices in the NEM. This study also included TAS in its analysis for the first time. The empirical analysis involved the application of the GARCH model and copulae to daily spot electricity prices from 2006 to 2010. These approaches allowed the estimation of time-varying volatilities and dependence structures between regional markets. This study found a significant interdependence between markets that were well connected via interconnector transmissions, particularly NSW and QLD, NSW and VIC, as well as SA and VIC. Ignatieva and Trück (2016) investigated the dependence structure of electricity spot prices in the NEM. The application of GARCH modelling with copulae to daily data from 2006 to 2010 showed a significant interdependence between markets that were well connected via interconnector transmissions. However, this dependence, particularly between NSW, QLD, SA, and VIC, appeared to decrease over time.

Nepal and Foster (2016) investigated the degree of market integration between physically connected regional markets in the NEM. Using econometric approaches and daily electricity spot prices, their findings suggested that market integration had not yet been fully realised. Apergis et al. (2017) assessed the convergence of weekly wholesale electricity prices across the NEM from 1999 to 2014. They found evidence of price convergence in states with a common regulatory framework, a generation technological structure, a competitive generation market structure, and a diversified number of retailers, namely NSW, QLD, and VIC. Clements et al. (2015) applied a multivariate self-exciting point process approach to model the occurrence and size of extreme price events in the NEM. The study demonstrated the transmission of price spikes between regional markets and that the transmission capacity affected the size of these spikes. Aiming to provide a better understanding of the transmission of risks in a multi-regional context and the potential of the NEM to achieve further integration, Han et al. (2020) investigated volatility spillovers in the NEM. The authors conducted both a static and a dynamic assessment of aggregated spillover effects and their directional decomposition between individual regional markets. Their findings suggest that the structure of the interconnectors highly influence the degree of volatility spillovers. The presence of physical links accompanied significant spillover effects, underscoring the role of interconnectors in promoting regional integration.

The review in this section has demonstrated the existence of significant electricity price volatility in the NEM, which differs across regional markets. Most studies apply GARCH-based models, finding the presence of significant own-mean spillovers and mean spillovers effects from other lagged markets. In other words, regional electricity markets in the NEM are shown to be interdependent, with more significant dependencies observed between adjoining and physically connected markets. The occurrence of shocks in one market affects the price volatility of not only that market but also other markets in the region. The degree of these spillovers effects depends on the size of the interconnector flows. To ensure successful regional integration, therefore, interconnectors are essential. Modelling volatility dynamics requires appropriate approaches to account for the stylized features of electricity prices. We build on these findings with a somewhat similar methodological approach based on an exponential GARCH-type model to investigate prices and volatility. Where this analysis differs from other analyses, however, is in its accounting for seasonality, electricity spikes, and explicit incorporation rather than removal of negative electricity prices.

1.2.3 The effect of regulatory changes

The CPM and the 5MS rule are two regulatory changes that have occurred over the past decade. We provide a detailed review of the literature related to these regulatory changes below.

Most of the post-CPM studies of interest in this analysis demonstrate significant changes in prices, demand, and emission intensity during the period in which the CPM was in operation.[25] These include Nazifi (2016), who carried out an investigation into the actual impact of the carbon price on wholesale electricity spot prices in the NEM from 2010 to 2013. Using econometric approaches, the author concluded that carbon costs translated into higher wholesale electricity spot prices. The findings also showed that in states such as QLD, SA, and TAS, the increase in electricity prices outpaced the carbon costs, potentially generating windfall profits for some generators. O'Gorman and Jotzo (2014) conducted a comprehensive analysis of the effect of the carbon price on the electrical industry in the NEM for the two years that the CPM was in place, between 2012 and 2014. Several important findings emerged from this study. In particular, the carbon tax led to a 59% increase in wholesale power spot prices and a fall in electricity demand of around 2.5–4.2 terawatt-hour (TWh) per year, equivalent to 1.3–2.3% of total annual electricity demand. The authors also demonstrated that output from coal generators declined significantly during this period.

Recently, Maryniak et al. (2019) studied the impact of the CPM on electricity prices by examining carbon premiums and pass-through rates in the NEM. The findings of this analysis revealed that carbon premiums rose following the CPM proposal and its subsequent legislation in 2011. They also found an inverse relationship between emission intensities and expected carbon pass-through rates, which ranged between 67% and 150%. In particular, low rates were observed in markets with the highest emission intensities, and high rates in markets with the lowest emission intensities. Furthermore, Han et al. (2020) found that the CPM dampened volatility spillover across the NEM. Their findings also

[25] Several studies were conducted both before and after the implementation of the CPM. The pre-CPM studies focused on forecasting the impact of carbon prices on electricity prices, also known as carbon pass-through, and the economic effects associated with the introduction of emissions trading (see Nelson et al. (2012) for further discussion).

suggested an increase in volatility spillover soon after the repeal of the CPM, especially between 2014 and 2017. The authors attributed this result to the shutdown of coal-fired power plants, which decreased generation capacity and, as a result, increased interregional trade and prices across the NEM.

To date, there has been no empirical study on the impact of switching to shorter trading intervals in the NEM. The study by Märkle-Huß et al. (2018) is probably the only relevant empirical analysis in this space. This study investigated the impact of moving from 1-hour to 15-minute products on the European Power Exchange (EPEX). Three findings emerged from this study: shorter trading intervals resulted in lower electricity prices while causing marginal changes in trading volume and incentivise wind and solar generators to offer additional supply in the market. Other studies, including that of Koch and Hirth (2019), have underscored the role of shorter trading intervals in reducing the reserve requirements and reserve use by mitigating predictable imbalances stemming from solar generation and electricity consumption diurnal patterns. Goutte and Vassilopoulos (2019) have also shown that short-term price volatility generated additional revenue for flexible resources that could respond swiftly at 15-minute intervals.

Collectively, these studies outline the CPM's critical role in shaping the behaviours of electricity prices and demand and exerting negative pressure on emission intensities. While spot prices increased after the CPM, price volatility was pushed down by the CPM. The findings also underscored the differences in the impact of the CPM across regional markets and across generation technologies. Although the CPM aimed to encourage energy efficiency for emission-intensive generators and investment in sustainable and renewable energy, very few studies have assessed how these generation technologies evolved during the CPM period, especially in relation to electricity spot price dynamics in the NEM. Furthermore, evidence from other markets suggests that increasing time granularity in electricity markets provide better market signals to the system operator and generators, leading to pricing efficiency and incentives for flexible generators to enter the market. We aim to explore these aspects in the NEM by examining how the 5MS, which only recently came into effect, impacts spot price dynamics and revenues earned by generators in the NEM.

1.3 Contributions

This thesis makes original contributions to the growing area of renewable energy with a focus on providing a deeper insight into the impact of high penetration of intermittent renewable energy generation on price dynamics to inform policies intended to support the transition underway in Australia. More specifically, this thesis contributes to the literature in several dimensions based on the three main chapters of this thesis, as outlined below.

1.3.1 Second chapter

First, we conduct a comprehensive analysis of the impact of wind generation on the volatility of electricity prices in the NEM. This is the first study of its type and of substantial duration (2011–2020) to examine the variability of electricity prices in Australia. Research findings regarding the volatility dynamics of electricity prices have been inconsistent and contradictory and vary across countries and time of day (reflecting changes in demand profiles). We aim to establish this relationship in the NEM. Moreover, we add to previous empirical studies on the MOE, such as Cutler et al. (2011), Forrest and MacGill (2013), McConnell et al. (2013), Cludius et al. (2014a), Bell et al. (2017), and Csereklyei et al. (2019), by including recent years that witnessed large-scale VRE investments in the NEM (Simshauser and Gilmore, 2020; de Atholia et al., 2020).

Second, this study is one of the first attempts to thoroughly examine the role of cross-border interconnectors and hydro generation in the NEM. Interconnectors are essential to optimizing the total generation supply through the transfer of energy between the major generation and demand centres. As such, we add to an earlier descriptive analysis by Rai and Nunn (2020b), which noted the role of interconnectors in offsetting the challenges associated with higher penetration of wind generation in SA. This study suggested that when interconnectors are unconstrained and electricity demand between regional markets is imperfectly correlated, the competitive tension between connected states (SA and VIC) has the potential to lower price levels and smooth out price volatility. We also extend the studies of Clements et al. (2015), Nepal and Foster (2016), Ignatieva and Trück (2016), Apergis et al. (2017), and Han et al. (2020) that underscored the role of interconnectors in promoting market integration.

Finally, we assess the extent to which federal regulatory measures, namely, the CPM and the COVID-19 lockdown restrictions, impacted the level and volatility of electricity prices in the NEM. Existing studies such as Nazifi (2016), O'Gorman and Jotzo (2014), Maryniak et al. (2019), and Han et al. (2020) have been unable to confirm either the MOE of wind generation or its impact on volatility dynamics during the CPM period. Moreover, a recent analysis by the AEMO suggested a moderate reduction in electricity demand during the implementation of COVID-19 restrictions and lockdowns (AEMO, 2020d,e). No known empirical research has focused on investigating how the pandemic restrictions impacted the NEM.

1.3.2 Third chapter

First, we treat large-scale and rooftop solar generation as two separate variables. We are the first to consider the effects of both large-scale and rooftop solar generation separately on the level and volatility of spot prices. We extend Csereklyei et al. (2019), who studied only the MOE of large-scale solar generation using only the sparse observations available at the time. We also extend Abban and Hasan (2021), who combined large-scale and rooftop generation, thereby obscuring the individual contributions of these two variables to the price dynamics. This study also likely suffered from endogeneity problems.

Second, we are the first to apply high-frequency data based on 30-minute trading intervals to concurrently investigate the intraday merit order effect and intraday volatility. This analysis adds to recent NEM studies such as those by Abban and Hasan (2021) that suggested that the increase in VRE tends to impact the average (daily) price level and volatility negatively and positively, respectively. Any analysis using daily data is also likely to overestimate or underestimate the impact of solar generation and wrongly inform VRE policies to provide incentives to large-scale and rooftop solar generation.

Third, underscoring the observed variation of VRE output and electricity prices throughout the day, we also investigate the intraday profile of the impact of solar generation on spot prices. Existing studies have investigated off-peak and peak price dynamics by taking a daily average (Pereira and Rodrigues, 2015; Rintamäki et al., 2017; Kyritsis et al., 2017; Maciejowska, 2020). In contrast, our approach captures this effect directly from the high-frequency data. Previous studies have also overlooked the seasonal effects, yet electricity markets exhibit different characteristics over different seasons (Knittel and Roberts, 2005; Hirth, 2016; Hirth and Müller, 2016; Mountain et al., 2018; Bushnell and Novan, 2021). We add to the literature by analysing the impact of VRE on spot price dynamics over all four seasons of the year.

Finally, we thoroughly examine the intraday relationships between solar generation, spot price dynamics, and electricity generation mixes. In doing so, we extend earlier studies, such as that of Forrest and MacGill (2013), who investigated the impact of wind generation on spot prices as well as gas and coal-fired generation in SA and VIC and which demonstrated the potential of wind generation to reduce electricity prices and displace fossil-fuel generation.

1.3.3 Fourth chapter

First, this study makes a major contribution to the research on the potential impact of changes to market rules by investigating how the introduction of the 5MS impacts spot price dynamics and spot market revenues. The effects of the 5MS on the latter are likely to differ for different generators depending on how fast their plants can react to the 5MS (flexible vis-á-vis inflexible technology). We add to the earlier literature on the NEM by Rai et al. (2019), Rai and Nunn (2020a), Burger et al. (2020), and Csereklyei et al. (2021) that opined that 5MS would add value and provide more efficient pricing signals for investment in fast-response technology, such as batteries, reciprocating gas engines, and demand response.

Second, by studying the relationship between spot prices and revenues and the 5MS before and after the rule change, this analysis extends earlier studies Clements et al. (2016), Hurn et al. (2016), and Dungey et al. (2018) that demonstrated how the 30-minute price setting process permitted generators to game the market.

1.4 Thesis Outline

The rest of this thesis is structured into three main chapters covering three studies on the following subjects:

Chapter 2: Wind generation and the dynamics of electricity prices in Australia

Chapter 3: Large scale and rooftop solar generation in the NEM: a tale of two renewables strategies

Chapter 4: From 30- to 5-minute settlement rule in the NEM: An early evaluation.

Chapter 5 summarizes the findings of this thesis, provides reflections on the findings, and suggestions for future research avenues.

Chapter 2

Wind generation and the dynamics of electricity prices in Australia

This chapter is based on the peer-reviewed journal publication Mwampashi et al. (2021).

2.1 Introduction

In recent years, there has been a dramatic increase in variable renewable energy (VRE) generation in the Australian National Electricity Market (NEM), with rates ten times higher than the global average.[1] This has been driven by high electricity prices, the declining cost of VRE, and government policy incentives, including the Renewable Energy Target (RET) scheme (Stocks et al., 2019; de Atholia et al., 2020; Simshauser and Gilmore, 2020). The RET consists of two sub-schemes, the Large-scale Renewable Energy Target (LRET) and the Small-scale Renewable Energy Scheme (SRES). The former provides an incentive for large-scale generation, such as VRE farms and hydro-electric power stations. The SRES incentivises small-scale generation, such as rooftop solar, small-scale wind and hydro systems. The LRET aims at achieving 33,000 GWh of electricity sourced from large-scale renewable projects by 2020, which is equivalent to about 23.5% of Australia's electricity generation capacity (AER, 2018b). This target was met in September 2019, one year ahead of schedule (CEC, 2020). Although this is a tremendous outcome, it has raised concern about the impact of VRE on the system security and reliability of the NEM.

The NEM is a diverse electricity market involving an interconnected network of states with very different generation mixes and VRE penetration rates. The surge in VRE has

[1]Between 2018 and 2020, Australia would install more than 16 GW of wind and solar, which is equivalent to an average rate of 220 W per person per year. This capacity is more than two and a half times that of Germany, the next fastest country in the installation of renewable electricity capacity, and is more than four to five times faster than the European Union, Japan, the United States, and China (Stocks et al., 2019; COAG, 2019).

been associated with a marked reduction in greenhouse gases, and an increase of the environmental sustainability of the electricity energy sector. Furthermore, compelling empirical evidence has demonstrated the negative impact of VRE output on the level of electricity prices known as merit order effect (MOE) (Forrest and MacGill, 2013; Cludius et al., 2014a; Ketterer, 2014; Clò et al., 2015; Kyritsis et al., 2017; Csereklyei et al., 2019; Maciejowska, 2020). However, one of the largest challenges currently facing the NEM is the assessment and management of electricity price volatility. This challenge primarily arises from the intermittent nature of VRE, which makes it harder to equilibrate supply and demand (Baldick, 2011; Hirth, 2013; Rai and Nunn, 2020b; Kelley et al., 2020). The cyclic nature of demand and constraints in supply due to outages in transmission networks, strategic bidding practices, ramping of plants, and volatility in fuel prices all combine so that electricity markets tend to exhibit substantially greater price variability than is typical in financial markets (Ward et al., 2019; Han et al., 2020). With the recent closure and mothballing of several coal-fired generators, price variability has become more pronounced in the NEM. Reacting to the sharp increase in VRE, the frequency of negative pricing increased substantially over the last few years. Between 2017–2020, major changes linked to policy uncertainties and the investment megacycle in the NEM jeopardized the power system's reliability and security and increased operator interventions in the security-constrained dispatch process (Simshauser and Gilmore, 2020). Higher volatility can result in higher wholesale contract prices and in turn, higher prices for end-consumers, offsetting some or all of the price reduction via the MOE.

Wind generation has been the dominant VRE and has been the main contributor to this increasing volatility and negative prices.[2] Therefore, it would be useful to focus on the effect of wind generation in the NEM and to comprehensively analyse the determinants of not only the MOE but also most importantly, the volatility dynamics of electricity prices. We also investigate the impact of government policies and regulations, including

[2]South Australia is on track to meet its 100% target for renewables output by 2030; that is, a targeted volume of renewables output that is equal to the volume of electricity consumption in 2030 (AEMO, 2019d; Stocks et al., 2019). By the same year, Victoria and Queensland are each targeting a renewables share of 50%. Perhaps the most interesting globally is Tasmania, which is on track to meet its 100% target as soon as 2022 (COAG, 2019). Recently, the large-scale solar penetration accounted for part of this transformation in the NEM's generation mix. Nonetheless, wind power generation still dominates across all states except Queensland (QLD) and has been the central concentration of the LRET scheme.

the Carbon Pricing Mechanism (CPM) and the COVID-19 lockdown restrictions on the price level and volatility dynamics.

This study aims to gauge the effects of increasing wind output on the level and volatility of wholesale electricity prices in the NEM. Variables such as electricity consumption and gas prices play an essential role in determining the dynamics of electricity prices. Natural gas–fired peak load generators are commonly the marginal producers of electricity in the NEM. They tend to drive prices. High gas prices in recent years due to the increase in the liquefied natural gas (LNG) exports (resulting in an export-driven deficit in the local supply) account substantially for the upward movement in electricity prices in the NEM (Csereklyei et al., 2019; Simshauser and Gilmore, 2020). We consider two additional factors reflecting the integration of the generation mix and the market connectedness, and assess their contributions to the NEM dynamics. These factors are hydro generation and interconnector flow. This is the first study on the NEM that integrates the impact of hydro and interconnectors, which are two key contributors, especially in the current fast-transforming network of the NEM. Cross-border interconnectors offer a potential strategic solution to the intermittency of VRE by allowing pooling and sharing of available generation capacities (Du et al., 2017; Alasseur and Féron, 2018; Mountain and Percy, 2019b; Rai and Nunn, 2020b). Furthermore, it is well-known that hydro and pumped hydro generation increased significantly during the carbon pricing period, at the expense of gas and some coal plants (AER, 2014). Hydro is fast-start and flexible (like some gas plants), and thus this extra generation might have contributed to reducing prices and smoothing price volatility during this period.[3] The changing energy landscape in the NEM also means that pumped hydropower generation is becoming increasingly important for supplementing generation from VRE (de Atholia et al., 2020; Huang et al., 2020).

We focus on the four most mature markets (in terms of wind generation) in the NEM, namely, New South Wales (NSW), South Australia (SA), Victoria (VIC), and Tasmania (TAS). In the spirit of Ketterer (2014), we apply the exponential generalized autoregressive conditional heteroscedasticity (eGARCH) model proposed by Nelson (1991)

[3]Empirically, we use the aggregated regional output from run-of-river and pumped hydro plants. However, the two types of plants can have different impacts on prices and volatility. For instance, pumped hydro is like a battery, and therefore, can reduce down-and up-side volatility.

to study the electricity price and volatility dynamics. The main advantage of this approach is that both prices and volatility are modelled simultaneously while taking into account heteroscedasticity and the asymmetry effect, which are understood to be very important features of price volatility. In contrast to previous studies (Cutler et al., 2011; Forrest and MacGill, 2013; Rintamäki et al., 2017), we include the negative prices and price spikes without truncating or transforming the time series. We find both behaviours are pronounced and important in studying price dynamics in the NEM.

Using daily data (aggregated from high-frequency data) from the NEM from 2011 to 2020, we confirm the merit order effect of wind generation for all four regional markets. We also find evidence that electricity consumption, gas prices, and hydro generation are positively correlated to electricity prices. The high generation costs due to the prolonged period of dry conditions that stretched across much of Australia may explain the absence of the MOE for hydro generation. The interconnectors exhibit substantial but varying impacts on electricity prices depending primarily on the state's position (exporter or importer) as well as the thermal capacity of the respective interconnectors. In particular, all interconnector flows to NSW (Terranora (NSW–QLD), QNI (NSW–QLD), and VNI (VIC–NSW)) contribute substantially to lowering electricity prices. NSW is the most traditional importing region and has the largest capacity of interconnectors in the NEM. The impact of the other interconnectors is not consistent, reflecting the changing positions over time due to the increase in VRE penetration and the closure of coal-fired plants. In SA, the Heywood (VIC–SA) interconnector contributes to lowering electricity prices due to relatively high average imports from VIC, while Murraylink (VIC–SA) is positively related to price levels due to relatively low average imports from VIC. Similarly, the high average exports to SA and NSW via the Heywood interconnector and VNI respectively, contribute to lowering prices in VIC. Although the exports from TAS to VIC via the Basslink (TAS–VIC) interconnector are relatively higher over the sample period, we find evidence for a positive relationship with electricity prices in VIC and TAS.

In terms of price volatility, we find pronounced own-innovation and lagged volatility spillovers, and positive shocks increase volatility more than negative shocks of the same magnitude in NSW. The positive shocks may represent an unanticipated increase in demand. When demand rises in the short run coupled with convex marginal costs, additional generators with greater marginal costs are brought online to match the demand, resulting in higher price volatility (Knittel and Roberts, 2005; Bowden and Payne, 2008). The fact that this effect is more pronounced in NSW could be explained by its demand profile which is larger than other states in the NEM. Moreover, in states with high wind generation, its impact on price volatility is significant. Specifically, volatility increases by 2% and 1% in SA and VIC, respectively, for each 1 GWh rise in daily wind generation. In contrast, we find strong evidence for the opposite effect in TAS, where an increase in wind generation by the same amount reduces price volatility by 3%. Wind penetration exhibits a significant effect of the same sign for states with moderate penetration levels (around 15% in 2020); that is, increasing wind penetration by a 1 percentage point reduces and amplifies price volatility by 1% in TAS and VIC, respectively.

Electricity consumption, gas prices, and hydro generation increase the volatility of electricity prices. Higher volatility due to hydro generation follows from its dependence on weather conditions, which tends to vary over time. SA experiences a substantial impact of wind generation and gas prices on volatility compared to the other regions in the NEM, reflecting the heavy reliance on and relatively higher proportions of these variables in the region's generation mix. The interconnectors impact price volatility significantly, and their varying impacts reflect the increasing investments in VRE and the withdrawal of coal-fired generation in the connected markets. The VNI and Murraylink interconnectors increase price volatility in NSW and SA, respectively, and smooth out price volatility in VIC. The effect observed in NSW and SA may be linked primarily to the withdrawal of the Hazelwood power station, which removed 1600 MW of brown coal generation in VIC (5% of the NEM's total output). In contrast, the Heywood interconnector impacts VIC's price variability positively. Furthermore, the Basslink interconnector contributes significantly to reducing price volatility in TAS. Based on an outlier treatment analysis, we conclude that higher volatility in the NEM is associated with the high frequency of prices between 100 AUD/MWh and 500 AUD/MWh rather than extreme prices outside this range.

At the turn of this decade, two major regulatory measures impacted price and volatility dynamics in the NEM, the CPM and the COVID-19 lockdown restrictions. The former was part of the Australian Clean Energy Act and operated from 1st July 2012 to 1st July 2014. The legislation targeted at reducing greenhouse emissions in the electricity sector. Existing studies restricted their investigations to the impact of this reform on the level of electricity prices, electricity demand, and changes in the emissions intensity (O'Gorman and Jotzo, 2014; Nazifi, 2016; Maryniak et al., 2019). No studies examined the contribution of inter alia wind and hydro generation despite the increased investment in VRE and the competitiveness of hydro generation during this period. In addition, no known empirical research has focused on exploring the impact of the CPM along with price determinants on the volatility of electricity prices. The COVID-19 lockdown restrictions were more recent nationwide government measures imposed in late March 2020 to prevent the spread of the COVID-19 pandemic. To date, little is known about the impact of this pandemic on the energy sector. This is the first study to shed light on how the dynamics of electricity prices and the associated determinants were affected by the imposition of these restrictions.

We find strong evidence that during the operation of the CPM, prices increased substantially in coal-dominant regions, namely, NSW and VIC, and less in renewables-rich states, that is, SA and TAS. Wind and hydro generation played an essential role by exerting substantial downward pressure on the level of electricity prices. SA and TAS, both of which had a relatively large share of wind generation during this period, experienced a more substantial impact. In the same line, wind generation contributed to a reduction in price volatility. Moreover, we find evidence that electricity prices decreased during the COVID-19 lockdown restrictions period. The drop in prices primarily reflects the decline in demand, lower gas and coal prices, lower-priced offers, and increased renewable output. We observe no major changes associated with the merit order effect of wind generation and the marginal impact of the restrictions on price volatility.

These findings have significant implications for understanding the challenges associated with the recent influx of VRE in the NEM. In particular, the surge in wind generation has increased the variability and uncertainty of electricity prices, posing a significant risk to investors and consumers. The infrequent, very high, or low prices for very short periods call for well-established strategies for dealing with real-time power system security and reliability to be set. Priority should be given to investing in a more flexible system to accommodate the intermittency of the VRE sector, enhancing effective trade among regional markets through effective interconnections, and investing in electricity storage. Moreover, system architecture, regulation, and governance should be designed appropriately to deal with a range of potential future disruptions, such as COVID-19 pandemic.

The subsequent sections of this chapter are organized as follows. Section 2.2 describes the data and the model for the dynamics of electricity prices. The effects of wind generation on electricity prices and volatility are discussed in section 2.3. Section 2.4 analyses the impact of federal regulatory measures on electricity dynamics. Concluding remarks and policy implications are presented in section 2.5.

2.2 Data and Methods

2.2.1 Data and preliminary analysis

We consider wind generation for four NEM regions, namely, NSW, SA, VIC, and TAS, and study the effect on the level and volatility of electricity prices from 1st January 2011 to 31st December 2020. The main datasets for this analysis were obtained from the NEM via NEOpoint (2022). We use daily data, aggregated from high-frequency (5- and 30-minute) wholesale electricity prices (depicted in Figure 2.1), electricity consumption, wind electricity generation,[4] hydro generation, and interconnector flows (imports and exports). The daily gas price data for the same period for Adelaide and Sydney, representing SA and NSW, respectively, were obtained from the Short Term Trading Market (STTM; AEMO 2022e). The four-hourly gas price data for VIC were obtained from the Declared Wholesale Gas Market (DWGM; AEMO 2022b).

Wind generation in the NEM has increased significantly since 2010. As shown in Figure 2.2a, large-scale wind generation has grown exponentially across all states. The

[4]Except wind generation data series for TAS and VIC, no missing values were observed in the other variables. For the first region, the percentage of missing values is 0.92, 0.03, and 0.11 for the years 2011, 2012, and 2013, respectively. For the latter region, only two data points for the year 2011 are missing. We apply Kalman filters to impute the missing wind generation values. This approach often produces the best results when one deals with longer and more complex time series with trend and seasonality (Moritz and Bartz-Beielstein, 2017).

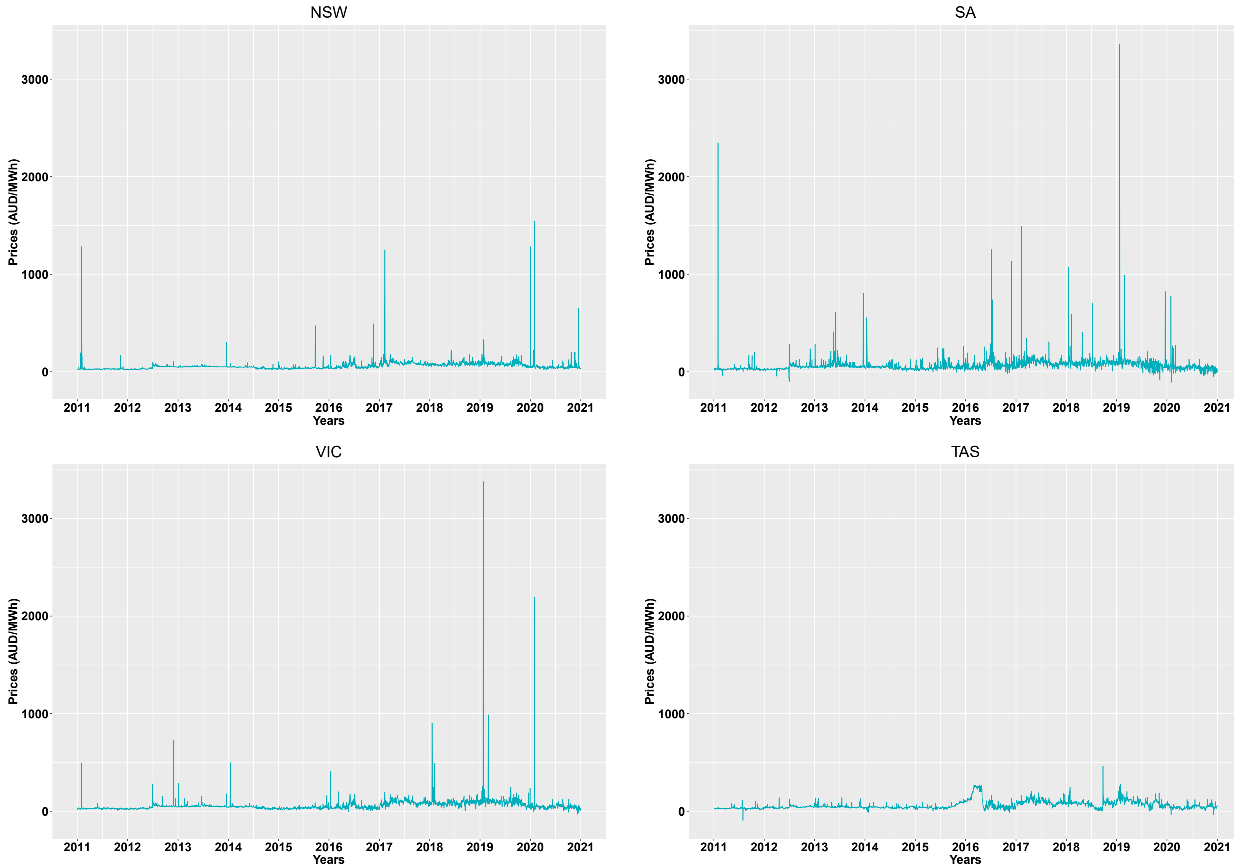
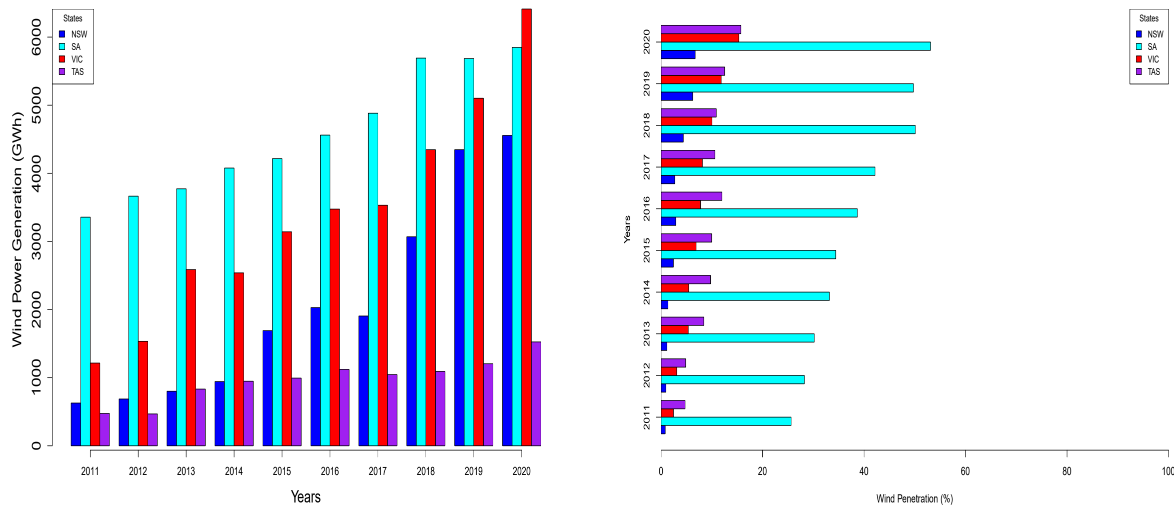


Figure 2.1 : **The equally weighted daily average spot price (regional reference price (RRP)) for NSW, SA, VIC, and TAS from 2011 to 2020.** The RRP is estimated on a half-hour basis by averaging six dispatch electricity prices.

constant level of wind generation in SA between 2018 and 2019 is attributed to the federal government's RET of 33,000 gigawatt-hours of national electricity capacity being met in 2019, accounting for 23.5% of Australian electricity. In 2020, VIC made the highest contribution to wind generation in the NEM. The MOE of wind generation is well-established in the literature, and we expect to observe the same impact in the NEM. However, the influence of wind on volatility remains unclear. Generally, observations from similar studies in European markets, for instance, Mauritzen (2010), Woo et al. (2011), Ketterer (2014), Clò et al. (2015), Rintamäki et al. (2017), and Maciejowska (2020), suggest that wind generation has a significant positive impact on price volatility. From these studies, and based on recent findings by Rai and Nunn (2020b) for the NEM, we infer that states with higher wind generation such as SA will exhibit a significant impact



(a) Wind generation (b) Wind penetration

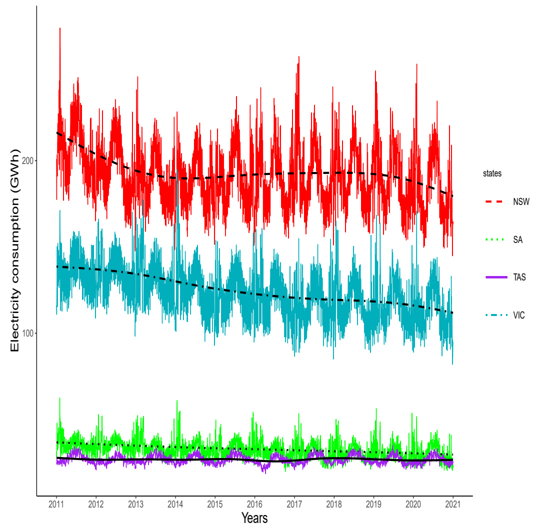
Figure 2.2 : **Large-scale wind generation (left panel) and wind penetration (right panel) for NSW, SA, VIC, and TAS, from 2011 to 2020.**

on volatility compared to states with lower wind generation such as NSW.

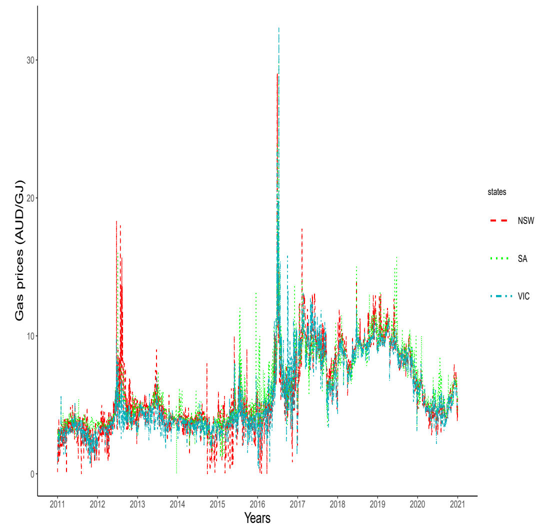
Two key factors driving the electricity price dynamics of the NEM are consumption and gas prices. Electricity consumption reflects demand profiles, which, given the non-storability of electricity, is expected to have a positive impact on prices across all NEM markets (Csereklyei et al., 2019; Forrest and MacGill, 2013). The latter is more pronounced in SA and VIC, where gas accounts for a substantial proportion of electricity generation. Notwithstanding this, Forrest and MacGill (2013) showed that the increase in wind generation displaces gas output in the two regions. The study by Csereklyei et al. (2019) suggested that the impact is still noteworthy. Since the second half of 2019 (see Figure 2.3), electricity prices have trended lower due to a combination of lower gas prices, decreasing consumption, and the influx of large-scale solar and wind generation as depicted in Figure 2.2a.[5] The uptake of rooftop solar PV generation contributed significantly to reducing consumption by meeting more than 5.5% of Australia's energy demand.[6] In 2020, the implementation of tighter pandemic restrictions due to COVID-19

[5]Detailed analysis of the price dynamics and its determinants during this period can be found in AEMO (2019c), AEMO (2020d), and AER (2020b).

[6]Australia is a global leader in solar PV generation, originating mainly from household rooftop in-



(a) Consumption



(b) Gas prices

Figure 2.3 : **The daily electricity consumption (left panel) and gas prices (right panel) for NSW, SA, VIC, and TAS from 2011 to 2020.**

may have accelerated the reduction in electricity consumption. Therefore, we examine the impact of wind generation on electricity prices and volatility dynamics while controlling for electricity consumption and gas prices.

Wind penetration is defined as the ratio between wind generation and consumption. This ratio therefore indicates the relative importance of wind output.[7] The same amount of wind generation could have a different impact on prices depending on the consumption levels over different times during the day. Wind penetration encompasses these effects and entails better predictions for price equilibrium. Figure 2.2a and 2.2b show the significant increase in wind generation and penetration from 2011 to 2020. This increase varies significantly between states. SA is the leader in the uptake of wind energy. Its penetration was approximately 50.1% in 2018, 49.7% in 2019 and 53.0% in 2020, which are the highest levels across the NEM. The drop in penetration between 2018 and 2019 reflects increasing

stallations. However, electricity generated from rooftop installations is not traded through the NEM. Given further that we estimate electricity consumption from grid demand (demand net of rooftop solar PV output), assessing the impact of rooftop solar generation on prices is beyond the scope of this study.

[7]Denoting the wind penetration by w_p, $w_p < 1$ indicates the volume of wind generation is less than the volume of consumption. $w_p = 1$ indicates these two volumes are the same, while $w_p > 1$ indicates wind output exceeds consumption. Scaling wind output by consumption provides an indicator of the relative importance of wind output on electricity consumption and also on prices.

instances of wind curtailment/spilling in 2019.

In addition to these variables, we control for cross-border interconnector flow and hydro generation. The interconnectors allow for inter-regional trade, up to their physical capacity limits (see Table A.1 in Appendix A.1) and electricity price variations among the regional markets (Brinsmead et al., 2014). There are six interconnectors, namely, Terranora (NSW-QLD), Queensland to New South Wales (QNI), Victoria to New South Wales (VNI), Basslink (T-V-MNSP1), Heywood (VIC-SA), and Murraylink (VIC-SA). The flow in these interconnectors can either be in a forward (export) or backward (import) direction. Evidence suggests that the interconnectors are among the essential determinants of price volatility in the NEM (Yan and Trück, 2020). This interrelationship was well-established by Han et al. (2020), who found volatility spillovers were more pronounced between adjoining and physically connected markets and less marked between geographically distant and unconnected markets.[8] Rai and Nunn (2020b) noted further that through the interconnectors, demand and supply between states with imperfectly correlated demand are equalized and thus, reduce price volatility. Figure 2.4 shows that NSW is a net importer of electricity from VIC and QLD. VIC experienced a significant drop in exports to NSW and SA in 2017 following the closure of the Hazelwood power station.[9]

We expect to observe varying impact of the interconnectors on prices depending on whether a state is an exporter or importer, and the capacity limit. Moreover, hydro generation influenced electricity price behaviour in the NEM. The increase in prices observed in 2015–16 resulted from extended drought conditions, which depleted dam levels for hydro generation (see Figure A.1 in Appendix A.1) (AER, 2015). The interrelation between carbon pricing and hydro generation is also of interest. Between 2012 and 2014, the noticeable upsurge and price plunge resulted from the introduction and repeal of carbon pricing (O'Gorman and Jotzo, 2014). The introduction triggered the competitiveness of hydro generators and contributed an approximate 36% output rise in the NEM during

[8]The most pronounced volatility spillover is observed between NSW and QLD, SA and VIC, NSW and VIC, and TAS and VIC. The spillover is less pronounced between SA and QLD, and TAS and QLD.

[9]The closure of the Hazelwood power station caused a decrease of around 5% in the NEM's output (Burke et al., 2019; Mountain and Percy, 2019b).

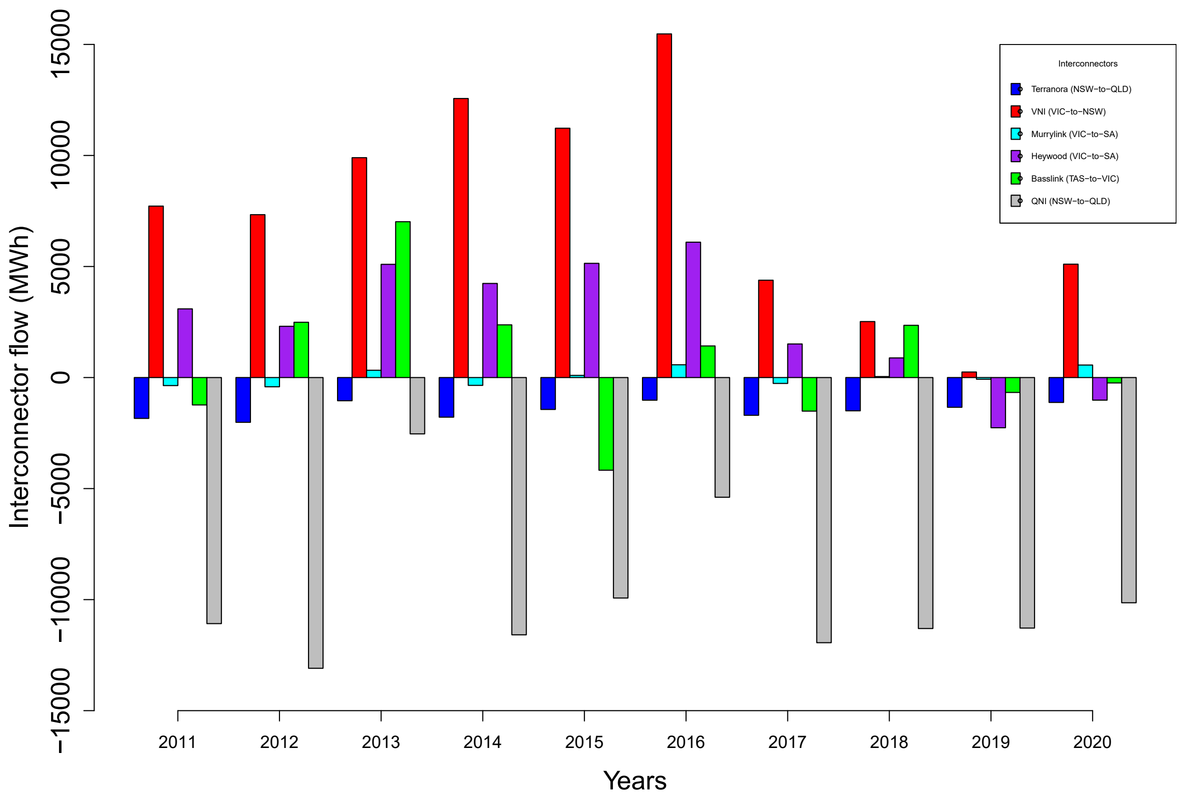


Figure 2.4 : **The average annual net interconnector flow for NSW, SA, VIC, and TAS from 2011 to 2020.** The positive sign indicates a forward flow (export to), and the negative sign indicates a backward flow (import from).

2012–13. This effect is evident in Figure 2.4 by the increase in exports from TAS to VIC from increased hydro generation. The impact of hydro generation and interconnectors in the NEM have not been studied previously despite being important determinants of price dynamics.

We include these variables in the analysis to ensure the estimated model does not suffer from endogeneity issues (Forrest and MacGill, 2013; Csereklyei et al., 2019).[10,11,12] Negative prices in all four regions under study are stipulated mainly by wind generation, especially in SA (AER, 2020b). In QLD, negative prices arise from solar generation. As wind generation in QLD is marginal, we do not consider QLD.[13] Genoese et al. (2010) showed that wind generation is the dominant factor for negative prices during off-peak periods (driven by low system load and low wind generation or low system load and high wind generation). Maciejowska (2020) also suggested that negative prices in Germany are due to wind generation only (not solar); corresponds to when demand is low, typically on weekends or public holidays. Furthermore, negative prices in Europe occur at night when wind generation is occasionally high (Paraschiv et al., 2014; Deschatre and Veraart, 2017). Thus, based on the available empirical evidence, we exclude large-scale solar from the analysis for two main reasons. First, we exclude QLD, and second, large-scale solar penetration in other NEM regions historically has been very low. We expect the omission of large-scale solar to have only a modest impact on the analysis.[14] We recognize that coal

[10]Large-scale solar generation represents the potential for omitted variable bias. It is excluded from the analysis, however, because data are available for only a few years (around five years for NSW, two years for VIC and SA, and none for TAS), and much of the impact is likely to emanate from rooftop solar PV for which data are harder to acquire. Rooftop solar generation meets around 20% of customers' needs and supplied around 5.2% (compare to 2.5% from solar farms) of the NEM's total electricity requirements in 2019 (AER, 2020b).

[11]We assume that solar and wind generation are exogenously determined. This allows us to establish a one-way causal relationship between the level of generator output and the spot price. We believe that this is a plausible assumption for two reasons: (i) Solar and wind generation are driven by natural phenomena, namely the level of sunlight and wind, respectively. (ii) Their low marginal cost of generation allows them to be dispatched under the vast majority of market conditions (Bell et al., 2017). Interconnector flows are likely to be endogenous with price volatility. Nonetheless, we believe we can draw causal conclusions about their impacts on electricity price dynamics, as in Rintamäki et al. (2017). This stems from the fact that five of the six interconnectors in the NEM are regulated. This means their revenues are set by the AER and fixed annually, regardless of flows or the spot prices between interconnected markets. Furthermore, even if this happens to be the case, it is unlikely to significantly bias the results. Typically, when the interconnectors are unconstrained and the electricity demand between regional markets is imperfectly correlated, price arbitrage forces prices to converge to a single price (ignoring electrical losses). In constrained interconnectors, the markets separate, and regions with access to lower-cost generation will be marginally lower.

[12]The data employed in this analysis are actual real-time data obtained from the NEM, not estimates or measurements. Therefore, unless there are reporting errors, there will be no measurement error in the dependent variable. Moreover, using a sufficiently large number of observations in the model ensures the estimators are unbiased and the standard errors are correct. Put differently, the robust standard errors asymptotically converge to the correct standard errors.

[13]The impact of solar generation is examined indirectly via the Terranora interconnector and the QNI. It is likely that part of the imports from QLD to NSW come from solar generation which tends to peak during the day.

[14]To test the plausibility of these assumptions, we re-ran the analysis by including both large-scale

prices can also affect the level and volatility of electricity prices because coal generators set electricity prices 50% to 60% of the time, even in SA (AER, 2020a). The importance of coal as a price-setter in non-coal dominant regions, such as SA, reflects the market's inter-connectedness, and thus, the impact of coal prices in NSW or VIC can be felt in neighbouring NEM regions. However, we omitted coal prices from the analysis for the following three reasons.

First, coal prices are unavailable at the same time-frequency as the proposed model (i.e., daily). Second, there is a wide variation in coal generators' fuel prices. This price variation is not just due to brown versus black coal generators. There is also a significant variation in coal prices paid across black coal plants. For example, AEMO shows a coal price range of 1.2 AUD/GJ to 3.99 AUD/GJ across black coal plants for the financial year 2020. This price variation reflects different grades of black coal used across the black coal fleet. Furthermore, the variation reflects differing degrees of exposure to international export prices, due to legacy long-term black coal contracts and differing degrees of exposure to spot versus forward export prices. For instance, NSW black coal generators obtain their coal at a discount through a long-standing contract, most of which will expire by 2022 to 2025 (ABC, 2018). Thus, there is no single black coal price within a particular region (AEMO, 2020b). Third, gas prices are the de facto electricity price-setter even when gas plants are not running, due to instances of black coal generators "shadow pricing" gas in their spot market offers (i.e., black coal plant offering their capacity at prices just below the short-run marginal cost (SRMC) of the gas plant; AEMO 2018). This means that excluding coal prices is unlikely to have a severe impact on this analysis, as electricity spot prices are based on the bids of generators, which as the "shadow pricing" dynamic illustrates, can be, and often are, above generators' SRMCs.

The descriptive statistics of electricity prices and exogenous variables considered in this analysis, namely, electricity consumption, wind generation, gas prices, hydro generation, and interconnector flows, are summarized in Table 2.1. We observe a considerable

and rooftop generation. We found that the inclusion of solar generation has only a slight impact on the coefficients and no effect on the overall conclusion of the impact of the exogenous variables on the price dynamics. The results for this supplementary analysis are available in Appendix A.4.1. We thank an anonymous referee who suggested to test these assumptions.

Table 2.1 : **Summary statistics of daily data (aggregated from high-frequency data) from 2011 to 2020.**

	Unit	Mean	Standard Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile
						NSW				
Electricity Prices	AUD/MWh	59.93	57.80	15.51	329.28	51.13	18.54	1539.50	36.24	73.20
Gas Prices	AUD/GJ	5.84	2.86	0.96	5.50	4.96	0.00	29.00	3.75	8.16
Wind Generation	MWh	5654.92	5327.58	1.46	5.08	3813.43	-1.54	29922.14	1623.26	8250.75
Hydro Generation	MWh	6544.96	4678.49	1.08	4.07	5421.42	-0.27	29509.67	2854.81	9245.71
Electricity Consumption	MWh	193359.00	18548.78	0.34	3.11	192034.00	144854.00	276893.00	180777.00	205819.00
						SA				
Electricity Prices	AUD/MWh	67.91	97.24	17.68	479.40	53.16	-107.16	3359.82	34.52	82.33
Gas Prices	AUD/GJ	6.12	2.60	1.22	6.61	5.22	0.00	29.99	3.99	8.21
Wind Generation	MWh	12525.39	7514.22	0.70	2.72	10892.88	57.68	36846.13	6643.36	17464.01
Electricity Consumption	MWh	32929.00	5425.67	0.72	4.36	32560.00	19907.00	62493.00	29214.00	36013.00
						VIC				
Electricity Prices	AUD/MWh	59.34	80.05	26.24	960.73	47.77	-31.66	3377.97	31.64	74.45
Gas Prices	AUD/GJ	5.60	2.71	1.15	6.15	4.50	0.30	32.32	3.55	7.98
Wind Generation	MWh	9275.61	7548.66	1.31	4.48	6891.24	30.54	44376.34	3584.59	13090.66
Hydro Generation	MWh	7213.13	5307.32	0.92	3.19	5904.35	-7.96	28751.15	2919.57	10454.51
Electricity Consumption	MWh	124993.00	15322.71	0.09	2.78	124981.00	81940.00	194849.00	113536.00	136125.00
						TAS				
Electricity Prices	AUD/MWh	60.88	42.34	2.30	11.15	44.94	-94.67	461.64	34.82	461.64
Wind Generation	MWh	2656.92	1911.00	0.88	3.32	2190.42	-14.85	11505.68	1156.15	3853.46
Hydro Generation	MWh	25328.00	8348.48	-0.01	2.04	25375.00	5820.00	45120.00	18413.00	32168.00
Electricity Consumption	MWh	26782.00	2474.18	0.35	2.76	26437.00	18558.00	35097.00	25007.00	28476.00
						Interconnector Flow				
Terranora (NSW-QLD)	MWh	-1479.70	707.85	-0.15	2.99	-1460.60	-3852.80	926.10	-1950.30	-993.00
QNI (NSW-QLD)	MWh	-9828.00	6836.75	0.04	2.31	-9653.00	-25216.00	8617.00	-15080.00	-4940.00
VNI (VIC-NSW)	MWh	7649.00	9035.16	-0.01	2.27	7808.30	-15983.40	14449.00	663.80	30337.50
Basslink (T-V-MNSP1)	MWh	782.20	6433.27	-0.16	2.07	266.30	-11472.00	14149.30	-3861.40	6131.70
Heywood (VIC-SA)	MWh	2508.90	4933.49	-0.25	2.48	2750.30	-11668.90	14142.20	-939.90	6297.20
Murraylink (VIC-SA)	MWh	13.81	1166.32	0.54	4.25	-35.25	-3611.30	5040.13	-699.51	616.97

The summary statistics of wind generation, hydro generation, electricity consumption, and interconnector flow are estimated by aggregating the 5-minute data series in megawatts divided by 12. The rationale behind this approach is to convert the given data series, which relates to power, into energy in megawatt hours. The summary statistics for the electricity prices are estimated from the daily averaged spot price or the regional reference price (RRP). The letters T and V in the interconnector flow stand for Tasmania and Victoria, respectively. The acronym MNSP stands for market network service provider, that is, merchant or economically unregulated.

variation in the level and volatility of electricity prices in all the markets. During the sample period, NSW is a net importer of electricity. This is consistent for all three interconnectors, that is, Terranora, QNI, and VNI. VIC is a net exporter of electricity to NSW and SA, through the VNI, and Heywood, interconnectors, respectively. However, VIC imports only 8% of the total exports from TAS via the Basslink interconnector. Figure 2.1 illustrates that extreme price spikes characterize the Australian electricity market. It is common in merit order effect studies to treat these observations as outliers (Cutler et al., 2011; Forrest and MacGill, 2013; Cludius et al., 2014b) and truncate prices series based on the marginal costs of generation.[15] We do not truncate the series and include all the observations to capture the volatility of prices more effectively.[16] Furthermore, we apply a two-stage method similar to those of Thomas and Mitchell (2005) and Ketterer (2014) and adjust the seasonal and trend effect using ordinary least squares (OLS) before fitting the proposed models.[17] The filtered series is a more robust explanator of the impact of the exogenous variables on electricity prices without the noise emerging from seasonality and trends. The approach, results, and statistical tests of the time series adjusted for the seasonal and trend effect for all the variables are presented in Appendix A.1.3 and A.1.4.

2.2.2 Negative prices in the NEM

Negative prices may occur when periods of relatively low demand coincide with a high supply of VRE and restrictions on inter-regional power flows (Forrest and MacGill, 2013; AEMO, 2019a). Before 2012–13, negative prices occurred overnight or in the early hours of the morning, due to low demand combined with the inflexibility of brown-coal electricity generation. Recently, negative prices have been observed during the middle parts of the day when generators, including intermittent renewable energy and coal-fired generators, compete to dispatch their energy. The system operator (AEMO) ensures the expected demand for electricity is met in the most cost-efficient way using an algorithm that dispatches generators from the cheapest to the most expensive. As the former sources have zero marginal cost, they are prioritized in the dispatch process. This, in turn, reduces demand for thermal generators and forces the plant back to its minimum stable generation

[15]The rationale behind this approach is that the truncated series represents the typical conditions of the market rather than times when the market is operating under extreme conditions. Factors such as capacity-limited generation, low renewable output, technical limits on the interconnectors, the restriction on the import capacities, as well as an unexpected and substantial change in demand are among the factors accounting for this market extremity (Geman and Roncoroni, 2006; Weron, 2007; Wood and Blowers, 2016; Ward et al., 2019; Yan and Trück, 2020).

[16]We find a slight difference between the actual price series and the one obtained by top capping prices at 500 AUD/MWh, which is the highest short-run marginal costs of generation in the NEM. Only 20, 8, and 6 observations in SA, VIC, and NSW exceed this threshold. As a robustness check, however, we run a separate analysis and treat price spikes as outliers (Ruiz et al., 2001; Mugele et al., 2005; Bierbrauer et al., 2007; Ketterer, 2014). The technical details of the approach employed for this adjustment are given in Appendix A.1.2. We will present the results of this approach and show how the two treatments of price spikes affect the empirical analysis.

[17]The present approach differs from that of Ketterer (2014) in two ways. First, the seasonal noises are removed in the independent and dependent variables, which is more econometrically sounding (Pineau et al., 2020). Second, we adjust for the trend effect in all variables and on either side of the equation.

level. The intermittent nature of solar PV generation, for instance, means that it cannot meet peak demand in the late afternoon and evening when solar radiation is low or not available. This calls for the supply from base-load generators and from more flexible sources (i.e., open-cycle gas turbines (OCGTs), combined cycle gas turbines (CCGTs), and hydro). Base-loads have low operating costs with high start-up and shutdown costs, making frequent shutdowns uneconomical to meet the variable demand. To guarantee dispatch and keep the plant running, coal-fired generators typically bid their minimum stable megawatts at the floor price.

As noted above, negative prices are an important feature of the electricity market in Australia. Over the 2011–2020 period, SA was the first state to experience negative prices when low demand coincided with high wind generation (see Figure 2.1). The current minimum price (market price floor) in the NEM is set at -1,000 AUD/MWh. During negative price periods, wind typically drives negative prices in SA, while brown coal is typically pushed down by wind in VIC. The 5-minute negative dispatch periods increased significantly between July and November in 2019 for SA and VIC, reaching more than 600 in October 2019 and February 2020 (Cornwall Insight, 2020). Storage technologies, such as pumped hydro and battery storage, capitalize on low price periods. These low or negative price periods occur more regularly and last longer, e.g., on 21st July 2019, the spot prices in SA remained in negative territory for 4.5 hours and in VIC for 1.5 hours.[18]

The treatment of negative prices varies. Many researchers either truncate prices series (Cutler et al., 2011; Forrest and MacGill, 2013; Cludius et al., 2014b) or simply remove them from the analysis (Rintamäki et al., 2017).[19] Given the increasing frequency of negative price periods and a desire to more accurately capture NEM dynamics, we contend that it is important to include them in any analysis.[20] Similar to Kyritsis et al. (2017) and

[18]This event occurred at 1:15 pm on Sunday, 21st July 2019, when low demand coincided with high generation from wind and solar and unrestricted transfer of electricity across the interconnectors.

[19]This approach eases the application of the log transformation, which, in turn, stabilizes the variance and simplifies the interpretation of the estimated coefficients as elasticity (Weron, 2007; Ketterer, 2014; Rintamäki et al., 2017).

[20]We initially attempted to employ an alternative transformation that allows one to retain zero-value and non-positive observations while maintaining an approximate interpretation of the model results as elasticity and stabilizes the variance, in particular, the approach based on the inverse hyperbolic sine transformation (Burbidge et al., 1988; Schneider, 2011; Uniejewski et al., 2017; Ziel and Weron, 2018).

Thomas et al. (2011), we find these values are valid observations, and ultimately, their inclusion will shed more light on the empirical analysis. We further observe a clear link between wind generation and negative prices. In particular, SA and TAS, with higher wind penetrations, exhibit more incidents of negative prices compared to states with lower wind penetration, such as VIC. We observed zero negatives price cases in NSW, the state with the lowest wind penetration. The absence of negative prices in NSW may also be due to the relative flexibility of the region's thermal plants and lower minimum stable generation levels.

2.2.3 Modelling level and volatility of electricity prices

We model the effects of various exogenous variables, such as wind generation and consumption, on the level and volatility of electricity prices, using an ARX-eGARCHX[21,22]

However, the direct application of this approach suppresses the upward spikes at the cost of amplifying the downward spikes (Schneider, 2011). By doing so, the resulting transformations fail to preserve the characteristics of the original time series. Although the transformation proposed by Schneider (2011) resolved this challenge, its application to the variables of interest complicates the interpretation of the model output.

[21]Few researchers on the subject have been able to investigate the impact on price behaviours as an integrated study. For instance, Woo et al. (2011) and Ketterer (2014) applied the AR-GARCH, Kyritsis et al. (2017) applied the GARCH-in-mean models, and Maciejowska (2020) applied the quantile regression model. Furthermore, previous volatility studies in the NEM found that the GARCH specification does not adequately accommodate the skewed and fat-tailed characteristics of electricity prices. In particular, Higgs and Worthington (2005) and Thomas and Mitchell (2005) found the skewed Student asymmetric power ARCH (APARCH) and eGARCH, respectively, to be the appropriate choices.

[22]To explore alternatives to the eGARCH modelling approach we examined realized variance modelling for comparison. We constructed lower frequency (daily) statistic volatility measures using the Realized Variance (RV) and Intraday Range (IR) from high-frequency prices. We then applied the realized GARCH (realGARCH) modelling approach of Hansen et al. (2012), to model prices and realized volatility measures jointly. The realGARCH includes the measurement equation that relates the observed realized measure to the conditional variance (the latent volatility). Furthermore, the measurement equation includes the asymmetric reaction to shocks for a more flexible model than the vanilla GARCH. We found that the realGARCH failed to outperform the eGARCH model under both the RV and IR measures. Also, the former fails to produce promising results for the impact of the exogenous variables on electricity price dynamics. Results of this analysis are presented in Appendix A.4.2. These findings contrast with several studies (Haugom et al., 2010; Frömmel et al., 2014). Exploring the issue of modelling power market dynamics other than for modelling or forecasting of volatility alone raises interesting questions which require further examination. However, this is beyond the scope of the present study as this analysis requires thorough investigation of variance measures and their applicability in electricity markets.

model specification:

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \xi_j' \boldsymbol{v}_{t-j} + \varepsilon_t, \tag{2.2.1}$$

$$\varepsilon_t = z_t \sigma_t, \quad \text{with,}$$

$$\log_e(\sigma_t^2) = \omega + \sum_{i=1}^{p} (\alpha_i z_{t-i} + \gamma_i (|z_{t-i}| - \mathbb{E}|z_{t-i}|)) + \sum_{j=1}^{q} \beta_j \log_e(\sigma_{t-j}^2) + \sum_{k=1}^{r} \delta_k' \boldsymbol{v}_{t-k}, \tag{2.2.2}$$

where equation (2.2.1) is the autoregressive (AR) structure of the conditional expectation, and equation (2.2.2) is the eGARCH model of the conditional variance with exogenous variables.[23] p_{t-i}, $i = 1, \ldots, m$, are lags of the electricity prices, $\boldsymbol{v}_t$ is a vector of variables, and ξ and δ are vectors of coefficients. The exogenous variables used in this analysis are defined in Table 2.2. σ_t is a time-dependent standard deviation given past information that defines the volatility of electricity prices. Thus, the volatility measure is an indirectly observed dynamic process which is inferred from the observed price dynamics via the estimated model parameters. ω is the intercept, and the parameters α_i and γ_j capture the sign and size effect of the standardized innovations on volatility. The expected value of the absolute standardized innovation is defined as $\mathbb{E}|z_t| = \int_{-\infty}^{\infty} |z| f(z, 0, 1, \ldots)\, dz$, and volatility persistence is given by $\sum_{j=1}^{q} \beta_j$ (Ghalanos, 2022). The autoregressive term is included to capture the serial correlation in prices; where applicable, the order is chosen to minimize the Bayesian information criterion (BIC).

Compared to vanilla GARCH, the eGARCH model considers the variance of $\log_e(\sigma_t^2)$, which guarantees that the conditional variance is positive regardless of the estimated coefficient values (Zivot, 2009). With no restrictions in the model, likelihood maximization tends to yield faster and more reliable optimizations results. Furthermore, electricity prices are characterized by some forms of non-linear dynamics, exhibiting strong dependence on price variability on its past (Weron, 2007). Using the eGARCH model, which accounts for heteroscedasticity, provides a more accurate tool of the heteroscedasticity in the errors and in turn, an efficient estimator of the coefficients in the equation. The proposed eGARCH model is also used to examine the sign effect in the electricity mar-

[23]The eGARCH model is the modification of the standard GARCH model proposed by Nelson (1991) which allows for the leverage effect to better capture temporal variations in market volatility.

Table 2.2 : **Exogenous variables**

Variable	*Description*
wind	*Regional daily average wind power generation in megawatt hour (MWh)*
$wind_{pen}$	*Regional wind penetration, defined as a ratio of daily average wind power generation to the daily average electricity consumption*
hydro	*Regional daily average hydro power generation in megawatt hour (MWh)*
consumption	*Regional daily average amount of power consumed in megawatt hour (MWh)*
gas	*Regional daily average gas price in AUD per GJ*
$exim_{murr}$	*Daily average exports and imports via Murraylink interconnecor (VIC-to-SA) in megawatt hour (MWh)*
$exim_{heyw}$	*Daily average exports and imports via Heywood interconnector (VIC-to-SA) in megawatt hour (MWh)*
$exim_{VNI}$	*Daily average exports and imports via New South Wales to Victoria interconnector (VNI) in megawatt hour (MWh)*
$exim_{bass}$	*Daily average exports and imports via Basslink interconnector (TAS-to-VIC) in megawatt hour (MWh)*
$exim_{terra}$	*Daily average exports and imports via Terranora interconnector (NSW-to-QLD) in megawatt hour (MWh)*
$exim_{QNI}$	*Daily average exports and imports via New South Wales to Queensland interconnector (QNI) in megawatt hour (MWh)*

ket.[24] In contrast, autoregressive moving average (ARMA)-type models, such as that of Rintamäki et al. (2017), are limited by the constant variance assumption, which is inconsistent with volatility dynamics observed in electricity markets.

2.3 Wind Generation and Electricity Dynamics in the NEM

We estimate separate regressions of the AR-eGARCH and ARX-eGARCHX specifications using a single autoregressive component and the Student distribution of the standardized residuals for each state.[25] The technical details regarding the optimal ARMA structure and the distribution of the standardized residuals are given in Appendix A.2. Tables 2.3 to 2.6 present the regression estimates for the four states, namely, NSW, SA, VIC, and TAS, respectively.[26]

[24]Empirical studies in financial time series often find evidence that negative shocks tend to have a more substantial impact on volatility than positive shocks of the same magnitude (Zivot, 2009).

[25]The models employed in the analysis consider each of the independent variables separately and the final model includes all independent variables to determine whether each of these variables captures independent sources of variation. The results reveal that, in general, coefficients remain almost unaffected by the inclusion of the other variables.

[26]Each table shows the estimated coefficients and the corresponding p values (in parentheses) for the mean and variance equations, the estimated shape parameters of the Student distribution, Akaike information criterion (AIC), and the BIC. We investigate the adequacy of the model fit using the weighted Ljung-Box test and the weighted Lagrange multiplier test (ARCH-LM tests) (Fisher and Gallagher, 2012). The former is the portmanteau test with the null of adequate ARMA fit, and the latter adequately fitted

Table 2.3 : **The effect of wind generation, electricity consumption, gas prices, hydro generation, and interconnectors flow on New South Wales' electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is the daily average electricity spot prices.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
					Mean Equation					
μ	53.3003	56.2815	-8.498	-3.1298	55.9352	49.6266	48.3720	49.4973	3.5314	46.8051
	(0.0000)	(0.0000)	(0.0001)	(0.3635)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0457)	(0.0000)
ϕ_1	0.8337	0.8395	0.8437	0.8501	0.8412	0.82971	0.8347	0.8465	0.8510	0.8464
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
wind		-5.7074		-5.3918					-4.4038	
		(0.0000)		(0.0000)					(0.0000)	
consumption			3.1970	3.0590					2.3761	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-100.0000					-90.7210
					(0.0000)					(0.0000)
gas						0.6360			0.1849	0.3389
						(0.0000)			(0.0953)	(0.0064)
hydro							7.7830		4.2338	6.9333
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-9.6408	-9.1751	-10.1740
								(0.0325)	(0.0262)	(0.0081)
$exim_{QNI}$								-3.7036	-1.7382	-2.0740
								(0.0000)	(0.0001)	(0.0000)
$exim_{VNI}$								-1.3849	-0.9897	-1.0153
								(0.0000)	(0.0000)	(0.0000)
					Variance Equation					
ω	2.7369	2.7862	-1.0294	-1.1943	2.8227	2.4392	2.3443	2.4957	-0.5354	1.8624
	(0.0000)	(0.0000)	(0.0453)	(0.0234)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3392)	(0.0000)
α	0.1667	0.1501	0.1742	0.1514	0.1511	0.1550	0.1545	0.1725	0.1337	0.1264
	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0004)	(0.0002)	(0.0000)	(0.0000)	(0.0002)	(0.0005)
β	0.4684	0.4624	0.4020	0.3928	0.4605	0.4475	0.4297	0.4408	0.3327	0.3620
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.5977	0.6294	0.6211	0.6532	0.6329	0.6022	0.6493	0.5404	0.6461	0.6404
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
wind		-0.0504		-0.0496					-0.0721	
		(0.4981)		(0.5316)					(0.3925)	
consumption			0.2066	0.2180					0.1313	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-1.9696					-1.9449
					(0.1651)					(0.2186)
gas						0.0661			0.0679	0.0714
						(0.0002)			(0.0007)	(0.0002)
hydro							0.6779		0.5598	0.6607
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-0.9515	-1.2272	-1.1685
								(0.1780)	(0.1218)	(0.1290)
$exim_{QNI}$								-0.0889	-0.1030	-0.1148
								(0.2095)	(0.2026)	(0.1426)
$exim_{VNI}$								0.1074	0.1491	0.1123
								(0.0032)	(0.0004)	(0.0055)
Shape	2.54860	2.5180	2.6504	2.6236	2.5136	2.5805	2.8043	2.6244	2.9335	2.8953
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log Likelihood	-13468.55	-13368.51	-13274.14	-13166.94	-13349.35	-13452.04	-13329.67	-13360.38	-13050.89	-13138.66
AIC	7.3778	7.3241	7.2725	7.2149	7.3136	7.3699	7.3029	7.3219	7.1568	7.2038
BIC	7.3897	7.3394	7.2877	7.2335	7.3289	7.3851	7.3181	7.3439	7.1925	7.2360
Q(20)	1.1959	1.1449	4.1808	4.3505	1.1809	1.16032	1.1501	1.0852	3.633	1.1653
	(0.9133)	(0.9229)	(0.1981)	(0.1750)	(1.1809)	(0.9200)	(0.9219)	(0.9333)	(0.2900)	(0.9191)
$Q^2(36)$	0.0048	0.0048	0.0157	0.0157	0.0048	0.0049	0.0033	0.0042	0.0054	0.0034
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0023	0.0025	0.0089	0.0093	0.0024	0.0023	0.0020	0.0022	0.0026	0.00211
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table 2.4 : **The effect of wind generation, electricity consumption, gas prices, and interconnectors flow on South Australia's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is the daily average electricity spot prices.

	Model A	Model B	Model C	Model D	Model E	Model F	Model H	Model I	Model J
					Mean Equation				
μ	59.8851	79.1461	-36.2916	14.4912	78.7160	11.8400	58.0674	-14.3282	40.4341
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.5851	0.6348	0.6108	0.6442	0.6270	0.4818	0.6293	0.5565	0.5292
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-15.3506		-12.9713				-13.2384	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			29.5007	18.8968				17.7031	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-48.1246				-46.8130
					(0.0000)				(0.0000)
gas						8.0323		5.9135	5.9099
						(0.0000)		(0.0000)	(0.0000)
$exim_{heyw}$							8.0595	-10.1971	-9.013
							(0.0000)	(0.0000)	(0.0000)
$exim_{murry}$							79.0538	40.5319	40.8871
							(0.0000)	(0.0000)	(0.0000)
					Variance Equation				
ω	3.0192	3.6270	1.2670	1.2655	3.5607	1.8279	4.4091	0.6940	2.6475
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0174)	(0.0000)
α	-0.1088	-0.0316	-0.069	-0.0222	-0.0589	-0.1710	0.0460	-0.0634	-0.1095
	(0.0093)	(0.5036)	(0.0529)	(0.5697)	(0.1915)	(0.0000)	(0.0865)	(0.0907)	(0.0104)
β	0.5865	0.4905	0.4875	0.4653	0.5089	0.6570	0.3742	0.4617	0.4723
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.5101	0.5047	0.5995	0.5758	0.4945	0.4490	0.6204	0.5235	0.4858
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
$wind$		0.0212		0.0944				0.1852	
		(0.5917)		(0.0243)				(0.0006)	
$consumption$			0.6776	0.6744				0.5782	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-0.2076				0.1892
					(0.0668)				(0.2414)
gas						0.1019		0.1119	0.1398
						(0.0001)		(0.0000)	(0.0000)
$exim_{heyw}$							0.1964	0.1054	0.1555
							(0.0261)	(0.2548)	(0.0913)
$exim_{murr}$							0.6265	0.5573	0.5402
							(0.1156)	(0.1310)	(0.1369)
Shape	2.4330	2.3352	2.7072	2.5608	2.3605	2.5107	2.3698	2.6614	2.4552
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-17051.19	-16519.94	-16692	-16317.15	-16448.35	-16924.94	-16566.96	-16177.4	-16279.68
AIC	9.3393	9.0495	9.1437	8.9396	9.0103	9.2713	9.0764	8.8664	8.9213
BIC	9.3512	9.0648	9.1590	8.9583	9.0256	9.2865	9.0950	8.8952	8.9467
Q(20)	0.3707	0.4813	6.191	5.325	0.5218	0.6061	0.5512	5.842	0.8485
	(0.9977)	(0.9944)	(0.0395)	(0.0819)	(0.9927)	(0.9882)	(0.9913)	(0.0533)	(0.9669)
$Q^2(36)$	0.0356	0.0340	0.0748	0.0739	0.0359	0.0366	0.0281	0.0955	0.0333
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0303	0.0278	0.0483	0.0479	0.0294	0.0312	0.0204	0.0662	0.0260
	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(1.0000)	(1.0000)	(1.0000)	(0.9998)	(1.0000)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table 2.5 : **The effect of wind generation, electricity consumption, gas prices, hydro generation, and interconnectors flow on Victoria's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is the daily average electricity spot prices.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
					Mean Equation					
μ	55.0753	62.1499	-27.1279	-0.2670	61.1217	43.8828	45.8466	58.4270	29.3533	49.5906
	(0.0000)	(0.0000)	(0.0000)	(0.6267)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.7574	0.7900	0.7840	0.8059	0.7929	0.7515	0.7909	0.7949	0.8004	0.7988
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-9.0553		-7.8953					-5.3734	
		(0.0000)		(0.0000)					(0.0000)	
$consumption$			6.5340	4.8924					1.6992	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-100.0000					-64.9995
					(0.0000)					(0.0000)
gas						1.9989			1.3367	1.4138
						(0.0000)			(0.0000)	(0.0000)
$hydro$							12.0954		4.9773	6.1525
							(0.0000)		(0.0000)	(0.0000)
$exim_{bass}$								9.33011	5.3544	5.9732
								(0.0000)	(0.0000)	(0.0000)
$exim_{heyw}$								0.2853	-1.6594	-1.8715
								(0.6768)	(0.0136)	(0.0004)
$exim_{VNI}$								-7.4743	-3.8487	-4.3896
								(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$								4.5349	-0.3166	-1.1211
								(0.0411)	(0.8822)	(0.3007)
					Variance Equation					
ω	0.9761	2.2278	-0.4496	-0.4155	2.1969	1.1257	1.6703	2.4171	-0.0766	2.0605
	(0.0000)	(0.0000)	(0.2079)	(0.2987)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8674)	(0.0000)
α	-0.1424	-0.1441	-0.1301	-0.0752	-0.1547	-0.1613	-0.1297	-0.1339	-0.0516	-0.0642
	(0.0000)	(0.0000)	(0.0001)	(0.0292)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.1314)	(0.0688)
β	0.8328	0.6080	0.5657	0.4886	0.6220	0.7722	0.6527	0.5724	0.4795	0.4847
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.3610	0.4531	0.5017	0.4686	0.4614	0.4147	0.4605	0.4518	0.4378	0.4301
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		0.0063		0.0770					0.1178	
		(0.8748)		(0.0921)					(0.0293)	
$consumption$			0.2282	0.2475					0.1768	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-0.5019					1.4619
					(0.2895)					(0.0298)
gas						0.0350			0.0601	0.0591
						(0.0064)			(0.0006)	(0.0007)
$hydro$							0.3843		0.2325	0.4057
							(0.0000)		(0.0024)	(0.0000)
$exim_{bass}$								0.0852	-0.0273	0.0267
								(0.0405)	(0.5719)	(0.5649)
$exim_{heyw}$								0.1905	0.1549	0.1497
								(0.0118)	(0.0708)	(0.0780)
$exim_{VNI}$								-0.0645	-0.0288	-0.0832
								(0.0352)	(0.4619)	(0.0253)
$exim_{murr}$								-0.8053	-0.6876	-0.7731
								(0.0098)	(0.0463)	(0.0243)
Shape	2.6308	2.5418	2.8802	2.8170	2.5160	2.6522	2.7629	2.5509	2.8154	2.7205
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-14785.68	-14361.29	-14507.81	-14171.71	-14326.42	-14747.16	-14536.42	-14310.71	-14040.06	-14060.28
AIC	8.0989	7.8677	7.9479	7.7650	7.8486	8.0789	7.9635	7.8433	7.6995	7.7094
BIC	8.1108	7.8829	7.9632	7.7836	7.8639	8.0942	7.9788	7.8687	7.7385	7.7451
Q(20)	1.8019	1.5582	6.612	6.606	1.763	1.8096	4.718	2.338	7.7385	4.759
	(0.7675)	(0.8322)	(0.0273)	(0.0275)	(0.7783)	(0.7653)	(0.1325)	(0.6130)	(0.01131)	(0.1284)
$Q^2(36)$	0.0314	0.0229	0.0226	0.0142	0.0250	0.0388	0.0320	0.0233	0.0153	0.0149
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0325	0.0214	0.0218	0.0141	0.0237	0.0387	0.0279	0.0214	0.0152	0.0135
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table 2.6 : **The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on Tasmania's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is the daily average electricity spot prices.

	Model A	Model B	Model C	Model D	Model E	Model G	Model H	Model I	Model J
					Mean Equation				
μ	58.6045	61.1765	18.6267	31.7893	61.1414	47.0742	58.2370	30.8046	60.0699
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9531	0.9602	0.9599	0.9605	0.9602	0.9595	0.9535	0.9626	0.9624
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-11.2421		-6.3946				-5.6483	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			15.0153	10.5638				8.8174	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-29.4964				-29.9279
					(0.0000)				(0.0000)
$hydro$						4.5963		1.9193	
						(0.0000)		(0.0000)	
$exim_{bass}$							1.7527		2.3193
							(0.0000)		(0.0000)
					Variance Equation				
ω	1.0103	1.2859	0.6782	1.1424	1.2877	1.3898	1.0848	1.1701	1.3496
	(0.0000)	(0.0000)	(0.0774)	(0.0083)	(0.0000)	(0.0000)	(0.0000)	(0.0086)	(0.0000)
α	0.0285	-0.0051	0.0045	-0.0121	-0.0063	0.0072	0.0174	-0.0223	-0.0216
	(0.5052)	(0.9154)	(0.9335)	(0.8159)	(0.8965)	(0.8874)	(0.6894)	(0.6879)	(0.6782)
β	0.8315	0.8044	0.8202	0.8105	0.8042	0.8030	0.8216	0.8041	0.7968
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.1298	1.3248	1.5146	1.4682	1.3449	1.4150	1.1773	1.5562	1.4449
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
$wind$		-0.3420		-0.3555				-0.3341	
		(0.0084)		(0.0095)				(0.0163)	
$consumption$			0.1785	0.0545				0.1150	
			(0.1687)	(0.6978)				(0.4461)	
$wind_{pen}$					-0.8544				-0.7202
					(0.0105)				(0.0341)
$hydro$						-0.0584		-0.0541	
						(0.0646)		(0.1049)	
$exim_{bass}$							-0.0777		-0.0656
							(0.0147)		(0.0547)
Shape	2.2477	2.1952	2.1347	2.1523	2.1878	2.1599	2.2306	2.1346	2.1602
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-13772.08	-13622.38	-13606.58	-13567.04	-13611.82	-13676.21	-13758.91	-13551.48	-13591.95
AIC	7.5440	7.4631	7.4545	7.4339	7.4573	7.4926	7.5379	7.4265	7.4475
BIC	7.5559	7.4784	7.4697	7.4526	7.4726	7.5079	7.5531	7.4486	7.4662
Q(20)	60.54	59.98	59.03	60.36	59.59	54.76	57.82 0	58.17	56.85
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	2.7618	3.5075	3.6670	3.9525	3.552	3.9948	2.9475	4.2260	3.8506
	(0.7975)	(0.6731)	(0.6457)	(0.5969)	(0.6654)	(0.5897)	(0.7676)	(0.5510)	(0.6143)
ARCH-LM Test	1.7987	2.189	2.2873	2.4575	2.2132	2.6074	1.9200	2.6323	2.4270
	(0.7598)	(0.6774)	(0.6566)	(0.6212)	(0.6722)	(0.5905)	(0.7343)	(0.5855)	(0.6275)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

2.3.1 Effects on the level of electricity prices

All coefficients for wind generation for all four states are consistently negative and statistically significant even after controlling for consumption, gas prices, hydro generation, and the interconnectors flow (see the top panel of Tables 2.3–2.6). These results confirm the merit order effect of wind generation. We observe a considerable reduction in SA where an increase in daily wind generation by 1 GWh per day reduces prices by approximately 1.3 AUD/MWh, followed by TAS (0.6 AUD/MWh), VIC (0.5 AUD/MWh), and NSW (0.4 AUD/MWh).[27] The pronounced effect in SA, the leading state in the NEM in wind generation, underscores the role wind generation plays in reducing electricity prices (Forrest and MacGill, 2013; Cludius et al., 2014a; Bell et al., 2017). According to AER (2018b), in 2018 wind generation met about 40% of SA's electricity requirements. The fact that wind generation continues during periods of low electricity demand is also likely to account for the substantial reduction in the region's electricity prices (Bell et al., 2015). Csereklyei et al. (2019) observed a similar effect in the Australian market with the daily merit order of wind generation, being statistically significantly larger in SA and lower in VIC with no firm evidence in NSW. Numerically, the estimated coefficients exceed the daily merit order from this study by 0.2 AUD/MWh for NSW and VIC, and by 0.4 AUD/MWh for SA. We account for the difference in the magnitude and statistical significance of the current results to the sample period under the analysis and the fact that the present models include the interconnectors and hydro generation.

We reassert that electricity prices increase with consumption (Forrest and MacGill, 2013; Ketterer, 2014; Clò et al., 2015; Csereklyei et al., 2019). We observe a stronger impact in states with lower consumption profiles (SA and TAS) and less impact in states

the ARCH process (Ghalanos, 2022). Overall, the weighted Ljung-Box test and the weighted ARCH-LM test (at lag 7) suggested that there is no evidence of remaining autocorrelation and ARCH effects. We also inspect the autocorrelation function (ACF) and partial autocorrelation (PACF) of the standardized residuals and the squared standardized residuals, which suggests little autocorrelation and the absence of a particular pattern due to a non-stationary or seasonal time series. We run the empirical analysis using the `rugarch` package in the R programming language (R Core Team, 2019; Ghalanos, 2022).

[27] All supply and demand variables in Tables 2.3 to 2.6 are scaled by a factor of 10^4 to ease the presentation of the estimated coefficients. To recover the original values—for a 1 GWh increase in either variable, one needs to divide the estimated coefficients by 10. Upon recovering the original values, our interpretation of the variables in the mean equation (2.2.1) is that a 1 unit increase in a jth independent variable is associated with a ξ_j AUD/MWh change in spot prices, where ξ_j, is the coefficient of the jth independent variable.

with larger consumption profiles (NSW and VIC). On this basis, we find compelling evidence that an increase in daily electricity consumption by 1 GWh per day in Model I increases prices in NSW and VIC by approximately 0.2 AUD/MWh. SA and TAS, states with lower demand profiles, experience approximately nine- and five-time increases, respectively. Similar to electricity consumption, gas prices have a positive and statistically significant effect on electricity prices in the NEM. We observe from Models I and J that increasing the daily gas price by 1 AUD/GJ raises electricity prices by 6 AUD/MWh and 0.3 AUD/MWh in SA and NSW, respectively. SA is the state most affected by gas prices, exceeding VIC by approximately 5 AUD/MWh as SA relies more on gas-powered generation than any other region across the NEM.[28] Between 2014 and 2018, Australia witnessed a threefold increase in gas prices (see Figure 2.3b), which had a notable impact on electricity prices. The lower magnitude compared to the estimated coefficients in Csereklyei et al. (2019) may be explained by several factors, in particular the significant decrease in gas prices after 2019 onward and the displacement of gas output due to marked investment in renewable energy generation.

The impact of hydro generation on electricity prices is consistently positive and statistically significant. This impact is substantial in NSW and VIC, where an increase in hydro generation of 1 GWh per day drives up the prices by approximately 0.4 AUD/MWh to 0.7 AUD/MWh. Although hydro generators do not pay the explicit purchase price for their primary fuel input (water), they have implicit fuel costs, which depend on several factors such as storage levels, an environmental obligation, existing electricity contracts, and spot market prices. In practice, therefore, hydro generator's market bids tend to be closely tied to other producers' bids, especially coal or gas producers. This means the implied fuel cost of electricity tends to rise as their bidding levels of coal or gas producers rise (AER, 2017a).

The fact that hydro generation affects prices in the same direction as higher fuel cost

[28] Gas generation is preferred in SA as it is a flexible source of energy and thus, is often employed as a supplement to the intermittent wind generation. According to AER (2018b), about 56% of SA local generation in 2017–18 was powered by gas. It is considered a transition fuel toward a lower carbon economy and accounted for more generation during the carbon pricing period from July 2012 to June 2014. However, this pace slowed following the abolition of carbon pricing in 2014, along with other factors, such as the lack of new gas supplies (AER, 2017b).

generators such as gas prices in the NEM reflects high implicit fuel cost due to persistent drought periods (Csereklyei et al., 2019). Insufficient rainfall resulted in multiple years of drought in Australia over the last decade. As a result, heavy irrigation, groundwater pumping, and low streamflow conditions lead to competing demand for water resources, reducing the water supply for electricity generation. The operation of hydropower is primarily limited by the availability of water, which tends to raise the effective price of the service (HT, 2019). The increase in the implicit fuel cost may also be linked to the increase in the bidding levels of coal and gas generators due to high coal and gas prices, especially between 2015 and 2019 (Simshauser and Gilmore, 2020). It has also been noted that higher cost black coal, gas, and hydro generation contributed to increased electricity prices in VIC after the closure of the Hazelwood power plant. Snowy hydro moved from offering their capacity from a low-price band (less than 50 AUD/MWh) to middle price bands (between 50 AUD/MWh to 150 AUD/MWh) to account for the increase in the value of the input fuel (water; AER 2018a). Moreover, as noted in footnote 3, the data for hydro generation is available in aggregated form and includes regional output from both run-of-river and pumped hydro plants. However, these two types of plants can have different impacts on prices and volatility. Pumped hydro, being more expensive than run-off river hydro generation, is likely to play a substantial role in increasing the level of electricity prices.

The cross-border interconnectors flow exhibits a differential effect on the level of electricity prices across the NEM. The analysis in Models I and J assumes that the two models have limited omitted variable bias. We find statistical evidence that the Terranora, QNI, and VNI reduced the price of electricity in NSW. Interestingly, the Terranora interconnector exhibits a substantial price reduction despite its lower nominal capacity. This may be because NSW traditionally is a net importer of electricity across the NEM due to the relatively high cost of fuel. VIC exports to NSW have been higher and frequent compared to NSW exports to VIC, even after the closure of the Hazelwood power station (Mountain and Percy, 2019b). Moreover, QNI and VNI have higher nominal capacities compared to other interconnectors in the NEM. The fact that two interconnectors link NSW to QLD is an added advantage. QLD has been a net electricity exporter in the NEM due to the state's surplus capacity and traditionally low fuel prices (AER, 2018b). The exports from QLD to NSW doubled in the year after the Hazelwood power plant closed.

The Heywood and Murraylink interconnectors in SA significantly impact the level of electricity prices, with Murraylink having a positive effect and the Heywood interconnector having a negative impact. The Heywood interconnector has a relatively sizeable nominal capacity, which allows more cheap brown coal exports from VIC than Murraylink. SA has traditionally been an importer of electricity because the state lacks a low-cost local supply. The recent influx of wind generation, however, has made SA less reliant on imports from other states. Generally, the effective trade between VIC and SA is limited by the low thermal capabilities of the Heywood and Murraylink interconnectors (Bell et al., 2015). We also observe that VIC, the most interconnected state in the region, experiences price reduction from the Heywood and VNI interconnectors. VIC traditionally has been a net exporter of electricity due to its low-cost brown coal generation. Nevertheless, the recent challenges associated with the closure of significant coal plants, such as the Hazelwood power station in March 2017, impacted VIC's position. Furthermore, the effect of the Basslink interconnector is positive and statistically significant for VIC and TAS. This reflects the changing position of both states during the sample period. The position of TAS tends to vary over time, depending on market conditions. During the carbon pricing period, the region was a net exporter of electricity. This position changed in late 2015 following the abolition of carbon pricing and the persistence of drought conditions. Favourable conditions such as the resumption of the Basslink interconnector to VIC and favourable conditions for hydroelectricity generation made the state a net exporter of electricity.

In summary, we find that beyond the customary factors of consumption and gas prices, hydro and interconnectors play an essential role in determining the merit order effect associated with wind generation in the NEM. We now analyse the impact of these factors on the volatility of electricity prices.

2.3.2 Volatility dynamics

The bottom panels of Tables 2.3–2.6 present the impact on the estimated variance equation. The first four rows capture the characteristics of NEM volatility dynamics.

The coefficients of the own-innovation or ARCH spillovers (γ) and the lagged volatility or GARCH spillovers (β) are large, relatively stable across the models, and statistically significant. The estimated innovation spillovers for NSW, SA, VIC, and TAS are 0.6461, 0.5235, 0.4378, and 1.5562, respectively (see Model I). Therefore, the memory of previous surprises or innovation has a substantial impact on future volatility for TAS, NSW, and SA, and is slightly lower in VIC. Similarly, the last period's volatility shocks exhibit a considerable effect on its future electricity price volatility in TAS (0.8041). The impact is almost half this in other regions, that is, VIC (0.4795), SA (0.4617), and NSW (0.3327).[29] Considering Models I and J, we find the estimated innovation spillovers exceed the volatility spillovers in NSW, SA, and TAS. The opposite effect is observed in VIC. The estimated innovation spillovers exceed those observed in the German market (Ketterer, 2014; Kyritsis et al., 2017). Kyritsis et al. (2017), for instance reported innovation spillovers of 0.226, while the estimated volatility spillover is closer to VIC and SA and is 0.447. The sign effect parameter α is positive and statistically significant for NSW. This means positive shocks tend to exert more impact on electricity price volatility than negative shocks of the same magnitude. This provides evidence for the reverse leverage effect in the NEM. Knittel and Roberts (2005) noted that a positive shock to prices signifies an unexpected positive demand shock, which, given the convexity of the marginal cost, tends to exert more upward pressure on prices than the negative shocks. The present results corroborate the results of Higgs and Worthington (2005), Thomas and Mitchell (2005), and Bowden and Payne (2008). In addition to the Australian market, Knittel and Roberts (2005) found similar behaviour for California electricity prices in the US. Contrary to these studies, however, we find the estimated coefficients for most of the other states are not statistically significant (at the 5% level). Positive and negative shocks have

[29] These results are generally consistent with the previous study by Higgs and Worthington (2005), who found the ARCH and GARCH effects of 0.4376 and 0.3677 for NSW, 0.2530 and 0.5422 for SA, and 0.5761 and 0.3057 for VIC, respectively. We attribute the difference between the estimated coefficients from this study to the difference in the sample period and the fact they applied the high-frequency data in the empirical analysis.

marginal differential effects on price volatility in all of the Australian states except NSW.

2.3.3 Effects on volatility of electricity prices

In the second panel in Tables 2.3–2.6 (the fifth row), the impact of wind generation on electricity price volatility is presented. The estimated coefficients (Model I) are positive and statistically significant at the 1% and 5% levels for SA and VIC, respectively. The effect is more pronounced in SA, where a 1 GWh increase in daily wind generation amplifies daily price volatility by 2%.[30] The increase in VIC differs moderately and is 1% lower. In contrast, we find evidence for the opposite effect in TAS, with a 3% decrease for each 1 GWh increase. NSW experiences a marginal and not statistically significant decrease in price volatility. SA is well-known for its relatively higher and more volatile electricity prices compared to other markets in the NEM. The price volatility stems from the intermittent and uncertain nature of wind generation, which varies during the day and seasons of the year. VRE generation is typically negatively correlated with demand (Hirth, 2013; Rai and Nunn, 2020b). Consequently, adding VRE to the generation mix makes it harder to equilibrate supply with demand and in turn, increases price volatility. Focusing on the European market, Rintamäki et al. (2017) found that wind power decreases daily electricity price volatility in Denmark but increases daily volatility in Germany (Ketterer, 2014; Kyritsis et al., 2017).

We find strong statistical evidence that electricity consumption increases price volatility in NSW, SA, and VIC. SA experiences a far higher impact, where a 1 GWh increase in daily electricity consumption increases price volatility by 6%. This increase is approximately three and six times the effect experienced in VIC and NSW, respectively. The impact of consumption in the smallest NEM market, TAS, is marginal and not statistically significant. The importance of gas in the SA generation mix is reflected in price volatility. We find strong statistical evidence that a 1 AUD/GJ increase in the daily gas price increases the daily price volatility by approximately 11% to 14% in SA and

[30] Since we are modelling the logarithm of σ_t^2, we treat this equation as a log-linear equation, that is, $\ln Y = \delta_0 + \delta_1 X$, so that a 1 unit increase in X is associated with a $100 \times \delta_1\%$ change in Y. Thus, our interpretation of the variance equation (2.2.2) is that a 1 unit increase in a kth independent variable is associated with a $100 \times \delta_k\%$ change in the spot price volatility, where δ_k, is the coefficient of the kth independent variable.

marginally in NSW and VIC, that is, around 6% to 7% (see Model I and J). The higher magnitude of volatility in SA follows its relatively higher reliance on gas-powered generation in the NEM. Contrasting with Denmark and Germany, gas prices seem to play a crucial role in influencing the volatility of electricity prices in Australia. Rintamäki et al. (2017) found no statistically significant effect of daily gas prices on the volatility of prices in Denmark and Germany. The results demonstrate further that price volatility increases with hydro generation. A more substantial effect is apparent in regions where hydro generation accounts for a smaller proportion of the generation mix, namely, NSW and VIC. Although more than 80% of the electricity generation in TAS comes from hydro, we find less evidence of a negative impact on price volatility.

Similar to the mean equation, the interconnector's influence on the volatility of electricity prices is significant across the states. In NSW, we find strong evidence that the VNI interconnector contributes to increasing daily price volatility. In contrast, we find no evidence for a negative effect of the Terranora interconnector and the QNI. The Heywood and Murraylink interconnectors in SA appear to positively influence price volatility. These results also suggest the impact of Murraylink interconnector on VIC moves in the opposite direction by reducing price volatility. We observe the same effect for the VNI interconnector, particularly in Model J. However, we find some evidence that the Heywood interconnector increases price volatility. Although the influence of the Basslink interconnector in VIC is not statistically significant, it appears to have a negative impact on price volatility in TAS. The effect observed for the VNI in NSW and the Heywood and Murraylink interconnectors in SA may be linked to VIC having the highest net volatility spillover in the NEM (Han et al., 2020). The interconnectors joining VIC to other regions likely were greatly impacted by the closure of the Hazelwood power station in VIC. According to Cornwall Insight (2020), the closure of base-load coal generation has the potential to increase volatility to the same extent as renewable generation. Similarly, QLD and TAS have the lowest net volatility spillovers, which explain the lack of significance of the Terranora and QNI interconnectors in NSW and the Basslink interconnector in VIC.

We find evidence that the variability in consumption, fuel prices, interconnector flow, and wind generation introduce volatility in NEM electricity prices.[31] Higher volatility is associated with the high frequency of prices between 100 AUD/MWh to 500 AUD/MWh, rather than with more frequent extreme prices (Rai and Nunn, 2020b). This range is above the market cap on prices typically excluded in studies after treatment for outliers. In Appendix A.3, we consider the $3 \times MAD$ adjustment for outliers excluding prices above around 150 AUD/MWh. We find no significant impact on the effect of wind generation on volatility in the NEM. This finding highlights the importance of considering the whole range of electricity prices, and it provides empirical evidence that the increased volatility is caused by the higher number of instances where prices fall within the 100 AUD/MWh to 500 AUD/MWh range.

2.3.4 The role of wind penetration

Different wind penetration levels have very different distributional properties, with reductions in mean prices and standard deviations expected as wind penetration increases (Jonsson et al., 2010). We undertake a similar preliminary analysis for all states by dividing the data into intervals based on wind penetration. The properties of the empirical price distributions are given in Table 2.7. It is apparent that prices decrease with wind penetration for NSW, VIC, and TAS. SA exhibits the same pattern for higher penetration levels. Nevertheless, we see no clear pattern in the standard deviation. Its magnitude, however, is relatively lower with higher levels of wind penetration.

The results summarized in Tables 2.3 to 2.6 concur with this analysis and suggest a consistent effect of wind penetration on the level of electricity prices across states. In particular, increasing wind penetration by a 1 percentage point in Model J leads to a statistically significant reduction in the level of electricity prices by 0.9 AUD/MWh and 0.7 AUD/MWh in NSW and VIC, respectively.[32] The magnitude of this reduction is relatively lower in SA and TAS, where the same increase in wind penetration reduces prices

[31] Other reasons include strategic bidding practices and plant ramping, which are beyond the scope of this study (Ward et al., 2019).

[32] The penetration variable is expressed as a ratio in the [0, 1] range. Thus, the coefficients of the mean equation (2.2.1) should be interpreted as a percentage point increase in a jth penetration variable is associated with a $\xi_j \times 0.01$ AUD/MWh change in spot prices, where ξ_j, is the coefficient of the jth penetration variable. We multiply the coefficient by 0.01 as the penetration variables are expressed in a ratio of 0 to 1 rather than in percentages.

Table 2.7 : **Price distribution properties for different wind penetration levels.**

Wind Penetration	< 5%	< 15%	< 5%	< 10%	< 15%	< 30%	< 5%	< 10%	< 15%	< 20%	≥ 20
	NSW		**VIC**				**TAS**				
Mean	61.090	51.52	82.22	69.89	54.27	32.85	68.94	62.59	58.64	54.60	48.93
Standard Deviation	56.90	19.32	77.43	116.18	68.31	34.60	36.84	29.09	27.57	32.68	32.35
Skewness	17.75	3.10	8.58	20.44	15.00	2.62	2.58	1.77	1.75	1.41	1.37
Kurtosis	378.08	18.29	95.20	502.10	285.04	28.65	18.04	7.34	8.61	5.75	5.61
Observations	3209	444	1215	1476	627	335	879	1123	820	488	343

Wind Penetration	< 5%	< 10%	< 15%	< 20%	< 25%	< 30%	< 35%	< 40%	< 45%	< 50%	≥ 50%
	SA										
Mean	110.68	83.66	102.65	81.00	84.88	81.37	71.96	62.69	60.16	59.27	43.61
Standard Deviation	118.48	40.35	112.56	51.81	148.05	183.63	91.85	30.32	37.35	25.84	29.48
Skewness	6.81	4.08	5.55	7.04	11.98	14.92	11.93	2.82	3.25	0.95	1.55
Kurtosis	53.38	25.78	37.38	77.62	167.06	249.59	165.09	19.15	25.44	4.28	20.93
Observations	143	153	202	325	336	372	317	258	236	208	1103

by 0.5 AUD/MWh and 0.3 AUD/MWh, respectively. The impact of wind penetration on price volatility is not uniform across the states. In TAS, price volatility decreases by 1% for a 1 percentage point increase in wind penetration.[33] We observe a similar sign effect in SA (Model E). However, the coefficient becomes non-statistically significant after controlling for other explanatory variables in Model J. Based on this model, we find evidence that increasing wind penetration by a 1 percentage point in VIC increases price volatility by 1%. The estimated effect in NSW is not statistically significant in either model.

We compare these results with the impact of wind generation in Model B, where SA and TAS experience the largest price reduction, while the other states experience moderate reductions. However, after accounting for the effects of consumption (via the wind penetration measure), the increase in the proportion of consumption served by wind generation is associated with a higher statistically significant impact on electricity prices in NSW and VIC, and much lower in SA and TAS. An explanation is that NSW and VIC have 15% or lower wind penetration, while SA sits at around 53%. This also explains

[33] We follow a similar interpretation of the coefficients as in Footnote 30 with a minor modification to account for the fact that penetration variables are expressed in ratios. In particular, a 1 percentage point increase in a kth penetration variable is associated with a $\delta_k \times 0.01 \times 100\% = \delta_k\%$ change in spot price volatility, where δ_k, is the coefficient of the kth penetration variable.

Figure 2.5 : **Evolution of the impact of wind penetration from 2014 to May 2020 for NSW, SA, VIC, and TAS.** The coefficients are estimated using the rolling regression with three-year windows while controlling for gas prices, hydro generation, and the interconnectors. The graph on the left shows the effect on the price level, and the graph on the right shows the effect on the price volatility.

why there is a positive impact on price volatility in VIC, whereas a higher level of wind penetration in TAS shows the opposite effect.

In the last decade, the NEM experienced substantial investment in renewable energy. In the next section, we investigate how the impact of wind penetration developed during this period.

2.3.5 The evolution of the impact of wind penetration

To study the evolution of the impact of wind penetration, we construct a rolling regression with a three-year window.[34] The results for the evolution of the impact of wind penetration in the mean and variance of the daily electricity prices are given in Figure 2.5. Note that the coefficients are re-estimated in windows moved forward one observation in time.

The negative impact of wind penetration is observed for all four states and trended higher over the years. The evolution is relatively stable for states with higher wind penetration and relatively unstable for states with lower penetration levels. According to

[34]We also estimated the coefficients using the four-year rolling window and obtained a similar impact of wind penetration over the years.

Marshman et al. (2020), the size of the wind penetration coefficient depends on which generators are marginal at the times of wind output. For instance, if it is relatively high SRMC CCGTs, then the wind penetration coefficient will be high; if it is coal (especially brown coal), then the coefficient is lower. NSW and VIC experienced the highest electricity price reduction for a given increase in wind penetration over time. This impact is likely triggered by the large increase in wind installations enhanced by LRET (Stocks et al., 2019) along with higher gas prices, which peaked in 2016, and the higher cost of hydro generation due to the persistent drought periods. The decrease in the magnitude, especially for NSW from late 2015 to late 2017, likely reflects a changing displacement effect, with CCGTs first displaced, moving the bid to black coal once gas generators have been fully displaced. The impact of moving the Hazelwood offline is evident in VIC by the reduction and swings in the MOE in early 2017 (Burke et al., 2019; Mountain and Percy, 2019b).[35] Similar reasons may account for the reduced MOE in SA from late 2015 to the end of 2017, specifically, the unexpected and sudden closure of Playford B (240 MWh) and Northern (546 MW) (Rai and Nunn, 2020b). TAS is less affected by either factor due to the large proportion of renewables in the generation mix.

We observe a variation in price volatility over the years for NSW and VIC, with the lowest penetration levels.[36] From mid–2017 onward, the increase in wind penetration is associated with a reduction in price volatility. This period coincided with the marked increase in investment in large-scale renewable energy between 2016 and 2019 (de Atholia et al., 2020). The same argument as in subsection 2.3.4 could explain this phenomenon; namely, price volatility tends to be lower for higher penetration levels. The pattern in SA, however, suggests that this is not always the case. In particular, the increase in wind penetration lowers price volatility to a specific level (in this case, around annual wind penetration of 50%) and then regresses to the previous phenomena.[37] One explanation is that incumbent thermal plants remain online up to a certain penetration rate (50% to

[35]According to AER (2018b) during 2017–18, VIC recorded the highest average prices that were about 43% higher than the year earlier and 30% higher than in any year since the NEM began.

[36]The p values from Figure A.9 in Appendix A.3 indicate, however, the estimated coefficients for all states are generally not statistically significant, especially between 2016 and 2019, with the slight exception of SA.

[37]This period concurs with when the last coal-fired generators winded up their operations in SA in 2016.

60%), thus smoothing out the price volatility from the higher wind output (Marshman et al., 2020). After thermal plants are offline, the price firming they provide ceases, and prices become more volatile, leading to an increase in the wind penetration coefficient. Kyritsis et al. (2017) observed a similar pattern in the daily variance in electricity prices in Germany, where wind penetration reduces the variance to around the 20% level but then reverts to the increasing pattern.

These results provide important insights into the expected changes in price behaviours as a result of government programs that target supporting renewable electricity growth. We find that increasing wind penetration in states with an annual wind share of around or less than 15%, that is, NSW and VIC, tends to result in price swings, which are currently biased below zero. States with high wind penetration, that is, SA and TAS, tend to exhibit a marginal reduction in price volatility.

2.4 Regulatory Implications

The NEM has experienced two significant shocks since 2010 which had a material impact on electricity dynamics, the CPM and the COVID-19 lockdown restrictions. The CPM was a federal government regulation based on emission control policies, whereas the lockdown restrictions consisted of state government measures to control the spread of COVID-19. We analyse the impact of these two regulatory shocks on the NEM and then discuss their implications.

2.4.1 Carbon Pricing Mechanism (CPM)

The CPM was introduced by the Australian government in July 2012, pricing carbon at 23 AUD/tonne of the equivalent emitted carbon dioxide. The scheme was repealed in June 2014. The CPM was the central component of the Clean Energy Future Plan aimed at reducing the emission of carbon and other greenhouse gases to at least 5% below 2000 levels by 2020 (AER, 2013). The pricing also aimed at shifting the reliance from coal-fired generation toward sustainable and renewable energy (Maryniak et al., 2019). At the time the scheme was terminated, the output from coal-fired generators had decreased by around 25% (16% from brown and 9% from black coal-fired generators), and the market share of coal generation had dropped markedly, reaching a historical proportion of 73.6% of NEM output in 2013–14. These changes, combined with the reduction in demand, reduced carbon emissions from the electricity sector by 10.3% during the two years the CPM was implemented (AER, 2015).

Table 2.8 provides a state-by-state breakdown of the regressions incorporating the dummy variable D_{ca} to examine the effect of the CPM on prices where $D_{ca} = 1$ during the CPM period, extending from the introduction of the CPM scheme on 1st July 2012, until it was repealed on 1st July 2014, and zero otherwise. We seek statistically significant differences between the times when the scheme was in operation ($D_{ca} = 1$) and when it was not ($D_{ca} = 0$), corresponding to the times before its introduction and after the repeal.

We find strong evidence that during the CPM period, electricity prices increased statistically significantly across all markets in the NEM. The price increase was much higher in NSW and VIC and relatively lower in SA and TAS. The generation mix in the former states is dominated by coal-fired generators statistically significantly impacted by the introduction of carbon pricing. Most of the older and higher-cost plants were forced to periodically shut down and then return, for example, during high-demand periods in summer. The increased reliance on flexible and expensive sources of generation, such as gas, triggered price increases. The reduced competitiveness of coal-fired generators and the imposition of the RET accelerated the increase in wind generation. We find statistically significant evidence that during the CPM period, wind generation caused a decrease in electricity prices across all states in the NEM. The largest reduction occurred in SA and TAS, and despite a greater increase in prices following the implementation of the CPM, we observe a significant reduction in VIC and NSW, which had relatively lower levels of wind generation.[38] The results show that increasing wind generation by 1 GWh during the CPM period reduced prices by 1.2 AUD/MWh and 0.4 AUD/MWh in SA and TAS and approximately 0.1 AUD/MWh and 0.2 AUD/MWh in NSW and VIC, respectively.[39]

[38] In SA, wind penetration increased from 28% to 33% during this period but was below 5% in VIC and NSW.

[39] The adjustment is required for coefficients in Table 2.8. For example, since the coefficient of *wind* generation in SA (Model K) is -13.8939 and $D_{ca} \times wind$ is 2.3020, then the coefficient for wind generation during the CPM period is recovered by summing the two coefficients, that is, $(-13.8939) + (2.3020) = -11.5919$. The same adjustment applies to other variables' coefficients and those in Table 2.9. Once

Table 2.8 : **The effect of wind generation, electricity consumption, gas prices, and hydro generation during the implementation of the Carbon Pricing Mechanism (CPM) on electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is the daily average electricity spot prices.

	NSW		**SA**		**VIC**		**TAS**	
	Model K	Model L	Model K	Model L	Model K	Model L	Model K	Model L
	Mean Equation							
D_{ca}	31.9361	15.9292	25.6896	11.9622	32.6573	8.3549	17.9118	2.4587
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0113)	(0.0000)	(0.0000)
$wind$	-4.3332		-13.8939		-5.7845		-7.4702	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$D_{ca} \times wind$	3.3994		2.3020		3.5725		3.0977	
	(0.0000)		(0.1182)		(0.0002)		(0.0000)	
$consumption$	2.6070		18.8439		2.4770		9.2371	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$D_{ca} \times consumption$	-1.0031		-4.2208		-2.0949		-0.3460	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$wind_{pen}$		-86.6351		-49.4717		-68.8874		-37.6384
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
$D_{ca} \times wind_{pen}$		31.1416		10.4098		42.1151		19.4042
		(0.2746)		(0.1400)		(0.0001)		(0.0000)
gas	0.1605	0.3040	5.7685	6.5070	1.3427	1.4696		
	(0.1173)	(0.2503)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$D_{ca} \times gas$	0.2622	0.2066	-0.4956	-0.8288	-0.5060	-0.7009		
	(0.3371)	(0.6648)	(0.2137)	(0.4059)	(0.3755)	(0.2558)		
$hydro$	6.7946	10.1664			5.3117	7.1664	3.4129	
	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	
$D_{ca} \times hydro$	-7.7013	-10.0268			-1.1299	-2.9125	-5.1282	
	(0.0000)	(0.0000)			(0.0474)	(0.0045)	(0.0000)	
	Variance Equation							
D_{ca}	-0.6344	-0.6396	0.1155	0.1673	-1.50591	-0.4893	-0.2739	-0.3416
	(0.6877)	(0.2322)	(0.8726)	(0.7489)	(0.1999)	(0.3943)	(0.7939)	(0.0017)
$wind$	-0.1089		0.2253		0.0863		-0.3039	
	(0.2266)		(0.0001)		(0.1349)		(0.0529)	
$D_{ca} \times wind$	0.0117		-0.4737		0.2815		0.0791	
	(0.9797)		(0.0064)		(0.1644)		(0.8463)	
$consumption$	0.1279		0.5857		0.1474		-0.0080	
	(0.0002)		(0.0000)		(0.0004)		(0.9648)	
$D_{ca} \times consumption$	0.0038		0.0274		0.1030		0.1903	
	(0.9638)		(0.8686)		(0.2654)		(0.6299)	
$wind_{pen}$		-2.7061		0.3856		1.1702		-0.7821
		(0.1033)		(0.0304)		(0.1042)		(0.0415)
$D_{ca} \times wind_{pen}$		2.3719		-1.8563		2.3370		0.5759
		(0.7806)		(0.0002)		(0.3421)		(0.5730)
gas	0.0945	0.0979	0.1133	0.1432	0.0671	0.0636		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0005)		
$D_{ca} \times gas$	-0.0161	-0.0300	0.0285	0.0599	-0.0536	0.0188		
	(0.8146)	(0.6464)	(0.6979)	(0.4123)	(0.5319)	(0.8282)		
$hydro$	0.7405	0.8032			0.2150	0.3678	0.0275	
	(0.0000)	(0.0000)			(0.0128)	(0.0000)	(0.4745)	
$D_{ca} \times hydro$	-0.5687	-0.4851			0.1011	0.1454	-0.2223	
	(0.0105)	(0.0157)			(0.6051)	(0.4370)	(0.0310)	
Shape	2.9731	2.9757	2.6862	2.4732	2.8423	2.7554	2.1620	2.1839
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-12918.39	-13008.51	-16123.45	-16228.55	-13974.49	-13999	-13473.62	-13518.51
AIC	7.0930	7.1402	8.8434	8.8987	7.6734	7.6846	7.3882	7.4106
BIC	7.1558	7.1962	8.8926	8.9412	7.7430	7.7475	7.4239	7.4395
Q(20)	3.659	1.2084	5.565	0.7786	7.253	5.095	54.04	52.71
	(0.2851)	(0.9109)	(0.0672)	(0.9744)	(0.0153)	(0.0986)	(0.0000)	(0.0000)
$Q^2(36)$	0.0052	0.0035	0.0975	0.0331	0.0103	0.0101	9.3750	9.349
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0680)	(0.0689)
ARCH-LM Test	0.0026	0.00216	0.0658	0.0260	0.0087	0.0086	9.5652	9.4479
	(1.0000)	(1.0000)	(0.9998)	(1.0000)	(1.0000)	(1.0000)	(0.0232)	(0.0247)
Observations	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses. We control for all variables in Model K and L, including the interconnector flows. However, for easy presentations, we only provide the coefficients for variables that are useful to the analysis.

Likewise, wind penetration had a dampening effect on electricity prices, with a greater reduction observed in SA and VIC and moderate reduction in TAS. We find no statistical evidence for this effect in NSW, likely reflecting the smallest share of demand served by wind generation. During the CPM period, wind generation accounted for 0.94% and 1.15% of consumption in NSW and 3.09% and 5.36% in VIC for the years 2012 and 2013, respectively.

The results further suggest a positive relationship between prices and consumption, and we find that this effect was stronger when the CPM was not implemented compared to the CPM period. This likely reflects the weakened commercial and residential demand due to higher electricity costs, lower demand from the manufacturing sector, and increased uptake of rooftop solar PV generation. The CPM pushed electricity demand down by 3.8% across the NEM (O'Gorman and Jotzo, 2014). Changes in weather conditions might also have contributed to reducing electricity demand. Furthermore, there is no statistically significant evidence that gas prices contributed to increasing electricity prices during the CPM period in the NEM. Last, it is evident in TAS that increasing hydro generation by 1 GWh during the CPM period reduced prices by 0.2 AUD/MWh. VIC exhibits the reverse effect where an increase in hydro during this period was associated with increased electricity prices.

We find a statistically significant decrease in price volatility during the CPM period in TAS only (see Model L). The influence of wind generation on price volatility during the CPM period is evident in SA, which had relatively higher levels of wind uptake. In particular, increasing wind generation during the CPM period by 1 GWh reduced the volatility of electricity prices by 2%. In the same vein, a 1 percentage point increase in wind penetration exerted negative pressure on price volatility by 1%. The imposition of carbon pricing stimulated investment in wind generation and supplied about 28%, 30%, and 33% of energy in SA in 2012, 2013, and 2014, respectively. Furthermore, we find statistically significant evidence that hydro generation increased volatility during the CPM period, specifically 2% to 3% for each 1 GWh increase in hydro generation in NSW. Although there is no statistical evidence for the impact of hydro in other regions, higher

these coefficients are adjusted, the same scaling and interpretations as in Footnotes 27 and 30 apply.

prices during this period increased the competitiveness of hydro generation, making TAS a net exporter of electricity in 2012–13 (see Figure 2.4). The impact of gas prices and electricity consumption is not statistically significant for all states in the NEM.

These findings have implications for the debate regarding the appropriate policy responses required to combat climate change and the security of the NEM. During the CPM period, the costs of generation from fossil fuel and electricity prices increased substantially across all markets in the NEM. However, the carbon pricing mechanism allowed an efficient market determination for the amount of wind generation in the electricity mix. Without this policy and the LRET in place, the market risks running into a trauma (Wood and Blowers, 2016; Simshauser and Gilmore, 2020). The LRET is a typical government intervention aimed at reducing greenhouse gas emissions by subsidizing large-scale renewable generation (Cludius et al., 2014a). The goal of the LRET is to produce 33,000 GWh of electricity by 2020 regardless of the need for additional supply. When demand has trended lower, this additional supply, which also varies over time due to the intermittent nature of wind and solar, adds challenges to system reliability and security, as well as electricity prices. The frequent occurrence of negative prices resulting from increasing supply from renewable energy is likely to affect investment and divestment in the energy sector.[40,41] In addition, the LRET is not technology-neutral and does not allow for abatement to occur from existing plants (i.e., only new renewable energy can drive abatement under the LRET). Thus, it is more costly and has more side effects compared to an emissions intensity scheme (EIS) or a carbon price. Technically, policies offering greater flexibility for generators to adjust their emissions, such as an EIS, are likely to perform best under uncertainty compared to mechanisms that are not technology-neutral (ACC,

[40] The increase in renewable energy has also been associated with more frequent instances of VRE curtailment in the NEM. Typically, this intervention occurs during low daytime demand, transmission outages, and extended periods of negative spot prices (AER, 2020b). Nevertheless, curtailment is not a problem but reflects market economics, and the fact that remote generators challenge the system strength means that it cannot be completely avoided (Simshauser and Gilmore, 2020).

[41] The frequent occurrence of negative prices resulting from the increasing supply of renewable energy can have a complex impact on investment and divestment decisions in the energy sector. The specific direction of this impact may vary depending on factors such as market conditions, investor strategies, and policy frameworks. Negative prices can create financial challenges for conventional fossil fuel-based power plants, potentially leading to reduced investment or divestment in such facilities. However, it is important to note that other factors, such as government support for renewable energy and evolving market dynamics, can also influence investment decisions and the overall energy landscape.

2017). Future climate change policies, therefore, must operate in a broader spectrum of considerations for energy policies to maintain safe and reliable energy systems.

2.4.2 COVID-19 and the NEM

A significant discussion of immediate interest is centred on the novel coronavirus (COVID-19) and its socioeconomic impacts. In Australia, the first person tested positive in VIC on 25$^{\text{th}}$ January 2020. The number of cases increased sharply, forcing government responses in increased pandemic restrictions and lockdowns from late March 2020. To evaluate the impact of these restrictions on the energy sector, and specifically, on the dynamics of electricity prices, we introduce the dummy variable D_{co}, taking value one ($D_{co} = 1$) during the lockdown period from 23$^{\text{rd}}$ March to 31$^{\text{st}}$ May 2020, after which the tightest restrictions were lifted in all states, and zero otherwise. For VIC, we also set $D_{co} = 1$ from 20$^{\text{th}}$ June to 26$^{\text{th}}$ October 2020, to capture the impact of the second statewide restrictions due to the second wave of infections. The results obtained are summarized in Table 2.9.

The results provide evidence of a statistically significant difference in the average prices between the lockdown and non-lockdown periods. Looking at Model M, we find strong evidence that prices decreased substantially in the NEM during the lockdown periods. The price reduction may have been driven by several factors, including lower gas and coal prices, the decline in demand, lower-priced offers, and increased renewable output (AEMO, 2020d,e). Focusing on the latter factor, we find statistically significant evidence that wind generation reduced electricity prices in SA, VIC, and NSW during the lockdown period. Wind penetration has the same sign effect, although the coefficients are only statistically significant in SA and VIC. In 2020, SA and VIC had wind penetration of around 53% and 15%, respectively.

During the pandemic, demand decreased noticeably in NSW by 5% in April after the government imposed tighter pandemic restrictions. Easing of restrictions in conjunction with cooler weather conditions which increased residential demand, brought the reduction level to about 1% during May and June (AEMO, 2020e). Despite the observed reductions, we find strong evidence that consumption increased electricity prices during the

Table 2.9 : **The effect of wind generation, electricity consumption, gas prices, and hydro generation during the implementation of nationwide restrictions due to COVID-19 on electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is the daily average electricity spot prices.

	NSW		SA		VIC		TAS	
	Model M	Model N	Model M	Model N	Model M	Model N	Model M	Model N
	Mean Equation							
D_{co}	-82.4384	-2.8953	-47.4266	-23.9707	-40.2243	-6.6973	-25.2781	1.5691
	(0.0000)	(0.7855)	(0.0000)	(0.0000)	(0.0000)	(0.2482)	(0.0001)	(0.7304)
$wind$	-4.4248		-5.1351		-5.9117		-5.6567	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$D_{co} \times wind$	1.9527		-0.2052		2.2075		4.6271	
	(0.0000)		(0.0002)		(0.0043)		(0.7072)	
$consumption$	2.3625		3.8246		1.5898		8.6894	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$D_{co} \times consumption$	3.6436		9.8790		2.8175		16.6740	
	(0.0000)		(0.0000)		(0.0000)		(0.0182)	
$wind_{pen}$		-91.8596		-16.7294		-72.1293		-30.1067
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
$D_{co} \times wind_{pen}$		44.4434		-1.88816		36.3396		15.2477
		(0.1509)		(0.0389)		(0.0192)		(0.1860)
gas	0.1673	0.3195	0.9473	1.0442	1.3590	1.4277		
	(0.0612)	(0.0164)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$D_{co} \times gas$	2.8392	0.2665	1.9849	3.4242	0.2933	0.2933		
	(0.0000)	(0.8838)	(0.0000)	(0.0000)	(0.7201)	(0.5037)		
$hydro$	4.2108	6.8931			5.0344	6.0641	2.0575	
	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	
$D_{co} \times hydro$	2.5298	1.5118			-1.1849	2.3741	-6.2336	
	(0.0000)	(0.7224)			(0.8668)	(0.2982)	(0.0000)	
	Variance Equation							
D_{co}	-17.1080	-1.2245	1.4702	-1.0519	1.6808	-0.2914	-3.6448	0.2079
	(0.0331)	(0.7209)	(0.6531)	(0.7007)	(0.4464)	(0.6898)	(0.4716)	(0.5553)
$wind$	-0.0944		-0.0543	-0.2819	0.1363		-0.3460	
	(0.2794)		(0.3364)	(0.0912)	(0.0213)		(0.0155)	
$D_{co} \times wind$	-0.9287		0.5801	0.9805	-0.2621		0.5358	
	(0.1029)		(0.2043)	(0.4849)	(0.1427)		(0.5329)	
$consumption$	0.1299		0.1955		0.1790		0.1042	
	(0.0000)		(0.0031)		(0.0000)		(0.4965)	
$D_{co} \times consumption$	0.5405		-0.4124		-0.1499		1.8407	
	(0.0885)		(0.6398)		(0.3429)		(0.3611)	
$wind_{pen}$		-2.3574		-0.2816		1.6503		-0.7302
		(0.1481)		(0.0911)		(0.0255)		(0.0352)
$D_{co} \times wind_{pen}$		2.3612		1.0192		-3.6411		0.8383
		(0.8114)		(0.4669)		(0.1051)		(0.6993)
gas	0.0685	0.0711	0.0951	0.0991	0.0556	0.0552		
	(0.0006)	(0.0002)	(0.0000)	(0.0000)	(0.0018)	(0.0019)		
$D_{co} \times gas$	1.4968	0.4796	-0.1961	0.0862	0.1247	0.1513		
	(0.0316)	(0.3947)	(0.6911)	(0.8347)	(0.4030)	(0.3212)		
$hydro$	0.5636	0.6620			0.2512	0.4283	-0.0588	
	(0.0000)	(0.0000)			(0.0015)	(0.0000)	(0.0872)	
$D_{co} \times hydro$	0.0559	-1.6915			-0.5055	-0.5186	-0.4412	
	(0.9683)	(0.1226)			(0.0571)	(0.0958)	(0.3738)	
Shape	2.9000	2.9000	2.6409	2.6191	2.8070	2.7235	2.1369	2.1604
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-13041.97	-13131.26	-13263	-13282.79	-14023.5	-14044.06	-13547.44	-13588.33
AIC	7.1607	7.2074	7.2773	7.2859	7.7002	7.7093	7.4287	7.4489
BIC	7.2235	7.2634	7.3266	7.3284	7.7699	7.7721	7.4643	7.4777
Q(20)	3.597	1.1613	1.1178	1.3047	7.955	4.991	58.39 0	57.34
	(0.2970)	(0.9199)	(0.9277)	(0.8914)	(0.0000)	(0.1071)	(0.0000)	(0.0000)
$Q^2(36)$	0.0054	0.0034	0.0046	0.0045	0.0156	0.0145	4.232	3.7936
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.5500)	(0.6240)
ARCH-LM Test	0.0026	0.0021	0.0024	0.0020	0.0156	0.0132	2.6675	2.3935
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.5784)	(0.6344)
Observations	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses. We control for all variables in Model M and N, including the interconnector flows. However, for easy presentations, we only provide the coefficients for variables that are useful to the analysis.

lockdown period in the NEM. Overall, VIC experienced a moderate operational demand reduction, whereas SA experienced a considerable increase in demand. This was due to the greater proportion of residential demand, which exceeds the commercial load. No concrete evidence of demand change was established in TAS. A visual inspection of Figure 2.3a suggests further that the trend of consumption reduction after the imposition of a strict nationwide lockdown on 23rd March to 31st May 2020, did not diverge substantially from the pre-lockdown period. The impact of gas during the lockdown period is evident in NWS and mostly in SA, which has a large proportion of gas in its generation mix. Since the start of 2020, gas was offered in the markets at increasingly lower prices and reached the historically lowest levels in all markets across the NEM around the mid 2020 (AEMO, 2020e). The lower gas prices were associated with falling gas prices in the international market and increased QLD gas production. Although high rainfall allowed increased output from hydro, we find strong evidence that the marginal increase was associated with higher NSW electricity prices. In contrast, we find strong evidence that hydro generation contributed to reducing electricity price in TAS.

These results suggest further that the lockdown restrictions lowered price volatility in NSW. The effect of wind generation and penetration during the lockdown period was less evident in VIC, where a marginal increase in wind generation and penetration was associated with a decrease in price volatility. We find less evidence for the positive impact of consumption in volatility dynamics in NSW. The marginal increase in hydro generation in VIC and NSW during the lockdown period exerted downward pressure on volatility dynamics. Moreover, we find modest evidence for the effect of gas prices in NSW, whereby the marginal increase in gas prices led to higher price volatility. These dynamics may be the aftermath of the COVID-19 pandemic, which caused price volatility in international gas prices, especially the Japan Korea Marker (JKM) LNG prices (AEMO, 2020e).

Overall, we find that the COVID-19 pandemic and the associated restrictions had a moderate impact on the NEM, with a direct impact reflected in the reduction in demand and electricity prices. Furthermore, no major changes were associated with the merit order effect of wind generation during the lockdown period. The effect on volatility was unremarkable across all regional markets. Nonetheless, sustained lower demand and prices are likely to hurt new investment projects, including renewable energy and coal-fired generators.[42] Therefore, the regulatory framework and market structure need to be adaptable and responsive enough to effectively address uncertainties and potential future challenges. With the pandemic's disruption of the economy and with the threat of future disruptions due to climate change and other unforeseen events, accelerating market reforms aimed at improving market operations and resiliency in the NEM should be the focus.

2.5 Conclusion and Policy Implications

The Australian electricity market (NEM) is experiencing one of the fastest-growing VRE generations in the world, raising new challenges to system security and reliability. This transformation has manifested in an extended period of negative prices and increased uncertainty and variability of electricity prices. Despite increased generation from solar generation recently, wind generation still leads this evolution and accounts for most of these variations. This necessitates a re-evaluation of the market dynamics and their determinants. We conditioned on a set of factors not previously considered, such as hydro generation and interconnectors, to model and evaluate the impact of wind generation on the dynamics of electricity prices and simultaneously capture the MOE and volatility dynamics. The results suggest that wind generation contributes to a statistically significant reduction in electricity prices in the NEM. Electricity consumption, gas prices, and hydro generation are positively related not only to electricity prices but also to their price volatility. The impact of wind generation on volatility dynamics is more pronounced in states with high wind penetration, such as South Australia, Tasmania, and Victoria.[43] Thus, we conclude that states with high wind penetration are more susceptible to variation in electricity prices. The six cross-border interconnectors have a measurable impact on price levels and volatility, an impact that depends on a state's position as an

[42]While it is acknowledged that both supply and demand dynamics influence investment decisions, the main focus in this context is on the impact of sustained lower demand on new investment projects. These projects may face challenges due to reduced revenue potential and a decrease in market demand for additional generation capacity.

[43]Specifically, volatility increases with high wind generation in South Australia and Victoria and decreases in Tasmania. The effect of wind penetration moves in the same direction and is statistically significant in states with moderate penetration levels, which are Victoria and Tasmania.

importer or exporter of electricity and the thermal capacity of the respective interconnector. The impact also depends on the extent to which the increase in VRE and the closure of coal-fired generators affects the respective connected markets.

We investigated the impact of two federal policies imposed on the dynamics of electricity prices; the carbon pricing mechanism and the nationwide lockdown restrictions in Australia due to COVID-19. We find that during the carbon pricing period, wind generation led to a marked merit order effect in the NEM with a negative impact on electricity price volatility. During the COVID-19 lockdown, we report a reduction in electricity prices, mostly due to the decline in electricity demand, yet only a marginal impact on volatility.

These findings provide insights into the complexity associated with the recent transformation in the NEM due to the fast-evolving generation mix. Based on the empirical analysis, this transformation accounts for a substantial increase in the variability and therefore, uncertainty in electricity prices. Negative prices have become a common feature in the NEM, and the magnitude of these instances has become more persistent and more pronounced. Price volatility potentially signals the need for new investment; such volatility characterized by infrequent, very high, or low prices for very short periods poses a considerable risk to investors and consumers (Han et al., 2020). The retirement of coal-fired generators (sometimes earlier than expected) poses further challenges in the market and has the potential to amplify price shocks in the future.[44] The level and volatility of wholesale electricity prices impact end-consumer prices and electricity bills. Evidence suggests that the costs of the RET accounted for a substantial portion of the increase in residential prices, among other factors. These costs are passed on to consumers in the form of retail electricity price premiums, offsetting the MOE (Cludius et al., 2014a). Despite the expected drop in residential prices in the next two years driven mostly by high VRE generation (AEMC, 2019b), the increasing price volatility has potential to counteract the anticipated trend by exerting upward pressure on the wholesale price contract. One of the major key challenges to the system operator going forward is managing the variability

[44] Many coal-fired powers plants are expected to wind up withdrawing around 63% (15 GW) of capacity from the NEM by 2040. More than 30 GW of large-scale renewable energy will be required by then to replace the lost output (AEMO, 2020a).

and uncertainty of prices, as the high penetration of wind and solar generation potentially endangers the system security and reliability (Simshauser and Gilmore, 2020).

As wind penetration continues to increase across the NEM, more investment in fast-start, firm, and flexible (dispatchable) capacity will be needed in coal-generation dominant regions, that is, NSW and VIC, to meet the lost output from wind generation.[45] In contrast, SA and TAS have a large proportion of gas and hydro generation, respectively, which serve to keep the system stable and secure. Eventually, the increase in wind generation in the NEM has the potential to displace intermediate as well as peaking generators (i.e., OCGTs have been less impacted than CCGTs by the entry of wind generation) (Forrest and MacGill, 2013; Marshman et al., 2020). This brings the market to a delicate balance. Furthermore, the demand patterns of electricity have been changing considerably in the NEM due to the changes behind the metered resources, especially rooftop solar PV generation. Thus, the new plant design and the demand side offer potential for system flexibility beyond the traditional fuel-type-based flexibility. The importance of having a flexible system can be further supplemented by effective market connectedness and storage technologies.

Effective market trade in the NEM has been restricted by the thermal, voltage, and transient stability limitations of the cross-border interconnectors leading to different interstate, volatile, and unnecessarily high electricity prices (Ignatieva and Trück, 2016; Bell et al., 2017). Furthermore, the NEM is not as heavily connected as other renewable-rich countries such as Denmark,[46] nor is the NEM connected to its own northern and western territories. Therefore, the NEM is solely dependent on local supply. As the market transitions to renewables, heavy investment in interconnectors is very important to keep the system stable and secure (Denny et al., 2010). Ultimately, this will reduce pressure on prices and enhance the efficient use of renewable energy generators. In the same vein, the changing energy landscape in the NEM is associated with the reversal

[45]AGL Energy is planning to replace the Liddell power station in NSW beyond its announced retirement in 2022 with these sorts of technologies (a mix of renewable generation, high-efficiency gas peaking capacity, battery storage, and an upgrade of its Bayswater power station (AER, 2020b).

[46]Denmark, which leads with the highest VRE penetration, is strongly interconnected with central European and Scandinavian power systems, which offers strong support for balancing the system (AEMO, 2020c).

of the flow direction in the existing interconnectors. For instance, VIC, which was a net exporter, has been increasingly reliant on NSW, SA, and TAS to supplement VIC's supply during peak periods.[47] To ensure maximum benefits from these interconnectors, future investments must align and account for the long-term ability of the states to deliver renewable energy generation and for future market conditions.

Investment in pumped hydro and battery storage has been slow compared to the speed at which the market is transitioning to renewable energy. Nonetheless, future developments and proposed storage projects are expected to shape the energy landscape and perhaps reduce the price swings currently observed in the NEM. SA, for instance, installed the world's largest lithium-ion battery at the Hornsdale wind farm (170 MW), which has played a substantial role in lowering the cost of frequency control services in the region (AER, 2020b). It is projected that battery storage installations will increase from nearly zero in 2020 to about 5.6 GW by 2036–37. Major proposed pumped hydro energy projects include the expansion of the Snowy Hydro Scheme, which will increase capacity by 50% (up to 2000 MW) and the Tasmanian hydroelectric system (2500 MW). Renewable hydrogen is also expected to provide vital support for increasing surplus from VRE generation and the potential for energy exports in Australia (COAG, 2019). Thus, the infrastructure and the expansion of the electricity grid and an effective mix of technology will be central to the transition from fossil fuel to clean energy generation.

Finally, the increase in price volatility from the increasing reliance on weather-based renewable energy sources underscores the importance of appropriate methods for data treatment and modelling. Misspecification may potentially underestimate price volatility leading to inaccurate derivative pricing and hedging strategies. Policies informed by any such misspecifications risk may fail to address the current challenges associated with higher penetration of VRE production in the NEM.

[47] Its exports to SA, for instance, have decreased substantially from an average of between 220 MW and 270 MW to 41 MW (Cornwall Insight, 2020).

Chapter 3

Large-scale and rooftop solar generation in the NEM: A tale of two renewables strategies

This chapter is based on the peer-reviewed journal publication Mwampashi et al. (2022).

3.1 Introduction

The uptake of variable renewable energy (VRE) at the grid-scale and individual customer levels continues to surge, imposing significant stress on ageing coal-fired and gas-powered generation in Australia's National Electricity Market (NEM). About 18 Gigawatts (GW) of new solar and wind energy, equivalent to 250 Watts per person per year, were installed during the three-year period from 2018 to 2020 (Blakers et al., 2021).[1,2] Although wind generation currently is the dominant weather-dependent renewable generation system in the NEM, rooftop solar photovoltaic (PV) systems have experienced the most rapid growth. Australia has one of the highest per-capita rates of rooftop solar PV installation in the world. Rooftop solar partially meets the electricity needs of around 24% of customers in the NEM who, in turn, sell their excess generation back to the grid (AER, 2021a). Moreover, investment in large-scale solar generation has increased significantly in the NEM since 2018, as this system became the cheapest form of new power-generation technology.[3] On 11th October 2020, a combination of large-scale and rooftop solar generation alone set a record in South Australia, which has the highest solar penetration in

[1] In the next two decades, around 26–50 GW of new large-scale wind and solar capacity and 13–24 GW of rooftop solar PV are expected to come online, replacing the 16 GW of thermal power (around 61% of the existing coal generation fleet) expected to retire during this period (Blakers et al., 2021).

[2] In the paper, we refer to solar generation as a combination of large-scale and rooftop solar generation unless specified otherwise. In the NEM, large-scale solar (also known as utility-scale solar or solar farm) refers to solar power plants with a capacity of 30 MW or more, whereas small-scale solar (rooftop solar) refers to plants with a capacity of 100 kW or less (Rai and Nunn, 2020b).

[3] Between 2010 and 2020, the global weighted-average levelized cost of electricity (LCOE) of utility-scale solar PV for newly commissioned projects declined by 85%, from USD 0.381/kWh to USD 0.057/kWh (IRENA, 2019).

the NEM by supplying more than 100% of the region's electricity demand. Rooftop solar generation supplied 77% of demand on several occasions and more than 70% for around four hours (AEMO, 2020f; AER, 2021a).

Although the influence of wind generation in the NEM has been well established in Chapter 2, there is a paucity of literature on how solar penetration affects spot price dynamics. Large-scale solar generation is a relatively new entrant with significant scale generation starting in 2018. This relatively recent commencement implies that previous studies potentially give an incomplete description of the merit order effect (MOE) of large-scale solar generation (Csereklyei et al., 2019). We also posit that combining large-scale and rooftop solar is not the best way to study the impact of solar generation on spot prices (Abban and Hasan, 2021), given that large-scale and rooftop solar are affected by different government policy incentives, differences in entrance periods, and different uptake rates. Several additional issues associated with solar generation necessitate revisiting its impact on spot price dynamics. First, the pace and scale of simultaneous new solar generation that entered the market between 2018 and 2021 have been significant. Second, evidence suggests that the new solar PV entrants quickly outpaced their respective markets due to the near-perfect correlation between fleets (Simshauser, 2021). Third, the rapid uptake of rooftop solar PV output lowers the grid demand in the middle of the day when generation is high, pushing prices down and putting the economics and operating capability of coal-fired generators to the test. The operator, in some instances, is forced to intervene and requires rooftop solar owners to draw power from the grid to ensure the security of the power system.

This study examines the impact of solar generation by separating the effects of large-scale solar and rooftop solar generation on the intraday (half-hourly) level and volatility of electricity spot prices in five NEM regional markets, namely, New South Wales (NSW), Victoria (VIC), South Australia (SA), Queensland (QLD), and Tasmania (TAS). By treating large-scale and rooftop solar generation as two separate variables, this study is the first to investigate the impact of rooftop solar generation on the level and volatility of spot prices. Motivated by the variation in electricity spot prices and their determinants throughout the day and over the four seasons of the year, we thoroughly examine the intraday profile of the impact of solar generation on electricity spot prices and generation mixes during each time interval and over seasons (summer, autumn, winter, and spring). Most studies that focused on the impact of VRE employed low-frequency (daily) data. In contrast, we use high-frequency data from March 2015 through July 2021 to investigate the intraday effect of VRE on the level and volatility of spot prices. In the same vein, we add to the MOE of large-scale solar generation studies by including in the analysis the last three years, which witnessed vastly increased large-scale solar generation investment. The use of intraday data provides rich information on the variability of spot prices and improves the robustness of the estimated model results (Zhang et al., 2014). Furthermore, we use the Nelson (1991) exponential generalized autoregressive conditional heteroscedasticity (eGARCH) model to capture the intraday dynamics.[4]

We find that large-scale and rooftop solar generation impact spot prices and volatility in the NEM. These effects differ across regional markets depending on several factors, such as solar penetration rates, prevailing weather conditions, and system flexibility. The MOE of large-scale and rooftop solar generation is more pronounced in states with moderate generation levels, such as SA and VIC, and relatively lower in states with high generation levels, such as QLD and NSW. Increasing large-scale solar generation in SA, which relies more on expensive gas generation, depresses electricity spot prices more substantially than in other states. We find that a 1 MWh increase in large-scale solar output reduces prices by around 0.15 AUD/MWh. Rooftop solar has a small effect, exhibiting a minimum of 0.01 AUD/MWh (NSW) and a maximum of 0.04 AUD/MWh (TAS) price drop for every 1 MWh increase in rooftop solar generation. The MOE of large-scale and rooftop solar generation remains apparent even after adjusting for the impact of electricity consumption. However, states with high penetration of large-scale and rooftop solar, such as SA and QLD, tend to exhibit lower price reductions than states with moderate penetration rates, such as NSW and VIC. Furthermore, adding large-scale and rooftop solar generation to the system tends to increase spot price volatility. Although states with moderate generation levels experience a relatively large MOE, this benefit comes at

[4]We demonstrate the robustness of the eGARCH model over the Ding et al. (1993) asymmetric power ARCH (apARCH) and the Engle and Sokalska (2012) multiplicative component GARCH (mscGARCH) models.

the cost of high price variability. When comparing the average effect of large-scale and rooftop solar generation, we find that the former exhibits a more substantial negative impact on the price level and a positive impact on volatility dynamics compared to the latter.

The intraday profile of the impact of large-scale and rooftop solar generation on spot prices provides a more illustrative view of the varying impact of solar generation throughout the day compared to the average impact observed over the entire sample period. Adding large-scale and rooftop solar generation to the system does not necessarily lower electricity spot prices, unlike wind generation, which appears to have a consistently negative impact on spot prices. We find that solar generation can impact prices positively through high ramping/cycling costs in the early morning and the evening when the sun is about to set. Put differently, our results show that the duck curve resulting from high penetration of rooftop solar generation also produces a duck curve in the spot prices. Our findings demonstrate that an increase in prices resulting from solar generation during the early morning and the evening are driven by the high cost associated with natural gas generation in NSW, natural gas and brown coal generation in VIC, natural gas and black coal generation in QLD, and natural gas, diesel and fuel oil generation in SA. Although the average over the sample period suggests a positive impact of solar generation on spot price volatility, the intraday profile shows that large-scale solar generation has a greater potential to reduce price variability than rooftop solar and wind generation. We posit that the difference in the impact of large-scale and rooftop solar generation is driven by the difference in the orientation of the solar panel systems and the power system flexibility. Increasing large-scale solar generation and rooftop solar generation in the system lowers electricity spot prices more significantly in the summer, followed by the spring, autumn, and winter. While the MOE appears the lowest in the winter, price volatility is more significant than in other seasons.

Important implications and policy recommendations can be drawn from these findings to maximize the benefits derived from the rapid uptake of solar generation, especially rooftop solar. We propose four courses of action to increase the correlation between rooftop generation and electricity demand,[5] which, in turn, would increase the MOE and reduce electricity price volatility. First, small-scale renewable energy schemes (SRESs) and state-based policies should allocate their support to PV-plus battery systems to enable owners of rooftop solar generation to store extra generation during the day and export later in the evening to meet the peak demand. Second, the Australian Energy Market Operator (AEMO) should design appropriate measures to curtail rooftop solar generation, especially via dynamic/flexible export management, to effectively absorb all excess rooftop generation and maintain system security. Third, state governments and retailers should transition to dynamic feed-in tariffs (FiTs), which are lower during the day and higher in the morning and evening peak hours, to incentivise rooftop owners to inject their electricity into the grid in the morning and evening when it is more valuable. Finally, the findings stress the importance of transitioning to a two-sided market to increase market flexibility by allowing demand-side participation. Demand-side participation is the cheaper option for providing flexibility compared to peaking (gas-fired or hydro) generation, and is expected to shape the future of clean energy.

The remaining sections proceed as follows: In section 3.2, we detail the data and methods. Section 3.3 presents the average impact of both large-scale and rooftop solar generation on the spot price dynamics over the whole sample period, while section 3.4 discusses these effects based on half-hourly time intervals and seasons of the year. In section 3.5, we present policy implications of the findings, and section 3.6 concludes.

3.2 Data and Methods

3.2.1 Data and preliminary analysis

Our analysis considers five NEM markets: NSW, VIC, QLD, SA, and TAS. We use high-frequency NEM data based on 30-minute trading intervals obtained from NEOpoint

[5]It is worth mentioning that some of these recommendations are similar to those submitted by the Energy Security Board (ESB) to energy ministers on the Energy National Cabinet Reform Committee. The ESB works in conjunction with the Australian Energy Market Commission (AEMC), Australian Energy Market Operator (AEMO), and the Australian Energy Regulator (AER) to provide recommendations for reforming the National Electricity Market (NEM) to meet the transitional needs up to and beyond 2025. The final advice on the post-2025 redesign of the National Electricity Market (NEM) can be found here https://esb-post2025-market-design.aemc.gov.au/

(2022). The sample period is from March 2015 to July 2021. The data include wholesale electricity prices,[6] large-scale solar generation, rooftop solar generation, large-scale wind generation, hydro generation, electricity consumption, and cross-border interconnector flows. The daily gas price data for NSW, SA, and VIC were obtained from the Short Term Trading Market (STTM; AEMO 2022e) and the four-hour gas price data for VIC from the Declared Wholesale Gas Market (DWGM; AEMO 2022b). While most of the control variables are available for many years, the main variables, large-scale solar generation and rooftop solar generation, are available for recent years only. The data (see Appendix B.1.1) presented two challenges. First, large-scale solar generation data for NSW and QLD are available since 2015 and 2017, respectively, and for SA and VIC since 2018. These years correspond to the construction of the first large-scale solar plants; that is, the lack of a longer-run large-scale PV output time series reflects the relatively short period large-scale solar generation has contributed to the NEM. There are no large-scale solar farms in TAS. Large-scale wind farms have historically had a lower LCOE than large-scale solar PV plants, resulting in more wind farms than solar PV plants being built to meet the large-scale renewable energy target (LRET) at the lowest cost. In contrast, and on a small scale, solar PV has been the cheapest means of meeting the SRES (Rai and Nunn, 2020b). Second, although rooftop solar generation has been available in Australia for the last decade, regional rooftop solar actual generation estimates for each half-hour interval have been available only since 2018.

In Figure 3.1, the annual growth of rooftop and large-scale solar generation per state is compared in terms of their generation levels and penetration rates.[7] It is apparent from this figure that large-scale solar generation increased substantially across states in the NEM following the decline in the cost of VRE and government policy incentives, especially since 2018 (de Atholia et al., 2020). NSW was the initial focus for solar farm development, accounting for the significant generation in NSW since 2015. Efforts to promote solar generation in QLD, VIC, and SA recently triggered a considerable uptake

[6] The dispatch prices in the NEM are calculated every five minutes, and six dispatch prices are averaged every half-hour to determine the spot price for each NEM region. All financial transactions for electricity traded in the NEM are settled using the spot price.

[7] Solar penetration refers to the percentage of electricity generated by solar power in a particular year relative to the electricity consumed.

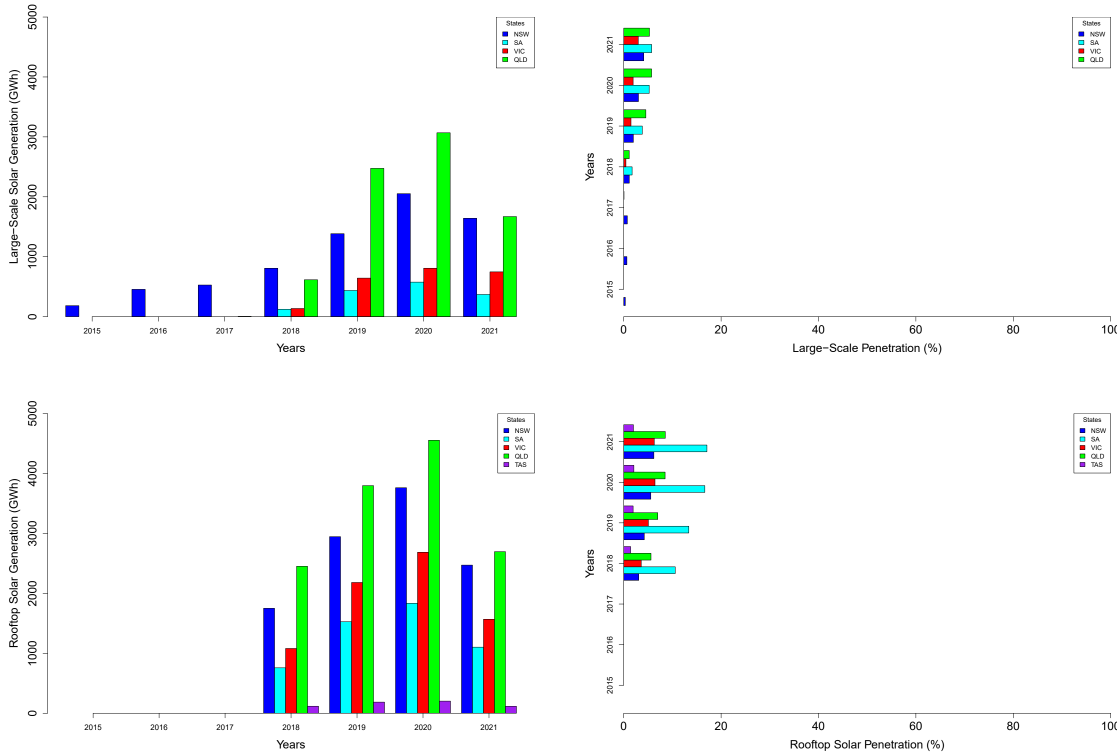


Figure 3.1 : **Large-scale solar (first row) and rooftop solar (second row) for NSW, SA, VIC, QLD, and TAS, between March 2015 and July 2021.** The first panel in each row shows the generation, and the second panel shows penetration. Note that data for rooftop solar generation are available only from 2018 onward (i.e., the zeros for 2017 and previous years do not reflect a lack of solar PV system installations). The generation levels and penetration rates for both large-scale and rooftop solar generation for the year 2021 capture electricity generated up until July 2021, not the entire 2021 year.

of large-scale solar generation in these regions, making QLD the leader across the NEM.[8] Although investment in large-scale solar generation has been slow in Australia, the uptake of rooftop solar generation has been dramatic. From Figure 3.1 we see that rooftop generation has increased substantially since 2018 across the NEM with the slight exception of TAS, where generation remained fairly constant. SA and QLD exhibit high rooftop solar penetration compared to other states.

Figure 3.2 displays average hourly electricity prices per state and per season. It is

[8]Australia is among the countries in the world with the highest average solar radiation. Most of Australia's solar resources are concentrated in the north-west and central areas, whereas the south and east have little solar exposure (Li et al., 2020).

evident that electricity prices vary over different hours of the day and the seasons for all five states, corresponding to variation in electricity demand. Although the peaks and troughs differ slightly between regions, roughly speaking, the peak period lasts from 16:00 to 21:00. Electricity demand fluctuates depending on the time of day, season, and ambient temperature. Demand often increases in the early evening, when many businesses are at their peak operations, and a large quantity of electricity is required for domestic purposes. This period overlaps with the decrease in rooftop PV generation. Seasonal peaks occur in the summer due to increased air conditioning and in the winter due to heating needs. High-marginal-cost generators, such as gas, set the price at peak periods. In contrast, low-marginal-cost generators, such as wind, solar, hydro, and coal, are typically sufficient at low-load times. It is worth mentioning that electricity prices in the past were lower overnight and early in the morning when demand is lower and relatively higher during other times. However, the dramatic increase in rooftop generation exerted substantial downward pressure on grid electricity prices in the middle of the day. Figure 3.3, showing the average hourly electricity consumption per state and season, depicts the hollowing out of the demand during the middle of the day, often termed the "duck curve". Furthermore, we observe a clear variation in electricity prices over four seasons in Figure 3.2, with the average higher prices occurring in the summer and the winter.

The generation profiles over time and seasons for rooftop solar and large-scale solar generation are plotted in Figures 3.4 and 3.5, respectively. Generation starts gradually at around 05:00 and decreases around 20:00. However, peak generation period differs across states. The differences in orientation may explain the differences in generation profiles between rooftop and large-scale PV. The former are largely north-facing fixed-panel systems, which typically give the greatest energy output during the middle of the day, in turn, producing the characteristic "bell-shaped" intraday generation profile. The latter has a higher share of axis-tracking systems, which maximize electricity output by moving the panels to track the sun throughout the day, making their generation profile flatter/less peaky. Solar trackers are usually used in utility-scale and commercial/industrial solar projects, such as ground-mounted solar panels, and rarely in residential solar projects. The availability of government policy incentives such as SRES and high FiTs triggered the dominance of

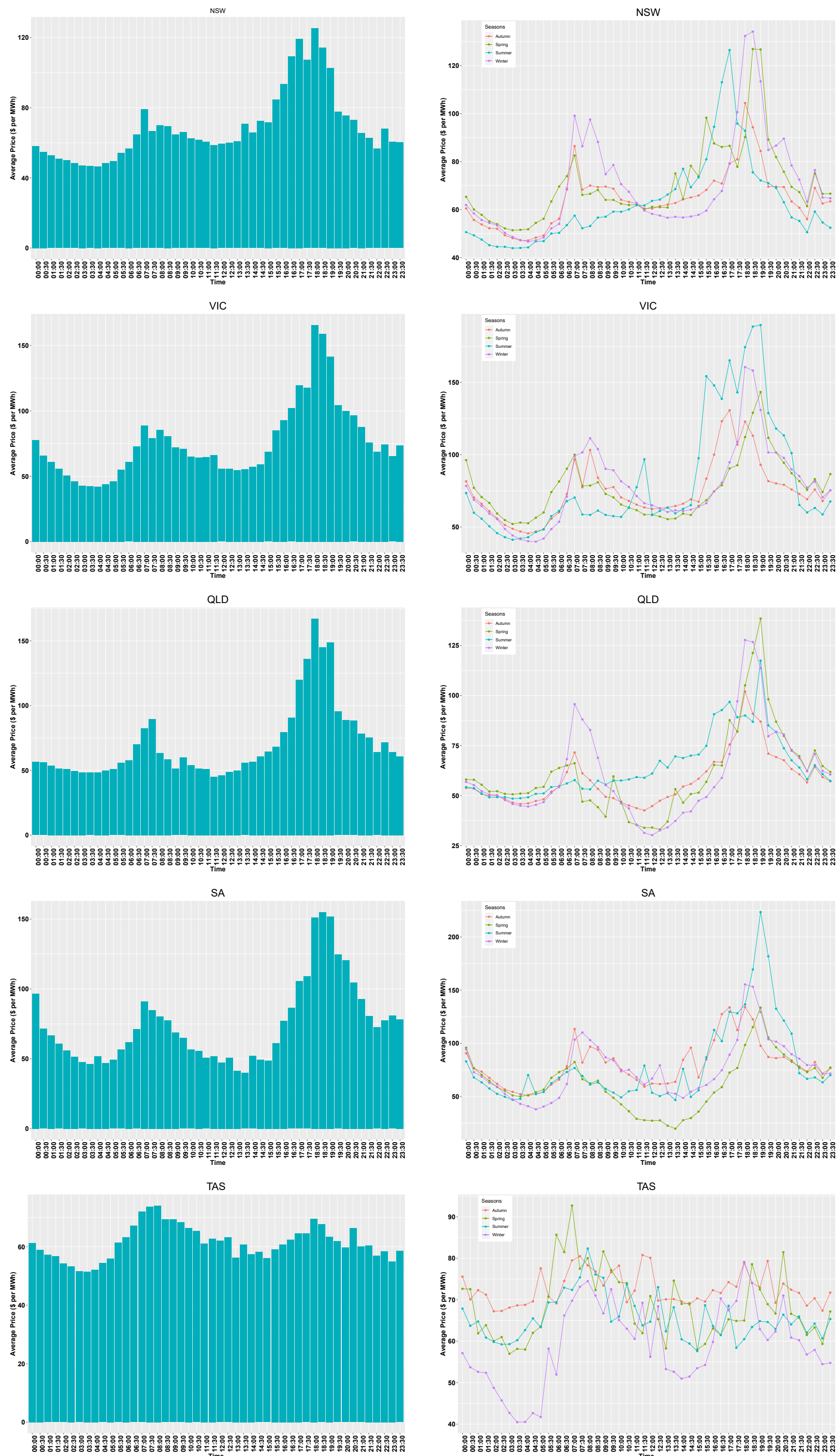


Figure 3.2 : **Average hourly electricity prices for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021).** The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of electricity spot prices over four seasons of the year.

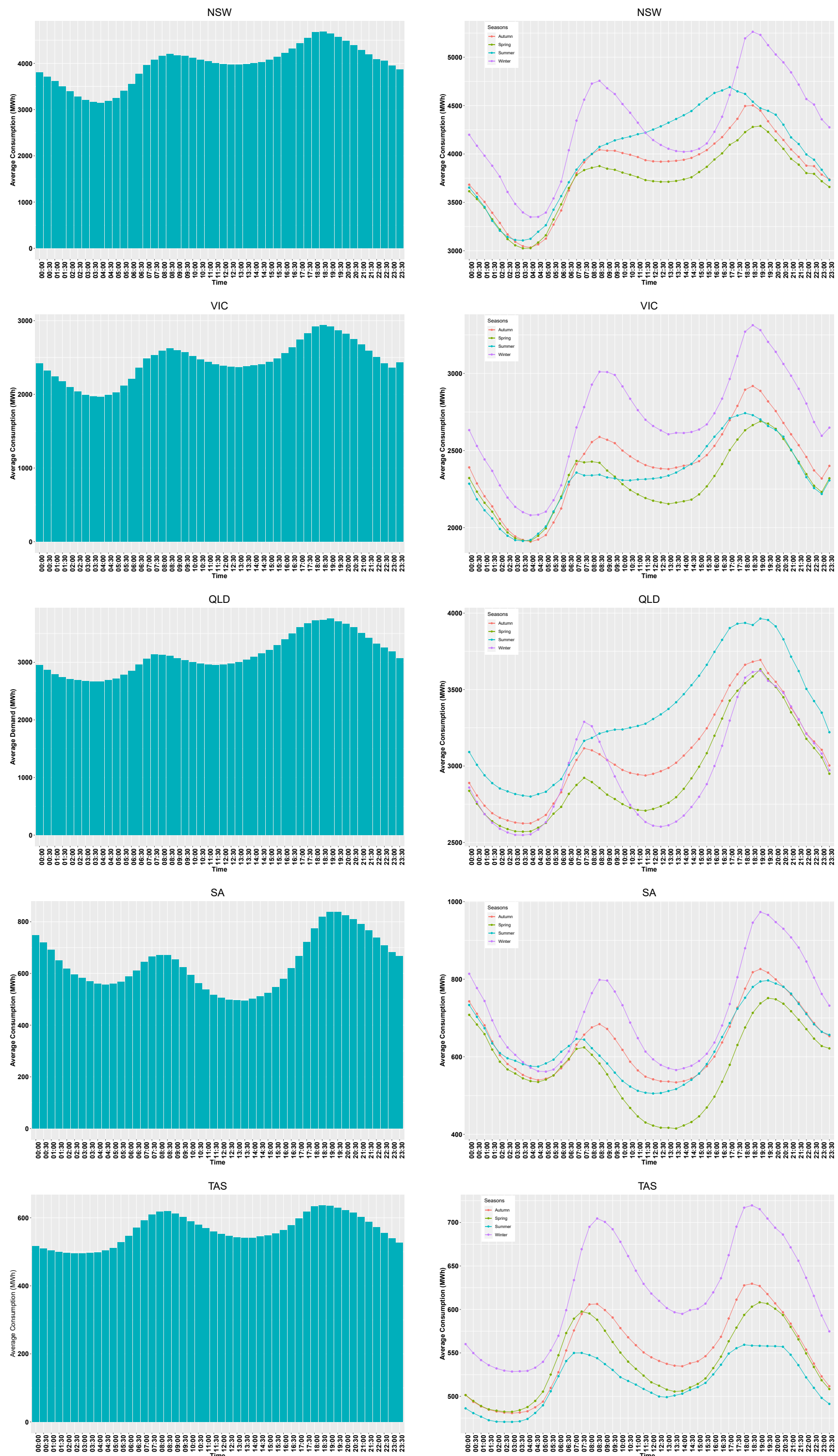


Figure 3.3 : **Average hourly electricity consumption for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021).** The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of electricity consumption over four seasons of the year and, most importantly, the duck curve.

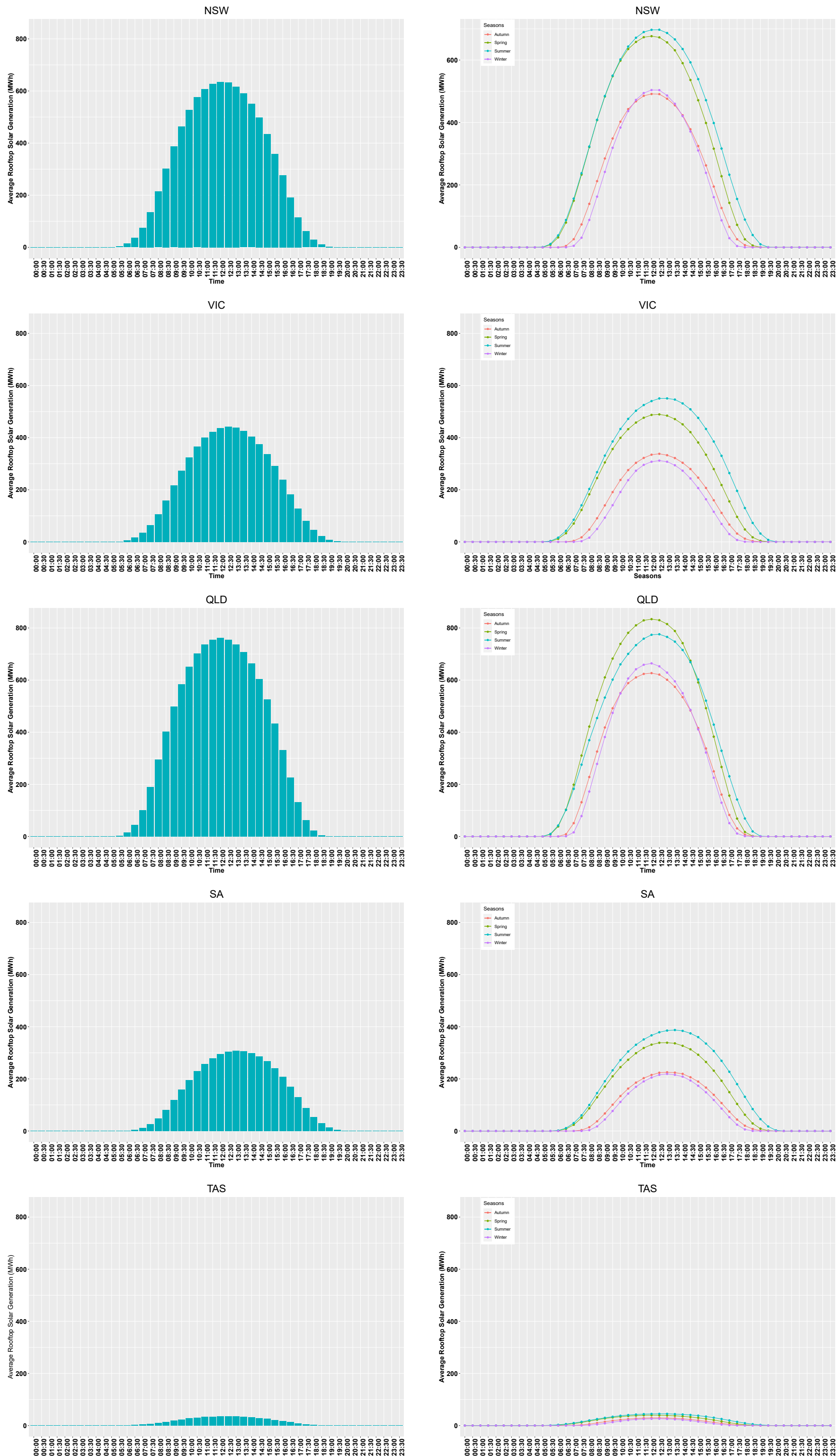


Figure 3.4 : **Average hourly rooftop solar generation for NSW, SA, VIC, TAS, and QLD from 2018 to 2021.**

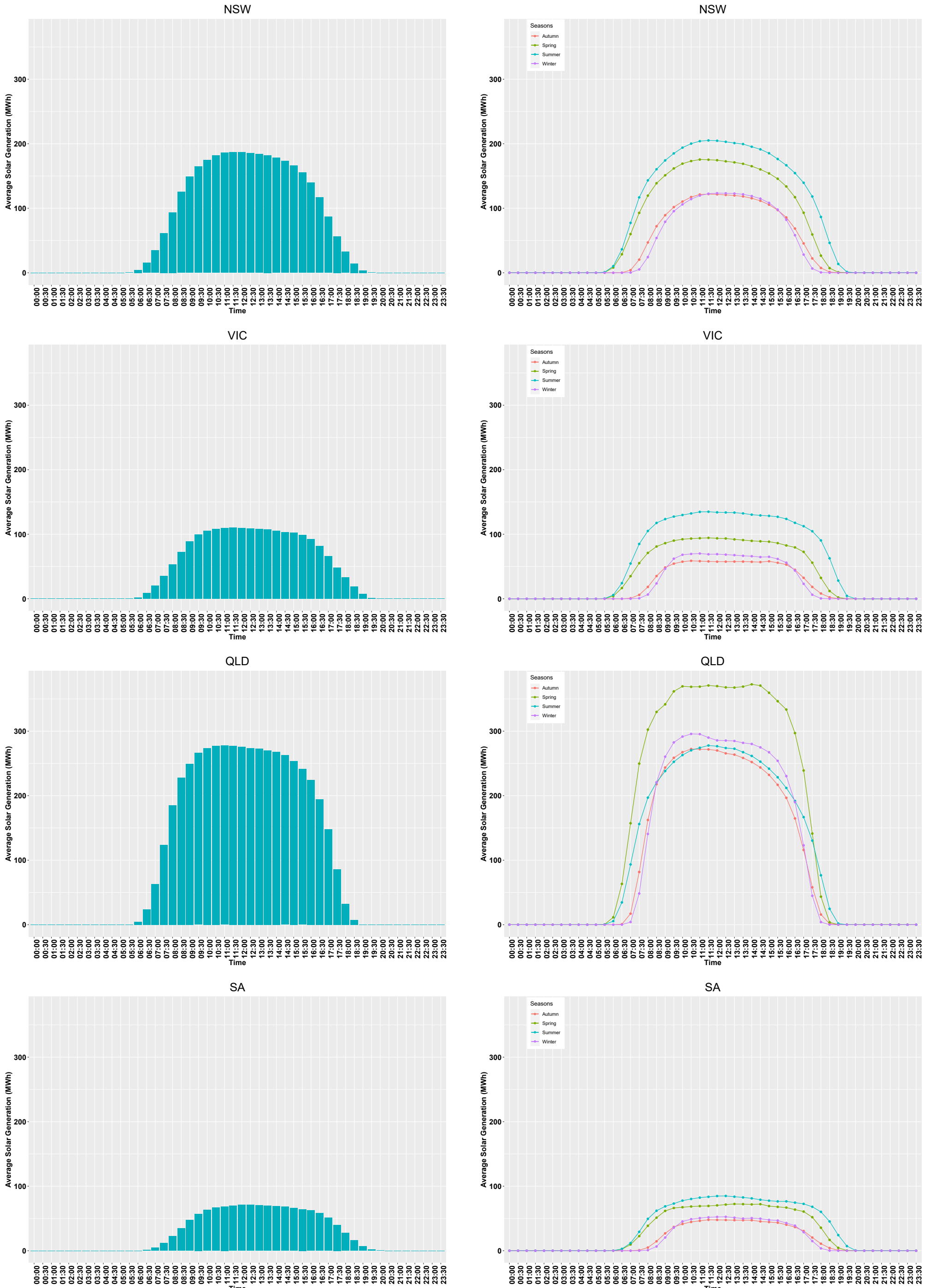


Figure 3.5 : **Average hourly large-scale solar generation for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021).**

north-facing rooftop solar panels. Northerly orientation guarantees household owners high solar generation during the day and, in turn, high FiTs payments. On average, days are longer in the spring and summer, resulting in more sunlight. This explains why there are more output and longer generation periods during these seasons. Comparing the variation in solar generation to that of wind (Figure 3.6), it is apparent that the two are negatively correlated. NSW, QLD, and SA attain peak wind generation at night, whereas VIC and TAS exhibit higher wind generation during daytime hours. Other states attain higher generation during spring and winter except QLD, which exhibits higher outputs during autumn and spring. Based on these observations, the present study raises the possibility that solar generation may exhibit a varying impact on the dynamics of spot prices based on the time of day.[9] Table 3.1 summarizes descriptive statistics for all variables used in our analysis.

3.2.2 Seasonality adjustments and time-series tests

From the previous discussion, it is evident that demand and supply exhibit seasonal fluctuations. These variations result in seasonal behaviour in spot electricity prices over daily, weekday, month, and yearly periods. The use of high-frequency data necessitates modification of the Ketterer (2014) and the approach presented in Chapter 2 to include an intraday seasonality term in the OLS model. Thus, we decompose the time series of the dependent and independent variables, π_t, as the sum of a stochastic component y_t and a seasonal component s_t; that is, $\pi_t = y_t + s_t$, $t > 0$. The seasonality component is then specified as

$$s_t = \hat{c} + \sum_{i=2}^{p} \hat{\psi} \cdot intraday_i + \sum_{j=2}^{q} \hat{\phi} \cdot day_j + \sum_{k=2}^{r} \hat{\zeta} \cdot month_j + \sum_{l=2}^{s} \hat{\chi} \cdot year_l + \varepsilon_t,$$

where $\hat{c}$ is the intercept; p, q, r, and s are the total number of half-hourly trading intervals in a day, days in a week, months, and years, respectively; and $\hat{\psi}$, $\hat{\phi}$, $\hat{\zeta}$, $\hat{\chi}$ are the corresponding estimated coefficients. We run the regressions for each of the dependent

[9] Rai and Nunn (2020b) noted that, although the increase in VRE triggered extreme price instances, these instances were more likely a seasonal phenomenon than a year-long effect. This seasonality effect appears more pronounced for solar PV than for wind generation due to the relatively high correlation of solar PV generation with demand and co-incident output.

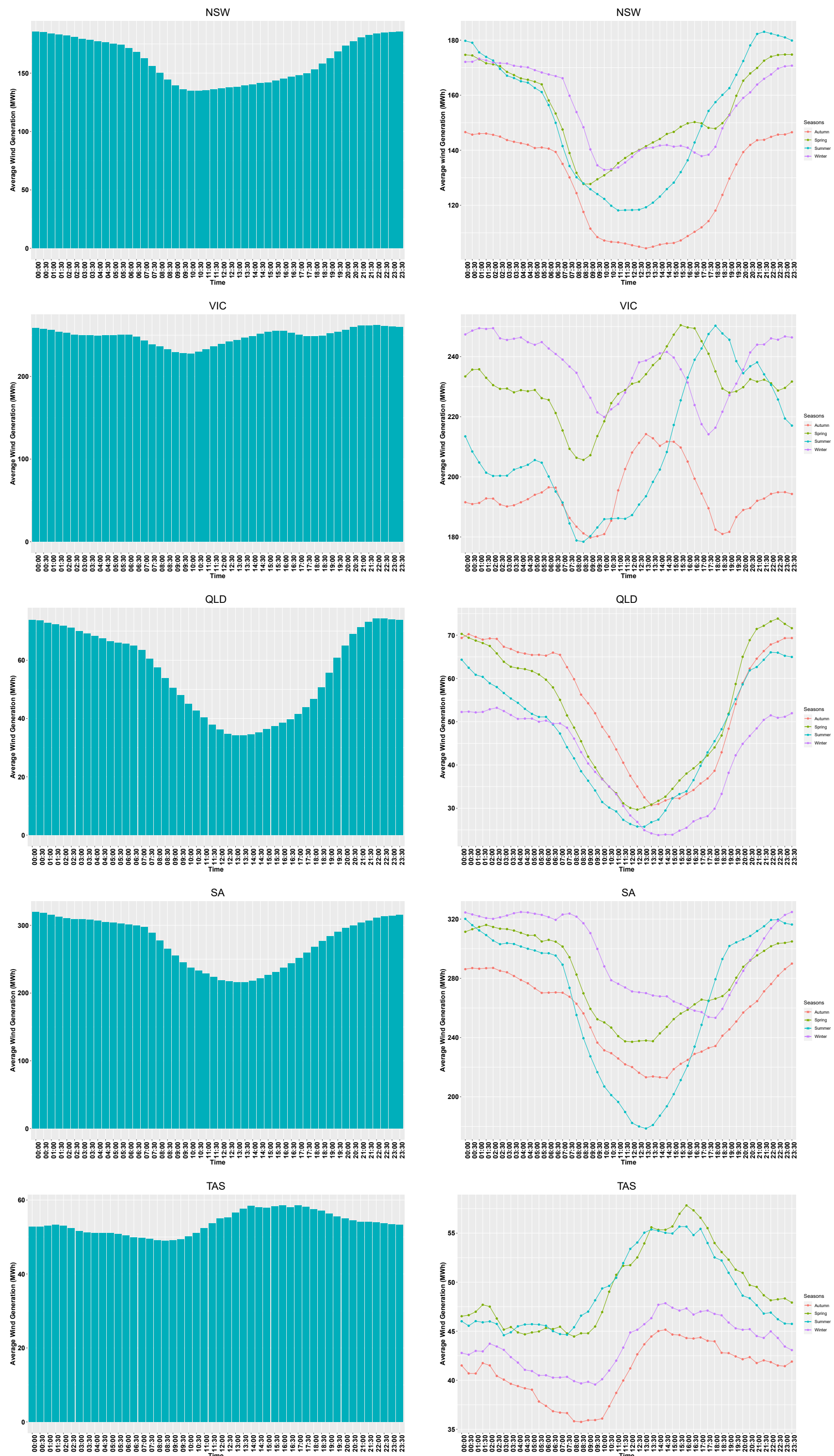


Figure 3.6 : **Average hourly large-scale wind generation for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021).** The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of wind generations over four seasons of the year.

Table 3.1 : **Summary statistics of the intraday (half-hourly) variables employed in the analysis.**

	Unit	Mean	Std Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile
					NSW					
Electricity Prices	AUD/MWh	72.40	191.61	49.15	3010.44	58.94	-139.93	14700.00	38.81	83.14
Large-scale Solar Generation	MWh	63.19	111.07	2.36	8.68	0.46	0.00	645.74	0.00	83.13
Rooftop Solar Generation	MWh	183.56	266.76	1.43	4.17	1.38	0.00	1270.98	0.00	335.73
Wind Generation	MWh	156.66	128.67	1.12	4.02	125.47	0.00	798.39	55.01	223.21
Natural Gas Generation	MWh	122.4	140.69	1.36	4.79	80.00	0.00	938.30	0.00	206.00
Black Coal Generation	MWh	3152.00	577.57	0.01	2.49	3162	1293.00	4844.00	2728.00	3559.00
Kerosene Generation	MWh	0.07	0.91	16.21	293.94	0.00	0.00	0.00	0.00	0.00
Gas Price	AUD/GJ	7.40	2.98	1.41	10.64	7.30	0.02	29.78	5.05	9.40
Hydro Generation	MWh	143.70	158.33	1.95	8.66	86.00	0.00	1366.6	26.5	219.4
Consumption (Grid)	MWh	3969.00	629.15	0.64	3.50	3922.00	2585.00	6993.00	3515.00	4331.00
Consumption (Underlying)	MWh	4116.00	658.33	0.46	3.40	4119.00	2683.00	7184.00	3647.00	4506.00
Terranora (NSW-QLD)	MWh	-27.45	19.12	-0.04	3.82	-27.84	-102.11	68.80	-39.64	-14.85
QNI (NSW-QLD)	MWh	-202.13	176.35	0.05	2.26	-198.50	-576.69	316.16	-336.37	-76.38
VNI (VIC-NSW)	MWh	133.02	239.13	0.09	2.09	124.94	-609.78	870.79	-67.01	326.18
					VIC					
Electricity Prices	AUD/MWh	77.40	286.26	42.36	1958.69	61.44	-676.37	14700.00	37.58	95.29
Large-scale Solar Generation	MWh	40.69	64.35	1.79	5.85	0.06	0.00	343.55	0.00	73.11
Rooftop Solar Generation	MWh	131.07	196.15	1.50	4.38	0.52	0.00	932.66	0.00	227.00
Wind Generation	MWh	242.23	185.30	0.97	3.84	203.84	0.00	1090.82	91.45	360.74
Brown Coal Generation	MWh	1968.00	243.70	-0.18	2.50	1954.00	1097.00	2440.00	1782.00	2150.00
Battery Generation	MWh	0.36	1.78	6.61	54.50	0.00	0.00	27.50	0.00	0.00
Natural Gas Generation	MWh	116.2	167.94	1.91	7.00	43.80	0.00	1164.00	0.00	173.80
Gas Price	AUD/GJ	7.53	2.69	2.32	28.77	7.77	0.00	58.44	5.35	9.35
Consumption (Grid)	MWh	2440.00	430.88	0.73	3.63	2382.00	1154.00	4754.00	2118.00	2698.00
Consumption (Underlying)	MWh	2571.00	449.52	0.60	3.71	2555.00	1547.00	4998.00	2225.00	2852.00
VNI (VIC-NSW)	MWh	86.75	222.18	0.23	2.20	63.02	-577.64	803.08	-95.36	261.93
Basslink (T-V-MNSP1)	MWh	11.00	155.27	-0.09	1.64	11.59	-239.00	239.00	-131.03	156.32
Heywood (VIC-SA)	MWh	-13.08	128.94	0.24	2.42	-18.32	-275.00	300.00	-108.33	73.39
Murraylink (VIC-SA)	MWh	7.89	37.05	-0.26	3.39	7.50	-98.28	110.00	-9.00	29.74
					SA					
Electricity Prices	AUD/MWh	73.97	289.41	39.31	1768.93	61.89	-919.78	14700.00	37.16	94.18
Large-scale Solar Generation	MWh	26.70	39.58	1.39	3.88	0.01	0.00	162.45	0.00	51.04
Rooftop Solar Generation	MWh	92.61	135.58	1.38	3.84	0.44	0.00	576.15	0.00	165.79
Wind Generation	MWh	274.49	184.81	0.23	1.80	252.69	0.01	748.54	106.78	445.63
Diesel Generation	MWh	0.55	5.03	14.88	281.34	0.00	0.00	157.84	0.00	0.00
Natural Gas/Diesel Generation	MWh	13.72	30.16	2.28	7.24	0.00	0.00	200.00	0.00	1.50
Natural Gas/Fuel Oil Generation	MWh	122.95	93.40	1.54	5.18	90.00	17.24	630.60	55.00	162.50
Battery Generation	MWh	1.02	3.64	5.89	50.76	0.00	0.00	72.50	0.00	0.00
Gas Price	AUD/GJ	8.18	2.74	1.68	10.77	8.34	3.15	28.01	5.99	9.83
Consumption (Grid)	MWh	639.50	168.89	0.57	4.43	625.40	142.30	1553.90	540.00	728.60
Consumption (Underlying)	MWh	732.10	152.23	1.39	6.94	713.90	416.60	1690.80	627.70	803.80
Murraylink(VIC-SA)	MWh	8.01	37.25	-0.26	3.36	7.83	-98.28	110.00	-9.00	30.00
Heywood (VIC-SA)	MWh	-14.65	128.49	0.25	2.44	-19.58	-275.00	300.00	-109.61	70.89
					QLD					
Electricity Prices	AUD/MWh	67.56	172.60	46.79	3330.20	56.51	-859.85	15000.00	38.16	75.89
Large-scale Solar Generation	MWh	121.83	181.34	1.23	3.05	0.81	0.00	680.42	0.00	232.58
Rooftop Solar Generation	MWh	226.69	312.91	1.15	3.05	226.69	0.00	1282.69	0.00	448.97
Wind Generation	MWh	59.03	53.12	1.16	3.70	43.22	0.00	282.64	18.34	83.14
Coal Seam Methane Generation	MWh	42.51	85.88	2.36	8.22	0.00	0.00	507.00	0.00	55.00
Kerosene Generation	MWh	1.40	11.23	10.38	125.91	0.00	0.00	198.00	0.00	0.00
Natural Gas Generation	MWh	272.70	169.57	0.64	2.58	241.50	0.00	909.80	128.90	387.20
Black Coal Generation	MWh	2819.00	329.03	-0.23	2.84	2826.00	1259.00	3746.00	2607.00	3050.00
Gas Price	AUD/GJ	7.40	2.33	0.66	4.57	7.21	2.31	19.10	5.95	9.00
Hydro Generation	MWh	48.80	37.71	1.37	6.46	44.00	0.00	353.67	18.08	72.00
Consumption (Grid)	MWh	3098.00	447.87	0.57	3.00	3039.00	1874.00	4994.00	2741.00	3407.00
Consumption (Underlying)	MWh	3322.00	507.19	0.48	2.99	3318.00	2346.00	5342.00	2927.00	3618.00
Terranora (NSW-QLD)	MWh	-26.28	19.70	-0.19	4.03	-25.84	-102.11	68.80	-37.84	-13.27
QNI (NSW-QLD)	MWh	-211.50	173.79	0.06	2.32	-204.60	-576.70	316.20	-345.40	-90.30
					TAS					
Electricity Prices	AUD/MWh	63.64	81.52	21.90	738.86	53.91	-844.65	4551.39	32.33	85.83
Rooftop Solar Generation	MWh	10.42	15.39	1.39	3.88	0.03	0.00	68.92	0.00	18.73
Wind Generation	MWh	51.19	44.89	1.01	3.71	42.39	0.00	203.49	12.73	78.99
Hydro Generation	MWh	509.36	207.32	0.04	2.07	516.37	51.66	1037.36	331.74	670.74
Natural Gas Generation	MWh	12.90	27.52	2.55	8.91	0.00	0.00	185.50	0.00	24.42
Consumption (Grid)	MWh	560.80	75.96	0.62	3.04	548.80	338.70	863.50	505.20	606.30
Consumption (Underlying)	MWh	571.20	75.06	0.49	3.00	562.90	345.70	866.60	518.10	616.20
Basslink (T-V-MNSP1)	MWh	10.27	153.31	-0.09	1.68	0.00	-239.00	239.00	-127.14	151.95

and independent variables and extract the seasonality-free time series from the estimated residuals, which is then aligned to the original series by adding the mean (Ketterer, 2014). As the same adjustment process is applied to all variables in the model, we measure the long-term effect of independent variables in spot electricity dynamics without seasonal noise, which may otherwise lead to false cause-and-effect conclusions.[10] Moreover, spot electricity prices tend to exhibit significant short-run upside and downside (low or negative prices) spikes, causing significant price deviations from the short-run marginal costs.[11] Typically, the former spikes reflect the shortage of supply due to inter alia unplanned generator outages, network outages, and lower-than-forecast VRE. The last occurs due to a combination of minimum electricity demand, high output from VRE, and unrestricted imports or restricted exports via cross-border interconnectors. As these observations are valid, we include them in the analysis to better capture the volatility of spot electricity prices (Kyritsis et al., 2017). Before specifying the models, we confirmed the stationarity of the time series using the augmented Dickey-Fuller (ADF) test, the presence of autocorrelation using the Ljung-Box test, conditional heteroscedasticity using Engle (1982) ARCH-LM test, and the absence of multicollinearity between explanatory variables using the variance inflation factors (VIFs). We provide further details in Appendix B.1.2.

3.2.3 Model specification for the mean and volatility process

Using high-frequency data requires a robust approach to capture the intraday volatility process effectively. To this end, we considered three ARCH models: the eGARCH, the apARCH, and the mscGARCH. ARCH models can potentially capture the volatility observed in electricity markets by allowing volatility shocks to cluster and persist over

[10]When a time series is measured in monetary values, inflation is often a significant contributor to its growth. By adjusting for inflation, we may determine whether there has been real growth or not. Inflation adjustment may also help to stabilize the variance of random or seasonal fluctuations and/or highlight cyclical patterns in the data. Given that we estimate our models using variables that are adjusted for seasonal and trend noise and an overall low level of inflation during the sample period, we expect inflation not to substantially impact the results of the analysis. Indeed, we deflated electricity spot and gas prices to 2018 dollars for each regional market using the quarterly consumer price index (CPI) obtained from the Australian Bureau of Statistics (ABS) and found marginal effects on the estimated coefficients. We provide the results of this supplementary analysis in Appendix B.3.1. We thank an anonymous reviewer for this suggestion.

[11]The maximum price cap and the market floor price are currently (i.e., for the 2021/22 financial year) set at –\$1,000/MWh and \$15,100/MWh and are adjusted annually for inflation.

time and revert to more normal levels (Higgs and Worthington, 2005; Frömmel et al., 2014). Comparing the performance of these models (see Appendix B.2), we find that the eGARCH produces the most robust results not only when modelling daily volatility, as shown by Pereira and Rodrigues (2015), Macedo et al. (2020), and in Chapter 2, but also when modelling high-frequency volatility. On this basis, we chose to employ eGARCH in the analysis. Before specifying a eGARCH equation for the variance, a primary requirement is to remove the predictable component of the electricity price to produce price innovations, ε_t, with a conditional mean of zero (Higgs and Worthington, 2005). Following inter alia Ketterer (2014) and the approach in Chapter 2, we generate an uncorrelated process by assuming the half-hourly price follows an autoregressive AR(m) process with exogenous variables given by

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{jt} + \varepsilon_t, \tag{3.2.1}$$

where p_t is the half-hour electricity price for each regional electricity market in the current period, p_{t-i} is the half-hour electricity price lagged i periods, μ is the long-term drift coefficient, ϕ_i is the degree of the mean spillover effect across time, $\boldsymbol{v}_t$ is the vector of n external regressors, which are passed pre-lagged, and ε_t is the random error or innovation at time t. The variance of the half-hour spot price innovation process is then modelled using the Nelson (1991) eGARCH specification, which allows for the leverage effect to better capture temporal variations in market volatility. The eGARCH(p, q) process for the random error term, ε_t, is specified as $\varepsilon_t = z_t \sigma_t$ and $z_t \sim \text{iid}(0, 1)$ is a standardized innovation that follows a specific distribution,[12] with

$$\log_e(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - \mathbb{E}|z_{t-i}|\right)\right) + \sum_{j=1}^{q} \beta_j \log_e(\sigma_{t-j}^2) + \sum_{k=1}^{r} \psi_k \boldsymbol{v}_{kt}, \tag{3.2.2}$$

[12]Instead of assuming that z_t is Gaussian by default, we chose the best conditional distribution of the standardized residuals by jointly estimating equations (3.2.1) and (3.2.2) under a range of univariate distributions; that is, normal distribution, skew normal distribution, generalized error distribution, skew generalized error distribution, Student-t distribution, skew Student-t distribution, normal inverse Gaussian distribution, and Johnson's reparametrized SU distribution. The best-performing model is the one that minimizes the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria.

where σ_t is the latent conditional standard deviation of volatility of ε_t at time t, ω is a variance intercept parameter, α_i and γ_i are coefficients that are associated with the sign and size effects of the standardized innovation from the previous period, respectively, and β_j is the coefficient associated with the degree of the previous period's volatility spillover effects. We refer to equations (3.2.1) and (3.2.2) as the mean and variance equations, respectively. The mean and variance equations and thus the parameters $(\mu, \phi, \zeta, \omega, \alpha, \gamma, \beta, \psi)$ are estimated concurrently by maximizing the log-likelihood.[13] Furthermore, the expected value of the absolute standardized innovation is defined by $\mathbb{E}|z_t| = \int_{-\infty}^{\infty} |z| f(z, 0, 1, \dots)\, dz$. The stationarity of the eGARCH(p, q) model is achieved when the roots of $\beta(z) = 1 - \sum_{i=1}^{p} \beta_i z^i$ lie outside the unit circle. For eGARCH(1,1), the stationarity condition requires that $|\beta_i| < 1$. One advantage of the eGARCH model is that it requires no restriction on the parameters, as it models the log variance instead of variance itself. This means the positivity of the variance is guaranteed regardless of the sign of the estimated coefficient. Thus, the likelihood maximization yields faster and more reliable optimizations. Existing research also suggests that compared to other GARCH specifications, the eGARCH is better at capturing the volatility persistence and asymmetry effect found in power markets (Thomas and Mitchell, 2005; Bowden and Payne, 2008; Hickey et al., 2012; Frömmel et al., 2014). It is also worth noting that our method allows investigation of the impact of exogenous variables on the level and volatility of spot prices while also accounting for downward and upward spikes and mean reversion.

The exogenous variables used in this analysis are defined in Table 3.2.[14,15] One ar-

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[13]We jointly estimated the AR-eGARCH and ARX-eGARCHX models in R programming language using the `rugarch` package (R Core Team, 2019; Ghalanos, 2022).

[14]We account for variations in spot prices caused by demand or non-renewable supply movements that could be correlated with solar generation and wind generation. They include hydro generation, gas prices, and interconnector flow, to avoid potential endogeneity bias in the estimated models. See Forrest and MacGill (2013) and Csereklyei et al. (2019) for further discussion.

[15]Although existing studies retain the megawatt as the unit for the generation variables (Csereklyei et al., 2019; Abban and Hasan, 2021), we find it important to express solar generation, rooftop solar generation, wind generation, electricity consumption, hydro generation, and interconnectors flow in megawatt-hours as the dependent variable is given on a per-megawatt-hour basis. We multiply all generation variables in megawatts by 1/2 to convert megawatts to megawatt-hours over a 30-minute time frame. This is because the megawatt data represent the instantaneous power at the end of 30-minute intervals. The adjustment does not affect the statistical significance of the coefficients, but it doubles the size of the coefficient when compared to megawatts. Moreover, as only daily gas prices are available, we assumed that the values over 48 trading intervals throughout the day are constant; that is, we replicate a single daily observation over 48 trading intervals.

gument against using rooftop solar generation as a regressor on the spot price is that it is not channelled through the NEM bidding process (Csereklyei et al., 2019) and is only visible to the market through reduced demand and dispatch targets during periods of rooftop PV generation. We postulate that, irrespective of whether rooftop PV generation is considered 'negative demand' or 'positive supply', the marginal generator (i.e., the price setter) is the same in both cases. If rooftop PV were to bid into the market, would effectively bid in its capacity at (close to) the spot price floor – this is the logical outcome of its automatic netting off from demand.

To justify this, lets consider, the following highly stylized situation: there are two utility-scale generators – one black coal, the other solar PV (both of 50MW available capacity). Coal bids in all its capacity at 10 AUD/MWh, while the utility-scale solar PV plant bids in all its capacity at 0 AUD/MWh. In a given interval, demand (excluding rooftop PV) is 100MW, and rooftop PV generation is 50MW.

- Case 1: Rooftop PV generation is netted off demand

  Here, operational/grid-sourced demand is 50MW. This is fully met by utility-scale solar PV with the market clearing at the spot price of 0 AUD/MWh.

- Case 2 : Rooftop PV generation is NOT netted off demand and rooftop PV bids into the spot market

  In this situation, operational/grid-sourced demand remains at 100MW. Rooftop PV generation would be dispatched first – since it bids in at (close to) the floor. The market clears at the spot price of 0 AUD/MWh, with the marginal generator being the utility-scale solar PV plant. In both cases, the spot price is the same: 0 AUD/MWh.

In practice, bidding would differ by price band due to minimum stable loadings (MSL) (e.g., in an example above, the coal plant might bid its MSL at the spot price floor and then its excess capacity at 10 AUD/MWh) and other real-world considerations. Thus, our assumption that spot price outcomes remain unchanged would still be correct. Our argument in relation to rooftop PV bidding in its capacity at (close to) the spot price floor, if rooftop PV were to bid into the market, reflects AEMO's approach to generator curtailment. That is, at times of oversupply, AEMO's order of curtailment is as follows:

- thermal plant are curtailed down to their MSL,
- if this doesn't resolve the oversupply problem, AEMO then curtails utility-scale solar and wind down,
- if oversupply still exists despite AEMO curtailing utility-scale solar and wind output down to zero, AEMO then curtails rooftop PV output,
- if oversupply still exists, AEMO would then be forced to curtail thermal down below their MSL—effectively tripping off the power plant.

As thermal plants bid in their MSL at the spot price floor, this curtailment order means rooftop PV effectively bids in its capacity at (close to) the spot price floor. We say "close to" as we understand AEMO prefers to curtail rooftop PV ahead of tripping off the thermal plant in order to maintain system security. We note that oversupply problems in the NEM have, to date, not required the last step, but the first three steps have been utilized in recent times in SA.

Following this assumption, we made an adjustment to the demand/consumption variable depending on whether we study the impact of large-scale or rooftop solar generation. We employ the *grid-sourced demand* or operational demand, which accounts for scheduled and semi-scheduled generation, as well as large-scale wind and solar power generation, for models that include large-scale solar generation and penetration. When studying the impact of rooftop and total solar generation and penetration, we change the demand variable and use the *underlying demand* instead to account for consumption associated with behind-the-meter technologies such as embedded rooftop solar PV. The underlying demand is estimated as the sum of grid-sourced demand and rooftop solar generation.

3.3 Impact of Solar Generation

Tables 3.3 to 3.7 present the estimated coefficients and the corresponding p-values for the conditional mean and conditional variance equations of the estimated ARX-

Table 3.2 : **Exogenous variables**

Variable	*Description*
large-scale solar	*Regional average large-scale solar power generation over a 30-minute period in megawatt hour (MWh)*
$large\text{-}scale\ solar_{pen}$	*Regional large-scale solar penetration, defined as a ratio of large-scale solar power generation to the total electricity consumption over a 30-minute period*
rooftop solar	*Regional estimate of actual rooftop solar generation over a 30-minute period in megawatt hour (MWh)*
$rooftop\ solar_{pen}$	*Regional large-scale rooftop solar penetration, defined as a ratio of rooftop solar generation to the total electricity consumption over a 30-minute period*
solar total	*Regional average solar power generation (large-scale and rooftop solar) over a 30-minute period in megawatt hour (MWh)*
$solar\ total_{pen}$	*Regional solar penetration, defined as a ratio of solar generation to the total electricity consumption over a 30-minute period*
wind	*Regional average wind power generation over a 30-minute period in megawatt hour (MWh)*
$wind_{pen}$	*Regional wind penetration, defined as a ratio of wind power generation to the total electricity consumption over a 30-minute period*
hydro	*Regional average hydro power generation over a 30-minute period in megawatt hour (MWh)*
consumption	*Regional average amount of power consumed over a 30-minute period in megawatt hour (MWh). Consumption (grid) denotes grid-sourced consumption, and consumption (underlying) denotes underlying consumption.*
gas price	*Regional average gas price in AUD per GJ over a 30-minute period*
$exim_{murr}$	*Average exports and imports via Murraylink interconnector (VIC-to-SA) over a 30-minute period in megawatt hour (MWh)*
$exim_{heyw}$	*Average exports and imports via Heywood interconnector (VIC-to-SA) over a 30-minute period in megawatt hour (MWh)*
$exim_{VNI}$	*Average exports and imports via New South Wales to Victoria interconnector (VNI) over a 30-minute period in megawatt hour (MWh)*
$exim_{bass}$	*Average exports and imports via Basslink interconnector (TAS-to-VIC) over a 30-minute period in megawatt hour (MWh)*
$exim_{terra}$	*Average exports and imports via Terranora interconnector (NSW-to-QLD) over a 30-minute period in megawatt hour (MWh)*
$exim_{QNI}$	*Average exports and imports via New South Wales to Queensland interconnector (QNI) over a 30-minute period in megawatt hour (MWh)*

eGARCHX models for each spot electricity market for the whole sample period. Because the starting points of the data series for NSW and QLD are different from those for the other states, we include more models than for the other states. Models A and B capture the impact of solar generation and penetration in the spot electricity price dynamics using data from 2015 and 2017 for NSW and QLD, respectively. Models C and D for QLD capture the impact of rooftop solar generation and penetration on electricity price dynamics using rooftop solar generation data without controlling for wind generation. Models E to J capture the impact of large-scale solar generation, rooftop solar generation, and wind generation from 2018 onward.[16]

3.3.1 The intraday mean and volatility dynamics

We observe significant mean and volatility spillovers in all five markets. From the mean equation in Tables 3.3 to 3.7; Models A to J, the magnitude of the mean spillovers effect is positive and is strongly pronounced in QLD, VIC, TAS, and NSW and ranges from 0.9302 to 0.9681; it is relatively less pronounced in SA (0.9147 to 0.9191). From the variance equation, we observe strong and statistically significant ARCH spillovers across all five markets. QLD, TAS, SA, and NSW exhibit a far higher effect, ranging from 1.0311 to 6.0482, compared to VIC (0.7538 to 0.7817). These results suggest that shocks from the previous period tend to affect future volatility to a lesser extent in VIC compared to the other markets. Similarly, the effect of positive and negative shocks is not consistent across all five markets. While we find that positive shocks tend to exert a larger impact on electricity price volatility than negative shocks of the same magnitude in VIC, SA, and TAS, the effect in NSW and QLD is the reverse. Moreover, we observe pronounced GARCH spillovers in which VIC, NSW, SA, and QLD experience a larger effect ranging from 0.6491 to 0.7359. TAS display a relatively small effect ranging from 0.4755 to 0.4827. Therefore, we infer that the last period's volatility shocks tend to affect future spot price volatility more strongly in VIC, NSW, SA, and QLD than in TAS.

The present findings suggest that at high frequency, the estimated ARCH and GARCH spillovers exhibited by spot prices are relatively large compared to those of the average (daily) spot prices examined in Chapter 2. In the following sections, we present the impacts of large-scale and rooftop solar generation, among other variables, on spot electricity price dynamics. The top and bottom panels of Tables 3.3 to 3.7 present the impact of

[16]We run the ARX-eGARCHX models by assuming the standardized residuals follow skew Student distribution in SA, QLD, and TAS, Student distribution in NSW, and Johnson's reparametrized SU distribution in TAS. A detailed analysis of the choice of these distributions is given in Appendix B.2. Tables 3.4 to 3.7 also present the corresponding skew and shape parameters of these distributions. The adequacy of the model fit is assessed using the weighted Ljung-Box test and the weighted Lagrange multiplier test (ARCH-LM tests), with the null adequate fitted autoregressive–moving-average (ARMA) models and the ARCH process (Ghalanos, 2022). In most cases, we fail to reject both hypotheses, and the models seem to account for a fair amount of the autocorrelation. The autocorrelation function (ACF) and the partial autocorrelation (PACF) of the standardized residuals and the squared standardized residuals, respectively, also indicate low autocorrelation and the absence of a specific pattern due to a non-stationary or seasonal time series.

Table 3.3 : **The effect of large-scale and rooftop solar generation on New South Wales' electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	Model A	Model B	Model E	Model F	Model G	Model H	Model I	Model J
	Mean Equation							
μ	-60.8897	-58.3025	-83.2652	-79.2736	-94.9897	-90.3796	-94.4312	-90.7101
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9315	0.9334	0.9302	0.9312	0.93080	0.9315	0.9309	0.9316
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-0.4077		-0.3061					
	(0.0000)		(0.0000)					
$large\text{-}scale\ solar_{pen}$		-100.0000		-100.0000				
		(0.0000)		(0.0000)				
rooftop solar					-0.1005			
					(0.0000)			
$rooftop\ solar_{pen}$						-43.4142		
						(0.0000)		
solar total							-0.0710	
							(0.0000)	
$solar\ total_{pen}$								-30.48001
								(0.0000)
wind	-0.2374		-0.2286		-0.2035		-0.2047	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$wind_{pen}$		-72.3117		-67.1832		-66.3695		-67.8913
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
hydro	0.1529	0.1597	0.2443	0.2489	0.2720	0.2714	0.2675	0.2706
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
consumption (grid)	0.3099	0.2997	0.3627	0.3493				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
consumption (underlying)					0.3686	0.3562	0.3680	0.3567
					(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas price	0.7962	0.7207	1.5246	1.4635	1.5950	1.5526	1.6033	1.6118
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{terrs}$	-0.5302	-0.5332	-0.7419	-0.7488	-0.8278	-0.8290	-0.8168	-0.8187
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{QNI}$	-0.1497	-0.1527	-0.1879	-0.1930	-0.1989	-0.1996	-0.1974	-0.1978
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{VNI}$	0.0247	0.0263	0.0401	0.0415	0.0487	0.0494	0.0475	0.0477
	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0176)
	Variance Equation							
ω	0.0324	-0.1201	-0.0814	-0.3581	0.3016	0.0751	0.2052	-0.0175
	(0.7069)	(0.1613)	(0.0570)	(0.0019)	(0.0000)	(0.2636)	(0.0775)	(0.9042)
α	-0.0907	-0.1073	-0.1408	-0.1396	-0.1550	-0.1574	-0.1464	-0.1496
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.7009	0.7056	0.7038	0.7063	0.7336	0.7359	0.7269	0.7300
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.1518	1.1684	1.0629	1.0697	1.0404	1.0311	1.0573	1.0458
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0231		0.0221					
	(0.0000)		(0.0000)					
$large\text{-}scale\ solar_{pen}$		7.9724		7.9170				
		(0.0000)		(0.0000)				
rooftop solar					0.0108			
					(0.0000)			
$rooftop\ solar_{pen}$						4.6459		
						(0.0000)		
solar total							0.0072	
							(0.0000)	
$solar\ total_{pen}$								3.0599
								(0.0000)
wind	0.0014		0.0007		0.0001		0.0005	
	(0.0096)		(0.2535)		(0.9237)		(0.3804)	
$wind_{pen}$		0.5769		0.3953		0.0132		0.1770
		(0.0035)		(0.0514)		(0.9414)		(0.3612)
hydro	0.0056	0.0054	0.0069	0.0062	0.0086	0.0086	0.0077	0.0079
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
consumption (grid)	0.0023	0.0027	0.0023	0.0030				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
consumption (underlying)					0.0010	0.0015	0.0013	0.0018
					(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas price	0.0427	0.0422	0.0498	0.0497	0.0474	0.0485	0.0481	0.0479
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{terra}$	-0.0113	-0.0115	-0.0104	-0.0109	-0.0153	-0.0147	-0.0157	-0.0129
	(0.0277)	(0.0218)	(0.0944)	(0.0728)	(0.0246)	(0.0161)	(0.0077)	(0.0493)
$exim_{QNI}$	-0.0012	-0.0012	-0.0006	-0.0006	0.0002	0.0001	-0.0002	-0.0003
	(0.0265)	(0.0326)	(0.3631)	(0.3633)	(0.8803)	(0.9230)	(0.7888)	(0.6385)
$exim_{VNI}$	0.0022	0.0022	0.0024	0.0023	0.0021	0.0021	0.0021	0.0021
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.5055	2.4796	2.8276	2.8161	2.7365	2.7401	2.7297	2.7414
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-415996.2	-416266.5	-230912.9	-231056.5	-231354.5	-231400.5	-231359	-231402.4
AIC	7.4555	7.4604	7.7537	7.7585	7.7685	7.7701	7.7687	7.7701
BIC	7.4575	7.4624	7.7572	7.7620	7.7720	7.7735	7.7721	7.7736
Q(40)	3.5107	2.8530	3.7751	3.0926	4.5213	3.8063	4.368	3.6622
	(0.3144)	(0.4692)	(0.2635)	(0.4083)	(0.1540)	(0.2580)	(0.1727)	(0.2844)
$Q^2(36)$	0.0026	0.0020	0.0020	0.0017	0.0010	0.0009	0.00129	0.0011
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0017	0.0013	0.0013	0.0011	0.00069	0.00066	0.00090	0.0008
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	111600	111600	59568	59568	59568	59568	59568	59568

The coefficients of the supply and demand variables should be divided by 10 to recover the original values. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 3.4 : **The effect of large-scale and rooftop solar generation on Victoria's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	Model E	Model F	Model G	Model H	Model I	Model J
	Mean Equation					
μ	-79.5598	-61.8610	-74.9387	-61.4523	-74.4286	-61.6632
	(0.0000)	(0.0000)	(0.0000)	(0.0659)	(0.0952)	(0.0000)
ϕ_1	0.9449	0.9458	0.9416	0.9424	0.9416	0.9424
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-0.8473					
	(0.0000)					
large-scale $solar_{pen}$		-99.9994				
		(0.0000)				
rooftop solar			-0.3285			
			(0.0000)			
rooftop $solar_{pen}$				-84.1081		
				(0.0000)		
solar total					-0.2814	
					(0.0000)	
solar $total_{pen}$						-72.3968
						(0.0000)
wind	-0.5842		-0.4524		-0.4578	
	(0.0000)		(0.0000)		(0.0000)	
$wind_{pen}$		-99.9990		-91.3069		-95.3212
		(0.0000)		(0.0000)		(0.0000)
hydro	-0.0624	0.0266	0.0793	0.1032	0.0678	0.0883
	(0.0003)	(0.1534)	(0.0045)	(0.2437)	(0.5225)	(0.0002)
consumption (grid)	0.7294	0.6308				
	(0.0000)	(0.0000)				
consumption (underlying)			0.6649	0.6052	0.6680	0.6101
			(0.0000)	(0.0000)	(0.0001)	(0.0000)
gas price	0.3670	0.2864	0.4217	0.3583	0.4192	0.4192
	(0.1756)	(0.1339)	(0.0384)	(0.0992)	(0.0065)	(0.0000)
$exim_{murr}$	0.6864	0.5942	0.5440	0.5058	0.5598	0.5203
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{hey}$	-0.0856	-0.1559	-0.1870	-0.2081	-0.1824	-0.1994
	(0.0041)	(0.0000)	(0.0000)	(0.0000)	(0.1249)	(0.0000)
$exim_{VNI}$	0.0592	-0.0080	-0.0737	-0.0837	-0.0674	-0.0732
	(0.0000)	(0.6069)	(0.0005)	(0.2697)	(0.5292)	(0.0000)
$exim_{bass}$	-0.1398	-0.0590	0.0101	0.0220	-0.0026	0.0049
	(0.0000)	(0.3247)	(0.7842)	(0.6566)	(0.9876)	(0.8727)
	Variance Equation					
ω	0.7074	0.4101	0.8304	0.5325	0.8637	0.4973
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
α	0.0418	0.0305	0.0577	0.0558	0.0677	0.0640
	(0.4037)	(0.0705)	(0.0002)	(0.0004)	(0.0171)	(0.0000)
β	0.6999	0.7048	0.6968	0.6963	0.6925	0.6928
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.7817	0.7796	0.7538	0.7545	0.7678	0.7607
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0337					
	(0.0000)					
large-scale $solar_{pen}$		7.5344				
		(0.0000)				
rooftop solar			0.0135			
			(0.0000)			
rooftop $solar_{pen}$				3.6175		
				(0.0000)		
solar total					0.0104	
					(0.0000)	
solar $total_{pen}$						2.8128
						(0.0000)
wind	0.0019		0.0029		0.0030	
	(0.0096)		(0.0000)		(0.0000)	
$wind_{pen}$		0.6308		0.7491		0.8092
		(0.0000)		(0.0000)		(0.0000)
hydro	0.0051	0.0044	0.0064	0.0058	0.0062	0.0058
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
consumption (grid)	0.0018	0.0029				
	(0.0099)	(0.0000)				
consumption (underlying)			0.0011	0.0023	0.0010	0.0024
			(0.0090)	(0.0000)	(0.0000)	(0.0000)
gas price	0.0445	0.0449	0.0426	0.0428	0.0442	0.0446
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$	-0.0145	-0.0160	-0.0128	-0.0132	-0.0136	-0.0146
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0000)
$exim_{hey}$	-0.0014	-0.0009	-0.0025	-0.0022	-0.0024	-0.0020
	(0.1217)	(0.1362)	(0.0001)	(0.0006)	(0.0010)	(0.0016)
$exim_{VNI}$	-0.0005	-0.0009	-0.0017	-0.0019	-0.0016	-0.0018
	(0.3622)	(0.0128)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{bass}$	0.0023	0.0026	0.0034	0.0035	0.0034	0.0036
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Skew	0.0797	0.0798	0.0916	0.0918	0.0971	0.0963
	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	1.0387	1.0318	1.0468	1.0453	1.0482	1.0487
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-236110.6	-236293.2	-236159.5	-236185.7	-236090.8	-236110.5
AIC	8.2335	8.2399	8.2352	8.2361	8.2328	8.2335
BIC	8.2376	8.2439	8.2393	8.2402	8.2369	8.2375
Q(40)	38.69	34.99	40.58	40.80	38.98	41.22
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	0.0412	0.02776	0.0818	0.0783	0.1168	0.0942
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0038	0.0038	0.0059	0.0052	0.0079	0.0057
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	57360	57360	57360	57360	57360	57360

The coefficients of the supply and demand variables should be divided by 10 to recover the original values. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 3.5 : **The effect of large-scale and rooftop solar generation on South Australia's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	Model E	Model F	Model G	Model H	Model I	Model J
			Mean Equation			
μ	-18.3237	16.4111	-26.1123	6.7737	-25.2983	6.684172
	(0.0000)	(0.0000)	(0.6017)	(0.0020)	(0.0000)	(0.0000)
ϕ_1	0.9156	0.9147	0.9188	0.9181	0.9191	0.9185
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-1.4898					
	(0.0000)					
large-scale $solar_{pen}$		-62.3698				
		(0.0000)				
rooftop solar			-0.3157			
			(0.0000)			
rooftop $solar_{pen}$				-21.8787		
				(0.0000)		
solar total					-0.2526	
					(0.0000)	
solar $total_{pen}$						-17.9787
						(0.0000)
wind	-1.2272		-0.9301		-0.9364	
	(0.0000)		(0.0000)		(0.0000)	
$wind_{pen}$		-67.1991		-60.5569		-60.5111
		(0.0000)		(0.0000)		(0.0000)
consumption (grid)	1.6203	1.0280				
	(0.0000)	(0.0000)				
consumption (underlying)			1.3908	0.9768	1.3844	0.9737
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas price	2.8529	2.7298	3.1830	3.0336	3.1443	3.0635
	(0.0000)	(0.0000)	(0.4636)	(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$	0.6393	0.5938	0.9814	0.7936	0.9735	0.7890
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$exim_{hey}$	-0.8213	-0.8091	-0.5074	-0.6279	-0.5126	-0.6304
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Variance Equation			
ω	1.3335	1.0827	1.2980	0.9946	1.2776	0.9889
	(0.0000)	(0.0000)	(0.0015)	(0.3015)	(0.0000)	(0.0302)
α	0.0165	0.0248	0.0571	0.0647	0.0538	0.0633
	(0.5147)	(0.3346)	(0.0279)	(0.4606)	(0.0344)	(0.0302)
β	0.7072	0.7081	0.6872	0.6850	0.6931	0.6901
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.2126	1.1947	1.1814	1.1499	1.1960	1.1924
	(0.0000)	(0.0000)	(0.0000)	(0.5148)	(0.0000)	(0.0000)
large-scale solar	0.0396					
	(0.0000)					
large-scale $solar_{pen}$		1.6603				
		(0.0000)				
rooftop solar			0.0178			
			(0.0000)			
rooftop $solar_{pen}$				1.4098		
				(0.0000)		
solar total					0.0131	
					(0.0000)	
solar $total_{pen}$						1.0456
						(0.0000)
wind	-0.0016		0.0011		0.0011	
	(0.0047)		(0.2283)		(0.0861)	
$wind_{pen}$		0.1253		0.1899		0.1997
		(0.0001)		(0.0000)		(0.0000)
consumption (grid)	0.0080	0.0098				
	(0.0000)	(0.0000)				
consumption (underlying)			0.0066	0.0098	0.0066	0.0097
			(0.1669)	(0.0000)	(0.0091)	(0.0000)
gas price	0.0284	0.0323	0.03670	0.0380	0.0360	0.0376
	(0.0000)	(0.0000)	(0.0028)	(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$	-0.0132	-0.0083	-0.0104	-0.0069	-0.0105	-0.0067
	(0.0001)	(0.0064)	(0.0017)	(0.0220)	(0.0016)	(0.0259)
$exim_{hey}$	-0.0038	-0.0008	-0.0004	0.0010	-0.0006	0.0010
	(0.0001)	(0.3290)	(0.6214)	(0.2381)	(0.5153)	(0.2200)
Skew	0.9711	0.9757	0.9771	0.9816	0.9757	0.9802
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.1779	2.1822	2.1935	2.2039	2.1876	2.1873
	(0.0000)	(0.0000)	(0.0000)	(0.0030)	(0.0000)	(0.0000)
log likelihood	-242961.9	-243236.4	-243921.9	-243667.5	-243956.4	-243686
AIC	8.6164	8.6261	8.6504	8.6414	8.6516	8.6421
BIC	8.6196	8.6293	8.6536	8.6446	8.6548	8.6452
Q(40)	7.258	6.425	3.432	3.915	3.506	3.976
	(0.0153)	(0.0322)	(0.3308)	(0.2393)	(0.3154)	(0.2293)
$Q^2(36)$	0.0006	0.0007	0.0005	0.0005	0.0004	0.0005
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0005	0.0005	0.0003	0.0003	0.0003	0.0003
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	56400	56400	56400	56400	56400	56400

The coefficients of the supply and demand variables should be divided by 10 to recover the original values. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 3.6 : **The effect of large-scale and rooftop solar generation on Queensland's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
					Mean Equation					
μ	-150.7442	-148.7505	-141.1599	-139.0536	-158.6972	-153.8876	-147.8659	-148.2737	-149.2415	-146.2304
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9619	0.9623	0.9638	0.9641	0.9671	0.9672	0.9680	0.9678	0.9681	0.9680
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-0.1997				-0.3052					
	(0.0000)				(0.0000)					
large-scale solar$_{pen}$		-53.4642				-86.7846				
		(0.0000)				(0.0000)				
rooftop solar			-0.0752				-0.0755			
			(0.0000)				(0.0000)			
rooftop solar$_{pen}$				-26.9394				-27.6314		
				(0.0000)				(0.0000)		
solar total									-0.0444	
									(0.0000)	
solar total$_{pen}$										-15.9300
										(0.0000)
wind					-0.5361		-0.4997		-0.5006	
					(0.0000)		(0.0000)		(0.0000)	
wind$_{pen}$						-100.0000		-100.0000		-100.0000
						(0.0000)		(0.0000)		(0.0000)
hydro	-0.0334	-0.0403	0.0358	0.0356	-0.1202	-0.1246	-0.0196	-0.0204	-0.0250	-0.0215
	(0.6229)	(0.5784)	(0.4473)	(0.5167)	(0.0040)	(0.0554)	(0.7176)	(0.6618)	(0.7118)	(0.8217)
consumption (grid)	0.6531	0.6454	0.5952	0.5894	0.6858	0.6667				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
consumption (underlying)							0.6227	0.6138	0.6250	0.6108
							(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas price	1.4728	1.4160	1.5189	1.5135	1.63756	1.7572	1.7424	1.8900	1.7876	1.8237
	(0.0000)	(0.0029)	(0.0000)	(0.0000)	(0.0000)	(0.0098)	(0.0797)	(0.0005)	(0.0736)	(0.0464)
exim$_{terra}$	0.0755	0.0982	0.1959	0.2034	0.1042	0.1510	0.2615	0.2729	0.2373	0.2604
	(0.4156)	(0.2548)	(0.1230)	(0.0107)	(0.3170)	(0.3997)	(0.0807)	(0.0835)	(0.0873)	(0.3167)
exim$_{QNI}$	-0.2505	-0.2533	-0.2302	-0.2314	-0.3238	-0.3169	-0.2732	-0.2690	-0.2757	-0.2711
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
					Variance Equation					
ω	2.0704	1.6665	2.1006	1.7567	2.1076	1.7195	2.3477	1.8322	2.2913	1.7908
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-1.6168	-1.6831	-1.5585	-1.5328	-1.8471	-1.8414	-1.5911	-1.7848	-1.5970	-1.7554
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.6491	0.6566	0.6609	0.6592	0.6575	0.6558	0.6573	0.6645	0.6594	0.6642
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	6.0482	5.9107	5.7762	5.7634	6.0079	6.0301	5.8051	5.5435	5.7408	5.5366
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0177				0.0171					
	(0.0000)				(0.0000)					
large-scale solar$_{pen}$		5.0936				5.0420				
		(0.0000)				(0.0000)				
rooftop solar			0.0103				0.0110			
			(0.0000)				(0.0000)			
rooftop solar$_{pen}$				3.7206				3.8410		
				(0.0000)				(0.0000)		
solar total									0.0068	
									(0.0000)	
solar total$_{pen}$										2.4039
										(0.0000)
wind					-0.0081		-0.0066		-0.0068	
					(0.0000)		(0.0000)		(0.0000)	
wind$_{pen}$						-2.5146		-2.2603		-2.1769
						(0.0000)		(0.0001)		(0.0000)
hydro	0.0152	0.0176	0.0145	0.0148	0.0190	0.0188	0.0125	0.0179	0.0149	0.0190
	(0.0005)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0020)	(0.0000)	(0.0014)	(0.0039)
consumption (grid)	0.0017	0.0027	0.0011	0.0022	0.0013	0.0027				
	(0.0000)	(0.0000)	(0.0062)	(0.0000)	(0.0812)	(0.0000)				
consumption (underlying)							0.0006	0.0020	0.0006	0.0020
							(0.0167)	(0.0000)	(0.0819)	(0.0000)
gas price	0.0553	0.0542	0.0591	0.0580	0.0638	0.0617	0.0591	0.0567	0.0619	0.0588
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0077)
exim$_{terra}$	0.0266	0.0217	0.0137	0.0126	0.0262	0.0259	0.0136	0.0158	0.0175	0.0216
	(0.0117)	(0.0293)	(0.2288)	(0.2112)	(0.0168)	(0.0724)	(0.1908)	(0.4117)	(0.1122)	(0.1825)
exim$_{QNI}$	-0.0013	-0.0007	0.0002	0.0003	-0.0011	-0.0011	0.0001	-0.0003	-0.0001	-0.0006
	(0.2371)	(0.5045)	(0.8548)	(0.7397)	(0.3736)	(0.4843)	(0.9520)	(0.8395)	(0.9429)	(0.6962)
Skew	1.0212	1.0183	1.0355	1.0362	1.0226	1.0245	1.0415	1.0354	1.0415	1.0383
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.0100	2.0100	2.0100	2.0100	2.0100	2.0100	2.0100	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-250622.7	-250637.6	-235832.4	-235821.4	-206724.5	-206796.5	-207878.2	-207881.2	-207897.7	-207901.2
AIC	7.7994	7.7999	7.9188	7.9184	7.9986	8.0013	8.0432	8.0433	8.0439	8.0441
BIC	7.8023	7.8027	7.9218	7.9214	8.0023	8.0051	8.0469	8.0471	8.0477	8.0478
Q(40)	3.466	3.646	3.388	3.439	3.887	3.817	3.142	3.319	2.992	3.118
	(0.3236)	(0.2876)	(0.3403)	(0.3293)	(0.2440)	(0.2561)	(0.3963)	(0.3555)	(0.4333)	(0.4023)
$Q^2(36)$	0.18226	0.2014	0.12741	0.1344	0.1901	0.2016	0.1346	0.1298	0.1387	0.14038
	(0.9999)	(0.9999)	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.2004	0.2272	0.1032	0.1072	0.2030	0.2211	0.0997	0.0899	0.1072	0.1067
	(0.9970)	(0.9961)	(0.9993)	(0.9993)	(0.9969)	(0.9963)	(0.9994)	(0.9995)	(0.9993)	(0.9993)
Observations	64272	64272	59568	59568	51696	51696	51696	51696	51696	51696

The coefficients of the supply and demand variables should be divided by 10 to recover the original values. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 3.7 : **The effect of large-scale and rooftop solar generation on Tasmania's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	Model C	Model D
	Mean Equation	
μ	13.7983	19.9785
	(0.0000)	(0.0000)
ϕ_1	0.9426	0.9421
	(0.0000)	(0.0000)
$rooftop\ solar$	-0.3696	
	(0.0000)	
$rooftop\ solar_{pen}$		-16.8281
		(0.0021)
$wind$	-1.3706	
	(0.0000)	
$wind_{pen}$		-65.8444
		(0.0000)
$hydro$	-0.1109	
	(0.0000)	
$consumption\ (underlying)$	1.2865	1.0715
	(0.0000)	(0.0000)
$exim_{bass}$		-0.1272
		(0.0000)
	Variance Equation	
ω	3.9785	4.0508
	(0.0000)	(0.0000)
α	0.8384	0.9068
	(0.0000)	(0.0000)
β	0.4827	0.4755
	(0.0000)	(0.0000)
γ	5.2358	5.2012
	(0.0000)	(0.0000)
$rooftop\ solar$	0.0424	
	(0.0000)	
$rooftop\ solar_{pen}$		2.2752
		(0.0000)
$wind$	0.0063	
	(0.0314)	
$wind_{pen}$		0.0905
		(0.5632)
$hydro$	0.0047	
	(0.0000)	
$consumption\ (underlying)$	0.0088	0.0133
	(0.0000)	(0.0000)
$exim_{bass}$		0.0060
		(0.0000)
Skew	1.1041	1.1067
	(0.0000)	(0.0000)
Shape	2.0100	2.0100
	(0.0000)	(0.0000)
log likelihood	-239475.4	-239453.1
AIC	8.0409	8.0402
BIC	8.0434	8.0426
Q(40)	5.562	5.499
	(0.0674)	(0.0710)
$Q^2(36)$	0.0394	0.0399
	(1.0000)	(1.0000)
ARCH-LM Test	0.0220	0.0223
	(1.0000)	(1.0000)
Observations	59568	59568

The coefficients of the supply and demand variables should be divided by 10 to recover the original values. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

large-scale and rooftop solar generation, among other variables, on the level (mean equation) and volatility (variance equation) of electricity spot prices, respectively. A detailed discussion of the findings follows.

3.3.2 Large-scale solar generation

3.3.2.1 Impact on spot electricity prices

The findings in the mean equation (Tables 3.3 to 3.6; Model E) confirm the MOE of large-scale solar generation in all four regional markets. This effect appears more substantial in VIC and SA, which have moderate large-scale solar generation levels. A 1 MWh increase in large-scale solar generation decreases prices by around 0.15 AUD/MWh and 0.08 AUD/MWh in SA and VIC, respectively.[17] In contrast, QLD and NSW, which experience higher large-scale solar generation during the sample period, exhibit a relatively moderate effect of around 0.03 AUD/MWh for each 1 MWh increase in solar generation.[18] These results are expected because solar generation has a low short-run marginal cost and is prioritized in the dispatch process, allowing it to push higher-marginal-cost thermal units out in the dispatch process and lower spot prices. The higher magnitude of the MOE in SA may be accounted for by the state's significant reliance on expensive gas-powered generation and limited interconnector capacity with other regions. Under these conditions, the market tends to experience high average electricity prices. Thus, an increase in large-scale solar generation displaces expensive gas-powered generators and lowers electricity prices. A link between the impact of large scale solar generation and the average electricity prices is evident from Table 3.1 and Figure 3.2. In particular, regions experiencing higher average electricity prices tend to exhibit higher MOE for an increase in large-scale solar generation.

[17] All supply and demand variables in Tables 3.3 to 3.7 are scaled by a factor of 10 to ease the presentation of the estimated coefficients. This adjustment means that the coefficients in these tables are ten times larger than the original coefficients. Thus, to recover the original values, one needs to divide the estimated coefficients by 10. Upon recovering the original values, our interpretation of the variables in the mean equation (3.2.1) is that a 1 unit increase in a jth independent variable is associated with a ζ_j AUD/MWh change in spot prices, where ζ_j, is the coefficient of the jth independent variable.

[18] We observe a slight difference between the MOE obtained by running the analysis using 2015 and 2017 data and that of 2018 for NSW and QLD. The estimated coefficients are lower and higher by 0.01 AUD/MWh for a 1 MWh increase in large-scale solar generation in QLD and NSW, respectively (see Models A and E in Tables 3.3 and 3.6).

The results in Model F further suggest that states with the highest solar penetration in the NEM, namely, SA and QLD, experience relatively lower price reductions for an increase in large-scale solar penetration. In particular, a 1 percentage point increase in large-scale solar penetration is associated with a 1 AUD/MWh decrease in electricity prices in NSW and VIC.[19] The decrease in QLD and SA is relatively small and is 0.9 AUD/MWh and 0.6 AUD/MWh, respectively. The results concur with those of Csereklyei et al. (2019), who found a strong contemporaneous MOE of large-scale solar generation in SA and VIC, a relatively lower MOE in QLD, and the absence of the MOE in NSW.

3.3.2.2 Impact on the volatility of electricity prices

The results in the variance equation (Tables 3.3 to 3.6; Model E) suggest that the impact of large-scale solar generation on price volatility is notable and consistent across four states in the NEM. An increase in large-scale solar generation is associated with an increase in price volatility in states with moderate generation levels. Specifically, for each 1 MWh increase in large-scale solar generation, volatility increases by 0.4% and 0.3% in SA and VIC, and only 0.2% in NSW and QLD.[20,21] Furthermore, large-scale solar penetration exhibits the same sign effect with statistical evidence observed for all states in the NEM (see Model F). A 1 percentage point increase in large-scale solar penetration is associated with a volatility increase of around 8% in NSW and VIC, 5% in QLD, and only 2% in SA.[22]

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[19] The penetration variable is expressed as a ratio in the [0, 1] range. Thus, the coefficients of the mean equation (3.2.1) should be interpreted as a percentage point increase in a jth penetration variable is associated with a $\zeta_j \times 0.01$ AUD/MWh change in spot prices, where ζ_j, is the coefficient of the jth penetration variable. We multiply the coefficient by 0.01 as the penetration variables are expressed in a ratio of 0 to 1 rather than in percentages.

[20] Since we are modelling the logarithm of σ_t^2, we treat this equation as a log-linear equation, that is, $\ln Y = \psi_0 + \psi_1 X$, so that a 1 unit increase in X is associated with a $100 \times \psi_1\%$ change in Y. Thus, our interpretation of the variance equation (3.2.2) is that a 1 unit increase in a kth independent variable is associated with a $100 \times \psi_k\%$ change in the spot price volatility, where ψ_k, is the coefficient of the kth independent variable.

[21] We find a marginal difference between the coefficients in the variance equation estimated using 2018 data and 2015 and 2017 data for NSW and QLD (see Model A and E in Tables 3.3 and 3.6).

[22] We follow a similar interpretation of the coefficients as in Footnote 20 with a minor modification to account for the fact that penetration variables are expressed in ratios. In particular, a 1 percentage point increase in a kth penetration variable is associated with a $\psi_k \times 0.01 \times 100\% = \psi_k\%$ change in spot price volatility, where ψ_k, is the coefficient of the kth penetration variable.

When solar PV generation is disrupted due to a lack of sunlight, market prices spike to balance the price-inelastic demand and fossil fuel generation required to meet the lost output (Milstein and Tishler, 2011). Specifically, the decrease in sunlight can increase spot prices significantly due to the higher marginal costs of generation associated with fast start-up and flexible plants and ramping costs associated with coal-fired power plants (Jha and Leslie, 2020). Despite the relatively higher penetration of solar generation, the positive impact on price volatility in SA is relatively lower than in other states. The lower magnitude of the estimated coefficient may be accounted for by the presence of more fast-start and flexible generating capacity, such as gas in SA's generation mix, which tends to smooth price volatility. Moreover, solar generation tends to have low variability during the day compared to wind generation, allowing mid-load power plants to efficiently adjust their power production to residual demand and stave off large and frequent price spikes (Kyritsis et al., 2017). Furthermore, large-scale solar generation tends to exhibit a substantial MOE compared to wind generation for the same marginal increase in the generation levels for all states except QLD. Although wind penetration in QLD is still modest, it has greater potential to lower spot prices and reduce price volatility compared to large-scale solar generation.

These findings suggest that the rapid increase in large-scale solar generation over the past three years played a significant role in depressing electricity spot prices in the NEM. It is evident that while this increase was associated with increased price volatility, the magnitude of this effect depends on several factors, including large-scale solar penetration rates and system flexibility. The latter is determined by the proportion of readily dispatchable natural gas generation, energy storage, cross-borders interconnector flows, and demand response resources in the state's generation mixes. Unlike conventional generation sources, large-scale solar generation is less likely to suffer from forced outages, which, in turn, minimizes the intensity and frequency of scarcity price spikes.

3.3.3 Rooftop solar generation

3.3.3.1 Impact on electricity spot prices

We observe in the mean equation (see Tables 3.3 to 3.7; Model G) that rooftop solar generation contributes to depressing spot prices in the NEM. Similar to large-scale solar generation, this effect is more pronounced in states with moderate and low rooftop solar generation levels. We find that a 1 MWh increase in rooftop solar generation decreases electricity prices in NSW, VIC, SA, and TAS in a range of 0.01 AUD/MWh (NSW) to 0.04 AUD/MWh (TAS). The effect in QLD is marginal. Moreover, incorporating the effect of consumption via the rooftop solar penetration in Model H reveals a consistently negative impact on electricity prices for all states in the NEM. In this respect, a 1 percentage point increase in rooftop solar penetration decreases prices substantially in states with moderate penetration rates by 0.84 AUD/MWh and 0.43 AUD/MWh in VIC and NSW, respectively. The effect in other states is lower, including in SA, which has the highest penetration of rooftop solar generation. In particular, prices decrease by 0.28 AUD/MWh, 0.22 AUD/MWh, and 0.17 AUD/MWh in QLD, SA, and TAS, respectively, for a 1 percentage point increase in rooftop penetration.

3.3.3.2 Impact on the volatility of electricity prices

Turning to price volatility (see the variance equation in Tables 3.3 to 3.7; Model G), we observe a considerable positive impact of increasing rooftop generation on the volatility dynamics in the NEM. Numerically, an increase in rooftop solar generation by 1 MWh increases price volatility by 0.4% in TAS and by almost half in SA and VIC. The effect in NSW and QLD is marginal, approximately 0.1% for each 1 MWh increase in rooftop generation.[23] Considering rooftop solar penetration in Model H, we observe a similar sign effect. For each 1 percentage point increase in rooftop solar penetration, volatility increase by 5%, 4%, 4%, and 2% in NSW, VIC, QLD, and TAS, respectively. A much lower effect of around 1% is found for SA. As noted, this lower positive impact on price volatility

[23] Using data from 2017 without controlling for wind generation in QLD suggests a marginal difference in the estimated coefficients (see Models C and D, as well as Models G and H in Table 3.6).

may result from the richness of flexible energy sources, especially gas generation, which contributes to smoothing price volatility resulting from the rooftop solar generation.

Large-scale solar and rooftop solar generation generally impact electricity spot prices in a similar manner. The main difference is that the magnitude of this effect is lower for rooftop solar generation. This may be due to network restrictions caused by the recent influx of rooftop solar PV power, which forces several networks to cap the amount of excess electricity that customers can export to the grid. Moreover, the results observed in sections 3.3.2 and 3.3.3 underscore the importance of examining the impact of large-scale and rooftop solar generation separately. We noted that combining large-scale and rooftop solar generation undercuts the MOE of large-scale solar generation, likely due to the opposing effects observed during the day. For instance, while the MOE of large-scale solar generation in SA is 0.15 AUD/MWh, adding rooftop solar generation reduces it to 0.03 AUD/MWh. Overall, these results for the MOE are in line with those of Abban and Hasan (2021). However, those authors combined large-scale and rooftop solar generation and observed a positive correlation between daily solar penetration and electricity prices in NSW and VIC. There are several reasons for this effect. First, the authors considered the sample period from 1st April 2014 to 28th February 2019, when solar generation, especially large-scale solar generation, was at the lowest levels. Second, their study did not account for the impact of hydro and cross-border interconnectors flow, signalling the potential omitted variable bias in their model estimation.

The findings of Csereklyei et al. (2019) and Abban and Hasan (2021) suggest that solar generation may positively affect electricity spot prices. In section 3.4, we explore the intraday effect rather than averaging over the whole sample period.

3.3.4 Other factors

In addition to large-scale and rooftop solar generation, there are several other important determinants of electricity spot prices. These are wind generation, electricity consumption, hydro generation, gas prices, and cross-border interconnectors flow. We provide a detailed discussion of the impacts of these other factors on the level and the volatility of spot electricity prices below.

3.3.4.1 Impact on spot electricity prices

We observe in the mean equation of Tables 3.3 to 3.7; Models A, C, E, G, and I, that wind generation exhibits a negative impact on the level of electricity prices in all states across the NEM. TAS and SA exhibit a far higher impact, in which a 1 MWh increase in wind output lowers spot prices by a maximum of around 0.14 AUD/MWh and 0.12 AUD/MWh, respectively. VIC and QLD follow with the effect ranging from 0.05 AUD/MWh to 0.06 AUD/MWh. The impact in NSW is small, approximately 0.02 AUD/MWh for the same increase in wind generation. When we factor in the effect of consumption via wind penetration in Models B, D, F, H, and J, we get the opposite result. In states with intermediate penetration rates, such as VIC and QLD, increasing wind penetration by 1 percentage point decreases electricity prices by 1 AUD/MWh, followed by NSW with a maximum of 0.72 AUD/MWh. TAS and SA exhibit a price reduction of up to 0.67 AUD/MWh and 0.66 AUD/MWh, respectively.

Results in Tables 3.3 to 3.7; Models A to J demonstrate that an increase in consumption and gas prices tend to impact electricity prices positively. In particular, increasing electricity consumption by 1 MWh tends to raise prices more in states with low demand profiles, that is, TAS and SA, by a maximum of 0.16 AUD/MWh.[24] The increase in NSW, VIC, and QLD is moderate, ranging from 0.03 AUD/MWh to 0.07 AUD/MWh. Increasing gas generation by 1 AUD/GJ is associated with substantial upward pressure on the level of electricity prices in states that rely more on gas generation, such as SA, by a maximum of 3.2 AUD/MWh, followed by QLD, by a maximum of around 1.9 AUD/MWh. The lowest effect is observed in VIC, which has the least amount of gas in its generation mix. Hydro generation negatively impacts electricity prices in TAS and QLD, with a 1 MWh increase in hydro generation exerting negative pressure on electricity prices by around 0.01 AUD/MWh. In NSW, an increase in hydropower has the opposite effect, with electricity prices rising by 0.02 AUD/MWh to 0.03 AUD/MWh for each 1 MWh increase in hydro generation. The impact of the interconnectors on the level of spot electricity prices varies. In NSW, the Terranora interconnector and the QNI tend to impact electric-

[24]Because the difference between *consumption (grid)* and *consumption (underlying)* variables' coefficients is marginal, the consumption variable interpretation includes both variables.

ity prices negatively. The latter interconnector exhibits the same effect in QLD, whereas the former shows the reverse effect. The interconnectors to VIC: Heywood, Basslink, and VNI impact electricity prices negatively, whereas the Murraylink interconnector impacts electricity prices positively. The Heywood and Murraylink interconnectors show similar effects in SA, and the Basslink interconnector shows the same impact in TAS.

3.3.4.2 Impact on the volatility of electricity prices

Models A, C, E, G, and I in the variance equation in Tables 3.3 to 3.7 show that wind generation tends to negatively and positively impact electricity volatility. A 1 MWh increase in wind generation is related to a maximum of 0.06%, 0.03%, and 0.01% increase in price volatility in TAS, VIC, and NSW, respectively. In contrast, the same increase in wind generation tends to smooth price variability in QLD by a maximum of 0.08%. Similarly, we observe in Models B, D, F, H, and J that an increase in wind penetration by 1 percentage point is linked to a maximum of 0.6% and 0.8% volatility increase in NSW and VIC, respectively, and a maximum of a 3% volatility decrease in QLD. Although wind generation appears to increase price volatility in TAS, adjusting for consumption via wind penetration produces a statistically insignificant effect.

The findings in Tables 3.3 to 3.7; Models A to J show that electricity consumption, hydro generation, and gas prices impact spot price volatility in a positive direction. For each 1 MWh of electricity consumed, price volatility increases substantially in low-demand-profile states such as TAS and SA by a maximum of 0.13% and 0.10%, respectively. The magnitude of this effect is marginal in other states, zero percent in one decimal point. The effect of hydro generation is more pronounced in QLD, whereby a 1 MWh increase impacts price volatility positively by a maximum of 0.19%. The effect observed in NSW, VIC, and TAS do not exceed 0.09% for the same increase in hydro generation. Gas prices appear to increase price volatility more substantially in QLD, in which a 1 AUD/GJ increase impacts price volatility by a maximum of 6%, followed by NSW (5%). VIC and SA exhibit the same effect of up to 4%, although, in more than two decimals, SA exhibits the lowest impact in the NEM. Most interconnectors tends to decrease price variability. We observe this effect for the Terranora interconnector and the QNI in NSW and the Murraylink and Heywood interconnectors in SA. The latter two interconnectors, in conjunction with the VNI, also exhibit a similar effect in VIC. In contrast, the Basslink interconnector positively impacts VIC and TAS spot price volatility. The same effect is true for the Terranora interconnector in QLD.

Collectively, the results of this analysis concur with previous findings regarding the impact of wind generation and other determinants, such as gas prices and consumption on price dynamics in the NEM (Forrest and MacGill, 2013; Cludius et al., 2014a; Csereklyei et al., 2019; Abban and Hasan, 2021), and those in Chapter 2. As the present study bears a resemblance to that in Chapter 2, we compare the findings and highlight points of divergence.

First, the intraday (half-hourly) MOE of wind generation and its impact on price volatility are higher than the average (daily) effects reported in Chapter 2. Second, while we observe a consistently positive impact of hydro generation across all states in the NEM in Chapter 2, the present study demonstrates the potential for hydro generation in reducing the level of electricity prices. The differences in the observed results are accounted for mainly by the difference in the sample period under investigation, the present findings being fuelled by low implicit fuel cost (water). The years 2018 to 2021 experienced relatively high rainfall compared to, for instance, 2015 and 2016, which witnessed significant drought conditions affecting water storage and hydro-generating capacity. Moreover, the reduction in the bidding levels of coal and gas generators following relatively low coal and gas prices may also have been a factor. Third, although we find in Chapter 2 that all interconnectors to NSW contribute to lowering electricity prices, reflecting the import position of the region, the present analysis shows that this is no longer the case for the VNI. This is most likely due to the huge reduction in inexpensive imports from VIC following the closure of the Hazelwood power plant in 2017, which removed roughly 5% of the NEM's total output. Finally, we include QLD, which is excluded in Chapter 2. We find that wind generation has the potential to reduce QLD's electricity prices and smooth price volatility, although wind generation began only in 2018.

3.4 Further Considerations of Solar Generation in the NEM

In this section, we explore the effects of large scale and rooftop solar generation on electricity spot price dynamics at the intraday timescale and over the four seasons of the year. We also investigate the link between the impact of solar generation on price dynamics with changes in the generation mix.

3.4.1 The intraday dynamics

To understand how solar generation impacts spot prices throughout the day, we run separate regressions for each half-hour interval resulting in a total of 48 estimated coefficients.[25] Figures 3.7 and 3.8 plot these coefficients for large-scale solar generation, rooftop solar generation, and wind generation only for easy presentation of the results. We provide the corresponding p-values in Appendix B.3.

3.4.1.1 Intraday MOE

We observe in Figures 7 and 8 that although the negative impact of wind generation on spot prices appears about the same throughout the day, the impact of solar generation varies and can be positive during some hours. The MOE is most pronounced during the middle of the day. High solar generation supplants expensive fossil fuel power generation during these times, translating into a substantial decline in electricity prices. In addition, the effect may be more pronounced due to the inability or unwillingness of incumbent coal-fired power plants to reduce their output during the day (Rai and Nunn, 2020b). Pereira and Rodrigues (2015), Rintamäki et al. (2017), Kyritsis et al. (2017), and Maciejowska (2020) noted that increasing solar power production tends to have a more pronounced negative impact on electricity prices during peak hours than during off-peak hours in Germany. The peak period aligns with the highest solar generation levels. A

[25] Running separate regressions for each 30-minute interval raises the possibility of spurious regression results due to possible similar generation patterns during these times. However, the fact that we employ time series, which are adjusted for seasonal and trend noise, minimizes, if not eliminates, the possibility of unit root and spurious regression results. We also rely on the assumption that we can directly control the factors that drive changes in electricity spot prices during 30-minute periods (Bushnell and Novan, 2021).

Figure 3.7 : **Change in spot electricity prices (left panels) and volatility (right panels) per MWh increase in large-scale solar and wind generation for NSW, SA, VIC, and QLD.**

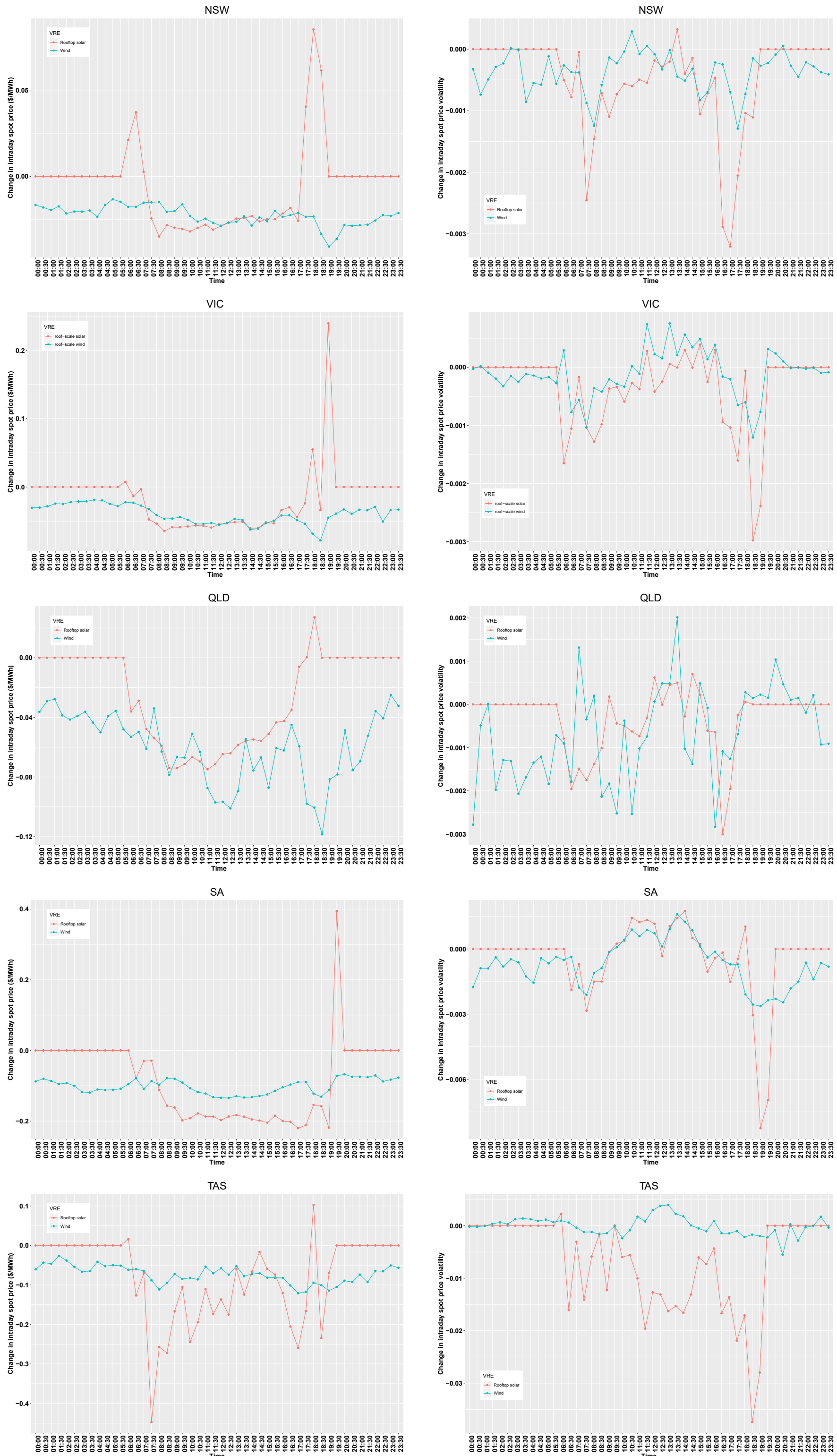

Figure 3.8 : **Change in spot electricity prices (left panels) and volatility (right panels) per MWh increase in rooftop solar and wind generation for NSW, SA, VIC, QLD, and TAS.**

striking observation from Figure 3.7 and 3.8 is that large-scale and rooftop solar generation (especially for NSW and VIC) tend to impact electricity prices positively early in the morning and in the evening when the sun is about to set. Specifically, the price coefficients are positive in the morning (06:00 and 6:30) and evening (18:00 to 19:30). Moreover, we observe a positive correlation between large-scale solar generation and spot prices in SA, which can be seen for most of the day. There is also evidence of a drop in the MOE of large-scale solar generation during the middle of the day in QLD.

3.4.1.2 Intraday volatility

In contrast to wind generation, which appears to impact price volatility positively for most of the time, the impact of large-scale and rooftop solar generation during the day varies (see Figures 3.7 and 3.8). An increase in large-scale solar generation tends to reduce price volatility most of the time across all states in the NEM. This effect is more apparent and pronounced in three states, SA, NSW, and VIC, and relatively less pronounced in QLD. The availability of flexible generation and interconnection capacities is a possible explanation as to why the increase in large-scale solar generation decreases volatility prominently in SA, especially during the shoulder hours. These findings are in line with those of Maciejowska (2020), who showed that solar power tends to stabilize price variability when demand is moderate. Moreover, adding rooftop generation to the systems tends to impact spot prices differently from large-scale solar generation. Generally, an increase in rooftop solar generation is associated with an increase in price volatility during most of the day. A likely explanation is that rooftop PV systems are largely north-facing, which means they have a higher impact on price volatility than large-scale systems, which typically tend to be axis-tracking. TAS behaves slightly differently in that an increase in rooftop solar generation appears to decrease price volatility most of the time compared to the other states. The availability of flexible generation sources, such as hydro and gas, could account for this effect.

The phenomenon observed in the present analysis likely occurs for two reasons: First, high solar generation during the day implies that more generation from fast-start and flexible plants is required to meet the lost output in the evening when the sun sets.

However, these plants have a higher marginal cost of production, which manifests in higher electricity prices. Second, the displaced fossil fuel plants during the day incur higher shutdown and start-up costs to compete effectively in the evening. These findings are in line with Bushnell and Novan (2021), who showed that daily solar generation leads to considerable increases in average prices in the morning between 06:00 and 07:00, as well as in the evening between 19:00 and 20:00 in California's electricity market. Jha and Leslie (2020) also found that an increase in solar capacity triggers an increase in the exercise of market power, operating profits, and wholesale prices in Western Australia. In the NEM, the study by Mountain et al. (2018) found that increasing rooftop solar generation leads to an increase in spot electricity prices in SA, especially in the late afternoon in the summer.

The present analysis provides a possible explanation as to why previous studies in the NEM found that an increase in solar generation positively impacted the average level of electricity prices in NSW (Csereklyei et al., 2019) and NSW and VIC (Abban and Hasan, 2021). Specifically, increased prices during the morning and evening hours likely outweigh the negative effect during the middle of the day, causing the increase in the solar generation to exhibit a positive effect on the level of electricity prices.

3.4.2 Why does solar generation drive up electricity spot prices?

To further explore why solar generation may increase electricity prices, we run separate regressions with the same explanatory variables. However, this time we set the dependent variable to be the generation sources available in a particular state rather than spot electricity prices.[26] We plot the results for the estimated coefficients in Figures 3.9 and 3.10.

We find that the increase in both large-scale and rooftop solar generation displaces incumbent coal-fired generators during the middle of the day when the sun is at the

[26] This means that we change the dependent variable depending on the number of generation sources in the respective state. In NSW, the generation mix includes black coal, hydro, natural gas, and kerosene. The generation mix in VIC includes brown coal, natural gas, battery, and hydro. The generation mix in QLD includes coal seam methane, kerosene, natural gas, black coal, and hydro. The generation mix in SA includes natural gas/diesel, natural gas/fuel oil, diesel, and battery. The generation mix in TAS includes hydro and gas.

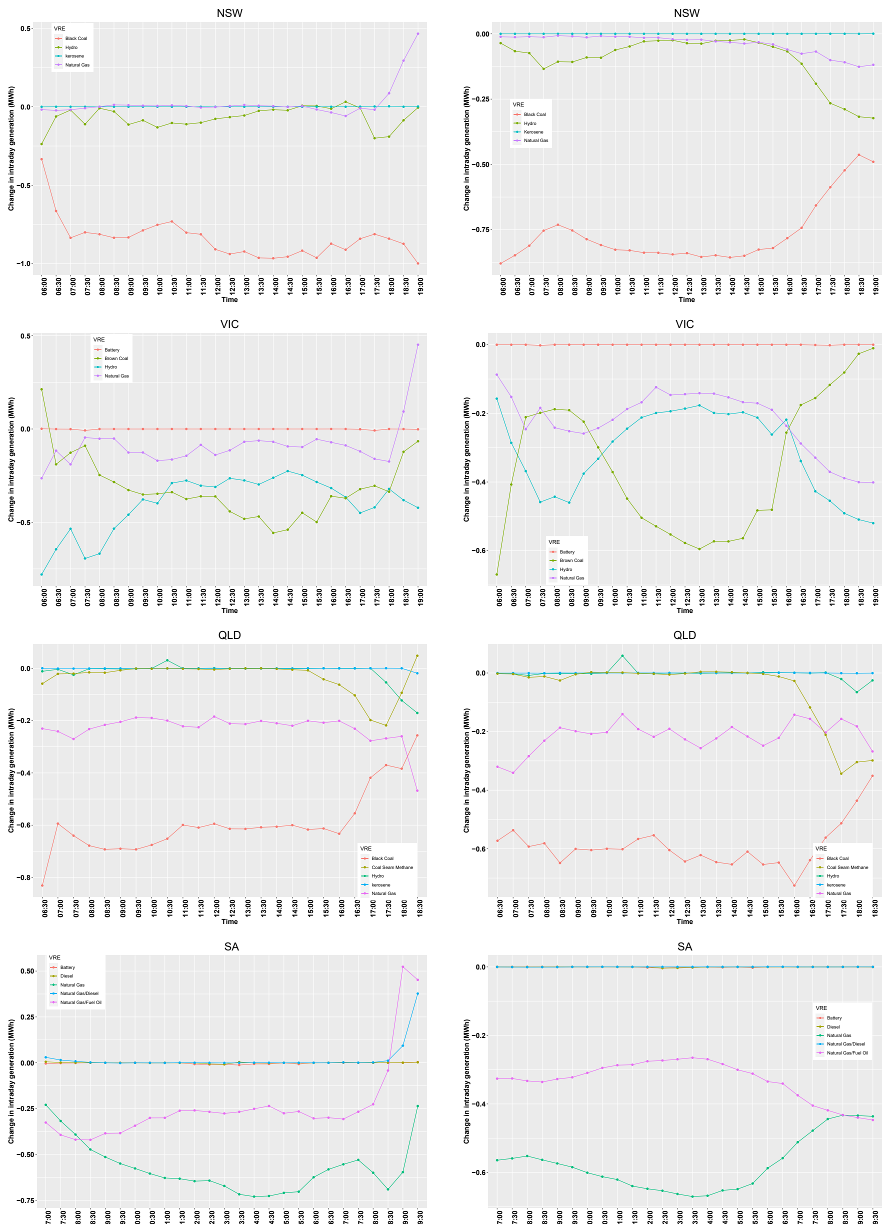

Figure 3.9 : **Change in generation by a source per MWh increase in large-scale solar (left panels) and wind generation (right panels) for NSW, SA, VIC, and QLD.**

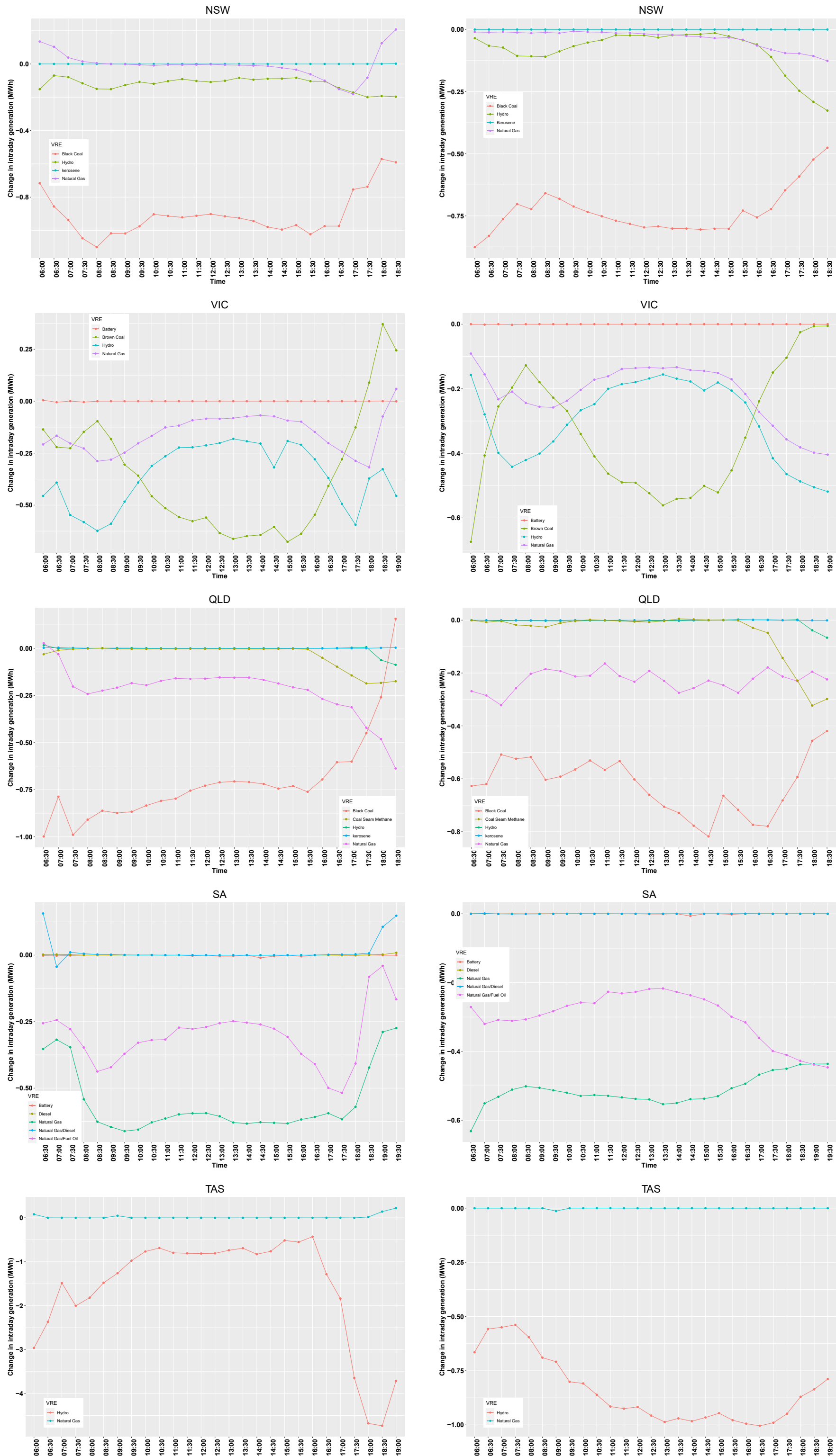

Figure 3.10 : **Change in generation by a source per MWh increase in rooftop solar (left panels) and wind generation (right panels) for NSW, SA, VIC, QLD, and TAS.**

maximum. We observe similar behaviour for other sources of generation, such as hydro and gas generation, although not as consistently as for coal-fired power plants. Interestingly, these figures clearly link the impact of solar generation to spot price dynamics.[27] While wind generation displacement effect is visible throughout the day, solar generation has the opposite effect during some hours. The increase in solar generation during the daytime is negatively associated with spot prices. However, the requirement to ramp up generation quickly in the evening to replace the lost output and the increase in demand can result in a rapid upsurge of the spot prices. Because solar generation is at its lowest during these hours, prices will equal the dispatch cost of the marginal generators (natural gas or coal). This then results in higher prices that solar generators benefit from, resulting in a positive coefficient of solar PV. These dispatch costs tend to be higher in a system with a lot of solar than they would be otherwise. This is because switching coal-fired plants on and off frequently is more expensive than maintaining continuous production. We observe that increasing solar generation in NSW during the evening is associated with an increase in natural gas generation. These hours align with the time when the increase in solar generation impacts electricity prices positively; that is, morning hours (6:00 to 6:30) and evening hours (18:00 to 19:00). We conclude that solar generation tends to increase electricity prices in NSW due to the high marginal costs associated with the natural gas generation required to replace the lost output when the sun is about to set. In VIC, the increase in large-scale solar generation is associated with an increase in brown coal generation in the early morning. In the evening, an increase in large-scale and rooftop solar generation is linked to an increase in brown coal and natural gas generation. This means that solar generation is more likely to impact electricity prices positively in VIC due to the high start-up and shutdown costs associated with brown coal-fired generation and the high marginal costs associated with natural gas generation. It is also worth mentioning that high prices during these periods could also result from strategic bidding behaviours of generators in the NEM (Clements et al., 2016; Hurn et al., 2016; Dungey et al., 2018). Although such behaviours remain challenging in the market, recent studies demonstrate that their role in influencing prices has declined over time, especially after

[27] Whenever the diversions occur, we find no strong evidence to back up the impact of solar generation on the generation levels.

the AEMC introduced the Bidding in Good Faith Rule in July 2016 (Han et al., 2022). This rule is aimed at addressing generators' strategic and misleading bidding behaviours. The AEMC also noted in the Gaming in Rebidding Assessment report of 2018 that the cost of gaming related to rebidding decreased in 2017 compared to the previous three years (AEMC, 2018).

Solar generation tends to positively impact electricity prices in QLD in the morning via natural gas generation and in the evening via black coal-fired generation. There is no clearer link between the impact of large-scale solar generation on the electricity generation mix and its effect on spot prices in SA. However, the curtailment of large-scale solar generation very likely drives the results.[28] AEMO curtails utility-scale (semi-scheduled) generators before rooftop generation (non-scheduled). In the middle of the day, when rooftop solar generation is at its peak, AEMO is likely to curtail utility-scale solar to maintain system security. As there is an excess supply of zero-short-run marginal cost (SRMC) generation at this time, prices are also low. Therefore, as prices fall, and coal generators' output is increasingly pushed down toward the minimum stable levels, AEMO curtails large-scale solar generation. This then translates to a positive correlation between prices and large-scale solar, as shown in Figure 3.7. Rooftop penetration is especially high in SA and QLD, which is why we do not see the same phenomenon in the other NEM regions.[29] Evidence from rooftop solar generation suggests that natural gas/diesel generation is responsible for driving prices up. Peaker plants are primarily gas turbines or gas engines that use natural gas or a liquid fuel, such as diesel. Although both types of plants have the highest SRMC of generation, diesel peaking plants have the highest marginal cost of generation, roughly 500 AUD/MWh. Finally, the absence of statistical evidence for the positive effect of rooftop solar generation in TAS can be accounted for by the dominance of hydro generation and the negligible proportion of gas generation in

[28]Curtailment describes a phenomenon where large-scale solar or wind resources are available, but the system cannot utilize them to avoid congestion and/or oversupply or for economic reasons to avoid exposure to negative prices (Bushnell and Novan, 2021). For example, 178 GWh of large-scale solar PV was curtailed in the QLD region in 2019/20, including 97 GWh due to economic reasons, 54 GWh due to system strength, and 27 GWh due to network congestion (Simshauser, 2021).

[29]States with higher penetration of solar generation provide evidence that the impact of curtailment is double-edged. It undermines the MOE of VRE generation during the middle of the day but with the benefit of reducing the price volatility (Martinez-Anido et al., 2016).

the state's generation mix. Overall, the present findings are in line with those of Bushnell and Novan (2021), who found that the increase in solar generation increased electricity prices in California due to the higher use of less fuel-efficient and higher marginal cost gas turbine (GT) production required to meet the evening peak when solar power is not available.

These results provide important insights into the varying impact of solar generation throughout the day. In general, adding solar capacity to the system may not result in lower spot electricity prices. Although studies that consider the average effect over the whole sample period, as in sections 3.3.2 and 3.3.3, may indicate this occurs, the intra-day profile of the impact of solar generation suggests the opposite effect often happens throughout the day.[30] These findings underscore the importance of interconnectors and battery storage technologies to store surplus energy from solar PV systems to meet peak demand. Investment in storage technologies and interconnectors is increasingly important given the increasing incidence of solar generation curtailment during the day (AER, 2021a). Moreover, the fact that energy resources are dispatched based on the costs of running the plant today, not the costs of keeping them running tomorrow, makes it hard for coal-fired generators to recover their high fixed costs.[31] In turn, high penetration of both large-scale and rooftop solar generation may render coal generation commercially unviable to operate, hastening retirement in advance of planned dates and placing the

[30]To further demonstrate how the average analysis may obscure the positive impact of solar generation, we run an additional analysis by applying the typical approaches of dividing the data into peak and off-peak hours. We define hours associated with the highest average electricity consumption as the "peak period" from 16:00 to 21:00 and hours with low and moderate average electricity consumption as the "off-peak period" from 00:00 to 07:00 and 21:00 to 00:00. We provide technical details and the corresponding results in Appendix B.2.5 and Appendix B.3, respectively. We find the depressing price effect of solar generation and its positive impact on price volatility during peak and off-peak hours. However, results in this section show that solar generation has great potential to smooth price volatility compared to wind generation.

[31]By stating 'the costs of running the plant today, not the costs of keeping them running tomorrow,' we refer to the dispatch mechanism in the electricity market, where generators are dispatched based on their short-term marginal costs. These marginal costs primarily include variables such as fuel costs and operational expenses incurred on a daily basis. However, the long-term fixed costs associated with infrastructure investments, maintenance, and capital recovery are not fully accounted for in the short-term market clearing prices. This becomes particularly challenging as VRE sources increase their penetration in the market, leading to negative prices. This creates a challenge for generators with high fixed costs, such as coal-fired plants, as they struggle to recover their long-term investments in the current market framework. As a result, the compensation they receive from the market may not adequately cover their overall cost structure, making it difficult for them to sustain their operations and recoup their high fixed costs.

system in jeopardy of blackout. The rapid increase of VRE would significantly impact numerous coal-fired generators by 2025, making shutdown a desirable or even unavoidable alternative for at least one power plant owner in the NEM (Edis and Bowyer, 2021). Gas generation, unlike coal, is more flexible, allowing it to quickly ramp up and down to manage fluctuations in solar generation or offer frequency control ancillary services. It often generates at the margin, making it at less financial stress compared to coal-fired units.

3.4.3 Seasonal effects

Table 3.8 presents the impact of large-scale and rooftop solar generation on the level and volatility of electricity spot prices during the four seasons of the year, that is, summer, autumn, winter, and spring.[32] The results suggest that solar generation impacts the level of electricity prices differently over the four seasons. We observe that adding large-scale solar generation and, to a lesser extent, rooftop solar generation into the mix tend to substantially decrease electricity prices during the summer followed by the spring, autumn, and winter. For instance, for each 1 MWh increase in large-scale solar generation, spot prices in SA decrease by 0.25 AUD/MWh and 0.11 AUD/MWh in the summer and winter, respectively.[33] However, the effect of rooftop solar generation is relatively small compared to that of large-scale solar generation. For instance, an increase in rooftop solar generation negatively impacts the level of electricity prices in SA by 0.10 AUD/MWh and 0.02 AUD/MWh during the summer and winter, respectively. The impact of rooftop solar generation in QLD is evident only in the winter and spring.

As Figures 3.5 and 3.4 demonstrate, the spring and summer seasons coincide with high solar generation in the NEM, except for QLD. One possible explanation for the substantial reduction in prices, especially in the summer, is that the days are longer than in the winter.

[32] Table 3.8 presents the estimated coefficients for large-scale solar generation, rooftop solar generation, and wind generation only for easy presentation of the results. However, we control for all determinants of electricity prices and provide the complete results in Appendix B.3.

[33] In Table 3.8, winter is used as a reference (base), thus no adjustment is required to the estimated coefficients for this season. However, the adjustment is required for coefficients in the other remaining seasons. For example, since the coefficient of large-scale solar generation in NSW (Model M) in winter is -0.1924 and $large\text{-}scale\ solar \times D_{spring}$ is -0.1159, then the coefficient for spring season is recovered by summing the two coefficients, that is, $(-0.1924)+(-0.1159) = -0.3083$. The same adjustment applies to other seasons and to both solar and wind generation coefficients. Once these coefficients are adjusted, the same scaling and interpretations as in Footnotes 17 and 20 apply. The seasonality approach is discussed in greater depth in Appendix B.2.5.

Table 3.8 : **The effect of large-scale and rooftop solar generation on spot price behaviour during summer, autumn, winter and spring.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	NSW		VIC		SA		QLD		TAS
	Model M	Model N	Model M	Model N	Model M	Model N	Model M	Model N	Model M
	Mean Equation								
μ	-82.4669	-98.0932	-76.7986	-79.9912	-17.8313	-31.5531	-158.1378	-149.5222	14.1663
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0047)	(0.0000)	(0.0000)	(0.8852)
ϕ_1	0.9292	0.9289	0.9413	0.9367	0.9091	0.9120	0.9670	0.9670	0.9413
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	-0.1924		-0.5174		-1.0723		-0.1170		
	(0.0000)		(0.0000)		(0.0000)		(0.0051)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0238		-0.1254		-0.1760		-0.0947		
	(0.0898)		(0.0067)		(0.0626)		(0.0697)		
$large\text{-}scale\ solar \times D_{spring}$	-0.1159		-0.3501		-0.4480		-0.2780		
	(0.0000)		(0.0000)		(0.0001)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.6794		-1.5917		-1.4067		-0.3573		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$rooftop\ solar_{winter}$		-0.0703		-0.2052		-0.1684		-0.0547	0.0192
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.9890)
$rooftop\ solar \times D_{autumn}$		0.0130		-0.0854		-0.0574		0.0181	-0.4495
		(0.0096)		(0.0000)		(0.0000)		(0.2155)	(0.4199)
$rooftop\ solar \times D_{spring}$		-0.0847		-0.1454		-0.24451		-0.0613	-0.6513
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.6614)
$rooftop\ solar \times D_{summer}$		-0.2208		-0.6693		-0.8229		-0.0742	-1.2006
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.5047)
$wind_{winter}$	-0.1859	-0.1578	-0.5544	-0.4589	-1.1915	-0.9619	-0.7041	-0.6651	-1.7713
	(0.0000)	(0.0028)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
$wind \times D_{autumn}$	0.0094	0.0062	0.0545	0.0732	0.0031	0.0649	0.1610	0.1481	0.5549
	(0.8386)	(0.9067)	(0.1023)	(0.0373)	(0.9423)	(0.0971)	(0.1547)	(0.0603)	(0.3905)
$wind \times D_{spring}$	-0.1095	-0.0948	-0.0650	-0.0454	0.0878	0.1439	0.2935	0.3347	0.2033
	(0.0218)	(0.2169)	(0.0559)	(0.2881)	(0.0294)	(0.0005)	(0.4061)	(0.0000)	(0.7283)
$wind \times D_{summer}$	-0.1231	-0.1245	-0.2079	-0.1468	-0.3168	-0.1803	0.1418	0.1500	0.6619
	(0.0003)	(0.0480)	(0.0000)	(0.0046)	(0.0000)	(0.0001)	(0.4038)	(0.0762)	(0.1133)
	Variance Equation								
ω	-0.1591	0.1069	0.6579	0.6851	1.3583	1.2658	1.9702	1.9498	4.1261
	(0.2693)	(0.1789)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-0.1469	-0.1600	0.0438	0.0605	0.0148	0.0418	-1.8804	-1.8466	0.9278
	(0.0000)	(0.0000)	(0.0071)	(0.0000)	(0.5418)	(0.0781)	(0.0000)	(0.0000)	(0.0537)
β	0.7013	0.7343	0.6956	0.6916	0.6992	0.6814	0.6581	0.6671	0.4635
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.0414	1.0067	0.7663	0.7458	1.1651	1.0981	5.8461	5.3673	5.1819
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	0.0285		0.0400		0.0459		0.0174		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0111		-0.0155		-0.0110		-0.0046		
	(0.0000)		(0.0000)		(0.0050)		(0.0000)		
$large\text{-}scale\ solar \times D_{spring}$	-0.0027		-0.0039		-0.0094		0.0049		
	(0.1310)		(0.2069)		(0.0169)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.0084		-0.0037		-0.0025		-0.0010		
	(0.0000)		(0.2254)		(0.5414)		(0.3883)		
$rooftop\ solar_{winter}$		0.0151		0.0189		0.0249		0.0120	0.0846
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0047)
$rooftop\ solar \times D_{autumn}$		-0.0056		-0.0066		-0.0087		-0.0033	-0.0851
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0032)
$rooftop\ solar \times D_{spring}$		-0.0046		-0.0082		-0.0102		0.0005	0.0214
		(0.0000)		(0.0000)		(0.0000)		(0.5619)	(0.4459)
$rooftop\ solar \times D_{summer}$		-0.0063		-0.0064		-0.0084		-0.0021	-0.0868
		(0.0000)		(0.0000)		(0.0000)		(0.0079)	(0.0081)
$wind_{winter}$	0.0005	-0.0012	0.0013	0.0015	-0.0015	-0.0000	0.0007	-0.0029	0.0023
	(0.5170)	(0.0908)	(0.0283)	(0.0084)	(0.0165)	(0.9469)	(0.8172)	(0.2986)	(0.7496)
$wind \times D_{autumn}$	-0.0005	-0.0001	-0.0006	-0.0003	-0.0022	-0.0012	-0.0077	-0.0036	-0.0074
	(0.5304)	(0.8808)	(0.2405)	(0.5581)	(0.0000)	(0.0193)	(0.0222)	(0.2287)	(0.2609)
$wind \times D_{spring}$	0.0008	0.0029	0.0018	0.0041	0.0019	0.0039	-0.0163	-0.0091	0.0175
	(0.3694)	(0.0014)	(0.0045)	(0.0000)	(0.0009)	(0.0000)	(0.0001)	(0.0122)	(0.0437)
$wind \times D_{summer}$	0.0007	0.0024	0.0012	0.0037	-0.0006	0.0018	-0.0150	-0.0065	0.0095
	(0.4315)	(0.0018)	(0.0513)	(0.0000)	(0.2611)	(0.0017)	(0.0000)	(0.0506)	(0.2918)
Skew			0.0819	0.0891	0.9686	0.9682	1.0227	1.0345	1.1060
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8382	2.7699	1.0380	1.0543	2.1947	2.2177	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-230527.7	-231110.2	-235822.3	-235856.4	-242747.9	-243598.3	-206487.9	-207792.7	-239307.7
AIC	7.7412	7.7607	8.2239	8.2250	8.6092	8.6394	7.9899	8.0403	8.0357
BIC	7.7464	7.7660	8.2298	8.2310	8.6092	8.6444	7.9957	8.0462	8.0399
Q(20)	3.9487	5.3558	36.24	41.41	7.161	3.905	4.018	3.576	5.677
	(0.2337)	(0.0798)	(0.0000)	(0.0000)	(0.0000)	(0.2409)	(0.2226)	(0.3012)	(0.0612)
$Q^2(36)$	0.0018	0.0010	0.0142	0.0402	0.0007	0.0005	0.1935	0.1266	0.0396
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)
ARCH-LM Test	0.0012	0.0007	0.0017	0.0030	0.0005	0.0003	0.2201	0.1050	0.0230
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9963)	(0.9993)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568

The coefficients of the supply and demand variables should be divided by 10 to recover the original values. Winter is used as a reference season. Recovering the coefficients for the other seasons (autumn, spring, and summer) requires the addition of an interaction variable to the reference variable. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Thus, the amount of electricity produced by a solar generation system in the summer at the same location could be twice that produced in the winter. Given a relatively higher correlation between solar generation and demand (both peak in the summer), an increase in large-scale solar generation significantly impacts electricity prices. In SA, this effect is enhanced further by the rapid uptake of domestic rooftop solar generation, which lowers demand during the middle of the day, leading to the occurrence of near-zero or negative prices. In contrast to other states, QLD does not experience high solar generation in the summer, which explains why rooftop solar generation shows an insignificant MOE during this season. Also, low rooftop solar generation in TAS may explain the lack of statistical evidence for its effect during the four seasons of the year. The findings for the MOE of large-scale solar generation agree with those of Mountain et al. (2018).[34]

Large-scale and rooftop solar generation have a consistent positive impact on the volatility of spot prices, an effect that is more pronounced in the winter than in the other seasons. The output from solar generation varies substantially in the winter because the days are shorter, there is more cloud cover, and the sun is lower in the sky. Fluctuations in solar generation force the electricity system to respond to significant and unexpected changes in output and plant operators' dispatch decisions. This means more fast starts and flexible, and fossil fuel–based generation is required to replace the lost power output from solar generation compared to other seasons. As stated in section 3.3.2, this can result in extreme price spikes when the market attempts to balance the price-inelastic demand and fossil fuel generation when solar PV output falls. The tendency of coal-fired generators to withdraw from the market for maintenance during this season is likely to trigger further price variability (AER, 2021a). The lack of statistical evidence for the impact of large-scale solar generation on spot price volatility during the summer reflects

[34] Mountain et al. (2018) showed that a 100 MW increase in average solar PV production in SA leads to a higher reduction in spot prices during the summer by around 11 AUD/MWh compared to 31 AUD/MWh in the winter. The authors argued that although the marginal impact of solar generation tends to be higher in the winter, the total impact tends to be lower. Moreover, they found an increase in solar generation increases spot prices in the late afternoon in the summer. As we consider the average over the whole summer season, the negative effect of solar generation likely outweighs its positive effect, as explained in subsection 3.4.1. The difference in the estimated results between the present and the Mountain et al. (2018) study may also be accounted for primarily by the difference in the sample period and the methodological approach employed in the analysis. We consider a period from 2018 to 2021 but Mountain et al. (2018) covered a period from 2012 to 2018. Furthermore, their approach did not adjust for the yearly variations or include lagged electricity prices.

the relatively higher correlation between demand and solar generation during this season. This correlation tends to minimize the probability of high price spikes. Solar generation profile is best aligned to the heat waves that typically occur during summer, causing price spikes. Having solar generation reaching its maximum during most hours of this season means that both large-scale and rooftop solar generation can significantly reduce the frequency and severity of scarcity prices. Furthermore, the results show that large-scale solar generation has a greater positive impact on spot price volatility over all four seasons than rooftop solar generation. This difference can be partly explained by the smaller volume of excess rooftop solar generation exported back in the grid due to export limits.

In general, the impact of large-scale and rooftop solar generation varies substantially over the four seasons of the year. The fact that solar generation amplifies prices volatility, especially in the winter season, shows that the system flexibility required to balance the demand and supply is still not yet in a position to cope with the rapid uptake of solar generation in the NEM.

3.5 Policy Implications

The high correlation between the output of solar plants implies that adding more solar capacity, especially rooftop solar generation, to the system will further depress prices and increase spot price volatility particularly in the middle of the day. Therefore, our findings suggest policy adjustments that increase the correlation between rooftop PV and operational demand to reduce the price volatility from increased solar PV output. Moreover, this study stress the need for unlocking relatively cheap options for market flexibility, such as allowing participation from the demand side of the market. We provide next a number of courses of action to ensure an effective transition to clean energy.

3.5.1 Small-scale renewable energy scheme (SRES) and state-based policies

The federal government's SRES policy aims at reducing carbon emissions from the electricity sector by incentivising small-scale energy generators, such as rooftop solar PV systems (Blakers et al., 2021). States such as QLD, VIC, and SA also run several local programs to achieve their ambitious renewable energy targets. These programs provide grants, rebates, or loans to support small-scale solar PV and battery systems. Numerous north-facing rooftop solar panels have been installed to achieve these policies by maximizing the overall solar energy generation and, in turn, maximizing CO_2-e emissions reductions. Given the volatility associated with rooftop PV, the need to allocate SRES subsidies and state-based supports to rooftop solar PV-plus-battery systems is increasingly crucial. In 2020, less than 3% of the 300,000 solar PV systems installed in the NEM had an attached battery system. In the same year, rooftop solar PV systems met only 0.44% of the NEM's electricity needs during peak demand hours. The rate was higher in SA, with rooftop generation meeting 1.75% of the electricity demand (AER, 2021a). Given that SA has the highest penetration of rooftop solar generation in the NEM, and given that these systems are mostly (if not solely) north-facing fixed-panel systems, the ability of rooftop PV to meet peak demand in SA is very small. By furthering and ideally changing the design of the SRES and state-based policies so that only solar-plus-battery systems are eligible for the scheme, stored electricity can be exported later in the day (i.e., via discharge from the batteries) to meet the peak demand. This would increase the MOE and lower the volatility effect of rooftop PV compared to the likely impacts from an SRES that also provides financial support for PV-only systems.

3.5.2 Rooftop solar curtailment

Evidence from this study suggests that the rapid uptake of rooftop solar generation is imposing significant challenges during the middle of the day by pushing demand down to levels where system security is threatened and, on some occasions, pushing spot prices into negative territory. Most generators in the electricity grid are controlled by AEMO, which allows dispatch by stacking the offer bids of all generators depending on the price offers and supply limitations, such as transmission network constraints. Unlike these generators, rooftop solar has long been unregulated by AEMO, which prioritized it over other types of generators (Reddaway, 2020). Lack of controllability not only cuts the share of large-scale solar generators when their capacities are curtailed but also causes significant distress to coal-fired generators, which are not designed to operate at low output levels. As we have demonstrated, the impact of rooftop solar generation is increasingly pronounced in SA and QLD, with the highest penetration of rooftop solar generation in the NEM to date. In response, and for the first time, in March 2021, AEMO instructed network operators in SA to turn off rooftop solar generators and withdraw power from the grid to ensure the security of the power system (AER, 2021a). This incident occurred during a low-demand period with excess supply from rooftop solar systems. Given the increasing uptake of rooftop solar generation at around 3,000 MW a year, and that battery storage capacity is still insufficient to enable extensive decarbonization at a cost-effective level, there is little doubt that curtailing rooftop solar generation is becoming increasingly important in the NEM. As QLD, VIC, and NSW are also witnessing high increases in rooftop solar generation, this is not exclusive to SA, and curtailment of rooftop solar generation may be required across the NEM in the not-too-distant future. However, one important question still remains, namely, identifying the best mechanism with which to curtail rooftop solar generation. The dynamic/flexible solar export mechanism being considered in SA, QLD, and VIC would probably provide a more robust solution to the increasing penetration of rooftop solar generation compared to current static or arbitrary limits.[35] This curtailment mechanism involves a central computer system instructing solar inverters on how much and when to export power to the main grid depending on the on-network conditions. This would allow absorption of all households' excess solar power, by varying the export amount from time to time based on the supply and demand conditions and other network constraints.[36] Effective management of rooftop exports via flexible export limits in conjunction with other planned mechanisms to support the penetration of solar generation, such as increased interconnections, would eliminate the need to switch off rooftop solar systems completely to maintain grid stability.

3.5.3 Feed-in tariffs (FiTs)

Rooftop solar generators often receive FiTs for the excess generation exported back into the grid as a means of encouraging renewable energy adoption (Li et al., 2020). These

[35] Solar installations are typically required to have a static export limit of 3–5 kW. These limits are dropping further to the near-zero limit and even permanent zero reports limits (Reddaway, 2020).

[36] Because modern solar inverters have a connector that can attach a demand response enabling device (DRED), implementing dynamic export management is becoming a feasible and potential solution to curtailing rooftop solar generation (Reddaway, 2020).

rates vary significantly across the NEM. For instance, the NSW and VIC governments recommend FiTs of at least 4.6 c/kWh to 5.5 c/kWh and 6.7 c/kWh, respectively (NSWGov, 2021; VICGov, 2021a). State governments and retailers should move from offering flat-rate FiTs to FiTs that vary throughout the day (dynamic FiTs). These rates should be set in such a way that they are lower during the day when demand, especially at the residential level, is typically low and higher during morning and evening demand peaks. This will trigger owners of solar generators to export their excess electricity to the grid when it is most valuable, in this case, the morning and evening. This reform has several potential benefits. First, it might incentivise north-facing PV systems to invest in batteries to store surplus energy and draw on it when needed in the evening. Second, it may attract owners to place their solar panels in other orientations, such as an east/west split, to maximize generation in the morning and evening hours. VIC offers a typical example of the proposed reform. Beginning 1$^{\text{st}}$ July 2020, all retailers were required by law to offer either a single-rate rate FiT, a time-varying FiT, or both. The time-varying rates depend on whether excess electricity is exported during off-peak, shoulder, or peak hours. The FiT rates currently stand at 9.1 c/kWh during off-peak hours, 9.8 c/kWh during shoulder hours, and 12.5 c/kWh during peak hours (VICGov, 2021b). However, per our findings, the rates during morning and evening hours should be substantially higher than daytime rates. Third, consumers would be encouraged to shift some of their electricity use from peak to solar generation hours, reducing peak-hour electricity demands.

3.5.4 Two-sided market reform

The increase in solar generation is pushing out traditional coal and gas-generating businesses during the day. However, these generators are required to complement the variability of solar power output because of the ramping up and down of solar plants, adding more costs to the system. As demonstrated in this study, the benefits derived by increasing solar generation depend substantially on the cost associated with dispatchable and flexible capacities. High flexibility costs are likely to undermine the merit order effect for solar generation. Therefore, the market needs cheap firming technologies to allow the benefits of renewables to translate to low electricity prices. A two-sided market that allows the supply and demand sides to participate in the dispatch and price-setting process is a potential solution. Since the inception of the NEM, electricity has generally been flowing one way, from large-scale centralized generators to homes and businesses. However, the advent of automation, digitalization, and the Internet of Things means that the market can allow for the effective participation of the demand side. This advancement in technology will enable the demand side to respond directly to price signals similar to the supply side without being energy traders and physically or consciously controlling their demand (Rai et al., 2021). In line with these transitions, the market will move from two-part structures with fixed daily charges and volumetric tariffs to more dynamic/time-varying retail pricing (time-of-use (ToU)) rates such as "solar-sponge" tariffs. The solar sponge aims at encouraging the "soaking up" of cheaper power during the day, when there is extra electricity generation, typically between 10:00 and 15:00, particularly in SA and QLD, and setting high prices during peak periods. Thus, allowing for effective demand-side participation can be a more cost-effective mechanism for dealing with peak demand than peaking generation, such as gas and pumped hydro. The October 2021 reform, namely Wholesale Demand Response (WDR) mechanism, which allows customers to offer demand response to the wholesale market directly (AEMO, 2021b), will likely translate into a potentially lower volatility effect for solar generation than currently observed in the market but may also reduce the MOE of solar PV. A two-sided market provides the potential for maximizing CO_2-e emission reduction by substituting thermal generation with demand-side resources and allowing for maximum generation from VRE, which would otherwise be curtailed to allow the thermal generators to run.

3.6 Conclusion

Solar generation is shaping the energy generation sector in Australia's NEM. The past three years have seen a significant increase in large-scale and rooftop solar generation. Rooftop solar PV installations have experienced the fastest development and account for more than one-third of the renewable energy capacity in the NEM. However, the weather-dependent nature of solar generation is challenging the system. More output is concentrated during the middle of the day when the sun is at the highest point, substantially impacting electricity spot prices and revenues earned by fossil fuel generators. Although solar generation, especially rooftop solar, is the leading installed capacity, its effect on electricity spot prices have not been adequately investigated to date. We separated large-scale solar generation and rooftop solar generation and investigate their effects over the whole sample period, intraday time intervals, and seasons of the year.

We find that the impact of large-scale and rooftop solar generation depends on the generation level and penetration rates. States with relatively low and moderate generation levels and penetration rates exhibit a strong MOE and a positive impact on price volatility than states with high generation levels and penetration rates. However, the intraday profile of the impact of solar generation reveals that by examining the average effect over the whole sample period, we obscure some of the interesting features of solar generation. Electricity prices tend to increase for an increase in large-scale and rooftop solar generation, especially in the early morning and evening hours, due to the high cost associated with fossil fuel generation. Rooftop solar generation tends to exhibit high average generation concentrated during the middle of the day, resulting in a small MOE and a substantial positive impact on price volatility compared to large-scale solar generation. Moreover, we find that the effect of solar generation varies over the four seasons of the year, with a more pronounced MOE observed during the summer (a season associated with high solar generation) and the lowest during the winter. The latter season experiences high price volatility for the increase in solar generation.

We recommend several policy adjustments to support the current transition to renewable energy in the NEM and ensure a reliable, secure, and affordable energy supply while cutting CO_2-e emissions. These include directing federal and state local policies to support PV-plus-battery systems rather than PV systems alone; transitioning to dynamic export management of rooftop solar generation; switching to dynamic FiTs; and effective demand-side participation via the two-sided market reforms.

Chapter 4

From a 30- to 5-minute settlement rule in the NEM: An early evaluation

4.1 Introduction

On 1st October 2021, Australia's National Electricity Market (NEM) underwent a major transformation since its commencement, namely aligning settlement (or trading) intervals with dispatch intervals. That is, from 1st October 2021, the settlement interval became 5 minutes in length, and therefore the settlement price in each region became the dispatch price. The previous 30-minute settlement (30MS) resulted in pricing inefficiencies by incentivising generators to behave strategically and accounted for spot price volatility unrelated to underlying demand and supply conditions (Clements et al., 2016). The increase in spot price risk impacted generators and consumers exposed to spot prices, leading to higher supply and hedging costs for retailers and, eventually, end consumers. Moreover, the 30MS distorted investment signals in fast response generation and demand-side response (AEMC, 2017b). The move to 5-minute settlement (5MS) is expected to avoid strategic bidding behaviours, improve system flexibility, and allow for more variable renewable energy (VRE) integration (AEMC, 2017b).

This study seeks to assess the impact of the introduction of 5MS on time- and dispatch-weighted spot prices.[1] We examine both immediate and short-term effects defined in this analysis as one month and eight months following the rule change on 1st October 2021, respectively. We study the evolution of the causal effect over time using the Bayesian structural time series model. The model combines information from the behaviour of the response variable, time series that are predictive of the response series before the

[1] The time-weighted spot price is the price used for making payments to electricity generators, also known as the settlement price. Dispatch-weighted price (DWP) is the volume-weighted price received by generators (Rai and Nunn, 2020a). It can be thought of as revenue earned by a merchant project, which takes spot prices without hedging or contracting.

rule change, and available prior knowledge about the model parameters. As such, this approach produces a more robust counterfactual estimation than the traditional and widely-used difference-in-differences approach. We extend on the earlier research of Märkle-Huß et al. (2018)—the only empirical analysis to use Bayesian structural time series in the electricity market in a similar context.

We find that the introduction of 5MS causes no immediate effect on spot price dynamics. We contend that the four years lead-up time to the start of 5MS allowed NEM participants to prepare for the rule change by constructing new plants with fast capability, upgrading existing generation assets, and changing the way they operate their assets. We conjecture that these preparations ensure no significant changes/disruptions in spot price dynamics immediately following the start of 5MS.

However, when examining short-term effects, we find evidence that 5MS causes 113%, 94%, and 49% increases in average spot prices in Tasmania, Queensland, and New South Wales, respectively. This increase in spot prices has been argued to reflect changes in generators' bidding behaviour to align their operations with 5MS (AEMO, 2021b). Contrary to the general expectation that the introduction of 5MS would trigger greater price volatility in regions dominated by coal-fired generation, we observe that this is not the case, at least within the sample period.

Moreover, the findings reveal DWPs either increase or remain unchanged for most generators over the eight-month period following the inception of 5MS. Batteries, which can be easily shut down at times of excess supply and quickly restarted in shortfall, generate more DWPs, especially in South Australia, by about 69%. Despite gas generation also being fast and flexible, the results point to its DWP increasing only in two states, namely Tasmania and Victoria. We observe no changes in states that rely more on gas generation, including South Australia. Shorter trading intervals also prove beneficial to VRE generators, with DWPs for both wind and solar generators increasing after the rule change. Unexpectedly, we observe an increase in the DWPs earned by black coal generators in New South Wales and Queensland by approximately 89% and 48%, respectively. We attribute this effect to the change in generators' operational and offer behaviour as well as the degree of flexibility in these plants' operations.

The findings of this study have a number of implications for market redesigns that seek to reflect real-time system operations and better accommodate the uncertainty and variability of VRE. Specifically, our findings highlight the fact that existing conventional gas generation, such as open cycle gas turbines (OCGTs) and combined cycle gas turbines (CCGTs), which are the most well-established in the NEM, are not flexible enough to effectively cope with 5MS.[2] This necessitates more investment in highly fast-start scheduled technologies or equivalently firm and flexible demand response that can better respond to changes in market conditions over short time periods. For peaking applications in the NEM, more flexible gas-fired generators with aero-derivative engines are a potential option, owing to their faster start-up times and operational flexibility (quick ramp-up and load-change capability). Furthermore, the recent rise in gas prices necessitates investment in flexible and fuel-efficient gas-producing technologies, such as reciprocating gas engines.

Moreover, the NEM is a highly concentrated market with great potential for generators to exercise market power and game the market. The three largest generators currently hold combined market shares in each NEM region of around 70% on the capacity measure and over 80% on the dispatched energy measure. Policies aiming to eliminate this industry problem and promote competition are key to realizing the benefits of 5MS market redesign and similar market rules. Without such policies, 5MS is unlikely to bring about substantial changes to the market.

Empirical studies on the impact of switching to shorter trading intervals in other markets are scarce. The study by Märkle-Huß et al. (2018) offered probably the most relevant empirical analysis. This study investigated the impact of moving from 1-hour to 15-minute products on the European Power Exchange (EPEX). Three findings emerged from this study: shorter trading intervals lowered electricity prices while causing marginal changes in trading volume and incentivising wind and solar generators to offer additional supply in the market. Other studies, such as that of Koch and Hirth (2019), underscored the role of shorter trading intervals in reducing the reserve requirements and reserve use by mitigating predictable imbalances stemming from solar generation and electricity

[2]The lack of significance for the impact of 5MS on gas generators' DWPs in our findings is likely due to averaging over both slow- and fast-start gas plants, with most of the gas fleet in the NEM being slow-start.

consumption diurnal patterns. Goutte and Vassilopoulos (2019) have also shown that short-term price volatility generated additional revenue for flexible resources that could respond swiftly at 15-minute intervals. We seek evidence as to whether trading in shorter intervals generates expected market outcomes in the NEM and add to the literature, including studies by Rai et al. (2019), Rai and Nunn (2020a), Burger et al. (2020), and Csereklyei et al. (2021), that posited that 5MS would add value and provide more efficient pricing signals for investment in fast response technology, such as batteries, reciprocating gas engines, and demand response.

The remainder of this chapter is organized as follows: Section 4.2 details the rule change along with the potential impact of the 5MS on spot price dynamics. Section 4.3 describes the data, preliminary analysis, and method for isolating and quantifying causal effects. Sections 4.4 and 4.5 present the empirical findings of the impact of the 5MS on price dynamics and spot market revenues, respectively. Section 4.6 discusses policy implications. Section 4.7 concludes.

4.2 Settlement Rule Change in the NEM

4.2.1 30MS and 5MS price setting processes

The NEM operates as a spot market in which demand and supply are matched instantaneously in real time through a centrally coordinated dispatch process (AEMO, 2021a). The system operator's central dispatch engine ensures that the expected demand for electricity is met in the most cost-efficient way possible by using an algorithm that orders and dispatches generators from the cheapest to the most expensive units. Offers to supply a given volume of electricity at a given price from various generators are submitted at 5-minute intervals. Generators specify the amount of output they are willing to offer at 10 different price points for the day. These bids are then stacked in what is known as the "merit order" according to price. The dispatch price is the highest bid for the most expensive generator that must be used to balance supply and demand.

When the market first opened in 1998, metering and data processing capabilities limited settlement to large time granularities. As a result, the dispatch prices differed from the settlement prices. The dispatch process determines the optimal mix of scheduled

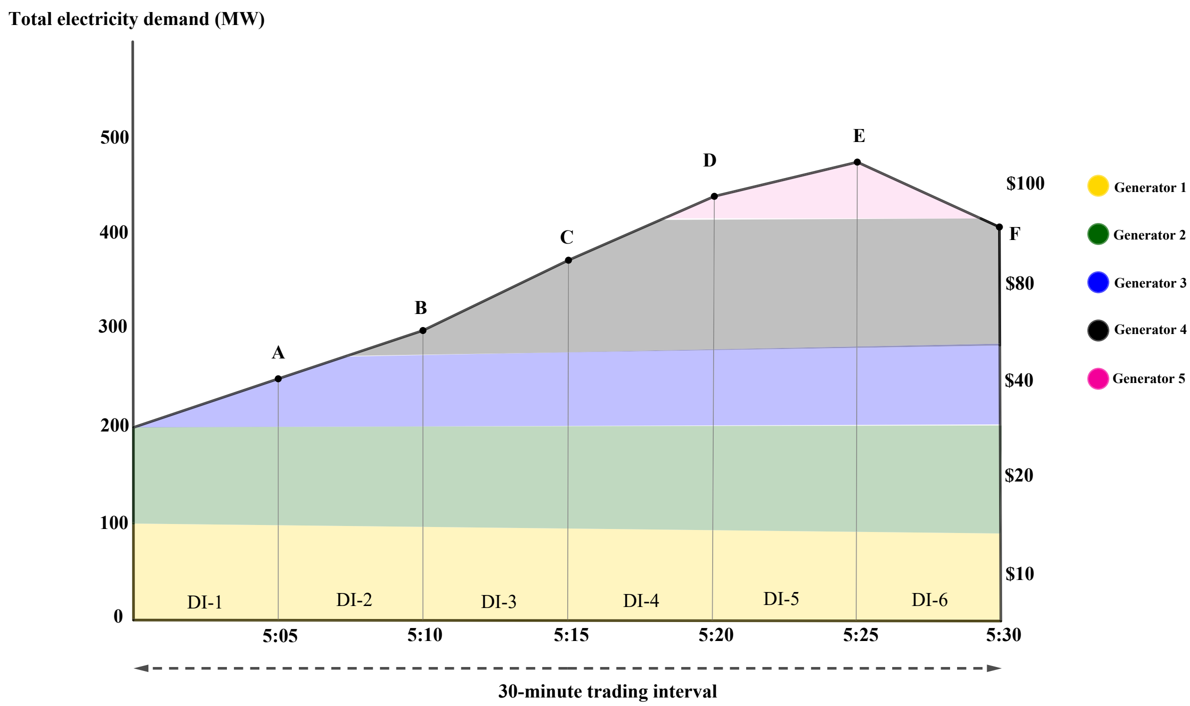

Figure 4.1 : **The price-setting process in the NEM under the 30-minute settlement regime.** A 30-minute trading period or financial settlement period is a period of time during which financial transactions for electricity that are being bid on the market are settled. DI-1 to DI-6 denote 5-minute dispatch intervals throughout a half-hour trading interval.

generators to meet demand and dispatch price every five minutes while accounting for network and other constraints. Six dispatch interval prices were then averaged out over 30 minutes to estimate the spot price or regional reference price (RRP) for financial settlement purposes, resulting in the so-called 5/30 problem.

Figure 4.1 illustrates the price setting process under a 30MS rule. At 5:05, only supply from Generators 1, 2, and 3 are required to meet demand. The marginal Generator 3 sets the price at this dispatch interval at \$40 per MWh. However, demand increases substantially at 5:25, rendering three generators insufficient to meet the demand. This high demand forces all five generators to come online, with Generator 5 setting a price at \$100 per MWh. The same pricing process applies to the remaining dispatch intervals. Denoting dispatch prices at intervals $A(\$40/\text{MWh}), B(\$80/\text{MWh}), \ldots, F(\$80/\text{MWh})$ as

Dispatch price_1, Dispatch price_2, . . . ,Dispatch price_6, respectively, then

$$\text{Spot price} = \frac{1}{6}\sum_{i=1}^{6} \text{Dispacth price}_i.$$

This means that the trading price at this half-hour interval is 80 per MWh. Retailers and large consumers pay this amount to buy power on the spot market, and all five generators receive this price irrespective of their bid prices in return for their output. The spot price is estimated separately for each regional market depending on the market demand and supply conditions. The minimum (market floor price) and maximum (market price cap) prices a generator may bid during a dispatch interval are currently (for the financial year 2021–22) -$1,000 per MWh and $15,100 per MWh, respectively.

Improvements in computer processing speed and data handling capabilities have made the factors behind the adoption of the 30MS rule irrelevant. Accordingly, the NEM implemented the 5MS on 1st October 2021, to provide better price signals for investment in faster response technologies and to minimize/eliminate gaming behaviour (AEMO, 2021a). Under the new rule, each dispatch interval is now a settlement interval; that is, the dispatch price is also the settlement price.

4.2.2 Dispatch-related inefficiencies under 30MS

Several studies have demonstrated how the misalignment of dispatch and trading intervals in conjunction with a market rule that allows rebidding resulted in operation and pricing inefficiencies in the NEM. To see why spot price under the 30MS regime may not reflect the generation cost, consider Generators 1 and 5. The fact that the same amount is paid to generators that supply electricity within half-hour intervals means that Generator 1 receives twice the price it is willing to supply electricity while Generator 5 incurs a loss of $20 per MWh. Clements et al. (2016) have demonstrated how the 30MS permitted strategic bidding (bid-splitting) and rebidding by large-scale base generators in the NEM. The bid-splitting strategy of baseload generators involved (i) bidding a reduced capacity at a lower price to guarantee continuous dispatch, and (ii) bidding the remaining capacity at the maximum possible price. The rebidding permitted baseload generators to reap from strategic bidding, causing significant changes in the supply conditions within a brief period of time. Ultimately, strategic bidding behaviours resulted in extreme prices that were not reflective of the fundamental cost of electricity supply.

Furthermore, Hurn et al. (2016) noted that strategic bidding occurred in the NEM due to its market-clearing arrangement—the different dispatch and settlement prices. This allowed generators to withhold capacity at low prices, which reflected their generation costs within a trading interval, and to bid all remaining capacity at (or near) the price cap whenever the market condition permitted. Put differently, generators had an incentive to act strategically during each half-hour interval since the price spike during the dispatch period translated into a higher average (spot) price received over the trading interval. Typically, the price hike drove the average settlement price well above the marginal cost of generation. For instance, consider the case in which, at 5:05, generators manage to skyrocket the dispatch price to a maximum allowable price of $15,100 per MWh. Assume further that generators increase their output and offer their capacity at the floor price, -$1000 per MWh, for the remaining dispatch intervals. In this case, the average of the six dispatch intervals is $1,750 per MWh, far from the maximum marginal cost of any type of generator in the NEM.

Baseload generators could rebid all available generation capacity at the floor price after a price spike because the rebidding arrangement in the NEM allowed generators to resubmit their bids up to 67 seconds before actual dispatch (Wood et al., 2018).[3] Late rebidding at the last minute provided an opportunity for generators to game the market under the 30MS. A generator rebidding very close to the time of dispatch could create artificial supply scarcity by reducing its available generation or moving output into higher wholesale price bands. Artificial supply forced prices to spike due to insufficient time to allow other generators to respond. Indeed, Dungey et al. (2018) constructed a theoretical framework to account for rebidding and examined how it would affect price levels and volatility under the 30MS regime. They demonstrated that the mismatch of trading and dispatch prices permitted dominant generators to manipulate their bids and capitalize on resubmission of bids to achieve this strategy. A typical strategy involved withholding

[3]The rebidding rule provides an opportunity to generators and loads to adjust their plans due to the changes in market conditions and other participants' bids.

capacity at lower prices for the first dispatch interval in a trading period, creating a price spike, and then adding capacity at lower prices to ensure dispatch.

4.2.3 Investment-related inefficiencies under 30MS

The 30MS distorted price signals for the value of variations in supply and demand across trading intervals and thus provided little incentives for fast-response technologies to enter the market. This distortion occurred in several ways.

First, 5-minute averaging muted price signals for fast-response generators responding to a price spike in a single dispatch interval. Averaging the 5-minute dispatch prices means that in certain instances, the price received by a generator turned out to be below the 5-minute dispatch price at the time when this generator was producing, as illustrated in section 4.2.2. Thus, even if the price spikes, fast-response generators such as batteries had less incentive to discharge during the dispatch interval and sometimes chose to withhold production until later in the half-hour.

Second, as the 30MS provided no signal for the value of electricity within the dispatch interval, it muted the signal for price-responsive loads to reduce or increase consumption in response to 5-minute price spikes or low prices, respectively. In some instances, loads restricted consumption over the entire 30-minute trading interval to avoid being "caught out" by high price events that may have only persisted for a single dispatch interval (AEMC, 2016). Other challenges arose from dispatch inefficiency, say, due to "pilling in", that is, when generators rebid their capacity negatively to maximize their chances of dispatch following the price spike, coupled with large users restricting their consumption in the same trading interval due to a price spike.

By aligning the dispatch and settlement prices, the 5MS offers precise information about the value of variations in supply and demand over the trading interval and may encourage investments in flexible technologies, such as batteries, demand response capacities, and alternative fast-start generators. The 5MS is also expected to encourage gas and coal power stations to upgrade their plants to increase their start-up and ramping capabilities. The AEMC (2017b) has asserted that matching price signals with physical operations would shape and support the ongoing transition in the NEM in several dimensions: First, it would improve price signals for more efficient generation and electricity use. Second, it would encourage more efficient bidding by aligning the generators' bidding strategies with the efficient outcome of the market. Third, it would enhance efficient demand-side participation by improving price signals for demand response and aligning the timing of such response with the physical needs of the power system. Fourth, an improved wholesale price signal would trigger efficient investment in generation capacity and demand response technologies. Finally, it would reinforce investment in fast-response technologies, such as batteries, new generation gas peaker plants, and demand response. As a result, these benefits are expected to translate to lower wholesale prices and volatility, to lower retail prices, to stabilize the impacts induced by high VRE penetration, and to ensure system security and reliability in the long term.

4.2.4 Potential impacts of 5MS on spot price dynamics and DWPs

It is unclear how the market would have reacted to the introduction of the 5MS in terms of both spot price levels and volatility dynamics, at least in the short term. The impact on spot prices is likely to be mixed for two reasons: First, the 5MS reduces "race-to-the-floor" bidding following the spot price hitting the MPC, which may result in high electricity prices. Second, the 5MS may reduce "rush-to-exit" following the spot price hitting the MPF, which may result in lower electricity prices.

Diverse viewpoints on the impact of the 5MS on price volatility also exist. Some commentators hold the view that the rule change makes prices more volatile by triggering higher prices during high demand periods and lower prices during low demand periods (ERM, 2020). The main argument behind this view is that the 30-minute average smoothed out high and low dispatch prices, leading to relatively low price volatility overall.

Furthermore, the inability of most incumbent dispatchable plants, namely, generators such as coal-fired plants and combined-cycle gas-fired plants, to ramp up and down quickly enough to follow fluctuations in demand from one 5-minute dispatch interval to the next would contribute to increased price volatility. The contrasting view is that 5MS is likely to lower price volatility as incidences of "extreme spikes followed by very low, zero, or negative prices", which was the function of the 30-minute settlement rule, are unlikely to occur under the new rule (AEMC, 2017e). Improved signals for new flexible capacities are expected to translate into lower electricity prices and reduced spot price volatility over time.

Overall, in the short term, the effect of the 5MS on spot price dynamics would depend on which impact dominates between positive and negative effects (aggregate effect). However, the 5MS would potentially lower volatility in the longer term if it incentivises the entry of flexible, fast-start, dispatchable capacity.

From an individual generator's perspective, the difference in the plants' ramp-up rates and synchronization times is expected to affect how much DWP generators make on the spot market. Flexible generators, especially batteries that can ramp up quickly when needed, are expected to benefit more than slower-responding generators such as large coal plants.

This study makes a major contribution to research on the potential impact of market rules change by investigating for the first time how the introduction of the 5MS impacts spot price dynamics and DWPs in the NEM. We add to the earlier study by Rai and Nunn (2020a) that demonstrated the value of generators for being dispatchable or the so-called dispatchability premium.[4] By studying the relationship between spot prices and DWPs and the 5MS before and after the rule change, we also extend the earlier literature such as Clements et al. (2016), Hurn et al. (2016), and Dungey et al. (2018) that demonstrated how the 30-minute price setting process permitted generators to game the market.

4.3 Data and Methods

4.3.1 Data and preliminary analysis

Five NEM regional market jurisdictions are examined in this study: New South Wales (NSW), Queensland (QLD), South Australia (SA), Tasmania (TAS), and Victoria (VIC). The sample period runs from 1st January 2020 to 31st May 2022. We use 5-minute wholesale electricity spot prices, supply and demand, and capacity data from the NEM.

[4] Rai and Nunn (2020a) estimated this premium as the difference between the DWPs received by non-dispatchable and dispatchable generators.

We also use 30-minute meteorological data from key Australian cities. These datasets were obtained from NEOpoint (2022). The weather data include temperature, wind speed, dew point, and humidity. The daily gas price data for NSW, SA, and VIC were obtained from the Short Term Trading Market (STTM; AEMO 2022e), and the four-hour gas price data for VIC were taken from the Declared Wholesale Gas Market (DWGM; AEMO 2022b).[5]

Despite the availability of data beyond 31st May 2022, we decided to end our analysis in May 2022 as disorderly bidding characterized the NEM in June 2022. Persistent high electricity prices forced the AEMO to impose administered price caps (APC) in QLD, NSW, VIC, and SA from 12th to 13th June 2022. In conjunction with high fuel costs, this price cap forced several generators to withdraw their generation from the market, causing supply shortfalls (AER, 2022a). To ensure a reliable supply of electricity, the AEMO assumed full control and shut down NEM operations between 15th and 24th June 2022 (see Figure 4.2), an action applied for the first time since the market's inception in 1998. Thus, during the month of June, generators bid their capacities in ways that were not consistent with the efficient operation of the market.

Typical intervention analysis normally considers shorter post-period windows, as the effects of interventions often become apparent immediately and fade away within a few weeks. However, this is unlikely to be the case for 5MS as the effect persists over time. With this in mind, we start by examining whether the 5MS had an "immediate effect" on price dynamics. We specify the first post-period from 1st to 31st October 2021 to capture the immediate effects of the 5MS shock. The early observation regarding the impact of the 5MS was made by the AEMO on 4th October 2021, suggesting an effective cessation of dispatch prices falling to the market price floor following a very high price dispatch interval (AEMO, 2021b).

To capture the effect of the 5MS over a relatively long term, we extend the post-period window over the entire sample period, covering from 1st January 2020 to 31st May 2022. Visual observations from Figure 4.3 showing the share of total daily average battery generation imply that the impact of 5MS may change over the extended post-period

[5]We impute the missing observations, especially in weather data, using the Kalman filter approach. The percentages of missing observations are plotted in Figure C.1.

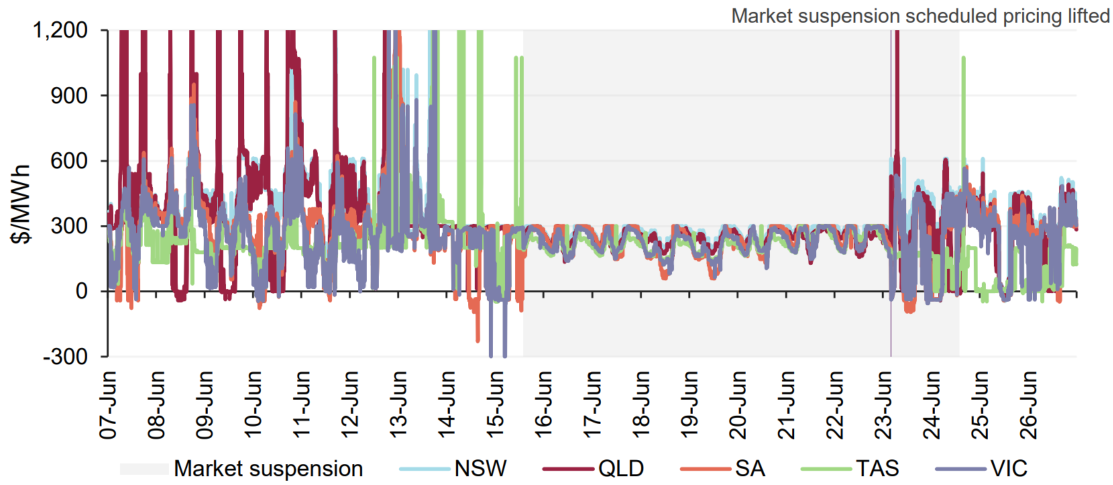

Figure 4.2 : **Electricity spot prices from 7th to 26th June 2022 for NSW, QLD, SA, TAS, and VIC.** The APCs were imposed in QLD, NSW, SA, and VIC from 12th to 14th June 2022. The market suspension occurred between 15th and 24th June 2022. Source: AEMO (2022d).

window or differ from that observed from 1st to 31st October 2021. Battery generation in SA and VIC is relatively mature compared to NSW and VIC.[6] We see that generation in NSW starts on 29th October 2021 and remains marginal in QLD until 2022. Generation in VIC also increased after the Victorian Big Battery (VBB) started operating at full capacity in December 2021 (AER, 2022a). Therefore, price dynamics may have changed over time as flexible generators, especially batteries, increased participation in the NEM and other generators adjusted their bidding strategies accordingly.

4.3.1.1 Electricity price dynamics

Figure 4.4 plots electricity price and volatility in daily intervals. The statistical summary of daily electricity prices one month following the 5MS and over the entire post-period sample is presented in Table 4.1.[7] We measure the daily spot price (p_d) and approximate

[6] We also plot the corresponding average available battery generation capacities for different plants in Appendix C.1.

[7] In Figure C.3, we plot spot price and volatility at relatively higher frequencies (30-minute intervals) and summarize statistics of the 5-minute prices in Table C.1. Spot prices appear to increase in periods leading up to the 5MS. However, there is no apparent upward or downward shock soon after the implementation of the 5MS. Furthermore, there are no visually observable changes in price volatility across states after the rule change.

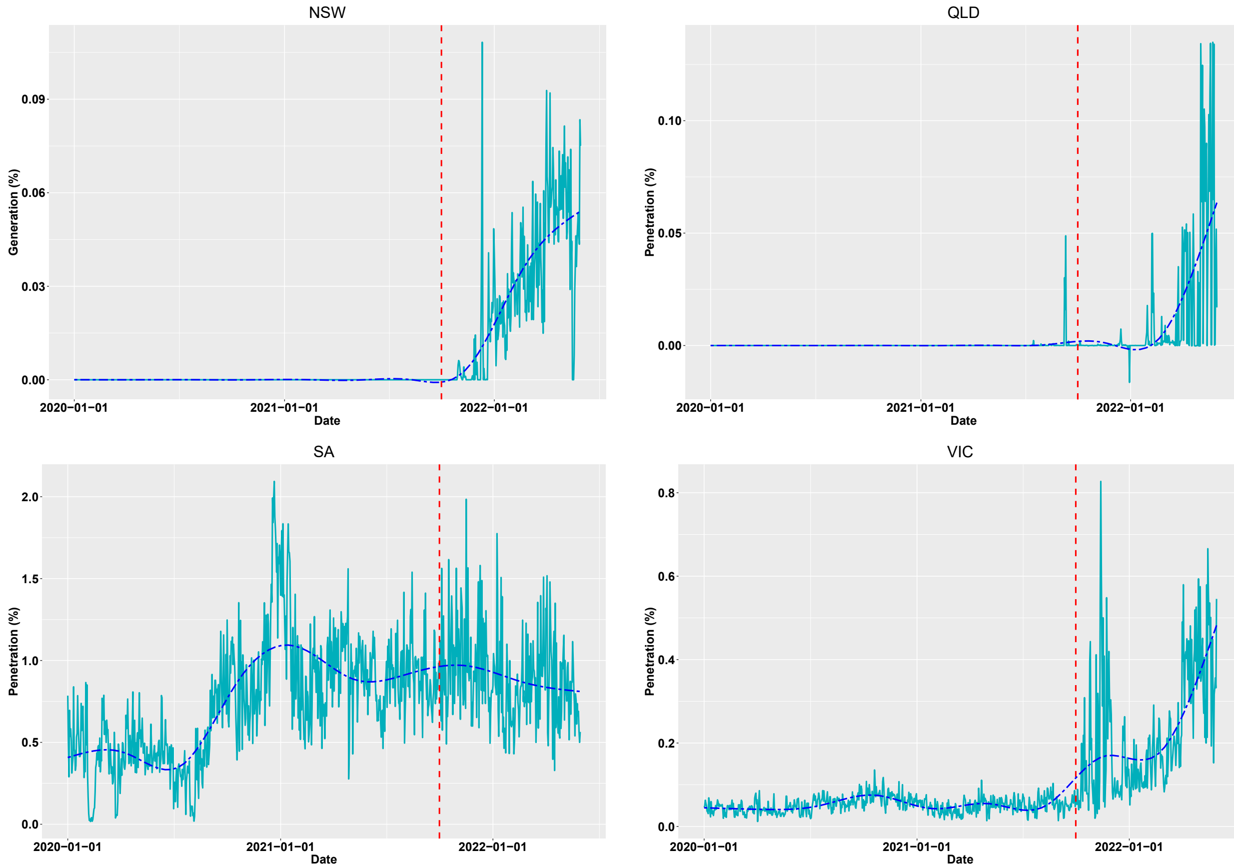

Figure 4.3 : **Share of average daily battery generation from all generators in NSW, QLD, SA, and VIC.** The 5MS rule was introduced on 1st October 2021 denoted by the dashed vertical red line. The trend (blue dot-dash) line represents generalized additive mode (GAM) smoothing. The installed battery generation capacity in the NEM as of 1st January 2022 was 483 MW: 50 MW in NSW, 102 MW in QLD, 124 MW in VIC, and 207 MW in SA (AER, 2022a).

volatility (v_d) for day d from the mean and the standard deviation of the 5-minute spot prices, such that $p_d = \frac{1}{288}\sum_{i=1}^{288} p_i$ and $v_d = \sqrt{\frac{1}{288}\sum_{i=1}^{288}(p_i - p_d)^2}$, respectively. We see that regional markets exhibit slightly different price dynamics after the introduction of the 5MS. The first panel of Figure 4.4 suggests an increase in electricity prices, especially in TAS. Price spikes are more apparent in other states and are likely to obscure changes in spot price. Similarly, no clear visual evidence is found for changes in price volatility soon after the 5MS took effect, especially when considering the $\log(\sigma_d^2)$, suggesting a negligible impact of the 5MS.

The summary statistics in Table 4.1 show that daily average prices increase by roughly

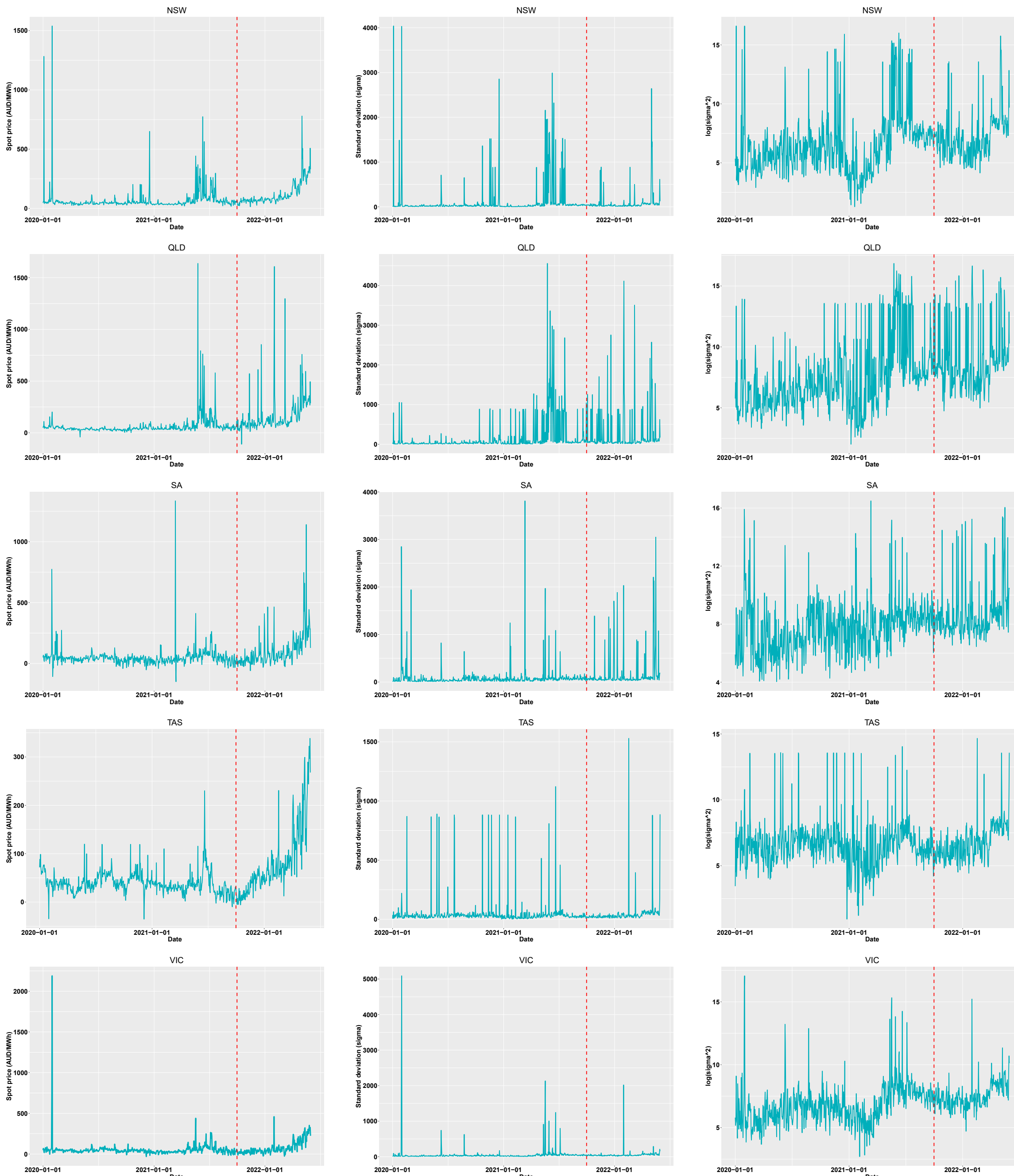

Figure 4.4 : **Equally weighted daily electricity spot prices (left panels) and volatility (two right panels for σ_d and $\log(\sigma_d^2)$, respectively) from January 1$^{\text{st}}$ January 2020 to 31$^{\text{st}}$ May 2022.** The 5MS rule was introduced on 1$^{\text{st}}$ October 2021, as denoted by the dashed vertical red line.

Table 4.1 : **Summary statistics for daily electricity prices before and after the new settlement rule was implemented on 1st October 2021.** The first panel depicts a comparison of one month prior to and after the 5MS. The pre-period window is from 1st to 31st September 2021, and the post-period window is from 1st to 31st October 2021. The comparison in the second panel is based on eight months before and after the 5MS. The pre-period window extends from 1st February to 30th September 2021 and the post-period window runs from 1st October 2021 to 31st May 2022.

		Mean	Std.Dev	Min	Q1	Median	Q3	Max	MAD	IQR	CV	Skewness	SE.Skewness	Kurtosis	Observations
		1 Month Comparison													
NSW	Pre	48.90	14.48	18.85	38.06	51.40	59.20	71.35	13.12	20.24	0.30	-0.47	0.43	-0.83	30
	Post	57.12	19.43	22.38	42.73	58.57	68.39	94.25	15.95	22.99	0.34	-0.13	0.42	-0.89	31
	% Change	16.79	34.18	18.75	12.29	13.95	15.52	32.10	21.55	13.58	14.89	-73.22	-1.49	7.76	
QLD	Pre	51.22	20.43	19.33	37.90	48.99	61.32	112.16	16.93	23.20	0.40	0.89	0.43	0.97	30
	Post	66.48	50.23	-110.05	33.36	69.02	93.69	187.09	39.54	55.27	0.76	-0.87	0.42	3.31	31
	% Change	29.80	145.90	-669.41	-11.97	40.87	52.80	66.81	133.55	138.29	89.45	-197.73	-1.49	242.21	
SA	Pre	18.77	32.84	-38.09	-6.08	21.23	48.03	77.90	40.12	51.71	1.75	-0.06	0.43	-1.19	30
	Post	14.54	29.51	-25.87	-10.96	14.68	26.86	121.08	20.21	33.13	2.03	1.30	0.42	3.15	31
	% Change	-22.52	-10.14	-32.09	80.23	-30.83	-44.07	55.44	-49.61	-35.93	15.99	-2290.15	-1.49	-365.12	
TAS	Pre	16.52	12.15	-9.86	6.09	20.25	27.26	33.87	13.83	20.46	0.74	-0.42	0.43	-1.09	30
	Post	9.38	9.67	-5.75	2.81	7.55	15.53	28.26	10.00	12.04	1.03	0.22	0.42	-1.03	31
	% Change	-43.23	-20.45	-41.72	-53.86	-62.72	-43.01	-16.56	-27.72	-41.16	40.12	-153.13	-1.49	-5.28	
VIC	Pre	27.72	23.86	-16.15	6.15	29.92	44.55	71.11	26.04	34.15	0.86	-0.32	0.43	-0.95	30
	Post	18.46	16.93	-12.57	7.50	14.62	29.73	59.44	15.58	21.73	0.92	0.21	0.42	-0.46	31
	% Change	-33.41	-29.02	-22.15	21.90	-51.15	-33.27	-16.40	-40.15	-36.37	6.59	-166.97	-1.49	-51.34	
		8 Months Comparison													
NSW	Pre	80.52	85.4	18.81	37.84	55.6	79.29	773.6	27.99	41.38	1.06	4.1	0.16	22.81	242
	Post	120.12	96.99	14.36	65.84	83.2	134.22	779.45	31.45	64.63	0.81	2.57	0.16	9.77	243
	% Change	49.00	14.00	-24.00	74.00	50.00	69.00	1.00	12.00	56.00	-24.00	-37.00	0.00	-57.00	
QLD	Pre	89.27	140.5	16.98	38.62	53.89	82.37	1637.57	26.23	43.14	1.57	7.05	0.16	64.59	242
	Post	163.61	179.96	-110.05	77.42	104.33	192.09	1607.75	52.34	113.12	1.1	4.12	0.16	23.81	243
	% Change	83.00	28.00	-748.00	100.00	94.00	133.00	-2.00	100.00	162.00	-30.00	-42.00	0.00	-63.00	
SA	Pre	57.26	99.09	-149.03	20.64	46.22	70.14	1335.27	36.85	49.23	1.73	9.15	0.16	112.44	242
	Post	100.27	132.58	-59.11	23.92	59.21	126.64	1140.88	65.82	101.77	1.32	3.33	0.16	17.86	243
	% Change	75.00	34.00	-60.00	16.00	28.00	81.00	-15.00	79.00	107.00	-24.00	-64.00	0.00	-84.00	
TAS	Pre	34.29	25.9	-9.86	21.04	30.43	37.37	230.01	12.41	16.23	0.76	2.83	0.16	14.28	242
	Post	82.47	71.86	-5.78	39.26	59.33	98.39	338.44	45.99	58.55	0.87	1.5	0.16	1.83	243
	% Change	140.00	177.00	-41.00	87.00	95.00	163.00	47.00	271.00	261.00	15.00	-47.00	0.00	-87.00	
VIC	Pre	53.99	52.66	-16.41	25.17	39.91	70.19	439.54	26.3	44.33	0.98	3.04	0.16	14.36	242
	Post	79.05	83.73	-26.47	27.09	48.07	98.13	459.5	42.37	70.27	1.06	1.65	0.16	2.48	243
	% Change	46.00	59.00	61.00	8.00	20.00	40.00	5.00	61.00	59.00	9.00	-46.00	0.00	-83.00	

17% and 30% in NSW and QLD, respectively, one month following the rule change, whereas prices in SA, TAS, and VIC decrease by around 22% to 44%. Price volatility moves in tandem with electricity prices. In particular, in NSW and QLD, volatility rises by 34% and 146%, respectively, but drops in SA, TAS, and VIC by 10%, 20%, and 29%, respectively. However, the observed changes during the first month appear to be temporal and generally inconsistent with the effects observed over the entire post-period sample. During this period, both spot price and volatility are relatively higher when the 5MS is in place compared to the period before. TAS experiences a more pronounced increase of about 140% and 177% for spot price and volatility, respectively.

In Figures 4.6 and 4.7, we extend the comparison by plotting the intraday average 5- and 30-minute spot prices before and after the introduction of the 5MS, respectively. One month following the 5MS, the difference, as measured by the mean absolute deviation (MAD),[8] drops in NSW, TAS, and VIC. In contrast, this difference increases in QLD and SA. We observe similar changes over the whole post-period sample. However, the average 30- and 5-minute spot prices are closer to each other in all coal-fired dominated regions during the post-5MS period. In particular, the MAD drops by approximately 46%, 2%, and 26% in NSW, QLD, and VIC, respectively. A significant difference between the 30- and 5-minute prices before the 5MS likely reflects generators' gaming strategies of skyrocketing dispatch prices in one interval to make the trading price high when averaged over 30 minutes.

To account for monthly seasonal variations, Figure 4.8 compares price distributions for three post-5MS months: October, November, and December, from 2011 to 2021.[9] In NSW, the 2021 average prices, as measured by the median, exceed those of 2020 but typically remain close to or below those of 2016 to 2019, with the slight exception of December. On the other hand, the overall spread of the price data captured by the ranges and the interquartile ranges change slightly compared to 2020, albeit below that of 2019 for October, 2016 for November, and 2018 for December. In QLD, the 2021 average

[8]The MAD in Table 4.1 stands for the median absolute deviation rather than the mean absolute deviation.

[9]We also compare the distribution of spot prices over the entire post-period sample. However, the large number of observations makes it difficult to visualize statistical properties of spot prices via boxplots. The figures for this analysis are presented in Appendix C.1 (see Figure C.3).

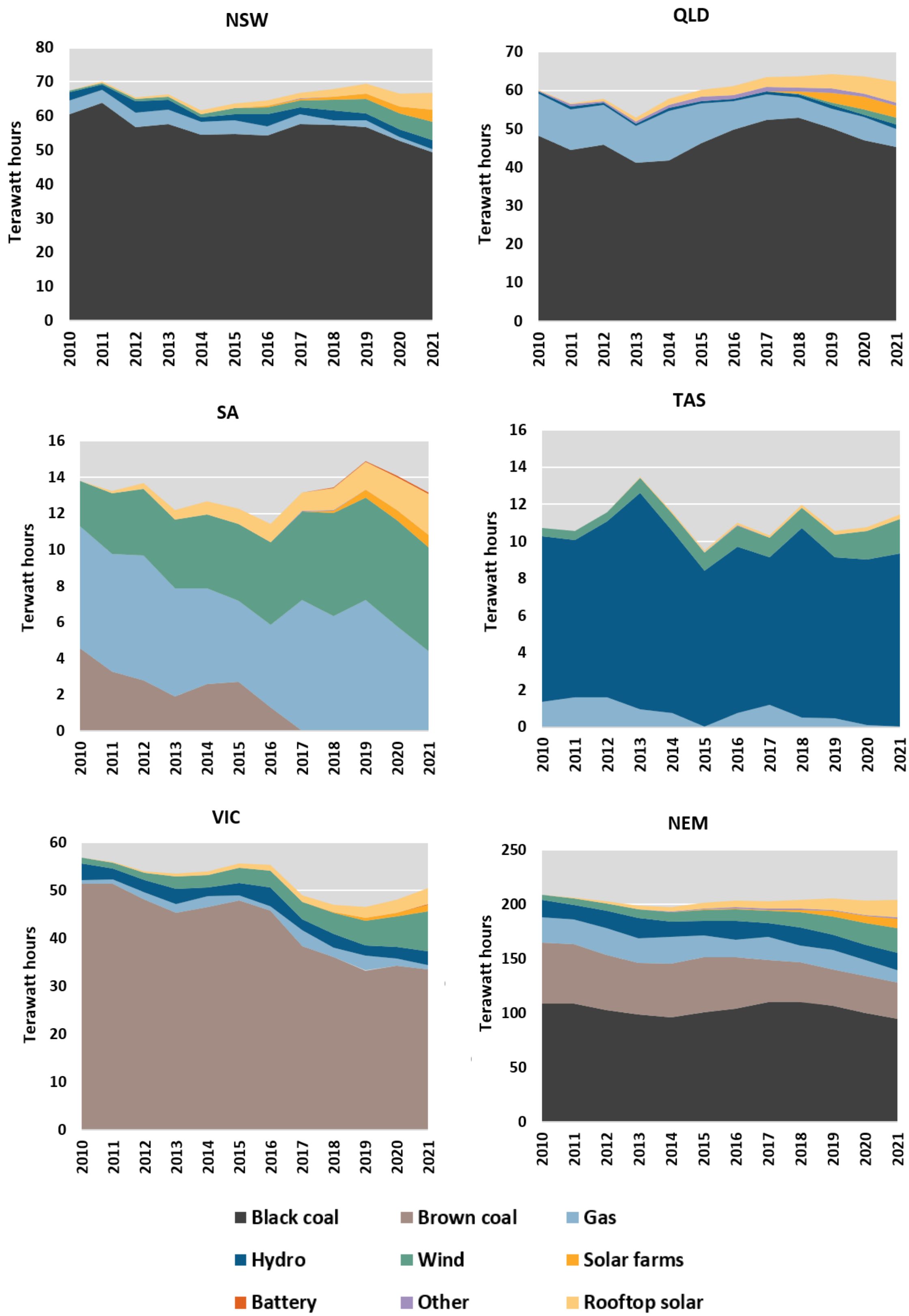

Figure 4.5 : **Electricity generation by fuel source in the NEM from 2011 to 2021.** Data source: AER (2022a).

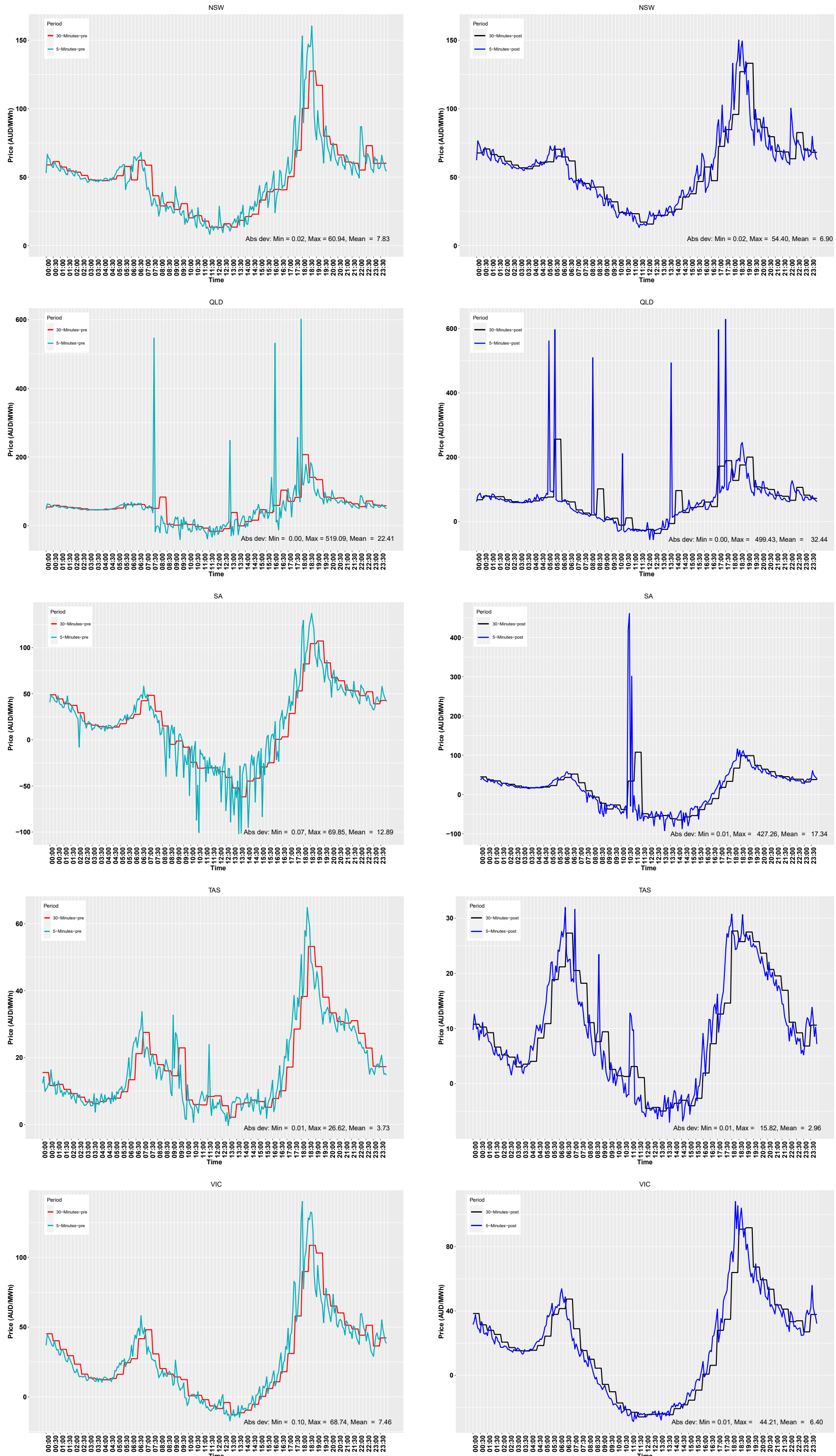

Figure 4.6 : **The average 5-minute and equally weighted 30-minute electricity prices before (left panels) and after (right panels) the implementation of the new settlement rule on 1st October 2021 for NSW, QLD, SA, TAS, and VIC.** The pre-period window is from 1st to 30th September 2021, and the post-intervention phase is from 1st to 31st October 2021. The y-axis scale for the left panel figures is not the same as the right panel figures to enhance the clarity of the intraday pattern of electricity prices.

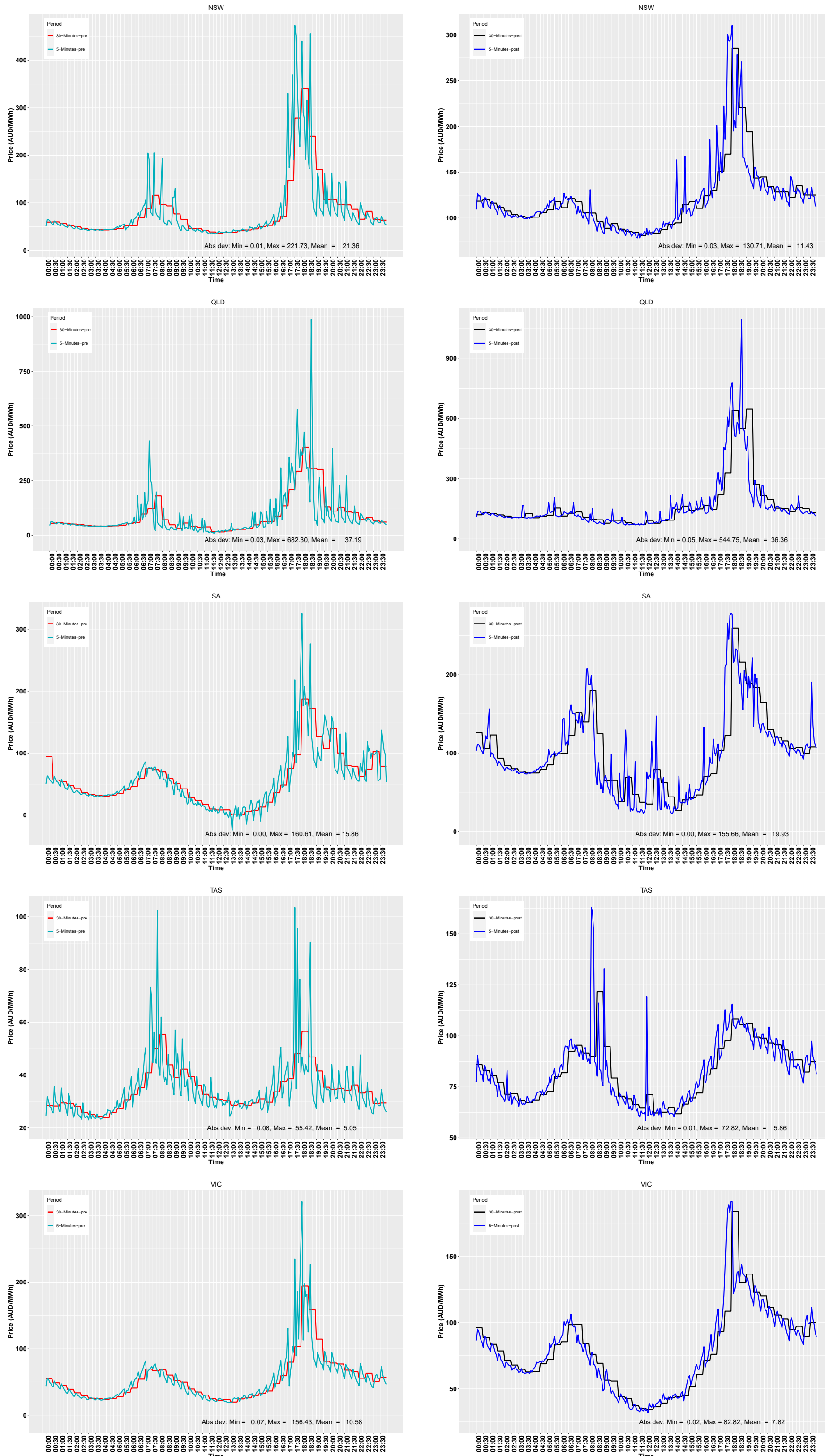

Figure 4.7 : **The average 5-minute and equally weighted 30-minute electricity prices before (left panels) and after (right panels) the implementation of the new settlement rule on 1st October 2021 for NSW, QLD, SA, TAS, and VIC.** The pre-period window is from 1st February to 30th September 2021, and the post-intervention phase is from 1st October 2021 to 31st May 2022. The y-axis scale for the left panel figures is not the same as the right panel figures to enhance the clarity of the intraday pattern of electricity prices.

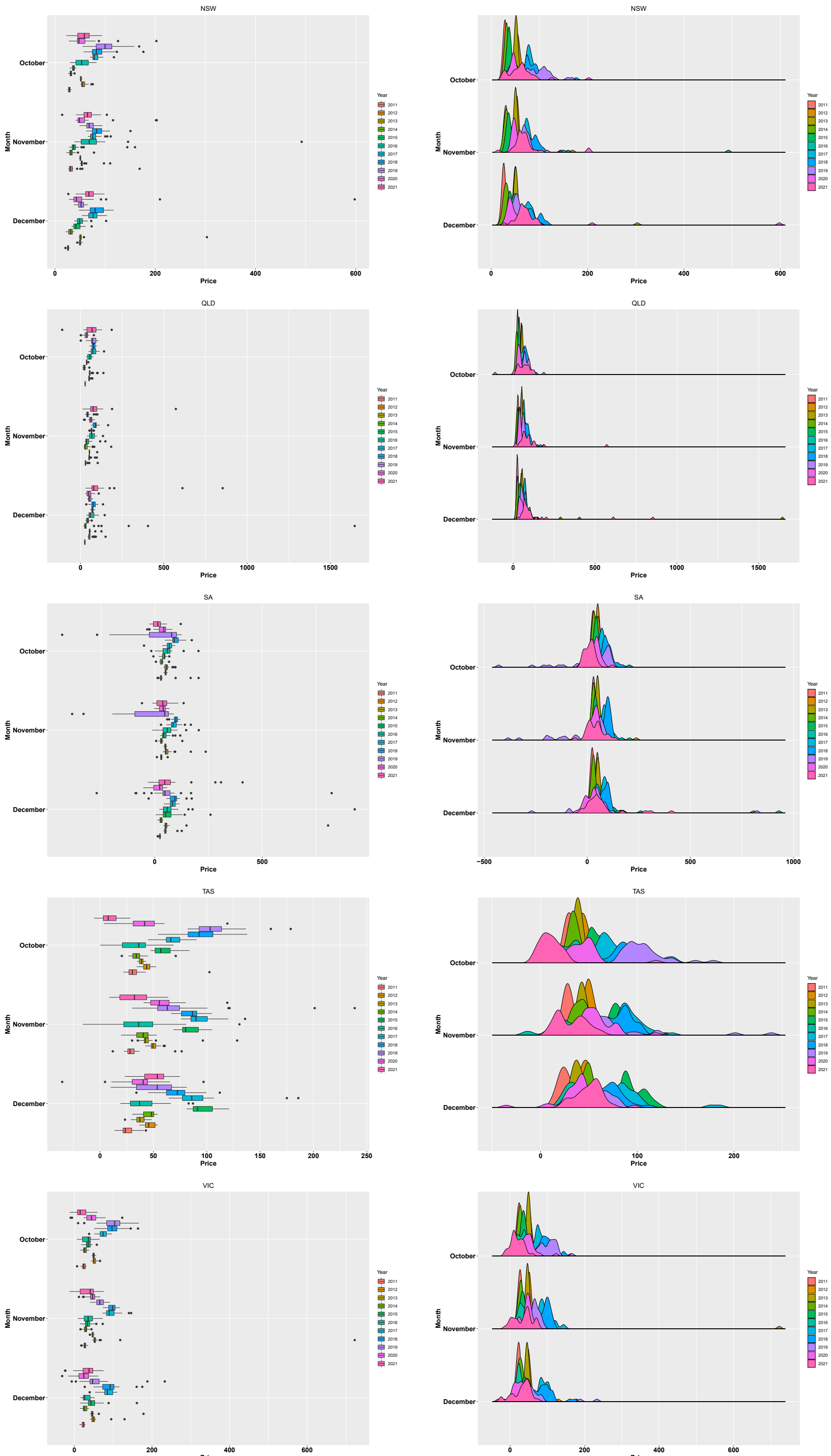

Figure 4.8 : **The monthly distribution of electricity prices for three post-period months: October, November, and December, from 2011 to 2021.** The left panels show grouped boxplots, and the right panels show density plots.

prices are higher than in 2020 but close to those in 2016 to 2019. The data are also more spread for all months in 2021 compared to other years. SA does not exhibit consistent changes in prices across the three months. When considering October, the average prices in 2021 are below those of other years. In November, prices are almost identical to the 2020 level and below those of other years. Prices in December are higher than in 2020 but lower than in previous years. The data spread is slightly higher in 2021 than in 2020 and is comparable to most years except for October and November in 2019. TAS 2021 average prices are lower in October and November than in previous years and surpass 2020 in December but remain close to or below the 2015, 2017, 2018, and 2019 levels. There are no noticeable changes in the spread compared to the other years. VIC exhibits similar changes to TAS. However, the 2021 prices are closer to 2015 and below the 2016 to 2020 levels for almost all months. In general, there is no apparent evidence to suggest that the introduction of the 5MS changed the distribution of spot electricity prices in a systematic way. Thus, the observed effects likely reflect the typical monthly and yearly seasonal patterns in conjunction with other external factors.

4.3.1.2 Dispatch-weighted price (DWP)

The differing characteristics of generation technologies in the NEM suggest the varying impact of the 5MS on generators' DWPs. The electricity generation mix comprises fossil fuel and renewable energy (wind, solar, and hydro) generation, the proportions of which differ between regional markets. Fossil fuel generation still dominates the market (see Figure 4.5), accounting for around 74% of the total electricity generated in the NEM (AER, 2022a).

These generation technologies have different operations and cost characteristics, which in turn accounts for the differences in bidding and generation strategies. Coal-fired generation may take a day or more to start up and thus has high start-up and shutdown costs. These costs make it unprofitable to turn coal plants on and off regularly. However, when running continually, their operational costs tend to be low. As a result, generators often bid their capacity at low prices to ensure dispatch and constant operations. Furthermore, several gas generation technologies operate in the NEM: gas turbines in both open-cycle gas turbine (OCGT) and combined-cycle gas turbine (CCGT) configurations,[10] and reciprocating engine generators.[11] Gas generation is more flexible than coal-fired generation and can ramp up to full operating capacity in a few minutes, allowing it to respond quickly to sudden changes in market conditions. Hydro has comparable characteristics to gas generation in that it is dispatchable and typically works as a flexible or peaking generation source.

A number of new battery generations are being commissioned and operate in SA and VIC, including the world's largest 150 MW lithium-ion battery at the Hornsdale wind farm and the 300 MW VBB. Battery technologies can react to market signals as required and can thus be dispatched when needed. Despite increased investments, utility-scale battery storage only supplies a small proportion of electricity demand in the NEM, primarily providing ancillary services or smooth short-term fluctuations in VRE generation. A small proportion of flexible generating units in the NEM generation mix means that in a situation where supply is constrained due to the inability of coal plants to ramp up quickly enough to meet demand, the opportunity exists for generators that are already online or that can ramp up quickly to game prices.[12] Wind and solar generation are intermittent in nature and do not respond to short-term price signals (Wood et al., 2018).

How much DWP generators would be able to maximize following the transition to shorter settlement intervals would depend primarily on their ability to respond from rest after receiving a dispatch target to delivering that target to the grid, specifically regarding fast-start inflexibility profiles, ramp rates, and minimum and maximum loading for those that are already running.[13] For instance, while a generator responding from rest may require between five and 30 minutes to start up, a generator already producing but not at full capacity may increase its output by more than 200 MW per minute (Clements

[10]There are two classes of gas turbines: aero-derivatives and industrial turbines. The former is more suited for peaking applications due to its faster start-up time, and the latter is more suited for baseload applications (Aurecon, 2020).

[11]Reciprocating engine gas plants operate in a similar manner to OCGTs but tend to be more flexible.

[12]Apart from the inflexibility of coal-fired plants, outages in the interconnectors and the inability of wind and solar generation to respond rapidly to price signals create a perfect environment for generators to game the market under the 30MS.

[13]The ramp-up rate is the speed at which the generator increases capacity while still in use before reaching its full capacity (Clements et al., 2016).

et al., 2016). Figure 4.9 plots the average daily DWPs estimated from 5-minute prices eight months before and after the rule change. We estimate DWP for each generator as

$$DWP_T = \frac{\sum_{t=1}^{T} P_t \times Q_t}{\sum_{t=1}^{T} Q_t},$$

where t denotes the 5-minute time index, P_t is the spot price paid to the generators in a 5-minute interval in dollars per megawatt-hour (AUD/MWh), Q_t is the dispatched generation in a 5-minute interval in MW, and T is a total number of five-minute intervals in a day (i.e., $T = 288$).

Figure 4.9 shows that, on average, DWPs earned by all generators in the NEM are relatively higher when the 5MS is in action than in the prior period. The only exception is the natural gas generation in NSW, where we observe slightly higher DWPs during the 30MS regime.

To summarize, there appears to be a change in spot prices and DWPs before and after the 5MS is implemented. However, a variety of factors may have contributed to these changes, and we cannot simply attribute the observed changes in spot price dynamics and DWPs solely to the introduction of the 5MS. The method for isolating and quantifying the causal impact is described in the following subsection.

4.3.2 The Bayesian structural time-series models

We apply state-space models for time-series data, specifically the structural time-series models proposed by Brodersen et al. (2015), to infer the causal effect of the settlement rule change on the spot electricity price dynamics and DWPs. We define the structural time-series models in the following state-space form:

$$y_t = Z_t^T \theta_t + \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0, H_t), \tag{4.3.1}$$

$$\theta_{t+1} = T_t \theta_t + R_t \eta_t, \qquad \eta_t \sim \mathcal{N}(0, Q_t). \tag{4.3.2}$$

Equation (2.2.2) is called the observation equation, linking the observed data y_t to an unobserved latent p-dimensional state vector θ_t, and equation (2.2.3) is a state or system equation determining how the state vector θ_t evolves over time. T_t is a $p \times p$ transition

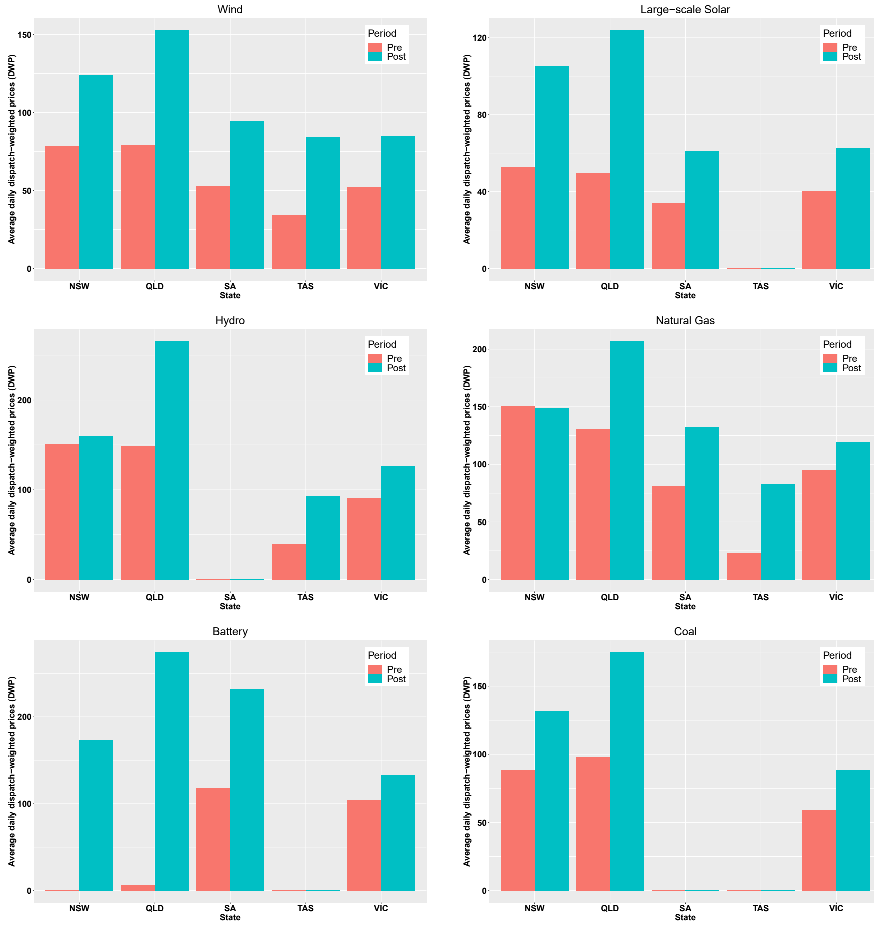

Figure 4.9 : **The average daily DWPs in AUD/MWh before and after the new settlement rule was implemented on 1st October 2021.** The pre-period window lasts from 1st February to 30th September 2021, while the post-period window lasts from 1st October 2021 to 31st May 2022. The zero DWPs for some states denote a lack of generation technology. There is no hydro or coal generation in SA and no large-scale solar, coal, or battery generation in TAS.

matrix, Z_t is a p-dimension output vector, and R_t is a $p \times h$ control matrix. ε_t and η_t are two independent sequences of independent Gaussian random vectors. The first is a scalar observation error with noise variance σ_t^2, whereas the second is a h dimension error term with $h \times h$ state-diffusion matrix Q_t, where $h \leq p$. Structural time-series models are flexible and modular, allowing the user to incorporate components for modelling trend, seasonality, and regression effects by setting [14,15]

$$y_t = \kappa_t + \vartheta_t + \beta^T \boldsymbol{x}_t + \epsilon_t, \tag{4.3.3}$$

$$\kappa_t = \kappa_{t-1} + \rho_{t-1} + u_t, \tag{4.3.4}$$

$$\rho_t = \rho_{t-1} + v_t, \tag{4.3.5}$$

$$\vartheta_t = -\sum_{s=1}^{S-1} \vartheta_{t-s} + w_t. \tag{4.3.6}$$

where $\beta^T x_t$ is a regression component,[16] κ_t and ρ_t are the current level of the trend and the current "slope" of the trend, respectively, and ϑ_t is the seasonal component. u_t, v_t, and w_t are independent components of Gaussian random noise with a constant diagonal matrix Q_t and diagonal elements σ_u^2, σ_v^2, σ_w^2, and H_t is a scalar σ_ϵ^2. We include contemporaneous covariates $\boldsymbol{x}_t$ (control time series) to account for the effects of unseen factors that would otherwise go unaccounted for, resulting in a robust counterfactual prediction for the post period. The Brodersen et al. (2015) approach allows selection from a large collection of potential controls (only a fraction of which are important) by applying a spike-and-slab prior to the set of regression coefficients (see Scott and Varian (2014) and Brodersen et al. (2015) for further details). The spike-and-slab also enables the model to average over the set of controls.[17] The state-space models are typically estimated recursively by estimating the conditional distribution of the quantities of interest while accounting for the available information. Thus, Brodersen et al. (2015) estimate the parameters and carry out the inference by adopting a Bayesian approach.

A Markov Chain Monte Carlo (MCMC) algorithm is used to simulate the posterior distribution of a causal effect. First, given the observed data $y_{1:n}$, we simulate draws

[14]The structural time-series models adopt the Kalman filter to decompose the time series into three components: trend, seasonality, and regression.

[15]ARIMA and VARMA models are two examples of models that can be built as special cases of state-space models.

[16]Linear regression with static coefficients often produces robust results when a stable relationship existed between controls and treated units in the past. Moreover, using contemporaneous covariates with dynamic coefficients may result in over-specification, especially when used in conjunction with the time-varying local trend or the time-varying local level (Brodersen et al., 2015).

[17]Similar to ridge and lasso regression, the spike-and-slab shrinks the "weak" β values from the regression towards zero. In particular, it sets the prior of β to have mass at zero (null effect), meaning $\mathbb{P}(\beta = 0) > 0$, resulting in a prior distribution of β that is a mix of discrete and continuous density.

of the model parameters ζ and θ in the training period. Second, given the observed series $y_{1:n}$ and $x_{1:m}$, we simulate the posterior incremental effect $p(\tilde{y}_{n+1:m}|y_{1:n}, x_{1:m})$ over the counterfactual response $\tilde{y}_{n+1:m}$ that would have occurred in the absence of treatment after the intervention. The posterior density is only influenced by the observed data and priors, not by parameter estimates or covariates, which has the advantage of avoiding arbitrary selection and overfitting.

Figure 4.10 plots graphical representation of the Brodersen et al. (2015) model. The causal effect attributed to the intervention ψ_t is obtained from the posterior causal effect samples computed from the posterior predictive distribution samples,

$$\psi_t = y_t - \tilde{y}_t, \quad t = n+1, \ldots, m.$$

The cumulative impact is then estimated by summing up the impact values from the intervention date up to a particular day, that is,

$$\sum_{t'=n+1}^{t} \psi_{t'}, \quad \forall t = n+1, \ldots, m.$$

The Bayesian structural time-series approach offers a more robust way of studying the causal impact of a treatment by constructing the counterfactual using a set of candidate predictor variables into a single synthetic control (model averaging). It is a generalization of the classical difference-in-differences approach, which is based on the "parallel trends" assumption, a premise that is often violated. In comparison to the difference-in-differences, the Bayesian structural time-series technique generates reliable post-period synthetic time series baseline predictions that consider uncertainties in historical time series relationships and unobserved trends (Larsen, 2021).

In addition to using the behaviour of the response and other time series that are predictive of the target series prior to the intervention as sources of information for inferring the counterfactual, the Bayesian framework allows the incorporation of the available prior knowledge about the model parameters. Most importantly, the chosen approach allows one to infer the evolution of causal impact over time while accounting for the trend and seasonality effects characterizing electricity data.

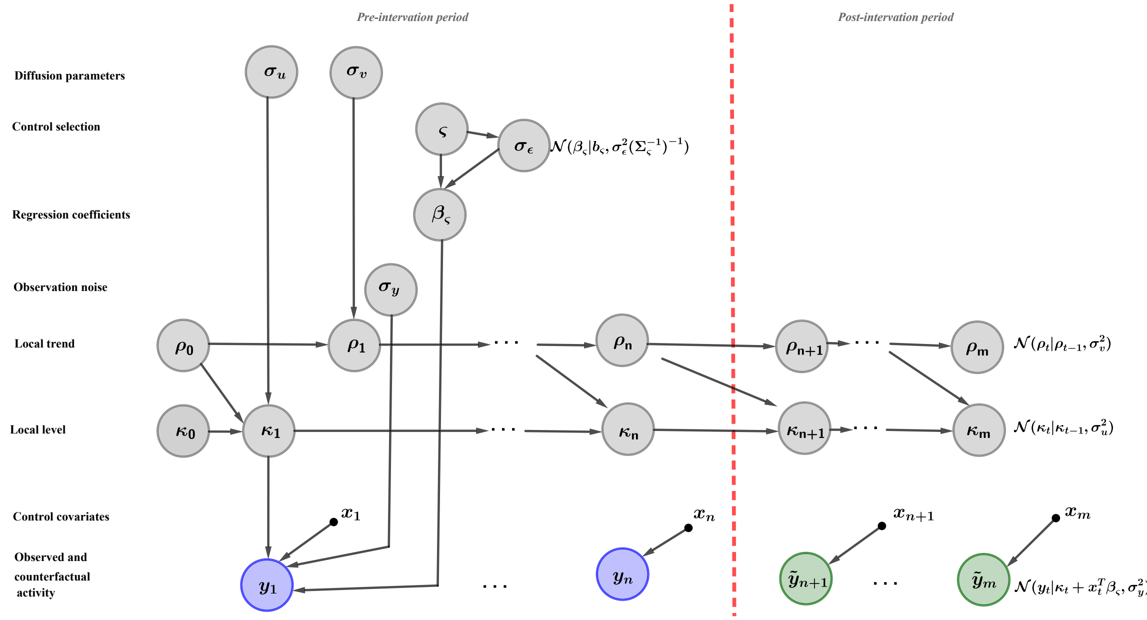

Figure 4.10 : **The graphical representation of the Brodersen et al. (2015) Bayesian structural time-series model with state components, a set of contemporaneous covariates, empirical priors on the parameters, and the initial states.** A probability density over the temporal evolution of causal impact is obtained by subtracting the posterior predictive density over the unobserved counterfactual responses $\tilde{y}_{n+1}, \ldots, \tilde{y}_m$ from the actual observed data $y_{n+1}, \ldots, y_m$.

4.3.3 Implementation of the Bayesian structural time-series model

4.3.3.1 The length of the pre- and post-period

In a Bayesian time-series model, specifying which period in the data should be used for training the model (pre-intervention period) and computing a counterfactual prediction (post-intervention period) is crucial. Different choices of pre- and post-intervention period may result in different estimates of the causal effect. In theory, a longer pre-treatment interval is preferable. However, if the pre-period is too long, the structural link between the response variable and the predictors may have shifted over time. If the pre-treatment period is too short, the model may miss crucial trends in the data, such as a day-of-week effect. To effectively capture seasonality effects, which are strongly pronounced in electricity data, we train the model over a year (Perles-Ribes et al., 2019). Accordingly, the matching (pre) period starts on 30$^{\text{th}}$ September 2020 and ends on 30$^{\text{th}}$ September 2021. We make a plausible assumption that the relationships between the controls and the response are unlikely to have changed over this period, and there were no major structural changes spanning the entire sample period.

The first post-period window runs from 1st to 31st October 2021 to capture the immediate effect of the 5MS, and the second post-period window runs from 1st October 2021 to 31st May 2022 to capture the impact of the 5MS over the longest time-frame available. From the modelling perspective, specifying the post-treatment period in advance rather than running the model over multiple different post-interventions and stopping where the causal effect is significant/detected is essential to avoid a multiple-testing problem.

One caveat for using shorter post-periods is that the model may fail to distinguish the signal from the noise and may sometimes produce insignificant results (Perles-Ribes et al., 2019). Typically, intervention analysis covers a period of two to six weeks of daily data. Thus, we believe that a four-week period considered in this analysis is plausible for the model to produce robust effects.

Furthermore, two challenges arise when using longer post-period windows. First, a longer post-period can result in insignificant results as the effect of the intervention is likely to have already worn off. Second, while longer post-period windows enable one to capture a more profound effect as the market participant slowly adapts to the intervention over time, it becomes harder to estimate the accurate counterfactual (Märkle-Huß et al., 2018).[18] Our study is unlikely to suffer from these challenges as the 5MS is expected to have both short- and long-term effects. In fact, the impact of 5MS is likely to become more apparent as time passes. While the second challenge is plausible, it is worth noting that the Brodersen et al. (2015) approach works like a forecasting method, the only difference being that we run the model while already knowing parts of the future (the control time series). Thus, the model's effectiveness in predicting the accurate counterfactual rests critically with the control time series (predictors). The fact that we have included a substantial number of all potential predictors ensures the robustness of the estimated counterfactual and the causal effect.[19]

[18] Based on Brodersen et al. (2015) and the other literature surveyed, there is no clear definition of how long a "long post-period window" is.

[19] Studies such as that by Märkle-Huß et al. (2018) are likely to suffer from the second challenge as the authors included only two predictors in their analysis. See the next subsection for further details.

4.3.3.2 Control time series

The Bayesian structural time-series model creates a synthetic baseline for the post-intervention period using multiple control time series as predictors and other time-series characteristics. In the absence of these predictors, the counterfactual prediction solely relies on the local level component and, if included, a seasonal component. Such a model setup, however, produces overly simplistic counterfactuals, and causal inference becomes as hard as forecasting.

While including the control time series, the Brodersen et al. (2015) approach relies on two assumptions. First, the intervention should not induce an effect on the sets of control time series. Otherwise, one may incorrectly underestimate or overestimate the underlying effect or detect a causal effect when none exists. Second, the pre-period relationship between the control and the response variable should remain steady during the post-period. In light of these assumptions, we consider a number of potential spot price and DWP determinants. These include contemporaneous supply and demand, capacity, and gas price variables from the NEM.[20] We also include weather data from major NEM cities to account for weather-driven changes in price and DWP dynamics. The full list of these predictors is provided in Table 4.2. These sets of controls are unlikely to have been affected by the introduction of the 5MS. If they were, the effect is likely to be minimal, thus inducing a marginal impact on the estimated causal effect. The slight exception here are batteries, the generation from which appears to increase in response to the introduction of 5MS (see Figure 4.3). It is also unlikely that the model would select this variable as there is essentially no generation in NSW and QLD during the training period.

Depending on which control variables are chosen, the number of control time series supplied to the Bayesian structural time-series model is likely to change the counterfactual prediction and hence the causal impact. Although the Brodersen et al. (2015) approach contains the variable selection procedure, namely the spike-and-slab prior, Larsen (2021) recommends trimming the list of controls in advance, especially when faced with a large number of controls at hand. We start by exploring this approach and performed our

[20]The capacity variables are included to account for the changes in price and DWP dynamics caused by coal plant outages, especially in 2022.

Table 4.2 : **Response and control/predictor variables used to construct a synthetic control for each state in the NEM.** The response variables include spot electricity price (AUD/MWh) and DWP. Predictors include supply, demand, and capacity (MW) and gas price (AUD/GJ) variables from the NEM, temperature (°C), dewpoint (°C), relative humidity (%), and wind speed (knot) from major cities in the NEM states. Supply, demand, and capacity variables are available in 5-minute intervals, weather statistics in 30-minute intervals, and gas prices on a daily basis (NSW, QLD, and SA) and four times a day (VIC).

		NSW	**QLD**	**SA**	**TAS**	**VIC**
Response Variables		Spot Price	Spot Price	Spot Price	Spot Price	Spot Price
	1	Spot Price Volatility (σ_d, $\log(\sigma_d^2)$)	Spot Price Volatility (σ_d, $\log(\sigma_d^2)$)	Spot Price Volatility (σ_d, $\log(\sigma_d^2)$)	Spot Price Volatility (σ_d, $\log(\sigma_d^2)$)	Spot Price Volatility (σ_d, $\log(\sigma_d^2)$)
	2	DWP for Wind Generators	DWP for Wind Generators	DWP for Wind Generators	DWP for Wind Generators	DWP for Wind Generators
	3	DWP for Solar Generators	DWP for Solar Generators	DWP for Solar Generators	DWP for Gas Generators	DWP for Solar Generators
	4	DWP for Battery Generators	DWP for Battery Generators	DWP for Battery Generators	DWP for Hydro Generators	DWP for Battery Generators
	5	DWP for Coal Generators	DWP for Coal Generators	DWP for Coal Generators		DWP for Coal Generators
	6	DWP for Gas Generators	DWP for Gas Generators	DWP for Gas Generators		DWP for Gas Generators
	7	DWP for Hydro Generators	DWP for Hydro Generators	DWP for Hydro Generators		DWP for Hydro Generators
	8			DWP for Battery Generators		DWP for Battery Generators
				From the National Electricity Market (NEM)		
Predictors	1	Black Coal Generation	Bagasse Generation	Natural Gas Diesel Generation	Hydro Generation	Brown Coal Generation
	2	Diesel Generation	Black Coal Generation	Diesel Generation	Natural Gas Generation	Hydro Generation
	3	Hydro Generation	Coal Seam Methane Generation	Natural Gas Fuel Oil Generation	Wind Generation	Natural Gas Generation
	4	Kerosene Generation	Hydro Generation	Heywood	Basslink	Large-scale Solar Generation
	5	Natural Gas Generation	Kerosene Generation	Large-scale Solar Generation	TAS Total Capacity	Wind Generation
	6	Large-scale Solar Generation	Natural Gas Generation	Wind Generation	TAS Total Availability	Murraylink
	7	Wind Generation	Large-scale Solar Generation	Rooftop Solar Generation	TAS Total Cleared	Heywood
	8	Terranora	Waste Coal Mine Gas Generation	Electricity Demand	Electricity Demand	VNI
	9	VNI	Wind Generation	Gas Price	Rooftop Solar Generation	Basslink
	10	QNI	Terranora	SA Total Capacity		VIC Total Capacity
	11	Rooftop Solar Generation	NQI	SA Total Availability		VIC Total Availability
	12	Gas Price	Rooftop Solar Generation	SA Total Cleared		VIC Total Cleared
	13	Electricity Demand	Electricity Demand			Rooftop Solar Generation
	14	NSW Total Capacity	Gas Price			Electricity Demand
	15	NSW Total Availability	QLD Total Capacity			Gas Price
	16	NSW Total Cleared	QLD Total Availability			
	17		QLD Total Cleared			
				Weather statistics control variables		
	18	Newcastle Wind Speed	Brisbane Dew Point	Mt Gambier Wind Speed	Hobart Dew Point	Ballarat Wind Speed
	19	Newcastle Temperature	Gold Coast Dew Point	Mt Gambier Temperature	Launceston Dew Point	Ballarat Temperature
	20	Wollongong Wind Speed	Cairns Dew Point	Whyalla Wind Speed	Devonport Dew Point	Bendigo Wind Speed
	21	Wollongong Temperature	Toowoomba Dew Point	Whyalla Temperature	Perth Dew Point	Bendigo Temperature
	22	Maitland Wind Speed	Mackay Dew Point	Murray Bridge Wind Speed	Hobart Wind Speed	Mildura Wind Speed
	23	Maitland Temperature	Rockhampton Dew Point	Murray Bridge Temperature	Hobart Temperature	Mildura Temperature
	24	Gold Coast Wind Speed	Bundaberg Dew Point	Mt Barker Wind Speed	Launceston Wind Speed	Shepparton Wind Speed
	25	Gold Coast Temperature	Townsville Dew Point	Mt Barker Temperature	Launceston Temperature	Shepparton Temperature
	26	Albury Wodonga Wind Speed	Brisbane Temperature	Victor Harbor Wind Speed	Devonport Wind Speed	Melbourne Airport Tullamarine Wind Speed
	27	Albury Wodonga Temperature	Brisbane Wind Speed	Victor Harbor Temperature	Devonport Temperature	Melbourne Airport Tullamarine Temperature
	28	Sydney Airport Wind Speed	Gold Coast Wind Speed	Port Lincoln Wind Speed	Norfolk Island Wind Speed	Melbourne Olympic Park Wind Speed
	29	Sydney Airport Temperature	Gold Coast Temperature	Port Lincoln Temperature	Norfolk Island Temperature	Melbourne Olympic Park Temperature
	30	Sydney Temperature	Cairns Wind Speed	Adelaide Wind Speed	Perth Wind Speed	Melbourne Airport Tullamarine Humidity
	31	Sydney Olympic Park Wind Speed	Cairns Temperature	Adelaide Temperature	Perth Temperature	Melbourne Olympic Park Humidity
	32	Sydney Olympic Park Temperature	Toowoomba Wind Speed	Mt Gambier Humidity	Launceston Humidity	Ballarat Humidity
	33	Newcastle Humidity	Toowoomba Temperature	Whyalla Humidity	Hobart Humidity	Bendigo Humidity
	34	Wollongong Humidity	Mackay Wind Speed	Murray Bridge Humidity	Devonport Humidity	Mildura Humidity
	35	Gold Coast Humidity	Mackay Temperature	Mt Barker Humidity	Norfolk Island Humidity	Shepparton Humidity
	36	Albury Wodonga Humidity	Rockhampton Wind Speed	Victor Harbor Humidity	Perth Humidity	Melbourne Olympic Park Dew Point
	37	Sydney Humidity	Rockhampton Temperature	Port Lincoln Humidity		Melbourne Airport Tullamarine Dew Point
	38	Sydney Airport Humidity	Bundaberg Wind Speed	Adelaide Humidity		Ballarat Dew Point
	39	Sydney Olympic Park Humidity	Bundaberg Temperature	Mt Gambier Dew Point		Bendigo Dew Point
	40	Newcastle Dew Point	Townsville Wind Speed	Whyalla Dew Point		Mildura Dew Point
	41	Wollongong Dew Point	Townsville Temperature	Murray Bridge Dew Point		Shepparton Dew Point
	42	Maitland Dew Point	Brisbane Humidity	Mt Barker Dew Point		
	43	Albury Wodonga Dew Point	Gold Coast Humidity	Victor Harbor Dew Point		
	44	Gold Coast Dew Point	Cairns Humidity	Port Lincoln Dew Point		
	45	Sydney Dew Point	Toowoomba Humidity	Adelaide Dew Point		
	46	Sydney Airport Dew Point	Mackay Humidity			
	47	Sydney Olympic Park Dew Point	Rockhampton Humidity			
	48		Bundaberg Humidity			
	49		Townsville Humidity			

analysis in two phases: the pre-screening phase and the inference phase. We create a list of viable control time series candidates by looping over all potential options in parallel and sorting by correlation and similarity via dynamic time warping. The dynamic time warping finds the best match between time series under specific constraints and restrictions. For two time series, a test (query index), $X = (x_1, \dots, x_N)$ and a control (query index), $Y = (y_1, \dots, y_M)$, the warping curve $\phi(t) = (\phi_x(t), \phi_y(t))$ remaps the indexes of the original time series through the warping functions $\phi_x(t)$ and $\phi_y(t)$. The average accumulated distortion between the warped time series X and Y given ϕ is calculated as

$$d_\phi(X, Y) = \frac{1}{M_\phi} \sum_{t=1}^{T} d(\phi_x(t), \phi_y(t)) m_\phi(t),$$

where $d(\phi_x(t), \phi_y(t))$ is the local distance between the remapped data points at index t, $m_\phi(t)$ is a per-step weighting coefficient, and M_ϕ is the normalisation constant, ensuring that cumulative distortions along different pathways are comparable (Giorgino, 2020). The dynamic time warping then finds the optimal alignment possible such that $D(X, Y) = \max_\phi d_\phi(X, Y)$. Two constraints are normally imposed on ϕ to achieve reasonable warps: monotonicity, to retain their time ordering and avoid meaningless loops so that $\phi_x(t+1) \geq \phi_x(t)$ and $\phi_y(t+1) \geq \phi_y(t)$, and warping limits, a maximum allowed time difference between two matched data points, which can be expressed as $|\phi_x(t) - \phi_y(t)| < L$, where L is the greatest difference allowed (Larsen, 2021).

We then compare the best controls obtained using the Larsen (2021) approach and those obtained when using all the controls. For illustration, we use only spot price and volatility and set the post-period window to one month as the interest is on the matching (pre) period (see Appendix C.2.1). In general, a lower mean absolute percentage error (MAPE, a measure of historical fit) is achieved when pre-screened controls are employed in the model.[21] However, this is not consistent with estimating spot price volatility. In some instances, the lowest MAPE is achieved when all control time series are included in the model. We also note that by pre-screening the controls, we miss out on more extreme prices. By including all control time series, we manage to slightly increase the model's

[21] The matching (pre) period's MAPEs are given in Appendix C.2.2.

ability to capture these spikes at the expense of slightly high MAPE.[22,23] Thus, we refrain from pre-screening the controls prior to employing them in the analysis. Part of the reason is that, except for price volatility, we obtain comparable results when estimating the effect of 5MS on spot prices. Most importantly, the Brodersen et al. (2015) approach estimates the causal effect of an intervention in terms of the variability seen in the response variable during the post-period *that cannot be explained away by other means (known trends or events).* This means that using all potential control variables is critical to estimating robust counterfactuals.[24] Indeed, Brodersen et al. (2015) underscore that one strength of their approach is its ability to incorporate all controls without regard to external attributes and solely on the basis of how well they explain the treated unit's pre-treatment outcome time series.[25] The spike-and-slab prior avoids overfitting by integrating posterior uncertainty about which covariates to include and the degree to which they affect the predictions.

4.3.3.3 Parameter assumptions

We apply an R package known as "CausalImpact" to implement the Bayesian structural time-series model (Brodersen, 2022). We set the number of MCMC samples to be drawn to 10,000 rather than the default value of 1,000 to increase the accuracy of the estimated results. More samples lead to more accurate inferences. The default value of 0.01 is used as the prior standard deviation of the Gaussian random walk of the local level. Using a lower standard error means relying more on the predictive power of the control time series while avoiding the cost borne for such a choice. When the test time series is volatile due to unexplained noise, large values such as 0.1 are typically advised. However, larger

[22] It is worth noting that spikes, which are more pronounced in spot price data, are likely to affect the accuracy of the estimated MAPE.

[23] By default, the Brodersen et al. (2015) approach assumes the Gaussian model family for the observation equation. As a robustness check, we replace Gaussian observation noise with t-distributed noise and note no improvement in the model's ability to capture the spikes (see Appendix C.2.3).

[24] It is recommended to include three to 50 predictors to ensure the robustness of the estimated counterfactual.

[25] The average posterior coefficients β used in the linear regression component of the structural time-series model and posterior inclusion probabilities for the most likely predictors of the response metrics are given in Appendix C.2.4.

standard errors result in wider posterior forecast intervals, making outcomes more likely to be inconclusive (Larsen, 2021). Given that electricity spot prices differ substantially during the week, we include a seasonal component to capture day-of-week seasonality with daily granularity.[26] The confidence interval for all analyses is 95%.

4.4 Impact on Spot Price Dynamics

Figures 4.11 and 4.12 plot the impact of 5MS on the spot price one month and eight months after the introduction of the 5MS, respectively, while Tables 4.3 and 4.4 present the numerical summaries of the impact of the 5MS on spot prices and volatility, respectively.[27] For the spot price dynamics, we present the estimated immediate and short-term effects for each state. In Tables 4.3 and 4.4 and similar tables thereafter, the "Average" column presents the average spot price (across time) during the post-5MS periods. In the first panel, this is a period from 1st to 31st October 2021; in the second panel, it is a period from 1st October 2021 to 31st May 2022. The "Cumulative" column accumulates the effects from individual time points.

The first panel of Figures 4.11 and 4.12 plots the data and a counterfactual prediction for the post-treatment period. The second panel shows the pointwise causal effect, as estimated by the difference between observed data and counterfactual predictions. The third panel presents the cumulative effect obtained by adding up the pointwise effects. These figures allow for studying the evolution of the impact of the rule change over time.[28] They complement the interpretation of the aggregated effects of the rule change across time during the post-intervention period, as summarized in Tables 4.3 and 4.4. The aggregated effects are of greater interest to this analysis.

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[26] In Appendix C.2.5, we estimate the causal impact of introducing the 5MS rule on 1st October 2021 on the equally daily weighted average spot price using different assumptions of prior standard deviation, with and without the seasonality component. We note that the posterior tail-area probability, which indicates the likelihood of obtaining the estimated effect by chance, increases for higher values of the prior standard deviation. Moreover, we find a negligible effect of including or excluding the seasonality component.

[27] The graphical representations of the impact of the 5MS are provided for the spot prices only for illustration and clarity. Other figures for changes in volatility and DWPs are provided in Appendices C.3.1 and C.3.2, respectively.

[28] Individual days or shorter intervals within the intervention period may have a significant impact, as indicated whenever the lower limit of the impact time series lies above zero (Brodersen, 2022).

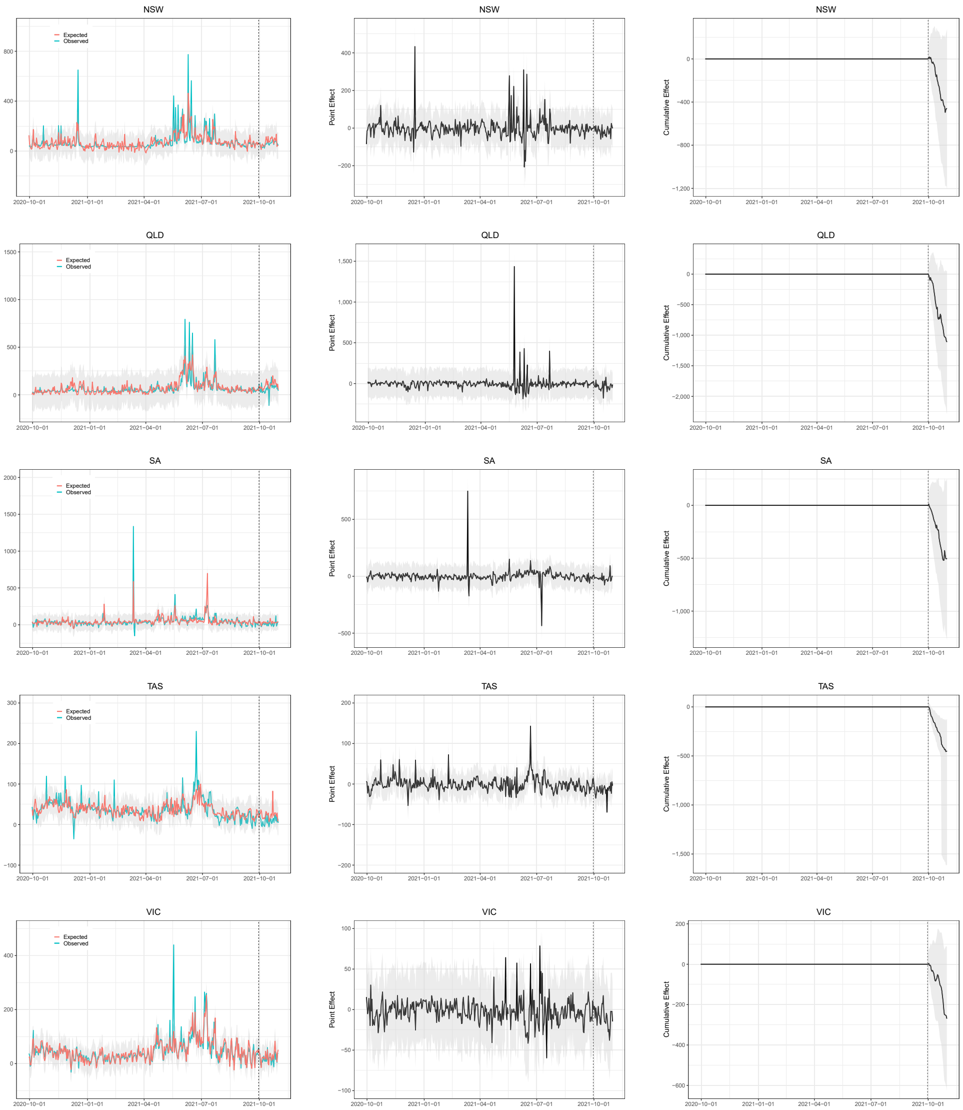

Figure 4.11 : **The causal impact of introducing the 5MS rule on 1st October 2021 (dashed vertical line) on equally daily weighted averaged spot price with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations). The first panels show the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

4.4.1 Impact on spot price

To interpret the findings in Table 4.3 and the other tables that follow, consider the estimated coefficients for TAS for the period of 1st to 31st October 2021 as an example. The observed spot price has an average value of 9.4 AUD/MWh during the post-5MS period.

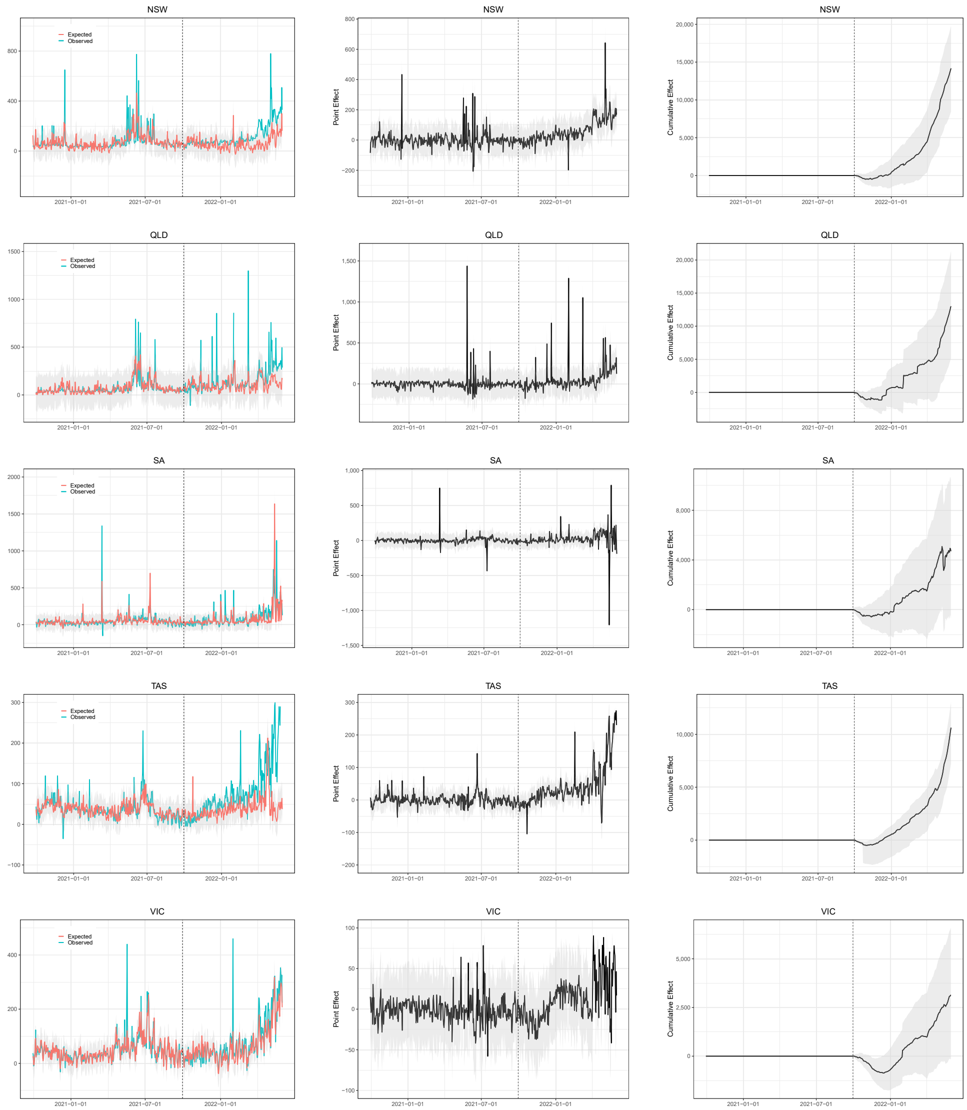

Figure 4.12 : **The causal impact of introducing the 5MS rule on 1st October 2021 (dashed vertical line) on equally daily weighted averaged spot price with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The first panels show the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

In the absence of the 5MS, we would have expected an average of 24 AUD/MWh. The 95% confidence interval of this counterfactual prediction is [13 AUD/MWh, 61 AUD/MWh]. A causal effect is then obtained by subtracting the predicted spot price from the observed price: that is, -15 AUD/MWh with a 95% interval of [-52 AUD/MWh, -4.1 AUD/MWh].

Table 4.3 : **The causal impact of introducing the 5MS rule on 1st October 2021 on equally daily weighted average spot price with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations) and 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative
	Immediate effect: One month after the 5MS (1st October 2021 to 31st October 2021)									
Actual	57	1771	66	2061	15	450	9.4	290.8	18	572
Prediction (s.d.)	72 (12)	2232 (374)	102 (19)	3171 (598)	31 (13)	957 (389)	24 (12)	745 (369)	27 (5.8)	842 (181.0)
95% CI	[48, 96]	[1496, 2971]	[65, 140]	[2008, 4349]	[6.4, 55]	[198.4, 1720]	[13, 61]	[417, 1904]	[16, 39]	[487, 1198]
Absolute effect (s.d.)	-15 (12)	-461 (374)	-36 (19)	-1111 (598)	-16 (13)	-507 (389)	-15 (12)	-454 (369)	-8.7 (5.8)	-269.7 (181.0)
95% CI	[-39, 8.8]	[-1201, 274.3]	[-74, 1.7]	[-2288, 52.7]	[-41, 8.1]	[-1269, 252.1]	[-52, -4.1]	[-1613, -125.9]	[-20, 2.7]	[-626, 84.9]
Relative effect (s.d.)	-21% (17%)	-21% (17%)	-35% (19%)	-35% (19%)	-53% (41%)	-53% (41%)	-61% (50%)	-61% (50%)	-32% (22%)	-32% (22%)
95% CI	[-54%, 12%]	[-54%, 12%]	[-72%, 1.7%]	[-72%, 1.7%]	[-133%, 26%]	[-133%, 26%]	[-217%, -17%]	[-217%, -17%]	[-74%, 10%]	[-74%, 10%]
Posterior tail-area probability p:	0.1069	0.1069	0.0318	0.0318	0.0974	0.0974	0.0047	0.0047	0.0701	0.0701
Posterior prob. of a causal effect:	89%	89%	96.82%	96.82%	90%	90%	99.53%	99.53%	93%	93%
	Short-term effect: Eight months after the 5MS (1st October 2021 to 31st May 2021)									
Actual	120	29189	164	39758	100	24365	82	20040	79	19210
Prediction (s.d.)	62 (12)	15012 (2883)	110 (17)	26755 (4114)	81 (12)	19659 (2848)	39 (5.7)	9410 (1375.4)	66 (7.1)	16068 (1717.6)
95% CI	[39, 85]	[9423, 20754]	[76, 143]	[18475, 34643]	[57, 103]	[13886, 25065]	[29, 53]	[7026, 12829]	[52, 80]	[12623, 19366]
Absolute effect (s.d.)	58 (12)	14177 (2883)	54 (17)	13004 (4114)	19 (12)	4706 (2848)	44 (5.7)	10630 (1375.4)	13 (7.1)	3142 (1717.6)
95% CI	[35, 81]	[8434, 19766]	[21, 88]	[5116, 21284]	[-2.9, 43]	[-700.6, 10479]	[30, 54]	[7211, 13014]	[-0.64, 27]	[-155.74, 6586]
Relative effect (s.d.)	94% (19%)	94% (19%)	49% (15%)	49% (15%)	24% (14%)	24% (14%)	113% (15%)	113% (15%)	20% (11%)	20% (11%)
95% CI	[56%, 132%]	[56%, 132%]	[19%, 80%]	[19%, 80%]	[-3.6%, 53%]	[-3.6%, 53%]	[77%, 138%]	[77%, 138%]	[-0.97%, 41%]	[-0.97%, 41%]
Posterior tail-area probability p:	0.0001	0.0001	0.0013	0.0013	0.0450	0.0450	0.0001	0.0001	0.0319	0.0319
Posterior prob. of a causal effect:	99.99	99.99	99.87%	99.87%	95.50%	95.50%	99.99%	99.99%	96.81%	96.81%

Put differently, the 5MS causes a 15 AUD/MWh decrease in the average TAS spot price (see the third panel of Figure 4.11 for TAS). Cumulatively, the spot price has an overall value of 290.8 AUD/MWh. In the absence of the 5MS, we would have expected a sum of 745 AUD/MWh with the 95% interval of [417 AUD/MWh, 1904 AUD/MWh]. In relative terms, the spot price shows a decrease of -61%, with a 95% interval of [-217%, -17%]. Since this interval excludes 0, it means that the negative effect observed during the 5MS period is statistically significant and unlikely to be due to random fluctuations (Brodersen, 2022). The probability of obtaining this effect by chance is very small ($p = 0.0047$), and the causal effect can thus be considered statistically significant.

The findings in Table 4.3 suggest consistent impact of the 5MS on the level of electricity prices in reference to a one-month post-period window intended to capture the immediate effect of the 5MS. We see that price decreases across the NEM by 21%, 35%, 53%, 61%, and 32% in NSW, QLD, SA, TAS, and VIC, respectively. However, apart from TAS, the estimated effects are not statistically significant, suggesting that these effects could result

Table 4.4 : **The causal impact of introducing the 5MS rule on 1st October 2021 on equally daily weighted averaged spot price volatility with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations) and 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative
	Immediate effect: One month after the 5MS (1st October 2021 to 31st October 2021)									
Actual	39	1195	216	6689	109	3374	21	653	41	1269
Prediction (s.d.)	166 (72)	5141 (2241)	378 (85)	11706 (2631)	83 (44)	2563 (1365)	27 (58)	845 (1789)	32 (32)	997 (981)
95% CI	[25, 308]	[771, 9544]	[211, 542]	[6552, 16795]	[-2.1, 168]	[-65.3, 5219]	[-77, 134]	[-2383, 4140]	[-29, 94]	[-912, 2899]
Absolute effect (s.d.)	-127 (72)	-3946 (2241)	-162 (85)	-5017 (2631)	26 (44)	811 (1365)	-6.2 (58)	-192.2 (1789)	8.8 (32)	271.9 (981)
95% CI	[-269, 14]	[-8350, 424]	[-326, 4.4]	[-10105, 137.4]	[-60, 111]	[-1845, 3440]	[-113, 98]	[-3488, 3036]	[-53, 70]	[-1630, 2180]
Relative effect (s.d.)	-77% (44%)	-77% (44%)	-43% (22%)	-43% (22%)	32% (53%)	32% (53%)	-23% (212%)	-23% (212%)	27% (98%)	27% (98%)
95% CI	[-162%, 8.3%]	[-162%, 8.3%]	[-86%, 1.2%]	[-86%, 1.2%]	[-72%, 134%]	[-72%, 134%]	[-413%, 359%]	[-413%, 359%]	[-164%, 219%]	[-164%, 219%]
Posterior tail-area probability p:	0.0390	0.0390	0.0289	0.0289	0.2740	0.2740	0.4600	0.4600	0.3919	0.3919
Posterior prob. of a causal effect:	96%	96%	97.11%	97.11%	73%	73%	54%	54%	61%	61%
	Short-term effect: Eight months after the 5MS (1st October 2021 to 31st May 2021)									
Actual	85	20577	280	68116	177	42978	49	11840	57	13774
Prediction (s.d.)	151 (74)	36592 (17975)	413 (76)	100401 (18414)	108 (41)	26213 (10070)	42 (21)	10313 (5042)	69 (25)	16690 (5983)
95% CI	[11, 300]	[2692, 72796]	[263, 561]	[63789, 136329]	[27, 189]	[6505, 45928]	[1.3, 83]	[313.3, 20078]	[19, 116]	[4731, 28129]
Absolute effect (s.d.)	-66 (74)	-16014 (17975)	-133 (76)	-32285 (18414)	69 (41)	16765 (10070)	6.3 (21)	1527.3 (5042)	-12 (25)	-2916 (5983)
95% CI	[-215, 74]	[-52218, 17886]	[-281, 18]	[-68213, 4327]	[-12, 150]	[-2951, 36473]	[-34, 47]	[-8238, 11527]	[-59, 37]	[-14355, 9043]
Relative effect (s.d.)	-44% (49%)	-44% (49%)	-32% (18%)	-32% (18%)	64% (38%)	64% (38%)	15% (49%)	15% (49%)	-17% (36%)	-17% (36%)
95% CI	[-143%, 49%]	[-143%, 49%]	[-68%, 4.3%]	[-68%, 4.3%]	[-11%, 139%]	[-11%, 139%]	[-80%, 112%]	[-80%, 112%]	[-86%, 54%]	[-86%, 54%]
Posterior tail-area probability p:	0.1853	0.1853	0.0409	0.0409	0.0461	0.0461	0.3805	0.3805	0.3077	0.3077
Posterior prob. of a causal effect:	81.00%	81.00%	95.91%	95.91%	95.39%	95.39%	62%	62%	69%	69%

from seasonal and other price drivers apart from the effect of the 5MS. The decrease in electricity prices observed following the change in market design to shorter trading intervals is in line with the findings in other electricity markets. Märkle-Huß et al. (2018) demonstrated that reducing the delivery duration of electricity from 1-hour to 15-minute intervals brought a maximum of around 28% reduction in electricity prices in hourly contracts. However, collectively, the results point to the fact that the introduction of 5MS generally has no immediate effect on spot prices.[29]

[29] As a robustness test, we extend the post-period window by one week to check the possibility of the model producing insignificant results due to its inability to distinguish signals from trends when using shorter post-periods. We also reduce the post-period window to exactly three weeks to eliminate the possibility of missing out on any immediate effects that occurred only a few days after the 5MS. We provide a summary of this supplementary analysis in Appendix C.3.3. The findings from these analyses are indeed consistent with those observed for a one-month post-period window, indicating no statistically significant differences between pre- and post-5MS spot price dynamics, with the exclusion of TAS. To further confirm these findings, we apply a typical ARX-eGARCH model used in previous studies on price dynamics, such as Ketterer (2014) and in Chapters 2 and 3. We use dummy variables to examine the effect of the 5MS on spot prices, with $D = 1$ during the 5MS period and zero otherwise. The findings

Turning now to a longer post-period window, defined in this analysis as eight months following the introduction of the 5MS, we find strong statistical evidence to suggest that the 5MS induces a positive impact on spot price in three NEM regions: NSW (94%), QLD (49%), and TAS (113%). Although the 5MS shows a similar effect in SA and VIC, the results are not statistically significant. The increase in electricity prices following the 5MS may be explained by the removal of generators' incentives to offer their capacity at the market price floor to ensure most of their generation is used following a sky-high price dispatch interval. According to the AEMO, the 5MS eliminated this incentive and resulted in the cessation of dispatch prices dropping all the way to the price floor by the end of the half-hour, even if this interval begins with a price spike.

4.4.2 Impact on price volatility

Table 4.4 presents the impact of the 5MS on spot price volatility as proxied by the standard deviation of the spot price. As for spot price, we explore both the immediate and short-term effects of the 5MS on price volatility. There is a consistent, though statistically insignificant, observable impact of the 5MS on volatility dynamics one month after the 5MS is activated. Volatility decreases in NSW, QLD, and TAS by 77%, 43%, and 23%, respectively, and increases in SA and VIC by 32% and 27%, respectively.[30] The average effects over the long term are somewhat similar to those observed one month after the introduction of the 5MS. Volatility decreases in NSW, QLD, and VIC by 44%, 32%, and 17%, respectively, and increases in SA and TAS by 64% and 15%, respectively. However, we find no statistical evidence to support these effects across the NEM.[31]

These findings suggest that the introduction of the 5MS to align operational dispatch and financial settlement at five minutes does not induce an immediate effect on the spot

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from this analysis are generally in line with those estimated using the Bayesian structural time-series model. The approach and the findings using the ARX-eGARCH model are given in Appendix C.3.4.

[30]Similar to spot price, we run two robustness checks by reducing and extending the post-period window by one week and re-running the analysis using the ARX-eGARCH model in Appendices C.3.3 and C.3.4, respectively. The findings from this analysis generally agree with those observed during the one-month post-period window and do not change the conclusion.

[31]We note in Figure C.17 that the model does not capture price spikes well when using standard deviation as a measure of volatility. As a robustness check, we use $\log(\sigma_d^2)$ to improve the fit. The results of this analysis are plotted in Figure C.18 and summarized in Table C.13. We demonstrate that the model fit improves after changing the volatility measure, but our conclusion regarding the impact of 5MS on price volatility remains the same.

price. However, the impact is likely to become more pronounced over time, as demonstrated by the price increase when considering the entire post-5MS period. Although it was expected for states with dominant inflexible generation sources to experience high price variability due to their inability to respond to changes in supply and demand in the shortest time-frame, this has not proven to be the case thus far, at least as far as the sample period used in this analysis is concerned. The lack of evidence for the effect of the 5MS on price volatility is somewhat surprising and may reflect the fact that the 5MS effect has been subsumed by other factors, including changes in the supply-demand balance due to forced generators and network outages, changes in forecast demand, unexpected changes in VRE generation, and changes in the bids of other generators (AEMO, 2021b, 2022c) between the pre-5MS and post-5MS periods.

4.4.3 Why did the 5MS not induce an immediate effect on spot price dynamics?

As the preliminary analysis and the empirical findings in sections 4.4.1 and 4.4.2 show, the introduction of the 5MS did not result in immediate changes in the market, especially in relation to the spot price dynamics. One key reason may explain this phenomenon: the market arguably had sufficient time to prepare for the rule change. The AEMC issued a final rule to change the settlement period from 30 minutes to five minutes on 28$^{\text{th}}$ November 2017. Implementation of this rule was scheduled to take effect nearly four years later on 1$^{\text{st}}$ July 2021. This time-frame aimed to provide enough time for the industry to prepare, as the 5MS had implications for the operations of spot and contract markets, metering, and IT systems (AEMC, 2017f). The commencement date was delayed further to 1$^{\text{st}}$ October 2021 following the energy regulator's shift in focus to maintaining a secure and resilient electricity system during the COVID-19 pandemic (AEMC, 2017a)

During the four years of lead-up time, generators prepared for the 5MS in several ways. First, new fast-response gas and battery technologies that could respond rapidly to price spikes came online. AGL's 211 MW Barker Inlet power station is one of the first gas-generating units with a fast response time built during the lead time to the 5MS. The plant was equipped with reciprocating engines replacing the old Torrens Island power station, which used steam turbines that were less flexible and more expensive to operate.

Barker Inlet is 28% more efficient than Torrens Island, with the ability to ramp from zero to full capacity in five minutes (AER, 2021b). Several battery generators, both existing and new, were also in operation at the time that the new rule came into action, especially in SA and VIC. According to the AER (2021b), about eight batteries came online from the time the rule change was announced to around the period when it was implemented. The number of battery energy storage systems also increased threefold after the rule change in 2021 (AER, 2022a).

Second, existing generation assets were upgraded. To increase existing plant flexibility, two significant upgrades of gas turbines were completed prior to the start of the 5MS. This included two key power stations in SA: Origin Energy's Quarantine and EnergyAustralia's Hallett. These plants underwent repowering upgrades with the installation of state-of-the-art GE LM2500 aeroderivative gas turbines, which could go from cold start to full load in as little as five minutes (Griffin, 2020). Third, those generators with less flexibility that did not carry out upgrades or build new plants are likely to have changed their operational strategies to align with the 5MS. Such strategies include "operating harder" and "warming up" their units (AER, 2021b). The former involves generators adjusting their technical specifications, such as ramp rates or fast-start inflexibility profiles, to allow them to respond quickly at the expense of higher maintenance or replacement costs. The latter involves generators readying their units by warming up but not dispatching output into the grid. This strategy made it possible for the generator to react quickly and operate during periods of high prices. It is worth mentioning that each of these strategies has their limitations. The "operating harder" strategy does not guarantee sufficient flexibility, and "warming up" may consume large amounts of fuel. In turn, generators may need to weigh the benefits of increased flexibility against fuel and maintenance costs.

Although it can be argued otherwise, the lead-up time allowed generators in the NEM to prepare for 5MS through investment and changes in operational strategies. Furthermore, given that the NEM has always been dispatched on the basis of 5-minute intervals, it is unlikely for the 5MS to have resulted in radical changes in the market, at least during the earlier period of its implementation. Following the observed changes in spot price dynamics over the long term, the next section explores how generators' spot market DWPs changed during this period.

4.5 Impact on Generators DWPs

Tables 4.5 to 4.8 present the impact of the 5MS on DWPs for battery, wind, solar, coal, natural gas, and hydro generators in the NEM. This analysis focuses on the average effect over the entire post-period window, that is, eight months after the implementation of the 5MS.

4.5.1 Grid-scale battery generators' DWP

Table 4.5 presents the impact of the 5MS on DWP earned by battery generators in SA and VIC.[32] The results indicate that the introduction of the 5MS significantly increases the DWPs earned by battery generators in SA by 69%.[33] This suggests that battery generators took advantage of their flexibility to capture more DWP with the same-sized battery. Under the 5MS, generators could also capture the same amount of revenue as in the 30MS regime with a smaller battery, possibly up to one-sixth the size (AEMC, 2017b). Under the 30MS rule, battery generators occasionally avoided dispatching electricity as the payment for all generators dispatched during a trading interval tended to be the same. The AEMO estimated an increase of approximately $0.4 million in net revenue in the last quarter of 2021 over what would have been obtained under a 30-minute settlement (AEMO, 2021b). Although a similar effect is observed in VIC, where DWPs increases by 14%, the effect is not statistically significant.

Compared to SA, battery generation has been low in VIC, which likely explains why we observe an insignificant increase in generators' DWPs. The VBB, one of the world's largest batteries, started operation in VIC in late November 2021. During its short existence, the VBB has benefited from the increased dispatch and volume-weighted average energy

[32]We focus only on SA and VIC as generation in NSW and QLD prior to the 5MS was zero or marginal (see Figure 4.3).

[33]Further studies utilizing alternative measures, such as "park spread" may be useful to gain a comprehensive understanding of how 5MS affects revenue earned by battery generators (AEMO, 2019b). Spreads are a better measure of profitability than DWPs for storage, as higher DWPs do not necessarily mean higher profits.

Table 4.5 : **The causal impact of introducing the 5MS rule on 1st October 2021 (dashed vertical line) on the daily DWPs for battery generators with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations) and 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid. The fourth panel depicts the cumulative effect.

	SA		VIC	
	Average	Cumulative	Average	Cumulative
Actual	232	56315	124	30123
Prediction (s.d.)	137 (43)	33343 (10397)	109 (23)	26435 (5576)
95% CI	[55, 219]	[13342, 53237]	[57, 145]	[13732, 35232]
Absolute effect (s.d.)	95 (43)	22972 (10397)	15 (23)	3688 (5576)
95% CI	[13, 177]	[3078, 42973]	[-21, 67]	[-5109, 16391]
Relative effect (s.d.)	69% (31%)	69% (31%)	14% (21%)	14% (21%)
95% CI	[9.2%, 129%]	[9.2%, 129%]	[-19%, 62%]	[-19%, 62%]
Posterior tail-area probability p:	0.0112	0.0112	0.2718	0.2718
Posterior prob. of a causal effect:	98.88%	98.88%	73.00%	73.00%

arbitrage value. By drawing on experience from SA, it is likely that the effect of the 5MS will manifest in higher DWP for battery generators in VIC over time.

With the introduction of the 5MS, batteries have taken on a larger role in the NEM. Recent analysis indicates that grid-scale batteries lead the overall provision of frequency control ancillary services (FCAS) in the first quarter of 2022 (AEMO, 2022c). Evidence from other markets (California) shows that the relevance of battery generation in supplying peak demand is growing as gas-generating units approach substantial capital expenditures associated with extended technical life (Rai and Nunn, 2020a). Given the increasing penetration of wind and solar generation and the declining cost of grid-scale batteries compared to gas-fired or pumped hydro, battery generators could gain more from arbitrage by charging at low-priced times and discharging at high-priced times. However, volatility and unpredictability of FCAS revenue, as well as the uncertainty of future electricity prices, means that more stable revenue streams, such as financial contracts, may be required to ensure that battery producers cover their initial investment during the battery's lifetime.

4.5.2 VRE generators' DWP

Table 4.6 presents the impact of the 5MS on the DWP received by wind and solar generators. We find strong evidence to suggest that the introduction of the 5MS leads to an increase in the DWP received by wind generators across the NEM. This effect is more pronounced in TAS, followed by states with lower wind penetration, namely NSW and QLD. SA and VIC, which have relatively higher wind penetrations, experience a smaller effect. More specifically, DWP increases by about 126%, 99%, 62%, 43%, and 23% in TAS, NSW, QLD, SA, and VIC, respectively. Similar to wind, DWP received by solar generators is relatively higher when the 5MS rule was in place compared to the period before. This effect is more pronounced and statistically significant in states with higher penetration of solar generation, namely SA and QLD. Specifically, DWP increases by approximately 105% and 69% in SA and QLD, respectively. In contrast, the states with low penetration of large-scale solar generation, namely NSW and VIC, experience marginal and statistically insignificant DWP increases of approximately 28% and 9%, respectively.

Trading in shorter intervals provides incentives for renewables to offer additional generation output to the market (Kiesel and Paraschiv, 2017; Märkle-Huß et al., 2018). The observed increase in DWPs likely results from the increase in trading volume and the ability of VRE to stop and start in relatively short spaces of time. This flexibility enabled VRE generators to capture upward price spikes during their operating times and avoid negative price periods. Changes in VRE bidding behaviour could also explain the increase in DWPs. According to the AEMO (2021b), the volume offered at the floor price declined substantially after the introduction of the 5MS as VRE generators moved their bids towards their break-even price or short-run marginal cost (SRMC) within the -\$100/MWh to -\$35/MWh range. This price, which is close to the value of large-scale generation certificates (LGC), allows many generators to break even.[34]

[34]Apart from the LGC, other factors determining break-even price include VRE generators' power purchase agreements (PPAs) and their portfolio position (AEMO, 2021b).

Table 4.6 : **The causal impact of introducing the 5MS rule on 1st October 2021 on daily DWPs for VRE generators with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations) and 1st to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative
	Wind generation									
Actual	118	28579	148	35914	89	21596	80	19420	78	19030
Prediction (s.d.)	59 (12)	14379 (2849)	91 (12)	22207 (2874)	62 (6.1)	15108 (1480.3)	35 (4.3)	8607 (1047.2)	64 (6.6)	15478 (1600.1)
95% CI	[37, 83]	[9085, 20091]	[69, 118]	[16874, 28736]	[50, 74]	[12125, 17968]	[27, 44]	[6527, 10689]	[51, 77]	[12291, 18682]
Absolute effect (s.d.)	58 (12)	14199 (2849)	56 (12)	13706 (2874)	27 (6.1)	6488 (1480.3)	44 (4.3)	10813 (1047.2)	15 (6.6)	3552 (1600.1)
95% CI	[35, 80]	[8487, 19494]	[30, 78]	[7178, 19040]	[15, 39]	[3628, 9471]	[36, 53]	[8731, 12892]	[1.4, 28]	[348.2, 6739]
Relative effect (s.d.)	99% (20%)	99% (20%)	62% (13%)	62% (13%)	43% (9.8%)	43% (9.8%)	126% (12%)	126% (12%)	23% (10%)	23% (10%)
95% CI	[59%, 136%]	[59%, 136%]	[32%, 86%]	[32%, 86%]	[24%, 63%]	[24%, 63%]	[101%, 150%]	[101%, 150%]	[2.2%, 44%]	[2.2%, 44%]
Posterior tail-area probability p:	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0148	0.0148
Posterior prob. of a causal effect:	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	99.99%	98.52%	98.52%
	Large-scale Solar generation									
Actual	99	24011	117	28423	58	14032			56	13664
Prediction (s.d.)	77 (11)	18752 (2784)	69 (9.4)	16770 (2294.0)	28 (8.5)	6829 (2069.9)			52 (9)	12532 (2178)
95% CI	[55, 100]	[13409, 24297]	[51, 88]	[12313, 21366]	[12, 45]	[2808, 10875]			[34, 68]	[8213, 16606]
Absolute effect (s.d.)	22 (11)	5259 (2784)	48 (9.4)	11652 (2294.0)	30 (8.5)	7203 (2069.9)			4.7 (9)	1131.6 (2178)
95% CI	[-1.2, 44]	[-285.9, 10602]	[29, 66]	[7056, 16110]	[13, 46]	[3157, 11224]			[-12, 22]	[-2943, 5450]
Relative effect (s.d.)	28% (15%)	28% (15%)	69% (14%)	69% (14%)	105% (30%)	105% (30%)			9% (17%)	9% (17%)
95% CI	[-1.5%, 57%]	[-1.5%, 57%]	[42%, 96%]	[42%, 96%]	[46%, 164%]	[46%, 164%]			[-23%, 43%]	[-23%, 43%]
Posterior tail-area probability p:	0.0299	0.0299	0.0001	0.0001	0.0012	0.0012			0.3082	0.3082
Posterior prob. of a causal effect:	97.01%	97.01%	99.99%	99.99%	99.88%	99.88%			69%	69%

4.5.3 Fossil-fuel and hydro generators' DWP

Tables 4.7 and 4.8 show the effect of the 5MS on fossil-fuel (coal and gas) and hydro generators' DWPs, respectively. We see that the introduction of the 5MS results in an increase of DWPs for black coal generators in both NSW and QLD by 89% and 48%, respectively. Although VIC exhibits a similar effect, where DWP appear to increase by 19%, this effect is not statistically significant. Generally, the increase in the DWPs for coal-fired generators is unexpected. It was anticipated that coal-fired generators would have a hard time deriving benefit from high price spikes under the 5MS regime due to their inability to respond rapidly to changes in price every 5 minutes. Under the 30MS regime, even if the conditions that created the price spike had passed, relatively slow generators that took 15 to 20 minutes to respond from rest could still benefit from that spike (AEMC, 2017b). This is not possible under the 5MS.

Table 4.7 : **The causal impact of introducing the 5MS rule on 1st October 2021 on daily DWPs for fossil-fuel generators with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations) and 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative
	Coal-fired generation									
Actual	124	30178	170	41294					82	19915
Prediction (s.d.)	66 (12)	15990 (2985)	115 (15)	27918 (3763)					69 (7)	16777 (1694)
95% CI	[42, 90]	[10096, 21816]	[83, 145]	[20255, 35185]					[55, 82]	[13312, 20015]
Absolute effect (s.d.)	58 (12)	14188 (2985)	55 (15)	13376 (3763)					13 (7)	3138 (1694)
95% CI	[34, 83]	[8363, 20083]	[25, 87]	[6109, 21039]					[-0.41, 27]	[-100.50, 6603]
Relative effect (s.d.)	89% (19%)	89% (19%)	48% (13%)	48% (13%)					19% (10%)	19% (10%)
95% CI	[52%, 126%]	[52%, 126%]	[22%, 75%]	[22%, 75%]					[-0.6%, 39%]	[-0.6%, 39%]
Posterior tail-area probability p:	0.0001	0.0001	0.0004	0.0004					0.0301	0.0301
Posterior prob. of a causal effect:	99.99%	99.99%	99.96%	99.96%					96.99%	96.99%
	Natural gas-fired generation									
Actual	141	34147	206	49949	129	31361	79	19104	102	24871
Prediction (s.d.)	95 (30)	23161 (7246)	151 (31)	36600 (7447)	115 (23)	27999 (5542)	42 (9.3)	10181 (2264.0)	50 (18)	12194 (4389)
95% CI	[35, 152]	[8607, 37027]	[89, 209]	[21520, 50806]	[67, 157]	[16278, 38139]	[25, 63]	[6107, 15378]	[19, 89]	[4561, 21626]
Absolute effect (s.d.)	45 (30)	10987 (7246)	55 (31)	13349 (7447)	14 (23)	3362 (5542)	37 (9.3)	8923 (2264.0)	52 (18)	12677 (4389)
95% CI	[-12, 105]	[-2880, 25540]	[-3.5, 117]	[-857.4, 28428]	[-28, 62]	[-6778, 15083]	[15, 53]	[3727, 12997]	[13, 84]	[3245, 20310]
Relative effect (s.d.)	47% (31%)	47% (31%)	36% (20%)	36% (20%)	12% (20%)	12% (20%)	88% (22%)	88% (22%)	104% (36%)	104% (36%)
95% CI	[-12%, 110%]	[-12%, 110%]	[-2.3%, 78%]	[-2.3%, 78%]	[-24%, 54%]	[-24%, 54%]	[37%, 128%]	[37%, 128%]	[27%, 167%]	[27%, 167%]
Posterior tail-area probability p:	0.0623	0.0623	0.0328	0.0328	0.2788	0.2788	0.0007	0.0007	0.0026	0.0026
Posterior prob. of a causal effect:	94.00%	94.00%	96.72%	96.72%	72%	72%	99.93%	99.93%	99.74%	99.74%

There are two possible explanations for the change in black coal generators' DWPs under the 5MS: (i) change in generators' operation strategies, as discussed in section 4.4.3, and (ii) change in bidding strategies. The increase in DWPs may also be attributed to generators adjusting their offers to avoid low prices in the middle of the day during periods of low demand and high supply from solar generation (AER, 2022b).

These findings also provide an interesting insight into the generation technologies underlying black and brown coal. Black coal generation tends to be significantly more flexible than brown coal and can thus respond to and follow the pricing patterns relatively faster than brown coal. This difference in flexibility may explain why generator DWPs increase in NSW and QLD but not in VIC.

Furthermore, the results suggest a consistent effect of the 5MS on the DWP received by gas generators across states (see Table 4.7). DWPs increase in NSW, QLD, SA, TAS, and VIC by 47%, 36%, 12%, 88%, and 104%, respectively. However, we only find statistical evidence to support these findings in TAS and VIC. There is a possibility for gas generators' DWPs to vary by technologies such as OCGT, CCGT, and truly fast-start technologies such as reciprocating engines and aero-derivative turbines. Such an analysis is obscured by the data aggregation.[35] The fact that the CCGT dominates the NEM may explain why the introduction of the 5MS has not impacted the DWPs received by gas generators in most states. OCGTs are less efficient but can respond rapidly to spikes in electricity demand. In contrast, CCGT tends to operate most of the time as a source of baseload and intermediate load generation rather than in response to peaks in demand (Cameron et al., 2018). These start-up delays and the subsequent inability to capture sudden price spike events may account to some extent for the reduction of both OCGT and CCGT DWPs compared to the period when the 30MS was in operation (Flottmann et al., 2022). Operating as peaking and baseload means that CCGT also generates during low-price periods. Lower capital costs compared to aero-derivative units and the persistence of low gas prices, especially through the end of 2010, resulted in the construction of more less-flexible CCGT and OCGT in the NEM (AEMC, 2017b).

The 5MS affects the DWPs earned by hydro generators differently (see Table 4.8). The results suggest a 16% decrease in DWPs in NSW and an increase in DWPs by 106%, 56%, and 34% in TAS, QLD, and VIC, respectively. However, we find statistical evidence to back up this effect in only two states, namely TAS and QLD. Hydro generation accounts for more generation in TAS than in other states in the NEM. Over the last year, hydro accounted for more than 80% of TAS total generation, whereas it only accounted for around or less than 5% in the other states.[36] Compared to 2020, Hydro Tasmania offers increased twofold in October 2021 (AER, 2021b). Furthermore, like gas generation, DWPs earned by hydro generation are likely to differ by technology. However, there is a slight difference in the hydro generation technologies currently deployed in the NEM: NSW,

[35] For the purpose of this analysis, we considered only natural gas-fired generation. Assessing changes in DWPs by gas technology type is limited by the fact that the AEMO does not provide aggregated data for different types of gas-fired generators. One would therefore need to collect generator-specific data and then aggregate it up to CCGT, OCGT, and reciprocating engines. Given the time required for this analysis, we decided to leave it to future research.

[36] See https://opennem.org.au/

Table 4.8 : **The causal impact of introducing the 5MS rule on 1st October 2021 on daily DWPs for the hydro generators with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations) and 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		TAS		VIC	
	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative
Actual	149	36259	278	67504	88	21395	119	28982
Prediction (s.d.)	179 (50)	43378 (12047)	178 (45)	43207 (10919)	43 (4.3)	10377 (1049.5)	89 (20)	21597 (4870)
95% CI	[69, 263]	[16797, 63827]	[88, 266]	[21399, 64629]	[34, 51]	[8280, 12436]	[45, 124]	[10987, 30215]
Absolute effect (s.d.)	-29 (50)	-7119 (12047)	100 (45)	24297 (10919)	45 (4.3)	11019 (1049.5)	30 (20)	7385 (4870)
95% CI	[-113, 80]	[-27567, 19462]	[12, 190]	[2875, 46105]	[37, 54]	[8959, 13115]	[-5.1, 74]	[-1232.6, 17995]
Relative effect (s.d.)	-16% (28%)	-16% (28%)	56% (25%)	56% (25%)	106% (10%)	106% (10%)	34% (23%)	34% (23%)
95% CI	[-64%, 45%]	[-64%, 45%]	[6.7%, 107%]	[6.7%, 107%]	[86%, 126%]	[86%, 126%]	[-5.7%, 83%]	[-5.7%, 83%]
Posterior tail-area probability p:	0.2570	0.2570	0.0155	0.0155	0.0001	0.0001	0.0479	0.0479
Posterior prob. of a causal effect:	74%	74%	98.45%	98.45%	99.99%	99.99%	95.21%	95.21%

TAS, and VIC use hydro-gravity technology, whereas QLD is dominated by run-of-river and a limited amount of pumped storage technology.

The findings from this section underscore the fact that the 5MS may pose challenges to the future operation of coal-fired generation, especially brown coal. If the increase in black coal generators' DWPs results from "operating harder" or "warming up" strategies, both maintenance and fuel are likely to have substantial cost implications for these generators. This effect is likely to be low for gas-fired generators due to their ability to operate flexibly. However, the fact that we observe no increase in DWPs in most states may also signal that more flexible generation technologies in the form of reciprocating engines and aero-derivative turbines are required for more effective firming capacity than the current dominant conventional OCGT and CCGT technologies. Moreover, the DWPs previously earned by coal, gas, and hydro may have been affected by the increasing uptake of battery technologies in the NEM. Despite batteries having a smaller capacity and limited run time, generators have been dissipating inflexible coal and hydro profits in both the spot and the FCAS markets.[37]

[37] The share of FCAS volumes in the NEM in the first quarter of 2021 included 31% from battery, 21% from black coal, 21% from hydro, 14% from demand response (DR), 7% from brown coal, and 5% from other generators (AEMO, 2022c).

4.6 Policy Implications

The findings from this study reflect the immediate and short-term changes in the market that can be linked to changes in generator operations and bidding behaviours as well as consumers' short-run decisions. The question of how the market will behave in the long term cannot be answered with certainty. Over time, especially in the medium-to-long term, the improved pricing signals are expected to influence the decisions of both new and existing generators on the type of plant and equipment in which to invest, or whether to invest at all. Flexible generators are expected to enter the market, resulting in lower spot prices and volatility and more efficient outcomes for the market and consumers. However, given the features of the NEM, the realization of these benefits will depend on the robustness of policies and technologies in place to support/address the following key issues:

4.6.1 Entry barriers and market concentration

It has been suggested that the 5MS may not completely eliminate gaming or strategic bidding, just like other market rules that have been implemented in the past, such as the *bidding in good faith* (Wood et al., 2018). Addressing the gaming problem by changing market rules is one part of solving the puzzle. However, the presence of a high concentration of generation ownership and the heavy reliance on generation technology that cannot respond rapidly to outages or spikes in demand mean that such market rules are unlikely to substantially change the strategic behaviours of generators. In each region of the NEM, a few major participants control a significant generation share.[38] The type of generating units that portfolio generators control may increase their ability to exercise market power. When the supply and demand balance is tight, a portfolio generator that owns baseload and peaking generation may engage in gaming behaviour by creating artificial scarcity of supply, for instance, by withdrawing generation to raise spot prices (ACCC,

[38] According to the AER (2021a), in 2020, AGL Energy, Origin Energy, and Energy Australia accounted for more than 75% of total generation in NSW; AGL Energy, Energy Australia, and Alinta Energy accounted for more than 80% in VIC; and AGL Energy, Engie, and Origin Energy accounted for around 65% in SA. AGL Energy has a significant share in these three states compared to other companies, accounting for about 39% in NSW and VIC and 28% in SA. Stanwell, CS Energy, and InterGen accounted for more than 79% in QLD (Stanwell dominated with around 32%), and around 95% of the total electricity generated in TAS came from Hydro Tasmania.

2018; Mountain and Carstairs, 2018). High market concentrations give generators the chance to develop novel/alternative market-gaming strategies, which could impede the entry of new generation capacity.

Two markets in which high prices have been linked to gaming behaviours are QLD and SA. Both have two features in common: a higher concentration of generation asset ownership and fewer interconnectors' capacities with other markets. In SA, generators could create artificial scarcity and price hikes due to the intermittency of the VRE that dominates its generation mix, and possible constraints in the interconnectors' flows. Similarly, high market concentration in TAS, where Hydro Tasmania is essentially a monopoly generator, and possible constraints in the interconnector provides opportunities for generators to strategically inflate prices. QLD is a large, concentrated, and isolated energy market and has historically been associated with significant gaming behaviour(Clements et al., 2016; Hurn et al., 2016; Dungey et al., 2018). However, the extreme price fluctuations, likely a function of gaming, have almost been eliminated, especially since 2017. This is after the QLD government instructed the state-owned generators to lower volatility and put downward pressure on wholesale pricing (Wood et al., 2018). In contrast, strategic bidding behaviours in VIC and NSW are relatively low due to high market competition resulting from lower generator ownership concentration and more interconnector capacities with other markets. However, the closure of coal-fired plants tends to tighten supply if lost output is not sufficiently replaced, and this is likely to play a role in increasing market concentration and gaming behaviour in these states. Gaming due to market concentration is said to have increased slightly after the closure of the Hazelwood power plant in VIC and may become apparent in NSW after the closure of AGL Energy's Liddell coal plant (2,000 MW) in phases between 2022 and 2023 (Wood et al., 2018).

In this setting, changes in the market design, such as the 5MS, are likely to bring small changes to price dynamics, especially by exerting downward pressure. This is because concentrations provide sufficient market power for generators to control price outcomes. If larger market participants end up controlling new fast-response technology, the anticipated decline in wholesale and therefore retail prices remains uncertain. Thus, for the benefits of the 5MS to be fully realized, policies that reduce entry barriers and encourage effective new investment to address market concentration should be a priority for the NEM. This may also require that prices remain above historical levels (or above the LRMC of new-build generation) to cover the costs associated with investments in new generation capacities and to support major transformations in the NEM (Wood et al., 2018).

4.6.2 Firming capacity and demand response infrastructures

With the increasing displacement effect of wind and solar generation and high maintenance and fuel costs, the revenues earned by coal plants are expected to decline substantially in the future. Compared to 2018, it is predicted that coal generators could experience earnings before interest and taxes (EBIT) decline of up to 119% in 2025, assuming 100% exposure of these plants to the spot market (no contracts and other revenue streams such as FCAS). As a result, closing would become a desirable or even inevitable option for at least one power plant owner (Edis and Bowyer, 2021). Although spot market revenues for black coal appear to be higher during the 5MS than during the 30MS regime, actual experience in the NEM indicates that spot market revenues have not been sufficient to adequately account for the capital costs of new builds (Marshall et al., 2022). Peaking plants, for instance, have only been developed where enough revenues have been made by selling caps (Rai and Nunn, 2020b). The need to operate more flexibility under the 5MS likely calls for regular maintenance of already-aged coal generation fleets and poses a further challenge to the financial viability of these plants, increasing the odds of sudden closure at a rate faster than new technologies are adopted. This would potentially tighten supply, resulting in high price spikes and increasing the risk of blackouts in times of extreme demand.

To address any potential future challenges brought on by the closure of coal-fired plants, the 5MS should be accompanied by appropriate and timely investment in generation, transmission, and demand response infrastructures. The inception of the 5MS is expected to reward those that can deliver supply-side or demand-side responses more accurately. The NEM initiated the operation of the wholesale demand response (WDR) mechanism on 24$^{\text{th}}$ October 2021 (AEMO, 2021b).[39] The WDR mechanism allows units to submit dispatch bids and receive dispatch instructions as scheduled participants to provide wholesale demand response up to a predetermined level. However, their role in providing the NEM with flexibility capacity is still limited. Only a few registered participants operate in the NEM, especially in NSW and VIC (AEMO, 2022d).

4.6.3 Fuel efficiency and generation technology flexibility

The fact that revenues earned by gas generators have not increased after the 5MS for most states may indicate that the existing gas generation fleets dominating the NEM are not flexible enough to respond within a 5-minute window. In fact, CCGT and OCGT, which currently dominate gas generation fleets in the NEM, can take around 10–20 minutes and 20–40 minutes, respectively, from start-up to full load (see Table 4.9). Unless revenue increases in the future to enable generators to cover their cost of generating electricity, gas generators may withdraw supply from the market. This underscores and calls for the NEM to direct future investment to highly flexible utility-scale energy storage and thermal plant technologies in the form of batteries, pumped storage hydro, internal combustion engines, and aero-derivative gas turbines, which could operate effectively under a 5MS market design (AEMC, 2017b). This generation mix would complement the challenges associated with each of these technologies. While chemical batteries can provide cost-competitive storage for a short duration, they are not considered a cost-effective option for storage beyond four hours, even by 2050 (Cameron et al., 2018). Most batteries that have been built in the NEM have energy storage times of under two hours. One recent study has shown that repurposed hydropower and new pumped hydro options have more potential to provide firming capacity than OCGT and batteries (Cameron et al., 2018).

Moreover, gas prices are rapidly rising and may continue to be higher than historical levels, increasing the cost of producing electricity in Australia.[40] The impact of high

[39]The WDR enables demand-side participants, particularly larger energy consumers, to participate in the wholesale electricity market, most commonly in response to a financial inducement, such as lower electricity costs, during periods of high electricity prices and limited electricity supply (AEMO, 2021b).

[40]The rise in the domestic price of liquefied natural gas (LNG) on Australia's east coast has been triggered by competition in international markets.

Table 4.9 : **Gas-fired generation technologies by technology, approximate thermal efficiency, new capital, start-up time to full load, and ability to follow dispatch targets.** The information is from March 2020; thus, the estimates, especially the capital costs, are likely to have changed. Source: Skinner (2020).

Technology	Thermal efficiency	New capital cost (machine only)	Start-up time to full load	Ability to follow dispatch targets
Steam turbine	35%-40%	Superceded technology	3-8 Hours	Variable above min. load approx. 20% with moderate ramp rates
Open cycle gas turbine (OCGT)	35%-41%	$0.9 Million/MW	10-20 Minutes	Variable, fast ramp rates but efficiency declines
Combined cycle gas turbine (CCGT)	50%-55%	$1.3 Million/MW	20-40 Minutes	Variable above min. load approx. 50% with moderate ramp rates, efficiency declines
Reciprocating engine	45%-48%	$1.2 Million/MW	5 Minutes	Fully variable, fast ramp-rates, no efficiency loss

gas prices is already felt in the NEM. Skyrocketing gas prices, influenced by the war in Ukraine and sanctions against Russia, were among the factors that led to the suspension of the NEM in June 2022 to ensure a reliable power supply (AEMO, 2022d). Given the uncertainty of market conditions, alternative technologies that are both fuel-efficient and have a high degree of flexibility, such as reciprocating engines, are increasingly important for providing firming capacity in the NEM.[41] Reciprocating engine plants—such as Barker Inlet, which has operational flexibility comparable to hydro plants—can synchronize to the grid within 90 seconds and reach full load less than four minutes after receiving a start signal (Skinner, 2020). The additional maintenance cost penalty for every start and shutdown of the reciprocating engine plants is also very minor. Furthermore, due to its dual-fuel capability (diesel and natural gas), the plant offers electrical security in case of a gas supply breakdown or economic unavailability.

4.7 Conclusion

The NEM is in the midst of a significant transition, with the market witnessing the retirement of the coal-fired generation at a rate two to three times faster than anticipated.

[41] Historically, high-speed spark-ignition engines powered by waste gas or coal seam methane, unsuitable for gas turbines, have been used in multi-unit reciprocating engine installations in the NEM (Aurecon, 2020). One hybrid generation in the form of reciprocating gas engines (72 MW) and battery (12 MW), which operate with greater flexibility and faster start-up speeds than conventional gas reciprocating engines, is expected to be built alongside an existing renewable energy farm in NSW (AER, 2021a).

More VRE is being added to the market to replace the lost output and meet climate change targets (Edis and Bowyer, 2021; AEMO, 2022a). By 2025, 40–50% of NEM generation is anticipated to come from wind and solar energy (Edis and Bowyer, 2021). With the increase in VRE, the role of flexible technologies to support the intermittences in power generation has become more pronounced. Flexible generators can respond in a shorter time-frame and address short-term energy imbalances caused by the variability of wind and solar generation and unplanned outages. The mismatch in dispatch and settlement periods in the NEM had been a challenge to the market. Apart from causing inefficiencies in pricing and strategic bidding behaviours, this mismatch limited entrances of flexible resources, such as fast-response generation or demand-side response. To address this problem, the AEMC introduced the 5MS rule to align prices with the physical operations of the electricity system.

This study sets out a preliminary (given the short time the rule has been in place) investigation of how the NEM responded to the introduction of the 5MS. Specifically, we examine the impact of the 5MS on both spot prices and DWPs received by generators over a period of eight months from 1st October 2021, when the new rule came into action, to 31st May 2022. Despite not having an immediate effect, we find evidence that the introduction of the 5MS results in an increase in the spot price in the NEM eight months after being implemented. When compared to the period in which the 30MS was in place, the dynamics of price volatility remain the same. The study also shows an increasing pattern of DWPs for several generators, including wind, solar, and hydro generators, eight months after the introduction of the new settlement rule. Battery technologies, which are able to provide generation almost instantly, generate more DWPs after the 5MS compared to the period prior. While DWPs for brown coal generators remain unaffected by the 5MS, those for black coal generators increase significantly.[42]

These findings underline the complexity of the NEM and, as noted by the AEMC

[42]We made a significant effort to control potential confounding factors to ensure a robust estimate of the rule change on spot prices and DWPs. We have included a number of relevant control variables from the NEM in our model, including supply, demand, weather, capacity, and gas prices. The only missing variable is coal prices, whose data in the same frequency needed for the analysis are harder to acquire (see discussion on page 43). However, as gas prices are the de facto electricity price-setter even when gas plants are not running due to instances of black coal generators "shadow pricing" gas in their spot market offers, we expect this exclusion to have a moderate impact on estimated coefficients.

(2018), that the challenges in the wholesale market caused by industry structure are unlikely to be resolved by changes to the regulations governing bidding in the NEM. For the 5MS to ultimately translate into affordable electricity for end consumers, policymakers need to focus on resolving the industry's concern in the NEM, namely market concentration. Policies that lower barriers to entry and promote efficient new investment are the keys to ensuring prices reflect market conditions rather than the strategic behaviours of certain generators. Such strategic behaviours are unlikely to be eliminated by changes in market rules. The fact that the rule change puts the financial viability of coal-fired plants to the test increases the likelihood of these generators exiting the market earlier than expected. Ensuring stable energy and climate-change policies to incentivize new investments is becoming increasingly important in the NEM. Finally, the rising input price for gas and coal generation in the domestic market highlights the need for investment in technologies that are both fuel-efficient (to minimize generation costs) and highly flexible (to cope with the settlement in larger time granularities), such as reciprocating engines.

Chapter 5

Conclusion

The advent of VRE has disrupted the design and typical operations of electricity markets globally. In Australia's NEM, the transition from incumbent coal-fired to VRE generation has been associated with the unexpected and sudden (disorderly) exit of coal-fired plants and unprecedented high rates of VRE penetration. With the contribution of variable and unpredictable weather-dependent generation increasing and coal generation as a primary source of "dispatchable" capacity exiting the market, system security and reliability are at stake. New modes of system failure, failing system strength, and non-credible contingent events once thought to be less impactful are increasingly challenging the NEM (Simshauser, 2022).[1] The increases in electricity demand and supply variability following the shift from dispatchable to non-dispatchable capacities has also triggered uncertainty and variability of spot prices. Crucially, these variabilities originate not only from genuine demand and supply conditions but also from generators' strategic exercise of market power.

This thesis examines the impact of the high penetration of VRE in the energy-only markets. Its central focus is electricity spot prices in the NEM, which has attained global VRE penetration rates. We conduct three main studies, the first on wind generation and the dynamics of electricity prices in Australia (Chapter 2), the second on large-scale and rooftop solar generation in the NEM (Chapter 3), and the third, an early evaluation of the move from 30- to 5-minute settlement rules in the NEM (Chapter 4). Several new findings, insights, and policy implications emerge from these studies, which we summarise below.

[1]Non-credible contingencies are power system events that cause very significant disturbances to the supply/demand balance but are considered not reasonably possible in the surrounding circumstances by AEMO. These events may include the simultaneous loss of multiple generators or the loss of interconnection with a neighbouring region as a result of the loss of multiple transmission circuits (AEMC, 2017c).

The results of the study in Chapter 2 demonstrates that wind generation contributes to reducing wholesale electricity prices in the NEM. The impact on price volatility is not consistent across states, that is, wind generation exhibits both negative and positive effects on price volatility. These varying effects reflect states' generation mixes in conjunction with their degree of interconnectedness with other markets. When studying the impact of wind generation on price dynamics over time, we find an increasing MOE and uneven effects on spot price volatility across states. Beyond consumption and gas prices, other drivers of electricity prices in the NEM, such as hydro generation and interconnector flows, also play a significant role in determining price levels and volatility dynamics. Furthermore, we find that the implementation of regulatory interventions, the carbon pricing mechanism, and nationwide lockdown restrictions due to the COVID-19 pandemic had notable impacts on electricity price dynamics. The former regulatory change increased the competitiveness of wind generators. Indeed, we find that during the CPM period, wind generation contributes to reducing prices and marginally increasing price volatility.

The findings in Chapter 3 demonstrate the MOE of both large-scale and rooftop solar generation. This MOE effect is especially acute in the middle of the day, when solar generation is at maximum, resulting in low prices or occasionally even negative prices at these times. In contrast, during the morning and evening peak-demand periods, prices skyrocket as gas and coal-fired power stations benefit from the reduced competition from solar PV. We find that the resulting price increase can more than offset the low-price effect during the middle of the day. Furthermore, this adds to intraday electricity price volatility, which also imposes costs on consumers. Output from solar not only varies during the day, it also varies substantially over different seasons, being typically lower in winter due to lower daylight hours and greater cloud cover. These fluctuations in solar generation account for the increase in variability of electricity prices during winter compared to the other seasons, particularly summer. We note that utility-scale solar output profiles differ from those of rooftop PV over the course of a day. Specifically, utility-scale generation is more evenly spread out over the day compared to rooftop PV output, as utility-scale solar panels rotate to track the sun, while rooftop PV systems are generally fixed in orientation throughout the day. We find that this difference in output profiles leads to differential price impacts: utility-scale solar output reduces price variability, while rooftop solar output increases it. This, in turn, means a greater need to manage the output from rooftop PV.

In Chapter 4, we find that reducing the duration of electricity settlement periods from 30 minutes to 5 minutes to better reflect real-time system conditions has no immediate impact on spot price dynamics. The lack of significant market shake-up following the rule change likely follows the four year lead-up time to the 5MS, which allowed generators to prepare for the change. These preparations included generators upgrading and investing in new fast capacities as well as changing their operational strategies. However, based on the eight months of observation following the rule change, we find profound effects as the market participants slowly adapt to the new settlement rule. We show that the 5MS leads to an increase in the level of spot prices in the NEM. However, the pre- and post-5MS volatility dynamics remain unchanged. Furthermore, the findings suggest the potential for the 5MS to provide incentives for existing generators to fully exploit flexibilities they possess and also provides incentives for new generators who are more flexible. This is especially true for both batteries and gas generators, whose revenue for some states increases significantly after the new rule comes into action. With the new settlement in place, VRE generators return higher revenues than when the 30MS is in place. Furthermore, it appears that the introduction of the 5MS has no adverse effects on the coal-fired generators' spot market revenues. We find that revenues for relatively flexible black-coal-fired generators increase, whereas those for highly inflexible brown coal generators remain unchanged.

Taken together, the findings from this thesis disrupt the conventional view that renewables are either uniformly "bad" or uniformly "good". We find that, renewables generally lower average prices but increase price volatility. As our findings reveal, avoiding increased price volatility while enjoying the benefit of lower prices associated with more renewables, therefore, requires several courses of action, including investments in cost-effective complementary technologies, such as in storage, transmission, and fast-start plant; furthering and changing the design of policies to provide support to solar-plus-battery systems; and transition to dynamic FiTs, flexible solar export mechanisms, and two-sided market reform. Policy changes aiming to support the transition already underway in the NEM should also go hand-in-hand with those aiming to address entry barriers for new technologies and the key industry problem of market concentration. Finally, it is crucial to ensure that climate change and energy policies are appropriately aligned to allow for a smooth transition with minimal electricity security, reliability, and affordability disruptions while maximising emissions reduction. In this way, our findings reveal both the existing benefits of renewables and the investments that policymakers, governments, and private investors can make to seize the opportunities and minimise the threats from additional renewables.

Despite this thesis's thorough investigation of the impact of VRE on spot electricity price dynamics, there are several avenues for further research.

First, climate change policy discontinuity has accounted for much of the dynamics in the NEM over the last decade. Thus, assessing the cost of policy discontinuity is another potential area for policy analysis research. This research could examine the impact of past policy changes, including the carbon pricing as well as an emissions trading scheme and Australia's 20% renewable portfolio standard (RPS), on investment and market outcomes. The research could also examine the economic costs of policy uncertainty, including the effects on business investment and competitiveness. Furthermore, researchers could analyse the potential benefits and costs of implementing more stable and predictable policy frameworks, such as long-term policy targets or more consistent regulatory frameworks.

Second, as the government continues to take a range of initiatives to support energy transition and as new technologies emerge, it would be interesting to conduct further research examining the impact of new reforms and technologies in the NEM. This research could, for instance, involve analysing the potential impacts of proposed changes to the structure and operation of the NEM, such as the introduction of the capacity market mechanisms on the penetration of VRE. Furthermore, the research could investigate the potential impacts of the increased deployment of behind-the-meter energy resources. A comprehensive examination of the increase in demand-side variations due to these resources is fundamental to the NEM's security and reliability.

Third, the analysis in Chapter 4 only provides an initial investigation of how spot prices and spot market revenues respond to the 5MS. Thus, the observed effects likely reflect changes in bidding strategies. New participants may enter the market in the long run with new equipment and services, and existing participants may make changes to their plants. To this end, the impact of the 5MS may vary from that documented in this thesis. Thus, a further study could assess how the 5MS impacts spot prices and market revenues, among other issues, when long-term data become available. More broadly, further research could investigate the impact of the 5MS on generators' revenues by considering all streams of revenues and costs. Such an analysis would provide a broader investment signal to generators than spot market revenues. This research may go in hand with the investigation of the potential impact of battery storage systems, which are increasingly penetrating the market, on the spot electricity prices, ancillary services, and system reliability.

Fourth, since the frequency with which the operator curtails renewable generation has risen markedly in the NEM, another possible area of future research would be to investigate the extent to which solar and wind curtailment impacts the dynamics of electricity prices in this market. Moreover, there is still little understanding of how the high penetration of VRE affects the distribution of electricity prices in the NEM. Only partial evidence of changes in the distribution of spot electricity prices following the increase in VRE exists (Rai and Nunn, 2020b). Given that several players in the market may be interested in understanding the impacts of VRE on the tails of price distributions rather than the central expectations, conducting such an empirical study would be interesting to consumers, suppliers, traders, and regulators in the NEM.

Appendices

Appendix A

Wind generation and the dynamics of electricity prices in Australia

A.1 Data

A.1.1 Preliminary analysis

Table A.1 : **Interconnectors capabilities in the NEM.** Source AEMO (2017)

Interconnector	From	To	Nominal Capacity (MW)
Terranora (N–Q–MNSP1)			
	NSW	QLD	107
	QLD	NSW	210
NSW1–QLD1 (QNI)			
	NSW	QLD	300–600
	QLD	NSW	1078
VIC1–NSW1 (VNI)			
	VIC	NSW	700–1600
	NSW	VIC	400–1350
Basslink (T–V–MNSP1)			
	TAS	VIC	594
	VIC	TAS	478
Heywood (V–SA)			
	VIC	SA	600
	SA	VIC	500
Murraylink (V–S–MNSP1)			
	VIC	SA	220
	SA	VIC	200

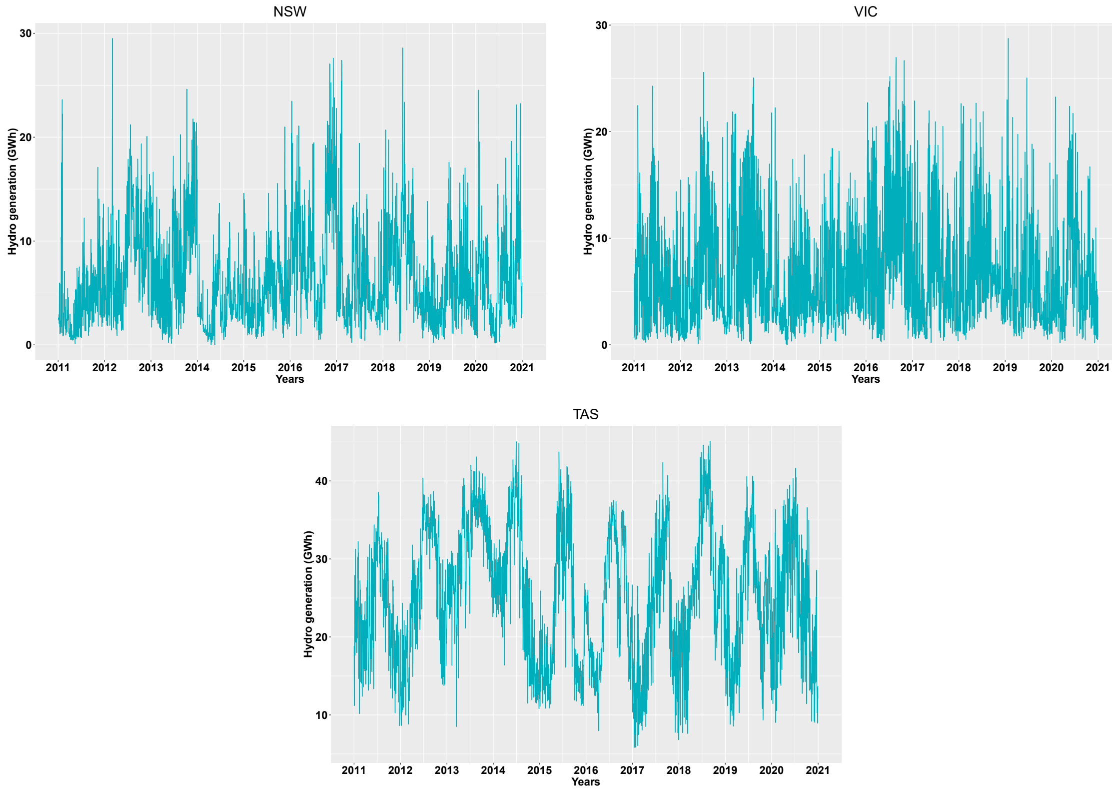

Figure A.1 : **The daily hydro generation for NSW, VIC, and TAS from 2011 to 2020.**

A.1.2 Adjustment of price spikes

We filter outliers using median absolute deviation (MAD) as the dispersion measure and follow Mugele et al. (2005), Bierbrauer et al. (2007), and Ketterer (2014). In particular, we create a time series of the original price series for each weekday to take into account cyclic nature of prices within a week. We then construct the threshold for filtering outliers as $F = \text{med} \pm 3 \cdot MAD$, where med is the median of the weekday prices, and the MAD[1] is defined as

$$MAD_i = b \cdot \text{med}_i(|x_i - \text{med}_j(x_j)|),$$

[1] Leys et al. (2013) noted that median is more robust to outliers compared to arithmetic mean (see also Weron (2007) and Mehrang et al. (2015)). Therefore, MAD and not standard deviation should be used as the measure of dispersion. Furthermore, we set the thresholds to three (described by Leys et al. (2013) as very conservative) in order to include many observations, and it is a typical threshold which is widely applied in the previous literature (Mugele et al., 2005; Bierbrauer et al., 2007; Ketterer, 2014; Bublitz et al., 2017).

where x_j is the weekday electricity price series, med_i is the median of the series, $b = 1.4826$ is a constant defined in the presence of outliers to make the distribution normal (Rousseeuw and Croux, 1993). Any observation surpassing the filter F is classified as an outlier. The number of outlying values identified for each regional market are presented in Table A.2. The total number of outliers in the NEM during the sample period is 656. TAS accounts for around half of the total spikes, and NSW has the lowest number of instances where prices exceeded the limit (12.0% of the total sample spikes). Furthermore, price spikes are more pronounced during business days than at the weekends. All values in Table A.2 are then replaced by the median of the respective weekday (Ketterer, 2014; Kyritsis et al., 2017).

A.1.3 Seasonality and trend adjustments

We assume that the time series v_t can be decomposed as a sum of the stochastic component y_t and the seasonal component s_t, that is, $v_t = y_t + s_t$, $t > 0$ (Bierbrauer et al., 2007; Trueck et al., 2007; Ketterer, 2014; Pereira and Rodrigues, 2015).[2] We then apply the ordinary least squares (OLS) approach by creating dummy variables for the days $(day_i, i = 1, 2, \dots, 7)$ corresponding to Monday to Sunday, months $(month_j, j = 1, 2, \dots, 12)$ corresponding to January to December and years $(year_k, k = 1, 2, \dots, 10)$ corresponding to 2011 to 2020, and specify the OLS as

$$v_t = \hat{c} + \sum_{i=2}^{p} \hat{\phi} \cdot day_i + \sum_{j=2}^{q} \hat{\zeta} \cdot month_j + \sum_{k=2}^{r} \hat{\eta} \cdot year_k + \varepsilon_t, \tag{1.1.1}$$

where v_t is the variable of interest and where applicable adjusted for the outlier effect. p, q and r are the total number of days in a week, months, and years, $\hat{c}$ is the estimate of the intercept, and $\hat{\phi}$, $\hat{\zeta}$, and $\hat{\eta}$ are the parameter estimates of the weekdays, monthly and yearly regressors. The deseasonalised time series of electricity prices and other explanatory variables is captured by the regression residuals ε_t. Similar to Ketterer (2014) we then

[2] In literature, researchers dealt with seasonal effect in different ways. This includes adding seasonal dummies (model seasonality) in the mean equation (Black, 2006; Hickey et al., 2012; Tang et al., 2014; Pereira da Silva and Horta, 2019). In this respect, the seasonal component is explained by dummies, and the GARCH part is free to model deseasonalised volatility. Also, there are those who add dummy variables (or model seasonality) in the variance (Higgs and Worthington (2005)) or both the mean and variance equation (Taylor and Buizza, 2004; Byström, 2005; Castagneto Gissey, 2015; Auer, 2014).

Table A.2 : **Occurrences of extreme spikes in prices by region and weekday.**

Weekday	NSW	SA	VIC	TAS	TOTAL
Monday	10	19	14	48	91
Tuesday	16	19	17	45	97
Wednesday	11	23	20	51	105
Thursday	18	24	23	49	114
Friday	15	27	15	50	107
Saturday	6	17	9	41	73
Sunday	3	13	8	45	69
TOTAL	79	142	106	329	656
	12.0%	21.6%	16.2%	50.2%	100.0%

align the mean of actual and the adjusted series. We apply the OLS approach separately for all the variables prior to fitting the ARX-eGARCHX models. We use the two-stage approach because the inclusion of seasonal dummies together with other explanatory variables in the same ARX-eGARCHX specification creates a complex model. Also, the `rugarch` package, which is employed for our analysis, supports only ARFIMA-GARCH based models (R Core Team, 2019; Ghalanos, 2022). The time series adjusted for seasonal and trend effects are presented in Tables A.3 to A.10.

We specify Monday, January, and the year 2011 in Table A.3 as our reference variables for weekdays, months, and years, respectively. Prices are relatively higher for all regions during workdays, although not statistically significantly different from that of Monday. For SA and VIC, we find some evidence that prices peak on Thursday. On Saturday and Sunday, coefficients are negative and statistically significant for almost all states indicating relatively lower price levels at the end of the week. We also observe variation in electricity prices across months of the year. The results for NSW, SA, and VIC suggest that prices in summer are relatively higher than that of winter and other months. TAS exhibits a slightly different behaviour where prices in autumn, especially March and April, exceed summer month prices.

Table A.3 : **Seasonal and trend adjustment of daily electricity electricity prices not adjusted for price spikes.**

	Estimate	Std. Error	t value	Pr($>\|t\|$)		Estimate	Std. Error	t value	Pr($>\|t\|$)	
	NSW					SA				
Intercept (c)	47.6073	4.6290	10.285	$< 2e-16$	***	66.9387	7.9583	8.411	$< 2e-16$	***
Tuesday	2.2620	3.3448	0.676	0.498904		-4.4759	5.7504	-0.778	0.436405	
Wednesday	2.9759	3.3448	0.890	0.373685		-0.5198	5.7504	-0.090	0.927985	
Thursday	2.7600	3.3448	0.825	0.409336		12.0560	5.7505	2.097	0.036106	*
Friday	5.4810	3.3465	1.638	0.101542		-1.715	8 5.7533	-0.298	0.765547	
Saturday	-4.0684	3.3448	-1.216	0.223931		-17.5694	5.7504	-3.055	0.002265	**
Sunday	-9.2601	3.3448	-2.769	0.005660	**	-20.2125	5.7504	-3.515	0.000445	***
February	4.7362	4.4426	1.066	0.286452		-20.6767	7.6378	-2.707	0.006818	**
March	-16.4139	4.3403	-3.782	0.000158	***	-30.6793	7.4619	-4.111	$4.02e-05$	***
April	-12.1148	4.3763	-2.768	0.005664	**	-31.0975	7.5238	-4.133	$3.66e-05$	***
May	-13.2090	4.3402	-3.043	0.002356	**	-26.6943	7.4618	-3.577	0.000352	***
June	-5.7614	4.3763	-1.316	0.188091		-16.4048	7.5239	-2.180	0.029294	*
July	-9.9458	4.3403	-2.292	0.021990	*	-3.7816	7.4619	-0.507	0.612331	
August	-9.4943	4.3403	-2.187	0.028772	*	-28.9023	7.4619	-3.873	0.000109	***
September	-9.1759	4.3763	-2.097	0.036086	*	-36.1200	7.5238	-4.801	$1.64e-06$	***
October	-9.5963	4.3403	-2.211	0.027098	*	-38.0183	7.4619	-5.095	$3.66e-07$	***
November	-8.1966	4.3763	-1.873	0.061154	.	-36.1464	7.5238	-4.804	$1.62e-06$	***
December	-14.0757	4.3403	-3.243	0.001193	**	-30.0596	7.4619	-4.028	$5.73e-05$	***
2012	4.1226	3.9972	1.031	0.302433		6.7876	6.8720	0.988	0.323358	
2013	14.9797	3.9999	3.745	0.000183	***	34.2397	6.8767	4.979	$6.69e-07$	***
2014	3.8508	3.9999	0.963	0.335754		10.6727	6.8767	1.552	0.120748	
2015	0.2313	3.9999	0.058	0.953891		12.0874	6.8767	1.758	0.078876	.
2016	20.0185	3.9972	5.008	$5.76e-07$	***	43.1616	6.8720	6.281	$3.77e-10$	***
2017	56.5880	3.9999	14.147	$< 2e-16$	***	67.9259	6.8767	9.878	$< 2e-16$	***
2018	43.4120	3.9999	10.853	$< 2e-16$	***	62.4335	6.8767	9.079	$< 2e-16$	***
2019	45.9237	3.9999	11.481	$< 2e-16$	***	61.4855	6.8767	8.941	$< 2e-16$	***
2020	20.9162	3.9972	5.233	1.76e−07	***	5.9766	6.8720	0.870	0.384518	
Multiple R-squared		0.1321					0.09371			
Adjusted R-squared		0.1259					0.08722			
	VIC					TAS				
Intercept (c)	54.777	6.426	8.524	$< 2e-16$	***	39.5702	2.7641	14.316	$< 2e-16$	***
Tuesday	1.515	4.644	0.326	0.744220		0.2412	1.9973	0.121	0.903895	
Wednesday	3.144	4.644	0.677	0.498354		-0.1901	1.9973	-0.095	0.924194	
Thursday	11.138	4.644	2.399	0.016508	*	-0.6423	1.9973	-0.322	0.747794	
Friday	7.297	4.646	1.571	0.116368		-2.5343	1.9983	-1.268	0.204792	
Saturday	-8.095	4.644	-1.743	0.081359	.	-4.8290	1.9973	-2.418	0.015664	*
Sunday	-11.084	4.644	-2.387	0.017037	*	-4.4218	1.9973	-2.214	0.026897	*
February	-27.816	6.168	-4.510	$6.69e-06$	***	2.7989	2.6528	1.055	0.291461	
March	-29.308	6.026	-4.864	$1.20e-06$	***	11.2404	2.5917	4.337	$1.48e-05$	***
April	-31.061	6.076	-5.112	$3.34e-07$	***	6.8538	2.6132	2.623	0.008759	**
May	-28.789	6.026	-4.778	$1.84e-06$	***	-15.6327	2.5917	-6.032	$1.78e-09$	***
June	-20.792	6.076	-3.422	0.000628	***	-12.2236	2.6133	-4.678	$3.01e-06$	***
July	-21.630	6.026	-3.590	0.000336	***	-12.2412	2.5917	-4.723	$2.41e-06$	***
August	-26.062	6.026	-4.325	$1.57e-05$	***	-21.4276	2.5917	-8.268	$< 2e-16$	***
September	-28.887	6.076	-4.755	$2.07e-06$	***	-22.6599	2.6132	-8.671	$< 2e-16$	***
October	-31.514	6.026	-5.230	$1.79e-07$	***	-13.9449	2.5917	-5.381	$7.90e-08$	***
November	-29.763	6.076	-4.899	$1.01e-06$	***	-9.7389	2.6132	-3.727	0.000197	***
December	-36.102	6.026	-5.991	$2.28e-09$	***	-14.9466	2.5917	-5.767	$8.74e-09$	***
2012	15.042	5.549	2.711	0.006748	**	12.6821	2.3868	5.313	$1.14e-07$	***
2013	23.463	5.553	4.225	$2.45e-05$	***	17.0524	2.3885	7.139	$1.13e-12$	***
2014	12.218	5.553	2.200	0.027853	*	9.7929	2.3885	4.100	$4.22e-05$	***
2015	4.440	5.553	0.800	0.424027		18.3135	2.3885	7.667	$2.24e-14$	***
2016	18.047	5.549	3.252	0.001156	**	66.6404	2.3868	27.920	$< 2e-16$	***
2017	62.859	5.553	11.320	$< 2e-16$	***	68.9337	2.3885	28.861	$< 2e-16$	***
2018	61.067	5.553	10.997	$< 2e-16$	***	44.4999	2.3885	18.631	$< 2e-16$	***
2019	79.968	5.553	14.401	$< 2e-16$	***	64.8009	2.3885	27.131	$< 2e-16$	***
2020	22.464	5.549	4.048	$5.27e-05$	***	13.7535	2.3868	5.762	$8.99e-09$	***
Multiple R-squared		0.1279					0.4233			
Adjusted R-squared		0.1217					0.4192			

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.4 : **Seasonal and trend adjustment of daily electricity prices adjusted for the outliers effect.** The threshold is set at 3×MAD.

	Estimate	Std. Error	t value	Pr(> $\|t\|$)		Estimate	Std. Error	t value	Pr(> $\|t\|$)	
	NSW					SA				
Intercept (c)	27.77085	1.15836	23.974	$< 2e-16$	***	29.9352	1.9921	15.027	$< 2e-16$	***
Tuesday	0.21815	0.83699	0.261	0.794390		0.5502	1.4394	0.382	0.702315	
Wednesday	1.47405	0.83700	1.761	0.078304	.	0.1559	1.4394	0.108	0.913783	
Thursday	0.53888	0.83701	0.644	0.519738		-0.5826	1.4394	-0.405	0.685700	
Friday	-0.01886	0.83742	-0.023	0.982037		-2.5092	1.4401	-1.742	0.081541	.
Saturday	-4.01035	0.83700	-4.791	$1.72e-06$	***	-9.4427	1.4394	-6.560	$6.14e-11$	***
Sunday	-6.31038	0.83700	-7.539 5	$.94e-14$	***	-10.3888	1.4394	-7.217	$6.43e-13$	***
February	1.23469	1.11172	1.111	0.266807		2.7145	1.9119	1.420	0.155756	
March	-0.80843	1.08611	-0.744	0.456724		-1.2830	1.8678	-0.687	0.492202	
April	3.56385	1.09512	3.254	0.001147	**	2.8630	1.8833	1.520	0.128555	
May	2.76219	1.08610	2.543	0.011025	*	5.5607	1.8678	2.977	0.002929	**
June	5.72896	1.09513	5.231	$1.78e-07$	***	13.9039	1.8833	7.383	$1.92e-13$	***
July	5.43525	1.08610	5.004	$5.87e-07$	***	11.8996	1.8678	6.371	$2.12e-10$	***
August	5.88711	1.08611	5.420 6	$.34e-08$	***	6.5853	1.8678	3.526	0.000428	***
September	3.59929	1.09512	3.287	0.001024	**	1.1351	1.8833	0.603	0.546744	
October	4.81855	1.08610	4.437	$9.41e-06$	***	-1.5830	1.8678	-0.848	0.396761	
November	3.92508	1.09512	3.584	0.000343	***	0.5354	1.8833	0.284	0.776195	
December	-1.08163	1.08611	-0.996	0.319378		-1.9025	1.8678	-1.019	0.308495	
2012	13.53249	1.00025	13.529	$< 2e-16$	***	13.6956	1.7202	7.962	$2.25e-15$	***
2013	23.67703	1.00093	23.655	$< 2e-16$	***	32.6887	1.7213	18.990	$< 2e-16$	***
2014	13.23470	1.00093	13.222	$< 2e-16$	***	15.4360	1.7213	8.967	$< 2e-16$	***
2015	7.91856	1.00093	7.911	$3.36e-15$	***	15.9165	1.7213	9.247	$< 2e-16$	***
2016	25.25879	1.00025	25.253	$< 2e-16$	***	28.0182	1.7202	16.288	$< 2e-16$	***
2017	56.90303	1.00093	56.850	$< 2e-16$	***	59.2031	1.7213	34.393	$< 2e-16$	***
2018	49.97781	1.00093	49.931	$< 2e-16$	***	56.4374	1.7213	32.787	$< 2e-16$	***
2019	48.58219	1.00093	48.537	$< 2e-16$	***	48.9411	1.7213	28.432	$< 2e-16$	***
2020	18.40805	1.00025	18.403	$< 2e-16$	***	9.2211	1.7202	5.361	$8.81e-08$	***
Multiple R-squared		0.6618					0.4463			
Adjusted R-squared		0.6593					0.4423			
	VIC					TAS				
Intercept (c)	23.1946	1.4541	15.951	$< 2e-16$	***	34.4352	1.5599	22.075	$< 2e-16$	***
Tuesday	1.2407	1.0507	1.181	0.237751		0.8438	1.1272	0.749	0.454152	
Wednesday	1.2354	1.0507	1.176	0.239769		-0.1721	1.1272	-0.153	0.878622	
Thursday	0.3936	1.0507	0.375	0.707989		-0.2668	1.1272	-0.237	0.812874	
Friday	0.3385	1.0512	0.322	0.747463		-1.8524	1.1277	-1.643	0.100554	
Saturday	-6.0822	1.0507	-5.789	$7.70e-09$	***	-3.0587	1.1272	-2.714	0.006687	**
Sunday	-8.9482	1.0507	-8.516	$< 2e-16$	***	-3.0371	1.1272	-2.694	0.007082	**
February	4.3058	1.3956	3.085	0.002049	**	-2.6267	1.4971	-1.754	0.079434	.
March	3.4995	1.3634	2.567	0.010308	*	-4.7614	1.4626	-3.255	0.001143	**
April	5.9295	1.3748	4.313	$1.65e-05$	***	-8.6995	1.4748	-5.899	$3.99e-09$	***
May	7.6400	1.3634	5.603	$2.26e-08$	***	-5.5347	1.4626	-3.784	0.000157	***
June	13.3955	1.3748	9.744	$< 2e-16$	***	-1.2269	1.4748	-0.832	0.405494	
July	12.7314	1.3634	9.338	$< 2e-16$	***	-3.3921	1.4626	-2.319	0.020441	*
August	8.7030	1.3634	6.383	$1.96e-10$	***	-7.5002	1.4626	-5.128	$3.08e-07$	***
September	5.1138	1.3748	3.720	0.000202	***	-10.2939	1.4748	-6.980	$3.49e-12$	***
October	5.0641	1.3634	3.714	0.000207	***	-2.8044	1.4626	-1.917	0.055271	.
November	5.3195	1.3748	3.869	0.000111	***	3.0099	1.4748	2.041	0.041327	*
December	-0.8234	1.3634	-0.604	0.545947		-1.2011	1.4626	-0.821	0.411606	
2012	14.2625	1.2557	11.359	$< 2e-16$	***	11.8621	1.3470	8.806	$< 2e-16$	***
2013	24.1678	1.2565	19.234	$< 2e-16$	***	15.6946	1.3479	11.644	$< 2e-16$	***
2014	12.2323	1.2565	9.735	$< 2e-16$	***	9.4192	1.3479	6.988	3.31e−12	***
2015	6.1406	1.2565	4.887	$1.07e-06$	***	17.3413	1.3479	12.865	$< 2e-16$	***
2016	17.0420	1.2557	13.572	$< 2e-16$	***	18.2503	1.3470	13.549	$< 2e-16$	***
2017	58.3910	1.2565	46.471	$< 2e-1$	***	48.2964	1.3479	35.830	$< 2e-16$	***
2018	54.8858	1.2565	43.681	$< 2e-16$	***	39.0154	1.3479	28.945	$< 2e-16$	***
2019	54.8438	1.2565	43.648	$< 2e-16$	***	37.4846	1.3479	27.809	$< 2e-16$	***
2020	16.6902	1.2557	13.292	$< 2e-16$	***	12.8234	1.3470	9.520	$< 2e-16$	***
Multiple R-squared		0.6164					0.4189			
Adjusted R-squared		0.6136					0.4144			

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.5 : **Seasonal and trend adjustment of daily gas prices.**

	Estimate	Std. Error	t value	$\Pr(>\|t\|)$		Estimate	Std. Error	t value	$\Pr(>\|t\|)$	
	NSW					SA				
Intercept (c)	2.70131	0.13587	19.882	$< 2e-16$	***	3.34836	0.11951	28.018	$< 2e-16$	***
Tuesday	0.06906	0.09817	0.703	0.481844		0.10426	0.08635	1.207	0.22738	
Wednesday	0.06935	0.09817	0.706	0.479992		0.16950	0.08635	1.963	0.04973	*
Thursday	0.10123	0.09817	1.031	0.302535		0.10016	0.08635	1.160	0.24618	
Friday	0.01162	0.09822	0.118	0.905872		0.06355	0.08640	0.736	0.46208	
Saturday	-0.32176	0.09817	-3.277	0.001057	**	-0.13945	0.08635	-1.615	0.10642	
Sunday	-0.35744	0.09817	-3.641	0.000275	***	-0.20355	0.08635	-2.357	0.01847	*
February	0.31161	0.13040	2.390	0.016912	*	0.30349	0.11470	2.646	0.00818	**
March	0.11807	0.12739	0.927	0.354098		0.03175	0.11205	0.283	0.77692	
April	-0.12092	0.12845	-0.941	0.346585		-0.11890	0.11298	-1.052	0.29271	
May	0.22445	0.12739	1.762	0.078171	.	0.15888	0.11205	1.418	0.15630	
June	1.19943	0.12845	9.338	$< 2e-16$	***	0.84224	0.11298	7.455	$1.12e-13$	***
July	1.06018	0.12739	8.322	$< 2e-16$	***	1.59259	0.11205	14.213	$< 2e-16$	***
August	0.61723	0.12739	4.845	$1.32e-06$	***	0.50203	0.11205	4.480	$7.68e-06$	***
September	0.07790	0.12845	0.606	0.544229		-0.11576	0.11298	-1.025	0.30565	
October	-0.16232	0.12739	-1.274	0.202684		-0.27502	0.11205	-2.454	0.01416	*
November	-0.15087	0.12845	-1.175	0.240239		-0.07337	0.11298	-0.649	0.51612	
December	-0.17514	0.12739	-1.375	0.169268		0.44358	0.11205	3.959	7.68e-05	***
2012	1.88332	0.11732	16.053	$< 2e-16$	***	0.87855	0.10320	8.514	$< 2e-16$	***
2013	1.57952	0.11740	13.454	$< 2e-16$	***	1.09048	0.10327	10.560	$< 2e-16$	***
2014	0.55991	0.11740	4.769	$1.92e-06$	***	0.13048	0.10327	1.264	0.20648	
2015	1.21127	0.11740	10.317	$< 2e-16$	***	0.94911	0.10327	9.191	$< 2e-16$	***
2016	3.22800	0.11732	27.514	$< 2e-16$	***	3.70008	0.10320	35.855	$< 2e-16$	***
2017	6.16864	0.11740	52.543	$< 2e-16$	***	4.79688	0.10327	46.452	$< 2e-16$	***
2018	6.57364	0.11740	55.993	$< 2e-16$	***	5.45174	0.10327	52.793	$< 2e-16$	***
2019	6.11979	0.11740	52.127	$< 2e-16$	***	5.81457	0.10327	56.307	$< 2e-16$	***
2020	2.19804	0.11732	18.735	$< 2e-16$	***	2.04051	0.10320	19.773	$< 2e-16$	***
Multiple R-squared		0.6953					0.7206			
Adjusted R-squared		0.6931					0.7186			

	Estimate	Std. Error	t value	$\Pr(>\|t\|)$	
	VIC				
Intercept (c)	2.635577	0.123363	21.364	$< 2e-16$	***
Tuesday	0.055414	0.089138	0.622	0.534204	
Wednesday	0.083077	0.089139	0.932	0.351402	
Thursday	0.109653	0.089140	1.230	0.218730	
Friday	-0.080001	0.089183	-0.897	0.369758	
Saturday	-0.149149	0.089139	-1.673	0.094369	.
Sunday	-0.165231	0.089138	-1.854	0.063870	.
February	0.313076	0.118395	2.644	0.008221	**
March	0.016377	0.115669	0.142	0.887416	
April	0.003715	0.116628	0.032	0.974588	
May	0.446048	0.115667	3.856	0.000117	***
June	1.003785	0.116629	8.607	$< 2e-16$	***
July	1.255848	0.115668	10.857	$< 2e-16$	***
August	0.424703	0.115668	3.672	0.000244	***
September	-0.060977	0.116628	-0.523	0.601125	
October	-0.050940	0.115667	-0.440	0.659674	
November	-0.129244	0.116628	-1.108	0.267859	
December	0.039149	0.115669	0.338	0.735035	
2012	1.067008	0.106524	10.017	$< 2e-16$	***
2013	1.154784	0.106597	10.833	$< 2e-16$	***
2014	0.579980	0.106597	5.441	$5.65e-08$	***
2015	0.958528	0.106597	8.992	$< 2e-16$	***
2016	3.574302	0.106524	33.554	$< 2e-16$	***
2017	5.677715	0.106597	53.264	$< 2e-16$	***
2018	6.066362	0.106597	56.909	$< 2e-16$	***
2019	5.869376	0.106597	55.062	$< 2e-16$	***
2020	2.156902	0.106524	20.248	$< 2e-16$	***
Multiple R-squared		0.7291			
Adjusted R-squared		0.7270			

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.6 : **Seasonal and trend adjustment of daily electricity consumption.**

	Estimate	Std. Error	t value	Pr($>|t|$)		Estimate	Std. Error	t value	Pr($>|t|$)	
	NSW					SA				
Intercept (c)	219841.1	961.1	228.748	$< 2e-16$	***	38850.5	355.4	109.312	$< 2e-16$	***
Tuesday	2968.5	694.4	4.275	$1.96e-05$	***	705.4	256.8	2.747	0.006046	**
Wednesday	2081.7	694.4	2.998	0.002739	**	807.3	256.8	3.144	0.001682	**
Thursday	2687.3	694.4	3.870	0.000111	***	922.7	256.8	3.593	0.000332	***
Friday	1577.8	694.8	2.271	0.023206	*	280.2	256.9	1.091	0.275482	
Saturday	-12639.8	694.4	-18.202	$< 2e-16$	***	-3115.3	256.8	-12.131	$< 2e-16$	***
Sunday	-17628.6	694.4	-25.386	$< 2e-16$	***	-4061.3	256.8	-15.814	$< 2e-16$	***
February	-730.8	922.4	-0.792	0.428198		98.4	341.1	0.288	0.773002	
March	-10458.9	901.1	-11.607	$< 2e-16$	***	-2674.9	333.2	-8.027	$1.34e-15$	***
April	-20064.7	908.6	-22.083	$< 2e-16$	***	-4420.0	336.0	-13.155	$< 2e-16$	***
May	-6742.9	901.1	-7.483	$9.07e-14$	***	-2423.8	333.2	-7.273	$4.27e-13$	***
June	8785.8	908.6	9.670	$< 2e-16$	***	761.0	336.0	2.265	0.023585	*
July	10856.6	901.1	12.048	$< 2e-16$	***	632.6	333.2	1.898	0.057749	.
August	2046.6	901.1	2.271	0.023191	*	-690.4	333.2	-2.072	0.038350	*
September	-16272.0	908.6	-17.909	$< 2e-16$	***	-4624.2	336.0	-13.762	$< 2e-16$	***
October	-22796.5	901.1	-25.298	$< 2e-16$	***	-6130.6	333.2	-18.397	$< 2e-16$	***
November	-17406.8	908.6	-19.158	$< 2e-16$	***	-4792.0	336.0	-14.262	$< 2e-16$	***
December	-15201.2	901.1	-16.869	$< 2e-16$	***	-3641.9	333.2	-10.929	$< 2e-16$	***
2012	-11411.2	829.9	-13.750	$< 2e-16$	***	-419.8	306.9	-1.368	0.171481	
2013	-17962.9	830.4	-21.631	$< 2e-16$	***	-1644.3	307.1	-5.354	$9.12e-08$	***
2014	-19490.9	830.4	-23.471	$< 2e-16$	***	-2203.0	307.1	-7.173	$8.82e-13$	***
2015	-18005.6	830.4	-21.682	$< 2e-16$	***	-2318.4	307.1	-7.549	$5.51e-14$	***
2016	-18036.8	829.9	-21.734	$< 2e-16$	***	-3660.3	306.9	-11.927	$< 2e-16$	***
2017	-16171.7	830.4	-19.474	$< 2e-16$	***	-4141.2	307.1	-13.485	$< 2e-16$	***
2018	-17514.4	830.4	-21.090	$< 2e-16$	***	-4757.7	307.1	-15.492	$< 2e-16$	***
2019	-18371.8	830.4	-22.123	$< 2e-16$	***	-4561.9	307.1	-14.854	$< 2e-16$	***
2020	-24517.6	829.9	-29.544	$< 2e-16$	***	-5800.5	306.9	-18.901	$< 2e-16$	***
Multiple R-squared		0.6368					0.4195			
Adjusted R-squared		0.6342					0.4153			
	VIC					TAS				
Intercept (c)	140373.0	766.0	183.250	$< 2e-16$	***	26295.66	122.46	214.723	$< 2e-16$	***
Tuesday	2568.5	553.5	4.640	$3.60e-06$	***	-33.35	88.49	-0.377	0.706258	
Wednesday	2910.0	553.5	5.257	$1.55e-07$	***	-222.78	88.49	-2.518	0.011858	*
Thursday	3445.9	553.5	6.225	$5.35e-10$	***	-138.85	88.49	-1.569	0.116719	
Friday	1639.2	553.8	2.960	0.00310	**	-268.94	88.53	-3.038	0.002401	**
Saturday	-11735.9	553.5	-21.203	$< 2e-16$	***	-1176.74	88.49	-13.298	$< 2e-16$	***
Sunday	-15798.9	553.5	-28.544	$< 2e-16$	***	-1217.57	88.49	-13.760	$< 2e-16$	***
February	2095.7	735.2	2.851	0.00439	**	-87.69	117.53	-0.746	0.455672	
March	-2904.6	718.2	-4.044	$5.36e-05$	***	-499.95	114.83	-4.354	$1.37e-05$	***
April	-7067.2	724.2	-9.759	$< 2e-16$	***	749.34	115.78	6.472	$1.09e-10$	***
May	1847.7	718.2	2.573	0.01013	*	2683.30	114.82	23.369	$< 2e-16$	***
June	10260.5	724.2	14.168	$< 2e-16$	***	4532.66	115.78	39.150	$< 2e-16$	***
July	10333.3	718.2	14.387	$< 2e-16$	***	4728.33	114.82	41.179	$< 2e-16$	***
August	6480.1	718.2	9.022	$< 2e-16$	***	3951.23	114.82	34.411	$< 2e-16$	***
September	-3327.1	724.2	-4.594	$4.49e-06$	***	2147.97	115.78	18.552	$< 2e-16$	***
October	-8009.2	718.2	-11.151	$< 2e-16$	***	759.05	114.82	6.611	$4.39e-11$	***
November	-7495.0	724.2	-10.349	$< 2e-16$	***	484.44	115.78	4.184	$2.93e-05$	***
December	-8710.7	718.2	-12.128	$< 2e-16$	***	-444.99	114.83	-3.875	0.000108	***
2012	-1603.3	661.5	-2.424	0.01541	*	-1071.85	105.75	-10.136	$< 2e-16$	***
2013	-5131.7	661.9	-7.753	$1.16e-14$	***	-350.51	105.82	-3.312	0.000934	***
2014	-9629.3	661.9	-14.548	$< 2e-16$	***	-818.67	105.82	-7.737	$1.32e-14$	***
2015	-12747.0	661.9	-19.258	$< 2e-16$	***	-136.15	105.82	-1.287	0.198322	
2016	-15405.2	661.5	-23.290	$< 2e-16$	***	-1880.11	105.75	-17.779	$< 2e-16$	***
2017	-18410.7	661.9	-27.815	$< 2e-16$	***	-421.90	105.82	-3.987	6.82e−05	***
2018	-18596.5	661.9	-28.095	$< 2e-16$	***	38.79	105.82	0.367	0.713959	
2019	-19474.7	661.9	-29.422	$< 2e-16$	***	-1096.72	105.82	-10.364	$< 2e-16$	***
2020	-23080.4	661.5	-34.893	$< 2e-16$	***	-938.39	105.75	-8.874	$< 2e-16$	***
Multiple R-squared		0.6619					0.6685			
Adjusted R-squared		0.6594					0.6662			

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.7 : **Seasonal and trend adjustment of daily wind generation.**

	Estimate	Std. Error	t value	Pr(> |t|)		Estimate	Std. Error	t value	Pr(> |t|)	
	NSW					SA				
Intercept (c)	646.87	311.06	2.080	0.037634	*	8920.62	602.63	14.803	$< 2e-16$	***
Tuesday	-17.38	224.76	-0.077	0.938379		-34.83	435.44	-0.080	0.936257	
Wednesday	-147.20	224.76	-0.655	0.512570		61.56	435.44	0.141	0.887578	
Thursday	-208.28	224.76	-0.927	0.354157		141.18	435.45	0.324	0.745785	
Friday	103.83	224.87	0.462	0.644296		-25.37	435.66	-0.058	0.953569	
Saturday	122.51	224.76	0.545	0.585745		-329.01	435.44	-0.756	0.449946	
Sunday	-51.64	224.76	-0.230	0.818310		-211.83	435.44	-0.486	0.626660	
February	415.29	298.53	1.391	0.164273		-961.35	578.36	-1.662	0.096558	.
March	137.02	291.66	0.470	0.638531		-1043.90	565.04	-1.847	0.064759	.
April	-135.66	294.07	-0.461	0.644597		-1896.62	569.72	-3.329	0.000880	***
May	1070.98	291.65	3.672	0.000244	***	355.33	565.03	0.629	0.529478	
June	582.11	294.08	1.979	0.047839	*	-307.55	569.73	-0.540	0.589351	
July	2116.74	291.65	7.258	$4.79e-13$	***	2456.98	565.03	4.348	$1.41e-05$	***
August	2526.55	291.65	8.663	$< 2e-16$	***	2340.84	565.04	4.143	$3.51e-05$	***
September	2115.29	294.08	7.193	$7.66e-13$	***	1816.34	569.73	3.188	0.001444	**
October	1316.32	291.65	4.513	$6.58e-06$	***	767.74	565.03	1.359	0.174308	
November	1400.36	294.07	4.762	$1.99e-06$	***	12.16	569.72	0.021	0.982974	
December	1585.30	291.66	5.436	$5.82e-08$	***	267.44	565.04	0.473	0.636015	
2012	159.87	268.60	0.595	0.551733		820.46	520.37	1.577	0.114955	
2013	474.41	268.78	1.765	0.077643	.	1140.69	520.72	2.191	0.028544	*
2014	864.70	268.78	3.217	0.001306	**	1974.98	520.72	3.793	0.000151	***
2015	2913.16	268.78	10.838	$< 2e-16$	***	2355.29	520.72	4.523	$6.29e-06$	***
2016	3826.30	268.60	14.245	$< 2e-16$	***	3270.50	520.37	6.285	$3.67e-10$	***
2017	3501.15	268.78	13.026	$< 2e-16$	***	4180.13	520.72	8.028	$1.33e-15$	***
2018	6688.73	268.78	24.885	$< 2e-16$	***	6396.72	520.72	12.284	$< 2e-16$	***
2019	10192.38	268.78	37.921	$< 2e-16$	***	6379.03	520.72	12.250	$< 2e-16$	***
2020	10731.79	268.60	39.955	$< 2e-16$	***	6784.11	520.37	13.037	$< 2e-16$	***
Multiple R-squared	0.5388					0.1298				
Adjusted R-squared	0.5355					0.1236				

	Estimate	Std. Error	t value	Pr(> |t|)		Estimate	Std. Error	t value	Pr(> |t|)	
	VIC					TAS				
Intercept (c)	1874.299	530.282	3.535	0.000414	***	972.29	145.34	6.690	$2.58e-11$	***
Tuesday	-48.064	383.164	-0.125	0.900183		76.08	105.02	0.724	0.468853	
Wednesday	-370.068	383.166	-0.966	0.334200		11.74	105.02	0.112	0.910997	
Thursday	130.419	383.171	0.340	0.733599		80.57	105.02	0.767	0.443042	
Friday	-9.971	383.357	-0.026	0.979251		102.10	105.07	0.972	0.331266	
Saturday	89.257	383.166	0.233	0.815817		162.74	105.02	1.550	0.121318	
Sunday	-52.855	383.165	-0.138	0.890294		78.36	105.02	0.746	0.455662	
February	-139.972	508.928	-0.275	0.783307		15.24	139.49	0.109	0.913010	
March	216.192	497.208	0.435	0.663725		-215.93	136.28	-1.584	0.113178	
April	-628.150	501.331	-1.253	0.210299		-289.46	137.41	-2.107	0.035222	*
May	2043.532	497.200	4.110	$4.04e-05$	***	212.27	136.28	1.558	0.119412	
June	565.851	501.334	1.129	0.259103		85.17	137.41	0.620	0.535431	
July	3727.897	497.203	7.498	$8.12e-14$	***	499.69	136.28	3.667	0.000249	***
August	3529.169	497.206	7.098	$1.52e-12$	***	398.32	136.28	2.923	0.003490	**
September	2853.214	501.333	5.691	$1.36e-08$	***	670.12	137.41	4.877	$1.12e-06$	***
October	2344.784	497.202	4.716	$2.50e-06$	***	477.56	136.28	3.504	0.000463	***
November	1554.795	501.331	3.101	0.001941	**	569.94	137.41	4.148	$3.43e-05$	***
December	1607.949	497.208	3.234	0.001232	**	611.79	136.28	4.489	$7.37e-06$	***
2012	866.618	457.899	1.893	0.058491	.	-21.42	125.51	-0.171	0.864510	
2013	3760.717	458.211	8.207	$3.11e-16$	***	980.93	125.59	7.811	$7.40e-15$	***
2014	3629.360	458.211	7.921	$3.11e-15$	***	1296.36	125.59	10.322	$< 2e-16$	***
2015	5279.673	458.211	11.522	$< 2e-16$	***	1422.83	125.59	11.329	$< 2e-16$	***
2016	6170.641	457.898	13.476	$< 2e-16$	***	1764.23	125.50	14.057	$< 2e-16$	***
2017	6347.340	458.211	13.852	$< 2e-16$	***	1565.28	125.59	12.463	$< 2e-16$	***
2018	8583.647	458.211	18.733	$< 2e-16$	***	1691.99	125.59	13.472	$< 2e-16$	***
2019	10651.400	458.211	23.246	$< 2e-16$	***	2000.65	125.59	15.930	$< 2e-16$	***
2020	14196.834	457.899	31.004	$< 2e-16$	***	2867.39	125.51	22.847	$< 2e-16$	***
Multiple R-squared	0.3324					0.2174				
Adjusted R-squared	0.3276					0.2118				

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.8 : **Seasonal and trend adjustment of aggregated hydro generation.**

	Estimate	Std. Error	t value	$\Pr(>\|t\|)$		Estimate	Std. Error	t value	$\Pr(>\|t\|)$	
	NSW					VIC				
Intercept (c)	4756.35	334.90	14.202	$< 2e-16$	***	6641.9	359.7	18.466	$< 2e-16$	***
Tuesday	129.00	241.99	0.533	0.594014		646.0	259.9	2.486	0.012979	*
Wednesday	-12.07	241.99	-0.050	0.960212		510.0	259.9	1.962	0.049807	*
Thursday	120.47	241.99	0.498	0.618627		455.7	259.9	1.753	0.079649	.
Friday	-105.82	242.11	-0.437	0.662092		-178.2	260.0	-0.685	0.493136	
Saturday	-2546.96	241.99	-10.525	$< 2e-16$	***	-4612.1	259.9	-17.745	$< 2e-16$	***
Sunday	-2838.97	241.99	-11.732	$< 2e-1$	6 ***	-5072.3	259.9	-19.516	$< 2e-16$	***
February	-115.77	321.41	-0.360	0.718725		685.5	345.2	1.986	0.047146	*
March	-899.44	314.01	-2.864	0.004203	**	-398.8	337.3	-1.183	0.237063	
April	-1782.74	316.62	-5.631	$1.93e-08$	***	-785.2	340.1	-2.309	0.020990	*
May	-1078.03	314.01	-3.433	0.000603	***	2317.8	337.2	6.873	$7.39e-12$	***
June	1796.36	316.62	5.674	1.51e-08	***	4120.3	340.1	12.117	$< 2e-16$	***
July	767.54	314.01	2.444	0.014560	*	3509.4	337.2	10.406	$< 2e-16$	***
August	822.36	314.01	2.619	0.008859	**	2398.7	337.2	7.113	$1.37e-12$	***
September	221.34	316.62	0.699	0.484540		1265.0	340.1	3.720	0.000202	***
October	1278.34	314.01	4.071	$4.78e-05$	***	651.9	337.2	1.933	0.053324	.
November	1406.66	316.62	4.443	$9.15e-06$	***	-692.6	340.1	-2.037	0.041752	*
December	1644.25	314.01	5.236	$1.73e-07$	***	-1079.8	337.3	-3.202	0.001379	**
2012	4770.80	289.19	16.497	$< 2e-16$	***	420.4	310.6	1.354	0.175918	
2013	3725.30	289.38	12.873	$< 2e-16$	***	2484.6	310.8	7.994	$1.74e-15$	***
2014	-497.54	289.38	-1.719	0.085642	.	-1292.1	310.8	-4.157	3.30e-05	***
2015	782.18	289.38	2.703	0.006906	**	659.3	310.8	2.121	0.033965	*
2016	5616.20	289.19	19.421	$< 2e-16$	***	4400.5	310.6	14.168	$< 2e-16$	***
2017	1070.53	289.38	3.699	0.000219	***	86.5	310.8	0.278	0.780783	
2018	3582.50	289.38	12.380	$< 2e-16$	***	1220.4	310.8	3.927	$8.78e-05$	***
2019	851.96	289.38	2.944	0.003260	**	-609.0	310.8	-1.959	0.050154	.
2020	2066.45	289.19	7.146	$1.08e-12$	***	104.9	310.6	0.338	0.735673	
Multiple R-squared			0.3067					0.3786		
Adjusted R-squared			0.3018					0.3741		

	Estimate	Std. Error	t value	$\Pr(>\|t\|)$	
	TAS				
Intercept (c)	18021.4	469.3	38.403	$< 2e-16$	***
Tuesday	198.7	347.6	0.572	0.567550	
Wednesday	144.8	347.6	0.417	0.677007	
Thursday	439.6	347.6	1.265	0.206070	
Friday	256.9	347.7	0.739	0.460090	
Saturday	-2404.1	347.6	-6.917	$5.44e-12$	***
Sunday	-3181.9	347.6	-9.155	$< 2e-16$	***
February	-449.7	461.7	-0.974	0.330040	
March	-1325.8	451.0	-2.940	0.003307	**
April	3141.5	454.8	6.908	$5.78e-12$	***
May	7786.2	451.0	17.264	$< 2e-16$	***
June	11836.2	454.8	26.027	$< 2e-16$	***
July	13747.0	451.0	30.480	$< 2e-16$	***
August	12931.6	451.0	28.672	$< 2e-16$	***
September	9210.3	454.8	20.253	$< 2e-16$	***
October	5160.3	451.0	11.441	$< 2e-16$	***
November	1896.9	454.8	4.171	$3.10e-05$	***
December	171.7	451.0	0.381	0.703496	
2012	2704.3	415.4	6.511	$8.52e-11$	***
2013	8657.5	415.6	20.829	$< 2e-16$	***
2014	3564.6	415.6	8.576	$< 2e-16$	***
2015	-235.4	415.6	-0.566	0.571127	
2016	1212.4	415.4	2.919	0.003534	**
2017	-1484.2	415.6	-3.571	0.000361	***
2018	4782.4	415.6	11.506	$< 2e-16$	***
2019	540.6	415.6	1.301	0.193437	
2020	1192.9	415.4	2.872	0.004102	**
Multiple R-squared			0.5508		
Adjusted R-squared			0.5476		

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.9 : **Seasonal and trend adjustment of daily cross-boarder interconnectors flows.**

	Estimate	Std. Error	t value	Pr(> |t|)		Estimate	Std. Error	t value	Pr(> |t|)	
	Basslink					Heywood				
Intercept (c)	-3617.39	431.32	-8.387	$< 2e-16$	***	3730.086	350.409	10.645	$< 2e-16$	***
Tuesday	327.60	311.66	1.051	0.293257		-54.315	253.194	-0.215	0.830154	
Wednesday	401.09	311.66	1.287	0.198190		-184.553	253.195	-0.729	0.466112	
Thursday	636.91	311.66	2.044	0.041064	*	-162.756	253.198	-0.643	0.520396	
Friday	548.99	311.81	1.761	0.078384	.	-238.941	253.322	-0.943	0.345626	
Saturday	-1202.49	311.66	-3.858	0.000116	***	-193.369	253.195	-0.764	0.445086	
Sunday	-1998.51	311.66	-6.413	$1.62e-10$	***	-235.557	253.195	-0.930	0.352258	
February	305.10	413.95	0.737	0.461148		-8.272	336.298	-0.025	0.980378	
March	-552.82	404.42	-1.367	0.171719		-48.357	328.554	-0.147	0.882997	
April	2245.82	407.77	5.508	$3.89e-08$	***	720.440	331.278	2.175	0.029715	*
May	3781.45	404.41	9.351	$< 2e-16$	***	123.797	328.549	0.377	0.706345	
June	5377.43	407.77	13.187	$< 2e-16$	***	909.315	331.280	2.745	0.006084	**
July	6761.32	404.41	16.719	$< 2e-16$	***	-1146.048	328.551	-3.488	0.000492	***
August	6277.10	404.41	15.521	$< 2e-16$	***	-456.310	328.553	-1.389	0.164964	
September	4776.01	407.77	11.712	$< 2e-16$	***	-1372.781	331.279	-4.144	$3.49e-05$	***
October	2064.93	404.41	5.106	$3.46e-07$	***	-2090.389	328.550	-6.362	$2.23e-10$	***
November	17.17	407.77	0.042	0.966423		-1893.967	331.278	-5.717	$1.17e-08$	***
December	-365.19	404.42	-0.903	0.366579		-498.620	328.554	-1.518	0.129197	
2012	3731.02	372.44	10.018	$< 2e-16$	***	-786.457	302.579	-2.599	0.009383	**
2013	8246.22	372.70	22.126	$< 2e-16$	***	2004.722	302.785	6.621	$4.09e-11$	***
2014	3601.74	372.70	9.664	$< 2e-16$	***	1144.958	302.785	3.781	0.000158	***
2015	-2943.57	372.70	-7.898	$3.73e-15$	***	2050.106	302.785	6.771	$1.49e-11$	***
2016	2660.93	372.44	7.145	$1.09e-12$	***	3001.309	302.578	9.919	$< 2e-16$	***
2017	-275.61	372.70	-0.740	0.459650		-1580.382	302.785	-5.219	$1.89e-07$	***
2018	3582.10	372.70	9.611	$< 2e-16$	***	-2209.079	302.785	-7.296	$3.63e-13$	***
2019	558.49	372.70	1.499	0.134090		-5353.843	302.785	-17.682	$< 2e-16$	***
2020	990.94	372.44	2.661	0.007833	**	-4111.551	302.579	-13.588	$< 2e-16$	***
Multiple R-squared		0.3919					0.3175			
Adjusted R-squared		0.3875					0.3126			
	VNI					Murraylink				
Intercept (c)	9613.76	644.68	14.912	$< 2e-16$	***	-509.297	94.153	-5.409	$6.74e-08$	***
Tuesday	-457.59	465.83	-0.982	0.32601		-9.788	68.032	-0.144	0.885611	
Wednesday	-793.45	465.83	-1.703	0.08860	.	29.255	68.032	0.430	0.667209	
Thursday	-707.20	465.84	-1.518	0.12907		-4.266	68.033	-0.063	0.950010	
Friday	-449.19	466.06	-0.964	0.33521		33.541	68.066	0.493	0.622208	
Saturday	1405.61	465.83	3.017	0.00257	**	-122.524	68.032	-1.801	0.071791	.
Sunday	2635.39	465.83	5.657	$1.66e-08$	***	-172.890	68.032	-2.541	0.011085	*
February	-1055.63	618.72	-1.706	0.08807	.	-19.401	90.361	-0.215	0.830007	
March	-1329.50	604.47	-2.199	0.02791	*	98.894	88.281	1.120	0.262694	
April	-401.41	609.49	-0.659	0.51019		181.792	89.013	2.042	0.041192	*
May	-4256.74	604.46	-7.042	$2.25e-12$	***	84.911	88.279	0.962	0.336192	
June	-5656.39	609.49	-9.281	$< 2e-16$	***	447.812	89.013	5.031	$5.12e-07$	***
July	-5170.89	604.47	-8.554	$< 2e-16$	***	516.125	88.280	5.846	$5.47e-09$	***
August	-3392.34	604.47	-5.612	$2.15e-08$	***	340.978	88.280	3.862	0.000114	***
September	-1481.59	609.49	-2.431	0.01511	*	244.979	89.013	2.752	0.005950	**
October	76.48	604.47	0.127	0.89932		83.740	88.280	0.949	0.342900	
November	-2415.28	609.49	-3.963	$7.55e-05$	***	4.564	89.013	0.051	0.959112	
December	-428.75	604.47	-0.709	0.47819		201.965	88.281	2.288	0.022209	*
2012	-391.39	556.69	-0.703	0.48206		-53.973	81.301	-0.664	0.506819	
2013	2185.63	557.06	3.923	$8.89e-05$	***	689.735	81.357	8.478	$< 2e-16$	***
2014	4851.15	557.06	8.708	$< 2e-16$	***	8.445	81.357	0.104	0.917335	
2015	3512.90	557.06	6.306	$3.21e-10$	***	457.557	81.357	5.624	$2.01e-08$	***
2016	7753.33	556.68	13.928	$< 2e-16$	***	936.050	81.301	11.513	$< 2e-16$	***
2017	-3339.92	557.06	-5.996	$2.23e-09$	***	96.618	81.357	1.188	0.235073	
2018	-5194.73	557.06	-9.325	$< 2e-16$	***	405.192	81.357	4.980	$6.64e-07$	***
2019	-7465.57	557.06	-13.402	$< 2e-16$	***	284.609	81.357	3.498	0.000474	***
2020	-2608.98	556.69	-4.687	2.88e-06	***	924.822	81.301	11.375	$< 2e-16$	***
Multiple R-squared		0.3112					0.1183			
Adjusted R-squared		0.3063					0.1120			

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

Table A.10 : **Seasonal and trend adjustment of daily cross-boarder interconnectors flows.**

	Estimate	Std. Error	t value	Pr($>\|t\|$)		Estimate	Std. Error	t value	Pr($>\|t\|$)	
	QNI					Terranora				
Intercept (c)	-7527.04	492.95	-15.269	$< 2e-16$	***	-1494.284	51.288	-29.135	$< 2e-16$	***
Tuesday	-260.80	356.19	-0.732	0.464093		-27.661	37.059	-0.746	0.455479	
Wednesday	-81.23	356.19	-0.228	0.819629		-18.670	37.060	-0.504	0.614450	
Thursday	-233.01	356.20	-0.654	0.513052		-37.777	37.060	-1.019	0.308101	
Friday	-345.80	356.37	-0.970	0.331942		-40.378	37.078	-1.089	0.276229	
Saturday	-901.71	356.19	-2.532	0.011399	*	-123.678	37.060	-3.337	0.000855	***
Sunday	-1097.45	356.19	-3.081	0.002078	**	-112.861	37.059	-3.045	0.002340	**
February	-1089.00	473.10	-2.302	0.021401	*	-7.787	49.223	-0.158	0.874316	
March	-1530.98	462.21	-3.312	0.000934	***	-184.495	48.090	-3.836	0.000127	***
April	-4783.67	466.04	-10.264	$< 2e-16$	***	-535.944	48.488	-11.053	$< 2e-16$	***
May	-3206.00	462.20	-6.936	$4.74e-12$	***	-461.326	48.089	-9.593	$< 2e-16$	***
June	-5631.73	466.04	-12.084	$< 2e-16$	***	-492.469	48.489	-10.156	$< 2e-16$	***
July	-5269.57	462.20	-11.401	$< 2e-16$	***	-367.299	48.089	-7.638	$2.81e-14$	***
August	-6159.02	462.21	-13.325	$< 2e-16$	***	-452.746	48.089	-9.415	$< 2e-16$	***
September	-3923.23	466.04	-8.418	$< 2e-16$	***	-303.179	48.488	-6.253	$4.51e-10$	***
October	-3160.55	462.20	-6.838	$9.38e-12$	***	-344.492	48.089	-7.164	$9.47e-13$	***
November	-2417.59	466.04	-5.188	$2.25e-07$	***	-287.289	48.488	-5.925	$3.42e-09$	***
December	-387.33	462.21	-0.838	0.402086		-72.395	48.090	-1.505	0.132305	
2012	-2017.91	425.67	-4.741	$2.21e-06$	***	-177.215	44.288	-4.001	$6.42e-05$	***
2013	8541.90	425.96	20.054	$< 2e-16$	***	794.234	44.318	17.921	$< 2e-16$	***
2014	-507.28	425.96	-1.191	0.233763		55.232	44.318	1.246	0.212741	
2015	1149.82	425.96	2.699	0.006979	**	402.865	44.318	9.090	$< 2e-16$	***
2016	5684.82	425.66	13.355	$< 2e-16$	***	819.314	44.288	18.500	$< 2e-16$	***
2017	-859.27	425.96	-2.017	0.043740	*	139.769	44.318	3.154	0.001625	**
2018	-223.88	425.96	-0.526	0.599203		341.304	44.318	7.701	$1.73e-14$	***
2019	-202.75	425.96	-0.476	0.634110		500.327	44.318	11.290	$< 2e-16$	***
2020	930.25	425.67	2.185	0.028924	*	718.332	44.288	16.220	$< 2e-16$	***
Multiple R-squared		0.2966					0.2897			
Adjusted R-squared		0.2916					0.2846			

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $.p < 0.1$, $p < 1$

After accounting for price spikes in Table A.4, the coefficients of monthly seasonality and year dummies become relatively more statistically significant. From this, we conclude that when the market is operating under typical conditions, electricity prices tend to be relatively higher during the winter months, except for TAS. Furthermore, we see from the year dummies that prices for all states dropped markedly in the year 2014 and 2015 though not statistically significant for all states. This is mostly accounted for by the repeal of the carbon pricing mechanism on July, 1 2014.

A.1.4 Summary statistics and time-series tests of the data series

The summary statistics and time-series tests of electricity prices adjusted for seasonal and trend effects are given in Table A.11. In Table A.12, we apply the augmented

Table A.11 : **Summary statistics of electricity prices and the corresponding JB tests for NSW, SA, VIC, and TAS.**

	Mean	Standard Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile	JB Test
						NSW				
30-min prices	59.93	161.18	61.86	4505.25	49.93	-147.03	14700.00	34.81	67.65	1.4821e+11
Daily	59.93	57.79	15.51	329.28	51.13	18.54	1539.50	36.24	73.20	16350316
Prices adjusted for outliers	55.28	23.18	0.79	2.98	51.04	18.54	133.14	36.24	70.70	383.77
Deseasonalised actual prices	59.93	53.84	18.48	419.37	55.16	-1.07	1525.42	46.58	65.50	26595657
Deseasonalised outliers-adjusted prices	55.28	13.47	0.97	5.73	53.97	16.19	128.52	47.30	61.71	1699.9
						SA				
30-min prices	67.91	235.82	41.23	2115.86	50.05	-996.70	14700.00	33.57	78.05	3.2665e+10
Daily	67.91	97.24	17.68	479.40	53.16	-107.16	3359.82	34.52	82.33	34734694
Prices adjusted for outliers	58.07	31.14	0.65	3.28	52.70	-45.74	160.98	34.60	160.98	266.19
Deseasonalised actual prices	67.91	92.57	19.14	539.36	61.15	-105.46	3287.25	44.29	77.69	44011451
Deseasonalised outliers-adjusted prices	58.07	23.17	0.39	5.27	56.57	-53.38	158.35	44.52	69.40	876.64
						VIC				
30-min prices	59.34	186.02	59.83	4092.03	46.22	-676.37	14700.00	30.61	70.35	1.2226e+11
Daily	59.34	80.05	26.24	960.73	47.77	-31.66	3377.97	31.64	74.45	140031543
Prices adjusted for outliers	53.26	27.31	0.84	2.95	47.57	-31.66	137.33	31.64	69.75	427.97
Deseasonalised actual prices	59.34	74.75	29.80	1144.08	56.88	-31.79	3291.42	44.82	67.39	198724005
Deseasonalised outliers-adjusted prices	53.26	16.91	0.33	4.94	52.65	-20.87	145.28	43.84	61.95	637.12
						TAS				
30-min prices	60.88	73.26	20.50	778.88	44.69	-956.35	4928.30	32.47	78.30	4410415614
Daily	60.88	42.34	2.30	11.15	44.94	-94.67	461.64	34.82	79.78	13330
Prices adjusted for outliers	50.62	23.58	0.88	3.00	44.00	-16.42	118.23	34.86	63.37	475.62
Deseasonalised actual prices	60.88	32.15	1.97	15.19	59.60	-56.70	461.12	44.44	72.59	24984
Deseasonalised outliers-adjusted prices	50.62	18.14	0.32	4.13	49.63	-18.46	131.46	41.20	58.83	257.02

JB test stands for the Jarque-Bera test of normality. Its corresponding p value is less than 2.2×10^{-16} for all states. Hypothesis for JB test: H_0: data are iid Normal, H_1: data are Non-Normal. JB is asymptotically distributed as chi-square with 2 degrees of freedom.

Dickey-Fuller (ADF) unit root test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to determine if the time series is stationary (Dickey and Fuller, 1979; Kwiatkowski et al., 1992). For the former test, we reject the null hypothesis of the presence of unit root at 1% for all the variables. On the other hand, we fail to reject the null hypothesis of stationarity for all the variables at 5% using the KPSS test, therefore confirming the stationarity of the data series. This eliminates the possibility of spurious regression results. In either case, we assume a constant (no visible trend) and choose optimal lag lengths based on the Bayesian information criterion (BIC). The BIC is more stringent for optimal lag selection than the Akaike information criterion (AIC).

The Jarque-Bera test for normality in Table A.11 suggests that the distribution of prices is non-normal with positive skewness and pronounced positive kurtosis. It is apparent that price spikes in the data series influences the non-normality of electricity prices. This is evident by the decrease of both values once the outliers are accounted for. However, the distribution of prices remains non-normal even after removal of outliers. This

Table A.12 : **The ADF and KPSS tests of stationarity.**

	NSW	SA	VIC	TAS	Interconnector	NSW	SA	VIC	TAS	Interconnector
	ADF test					**KPSS test**				
Actual prices	-9.9669	-46.5848	-46.0095	-7.0819		0.0407	0.0448	0.0516	0.0596	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
Outlier adjusted prices	-11.6912	-12.8837	-11.7403	-11.8680		0.0559	0.0762	0.0517	0.0376	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
wind	-32.8037	-38.8298	-29.8815	-32.9686		0.0298	0.0167	0.0328	0.0423	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
consumption	-22.3519	-25.8611	-25.1798	-18.6953		0.0217	0.0390	0.0419	0.0381	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
wind pen	-32.5826	-30.7301	-29.8060	-33.1109		0.0292	0.0249	0.0304	0.0448	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
gas	-10.5100	-8.4768	-7.0452			0.0525	0.0492	0.0570		
	(0.0000)	(0.0000)	(0.0000)			(0.1000)	(0.1000)	(0.1000)		
hydro	-11.4933		-13.9922	-10.4045		0.0409		0.0290	0.0566	
	(0.0000)		(0.0000)	(0.0000)		(0.1000)		(0.1000)	(0.1000)	
Basslink					-9.5848					0.0607
					(0.0000)					(0.1000)
Heywood					-10.9822					0.0742
					(0.0000)					(0.1000)
Murrylink					-15.3330					0.0482
					(0.0000)					(0.1000)
Terranora					-16.2033					0.0305
					(0.0000)					(0.1000)
QNI					-16.7384					0.0375
					(0.0000)					(0.1000)
VNI					15.0728					0.0323
					(0.0000)					(0.1000)

Hypothesis for ADF test: H_0: unit root (non-stationary); H_1: no unit root (stationary). Hypothesis for KPSS test: H_0: the data is stationary and H_1: the data is non-stationary.

property suggests that ARCH type models may be appropriate to capture the volatility dynamics of electricity prices. This is further supported by clustering of price volatility as shown in Figures A.2 and A.3. We then apply the Ljung-Box or modified Q-statistic and the Engle (1982) autoregressive conditional heteroscedasticity-Lagrange multiplier (ARCH-LM) to check for the presence of autocorrelation and conditional heteroscedasticity (ARCH effects) in the time series. The estimated statistics for these tests for different lag values are given in Table A.13. For the Ljung-Box test, we reject the null of no autocorrelation at a 1% level of significance for all lags and states. For the ARCH-LM test, we reject the null of no conditional heteroscedasticity at the same level of significance for NSW and TAS. The ARCH effect is, however, less pronounced in SA and VIC, where we find evidence only at lower lags. The significance of the estimated statistics for the series adjusted for price spikes reflects the impact of extreme observations and outliers in the actual price series. The results overall support the appropriateness of GARCH type models to adequately capture the conditional heteroscedasticity of the price series we examine.

Table A.13 : **Tests for the autocorrelation and the conditional heteroscedasticity (ARCH effects) in prices series.**

	Actual Prices											
	NSW			SA			VIC			TAS		
Lag	1	7	30	1	7	30	1	7	30	1	7	30
Ljung-Box statistic	513.71	711.47	838.2	236.23	306.21	350.39	258.3	289.15	317.8	2477.2	13339	35778
p−value	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)
ARCH-LM Test	152.68	159.44	427.32	4.6958	4.7463	4.9518	10.115	10.113	10.128	1757.9	1965.6	2008.9
p−value	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	(0.0302)	(0.4476)	(1.0000)	(0.00147)	(0.0721)	(0.9997)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)
	Adjusted Prices											
Ljung-Box statistic	1305	4161.4	8322.9	543.06	1040.6	2224.5	954.07	3013.6	6049.2	1371.4	5765.7	11173
p−value	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)
ARCH-LM Test	1117.1	1241.4	1301.3	436.79	472.55	567.52	933.49	1083.2	1163.2	1182.3	1411.7	1451.5
p−value	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)	($< 2.2\times10^{-16}$)

Hypothesis for Ljung-Box test: H_0: the residuals are independently distributed (no autocorrelation); H_1: the residuals exhibits autocorrelation. Hypothesis for ARCH-LM test: H_0: the residuals does not exhibits conditional heteroscedasticity (ARCH effects) and H_1: the residuals exhibits conditional heteroscedasticity (ARCH effects).

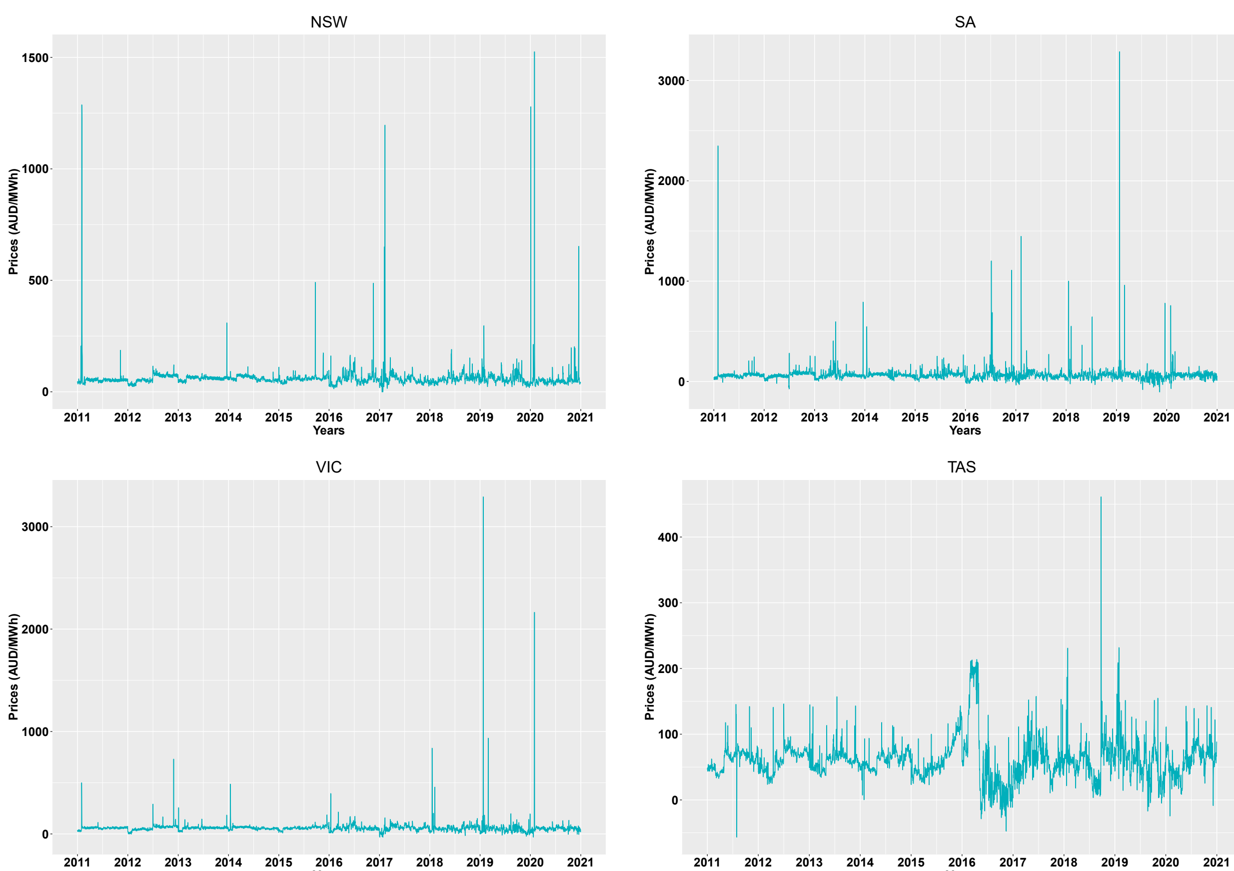

Figure A.2 : **The daily average actual spot price adjusted for both the seasonal and trend effects for NSW, SA, VIC, and TAS from 2011 to 2020.**

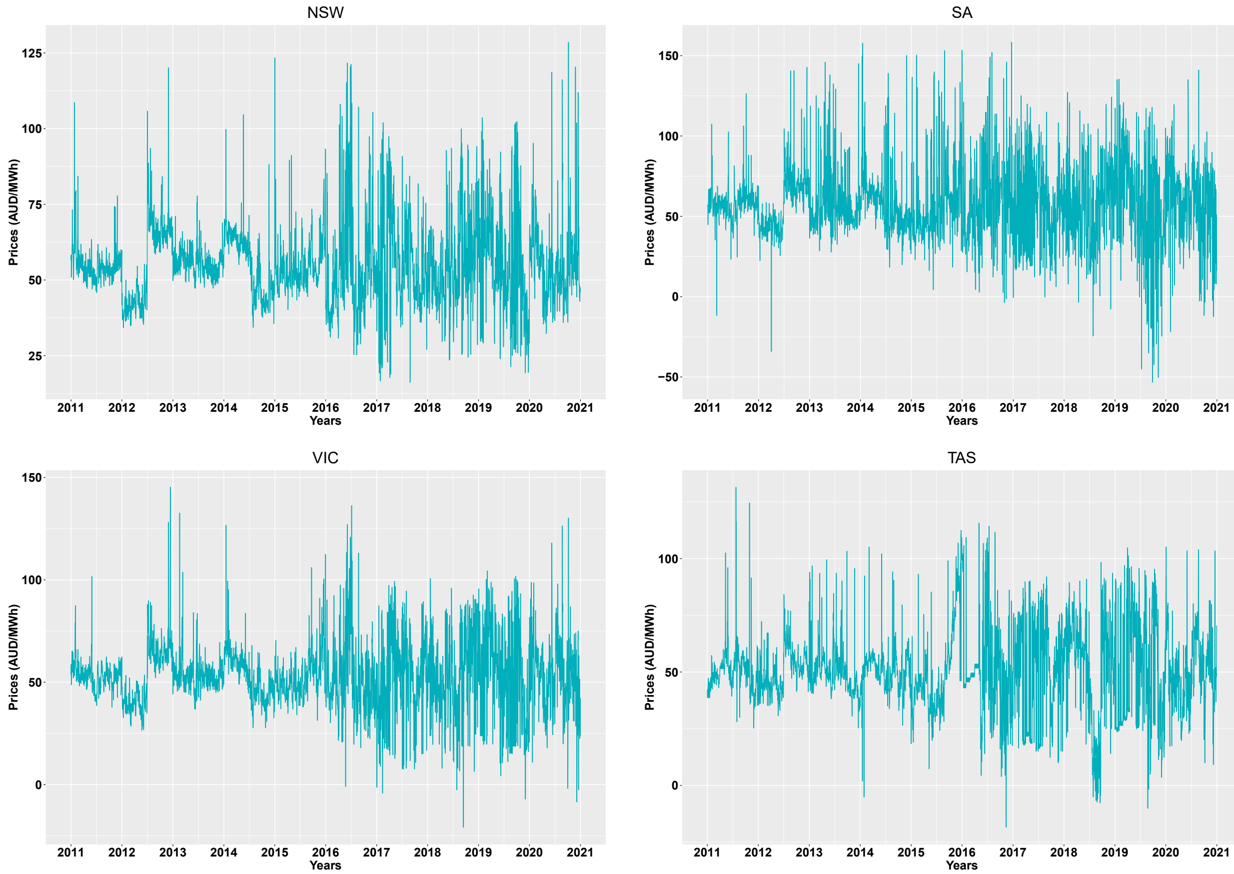

Figure A.3 : **The daily average actual spot price adjusted for price spikes (outliers), seasonal and trend effects for NSW, SA, VIC, and TAS from 2011 to 2020.**

Finally, we examined the regressors for collinearity using the correlation coefficient matrix (Figure A.4 and A.5) and variance inflation factors (VIF) in Table A.14. Multicollinearity creates shared variance between variables, which inter-alia complicates attribution of causality amongst the regressors (Hair et al., 2019). It can also have substantial impact on the estimation of the regression coefficients and their statistical significance tests. Fixing the cut-off threshold of VIF at 3, we identify three variables for all states that might be the source of collinearity, that is, wind generation, electricity consumption, and wind penetration. In the same line, it is apparent that collinearity in TAS may also be brought about by having hydro generation and the Basslink interconnector flow in the same specification. To avoid multicollinearity issues we set up our models to study the effects of highly correlated variables separately.

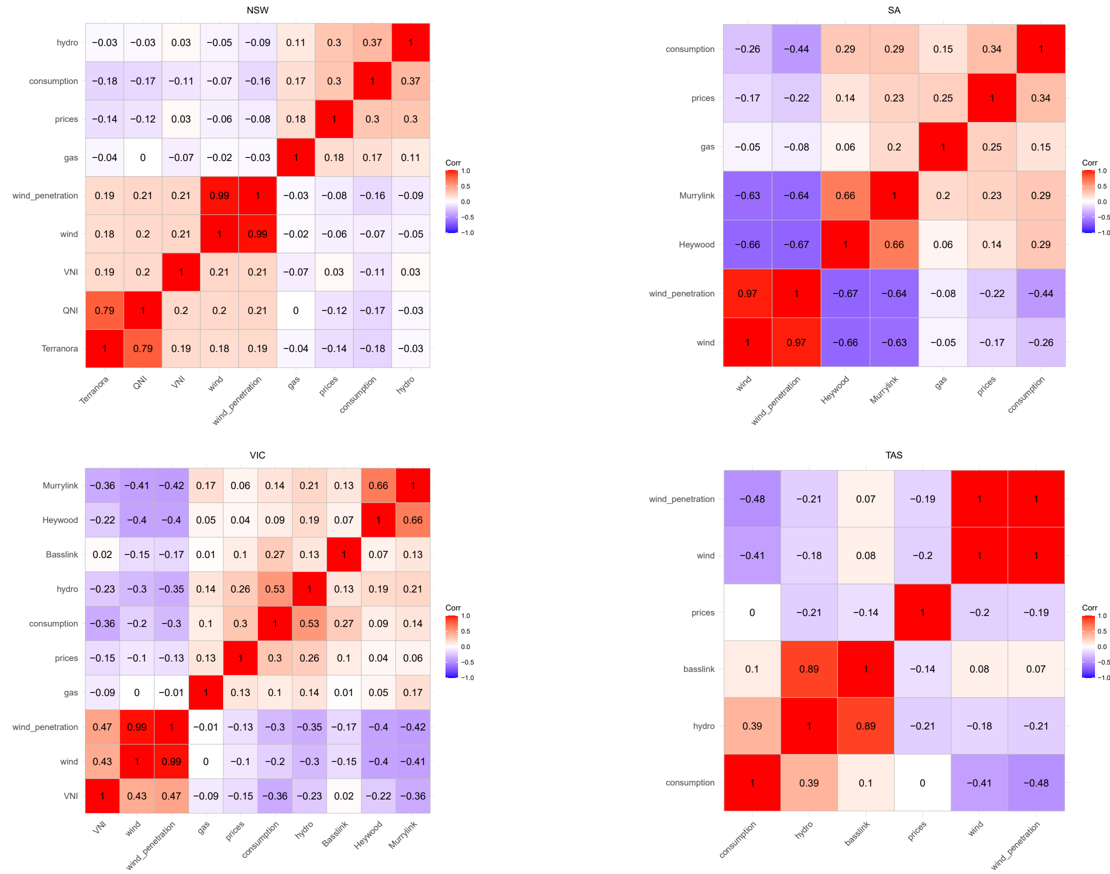

Figure A.4 : **Correlation coefficient matrix of the variables. Prices stands for daily averaged prices adjusted for the seasonality and trend effects.**

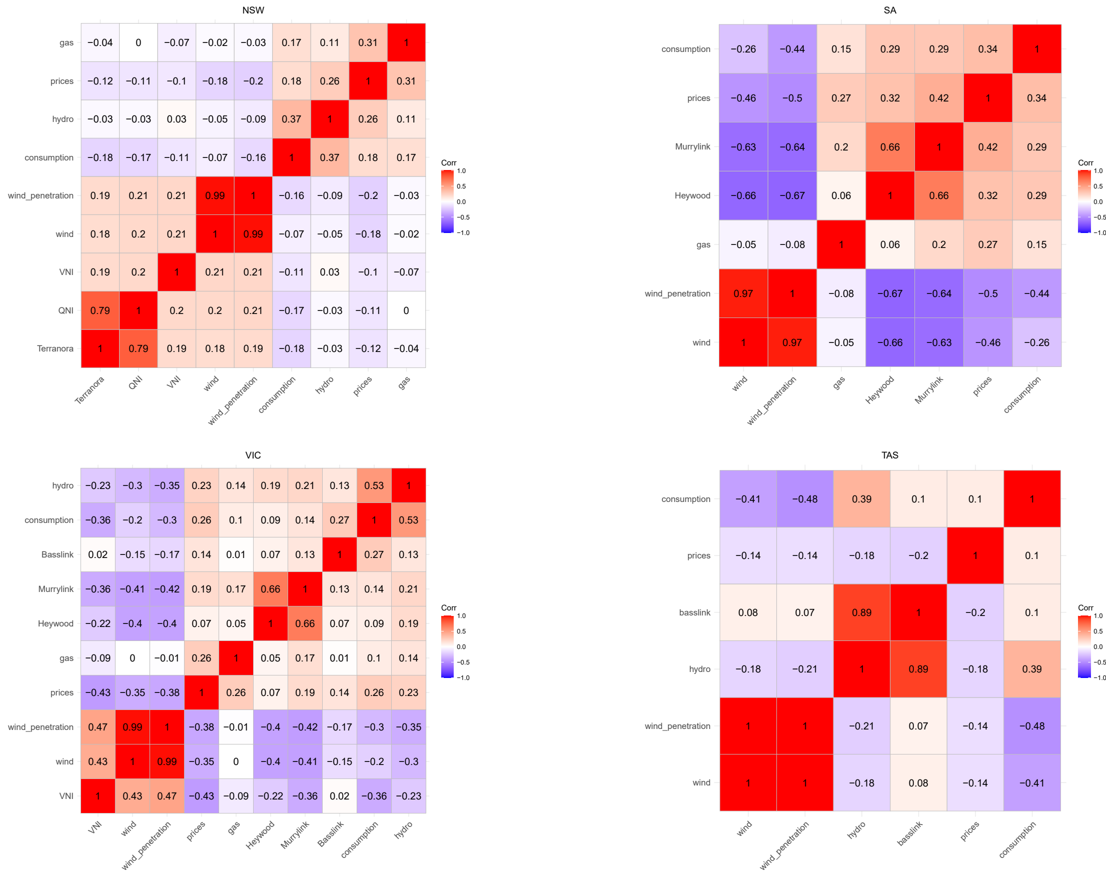

Figure A.5 : **Correlation coefficient matrix of the variables. Prices stands for daily averaged prices adjusted for price spikes, seasonality and trend effects.**

Table A.14 : **VIF collinearity diagnostic measure.**

	NSW	SA	VIC	TAS	NSW	SA	VIC	TAS
	Actual Prices				Adjusted Prices			
wind	372.6030	66.8849	230.3949	302.3791	372.6030	66.8849	230.3949	302.3791
wind pen	380.9770	76.8592	244.0020	326.6790	380.9770	76.8592	244.0020	326.6790
consumption	4.5082	4.1393	4.5470	4.0087	4.5082	4.1393	4.5470	4.0087
gas	1.0413	1.0680	1.0697		1.0413	1.0680	1.0697	
hydro	1.1765		1.5209	10.9202	1.1765		1.5209	10.9202
QNI	2.6892				2.6892			
VNI	1.0945		1.5228		1.0945		1.5228	
Terranora	2.6756				2.6756			
Heywood		2.2086	1.8861			2.2086	1.8861	
Murrylink		2.1324	2.0698			2.1324	2.0698	
Basslink			1.1562	9.4856			1.1562	9.4856

A.2 Choosing the Optimal ARMA Structure and Distribution of the Standardized Residuals

Guided by the literature, we apply eGARCH(1,1) as an adequate model of the conditional variance of electricity prices. We then add the autoregressive terms to capture the autocorrelation in electricity prices. This choice is supported by visual inspection of the autocorrelation (ACF) and partial autocorrelation (PACF) functions, which suggest insignificance of the moving average terms. Studies such as Woo et al. (2011), Ketterer (2014), and Kyritsis et al. (2017) come to the similar conclusions. We choose the order of AR(p) and the distribution of the standardized innovation by jointly estimating the AR-eGARCH model. We consider three common distributions, namely, the normal distribution, Nelson (1991) generalized error distribution (GED), and the Student distribution. We investigate the adequacy of the model fit using the weighted Ljung-Box test on standardized squared residuals and weighted ARCH LM tests (Fisher and Gallagher, 2012). The former is the portmanteau test with null the adequacy of the ARMA fit, and the latter adequately fitted the ARCH process (Ghalanos, 2022). The optimal lag is then adapted for the rest of the models, and the adequacy of the model fit assessed in the same manner.

The AR-eGARCH estimates of the actual prices adjusted for the seasonal and trend effects suggest adequate model fit using a single AR component. Both the Ljung-Box and the ARCH-LM test in Table A.15 suggests the model is correctly specified as both the autocorrelation (with a slight exception of TAS) and the ARCH effects are well captured. We further inspects the ACF and PACF of the standardized residuals and square standardized residuals (see Figure A.6) which suggests little autocorrelation and absence of particular pattern due to the non-stationarity or seasonality of time series (Kyritsis et al., 2017). However, this is not the case for prices adjusted for outliers (see Figure A.7), and the inclusion of a single AR structure fails to adequately capture the autocorrelations and the ARCH effects. Therefore, we choose the lag order p that minimizes the BIC, that is, $p = 7$ (see Figure A.8, Table A.16 and Table A.17). Based on the BIC information criterion, the Student distribution outperforms the Normal Distribution (see Table A.16 and A.18) reflecting the non-normality characteristics of the Australian electricity price data, and Nelson (1991) generalized error distribution (GED).

Table A.15 : **The weighted Ljung-Box test on standardized residuals, standardized squared residuals, and the weighted ARCH LM tests of the AR-eGARCH fitted models for NSW, SA, VIC, and TAS.** The models estimated using actual prices adjusted for the seasonality and trend effect, one autoregressive component, and Student distribution. Corresponding p value in parenthesis.

	Lag 1	Lag 4	Lag 20	Lag 1	Lag 10	Lag 36	Lag 3	Lag 5	Lag 7
	Ljung-Box on $\hat{z}_t$			**Ljung-Box on $\hat{z}_t^2$**			**ARCH LM Tests**		
NSW	0.0052	0.5272	1.1961	0.0015	0.0029	0.0048	2.348e-05	0.0011	0.0023
	(0.9422)	(0.9575)	(0.9133)	(0.9692)	(1.0000)	(1.0000)	(0.9961)	(1.0000)	(1.0000)
SA	0.0004	0.0284	0.3707	0.0060	0.0188	0.0356	0.0053	0.0195	0.0303
	(0.9848)	(1.0000)	(0.9977)	(0.9382)	(0.9999)	(1.0000)	(0.9422)	(0.9987)	(1.0000)
VIC	0.9437	1.3576	1.8020	0.0020	0.0122	0.0314	0.0060	0.0200	0.0326
	(0.3313)	(0.5195)	(0.7674)	(0.9640)	(1.0000)	(1.0000)	(0.9383)	(0.9987)	(1.0000)
TAS	42.71	53.03	60.54	0.3493	1.8248	2.7618	0.6589	1.2632 1	1.7987
	(0.0000)	(0.0000)	(0.0000)	(0.5545)	(0.6604)	(0.7975)	(0.4169)	(0.6567)	(0.7598)

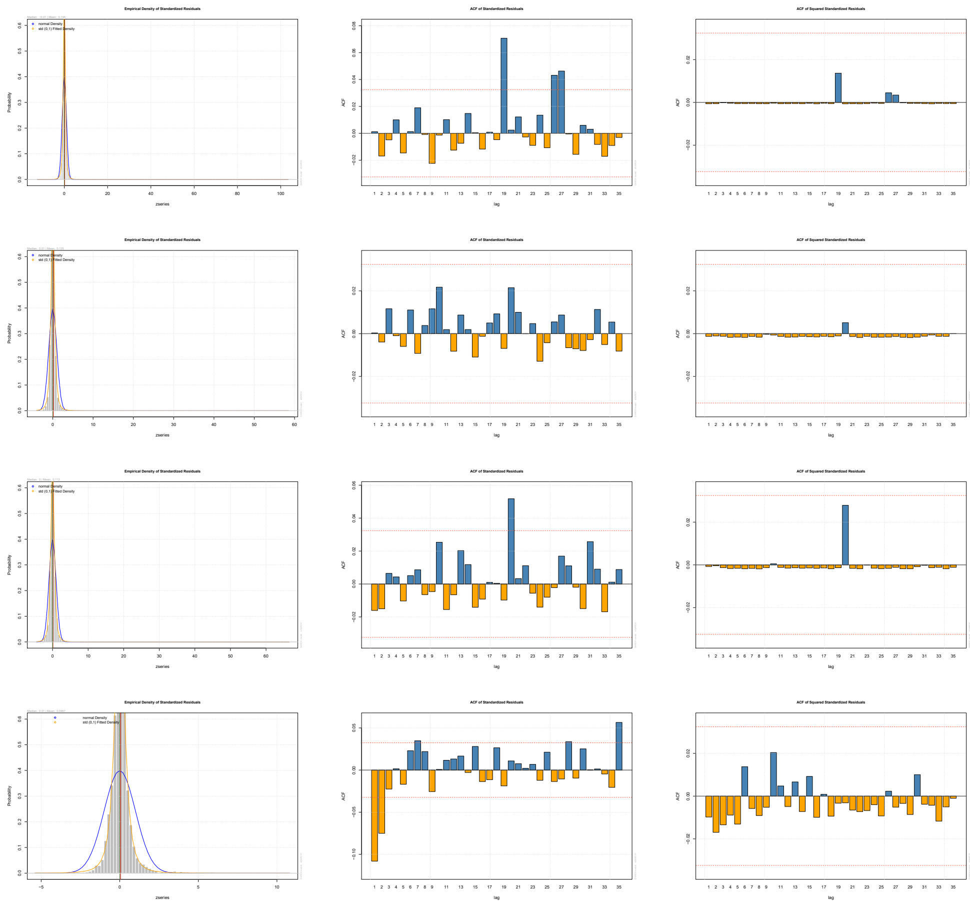

Figure A.6 : **The empirical density of standardized residuals, ACF of standardized residuals, and ACF of standardized squared residuals of the AR-eGARCH fitted models for NSW (first row), SA (second row), VIC (third row), and TAS (fourth row).** All models estimated using actual prices adjusted for the seasonality and trend effect, one autoregressive component, and Student distribution.

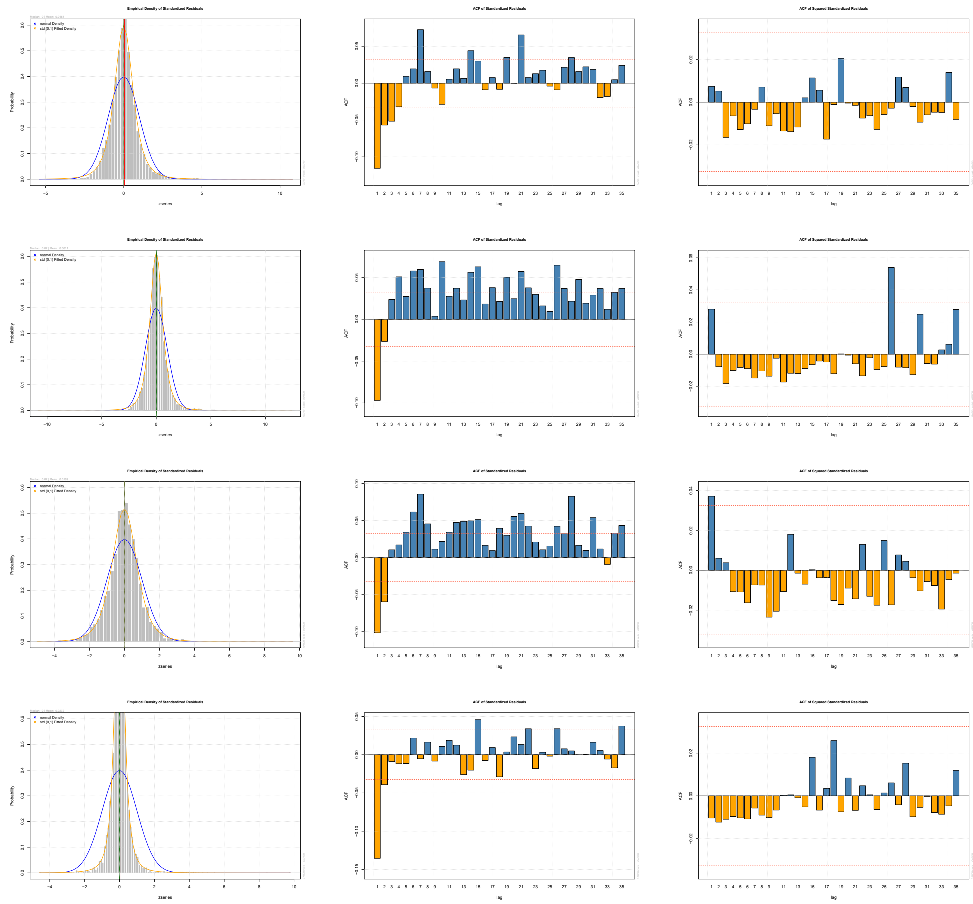

Figure A.7 : **The empirical density of standardized residuals, ACF of standardized residuals, and ACF of standardized squared residuals of the AR-eGARCH models for NSW (first row), SA (second row), VIC (third row), and TAS (fourth row).** All models estimated using prices adjusted for outliers, seasonality, and trend effect, one autoregressive component, and Student distribution.

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Table A.16 : **Log-likelihood, BIC, and AIC estimates of the AR-eGARCH model for the outliers adjusted prices under the Normal Distribution (Normal), the Student Distribution (Student's-t), and Generalized Error Distribution (GED).**

		Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED
		NSW			**SA**			**VIC**			**TAS**		
1													
	Log-Likelihood	-12745.12	-12233.51	-12279.57	-16014.66	-15595.97	-15646.44	-13801.34	-13572.41	-13592.96	-14183.52	-13282.77	-13329.41
	AIC	6.9812	6.7016	6.7268	8.7712	8.5425	8.5702	7.5595	7.4347	7.4459	7.7687	7.2761	7.3016
	BIC	6.9914	6.7135	6.7387	8.7814	8.5544	8.5821	7.5696	7.4466	7.4578	7.7789	7.2880	7.3135
2													
	Log-Likelihood	-12719.52	-12213.42	-12261.72	-16005.00	-15580.53	-15636.50	-13782.33	-13561.25	-13583.55	-14149.31	-13220.48	-13288.87
	AIC	6.9677	6.6912	6.7176	8.7665	8.5346	8.5653	7.5496	7.4291	7.4413	7.7505	7.2425	7.2800
	BIC	6.9796	6.7048	6.7312	8.7784	8.5482	8.5789	7.5615	7.4427	7.4549	7.7624	7.2561	7.2936
3													
	Log-Likelihood	-12702.07	-12195.10	-12248.99	-15990.25	-15547.89	-15607.08	-13738.66	-13521.83	-13547.62	-14135.76	-13193.74	-13273.20
	AIC	6.9587	6.6817	6.7112	8.7590	8.5173	8.5497	7.5262	7.4081	7.4222	7.7436	7.2284	7.2719
	BIC	6.9723	6.6970	6.7265	8.7726	8.5326	8.5650	7.5398	7.4234	7.4375	7.7572	7.2437	7.2872
4													
	Log-Likelihood	-12678.67	-12167.67	-12224.36	-15976.20	-15526.67	-15588.12	-13715.08	-13502.18	-13526.67	-15976.20	-15526.67	-15588.12
	AIC	6.9464	6.6672	6.6983	8.7518	8.5063	8.5399	7.5139	7.3979	7.4113	8.7518	8.5063	8.5399
	BIC	6.9617	6.6842	6.7152	8.7671	8.5232	8.5569	7.5292	7.4148	7.4282	8.7671	8.5232	8.5569
5													
	Log-Likelihood	-12639.66	-12130.69	-12186.80	-15970.45	-15504.43	-15568.60	-13690.28	-13475.27	-13500.01	-14127.21	-13168.36	-13321.15
	AIC	6.9256	6.6475	6.6782	8.7492	8.4946	8.5298	7.5008	7.3837	7.3972	7.7401	7.2156	7.2993
	BIC	6.9426	6.6662	6.6969	8.7662	8.5133	8.5484	7.5178	7.4023	7.4159	7.7570	7.2343	7.3180
6													
	Log-Likelihood	-12618.21	-12104.39	-12162.66	-15956.86	-15474.22	-15539.12	-13662.77	-13443.71	-13467.10	-14121.06	-13156.55	-13282.48
	AIC	6.9144	6.6337	6.6656	8.7423	8.4786	8.5142	7.4863	7.3669	7.3797	7.7372	7.2097	7.2787
	BIC	6.9331	6.6540	6.6859	8.7610	8.4990	8.5345	7.5050	7.3873	7.4001	7.7559	7.2301	7.2990
7													
	Log-Likelihood	-12608.78	-12079.86	-12136.84	-15950.18	-15454.06	-15516.65	-13647.27	-13426.04	-13451.59	-14116.61	-13151.66	-67386.93
	AIC	6.9098	6.6208	6.6520	8.7392	8.4681	8.5024	7.4784	7.3578	7.3718	7.7353	7.2076	36.9011
	BIC	6.9302	$\boxed{6.6429}$	6.6741	8.7596	$\boxed{8.4902}$	8.5245	7.4988	$\boxed{7.3799}$	7.3939	7.7557	$\boxed{7.2297}$	36.9232
8													
	Log-Likelihood	-12608.53	-12078.83	-12136.64	-15949.19	-15451.71	-15515.16	-13647.79	-13426.31	-13451.51	-14114.59	-13150.18	-13343.46
	AIC	6.9102	6.6208	6.6524	8.7392	8.4674	8.5021	7.4792	7.3585	7.3723	7.7348	7.2073	7.3131
	BIC	6.9323	6.6445	6.6762	8.7613	8.4912	8.5259	7.5013	7.3823	7.3961	7.7569	7.2311	7.3369
9													
	Log-Likelihood	-12608.00	-12079.56	-12137.46	-15947.28	-15449.18	-15512.69	-13648.43	-13427.16	-13452.56	-14114.80	-13150.86	-13256.32
	AIC	6.9105	6.6217	6.6534	8.7387	8.4666	8.5013	7.4801	7.3595	7.3734	7.7354	7.2082	7.2660
	BIC	6.9343	6.6472	6.6789	8.7625	8.4920	8.5268	7.5039	7.3850	7.3989	7.7592	7.2337	7.2915
10													
	Log-Likelihood	-12608.05	-12080.82	-12150.88	-15939.32	-15442.46	-15506.26	-13649.37	-13427.63	-13453.24	-14109.28	-13151.04	-13427.99
	AIC	6.9111	6.6230	6.6613	8.7349	8.4634	8.4984	7.4812	7.3603	7.3743	7.7330	7.2089	7.3605
	BIC	6.9365	6.6501	6.6885	8.7604	8.4906	8.5255	7.5066	7.3875	7.4015	7.7584	7.2361	7.3877

Table A.17 : **The weighted Ljung-Box test on standardized residuals, standardized squared residuals, and the weighted ARCH LM tests of the AR-eGARCH fitted models for NSW, SA, VIC, and TAS.** All models estimated using prices adjusted for outliers, seasonality and trend effect, seven autoregressive components, and Student distribution. Corresponding p value in parenthesis.

	Lag 1	Lag 40	Lag 136	Lag 1	Lag 10	Lag 36	Lag 3	Lag 5	Lag 7
	Ljung-Box on $\hat{z}_t$			**Ljung-Box on $\hat{z}_t^2$**			**ARCH LM Tests**		
NSW	3.137	24.649	39.234	0.3998	1.0244	1.6989	0.5137	1.2474	1.6032
	(0.0314)	(0.0000)	(0.0000)	(0.5272)	(0.8541)	(0.9377)	(0.4735)	(0.6612)	(0.8004)
SA	3.897	23.734	35.782	0.2150	0.8546	1.4395	0.6207	0.9216	1.2236
	(0.0484)	(0.0000)	(0.0000)	(0.6429)	(0.8916)	(0.9604)	(0.4308)	(0.7563)	(0.8747)
VIC	3.40	12.85	24.57	1.170	1.524	2.666	0.1498	0.7247	1.4764
	(0.0652)	(0.0000)	(0.0187)	(0.2793)	(0.7339)	(0.8126)	(0.6987)	(0.8160)	(0.8261)
TAS	11.09	24.37	34.15	0.2487	0.8967	1.4785	0.3150	0.7352	1.0519
	(0.0000)	(0.0000)	(0.0009)	(0.6180)	(0.8826)	(0.9573)	(0.5746)	(0.8127)	(0.9050)

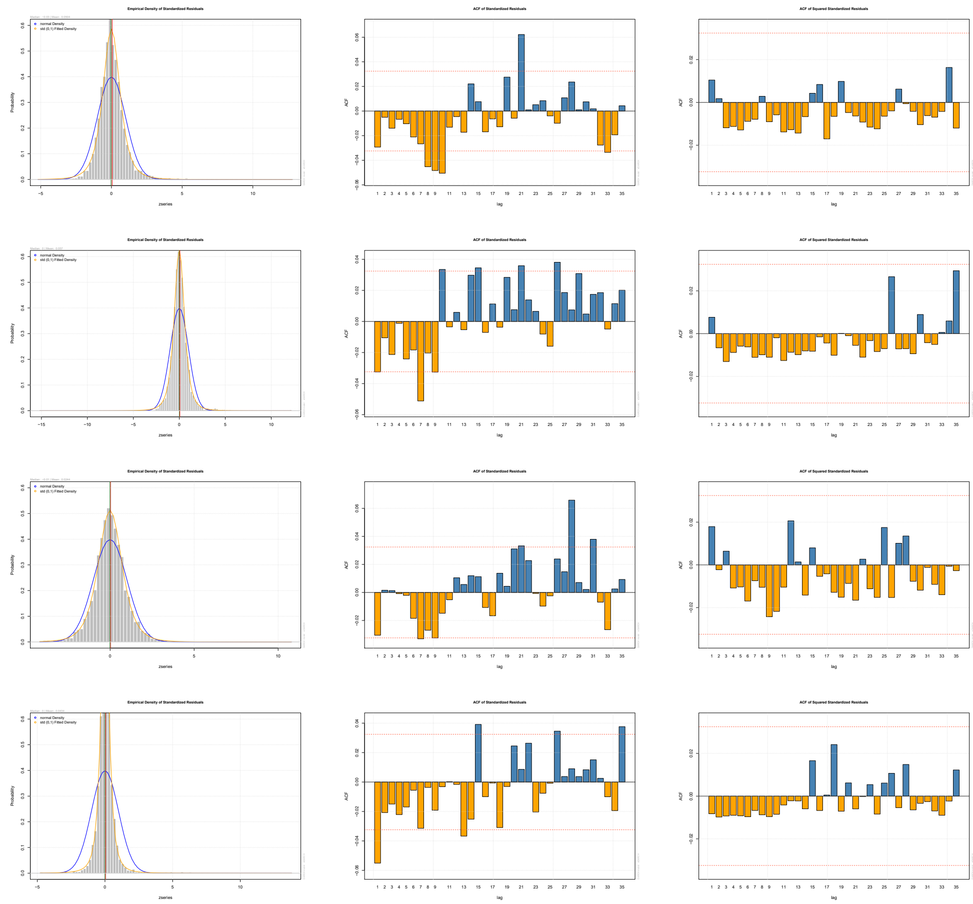

Figure A.8 : **The empirical density of standardized residuals, ACF of standardized residuals, and ACF of standardized squared residuals of the AR-eGARCH models for NSW (first row), SA (second row), VIC (third row), and TAS (fourth row).** All models estimated using prices adjusted for the outliers, seasonality, and trend effects, seven autoregressive components, and Student distribution.

Table A.18 : **Log-likelihood, BIC, and AIC of AR-eGARCH for the actual prices adjusted for the seasonality and trend effects under the Normal Distribution (Normal), the Student Distribution (Student's-t), and Generalized Error Distribution (GED)**

Lag	Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED
		NSW			SA			VIC			TAS	
1												
Log-Likelihood	-15459.87	-13468.55	-13699.65	-19218.06	-17051.19	-17326.43	-18252.48	-14785.68	-15221.61	-14717.57	-13772.08	-13821.72
AIC	8.4675	7.3778	7.5043	10.525	9.3393	9.4900	9.9964	8.0989	8.3376	8.0611	7.5440	7.5712
BIC	8.4777	$\boxed{7.3897}$	7.5162	10.535	$\boxed{9.3512}$	9.5019	10.0066	$\boxed{8.1108}$	8.3495	8.0713	$\boxed{7.5559}$	7.5830

A.3 Model Results

Table A.19 : **The effect of wind generation, electricity consumption, hydro generation, gas prices, and interconnectors flow on New South Wales' electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
	Mean Equation									
μ	53.4317	56.1288	14.9217	17.1176	56.2716	51.5622	50.5803	53.0858	21.7288	51.9468
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.7074	0.6869	0.6678	0.6546	0.6831	0.6985	0.6708	0.7157	0.6516	0.6555
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	0.0177	0.0454	0.0224	0.0386	0.0482	0.0200	0.0297	0.0264	0.0498	0.0622
	(0.0370)	(0.0004)	(0.1527)	(0.0241)	(0.0001)	(0.0010)	(0.0000)	(0.0331)	(0.0007)	(0.0082)
ϕ_3	0.0016	-0.0008	0.0091	0.0091	-0.0020	0.0025	0.0064	-0.0047	0.0053	-0.0002
	(0.5443)	(0.9190)	(0.6336)	(0.5869)	(0.5535)	(0.3994)	(0.0494)	(0.5977)	(0.6142)	(0.9917)
ϕ_4	0.0161	0.0231	0.0240	0.0340	0.0239	0.0176	0.0252	0.0140	0.0308	0.0292
	(0.0131)	(0.0170)	(0.0514)	(0.0197)	(0.0852)	(0.0651)	(0.0000)	(0.1193)	(0.3027)	(0.0123)
ϕ_5	0.0552	0.0518	0.0638	0.0627	0.0530	0.0536	0.0529	0.0535	0.0564	0.0474
	(0.0000)	(0.0007)	(0.0000)	(0.0001)	(0.0034)	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0038)
ϕ_6	0.0462	0.0377	0.0580	0.0450	0.0375	0.0503	0.0547	0.0443	0.0479	0.0506
	(0.0000)	(0.0750)	(0.0010)	(0.0170)	(0.0303)	(0.0000)	(0.0000)	(0.0007)	(0.0182)	(0.0010)
ϕ_7	0.1032	0.1042	0.1171	0.1163	0.1064	0.1034	0.1111	0.1028	0.1168	0.1091
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
wind		-4.7914		-4.5522					-3.9236	
		(0.0000)		(0.0000)					(0.0000)	
consumption			2.0552	2.0455					1.6675	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-100.0000					-85.2058
					(0.0000)					(0.0000)
gas						0.3393			0.1667	0.2374
						(0.0000)			(0.0000)	(0.0025)
hydro							4.2196		1.8511	3.7730
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-1.7240	-1.7470	-1.5614
								(0.5207)	(0.4583)	(0.5884)
$exim_{QNI}$								-1.3105	-0.6877	-0.8024
								(0.0000)	(0.0028)	(0.0026)
$exim_{VNI}$								-1.3859	-1.0418	-1.0725
								(0.0000)	(0.0000)	(0.0000)
	Variance Equation									
ω	0.1151	0.1627	-0.2703	-0.2652	0.1732	0.1222	0.1229	0.1076	-0.2598	0.1303
	(0.0000)	(0.0000)	(0.0747)	(0.0023)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2458)	(0.0201)
α	0.1191	0.1295	0.1024	0.1026	0.1286	0.1163	0.0955	0.1215	0.0939	0.1027
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.9701	0.9601	0.9661	0.9542	0.9593	0.9701	0.9640	0.9677	0.9435	0.9467
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.3096	0.3443	0.3245	0.3657	0.3467	0.3140	0.3583	0.3118	0.4110	0.4046
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
wind		-0.0194		-0.0301					-0.0171	
		(0.5209)		(0.3617)					(0.6571)	
consumption			0.0206	0.0235					0.0222	
			(0.0081)	(0.0000)					(0.1030)	
$wind_{pen}$					-0.6399					-0.2443
					(0.1100)					(0.7282)
gas						-0.0013			0.0026	0.0040
						(0.7441)			(0.6676)	(0.4894)
hydro							0.0222		0.0230	0.0396
							(0.2300)		(0.3790)	(0.1312)
$exim_{terra}$								0.0198	0.0837	0.0247
								(0.9160)	(0.7326)	(0.9181)
$exim_{QNI}$								-0.0192	-0.0349	-0.0352
								(0.3141)	(0.1684)	(0.1552)
$exim_{VNI}$								-0.0002	-0.0007	-0.0029
								(0.9866)	(0.9588)	(0.8113)
Shape	3.3301	3.3351	3.3241	3.2768	3.3135	3.3519	3.5026	3.2588	3.2854	3.3904
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-12079.86	-11972.35	-11890.76	-11780.28	-11943.2	-12072.28	-12005.63	-11997.32	-11719.63	-11819.49
AIC	6.6208	6.5630	6.5183	6.4590	6.5471	6.6177	6.5812	6.5789	6.4312	6.4848
BIC	6.6429	6.5885	6.5438	6.4878	6.5725	6.6432	6.6067	6.6111	6.4771	6.5273
Q(136)	39.238	40.151	41.679	40.448	40.712	39.06	43.711	41.889	43.55	44.705
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	1.6993	1.6957	1.8996	1.6361	1.6320	1.5537	2.0424	1.726	1.7103	1.7978
	(0.9377)	(0.9380)	(0.9167)	(0.9437)	(0.9441)	(0.9511)	(0.8999)	(0.9350)	(0.9366)	(0.9277)
ARCH-LM Test	1.6028	1.8720	1.8563	1.8216	1.826	1.5201	2.1507	1.7625	2.0210	2.1328
	(0.8005)	(0.7444)	(0.7477)	(0.7550)	(0.7542)	(0.8173)	(0.6854)	(0.7674)	(0.7129)	(0.6892)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table A.20 : **The effect of wind generation, electricity consumption, gas prices, and interconnectors flow on South Australia's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model F	Model H	Model I	Model J
	Mean Equation								
μ	53.9864	66.5155	3.7712	31.9326	65.7446	31.3499	52.2718	22.7053	50.4323
	(0.0000)	(0.0000)	(0.0214)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.4726	0.4926	0.4704	0.4936	0.4816	0.4368	0.4997	0.4682	0.4372
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	0.0083	0.0525	0.0235	0.0468	0.0516	0.0068	0.0558	0.0512	0.0576
	(0.5881)	(0.0000)	(0.0009)	(0.1659)	(0.0026)	(0.7298)	(0.0000)	(0.0000)	(0.0000)
ϕ_3	0.0592	0.0607	0.0637	0.0729	0.0678	0.0575	0.0616	0.0703	0.0671
	(0.0001)	(0.0000)	(0.0000)	(0.0016)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_4	0.0454	0.0394	0.0479	0.0448	0.0413	0.0522	0.0314	0.0530	0.0518
	(0.0024)	(0.0000)	(0.0002)	(0.0021)	(0.0042)	(0.0013)	(0.0000)	(0.0000)	(0.0051)
ϕ_5	0.0442	0.0373	0.0534	0.0447	0.0392	0.0408	0.0429	0.0410	0.0420
	(0.0604)	(0.0002)	(0.0000)	(0.0007)	(0.0090)	(0.0036)	(0.0001)	(0.0000)	(0.0087)
ϕ_6	0.0707	0.0767	0.0906	0.0863	0.0816	0.0687	0.0691	0.0764	0.0726
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0907	0.0941	0.1032	0.0967	0.1031	0.0809	0.0822	0.0963	0.1029
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-10.8282		-9.0908				-9.9873	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			15.6925	10.0083				9.4154	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-33.0721				-34.0072
					(0.0000)				(0.0000)
gas						3.8160		2.4495	3.0006
						(0.0000)		(0.0000)	(0.0000)
$exim_{heyw}$							5.1755	-8.8204	-8.5118
							(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$							56.3972	30.3230	32.7630
							(0.0000)	(0.0000)	(0.0000)
	Variance Equation								
ω	0.0612	0.2070	-0.0830	-0.0304	0.3119	0.0433	0.2274	-0.2015	0.2949
	(0.0000)	(0.0000)	(0.0350)	(0.8129)	(0.0000)	(0.0261)	(0.0000)	(0.1879)	(0.0000)
α	0.0286	0.0335	0.0124	-0.0342	0.0098	0.0218	0.0408	-0.0887	-0.0445
	(0.0361)	(0.1279)	(0.2231)	(0.3254)	(0.7411)	(0.1127)	(0.0954)	(0.0549)	(0.1940)
β	0.9896	0.9698	0.9733	0.9225	0.9576	0.9882	0.9624	0.9017	0.9443
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.2427	0.4603	0.3756	0.7654	0.5582	0.2453	0.4441	0.9431	0.6825
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0000)
$wind$		-0.0098		0.0011				0.0208	
		(0.6079)		(0.9642)				(0.5366)	
$consumption$			0.0735	0.1621				0.1917	
			(0.0000)	(0.0000)				(0.0001)	
$wind_{pen}$					-0.0949				-0.1160
					(0.1124)				(0.1146)
gas						0.0043		0.0305	0.0191
						(0.1742)		(0.0033)	(0.0051)
$exim_{heyw}$							0.0228	0.0440	0.0101
							(0.4385)	(0.3684)	(0.7781)
$exim_{murr}$							0.0106	-0.0256	-0.0449
							(0.9320)	(0.9015)	(0.7766)
Shape	3.05117	2.2966	2.8110	2.2470	2.2711	3.0895	2.4120	2.1937	2.2163
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-15454.06	-14740.69	-15096.45	-14567.26	-14643.1	-15407.81	-14833.17	-14424.04	-14494.66
AIC	8.4681	8.0787	8.2734	7.9848	8.0252	8.4439	8.1304	7.9097	7.9473
BIC	8.4902	8.1041	8.2989	8.0137	8.0507	8.4694	8.1593	7.9487	7.9829
Q(136)	35.744	39.70	40.157	45.95	42.57	33.342	41.82	43.90	36.75
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	1.4395	2.6570	2.6546	4.1077	2.6860	1.3928	2.22035	4.497	2.2035
	(0.9604)	(0.8140)	(0.8143)	(0.5707)	(0.8095)	(0.9639)	(0.8771)	(0.5068)	(0.8794)
ARCH-LM Test	1.2240	2.554	2.461	3.208	2.3939	1.1555	2.1033	3.318	1.8131
	(0.8746)	(0.6013)	(0.6205)	(0.4752)	(0.6344)	(0.8870)	(0.6954)	(0.4557)	(0.7568)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table A.21 : **The effect of wind generation, electricity consumption, hydro generation, gas prices, and interconnectors flow on Victoria's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
	Mean Equation									
μ	51.6831	57.2933	1.8246	19.9892	57.1568	44.2565	46.1768	54.6624	39.1689	48.2110
	(0.0000)	(0.0000)	(0.3280)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.6331	0.6400	0.5902	0.6089	0.6323	0.6140	0.6044	0.6165	0.5675	0.5683
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	-0.0357	-0.0106	-0.0147	-0.0018	-0.0060	-0.0230	-0.0264	-0.0179	0.0012	0.0034
	(0.3389)	(0.5412)	(0.3471)	(0.5108)	(0.8040)	(0.0263)	(0.0681)	(0.0418)	(0.9734)	(0.4279)
ϕ_3	0.0639	0.0601	0.0810	0.0711	0.0595	0.0643	0.0765	0.0482	0.0599	0.0537
	(0.0933)	(0.0415)	(0.0000)	(0.0000)	(0.0072)	(0.0000)	(0.0000)	(0.0000)	(0.0533)	(0.0017)
ϕ_4	0.0205	0.0291	0.0236	0.0328	0.0310	0.0209	0.0287	0.0121	0.0386	0.0395
	(0.6029)	(0.7318)	(0.1457)	(0.0226)	(0.0819)	(0.0970)	(0.0005)	(0.0037)	(0.0406)	(0.0000)
ϕ_5	0.0421	0.0308	0.0346	0.0254	0.0301	0.0411	0.0460	0.0294	0.0197	0.0219
	(0.1934)	(0.5719)	(0.0270)	(0.0720)	(0.1101)	(0.0000)	(0.0000)	(0.0093)	(0.1632)	(0.0187)
ϕ_6	0.0743	0.0733	0.0848	0.0810	0.0750	0.0728	0.0858	0.0753	0.0846	0.0838
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0945	0.0869	0.1120	0.1017	0.0891	0.0984	0.0975	0.1289	0.1388	0.1366
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-6.9581		-5.9319					-4.2145	
		(0.0000)		(0.0000)					(0.0000)	
$consumption$			3.9896	2.8798					0.7472	
			(0.0000)	(0.0000)					(0.0075)	
$wind_{pen}$					-86.5100					-52.0239
					(0.0000)					(0.0000)
gas						1.3277			1.1327	1.1268
						(0.0000)			(0.0000)	(0.0000)
$hydro$							8.0014		3.5619	3.9128
							(0.0000)		(0.0000)	(0.0000)
$exim_{bass}$								5.9309	3.7402	3.8754
								(0.0000)	(0.0000)	(0.0000)
$exim_{heyw}$								-0.3871	-2.4426	-2.4923
								(0.2940)	(0.0000)	(0.0000)
$exim_{VNI}$								-5.3289	-3.1766	-3.3468
								(0.0000)	(0.0000)	(0.0000)
$exim_{murry}$								3.7364	1.2770	0.9764
								(0.0208)	(0.0550)	(0.0557)
	Variance Equation									
ω	0.1113	0.2398	-0.5033	-0.5268	0.2605	0.1140	0.0938	0.1505	-0.4371	0.1089
	(0.0000)	(0.0000)	(0.0000)	(0.1044)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0320)	(0.0553)
α	0.0529	0.0289	0.0341	0.0146	0.0204	0.0512	0.0303	0.0089	0.0026	-0.0054
	(0.0032)	(0.1589)	(0.0634)	(0.5167)	(0.3201)	(0.0052)	(0.1158)	(0.6400)	(0.9011)	(0.7921)
β	0.9760	0.9602	0.9687	0.9494	0.9586	0.9752	0.9611	0.9647	0.9463	0.9471
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.3819	0.4664	0.4308	0.5212	0.4741	0.3836	0.4811	0.4287	0.5233	0.5233
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.0650		-0.0552					-0.0283	
		(0.0000)		(0.0287)					(0.3295)	
$consumption$			0.0517	0.0641					0.0442	
			(0.0000)	(0.0749)					(0.0085)	
$wind_{pen}$					-0.9930					-0.4527
					(0.0003)					(0.2026)
gas						0.0002			0.0082	0.0084
						(0.9727)			(0.2645)	(0.2565)
$hydro$							0.1162		0.1044	0.1313
							(0.0000)		(0.0012)	(0.0000)
$exim_{bass}$								0.0238	0.0071	0.0207
								(0.0884)	(0.6957)	(0.2221)
$exim_{heyw}$								0.0876	0.1016	0.0954
								(0.0062)	(0.0109)	(0.0162)
$exim_{VNI}$								-0.0213	-0.0089	-0.0185
								(0.0871)	(0.5883)	(0.2542)
$exim_{murry}$								-0.2581	-0.3530	-0.3819
								(0.0547)	(0.0373)	(0.0243)
Shape	4.3465	3.4342	3.9779	3.4710	3.4068	4.2859	4.0229	3.3703	3.3989	3.3797
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-13426.04	-12952.6	-13134.97	-12770.62	-12898.24	-13400.35	-13154.8	-12830.16	-12516.71	-12526.93
AIC	7.3578	7.0997	7.1995	7.0012	7.0699	7.3448	7.2104	7.0359	6.8687	6.8732
BIC	7.3799	7.1252	7.2250	7.0300	7.0954	7.3703	7.2359	7.0716	6.9180	6.9191
Q(136)	24.571	25.212	33.7380	29.936	25.616	25.407	28.458	31.57	33.80	33.168
	(0.0187)	(0.0124)	(0.0000)	(0.0004)	(0.0095)	(0.0109)	(0.0012)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	2.666	1.7691	5.552	2.7735	1.7168	2.775	3.593	0.9820	2.9969	2.8925
	(0.8126)	(0.9307)	(0.3529)	(0.7957)	(0.9360)	(0.7954)	(0.6585)	(0.9870)	(0.7595)	(0.7766)
ARCH-LM Test	1.4763	1.3443	3.2740	2.2885	1.35303	1.6820	1.9758	0.9365	2.4285	2.397
	(0.8261)	(0.852)	(0.4634)	(0.6564)	(0.8503)	(0.7842)	(0.7225)	(0.9237)	(0.6272)	(0.6338)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table A.22 : **The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on Tasmania's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model G	Model H	Model I	Model J
	Mean Equation								
μ	46.9030	46.8472	11.3277	19.9655	46.6959	36.0995	46.7634	19.5396	46.0526
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.6484	0.6551	0.6610	0.6598	0.6554	0.6782	0.6525	0.6665	0.6667
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	0.0960	0.0943	0.0929	0.0937	0.0947	0.0930	0.0965	0.0913	0.0919
	(0.0000)	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2128)	(0.0000)	(0.0000)
ϕ_3	0.0549	0.0524	0.0537	0.0548	0.0524	0.0503	0.0535	0.0525	0.0490
	(0.0000)	(0.0000)	(0.0000)	(0.0544)	(0.0166)	(0.0000)	(0.1819)	(0.0000)	(0.0000)
ϕ_4	0.0404	0.0404	0.0445	0.0418	0.0403	0.0408	0.0394	0.0423	0.0404
	(0.0000)	(0.0011)	(0.0000)	(0.0014)	(0.0024)	(0.0000)	(0.0019)	(0.0000)	(0.0000)
ϕ_5	0.0273	0.0318	0.0325	0.0331	0.0315	0.0281	0.0279	0.0323	0.0313
	(0.0000)	(0.0082)	(0.0048)	(0.0003)	(0.0088)	(0.0059)	(0.0004)	(0.0092)	(0.0473)
ϕ_6	0.0429	0.0464	0.0366	0.0404	0.0457	0.0379	0.0415	0.0396	0.0439
	(0.0000)	(0.0017)	(0.0002)	(0.0018)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0351	0.0331	0.0353	0.0335	0.0336	0.0346	0.0334	0.0333	0.0329
	(0.0000)	(0.0069)	(0.0001)	(0.0020)	(0.0016)	(0.0000)	(0.0162)	(0.0000)	(0.0003)
wind		-8.4314		-4.3706				-4.0585	
		(0.0000)		(0.0000)				(0.0000)	
consumption			12.3130	9.4369				8.6044	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-22.6653				-22.6600
					(0.0000)				(0.0000)
hydro						2.9775		0.9561	
						(0.0000)		(0.0040)	
$exim_{bass}$							0.9736		1.2535
							(0.0000)		(0.0002)
	Variance Equation								
ω	0.5788	0.7808	0.5672	0.7672	0.7901	0.7956	0.5939	0.6921	0.8359
	(0.0000)	(0.0000)	(0.0357)	(0.0093)	(0.0000)	(0.0000)	(0.0000)	(0.0223)	(0.0000)
α	-0.1246	-0.1579	-0.1814	-0.1777	-0.1599	-0.1864	-0.1319	-0.1811	-0.1789
	(0.0046)	(0.0132)	(0.0006)	(0.0008)	(0.0088)	(0.0003)	(0.0023)	(0.0006)	(0.0007)
β	0.9000	0.8816	0.8833	0.8802	0.8803	0.8870	0.8975	0.8777	0.8752
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.9764	1.3273	1.4499	1.4750	1.3602	1.4148	0.9705	1.4887	1.4936
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
wind		-0.1556		-0.1643				-0.1375	
		(0.1601)		(0.1525)				(0.2364)	
consumption			0.0680	0.0167				0.0871	
			(0.4939)	(0.8732)				(0.4479)	
$wind_{pen}$					-0.3729				-0.2634
					(0.1937)				(0.3685)
hydro						-0.0255		-0.0416	
						(0.2536)		(0.1088)	
$exim_{bass}$							-0.0606		-0.0604
							(0.0098)		(0.0000)
Shape	2.2181	2.1251	2.1000	2.1000	2.1194	2.1000	2.2264	2.1000	2.1000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-13151.66	-13055.39	-13018.95	-12996.82	-13048.03	-13096.72	-13143.7	-12991.11	-13038.22
AIC	7.2076	7.1560	7.1360	7.1250	7.1519	7.1786	7.2043	7.1230	7.1477
BIC	7.2297	7.1814	7.1615	7.1539	7.1774	7.2041	7.2298	7.1552	7.1765
Q(136)	34.15	37.37	38.43	38.98	37.68	36.55	33.30	38.26	37.65
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	1.4785	3.0634	3.3030	3.8281	3.2806	2.1846	1.5535	4.0445	3.4174
	(0.9573)	(0.7484)	(0.7081)	(0.6181)	(0.7119)	(0.8819)	(0.9511)	(0.5813)	(0.6885)
ARCH-LM Test	1.0519	1.9389	2.1379	2.3914	2.0512	1.4805	1.0964	2.5192	2.1085
	(0.9050)	(0.7303)	(0.6881)	(0.6349)	(0.7065)	(0.8253)	(0.8974)	(0.6085)	(0.6944)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

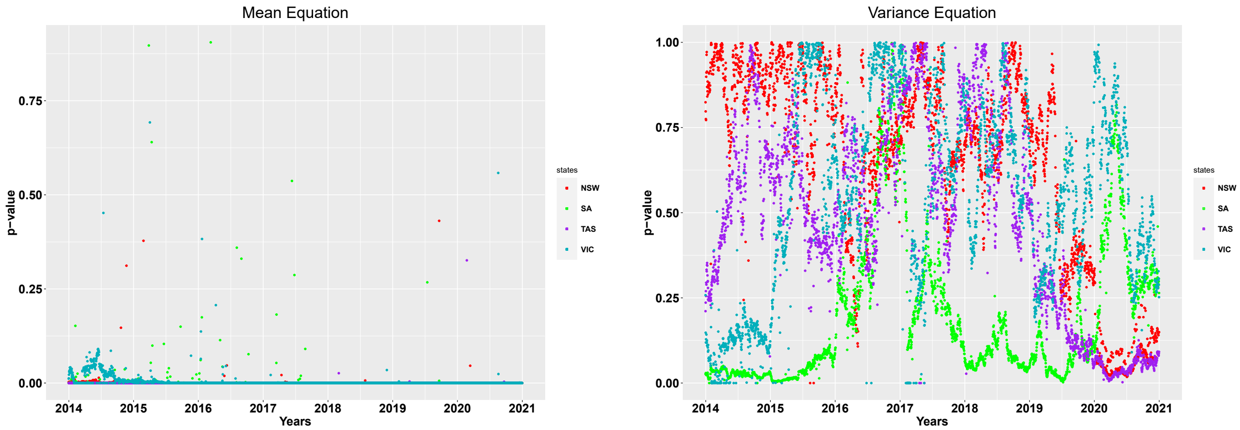

Figure A.9 : **Estimated p-values for the evolution of the impact of wind penetration from 2014 to 2020 for NSW, SA, VIC, and TAS.** The coefficients estimated using the rolling regression with three years windows while controlling for gas prices, hydro generation and the interconnectors. The effect on price level is given by the figures on the left and on price volatility by the figures on the right panel.

A.4 Additional Analyses

A.4.1 Exclusion of solar generation

We re-ran all models by including large-scale and rooftop solar generation as one of the control variables to examine the plausibility of the underlying assumptions.[3] The results for this analysis are presented in Table A.23.

We compare the results in Table A.23 and that of Tables 2.3 to 2.6. Looking at the main variable of interest, that is, wind generation, it appears that the inclusion of large-scale and rooftop solar generation has only a small impact on the estimated coefficients. For instance, the wind generation coefficient in Table 2.4 for SA is -13.2384, whereas including large-scale and rooftop solar generation changes the coefficient to -12.7151 and -13.3195, respectively. For volatility, the coefficient is 0.1852 in Table 2.4, whereas the coefficient changes to 0.1949 and 0.1903 after including large-scale and rooftop solar generation. The conclusion does not change; namely, an increase in wind generation leads to a 1.3 AUD/MWh decline in electricity prices and a 2% increase in price volatility, and this finding remains statistically significant even with the inclusion of solar output.

[3]We include large-scale and rooftop solar generation in separate models to avoid multicollinearity problems as the two generations happen during the day, and hence they are highly correlated.

Table A.23 : **The effect of wind generation, large-scale solar generation, rooftop solar generation, electricity consumption, hydro generation, gas prices, and interconnector flows on electricity price dynamics.** The effect on price levels is given by the mean equation and price volatility by the variance equation.

	NSW				SA				VIC				TAS	
	Model I	Model J	Model I'	Model J'	Model I	Model J	Model I'	Model J'	Model I	Model J	Model I'	Model J'	Model I	Model J
	Mean Equation													
μ	4.2435	47.7451	3.9531	47.0995	-17.1826	40.3728	-11.5184	41.0269	29.8643	49.7997	30.9218	49.7547	31.2015	60.2195
	(0.0095)	(0.0000)	(0.0149)	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.8515	0.84542	0.8521	0.8469	0.5642	0.5286	0.5557	0.5285	0.8000	0.7985	0.7998	0.7982	0.9625	0.9623
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$	$\boxed{-4.4674}$		$\boxed{-4.4857}$		$\boxed{-12.7151}$		$\boxed{-13.3195}$		$\boxed{-5.3078}$		$\boxed{-5.4735}$		$\boxed{-5.7439}$	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$large-scale\ solar$	-2.8052				43.9531				-0.2221					
	(0.1475)				(0.0002)				(0.9637)					
$rooftop\ solar$			-12.0688				-43.6198				-17.6226		-99.9877	
			(0.0309)				(0.0722)				(0.0631)		(0.1397)	
$consumption$	2.3636		2.3821		18.3599		17.1548		1.6664		1.6140		8.7357	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$wind_{pen}$		$\boxed{-92.8222}$		$\boxed{-91.6540}$		$\boxed{-47.3532}$		$\boxed{-47.1822}$		$\boxed{-64.3526}$		$\boxed{-64.9283}$		$\boxed{-29.9821}$
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
$large-scale\ solar_{pen}$		-100.0000				-16.9745				-29.2753				
		(0.0107)				(0.6090)				(0.6345)				
$rooftop\ solar_{pen}$				-100.0000				-100.0000				-46.0349		-100.0000
				(0.4398)				(0.14751)				(0.6868)		(0.7367)
gas	0.1964	0.3462	0.1879	0.3417	5.6722	6.7244	5.9024	6.6802	1.3145	1.3907	1.3370	1.3998		
	(0.0679)	(0.0249)	(0.0970)	(0.0069)	(0.0069)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$hydro$	4.2793	6.7376	4.2736	6.9639					5.0754	6.2005	5.0609	6.1954	1.9356	
	(0.0000)	(0.0000)	(0.0422)	(0.0000)					(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
$exim_{bass}$									5.2536	5.8609	5.2574	5.9029		2.3304
									(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
$exim_{heyw}$					-9.6040	-9.1543	-10.2287	-9.16506	-1.6169	-1.8491	-1.65819	-1.8493		
					(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0271)	(0.0317)	(0.0047)	(0.0629)		
$exim_{VNI}$	-1.0100	-1.0469	-0.9792	-0.9824					-3.8599	-4.4033	-3.7889	-4.3741		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$exim_{murry}$					39.6977	40.558	41.0960	40.7007	-0.1898	-0.9453	-0.0923	-1.0626		
					(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9368)	(0.7892)	(0.9687)	(0.8320		)
$exim_{terra}$	-8.4300	-9.7015	-7.9675	-9.2662										
	(0.0588)	(0.0081)	(0.0000)	(0.0848)										
$exim_{QNI}$	-1.7626	-2.0858	-1.8519	-2.1412										
	(0.0003)	(0.0000)	(0.0000)	(0.0005)										
	Variance Equation													
ω	-0.7688	1.7749	-0.7429	1.7318	0.6909	2.759	0.5574	2.6291	-0.2004	2.0222	-0.2849	2.0219	1.1269	1.3285
	(0.1726)	(0.0000)	(0.1834)	(0.0000)	(0.0226)	(0.0000)	(0.0576)	(0.0000)	(0.6630)	(0.0000)	(0.5376)	(0.0000)	(0.0116)	(0.0000)
α	0.1375	0.1298	0.1505	0.1365	-0.0545	-0.114	-0.0601	-0.1094	-0.0366	-0.0527	-0.0459	-0.0635	-0.0273	-0.0223
	(0.0001)	(0.0004)	(0.0000)	(0.0001)	(0.1489)	(0.0076)	(0.1069)	(0.0101)	(0.2888)	(0.1376)	(0.1778)	(0.0752)	(0.6630)	(0.6673)
β	0.3324	0.3570	0.3330	0.3625	0.4499	0.4593	0.4660	0.4762	0.4758	0.4814	0.4812	0.4848	0.8020	0.7958
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.6390	0.6371	0.6308	0.6359	0.5248	0.4872	0.5195	0.4816	0.4245	0.4175	0.4273	0.4268	1.7781	1.4374
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$wind$	$\boxed{-0.0533}$		$\boxed{-0.0839}$		$\boxed{0.1949}$		$\boxed{0.1903}$		$\boxed{0.1286}$		$\boxed{0.1326}$		$\boxed{-0.3192}$	
	(0.5284)		(0.3179)		(0.0005)		(0.0004)		(0.0176)		(0.0140)		(0.0232)	
$large-scale\ solar$	0.9637				-0.4431				1.8574					
	(0.0051)				(0.6449)				(0.0013)					
$rooftop\ solar$			4.3355				3.9121				2.4693		11.2553	
			(0.0000)				(0.0117)				(0.0117)		(0.2389)	
$consumption$	0.1352		0.1342		0.6013		0.5978		0.1836		0.1886		0.1501	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.3314)	
$wind_{pen}$		$\boxed{-1.8641}$		$\boxed{-2.1375}$		$\boxed{0.1596}$		$\boxed{0.1796}$		$\boxed{1.5515}$		$\boxed{1.5643}$		$\boxed{-0.7167}$
		(0.2412)		(0.1752)		(0.3264)		(0.2633)		(0.0218)		(0.0210)		(0.0351)
$large-scale\ solar_{pen}$		12.224				-7.4244				18.9831				
		(0.0524)				(0.0112)				(0.0064)				
$rooftop\ solar_{pen}$				65.1170				-0.7473				21.5669		30.2061
				(0.0011)				(0.8709)				(0.0708)		(0.2270)
gas	0.0594	0.0662	0.0615	0.0665	0.1120	0.1477	0.1043	0.1390	0.0538	0.0545	0.0542	0.0555		
	(0.0031)	(0.0008)	(0.0020)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0022)	(0.0018)	(0.0020)	(0.0016)		
$hydro$	0.5894	0.6857	0.5812	0.6875					0.2381	0.4194	0.2329	0.4177	-0.0583	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					(0.0019)	(0.0000)	(0.0022)	(0.0000)	(0.0858)	
$exim_{bass}$									-0.0277	0.0315	-0.0314	0.0276		-0.0671
									(0.5667)	(0.4984)	(0.5135)	(0.5516)		(0.0505)
$exim_{heyw}$					0.1021	0.1427	0.1083	0.1555	0.1548	0.1504	0.1556	0.1490		
					(0.2780)	(0.1257)	(0.2404)	(0.0889)	(0.0707)	(0.0764)	(0.0676)	(0.0797)		
$exim_{VNI}$	0.1539	0.1170	0.1411	0.1050					-0.0340	-0.0905	-0.0328	-0.0890		
	(0.0002)	(0.0040)	(0.0007)	(0.0093)					(0.3849)	(0.0154)	(0.3986)	(0.0175)		
$exim_{murry}$					0.6169	0.584	0.4804	0.5211	-0.7563	-0.8419	-0.7055	-0.7998		
					(0.0992)	(0.1122)	(0.1906)	(0.1501)	(0.0284)	(0.0143)	(0.0395)	(0.0199)		
$exim_{terra}$	-1.2576	-1.2034	-1.2761	-1.1928										
	(0.1115)	(0.1190)	(0.1048)	(0.1214)										
$exim_{QNI}$	-0.1103	-0.1249	-0.0926	-0.1148										
	(0.1711)	(0.1119)	(0.2484)	(0.1422)										
Shape	2.9605	2.8921	2.9894	2.9333	2.6709	2.4747	2.6726	2.4575	2.8246	2.7282	2.8263	2.7152	2.1000	2.1606
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-13045.6	-13129.55	-13040.06	-13130.26	-14035.21	-16172.2	-16275.83	-16172.76	-16272.74	-14034.65	-14056.22	-14057.76	-13548.06	-13589.53
AIC	7.1550	7.1999	7.1520	7.2003	8.8646	8.9202	8.8649	8.9186	7.6976	7.7083	7.6979	7.7091	7.4257	7.4473
BIC	7.1941	7.2355	7.1910	7.2359	8.8969	8.9491	8.8972	8.9474	7.7400	7.7474	7.7404	7.7482	7.4512	7.4694
Q(20)	4.010	1.1988	4.218	1.3648	6.243	0.8840	5.830	0.8552	8.329	5.041	8.708	5.175	57.61	56.70
	(0.2238)	(0.9128)	(0.1928)	(0.8783)	(0.0378)	(0.9627)	(0.0538)	(0.9661)	(0.0056)	(0.1029)	(0.0039)	(0.0924)	(0.0000)	(0.0000)
$Q^2(36)$	0.0057	0.0034	0.0072	0.0038	0.0964	0.0352	0.0961	0.0330	0.0186	0.0156	0.0172	0.0163	4.297	3.9042
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.5392)	(0.6051)
ARCH-LM Test	0.0029	0.0022	0.00363	0.0024	0.0656	0.0273	0.0680	0.0259	0.0171	0.0139	0.0160	0.0147	2.648	2.4444
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9998)	(1.0000)	(0.9997)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.5823)	(0.6239)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

As indicated on page 19 of the original manuscript, the MOE results differ slightly from that of Csereklyei et al. (2019), who studied the impact of both solar and wind generation on the level of electricity prices in the NEM from 2010 to 2018.

A.4.2 Realized Volatility

The realized GARCH of Hansen et al. (2012) jointly models the returns and realized measures of volatility. This approach differs from the conventional GARCH in the ways that it includes the measurement equation that relates the observed realized measure to the conditional variance (latent volatility). Furthermore, the measurement equation includes the asymmetric reaction to shocks parameter leading to more flexible model compared to the vanilla GARCH. Formally, define the conditional mean as $\mu_t = E(p_t|\mathcal{F}_{t-1})$ and conditional variance as $\sigma_t^2 = var(p_t|\mathcal{F}_{t-1})$ with $\mathcal{F}_t = \sigma(p_t, x_t, p_{t-1}, x_{t-1}, \dots)$, then the realized GARCH(p,q) specification is given by[4]

$$p_t = \mu + \sigma_t z_t, \tag{1.4.1}$$

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \log x_{t-i} + \sum_{j=1}^{q} \beta_j \log \sigma_{t-j}^2, \tag{1.4.2}$$

$$\log x_t = \xi + \delta \log \sigma_t^2 + \tau\left(z_t\right) + u_t, \tag{1.4.3}$$

where p_t is electricity prices, x_t a realized measure of volatility, $z_t \sim$i.i.d.(0, 1) and $u_t \sim$ i.i.d.(0, σ_u^2) with z_t and u_t being mutually independent. The measurement equation relating the observed realized measure to the latent volatility is by equation (1.4.3). $\tau\left(z_t\right)$ is the leverage function which captures the dependence between returns and future volatility or the asymmetric reaction to shocks. Hansen et al. (2012) specified this function as a

[4]We choose the logarithmic specification because it has better numerical and statistical properties compared to the linear specification. Specifically, the conditional variance is guaranteed to be positive regardless of the values of the estimated parameters and it reasonably fit well to the distributional assumption applied in the quasi-maximum likelihood estimation.

simple quadratic form given by[5]

$$\tau\left(z_t\right) = \eta_1 z_t + \eta_2\left(z_t^2 - 1\right).$$

It can be shown that $\tau\left(z_t\right)$ has the property $\mathbb{E}_\tau(z_t) = 0$, for any distribution with $\mathbb{E}(z_t) = 0$ and $var(z_t) = 1$. From the function $\tau\left(z_t\right)$, if $\tau_1 < 0$ and $\tau_2 > 0$ then, negative shocks will have larger impacts than positive ones. The parameter τ_1 accounts for the size of the asymmetry between negative and positive shock, whereas τ_2, governs the level at which this occurs. δ captures how much realized volatility is explained by conditional variance. The parameters ξ and δ adjust for the microstructure noise, which can introduce bias in the realized variance. In an instance where there is no bias and the realized volatility is an unbiased estimator of true volatility then $\xi = 0$ and $\delta = 1$ (Contino and Gerlach, 2017). β measures the persistence of the conditional variance, α measures how the shocks to the realized measure affect the conditional variance.

To allow the analysis of the impact of exogenous variables on the dynamics of electricity prices, we modify equation (1.4.1) and (1.4.2) by additively including the ARMAX dynamics in the mean equation and the GARCHX dynamics in the variance equation as follows:

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \kappa_j' \boldsymbol{v}_{t-j} + \sigma_t z_t, \tag{1.4.4}$$

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \log x_{t-i} + \sum_{j=1}^{q} \beta_j \log \sigma_{t-j}^2 + \sum_{k=1}^{r} \rho_k' \boldsymbol{v}_{t-k}, \tag{1.4.5}$$

$$\log x_t = \xi + \delta \log \sigma_t^2 + \tau\left(z_t\right) + u_t, \tag{1.4.6}$$

where P_{t-i}, $i = 1, \ldots, k$, are lags of electricity prices, $\boldsymbol{v}_t$ is an $m \times 1$ vector of variables, and κ and ρ are the $m \times 1$ vector of coefficients.

Using the high-frequency regional reference prices (spaced in the 30-min interval), we construct the lower frequency (daily) statistic volatility measures of x_t using the realized

[5]This function is a result of truncation from the Hermite polynomials given by $\tau\left(z_t\right) = \eta_1 z_t + \eta_2\left(z_t^2 - 1\right) + \eta_3(z^3 - 3z) + \eta_4(z^4 - 6z^2 + 3) + \ldots$. One can show that the leverage function in the eGARCH model of Nelson (1991) falls within the class of this leverage functions (Hansen et al., 2012).

variance (RV) and the square of intraday range (IR) as in Frömmel et al. (2014).[6] The fact that we employ low-frequency data estimated on a half-hour basis by averaging six dispatch electricity prices minimizes microstructure noise which may induce bias in the RV measure (Sharma et al., 2016). Typically, this bias increases progressively as the sampling frequency is increased. The RV measure for day t is given by

$$RV_t = \sum_{i=1}^{M}(p_i - p_{i-1})^2, \quad i = 1, \ldots, M, \quad t = 1, \ldots T,$$

where p_i denotes electricity prices adjusted for both seasonality and trend effects,[7] M is the sampling frequency, totalling 48 intervals in a day, and T is the total number of days in our sample. In the same vein and the context of the electricity market, Frömmel et al. (2014) showed that the square of the intraday range has the potential to improve the in-sample fit of the data due to the robustness against microstructure noise bias than the RV. The square IR measure for day t is given by

$$IR_t = \left(\max_j p_{t,j} - \min_j p_{t,j}\right)^2, \quad j = 1, \ldots, M, \quad t = 1, \ldots T,$$

where $\max_j p_{t,j}$ denote the maximum price and $\min_j p_{t,j}$ the minimum price within the day.[8]

It is apparent from Figure A.10 and A.11 that the logarithm of the variance measures estimated by RV and IR are highly correlated. We choose the best measure using the log-likelihood and information criteria, the AIC and BIC. Their estimated values are given in

[6]A number of realized measured have been suggested in the literature for constructing the realized variance from high-frequency returns, such as realized variance, the realized bipower variation measure, realized kernel, and intraday range. However, the direct applications of these measures to power markets remain an open research question.

[7]Since we are using high frequency data, we add dummy variables for the half-hourly trading interval in a day to account for the intraday seasonality as follows: $p_t = \hat{c} + \sum_{i=2}^{p} \hat{\psi} \cdot time_i + \sum_{j=2}^{q} \hat{\phi} \cdot day_j + \sum_{k=2}^{r} \hat{\zeta} \cdot month_k + \sum_{l=2}^{s} \hat{\eta} \cdot year_l + \varepsilon_t$, where p_t is the electricity prices, p, q, r and s are the total number of days in a week, months, half-hourly trading interval in a day and years, $\hat{c}$ is the estimate of the intercept, and $\hat{\phi}$, $\hat{\zeta}$, $\hat{\psi}$, $\hat{\eta}$ are the parameter estimates of the weekdays, monthly, time and yearly regressors. We fix the reference variables for time, weekdays, months, and years to 00:00 Hrs., Monday, January and 2011, respectively.

[8]Since there is no study in the electricity market yet which suggests an appropriate method for estimating the IR, we follow the approach by Frömmel et al. (2014) and apply no scaling factor of 4 log (2) to the square of IR. This omission imposes no impact on the relationship between the log of realized measure and the conditional variance.

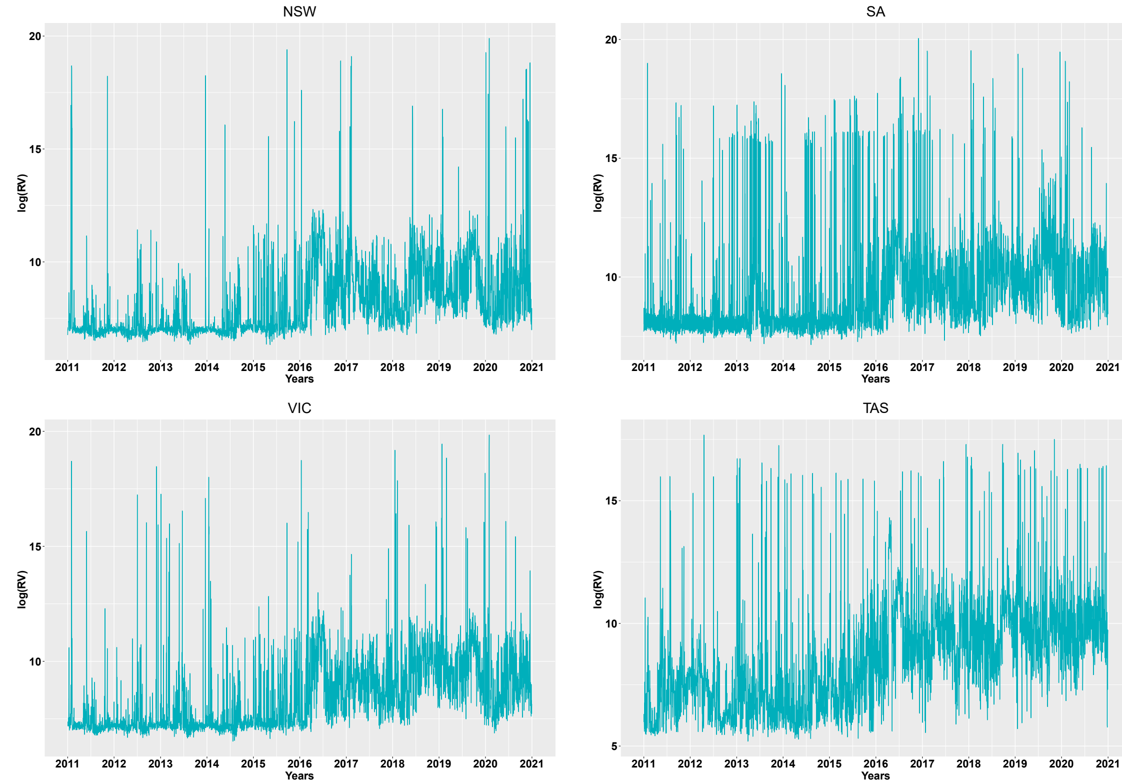

Figure A.10 : **The realized variance (RV) in logarithmic scale for NSW, SA, VIC, and TAS from 2011 to 2020.**

Table A.24. As shown in this table, the best realized GARCH model is attained by using the Student's t distribution and the IR measure.[9] This conclusion concurs with that of Frömmel et al. (2014) who showed that the intraday range produces better results when employed to estimate the daily price volatility in the EPEX power markets compared to the realized variance. To that end, we use the IR and Student's t distribution for our analysis, and the results are shown in Table A.25 to A.28.[10,11]

We see that the coefficient of α, which measures how the shocks to the realized measure

[9]We reached the same conclusion using high-frequency prices adjusted for both outliers, seasonality, and trend effects.

[10]However, when we compare the realized GARCH and eGARCH models, the latter outperforms the former under all distribution assumptions. Moreover, the inclusion of more autoregressive components slightly alters the coefficients but not the conclusion.

[11]It is worth mentioning that the estimated coefficients from the realize GARCH appear to be sensitive to changes in the `rugarch` package solvers and in some cases leading to a significant change in the parameter values, including the leverage parameters. We applied the `hybrid` solver as recommended by Ghalanos (2022). However, where `gosolnp` solver produces better results in terms of log-likelihood, AIC, and BIC, it is used instead.

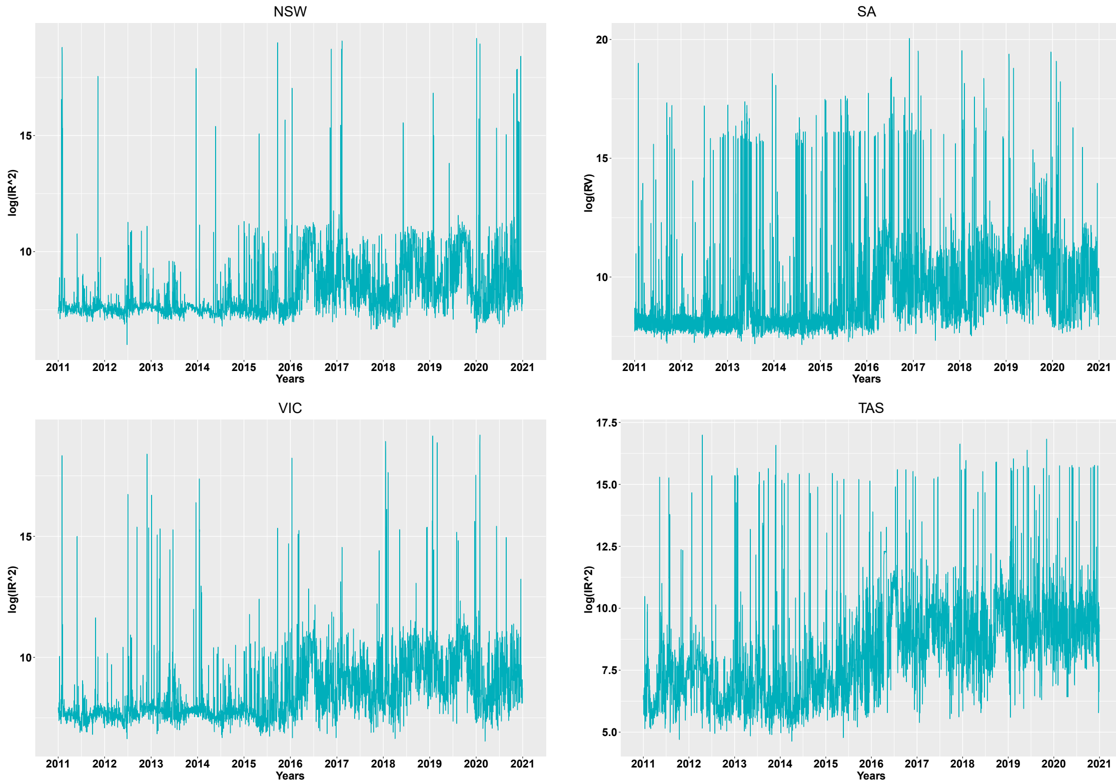

Figure A.11 : **The square of intraday range (IR) in logarithmic scale for NSW, SA, VIC, and TAS from 2011 to 2020.**

affect the conditional variance, is significant in all states signifying a strong emphasis placed in the realized measure, the IR. There is also strong evidence that volatility is persistent, as indicated by the statistical significance of the parameter β in all states. However, the magnitude of α and β are relatively small compared to the ARCH and GARCH parameters in the eGARCH model. As expected, the coefficient of the leverage function are such that $\tau_1 > 0$ and $\tau_2 < 0$ for NSW, SA, and VIC, and $\tau_1 > 0$ and $\tau_2 > 0$ for TAS. The fact that $\tau_1 > 0$ suggests the "inverse leverage effect" where positive shocks exert more impact on the volatility than the negative shocks of the same magnitude. The coefficient of δ is approximately a unit suggesting that the realized measure, the IR is roughly proportional to the conditional variance. The parameter σ_u^2 is required as an input for the likelihood function of the measurement equation, and it has no practical interpretation.

Looking at the exogenous variables, we see that the mean equation's coefficients are

Table A.24 : **Log-likelihood, BIC, and AIC estimates of the AR(1)-eGARCH and AR(1)-realized GARCH (rGARCH) model under the Normal Distribution (Normal), the Student Distribution (Student's-t), and Generalized Error Distribution (GED).** RV and IR stand for the realized variance and intraday range measures, respectively.

		Normal			Student's-t			GED		
		eGARCH	rGARCH-RV	rGARCH-IR	eGARCH	rGARCH-RV	rGARCH-IR	eGARCH	rGARCH-RV	rGARCH-IR
NSW										
	Log-Likelihood	-15459.87	-20358.04	-19908.43	-13468.55	-18379.35	-17967.00	-13738.05	-18693.72	-18270.84
	AIC	8.4675	11.1514	10.9052	7.3778	10.0686	9.8429	7.5253	10.2407	10.0092
	BIC	8.4777	11.1684	10.9222	7.3897	10.0873	9.8615	7.5372	10.2594	10.0279
SA										
	Log-Likelihood	-19685.41	-26504.56	-26629.39	-17051.19	-24124.18	-23694.12	-17326.44	-42863.71	-23984.82
	AIC	10.781	14.5166	14.5849	9.3393	13.2139	12.9784	9.4900	23.4737	13.1376
	BIC	10.791	14.5336	14.6019	9.3512	13.2326	12.9971	9.5019	23.4924	13.1563
VIC										
	Log-Likelihood	-18252.48	-23224.61	-22951.00	-14785.68	-20149.56	-19719.59	-15221.61	-20531.62	-20351.46
	AIC	9.9964	12.7208	12.5710	8.0989	11.0378	10.8024	8.3376	11.2470	11.1483
	BIC	10.0066	12.7378	12.5880	8.1108	11.0565	10.8211	8.3495	11.2657	11.1670
TAS										
	Log-Likelihood	-14717.57	-23445.06	-23254.71	-13772.08	-20147.71	-19922.55	-13821.61	-20222.54	-20013.63
	AIC	8.0611	12.8415	12.7373	7.5440	11.0368	10.9135	7.5711	11.0778	10.9634
	BIC	8.0713	12.8585	12.7543	7.5559	11.0555	10.9322	7.5830	11.0964	10.9821

similar to that of the eGARCH model. This is no surprise since there are no changes made in equation (1.4.4). However, most of the exogenous variables in the variance equation are very small in magnitude and statistically insignificant.

Table A.25 : **The effect of wind generation, electricity consumption, hydro generation, gas prices, and interconnectors flow on New South Wales' electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
					Mean Equation					
μ	54.7992	56.4066	5.8574	8.7095	57.3724	52.2216	51.5118	52.0573	12.9870	51.0602
	(0.0000)	(0.0000)	(0.0511)	(0.0029)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.8357	0.8063	0.8450	0.8483	0.8404	0.8309	0.8364	0.8484	0.8512	0.8420
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-5.0145		-4.6104					-3.7313	
		(0.0000)		(0.0000)					(0.0000)	
$consumption$			2.5256	2.5014					2.0218	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-98.5389					-99.5053
					(0.0000)					(0.0000)
gas						0.4566			0.2158	0.2805
						(0.0000)			(0.0603)	(0.0181)
$hydro$							5.1213		2.3888	4.1155
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-7.4200	-7.0235	-7.9313
								(0.1380)	(0.0703)	(0.0453)
$exim_{QNI}$								-3.0960	-2.6049	-1.6679
								(0.0000)	(0.0000)	(0.0002)
$exim_{VNI}$								-1.3651	-1.3838	-0.9179
								(0.0000)	(0.0000)	(0.0000)
					Variance Equation					
ω	-0.5867	-0.1264	-1.8004	-1.8267	-0.5750	-0.5857	-0.5207	-0.5671	-1.7973	-0.5227
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.00000)	(0.0004)	(0.0001)
α	0.4260	0.2322	0.4178	0.4198	0.4287	0.4257	0.4244	0.4272	0.4525	0.4310
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.3740	0.6525	0.3230	0.3140	0.3655	0.3741	0.3329	0.3648	0.3078	0.3479
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_1	0.5000	0.4590	0.5000	0.5000	0.50000	0.5000	0.5000	0.5000	0.5000	0.5000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_2	-0.0024	-0.0007	-0.0027	-0.0027	-0.0024	-0.0024	-0.0023	-0.0024	-0.0027	-0.0024
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	1.0456	1.3616	1.0886	1.0938	1.0502	1.0459	1.0738	1.0543	1.0989	1.0630
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ξ	3.3394	1.2256	3.2672	3.2556	3.3238	3.3404	3.2812	3.3216	3.2575	3.2845
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
σ_u^2	0.8713	0.9229	0.8717	0.8747	0.8756	0.8715	0.8750	0.8727	0.8767	0.8828
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		10.0000e-09		1.0745e-11					2.1017e-08	
		(0.9748)		(1.0000)					(1.0000)	
$consumption$			0.0747	0.0770					0.0760	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					2.5594e-08					1.0016e-08
					(1.0000)					(1.0000)
gas						2.6663e-11			3.3363e-08	2.1006e-09
						(1.0000)			(1.0000)	(1.0000)
$hydro$							0.1490		3.4890e-08	1.4641e-08
							(0.0000)		(1.0000)	(1.0000)
$exim_{terra}$								5.9106e-09	1.6773e-08	8.7806e-09
								(1.0000)	(1.0000)	(1.0000)
$exim_{QNI}$								3.8022e-08	2.1773e-14	3.5435e-20
								(1.0000)	(1.0000)	(1.0000)
$exim_{VNI}$								3.1239e-08	2.8720e-08	5.8103e-10
								(1.0000)	(1.0000)	(1.0000)
Shape	3.0987	2.4812	3.1840	3.0913	2.9902	3.0963	3.1736	3.0626	3.0939	2.9188
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-17967	-18224.4	-17813.53	-17733.54	-17877.63	-17960.28	-17896.82	-17888.8	-17680.15	-17782.94
AIC	9.8429	9.9849	9.7599	9.7172	9.7950	9.8403	9.8055	9.8033	9.6935	9.7487
BIC	9.8615	10.0070	9.7820	9.7427	9.8171	9.8624	9.8276	9.8322	9.7359	9.7877
Q(20)	9.078	92.77	15.49	15.73	9.248	8.9560	11.18	9.518	15.99	9.869
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0018)	(0.0000)	(0.0000)
$Q^2(36)$	0.0519	6.385	0.1051	0.103	0.0487	0.0514	0.0543	0.0533	0.1033	0.0460
	(1.0000)	(0.2563)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0016	0.0023	0.0015	0.0016	0.0017	0.0016	0.0015	0.0017	0.0017	0.0017
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table A.26 : **The effect of wind generation, electricity consumption, gas prices, and interconnectors flow on South Australia's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model F	Model H	Model I	Model J
	Mean Equation								
μ	61.2327	68.3050	31.8663	37.7870	64.1314	47.5394	59.4044	-6.6643	41.2748
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1241)	(0.0000)
ϕ_1	0.6217	0.6086	0.6177	0.6047	0.6169	0.5884	0.6426	0.5848	0.5726
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-12.7450		-12.7857				-12.5332	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			1.5247	1.5856				15.4720	
			(0.0004)	(0.0002)				(0.0000)	
$wind_{pcn}$					-100.0000				-43.5598
					(0.0000)				(0.0000)
gas						2.3410		5.7846	6.4438
						(0.0000)		(0.0000)	(0.0000)
$exim_{murr}$							69.5257	37.0490	36.8594
							(0.0000)	(0.0000)	(0.0000)
$exim_{hey}$							8.1147	-9.0197	-8.0446
							(0.0000)	(0.0000)	(0.0000)
	Variance Equation								
ω	0.6328	0.6217	0.6371	0.6298	0.6196	0.6530	0.6206	-0.1895	0.5506
	(0.0002)	(0.0003)	(0.0252)	(0.0285)	(0.0002)	(0.0002)	(0.0002)	(0.4120)	(0.0031)
α	0.3732	0.3695	0.3745	0.3713	0.3733	0.3602	0.4013	0.3401	0.3707
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.3742	0.3778	0.3714	0.3737	0.3739	0.3640	0.3147	0.2736	0.2804
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_2	-0.0056	-0.0056	-0.0056	-0.0056	-0.0056	-0.0056	-0.0054	-0.0064	-0.0054
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	0.8643	0.8691	0.8630	0.8677	0.8639	0.8901	0.8430	0.9777	0.9058
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ξ	3.6900	3.6880	3.7023	3.7006	3.7124	3.5219	4.0081	3.2845	3.7100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
σ_u^2	1.5544	1.5525	1.5565	1.5547	1.5533	1.5529	1.5517	1.5452	1.5440
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		1.2061e-08		3.8665e-09				8.6441e-09	
		(1.0000)		(1.0000)				(1.0000)	
$consumption$			1.6031e-08	3.1691e-06				0.3465	
			(1.0000)	(0.9998)				(0.0000)	
$wind_{pcn}$					1.7848e-08				3.1446e-08
					(1.0000)				(1.0000)
gas						0.0289		0.0673	0.0810
						(0.0040)		(0.0000)	(0.0000)
$exim_{murr}$							9.7491e-09	6.0064e-08	1.8786e-09
							(1.0000)	(1.0000)	(1.0000)
$exim_{hey}$							3.6942e-08	2.4063e-08	3.9243e-09
							(1.0000)	(1.0000)	(1.0000)
Shape	3.0853	3.0937	3.0905	3.0972	3.0884	3.0681	2.9566	2.9618	2.9401
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-23694.12	-23628.45	-23687.7	-23621.29	-23650.43	-23669.41	-23221.15	-22882.35	-22954.89
AIC	12.978	12.944	12.976	12.941	12.956	12.966	12.722	12.539	12.578
BIC	12.997	12.966	12.998	12.966	12.978	12.988	12.747	12.575	12.610
Q(20)	13.38	13.53	13.19	13.28	13.36	12.16	15.73	25.19	16.13
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	0.5064	0.4912	0.4861	0.4684	0.4883	0.5076	0.3511	0.7737	0.3836
	(0.9984)	(0.9986)	(0.9910)	(0.9988)	(0.9986)	(0.9984)	(0.9995)	(0.9938)	(0.9994)
ARCH-LM Test	0.0316	0.0314	0.0317	0.0316	0.0314	0.0337	0.0271	0.0392	0.0268
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(0.9999)	(1.0000)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table A.27 : **The effect of wind generation, electricity consumption, hydro generation, gas prices and interconnectors flow on Victoria's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H	Model I	Model J
	Mean Equation									
μ	56.2689	62.7019	-10.6078	12.3084	62.6047	47.1736	49.2590	59.1875	37.4253	52.7166
	(0.0000)	(0.0000)	(0.0013)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.7904	0.8078	0.8089	0.8218	0.8107	0.7837	0.8064	0.8105	0.8156	0.8137
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-8.0417		-7.1158					-5.0158	
		(0.0000)		(0.0000)					(0.0000)	
$consumption$			5.3142	3.9417					1.2676	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-99.9999					-61.6157
					(0.0000)					(0.0000)
gas						1.6267			1.1830	1.2366
						(0.0000)			(0.0000)	(0.0000)
$hydro$							9.0800		3.6387	4.2777
							(0.0000)		(0.0000)	(0.0000)
$exim_{murr}$								5.5494	1.0466	0.6334
								(0.0080)	(0.6031)	(0.7530)
$exim_{hey}$								-0.3232	-1.9041	-2.0446
								(0.6019)	(0.0017)	(0.0007)
$exim_{VNI}$								-6.4531	-3.6340	-3.9780
								(0.0000)	(0.0000)	(0.0000)
$exim_{bass}$								7.8251	5.0022	5.3421
								(0.0000)	(0.0000)	(0.0000)
	Variance Equation									
ω	-0.8298	-0.6777	-1.3479	-1.2797	-0.6893	-0.8264	-0.7456	-0.7760	-1.0485	-0.6760
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.4431	0.4558	0.4411	0.4413	0.4585	0.4398	0.4286	0.4637	0.4377	0.4466
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.4554	0.3921	0.4081	0.3576	0.3870	0.4590	0.4330	0.3883	0.3393	0.3469
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_1	0.4699	0.4641	0.4395	0.4373	0.4614	0.4681	0.4420	0.4662	0.4416	0.4482
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_2	-0.0048	-0.0045	-0.0043	-0.0041	-0.0044	-0.0048	-0.0044	-0.0045	-0.0042	-0.0043
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	0.8681	0.9150	0.9118	0.9647	0.9149	0.8715	0.9106	0.9021	0.9828	0.9621
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ξ	3.8125	3.6780	3.7285	3.5400	3.7004	3.80312	3.6870	3.7682	3.4764	3.5645
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
σ_u^2	0.9921	0.9906	1.0025	0.9981	0.9912	0.9932	1.0036	0.9910	0.9961	0.9952
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		1.0407e-08		2.3167e-13					1.2552e-07	
		(1.0000)		(1.0000)					(1.0000)	
$consumption$			0.0556	0.0663					0.0390	
			(0.0001)	(0.0000)					(0.0207)	
$wind_{pen}$					3.3266e-08					2.5555e-08
					(1.0000)					(1.0000)
gas						6.6846e-08			0.0153	0.0145
						(1.0000)			(0.0567)	(0.0716)
$hydro$							0.1364		0.1271	0.1567
							(0.0000)		(0.0002)	(0.0000)
$exim_{murr}$								3.6326e-08	2.9243e-08	3.9231e-09
								(1.0000)	(1.0000)	(1.0000)
$exim_{hey}$								0.0595	0.0539	0.0521
								(0.1056)	(0.1556)	(0.1681)
$exim_{VNI}$								0.0226	0.0339	0.0250
								(0.1551)	(0.0613)	(0.1541)
$exim_{bass}$								0.0232	5.2252e-06	0.0063
								(0.9998)	(0.9998)	(0.7729)
Shape	3.1414	2.9697	3.2576	3.0743	2.9744	3.1238	3.1525	2.9588	2.9840	2.9539
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-19719.59	-19332.11	-19514.26	-19204.49	-19292.27	-19692.47	-19557.46	-19276.97	-19074.12	-19078.84
AIC	10.802	10.591	10.691	10.523	10.570	10.789	10.715	10.564	10.458	10.459
BIC	10.821	10.613	10.713	10.548	10.592	10.811	10.737	10.597	10.504	10.502
Q(20)	5.183	6.869	10.645	12.40	7.192	5.409	9.793	8.361	13.48	11.697
	(0.0918)	(0.0217)	(0.0006)	(0.0000)	(0.0000)	(0.0764)	(0.0013)	(0.0054)	(0.0000)	(0.0002)
$Q^2(36)$	0.1437	0.1514	0.1602	0.1990	0.1480	0.1497	0.1935	0.1236	0.1849	0.1644
	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(0.9999)	(1.0000)
ARCH-LM Test	0.0237	0.0174	0.0188	0.0136	0.0172	0.0239	0.01951	0.0188	0.0131	0.0144
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Table A.28 : **The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on Tasmania's electricity price behaviour.** The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	Model A	Model B	Model C	Model D	Model E	Model G	Model H	Model I	Model J
	Mean Equation								
μ	63.3295	65.7588	25.7399	39.7928	65.7542	51.7027	62.9756	39.0925	65.1592
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9501	0.9561	0.9575	0.9581	0.9563	0.9575	0.9511	0.9597	0.9578
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-11.2199		-6.7010				-6.0648	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			14.1615	9.3709				7.8262	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-29.4344				-30.1405
					(0.0000)				(0.0000)
$hydro$						4.4466		1.7474	
						(0.0000)		(0.0000)	
$exim_{bass}$							1.5030		2.1432
							(0.0001)		(0.0000)
	Variance Equation								
ω	-0.4910	-0.5287	-0.5596	-0.5600	-0.5377	-0.4891	-0.4831	-0.5520	-0.5280
	(0.0000)	(0.0000)	(0.0101)	(0.0179)	(0.0000)	(0.0000)	(0.0000)	(0.0225)	(0.0000)
α	0.3472	0.3532	0.3545	0.3559	0.3538	0.3510	0.3473	0.3563	0.3542
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.5423	0.5349	0.5419	0.5370	0.5352	0.5364	0.5413	0.5353	0.5333
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_1	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
η_2	0.0684	0.0623	0.0630	0.0609	0.0616	0.0663	0.0688	0.0608	0.0616
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	1.0407	1.0373	1.0207	1.0258	1.0350	1.0404	1.0423	1.0276	1.0373
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
σ_u^2	1.3663	1.3647	1.3679	1.3663	1.3647	1.3669	1.3662	1.3664	1.3645
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ξ	2.8250	2.8971	2.9517	2.9537	2.9131	2.8192	2.8088	2.9378	2.8934
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		2.8180e-08		9.3768e-11				3.5247e-08	
		(1.0000)		(1.0000)				(1.0000)	
$consumption$			2.5819e-08	1.2164e-08				2.5762e-08	
			(1.0000)	(1.0000)				(1.0000)	
$wind_{pen}$					4.8808e-09				1.6830e-08
					(1.0000)				(1.0000)
$hydro$						2.1073e-08		2.5929e-08	
						(1.0000)		(1.0000)	
$exim_{bass}$							3.2186e-08		2.6424e-08
							(1.0000)		(1.0000)
Shape	2.6455	2.6030	2.5575	2.5650	2.60000	2.5680	2.6290	2.5493	2.5788
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-19922.55	-19767.96	-19758.33	-19717.67	-19755.76	-19829.81	-19915.14	-19704.78	-19738.76
AIC	10.914	10.830	10.825	10.804	10.823	10.864	10.911	10.798	10.815
BIC	10.932	10.852	10.847	10.829	10.845	10.886	10.933	10.826	10.841
Q(20)	88.11	89.93	90.76	90.72	89.84	88.32	87.72	90.01	88.54
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	17.35	16.16	15.11	15.22	15.94	16.36	17.35	15.11	15.90
	(0.0010)	(0.0019)	(0.0034)	(0.0032)	(0.0021)	(0.0017)	(0.0009)	(0.0034)	(0.0022)
ARCH-LM Test	6.3968	6.1803	5.6339	5.7780	6.1404	6.2145	6.4086	5.8045	6.1363
	(0.1167)	(0.1296)	(0.1678)	(0.1569)	(0.1321)	(0.1275)	(0.1161)	(0.1549)	(0.1323)
Observations	3653	3653	3653	3653	3653	3653	3653	3653	3653

Wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10^4 to clarify the presentation of the results. The corresponding coefficients should, therefore, be multiplied by 0.1 AUD/MWh and 0.1 for a 1 GWh increase in either variable for the mean equation and the variance equation, respectively. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion and ARCH LM is the Lagrange multiplier test for ARCH effect. The p values are in parentheses.

Appendix B

Large scale and rooftop solar generation in the NEM: a tale of two renewables strategies

B.1 Data

B.1.1 Data availability

Table B.1 : **Available data for large-scale solar, rooftop solar, and wind generation.** The date indicates the starting point of the datasets in each state.

	NSW	VIC	QLD	SA	TAS
Rooftop Solar	2018-03-09 00:00:00	2018-03-09 00:00:00	2018-03-09 00:00:00	2018-03-09 00:00:00	2018-03-09 00:00:00
Large-scale Solar	2015-03-21 00:00:00	2018-04-24 00:00:00	2017-12-01 00:00:00	2018-05-14 00:00:00	No large-scale plants
Large-scale wind	More than a decade	More than a decade	2018-08-20 00:00:00	More than a decade	More than a decade

B.1.2 Summary statistics and time-series tests of the adjusted data series

Table B.2, B.3, and B.4 present the summary statistics of the original and adjusted electricity prices and the normality test, tests for autocorrelation and conditional heteroscedasticity, as well as the stationarity test, respectively. We confirm the stationarity of the electricity spot price series and explanatory variables by rejecting the null hypothesis for the presence of the unit root at the 1% significance level for all the variables and for all five regional markets using the augmented Dickey-Fuller (ADF) test. The Jarque-Bera test for normality indicates that the distribution of prices is non-normal with positive skewness and pronounced positive kurtosis. Moreover, we confirmed the presence of autocorrelation and conditional heteroscedasticity in spot electricity prices after rejecting the null hypotheses for the Ljung-Box and Engle (1982) ARCH-LM tests at the 1% significance level for all lags and in all regional markets. The clustering of price volatility

Table B.2 : **Summary statistics of the original and adjusted electricity prices and the corresponding JB tests.**

	Unit	Mean	Standard Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile	JB test
						NSW					
Electricity Prices 2015	AUD/MWh	72.40	191.61	49.15	3010.44	58.94	-139.93	14700.00	38.81	83.14	4.2103e+10
Electricity Prices 2018	AUD/MWh	76.84	213.52	41.31	2202.72	60.15	-139.93	14700.00	41.29	83.83	1.2027e+10
Adjusted Electricity Prices 2015	AUD/MWh	72.40	189.32	50.23	3109.01	65.17	-179.55	14664.29	49.27	80.51	4.4907e+10
Adjusted Electricity Prices 2018	AUD/MWh	76.84	210.76	42.10	2272.64	68.57	-199.91	14641.42	50.34	86.86	1.2803e+10
						VIC					
Electricity Prices	AUD/MWh	77.40	286.26	42.36	1958.69	61.44	-676.37	14700.00	37.58	95.29	9158204713
Adjusted Electricity Prices	AUD/MWh	77.40	282.61	42.65	1977.74	70.76	-621.28	14626.65	44.32	93.36	9337388164
						QLD					
Electricity Prices 2017	AUD/MWh	67.56	172.60	46.79	3330.20	56.51	-859.85	15000.00	38.16	75.89	2.967e+10
Electricity Prices 2018 rooftop	AUD/MWh	67.17	178.76	45.40	3122.65	54.89	-859.85	15000.00	37.29	74.91	2.4176e+10
Electricity Prices 2018 wind	AUD/MWh	66.87	191.09	42.77	2755.24	51.81	-859.85	15000.00	35.81	74.51	1.6332e+10
Adjusted Electricity Prices 2017	AUD/MWh	67.56	168.95	48.21	3505.23	64.36	-849.02	14918.73	40.42	82.03	3.2872e+10
Adjusted Electricity Prices 2018 rooftop	AUD/MWh	67.17	174.87	46.78	3289.72	63.40	-851.87	14916.35	38.68	82.15	2.6834e+10
Adjusted Electricity Prices 2018 wind	AUD/MWh	66.87	186.80	44.05	2902.00	62.42	-848.63	14907.64	36.16	83.05	1.8119e+10
						SA					
Electricity Prices	AUD/MWh	77.40	286.26	42.36	1958.69	61.44	-676.37	14700.00	37.58	95.29	9158204713
Adjusted Electricity Prices	AUD/MWh	77.40	282.61	42.65	1977.74	70.76	-621.28	14626.65	44.32	93.36	9337388164
						TAS					
Electricity Prices	AUD/MWh	63.64	81.52	21.90	738.86	53.91	-844.65	4551.39	32.33	85.83	1348739321
Adjusted Electricity Prices	AUD/MWh	63.64	77.19	25.36	901.74	59.08	-847.71	4516.49	42.76	76.57	2011190775

JB test stands for the Jarque-Bera test of normality. Its corresponding p value is less than 2.2e-16 for all states. Hypothesis for JB test: H_0: data are iid Normal, H_1: data are Non-Normal. JB is asymptotically distributed as chi-square with 2 degrees of freedom.

suggests further that the ARCH-type models are appropriate for capturing the volatility dynamics in electricity markets. To isolate the relationship between each explanatory variable and the dependent variable and to avoid collinearity problem, we specify the models by examining the correlation coefficient matrix and variance inflation factors (VIFs). The results for these tests are presented in Table B.1 and Figure B.5.

Table B.3 : **Tests for the autocorrelation and the conditional heteroscedasticity (ARCH effects) in the adjusted prices series.**

	NSW (2015)				VIC				QLD (2017)			
Lag	1	7	24	48	1	7	24	48	1	7	24	48
Ljung-Box test	45017	75621	76585	80674	38386	112959	115589	124420	28135	59273	60826	64639
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
ARCH-LM test	36012	37503	37546	37650	34644	35541	35858	36717	40549	44229	44403	44424
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
	NSW (2018)								QLD (2018 - roof)			
Ljung-Box test	23110	44439	44889	46745					26291	55353	5678	60284
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)					(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
ARCH-LM test	20905	23494	23777	23778					37597	41019	41183	41201
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)					(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
	SA				TAS				QLD (2018 - wind)			
Ljung-Box test	31495	83206	86518	89432	4265.8	16292	28130	43169	23029	48267	49429	52317
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
ARCH-LM test	29942	30866	31184	31609	324.66	717.93	846.80	955.95	32637	35615	35758	35771
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)

Hypothesis for Ljung-Box test: H_0: the residuals are independently distributed (no autocorrelation); H_1: the residuals exhibits autocorrelation. Hypothesis for ARCH-LM test: H_0: the residuals does not exhibits conditional heteroscedasticity (ARCH effects) and H_1: the residuals exhibits conditional heteroscedasticity (ARCH effects). The p values are in parentheses.

Table B.4 : **The augmented Dickey-Fuller (ADF) tests of stationarity.** We assume a constant (no visible trend) and choose optimal lag lengths based on the Bayesian information criterion (BIC).

	NSW (2015)	NSW (2018)	SA	VIC	QLD (2017)	QLD (2018 - rooftop)	QLD (2018 - wind)	TAS
	ADF test							
intraday prices	-34.9874	-26.4923	-31.6286	-25.0221	-26.7923	-25.8289	-24.2561	-16.7065
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-20.7275	-17.3524	-19.7240	-19.3157	-15.2161		-13.2079	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	
large-scale solar pen	-20.2462	-16.0736	-19.6811	-17.9223	-16.3456		-14.6473	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	
rooftop solar		-18.8419	-21.8044	-20.5349		-18.7314	-18.2223	-24.2790
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
rooftop solar pen		-18.4750	-20.5752	-20.8984		-18.2334	-17.1574	-24.0473
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
solar total		-17.3532	-20.5188	-20.1126			-16.2464	
		(0.0000)	(0.0000)	(0.0000)			(0.0000)	
solar total pen		-16.8626	-20.0162	-19.9770			-15.9810	
		(0.0000)	(0.0000)	(0.0000)			(0.0000)	
wind	-29.2005	-20.7268	-33.0654	-25.7079			-13.7774	-24.4109
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)
wind pen	-29.7822	-21.5150	-33.9346	-27.7088			-13.8648	-25.2239
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)
consumption	-22.2513	-15.9641	-17.1399	-17.7405	-13.6983	-13.2551	-12.2678	-19.8793
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hydro	-20.6285	-15.8939		-18.6644	-10.3422	-10.3195	-9.2985	-16.9282
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	-10.0696	-15.8939	-6.3108	-7.6258	-6.9247	-6.5921	-6.1975	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Basslink				-15.5687				-15.7429
				(0.0000)				(0.0000)
Heywood			-21.6460	-21.8392				
			(0.0000)	(0.0000)				
Murrylink			-21.1390	-21.3795				
			(0.0000)	(0.0000)				
Terranora	-19.1589	-15.0073			-15.5351	-15.0073	-14.1811	
	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	
QNI	-18.1018	-14.9023			-15.2865	-14.9023	-14.1366	
	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	
VNI	-22.2530	-17.7476		-17.3851				
	(0.0000)	(0.0000)		(0.0000)				

Hypothesis for ADF test: H_0: unit root (non-stationary); H_1: no unit root (stationary).

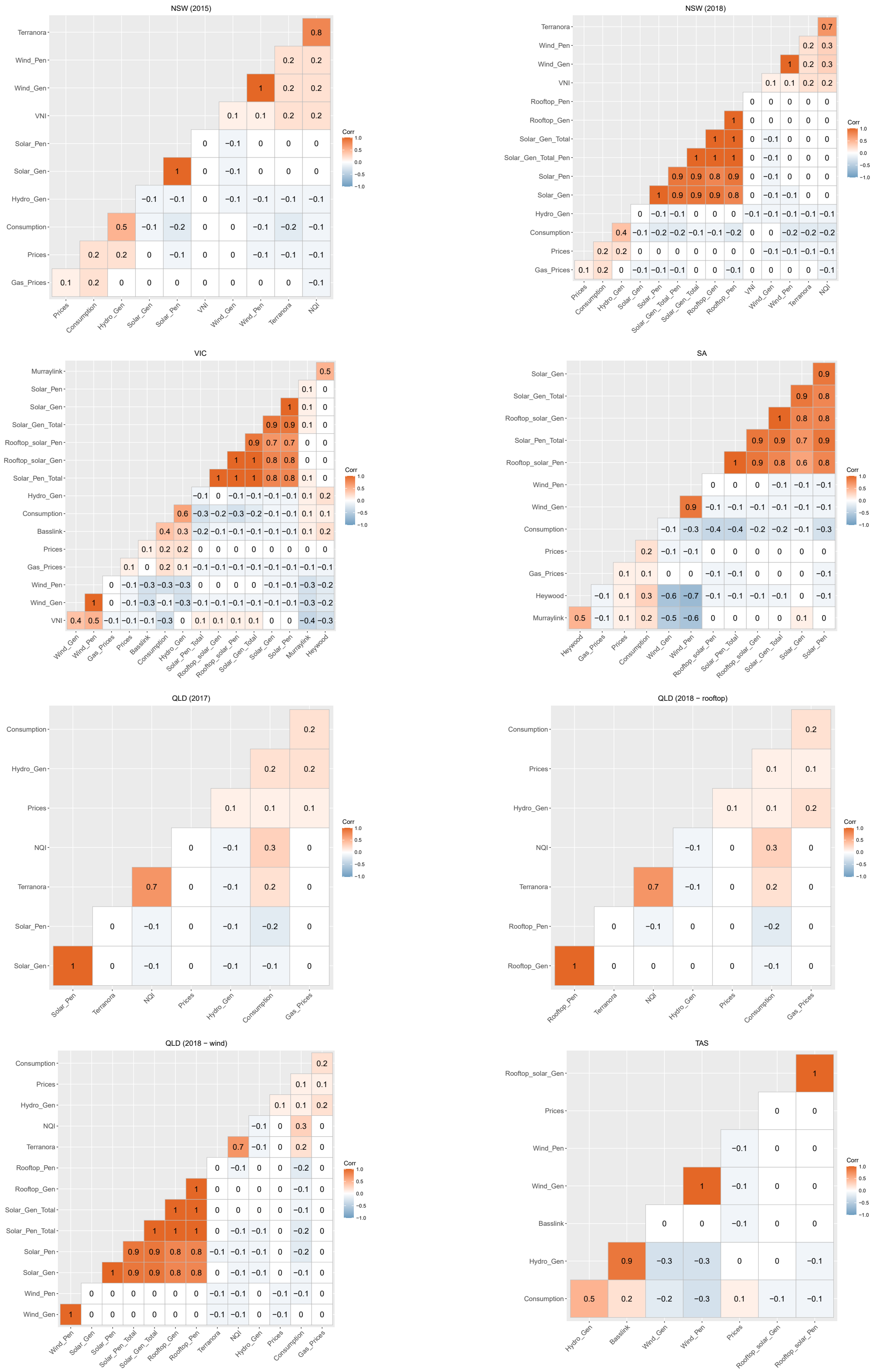

Figure B.1 : **Correlation coefficient matrix of the variables.**

Table B.5 : **The variance inflation factors (VIF) collinearity diagnostic measure according to model specifications.**

	NSW (2015)		NSW (2018)					
	Model A	Model B	Model E	Model F	Model G	Model H	Model I	Model J
Solar Gen	1.3567		1.0256					
Solar Pen		1.0592		1.0602				
Rooftop Gen					1.0144			
Rooftop Pen						1.0479		
Solar Gen Total							1.0181	
Solar Pen Total								1.0531
Wind Gen	1.0681		1.0844		1.0786		1.0802	
Wind Pen		1.0829		1.1056		1.0998		1.1014
Consumption	1.3567	1.3968	1.3543	1.4041	1.3520	1.4002	1.3534	1.4035
Hydro Gen	1.2828	1.2816	1.2243	1.2211	1.2249	1.2223	1.2246	1.2219
Gas	1.0326	1.0325	1.0580	1.0579	1.0568	1.0566	1.0571	1.0569
QNI	2.4824	2.4850	2.3699	2.3655	2.3714	2.3675	2.3703	2.3662
VNI	1.0608	1.0604	1.0779	1.0791	1.0781	1.0794	1.0780	1.0793
Terranora	2.4114	2.4113	2.2319	2.2319	2.2328	2.2332	2.2323	2.2325

	VIC						SA					
	Model E	Model F	Model G	Model H	Model I	Model J	Model E	Model F	Model G	Model H	Model I	Model J
Solar Gen	1.0634						1.0493					
Solar Pen		1.0595						1.1914				
Rooftop Gen			1.0531						1.0684			
Rooftop Pen				1.1298						1.2139		
Solar Gen Total					1.0567						1.0688	
Solar Pen Total						1.1335						1.2244
Wind Gen	1.6228		1.6173		1.6207		2.0285		2.0235		2.0290	
Wind Pen		1.6856		1.6864		1.6896		2.3404		2.2733		2.2917
Consumption	2.3322	2.1731	2.3494	2.2724	2.3425	2.2573	1.2081	1.3079	1.2296	1.3568	1.2263	1.3609
Gas Prices	1.0484	1.0484	1.0442	1.0441	1.0449	1.0448	1.0539	1.0592	1.0530	1.0574	1.0533	1.0579
Hydro Gen	2.0693	1.9651	2.0610	1.9667	2.0611	1.9631						
QNI												
VNI	1.8693	1.8827	1.8668	1.8865	1.8686	1.8884						
Terranora												
Heywood	1.4408	1.4408	1.4410	1.4404	1.4406	1.4407	1.9753	2.0001	1.9746	1.9819	1.9764	1.9882
Murraylink	1.4493	1.4525	1.4286	1.4351	1.4328	1.4409	1.5124	1.5469	1.5123	1.5469	1.5122	1.5469
Basslink	1.4668	1.4722	1.4551	1.4638	1.4585	1.4675						

	QLD (2017)		QLD (2018 - roof)	
	Model A	Model B	Model C	Model D
Solar Gen	1.0164			
Solar Pen		1.0448		
Rooftop Gen			1.0142	
Rooftop Pen				1.0522
Solar Gen Total				
Solar Pen Total				
Wind Gen				
Wind Pen				
Consumption	1.1453	1.1682	1.1420	1.1787
Hydro Gen	1.0885	1.0883	1.0728	1.0728
Gas	1.0495	1.0494	1.0518	1.0521
QNI	2.3769	2.3771	2.3391	2.3398
VNI				
Terranora	2.2666	2.2667	2.2411	2.2425
Heywood				
Murrylink				
Basslink				

	QLD (2018 - wind)						TAS	
	Model E	Model F	Model G	Model H	Model I	Model J	Model G	Model H
Solar Gen	1.0107							
Solar Pen		1.0345						
Rooftop Gen			1.0142				1.0141	
Rooftop Pen				1.0527				1.0257
Solar Gen Total					1.0113			
Solar Pen Total						1.0453		
Wind Gen	1.0198		1.0202		1.0200		1.1140	
Wind Pen		1.0224		1.0226		1.0226		1.1108
Consumption	1.1435	1.1640	1.1530	1.1920	1.1484	1.1816	1.3044	1.1638
Hydro Gen	1.0861	1.0854	1.0826	1.0822	1.0833	1.0828	1.3362	1.0342
Gas	1.0648	1.0643	1.0642	1.0648	1.0641	1.0643		
QNI	2.2470	2.2466	2.2466	2.2465	2.2469	2.2468		
VNI								
Terranora	2.1380	2.1386	2.1397	2.1417	2.1387	2.1399		
Heywood								
Murrylink								
Basslink								

B.2 Modeling Approaches

We considered the multiplicative component GARCH (mscGARCH) model for high-frequency data, which has not been previously employed to study the dynamics of electricity prices. Moreover, we tested two models that have been shown to perform better in electricity markets, the exponential GARCH model (eGARCH) (Frömmel et al., 2014; Thomas and Mitchell, 2005) and the asymmetric power ARCH model (apARCH). Thomas and Mitchell (2005) and Higgs and Worthington (2005) showed that the power ARCH (apARCH) and the apARCH specification outperformed other GARCH-specifications and can better account for the right-skewed and fat-tailed characteristics of electricity prices in the NEM. To this end, we find it important to include them in the analysis.

B.2.1 The Multiplicative Component GARCH (mcsGARCH)

Our understanding of high-frequency volatility is constrained by data availabilty, and also is largely based on the standard GARCH models (Higgs and Worthington, 2008). However, conventional GARCH approach arguably produces unsatisfactory results when applied to high-frequency data due to the seasonality effects characterizing the intraday time series (Zhang et al., 2014). Although such models can explain well the exponential decay in the autocorrelation structure of the returns, they cannot accommodate the intraday seasonality pattern observed in high-frequency financial returns (Andersen and Bollerslev, 1997, 1998). Following the two-stage approach proposed by Thomas and Mitchell (2005) and most notably Ketterer (2014), it has been a custom to bypass this issue in the Energy and related literatures by deseasonalising the time series prior to applying the GARCH-based models (Ketterer, 2014; Pereira and Rodrigues, 2015) or to include dummy variables in the mean or variance equations (or both) to account for these effects. Engle and Sokalska (2012) proposed a robust approach, the mscGARCH for modelling and forecasting intraday volatility. In this approach, the conditional variance is expressed as a product of daily, diurnal, and stochastic intraday volatility components, which can be easily estimated and interpreted. These authors found that this model produced better volatility forecasts than benchmark models when applied to a sample of more than 2500, 10-minute returns.

A considerable number of studies have used the mscGARCH to model and forecast volatility of high-frequency returns. Singh et al. (2013) used the intraday prices spaced over 1, 5, and 10 minutes from the S&P/ASX-50 stock market from January 4, 2012, to March 31, 2012, to forecast the intraday volatility of Australia's stock market and the intraday Value at Risk (VaR). This analysis suggested that the mscGARCH provides a good fit for the dynamics of intraday returns, producing the best forecast results. Diao and Tong (2015) reached a similar conclusion when applying mcsGARCH to forecast intraday volatility and VaR for 5-minute returns of the CSI 300 index. Zhang et al. (2014) argued that the typical GARCH models do not consider the trend and seasonality in data, thus providing inadequate results when applied to high-frequency data. The authors studied travel time prediction using three GARCH specifications, the standard GARCH (sGARCH), component GARCH (cGARCH), and the mscGARCH models. Using the high-frequency travel-time data obtained along a freeway corridor in Houston, TX, USA, the study concluded that the mscGARCH outperformed sGARCH and cGARCH models and that cGARCH and mscGARCH models could produce better results with data having trend and cyclical components. Narsoo (2016) in studying the intraday volatility of EUR/USD exchange rates for 2015 using the mscGARCH demonstrated that the mscGARCH could accurately forecast volatility and VaR of intraday EUR/USD exchange rates. Summinga-Sonagadu and Narsoo (2019) analysed the mscGARCH model's performance in forecasting the intraday risk metrics, VaR, and the Expected Shortfall (ES). Using intraday 1-min EUR/USD exchange rate prices for February 2016, the study demonstrated that the mscGARCH produced the best forecast results for VaR and ES under the generalised error distribution (ged) and the asymmetric Skewed Student's-t innovation assumption, respectively.

Based on the observation that mscGARCH had proven suitable for forecasting intraday volatility in many different contexts, we conjecture that this model could also be applied in electricity markets to study intraday price dynamics. To this end, this is the first study to comprehensively assess the intraday prices and volatility using the mscGARCH model. In contrast to existing literature, which applied the mscGARCH to model and forecast the intraday VaR and ES, we adopt the Engle and Sokalska (2012) approach to measure high-frequency cause-and-effect between price dynamics and their determinants.[1] Using a modified version of the Engle and Sokalska (2012) allows us to add the exogenous variables and to study the intra-day impact of solar generation (large-scale and rooftop solar) on price dynamics. This is another contribution of this study.

Formally, let $p_{t,i}$ denote electricity prices, where $t, (t = 1, 2, 3, \dots, T)$ is the day and $i, (i = 1, 2, 3, \dots, N)$ is the regularly spaced time interval. Define the conditional mean and variance of the price series as $\mathbb{E}(p_{t,i}|\mathscr{F}_{t,i-1}) = \mu_{t,i}$ and $\mathrm{Var}(p_{t,i}|\mathscr{F}_{t,i-1}) = u_{t,i}$, respectively. The sigma field $\mathscr{F}_{t,i-1}$ denotes publicly available information at the time $(t, t-1)$ (Diao and Tong, 2015). We employ the mcsGARCH of Engle and Sokalska (2012) with some modifications (Ghalanos, 2022). Our first assumption and modification is the inclusion of the ARMAX dynamics in the conditional mean ($\mu_{t,i}$). Following the Engle and Sokalska (2012) approach, we then express the conditional variance as a product of daily, diurnal, and stochastic intraday volatility components. The intraday prices are therefore described by the following process:

$$
\begin{aligned}
p_{t,i} &= \mu + \sum_{j=1}^{m} \phi_j p_{t,i-j} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{t,ij} + \varepsilon_{t,i}, \\
\varepsilon_{t,i} &= u_{t,i} z_{t,i}, \quad u_{t,i} = \sqrt{h_t s_i q_{t,i}},
\end{aligned}
\tag{2.2.1}
$$

where h_t is a daily exogenously determined forecast volatility, s_i the diurnal/calendar volatility in each regularly spaced interval i, $q_{t,i}$ is the stochastic intraday volatility, and $z_{t,i}$ is the i.i.d $(0, 1)$ standardized innovation which follows a certain specified distribution. $\boldsymbol{v}_t$ is a vector of exogenous explanatory variables.

The daily variance component (h_t) can be estimated in various ways. Engle and Sokalska (2012) pointed out that the daily sGARCH and realized volatility are alternative estimation approaches for estimating the daily volatility component. Many recent studies leverage GARCH based models to estimate the daily volatility component. Diao and Tong (2015), Narsoo (2016) and Summinga-Sonagadu and Narsoo (2019) compared the performance of sGARCH and eGARCH models under several innovations distributions, concluding that eGARCH outperformed sGARCH under the Student-t distribution (std),

[1] The diversions from Engle and Sokalska (2012) approach are detailed in the method section.

skew Student-t distribution (sstd), and ged assumptions, respectively. In contrast, Singh et al. (2013) and (Zhang et al., 2014) employed the sGARCH model.

In this study, we test the sGARCH, apARCH, and eGARCH models chosen based on performance under the normal distribution (norm), skew normal distribution (snorm), generalized error distribution (ged), skew generalized error distribution (sged), Student-t distribution (std), skew Student-t distribution (sstd), normal inverse Gaussian (nig) distribution, and Johnson's reparametrized SU (jsu) distribution. We choose the best distribution assumption based on four information criteria methods, the Akaike (AIC), Bayesian (BIC), Hannan-Quinn (HQIC), and Shibata (SIC) information criteria. We use daily electricity prices from January 2010 to July 2021 to forecast the daily volatility component.[2] From Table B.6, the AR(1)-apARCH(1,1) outperforms the competing models under the sstd distribution assumption for NSW, SA, VIC, and QLD and jsu distribution assumption for TAS. Therefore, the AR(1)-apARCH(1,1) is employed in forecasting the daily volatility component.

The seasonal (diurnal) part of the process represents the regular intraday variations and is estimated from equation (2.2.1) for each time index scaled by its corresponding variance for each day as follows:

$$\hat{s}_i = \frac{1}{T} \sum_{t=1}^{T} \frac{\varepsilon_{t,i}^2}{h_t}.$$

The remaining component in the variance part, the stochastic intraday component is then modelled as a sGARCH(p, q) process, where the normalized residuals ($\bar{\varepsilon}$) are obtained by dividing residuals by the diurnal and daily volatility components, leading to the following

[2]There is no established criterion for the choice of the length of the sample period. We use a long period to enhance the model performance. Chanda et al. (2005), for instance, estimated the intraday volatility using tick data spaced in the 10-minutes interval from January 2, 1998, to June 30, 1999, and forecasted the daily component using daily data from August 1985 to June 1999. Singh et al. (2013) used the intraday prices from the ASX-50 stock market for three months from January 4, 2012, to March 31, 2012, and forecasted the daily volatility component using daily data from February 4, 2004, to March 31, 2012 (2062 days). Diao and Tong (2015) used intraday data for the CSI 300 stock price index covering a period from January 4, 2011, to December 31, 2013, and estimated the daily variance component from April 16, 2010, to December 31, 2013. Summinga-Sonagadu and Narsoo (2019) applied the intraday 1-min EUR/USD exchange rate price for February 2016 and estimated the daily variance component using daily EUR/USD exchange rate prices data from December 2, 2003, to February 29, 2016.

expressions:

$$\bar{\varepsilon}_{t,i} = \frac{\varepsilon_{t,i}}{\sqrt{h_t s_i}} = \sqrt{q_{t,i}} z_{t,i},$$
$$q_{t,i} = \omega + \sum_{j=1}^{p} \alpha_j \bar{\varepsilon}^2_{t,i-j} + \sum_{j=1}^{q} \beta_j q_{t,i-j} + \sum_{j=1}^{m} \psi \boldsymbol{v}_{t,ij},$$

where $q_{t,i}$ denotes the conditional variance, ω the intercept and α_j $(j = 1, \ldots p)$ and β_j $(j = 1, \ldots q)$ are coefficients that are associated with the degree of innovation from previous period, ε^2_{t-j} (ARCH term) and previous period's volatility spillover effects, σ^2_{t-j} (GARCH term), respectively. The conditions $\omega > 0$, $\alpha_j \geq 0$, $\beta_j \geq 0$, and $\alpha_j + \beta_j < 1$ ensure positivity of the variance, stability and covariance stationarity. $\boldsymbol{v}_t$ is a vector of m exogenous explanatory variables which are passed pre-lagged.

Based on the information criteria in Table B.7, the best AR(1)-mscGARCH(1,1) model is attained by the nig distribution assumption for NSW, SA, VIC, and TAS, and jsu for QLD. The estimated daily, diurnal, and stochastic intraday volatility components of the AR(1)-mscGARCH(1,1) are presented in Figure B.2 to Figure B.6. The estimated model results for AR-mscGARCH are given in Table B.10 and for ARX-mscGARCHx in Table B.11.

B.2.2 The exponential GARCH model (eGARCH)

The exponential GARCH model of Nelson (1991) with ARMA dynamics and exogenous variables may be written as

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{tj} + \varepsilon_t, \tag{2.2.2}$$

$$\epsilon_t = z_t \sigma_t \quad \text{with} \quad \log_e(\sigma^2_t) = \omega + \sum_{i=1}^{p} \left(\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - \mathbb{E}|z_{t-i}|\right)\right) + \sum_{j=1}^{q} \beta_j \log_e(\sigma^2_{t-j}) + \sum_{k=1}^{r} \psi_k \boldsymbol{v}_{tk}, \tag{2.2.3}$$

Where p_{t-i}, $i = 1, \ldots, k$ are lags of the electricity prices, α_i and γ_j capture the sign and size effect of the standardized innovations on volatility. We choose the best distribution assumption based on four information criteria methods, AIC, BIC, HQIC, and SIC information criteria. According to the estimated AR(1)-eGARCH(1,1) model in Table B.8,

Table B.6 : **The performance of the AR(1)-sGARCH(1,1), AR(1)-apARCH(1,1) and AR(1)-eGARCH(1,1) models under a range of univariate distributions, that is, Normal (norm), skew Normal (snorm), Student-t (std), skew Student-t (sstd), Generalized Error (ged), skew Generalized Error (sged), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.** Daily data extends from January 2010 to July 2021.

	norm	snorm	std	sstd	ged	sged	nig	jsu	norm	snorm	std	sstd	ged	sged	nig	jsu
	NSW								**SA**							
	sGARCH								**sGARCH**							
AIC	8.7342	8.5849	7.5304	7.5056	12.0408	12.0413	7.5559	7.5194	10.9531	10.6938	9.3153	9.3114	9.4592	9.4544	9.3565	9.3281
BIC	8.7417	8.5939	7.5394	7.5161	12.0498	12.0518	7.5664	7.5299	10.9621	10.7043	9.3258	9.3234	9.4698	9.4664	9.3686	9.3401
SIC	8.7342	8.5849	7.5304	7.5056	12.0408	12.0413	7.5559	7.5194	10.9621	10.7043	9.3258	9.3234	9.4698	9.4664	9.3686	9.3401
HQIC	8.7368	8.5881	7.5336	7.5093	12.0440	12.0450	7.5596	7.5231	10.9563	10.6975	9.3190	9.3156	9.4630	9.4586	9.3608	9.3324
	eGARCH								**eGARCH**							
AIC	8.6249	8.2691	7.5082	7.4522	12.0033	12.0037	7.4917	7.4624	10.7638	10.4802	9.2713	9.2640	13.7205	13.5923	9.3136	9.2808
BIC	8.6354	8.2811	7.5202	7.4657	12.0153	12.0172	7.5052	7.4759	10.7713	10.4893	9.2803	9.2745	13.7295	13.6028	9.3241	9.2913
SIC	8.6249	8.2691	7.5082	7.4522	12.0033	12.0037	7.4917	7.4624	10.7638	10.4802	9.2713	9.2640	13.7205	13.5923	9.3136	9.2808
HQIC	8.6287	8.2734	7.5125	7.4570	12.0075	12.0085	7.4965	7.4671	10.7665	10.4834	9.2745	9.2677	13.7237	13.5960	9.3173	9.2845
	apARCH								**apARCH**							
AIC	8.8248	8.3614	7.5622	7.5328	7.6918	7.6483	7.5762	7.5478	10.5806	10.5596	9.2610	9.2487	13.7367	13.5535	9.2906	9.2635
BIC	8.8338	8.3719	7.5728	7.5448	7.7023	7.6603	7.5882	7.5598	10.5911	10.5716	9.2730	9.2622	13.7487	13.5670	9.3041	9.2770
SIC	8.8248	8.3614	7.5622	7.5328	7.6918	7.6483	7.5762	7.5478	10.5806	10.5596	9.2610	9.2487	13.7367	13.5535	9.2906	9.2635
HQIC	8.8280	8.3651	7.5660	7.5370	7.6955	7.6525	7.5804	7.5520	10.5843	10.5638	9.2652	9.2534	13.7409	13.5583	9.2953	9.2683
	VIC								**QLD**							
	sGARCH								**sGARCH**							
AIC	9.4746	9.2403	8.1421	8.1419	Failed	Failed	8.2091	8.1617	9.2650	8.8852	7.8784	7.8695	12.4080	12.4085	7.9244	7.8829
BIC	9.4821	9.2493	8.1512	8.1524	Failed	Failed	8.2196	8.1722	9.2725	8.8942	7.8874	7.8800	12.4170	12.4190	7.9349	7.8934
SIC	9.4746	9.2403	8.1421	8.1419	Failed	Failed	8.2091	8.1617	9.2650	8.8852	7.8784	7.8695	12.4080	12.4085	7.9244	7.8829
HQIC	9.4773	9.2435	8.1453	8.1456	Failed	Failed	8.2128	8.1654	9.2677	8.8884	7.8816	7.8732	12.4112	12.4122	7.9281	7.8866
	eGARCH								**eGARCH**							
AIC	9.4734	9.5762	8.1706	8.1681	8.3038	8.3037	8.2356	8.1889	8.9929	9.1217	7.9316	7.9149	8.1883	8.0573	8.0498	7.9321
BIC	9.4824	9.5867	8.1811	8.1801	8.3143	8.3157	8.2476	8.2010	9.0019	9.1322	7.9421	7.9269	8.1988	8.0693	8.0618	7.9442
SIC	9.4734	9.5762	8.1706	8.1681	8.3038	8.3037	8.2356	8.1889	8.9929	9.1217	7.9316	7.9149	8.1883	8.0573	8.0498	7.9321
HQIC	9.4766	9.5799	8.1743	8.1724	8.3075	8.3079	8.2398	8.1932	8.9961	9.1254	7.9353	7.9192	8.1920	8.0616	8.0540	7.9364
	apARCH								**apARCH**							
AIC	9.0725	9.0886	8.1315	8.1295	Failed	Failed	8.1912	8.1479	8.8496	8.8011	7.8320	7.8063	12.3695	12.3700	7.8483	7.8179
BIC	9.0830	9.1006	8.1435	8.1431	Failed	Failed	8.2047	8.1614	8.8601	8.8131	7.8440	7.8198	12.3815	12.3835	7.8618	7.8314
SIC	9.0725	9.0886	8.1315	8.1295	Failed	Failed	8.1912	8.1479	8.8496	8.8011	7.8320	7.8062	12.3695	12.3700	7.8483	7.8179
HQIC	9.0763	9.0929	8.1357	8.1343	Failed	Failed	8.1959	8.1526	8.8533	8.8054	7.8362	7.8110	12.3738	12.3748	7.8531	7.8227
	TAS															
	sGARCH															
AIC	8.6827	8.4522	7.4954	7.4930	9.8820	9.8824	7.4964	7.4838								
BIC	8.6902	8.4612	7.5044	7.5035	9.8910	9.8929	7.5069	7.4943								
SIC	8.6827	8.4522	7.4954	7.4930	9.8820	9.8824	7.4964	7.4838								
HQIC	8.6854	8.4554	7.4986	7.4967	9.8851	9.8861	7.5001	7.4875								
	eGARCH															
AIC	8.5600	8.3349	7.4899	7.4896	Failed	Failed	7.4961	7.4876								
BIC	8.5690	8.3455	7.5004	7.5016	Failed	Failed	7.5081	7.4996								
SIC	8.5600	8.3349	7.4899	7.4896	Failed	Failed	7.4961	7.4876								
HQIC	8.5632	8.3387	7.4936	7.4939	Failed	Failed	7.5003	7.4919								
	apARCH															
AIC	8.4864	8.4220	7.4272	7.4220	9.9109	9.9114	7.4273	7.4173								
BIC	8.4970	8.4340	7.4392	7.4355	9.9229	9.9249	7.4408	7.4308								
SIC	8.4864	8.4220	7.4272	7.4220	9.9109	9.9114	7.4273	7.4173								
HQIC	8.4902	8.4262	7.4315	7.4267	9.9151	9.9162	7.4320	7.4220								

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria. "Failed" denotes modes that failed to converge.

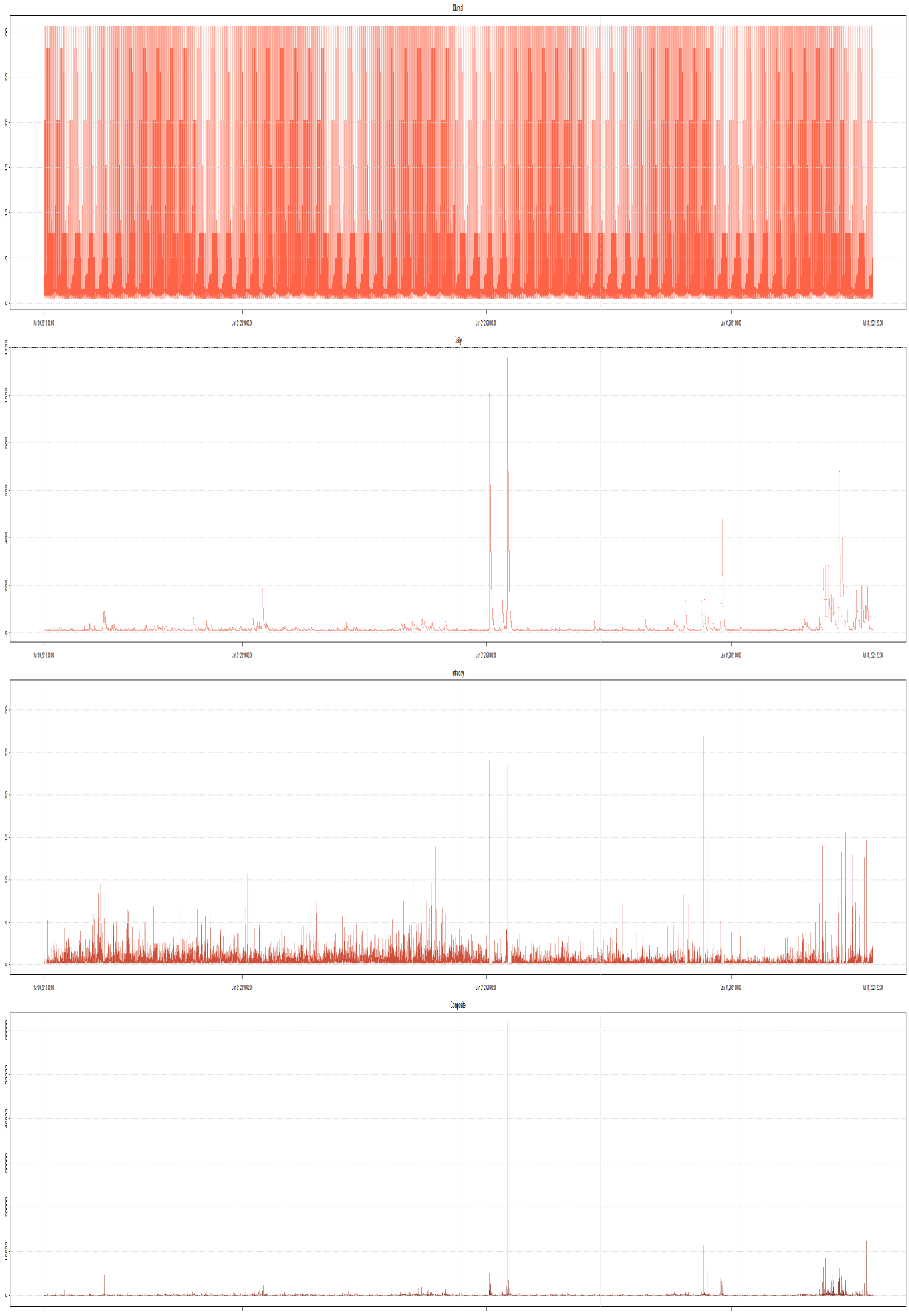

Figure B.2 : **The diurnal, daily, intraday, and total composite volatility components for NSW from 2018 to 2021.**

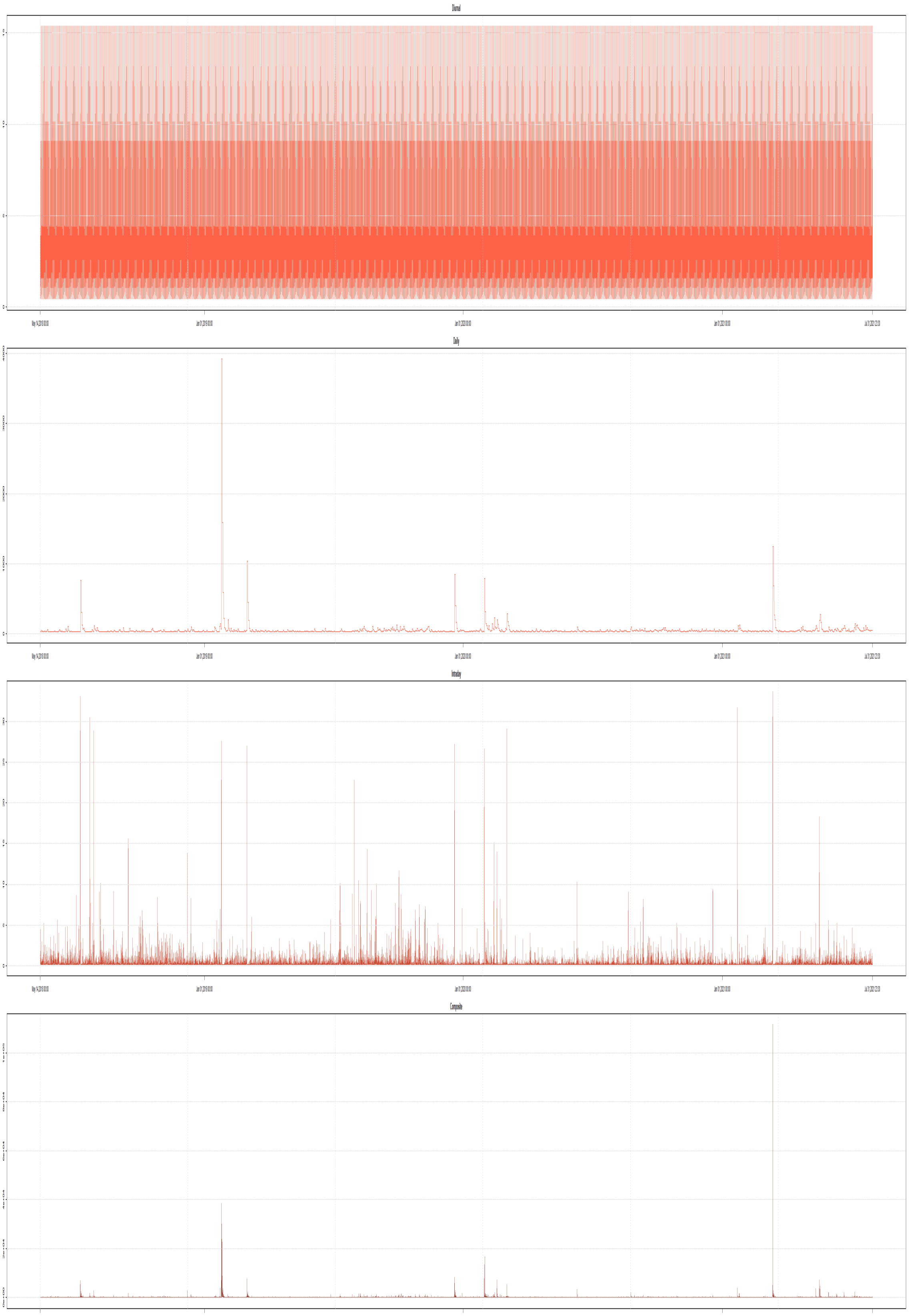

Figure B.3 : **The diurnal, daily, intraday, and total composite volatility components for SA from 2018 to 2021.**

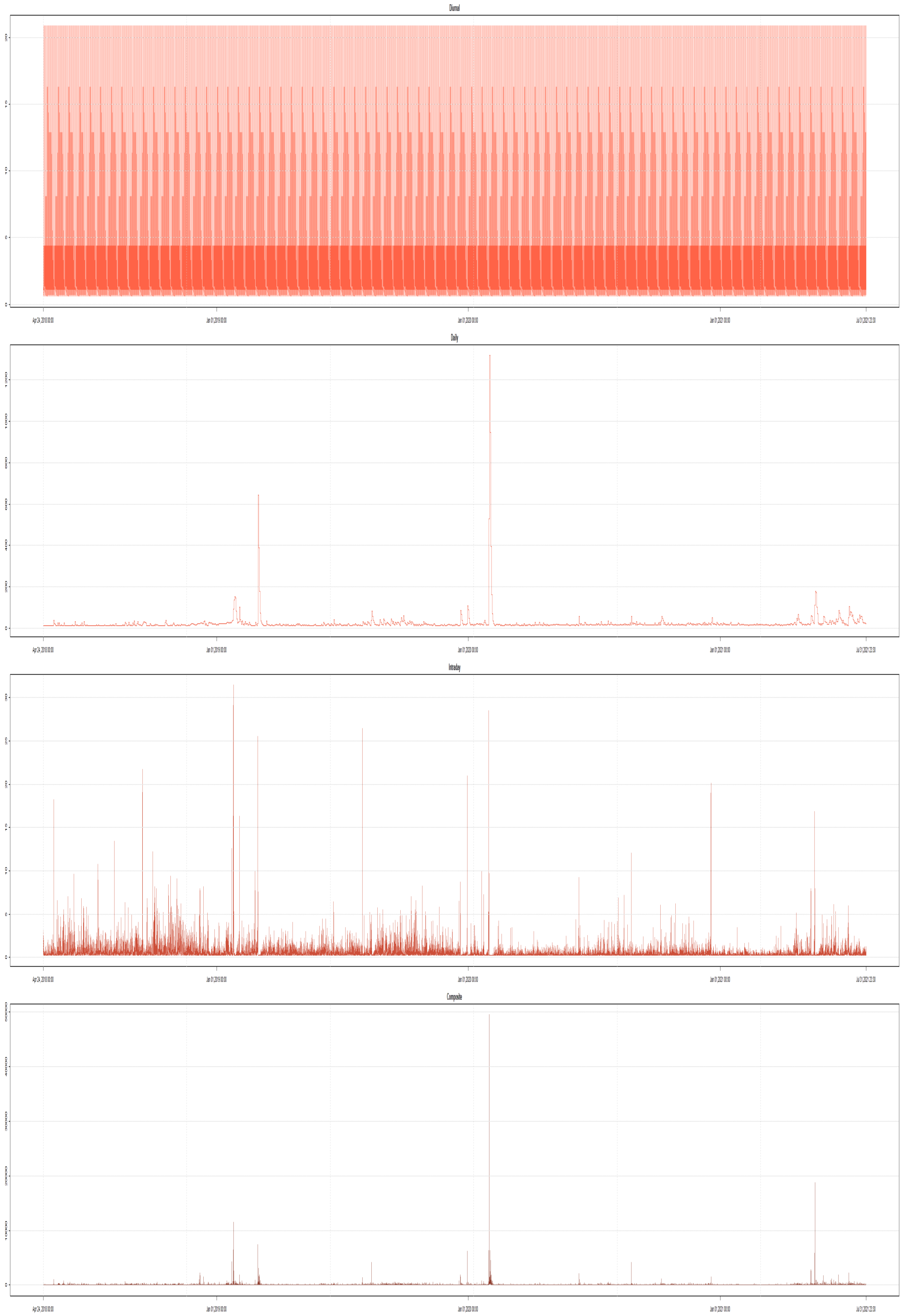

Figure B.4 : **The diurnal, daily, intraday, and total composite volatility components for VIC from 2018 to 2021.**

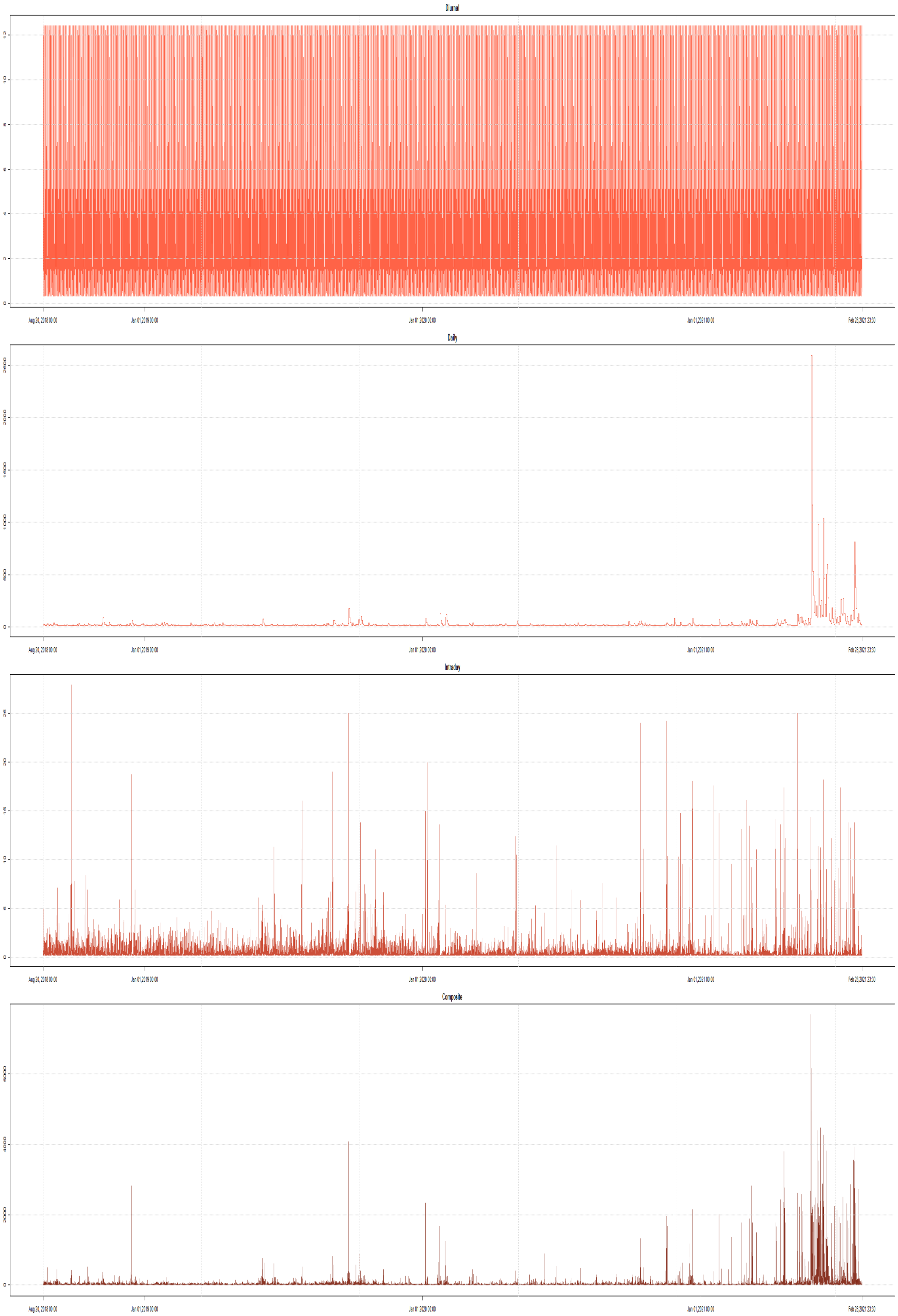

Figure B.5 : **The diurnal, daily, intraday, and total composite volatility components for QLD from 2018 to 2021.**

Figure B.6 : **The diurnal, daily, intraday, and total composite volatility components for TAS from 2018 to 2021.**

Table B.7 : **The performance of the AR(1)-mscGARCH(1,1) models under a range of univariate distributions, that is, Normal (norm), skew Normal (snorm), Student-t (std), skew Student-t (sstd), Generalized Error (ged), skew Generalized Error (sged), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.**

	norm	snorm	std	sstd	ged	sged	nig	jsu	norm	snorm	std	sstd	ged	sged	nig	jsu
	NSW								**SA**							
AIC	10.5664	8.6376	7.8187	7.8184	12.5846	10.6872	7.7743	7.7820	10.1815	10.1423	8.8866	8.8857	14.3683	14.3684	8.8039	8.8129
BIC	10.5671	8.6385	7.8196	7.8194	12.5855	10.6883	7.7754	7.7830	10.1823	10.1433	8.8875	8.8868	14.3693	14.3695	8.8050	8.8140
SIC	10.5664	8.6376	7.8187	7.8184	12.5846	10.6872	7.7743	7.7820	10.1815	10.1423	8.8866	8.8857	14.3683	14.3684	8.8039	8.8129
HQIC	10.5666	8.6379	7.8190	7.8187	12.5848	10.6875	7.7747	7.7823	10.1818	10.1426	8.8869	8.8860	14.3686	14.3687	8.8042	8.8133
	VIC								**QLD**							
AIC	9.0757	9.0752	8.3071	8.3070	10.9603	10.5248	8.2643	8.2720	8.9440	9.1242	7.7399	7.7394	7.7201	7.7188	7.7336	7.7151
BIC	9.0764	9.0762	8.3081	8.3081	10.9612	10.5259	8.2654	8.2731	8.9449	9.1252	7.7409	7.7406	7.7212	7.7200	7.7348	7.7163
SIC	9.0757	9.0752	8.3071	8.3070	10.9603	10.5248	8.2643	8.2720	8.9440	9.1242	7.7399	7.7394	7.7201	7.7188	7.7336	7.7151
HQIC	9.0759	9.0755	8.3074	8.3074	10.9606	10.5252	8.2647	8.2723	8.9443	9.1245	7.7402	7.7398	7.7205	7.7191	7.7339	7.7154
	TAS															
AIC	9.8984	9.6597	8.1696	8.1666	12.0140	11.6115	8.0794	8.0828								
BIC	9.8991	9.6606	8.1705	8.1677	12.0149	11.6126	8.0805	8.0838								
SIC	9.8984	9.6597	8.1696	8.1666	12.0140	11.6115	8.0794	8.0828								
HQIC	9.8986	9.6600	8.1698	8.1669	12.0143	11.6118	8.0797	8.0831								

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria.

the best performing distribution assumption is sstd for SA, QLD, and TAS electricity prices, std for NSW, and jsu for VIC. We estimate both the AR-eGARCH and ARX-eGARCHX. The results obtained from running these models are presented in Table B.10 and Table B.11, respectively.

B.2.3 The asymmetric power ARCH model (apARCH)

The GARCH types models are built assuming a squared power term, which may not always hold. The apARCH model of Ding et al. (1993) accounts for the leverage and the Taylor effect, and it also allows the power parameter (δ) to be estimated rather than imposed. The apARCH model with exogenous variables and ARMAX dynamics is given by

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{tj} + \varepsilon_t,$$

$$\varepsilon_t = z_t \sigma_t \quad \text{with} \quad \sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_j (|z_{t-j}| - \gamma_j z_{t-j})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum_{k=1}^{r} \psi_k \boldsymbol{v}_{tk},$$

Table B.8 : **The performance of the AR(1)-eGARCH(1,1) model under a range of univariate distributions, that is, Normal (norm), skew Normal (snorm), Generalized Error (ged), skew Generalized Error (sged), Student-t (std), skew Student-t (sstd), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.**

	norm	snorm	std	sstd	ged	sged	nig	jsu	norm	snorm	std	sstd	ged	sged	nig	jsu
	NSW								VIC							
AIC	9.3259	9.0747	7.9578	7.9578	8.0404	8.1569	8.5750	7.9666	8.9869	9.5085	8.4807	8.4651	8.4277	8.4277	8.3986	8.3919
BIC	9.3268	9.0758	7.9588	7.9590	8.0414	8.1581	8.5762	7.9678	8.9878	9.5096	8.4818	8.4663	8.4288	8.4289	8.3998	8.3931
SIC	9.3259	9.0747	7.9578	7.9578	8.0404	8.1569	8.5750	7.9666	8.9869	9.5085	8.4807	8.4651	8.4277	8.4277	8.3986	8.3919
HQIC	9.3262	9.0750	7.9581	7.9582	8.0407	8.1573	8.5753	7.9670	8.9872	9.5089	8.4810	8.4655	8.4280	8.4281	8.3990	8.3923
	SA								QLD							
AIC	10.1589	10.1233	8.8694	8.7625	8.8385	8.9257	8.8644	8.7708	9.5828	9.7640	8.1776	8.1721	8.2816	8.2816	8.2300	8.1904
BIC	10.1598	10.1244	8.8705	8.7638	8.8396	8.9270	8.8657	8.7720	9.5838	9.7652	8.1788	8.1735	8.2828	8.2830	8.2314	8.1917
SIC	10.1589	10.1233	8.8694	8.7625	8.8385	8.9257	8.8644	8.7708	9.5828	9.7640	8.1776	8.1721	8.2816	8.2816	8.2300	8.1904
HQIC	10.1592	10.1237	8.8698	8.7629	8.8388	8.9261	8.8648	8.7712	9.5831	9.7644	8.1779	8.1726	8.2819	8.2821	8.2305	8.1908
	TAS															
AIC	9.1594	9.3703	8.0948	8.0450	8.1453	8.1411	8.0846	8.0740								
BIC	9.1603	9.3713	8.0959	8.0469	8.1464	8.1423	8.0858	8.0752								
SIC	9.1594	9.3703	8.0948	8.0450	8.1453	8.1411	8.0846	8.0740								
HQIC	9.1597	9.3706	8.0952	8.0456	8.1456	8.1415	8.0850	8.0743								

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria.

$\omega > 0$, $\delta \geq 0$, $\alpha_i \geq 0$ $(i = 1, \ldots, p)$, $\beta_j \geq 0$ $(j = 1, \ldots, q)$, $-1 < \gamma_i < 1$ $(i = 1, \ldots, p)$. Positive γ_i values indicate that negative shocks have a deeper impact on conditional volatility, whereas a negative γ_i indicate that positive shocks have a larger impact on the current conditional variance. δ plays the role of a Box-Cox transformation of the conditional standard deviation σ_t. The persistence of the model is given by $\sum_{j=1}^{p} \beta_j + \sum_{j=1}^{q} \alpha_j \kappa_j$, where κ_j is the expected value of the standardized residuals z_t under the Box-Cox transformation of the term which includes the leverage coefficient γ_j, $\kappa_j = E(|z| - \gamma_j z)^{\delta} = \int_{-\infty}^{\infty} (|z| - \gamma_j z)^{\delta} f(z, 0, 1, ...)\, dz$. The results obtained after running this model presented in Table B.9 indicate that the best AR(1)-apARCH(1,1) model is obtained by assuming the sstd distribution assumption for SA, std for NSW, and jsu for VIC and TAS. We employ these distributions while running the AR-apARCH and ARX-apaRCHX models.

Table B.9 : **The performance of the AR(1)-apARCH(1,1) model under a range of univariate distributions, that is, Normal (norm), skew Normal (snorm), Generalized Error (ged), skew Generalized Error (sged), Student-t (std), skew Student-t (sstd), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.**

	norm	snorm	std	sstd	nig	jsu	norm	snorm	std	sstd	nig	jsu
	NSW						**VIC**					
AIC	8.9320	8.5824	7.9057	7.9057	7.9581	7.9142	9.1381	8.8948	8.3683	8.3671	8.3784	8.3664
BIC	8.9330	8.5837	7.9070	7.9071	7.9595	7.9155	9.1392	8.8961	8.3695	8.3685	8.3798	8.3678
SIC	8.9320	8.5824	7.9057	7.9057	7.9581	7.9142	9.1381	8.8948	8.3683	8.3671	8.3784	8.3664
HQIC	8.9323	8.5828	7.9061	7.9061	7.9586	7.9146	9.1385	8.8952	8.3686	8.3675	8.3788	8.3668
	SA						**QLD**					
AIC	9.8012	9.7973	8.7387	8.7383	8.7712	8.7448	9.6338	9.6043	8.0802	8.0802	8.1328	8.0905
BIC	9.8023	9.7986	8.7400	8.7397	8.7726	8.7462	9.6350	9.6056	8.0815	8.0818	8.1343	8.0920
SIC	9.8012	9.7973	8.7387	8.7383	8.7712	8.7448	9.6338	9.6043	8.0802	8.0802	8.1328	8.0905
HQIC	9.8016	9.7977	8.7391	8.7387	8.7716	8.7452	9.6342	9.6047	8.0806	8.0807	8.1333	8.0909
	TAS											
AIC	9.1763	11.1368	8.0391	8.0175	8.0137	8.0047						
BIC	9.1773	11.1380	8.0403	8.0189	8.0151	8.0061						
SIC	9.1763	11.1368	8.0391	8.0175	8.0137	8.0047						
HQIC	9.1766	11.1372	8.0394	8.0179	8.0141	8.0052						

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria. We have not included "ged" and "sged" distributions assumptions because their application causes convergence problems.

B.2.4 Comparison of Models Performance

Table B.10 compares the performance of the mscGARCH, eGARCH, and apARCH models with a single autoregressive component. According to the AIC and BIC, the apARCH model outperforms the competing models in SA and TAS, the mscGARCH outperforms the competing models in VIC and QLD, and the eGARCH outperforms the competing models in NSW. Of these three models, however, the eGARCH appears best capture the autocorrelation and the ARCH effect as evidenced by the weighted Ljung-Box and the weighted Lagrange multiplier tests. In Table B.11 we extend our comparison and include exogenous variables to the mscGARCH, apARCH, and eGARCH models. To easily illustrate the performance of the models, we run a single model only that includes solar generation along with other control variable. The results are similar to other combinations of the exogenous variables. One observation from this analysis is that the estimated coefficients of the variance equation are very small in magnitude, especially for the mscGARCH. We observe similar behaviour for the apARCH model though not for all estimated coefficients. Moreover, the estimated own innovation coefficient in the mscGARCH is 1 for all states. For the apARCH, it is less than 1 in NSW and VIC; in general however, the sum of α and β exceeds 1, suggesting that the proposed models are unstable and that the volatility process is highly persistent. As a robustness test, we add more autoregressive, moving average, and the two together in the ARMAX dynamics slightly improves the model fit in terms of AIC and BIC but no notable changes in the estimated coefficients and the conclusion.[3] In addition to the tiny magnitude and statistical significance of $p = 1$ for all models in the variance equation, we conclude that the proposed models may not be the appropriate choice given our objective of studying the impact of exogenous variables on the price level and volatility. Our results contrast with Higgs and Worthington (2005) who found that the apARCH model performed better when employed to model price volatility in the NEM. We account for the poor performance of the apARCH model in the present analysis for two reasons. First, Higgs and Worthington (2005) modelled the log-returns rather than price levels employed in this analysis. Second, the researchers' analysis and conclusion were solely based on the performance of AR-GARCH type models without exogenous variables being included. Moreover, the results for the mscGARCH from Table B.10 and B.11 potentially suggest the model may be well suited for modelling or forecasting volatility alone rather than for studying the cause-effect, making it unsuitable for this analysis.

Following these challenges, we also considered the eGARCH model with exogenous variables. In contrast to the mscGARCH and the apARCH models, the eGARCH yields sound results in both the mean and variance equation. In contrast to other GARCH type models, the eGARCH does not require any restriction on the parameters. Since the logarithm of variance rather than variance itself is modelled, the positivity of the variance is automatically satisfied. Normally, likelihood maximization with no restrictions leads to faster and more reliable optimizations. These results concur with that of Thomas and Mitchell (2005) who found that although the AIC and SBC favoured a pARCH specification, the restriction governing the pARCH model failed to hold for all states making the

[3]The results for this analysis are available upon request.

Table B.10 : **The estimated AR(1)-mscGARCH(1,1), AR(1)-apARCH(1,1), and AR(1)-eGARCH(1,1) for New South Wales, Victoria, South Australia, Queensland, and Tasmania.**

	NSW			VIC			SA			QLD			TAS		
	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH
Mean Equation															
μ	42.2542	72.6544	64.9387	48.3535	82.7843	74.0262	46.4770	78.1082	73.1549	29.7595	58.2548	60.5476	72.1060	106.7956	58.9070
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9609	0.9432	0.9476	0.9455	0.9536	0.9329	0.9554	0.9276	0.9324	0.9822	0.9709	0.9648	0.9915	0.95938	0.9463
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Variance Equation															
ω	0.0154	3.0119	1.4979	0.0290	5.9508	1.8148	0.0136	21.3770	2.9503	0.0146	1.9330	3.1325	0.0180	7.4232	3.4448
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.6063	0.8602	-0.1741	0.5482	0.6188	0.0350	0.6346	1.0000	0.3109	0.6165	1.0000	-1.8740	0.7709	1.0000	0.0844
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1512)	(0.0000)	(0.0000)	(0.0093)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0043)
β	0.3926	0.3636	0.7464	0.4508	0.4158	0.7188	0.3644	0.3990	0.7115	0.3825	0.4416	0.6663	0.2281	0.2477	0.5098
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ		0.0838	1.3885		-0.0745	0.78113		-0.0578	5.1072		0.3232	6.3972		-0.6299	1.7821
		(0.0000)	(0.0000)		(0.0003)	(0.0000)		(0.0001)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
δ		0.9421			1.0671			1.2805			0.6472			0.9423	
		(0.0000)			(0.0000)			(0.0000)			(0.0000)			(0.0000)	
Skew	-0.0192			-0.0136	0.0850	-0.0396	-0.0558		0.9710	-0.0297		1.0087	0.1221	0.2294	
	(0.0004)			(0.0414)	(0.0000)	(0.0002)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Shape	0.2044	2.5967	2.3062	0.1892	0.9895	0.9089	0.0928	2.3005	2.0100	0.9618	2.1052	2.0100	0.0751	0.7874	2.1000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-231543.5	-235456.8	-425163.6	-237014.1	-239939.6	-247327.5	-248262.7	-246423.7	-247095.2	-199412.1	-208847.9	-255673.8	-240630.2	-238404.4	-241089.8
AIC	7.7743	7.9057	7.6195	8.2643	8.3664	8.7708	8.8039	8.7387	8.7625	7.7151	8.0802	7.9562	8.0794	8.0047	8.0948
BIC	7.7754	7.9070	7.6201	8.2654	8.3678	8.7720	8.8050	8.7400	8.7638	7.7163	8.0815	7.9574	8.0805	8.0061	8.0959
Q(20)	8.129	1.1749	0.8542	43.9670	21.40	2.325	33.129	7.957	2.090	15.89	25.24	1.1447	86.30	10.911	7.065
	(0.0000)	(0.9173)	(0.9662)	(0.0000)	(0.0000)	(0.6167)	(0.0000)	(0.0080)	(0.6853)	(0.0000)	(0.0000)	(0.9229)	(0.0000)	(0.0001)	(0.0182)
$Q^2(36)$	0.1354	0.0006	0.0003	0.3746	0.0225	0.0013	0.0256	0.0009	0.0013	0.1314	0.0416	0.0963	0.0858	0.0331	0.0425
	(1.0000)	(1.0000)	(1.0000)	(0.9994)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0947	0.0004	0.0003	0.1854	0.0065	0.0009	0.0163	0.0008	0.0009	0.0801	0.0432	0.0560	0.0623	0.0219	0.0233
	(0.9994)	(1.0000)	(1.0000)	(0.9975)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9996)	(0.9999)	(0.9998)	(0.9998)	(1.0000)	(1.0000)
Observations	59568	59568	59568	57360	57360	57360	56400	56400	56400	51696	51696	51696	56400	56400	56400

AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

eGARCH the best model. Indeed, existing literature suggests that the eGARCH model has the ability to capture the asymmetry and complexity of price volatility in electricity markets (Bowden and Payne, 2008; Hickey et al., 2012; Frömmel et al., 2014). Moreover, we see that $\beta < 1$ for all models suggesting that the stationarity condition is satisfied. To further investigate the model performance, we add more autoregressive structures up to 48 lags corresponding to a complete day and also by choosing the optimal ARMA structure using the `auto.arima` package in R (Hyndman et al., 2021). We observe only a slight improvement in the AIC and BIC but no significant changes in the estimated coefficients, especially when approximated to two decimal points. To avoid creating complex models due to the number of exogenous variables under investigation, we, therefore, run the analysis using ARX-eGARCHX with a single autoregressive structure for all models and states based on the distribution assumptions provided in Table B.8.

Table B.11 : **The effect of large-scale and rooftop solar generation on electricity price behaviour for New South Wales, Victoria, South Australia, Queensland, and Tasmania.** The models are estimated using the ARX-mscGARCHX, ARX-apARCHX, and ARX-eGARCHX. The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	NSW			VIC			SA			QLD			TAS		
	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH
Mean Equation															
μ	-13.5161	-79.4664	-83.2652	14.8972	-71.4141	-79.5598	-6.2029	-11.6603	-18.3237	-34.5787	-162.0577	-158.6972	48.76289	47.9164	12.7981
	(0.0008)	(0.0000)	(0.0000)	(0.0041)	(0.0000)	(0.0000)	(0.1710)	(0.9948)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0019)	(0.0000)	(0.0000)
ϕ_1	0.9377	0.9303	0.9302	0.9210	0.9435	0.9449	0.9242	0.9123	0.9156	0.9794	0.9729	0.9671	0.9890	0.9562	0.9421
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0292	-0.2682	-0.3061	0.0969	-0.9052	-0.8473	-0.2008	-1.4759	-1.4898	-0.0666	-0.3293	-0.3052			
	(0.0011)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.5635)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
$rooftopsolar$													0.1074	-0.2121	-0.1630
													(0.1074)	(0.0001)	(0.0329)
wind	-0.1713	-0.2354	-0.2286	-0.1912	-0.6114	-0.5842	-0.6213	-1.2339	-1.2272	-0.2596	-0.5465	-0.5361	-0.7206	-1.2048	-1.3926
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3630)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hydro	-0.0085	0.2340	0.2443	0.1123	-0.0778	-0.0624				-0.3573	-0.1406	-0.1202	-0.1373	-0.0367	-0.1267
	(0.4843)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)				(0.0000)	(0.0000)	(0.0040)	(0.0000)	(0.0014)	(0.0000)
consumption	0.0982	0.3544	0.3627	0.1254	0.7096	0.7294	0.6819	1.5544	1.6203	0.2230	0.6850	0.6858	0.6109	1.1558	1.3470
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7304)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
gas	3.1283	1.5831	1.5246	1.5060	0.2358	0.3670	3.6761	2.8823	2.8529	0.4747	1.6374	1.6887			
	(0.0000)	(0.0006)	(0.0000)	(0.0008)	(0.0856)	(0.1756)	(0.0000)	(0.9868)	(0.0000)	(0.0583)	(0.0000)	(0.0000)			
$exim_{terra}$	-0.3346	-0.7177	-0.7419							0.4220	-0.0065	0.1042			
	(0.0000)	(0.0257)	(0.0000)							(0.0035)	(0.9231)	(0.3170)			
$exim_{QNI}$	-0.0599	-0.1766	-0.1879							-0.1032	-0.3237	-0.3238			
	(0.0000)	(0.0000)	(0.0000)							(0.0000)	(0.0000)	(0.0000)			
$exim_{murray}$				0.3396	0.6817	0.6864	1.0699	0.5993	0.6393						
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8026)	(0.0000)						
$exim_{heyw}$				-0.0817	-0.0704	-0.0856	-0.2267	-0.8082	-0.8213						
				(0.0007)	(0.0035)	(0.0041)	(0.0000)	(0.0020)	(0.0000)						
$exim_{VNI}$	-0.0735	0.0366	0.0401	-0.2478	0.0722	0.0592									
	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)									
$exim_{bass}$				0.0330	-0.1611	-0.1398									
				(0.0852)	(0.0000)	(0.0000)									
Variance Equation															
ω	0.0062	3.3118	-0.0814	0.0163	5.1976	0.7074	0.0086	16.6967	1.3335	0.0079	2.0330	2.1076	0.0002	5.8485	3.9125
	(0.0062)	(0.0000)	(0.0570)	(0.0005)	(0.0000)	(0.0000)	(0.0519)	(0.1633)	(0.0000)	(0.2911)	(0.0010)	(0.0000)	(0.9877)	(0.0000)	(0.0000)
α	1.0000	0.9331	-0.1408	1.0000	0.6389	0.0418	1.0000	1.0000	0.0165	1.0000	1.0000	-1.8471	1.0000	1.0000	0.8982
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	0.0418	(0.0000)	(0.0000)	(0.5147)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.4519	0.3463	0.7038	0.4770	0.4136	0.6999	0.4273	0.4091	0.7072	0.4372	0.3981	0.6575	0.3727	0.2413	0.4735
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0477)	(0.0000)	(0.0000)
γ		0.1093	1.0629		-0.0779	0.7817		-0.0097	1.2126		0.2404	6.0079		-0.6563	5.2137
		(0.0000)	(0.0000)		(0.0003)	(0.0000)		(0.9864)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
δ		1.0351			1.0654			1.2466			0.8495			0.9457	
		(0.0000)			(0.0000)			(0.0001)			(0.0000)			(0.0000)	
large-scale solar	1.8188e-11	9.5686e-08	0.0221	5.1292e-12	2.2397e-06	0.0337	3.2448e-09	4.0474e-08	0.0396	2.5397e-10	0.0990	0.0171			
	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(0.9997)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)	(0.0000)			
$rooftopsolar$													4.5849e-16	4.3012e-08	0.0463
													(1.0000)	(1.0000)	(0.0000)
wind	8.5561e-09	1.0475e-08	0.0007	7.0043e-09	2.7960e-08	0.0019	1.0997e-08	7.2430e-09	-0.0016	9.1958e-09	9.1025e-19	-0.0081	1.3006e-08	1.8521e-07	0.0065
	(0.9999)	(1.0000)	(0.2535)	(1.0000)	(1.0000)	(0.0096)	(0.9998)	(1.0000)	(0.0047)	(0.9999)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0303)
hydro	1.6055e-08	1.1984e-08	0.0069	4.9282e-08	5.6761e-08	0.0051				1.0739e-08	1.1248e-08	0.0190	1.9678e-04	0.0355	0.0045
	(0.9996)	(1.0000)	(0.0000)	(0.9998)	(1.0000)	(0.0001)				(1.0000)	(1.0000)	(0.0000)	(0.3462)	(0.0000)	(0.0000)
consumption	2.3070e-08	3.13980e-08	0.0023	1.0786e-07	3.0017e-07	0.0018	2.1060e-08	2.2434e-08	0.0080	1.5159e-08	1.1509e-08	0.0013	3.0055e-08	4.3196e-06	0.0118
	(0.5961)	(1.0000)	(0.0000)	(0.9922)	(1.0000)	(0.0099)	(0.9997)	(1.0000)	(0.0000)	(0.9867)	(1.0000)	(0.0812)	(0.9999)	(0.9998)	(0.0000)
gas	9.5583e-09	1.2182e-08	0.0498	1.1065e-08	1.7084e-08	0.0445	1.1453e-08	1.4908e-08	0.0284	9.9206e-09	1.7280e-08	0.0638			
	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)			
$exim_{terra}$	9.4228e-09	1.0042e-08	-0.0104							9.9751e-09	1.1966e-08	0.0262			
	(1.0000)	(1.0000)	(0.0944)							(1.0000)	(1.0000)	(0.0168)			
$exim_{QNI}$	5.5085e-09	9.7312e-09	-0.0006							9.6602e-09	2.9704e-08	-0.0011			
	(0.9999)	(1.0000)	(0.3631)							(0.9999)	(1.0000)	(0.3736)			
$exim_{murray}$				9.4685e-09	5.4105e-09	-0.0145	7.6305e-09	7.2349e-09	-0.0132						
				(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0001)						
$exim_{heyw}$				5.1970e-09	1.1247e-12	-0.0014	4.2610e-09	1.8412e-09	-0.0038						
				(1.0000)	(1.0000)	(0.1217)	(1.0000)	(1.0000)	(0.0001)						
$exim_{VNI}$	1.2383e-08	2.1588e-08	0.0024	9.4217e-09	1.7905e-08	-0.0005									
	(0.9998)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.3622)									
$exim_{bass}$				1.8373e-08	1.4461e-08	0.0023									
				(0.9999)	(1.0000)	(0.0000)									
Skew	-0.0317			-0.0254	0.0818	0.0797	-0.0854	0.9809	0.9711	-0.0258		1.0226	0.1268	0.2355	1.1061
	(0.0002)			(0.2253)	(0.0000)	(0.0004)	(0.0000)	(0.0050)	(0.0000)	(0.0000)		(0.0000)	(0.0161)	(0.0000)	(0.0000)
Shape	0.1623	2.6514	2.8276	0.1373	1.0084	1.0387	0.0761	2.2962	2.1779	0.8900	2.2159	2.0100	0.0667	0.78638	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0756)	(0.0000)	(0.0000)
log likelihood	-228170.9	-230718	-230912.9	-233623.1	-236373	-236110.6	-244331.6	-242839.6	-242961.9	-197094.3	-204364.2	-206724.5	-238827.6	-237196.4	-239421.2
AIC	7.6616	7.7472	7.7537	8.1467	8.2427	8.2335	8.6649	8.6121	8.6164	7.6259	7.9072	7.9986	8.0192	7.9645	8.0391
BIC	7.6651	7.7508	7.7572	8.1506	8.2469	8.2376	8.6679	8.6154	8.6196	7.6295	7.9110	8.0023	8.0214	7.9670	8.0415
Q(20)	7.583	0.9201	3.7751	29.0159	42.04	38.69	23.3775	13.39	7.258	8.730	23.49	3.887	56.37	11.40	5.644
	(0.0113)	(0.9581)	(0.2635)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0153)	(0.0038)	(0.0000)	(0.2440)	(0.0000)	(0.0003)	(0.0629)
$Q^2(36)$	0.1270	0.0005	0.0020	0.3116	0.0064	0.0412	0.0298	0.0011	0.0006	0.0466	0.0373	0.1901	0.0413	0.0317	0.0392
	(1.0000)	(1.0000)	(1.0000)	(0.9997)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0916	0.0003	0.0013	0.2495	0.0037	0.0038	0.0213	0.0009	0.0005	0.0353	0.0347	0.2030	0.0317	0.0206	0.0216
	(0.9995)	(1.0000)	(1.0000)	(0.9952)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(0.9969)	(1.0000)	(1.0000)	(1.0000)
Observations	59568	59568	59568	57360	57360	57360	56400	56400	56400	51696	51696	51696	59568	59568	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

B.2.5 Intraday and Seasonality Analysis

In existing literature on peak and off-peak analysis (Pereira and Rodrigues, 2015; Rintamäki et al., 2017; Kyritsis et al., 2017; Maciejowska, 2020), the authors simply aggregate the daily peak/off-peak periods onto one (average) value to avoid the non-contiguous time problem and then compare statistics on these (now daily) time-series. However, there is little literature based on the seasons, probably reflecting the challenges associated with data partitioning and the resulting non-contiguous time problem between seasons of the year. We propose an alternative approach based on intraday and seasonal dummies to capture these effects while retaining the high-frequency data. Following the objective of the study which is to examine the impact of VRE on the spot prices dynamics, we base the intraday and seasonality analysis on the two variables of interest, solar and wind generation while controlling for other price determinants.

B.2.5.1 Intraday effects

Denote solar generation by S_t, wind generation by W_t, hydro generation H_t, electricity consumption C_t, gas prices G_t and interconnectors I_t, then the AR(1)-eGARCH(1,1) with these exogenous variables can be expressed mathematically as

$$p_t = \mu + \phi p_{t-1} + \zeta_1 S_t + \zeta_2 W_t + \zeta_3 H_t + \zeta_4 C_t + \zeta_5 I_t + \varepsilon_t, \quad \varepsilon_t = z_t \sigma_t \quad \text{with} \tag{2.2.4}$$

$$\log_e(\sigma_t^2) = \omega + \tau(z_{t-1}) + \beta \log_e(\sigma_{t-1}^2) + \psi_1 S_t + \psi_2 W_t + \psi_3 H_t + \psi_4 C_t + \psi_5 I_t, \tag{2.2.5}$$

the leverage function, $\tau(\cdot)$, is given by $\tau(z_{t-1}) = (\tau_1 z_{t-1} + \tau_2 (|z_{t-1}| - \mathbb{E}|z_{t-1}|)$. Now assume that one is interested in examining coefficients and the statistical differences of the impact of solar and wind generation within the day, namely off-peak and peak hours. To capture this effect, we introduce one dummy variable for solar and wind generation, D_1, corresponding peak hours, with the reference level being off-peak hours, when $D_1 = 0$. We then add the variables $D_1 \times S_t$, and $D_1 \times W_t$ as extra terms in the regression to capture the intraday effect. Since we are not interested in investigating the variation of the other variables, we include them in the regression as controls to avoid endogeneity problems.

Equations (2.2.4) and (2.2.5) becomes

$$p_t = \mu + \phi p_{t-1} + \zeta_1 S_t + \zeta_{1,1}(D_1 S_t) + \zeta_2 W_t + \zeta_{2,1}(D_1 W_t) + \zeta_3 H_t + \zeta_4 C_t + \zeta_5 I_t + \varepsilon_t,$$

$$\varepsilon_t = z_t \sigma_t \quad \text{with} \tag{2.2.6}$$

$$\log_e(\sigma_t^2) = \omega + \tau(z_{t-1}) + \beta \log_e(\sigma_{t-1}^2) + \psi_1 S_t + \psi_{1,1}(D_1 S_t) + \psi_2 W_t + \psi_{2,1}(D_1 W_t) +$$

$$+ \psi_3 H_t + \psi_4 C_t + \psi_5 I_t, \tag{2.2.7}$$

equation (2.2.6) and (2.2.7) simplify to

$$p_t = \mu + \phi p_{t-1} + (\zeta_1 + \zeta_{1,1} D_1) S_t + (\zeta_2 + \zeta_{2,1} D_1) W_t + \zeta_3 H_t + \zeta_4 C_t + \zeta_5 I_t + \varepsilon_t,$$

$$\varepsilon_t = z_t \sigma_t \quad \text{with}$$

$$\log_e(\sigma_t^2) = \omega + \tau(z_{t-1}) + \beta \log_e(\sigma_{t-1}^2) + (\psi_1 + \psi_{1,1} D_1) S_t + (\psi_2 + \psi_{2,1} D_1) W_t + \psi_3 H_t +$$

$$\psi_4 C_t + \psi_5 I_t.$$

Then, the estimated coefficients for the peak and off-peak hours in the mean and variance equation are given by

	Solar Generation	Wind Generation	
Mean Equation	$\zeta_1 + \zeta_{1,1} D_1$,	$\zeta_2 + \zeta_{2,1} D_1$	(2.2.8)
Variance Equation	$\psi_1 + \psi_{1,1} D_1$,	$\psi_2 + \psi_{2,1} D_1$	(2.2.9)

The estimated coefficients for peak and off-peak hours are recovered as follows:

When $D_1 = 0$, we have the (base) off-peak coefficient of S_t and W_t, namely ζ_1 and ζ_2 in the mean equation and ψ_1 and ψ_2 in the variance equation.

The peak coefficient for solar and wind generation are recovered when $D_1 = 1$, that is, $\zeta_1 + \zeta_{1,1}$ and $\zeta_2 + \zeta_{2,1}$ in the mean equation and $\psi_1 + \psi_{1,1}$ and $\psi_2 + \psi_{2,1}$ in the variance equation.

B.2.5.2 Seasonal effects

We estimate the effect of wind and solar generation on spot prices over four seasons using the same approach as in the intraday analysis. The only difference is that here we introduce three dummy variables for solar generation and wind generation, D'_1, D'_2, D'_3, corresponding to autumn, spring, and summer, with the reference level being winter, when all $D_i = 0$. Following the same approach one can show that the estimated coefficients for wind and solar generation are given by

$$\begin{array}{lll} & \text{Solar Generation} & \text{Wind Generation} \\ \text{Mean Equation} & \zeta'_1 + \sum_{i=1}^{3} \zeta'_{1,i} D_i, & \zeta'_2 + \sum_{i=1}^{3} \zeta'_{2,i} D'_i \end{array} \tag{2.2.10}$$

$$\begin{array}{lll} \text{Variance Equation} & \psi'_1 + \sum_{i=1}^{3} \psi'_{1,i} D_i, & \psi'_2 + \sum_{i=1}^{3} \psi'_{2,i} D'_i \end{array} \tag{2.2.11}$$

Then the estimated coefficients for the four seasons of the year are recovered as follows:

When all the $D'_i = 0$, we have the (base) winter coefficient of S_t and W_t, namely ζ_1 and ζ'_2 in the mean equation and ψ'_1 and ψ'_2 in the variance equation.

The autumn coefficient for solar and wind generation is recovered when $D'_1 = 1$ and the other $D'_i = 0$, that is, $\zeta'_1 + \zeta'_{1,1}$ and $\zeta'_2 + \zeta'_{2,1}$ in the mean equation and $\psi_1 + \psi'_{1,1}$ and $\psi'_2 + \psi'_{2,1}$ in the variance equation.

The spring coefficient for solar and wind generation is recovered when $D_2 = 1'$ and the other $D'_i = 0$, that is, $\zeta'_1 + \zeta'_{1,2}$ and $\zeta'_2 + \zeta'_{2,2}$ in the mean equation and $\psi_1 + \psi'_{1,2}$ and $\psi'_2 + \psi'_{2,2}$ in the variance equation.

The autumn coefficient for solar and wind generation is recovered when $D'_3 = 1$ and the other $D'_i = 0$, that is, $\zeta'_1 + \zeta'_{1,3}$ and $\zeta'_2 + \zeta'_{2,3}$ in the mean equation and $\psi'_1 + \psi'_{1,3}$ and $\psi'_2 + \psi'_{2,3}$ in the variance equation.

B.3 Results

B.3.1 Using real spot electricity prices

The spot prices plotted in Figure B.7, as well as gas prices, which is one of the independent variables, are both expressed in nominal terms. We deflate electricity spot and gas prices using the quarterly consumer price index (CPI), which is the most comprehensive indicator of the inflation in the price of goods and services faced by all consumer households. We obtained the datasets from the Australian Bureau of Statistics (ABS).[4] All series are adjusted to 2018 dollars.[5] We deflated the time series using the separate price index for each regional market. As ABS does not provide CPI for entire states, we use CPI data available for major capitals corresponding to each of the five states considered in our study, that is, Sydney (NSW), Melbourne (VIC), Brisbane (QLD), Adelaide (SA), and Hobart (TAS). Using different CPIs is more robust in capturing state-wise inflation than using the CPI of the whole country for each state. Nominal and deflated series are plotted in Figure B.7, and the results of this supplementary analysis are given in Table B.12 of this report. For demonstration purposes, we present only one model in Table B.12, the model of large-scale solar generation, except for TAS. However, we have ran the analysis for all models of this study and we confirm similar results. For the sake of brevity, these results are not presented in the report but they are available upon request.

We observe a marginal difference between nominal and real electricity spot prices in Figure B.7 for all states in the NEM. Further, the supplementary analysis summarized in Table B.12 demonstrates that using inflation-adjusted time series as a dependent variable has a marginal effect on the magnitude of the estimated coefficients. Most importantly, although the coefficients have slightly changed when using real instead of nominal prices, scaling these coefficients by a factor of 10 to recover the original values renders the estimated effect unchanged (especially when converted to one or two decimals used for the analysis).

[4] Data available at https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/consumer-price-index-australia/jun-2022/640101.xlsx

[5] Since changing the reference point simply multiplies or divides the entire series by a constant, using a reference year different from 2018 is unlikely to have a substantial impact on the estimated coefficients.

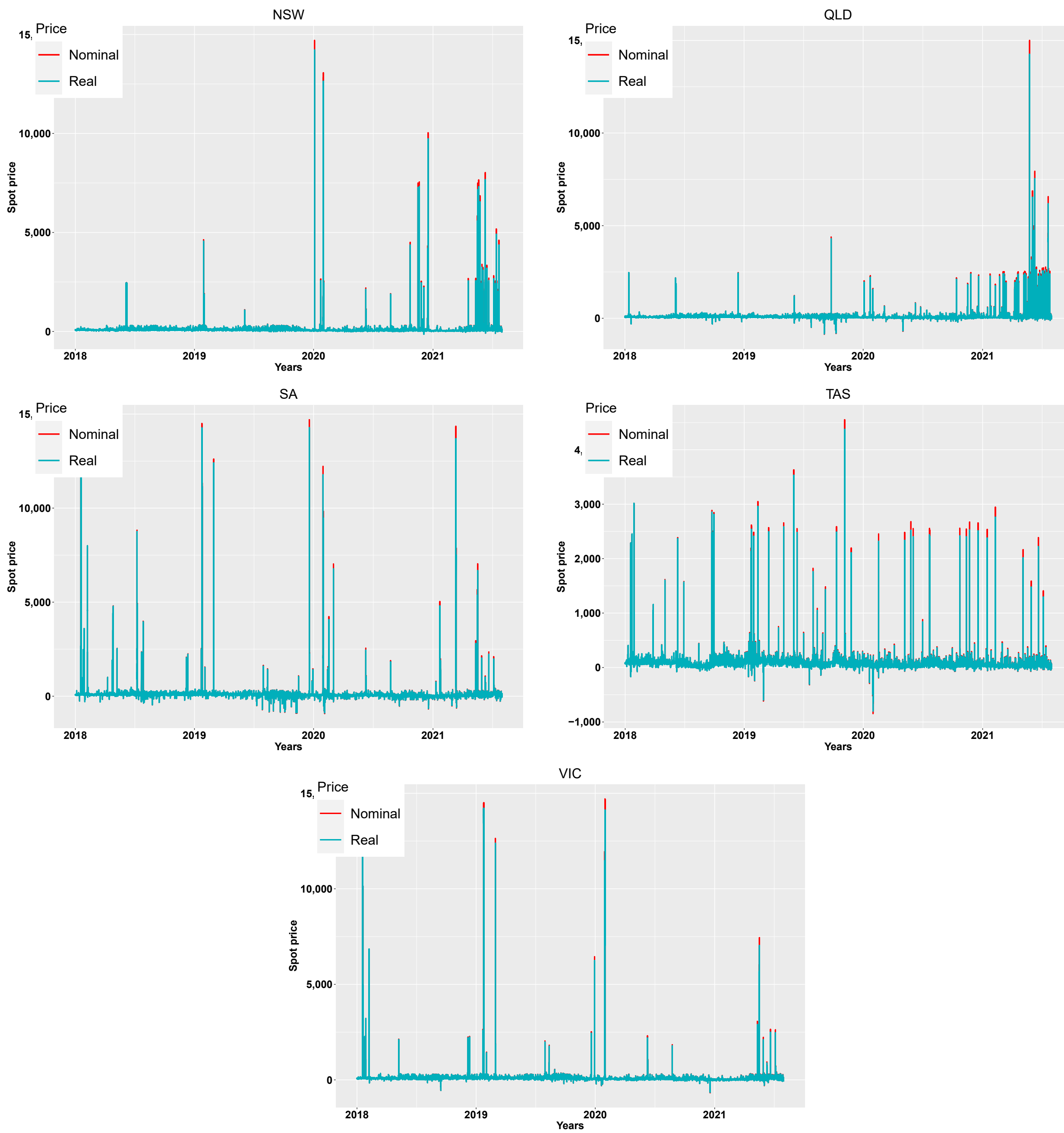

Figure B.7 : **Nominal and real electricity spot prices for NSW, QLD, SA, TAS, and VIC.** The real spot price series is in constant (inflation-adjusted) dollars, with 2018 taken as the reference point.

Table B.12 : **The effect of large-scale and rooftop solar generation on nominal and real (inflation-adjusted) spot price behaviour.** Model N shows the effects when using nominal prices, and Model R shows the impact when using real prices. The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	NSW		**VIC**		**SA**		**QLD**		**TAS**	
	Model N	Model R	Model N	Model R	Model N	Model R	Model N	Model R	Model N	Model R
	Mean Equation									
μ	-83.2652	-81.4924	-79.5598	-75.1725	-18.3237	-16.6881	-158.6972	-154.9828	13.7983	17.1342
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9302	0.9291	0.9449	0.9456	0.9156	0.9176	0.9671	0.9661	0.9426	0.9435
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-0.3061	-0.3003	-0.8473	-0.8277	-1.4898	-1.4675	-0.3052	-0.2947		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
rooftop solar									-0.3696	-0.3750
									(0.0000)	(0.0000)
wind	-0.2286	-0.2214	-0.5842	-0.5680	-1.2272	-1.2007	-0.5361	-0.5203	-1.3706	-1.3332
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hydro	0.2443	0.2355	-0.0624	-0.0552			-0.1202	-0.1238	-0.1109	-0.1074
	(0.0000)	(0.0000)	(0.0003)	(0.0079)			(0.0040)	(0.0329)	(0.0000)	(0.0000)
consumption (grid)	0.3627	0.3545	0.7294	0.7057	1.6203	1.5675	0.6858	0.6700		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
consumption (underlying)									1.2865	1.2653
									(0.0000)	(0.0000)
gas price	1.5246	1.5350	0.3670	0.3394	2.8529	2.8619	1.63756	1.6647		
	(0.0000)	(0.0000)	(0.1756)	(0.0957)	(0.0000)	(0.0000)	(0.0000)	(0.0036)		
$exim_{terra}$	-0.7419	-0.7352					0.1042	0.0946		
	(0.0000)	(0.0000)					(0.3170)	(0.6312)		
$exim_{QNI}$	-0.1879	-0.1835					-0.3238	-0.3167		
	(0.0000)	(0.0000)					(0.0000)	(0.0000)		
$exim_{murray}$			0.6864	0.6589	0.6393	0.6105				
			(0.0000)	(0.0000)	(0.0000)	(0.0000)				
$exim_{heyw}$			-0.0856	-0.0873	-0.8213	-0.7992				
			(0.0041)	(0.0003)	(0.0000)	(0.0000)				
$exim_{VNI}$	0.0401	0.0377	0.0592	0.0538						
	(0.0003)	(0.0000)	(0.0000)	(0.0029)						
$exim_{bass}$			-0.1398	-0.1341						
			(0.0000)	(0.0000)						
	Variance Equation									
ω	-0.0814	-0.0285	0.7074	0.7005	1.3335	2.1598	2.1076	2.0851	3.9785	4.1735
	(0.0570)	(0.7167)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-0.1408	-0.1314	0.0418	0.0424	0.0165	0.0649	-1.8471	-1.7989	0.8384	1.5980
	(0.0000)	(0.0000)	(0.4037)	(0.0069)	(0.5147)	(0.5321)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.7038	0.7023	0.6999	0.6986	0.7072	0.7057	0.6575	0.6562	0.4827	0.4594
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.0629	1.0678	0.7817	0.7815	1.2126	4.7627	6.0079	6.0017	5.2358	4.7960
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0221	0.0220	0.0337	0.0336	0.0396	0.0398	0.0171	0.0170		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
rooftop solar									0.0424	0.0395
									(0.0000)	(0.0000)
wind	0.0007	0.0006	0.0019	0.0019	-0.0016	-0.0016	-0.0081	-0.0086	0.0063	0.0061
	(0.2535)	(0.2854)	(0.0096)	(0.0036)	(0.0047)	(0.0548)	(0.0000)	(0.0000)	(0.0314)	(0.0430)
hydro	0.0069	0.0060	0.0051	0.0051			0.0190	0.0193	0.0047	0.0048
	(0.0000)	(0.0000)	(0.0001)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	(0.0000)
consumption (grid)	0.0023	0.0021	0.0018	0.0018	0.0080	0.0079	0.0013	0.0013		
	(0.0000)	(0.0000)	(0.0099)	(0.0000)	(0.0000)	(0.0002)	(0.0812)	(0.1363)		
consumption (underlying)									0.0088	0.0087
									(0.0000)	(0.0000)
gas price	0.0498	0.0514	0.0445	0.0457	0.0284	0.0291	0.0638	0.0651		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$exim_{terra}$	-0.0104	-0.0087					0.0262	0.0262		
	(0.0944)	(0.1833)					(0.0168)	(0.0225)		
$exim_{QNI}$	-0.0006	-0.0008					-0.0011	-0.0012		
	(0.3631)	(0.2587)					(0.3736)	(0.4276)		
$exim_{murray}$			-0.0145	-0.0145	-0.0132	-0.0131				
			(0.0000)	(0.0000)	(0.0001)	(0.0045)				
$exim_{heyw}$			-0.0014	-0.0014	-0.0038	-0.0038				
			(0.1217)	(0.0451)	(0.0001)	(0.0049)				
$exim_{VNI}$	0.0024	0.0024	-0.0005	-0.0005						
	(0.0000)	(0.0000)	(0.3622)	(0.1862)						
$exim_{bass}$			0.0023	0.0023						
			(0.0000)	(0.0000)						
Skew			0.0797	0.0832	0.9711	0.9735	1.0226	1.0219	1.1041	1.1294
			(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8276	2.8143	1.0387	1.0397	2.1779	2.0100	2.0100	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-230912.9	-229381	-236110.6	-234930.7	-242961.9	-241597.2	-206724.5	-205273.6	-239475.4	-237210.4
AIC	7.7537	7.7023	8.2335	8.1924	8.6164	8.5680	7.9986	7.9424	8.0409	7.9649
BIC	7.7572	7.7057	8.2376	8.1964	8.6196	8.5712	8.0023	7.9462	8.0434	7.9673
Q(20)	3.7751	3.2856	38.69	38.32	7.258	7.722	3.887	4.069	5.562	6.116
	(0.2635)	(0.3629)	(0.0000)	(0.0000)	(0.0153)	(0.0099)	(0.2440)	(0.2147)	(0.0674)	(0.0421)
$Q^2(36)$	0.0020	0.0019	0.0412	0.0381	0.0006	0.0007	0.1901	0.1905	0.0394	0.0400
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(1.0000)	(1.0000)
ARCH-LM Test	0.0013	0.0013	0.0038	0.0035	0.0005	0.0005	0.2030	0.2032	0.0220	0.0208
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9969)	(0.9969)	(1.0000)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and cross-border interconnector flows are scaled by 10 to clarify the results' presentation. Thus, the coefficients corresponding to these variables should be divided by 10 to recover the original values. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table B.13 : **The effect of large-scale and rooftop solar generation on spot price behaviour during off-peak and peak hours.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	NSW		VIC		SA		QLD		TAS
	Model A	Model B	Model A	Model B	Model A	Model B	Model A	Model B	Model B
	Mean Equation								
μ	-81.3859	-90.8426	-77.2630	-73.8349	-15.2661	-25.8837	-155.2346	-148.2879	13.1211
	(0.0000)	(0.0000)	(0.0000)	(0.0271)	(0.0000)	(0.0517)	(0.0000)	(0.0000)	(0.2693)
ϕ_1	0.9304	0.9305	0.9445	0.9415	0.9197	0.9139	0.9690	0.9683	0.9426
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{off-peak}$	-0.1842		-0.6465		-1.3178		-0.2961		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$large\text{-}scale\ solar \times D_{peak}$	-0.7533		-0.9282		-0.6527		-0.1412		
	(0.0000)		(0.0000)		(0.0000)		(0.0013)		
$rooftop\ solar_{off-peak}$		-0.0812		-0.2487		-0.2451		-0.0512	-0.3492
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0000)
$rooftop\ solar \times D_{peak}$		-0.3219		-0.3332		-0.3100		-0.2196	-0.1375
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0898)
$wind_{off-peak}$	-0.2304	-0.2093	-0.5419	-0.4063	-1.1670	-0.8553	-0.5393	-0.5075	-1.3701
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind \times D_{peak}$	-0.0334	-0.0473	-0.1928	-0.1880	-0.2507	-0.2455	-0.2771	-0.1214	-0.0158
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4449)
$hydro$	0.2328	0.2557	-0.0439	0.0888			-0.1026	0.0176	-0.1150
	(0.0000)	(0.0000)	(0.2311)	(0.4850)			(0.1228)	(0.7873)	(0.0000)
$consumption\ (grid)$	0.3568		0.7081		1.5493		0.6903		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$consumption\ (underlying)$		0.3588		0.6507		1.3342		0.6268	1.3069
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0000)
$gas\ price$	1.7481	1.8621	0.3875	0.5144	3.0773	3.5430	1.9266	2.0612	
	(0.1526)	(0.0000)	(0.0791)	(0.0041)	(0.0000)	(0.0009)	(0.0215)	(0.0024)	
$exim_{terra}$	-0.7681	-0.8087					0.0622	0.2451	
	(0.0000)	(0.0000)					(0.6491)	(0.0801)	
$exim_{QNI}$	-0.1802	-0.1900					-0.3008	-0.2567	
	(0.0000)	(0.0000)					(0.0000)	(0.0000)	
$exim_{murray}$			0.6716	0.5307	0.6901	1.0432			
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			
$exim_{heyw}$			-0.0925	-0.1944	-0.7721	-0.4595			
			(0.0010)	(0.0806)	(0.0000)	(0.0000)			
$exim_{VNI}$	0.0343	0.0411	0.0361	-0.0922					
	(0.0020)	(0.0000)	(0.2516)	(0.4202)					
$exim_{bass}$			-0.1221	0.0234					
			(0.0027)	(0.8347)					
	Variance Equation								
ω	0.0666	0.4008	0.7007	0.8833	1.4541	0.8551	1.7048	1.5881	4.0852
	(0.5137)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2934)	(0.0000)	(0.0000)
α	0.0071	0.0156	0.0677	0.0961	0.0718	0.0606	-1.2684	-1.2887	0.8867
	(0.6047)	(0.2877)	(0.0000)	(0.0000)	(0.0056)	(0.0001)	(0.0000)	(0.0000)	(0.0010)
β	0.6271	0.6961	0.6528	0.6708	0.6677	0.7293	0.6999	0.7277	0.4779
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.8808	0.7603	0.7169	0.6641	1.1453	0.6277	3.5278	2.9536	5.1828
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{off-peak}$	0.0160		0.0248		0.0196		0.0109		
	(0.0000)		(0.0000)		(0.0000)		(0.0016)		
$large\text{-}scale\ solar \times D_{peak}$	0.0459		0.0650		0.0912		0.0264		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$rooftop\ solar_{off-peak}$		0.0075		0.0093		0.0092		0.0074	0.0266
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0033)
$rooftop\ solar \times D_{peak}$		0.0267		0.0301		0.0352		0.0158	0.0580
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0011)
$wind_{off-peak}$	-0.0014	-0.0015	0.0007	0.0026	-0.0035	0.0010	-0.0173	-0.0151	0.0021
	(0.0367)	(0.0037)	(0.1451)	(0.0000)	(0.0000)	(0.0642)	(0.0648)	(0.0000)	(0.4907)
$wind \times D_{peak}$	0.0078	0.0069	0.0029	-0.0029	0.0006	-0.0050	0.0460	0.0422	0.0171
	(0.0000)	(0.0000)	(0.0004)	(0.0001)	(0.3820)	(0.0000)	(0.1670)	(0.0000)	(0.0001)
$hydro$	0.0085	0.0072	0.0061	0.0061			0.0126	0.0119	0.0048
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0126)	(0.0000)	(0.0000)
$consumption\ (grid)$	0.0023		0.0024		0.0099		0.0014		
	(0.0000)		(0.0000)		(0.0000)		(0.4740)		
$consumption\ (underlying)$		0.0009		0.0011		0.0057		0.0011	0.0077
		(0.0001)		(0.0057)		(0.0000)		(0.0008)	(0.0084)
$gas\ price$	0.0620	0.0510	0.0515	0.0469	0.0321	0.0316	0.0533	0.0438	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0014)	(0.0000)	
$exim_{terra}$	-0.0114	-0.0140					0.0149	0.0067	
	(0.0721)	(0.0083)					(0.0917)	(0.3227)	
$exim_{QNI}$	-0.0018	-0.0009					-0.0017	-0.0002	
	(0.0116)	(0.1237)					(0.1698)	(0.7574)	
$exim_{murray}$			-0.0176	-0.0133	-0.0165	-0.0088			
			(0.0000)	(0.0000)	(0.0000)	(0.0014)			
$exim_{heyw}$			-0.0017	-0.0029	-0.0055	-0.0009			
			(0.0142)	(0.0000)	(0.0000)	(0.2382)			
$exim_{VNI}$	0.0033	0.0025	-0.0004	-0.0013					
	(0.0000)	(0.0000)	(0.3993)	(0.0007)					
$exim_{bass}$			0.0027	0.0034					
			(0.0000)	(0.0000)					
Skew			0.0585	0.0830	0.9789	0.9851	1.0462	1.0460	1.1060
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8315	2.8072	1.0756	1.0961	2.1936	2.5544	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-227871.7	-228334.0	-234725.8	-234457.7	-241664.9	-242674.1	-204591.5	-205338.9	-239413.3
AIC	7.6517	7.6672	8.1853	8.1760	8.5705	8.6063	7.9162	7.9451	8.0390
BIC	7.6558	7.6713	8.1900	8.1807	8.5743	8.6101	7.9206	7.9495	8.0420
Q(20)	8.062	9.279	52.85	56.92	9.609	5.845	8.051	12.08	5.544
	(0.0072)	(0.0022)	(0.0000)	(0.0000)	(0.0016)	(0.0053)	(0.0073)	(0.0001)	(0.0684)
$Q^2(36)$	0.0019	0.0017	0.0417	0.1098	0.0007	0.0005	0.0225	0.0437	0.0391
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0010	0.0013	0.0019	0.0021	0.0005	0.0003	0.0154	0.0288	0.0215
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and cross-border interconnector flows are scaled by 10 to clarify the results' presentation. Thus, the coefficients corresponding to these variables should be divided by 10 to recover the original values. Off-peak is used as a reference season. Recovering the coefficients for the peak hours requires the addition of an interaction variable to the reference variable. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table B.14 : **The effect of large-scale and rooftop solar generation on spot price behaviour during summer, autumn, winter and spring.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

	NSW		VIC		SA		QLD		TAS
	Model M	Model N	Model M	Model N	Model M	Model N	Model M	Model N	Model M
	Mean Equation								
μ	-82.4669	-98.0932	-76.7986	-79.9912	-17.8313	-31.5531	-158.1378	-149.5222	14.1663
	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0047)	(0.0000)	(0.0000)	(0.8852)
ϕ_1	0.9292	0.9289	0.9413	0.9367	0.9091	0.9120	0.9670	0.9670	0.9413
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	-0.1924		-0.5174		-1.0723		-0.1170		
	(0.0000)		(0.0000)		(0.0000)		(0.0051)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0238		-0.1254		-0.1760		-0.0947		
	(0.0898)		(0.0067)		(0.0626)		(0.0697)		
$large\text{-}scale\ solar \times D_{spring}$	-0.1159		-0.3501		-0.4480		-0.2780		
	(0.0000)		(0.0000)		(0.0001)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.6794		-1.5917		-1.4067		-0.3573		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$rooftop\ solar_{winter}$		-0.0703		-0.2052		-0.1684		-0.0547	0.0192
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.9890)
$rooftop\ solar \times D_{autumn}$		0.0130		-0.0854		-0.0574		0.0181	-0.4495
		(0.0096)		(0.0000)		(0.0000)		(0.2155)	(0.4199)
$rooftop\ solar \times D_{spring}$		-0.0847		-0.1454		-0.24451		-0.0613	-0.6513
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.6614)
$rooftop\ solar \times D_{summer}$		-0.2208		-0.6693		-0.8229		-0.0742	-1.2006
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.5047)
$wind_{winter}$	-0.1859	-0.1578	-0.5544	-0.4589	-1.1915	-0.9619	-0.7041	-0.6651	-1.7713
	(0.0000)	(0.0028)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
$wind \times D_{autumn}$	0.0094	0.0062	0.0545	0.0732	0.0031	0.0649	0.1610	0.1481	0.5549
	(0.8386)	(0.9067)	(0.1023)	(0.0373)	(0.9423)	(0.0971)	(0.1547)	(0.0603)	(0.3905)
$wind \times D_{spring}$	-0.1095	-0.0948	-0.0650	-0.0454	0.0878	0.1439	0.2935	0.3347	0.2033
	(0.0218)	(0.2169)	(0.0559)	(0.2881)	(0.0294)	(0.0005)	(0.4061)	(0.0000)	(0.7283)
$wind \times D_{summer}$	-0.1231	-0.1245	-0.2079	-0.1468	-0.3168	-0.1803	0.1418	0.1500	0.6619
	(0.0003)	(0.0480)	(0.0000)	(0.0046)	(0.0000)	(0.0001)	(0.4038)	(0.0762)	(0.1133)
$hydro$	0.2426	0.2675	-0.0637	0.0650			-0.1187	-0.0208	-0.1085
	(0.0000)	(0.0000)	(0.0001)	(0.0796)			(0.0329)	(0.7239)	(0.5266)
$consumption\ (grid)$	0.3587		0.7140		1.6065		0.6806		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$consumption\ (underlying)$		0.3743		0.6846		1.4453		0.6204	
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
$gas\ price$	1.6647	1.7325	0.4927	0.5155	2.8961	3.3297	1.8722	1.8853	
	(0.0000)	(0.0000)	(0.0247)	(0.2486)	(0.0000)	(0.0000)	(0.0005)	(0.2798)	
$exim_{terra}$	-0.7844	-0.8446					0.0810	0.2370	
	(0.0000)	(0.0000)					(0.5732)	(0.1112)	
$exim_{QNI}$	-0.1927	-0.2008					-0.3279	-0.2752	
	(0.0000)	(0.0000)					(0.0000)	(0.000)	
$exim_{murray}$			0.7122	0.5744	0.6045	0.9183			
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			
$exim_{heyw}$			-0.0863	-0.1651	-0.8336	-0.5276			
			(0.0001)	(0.0000)	(0.0000)	(0.0000)			
$exim_{VNI}$	0.0401	0.0493	0.0574	-0.0533					
	(0.0004)	(0.0000)	(0.0000)	(0.0806)					
$exim_{bass}$			-0.1392	-0.0114					
			(0.0000)	(0.7919)					
	Variance Equation								
ω	-0.1591	0.1069	0.6579	0.6851	1.3583	1.2658	1.9702	1.9498	4.1261
	(0.2693)	(0.1789)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-0.1469	-0.1600	0.0438	0.0605	0.0148	0.0418	-1.8804	-1.8466	0.9278
	(0.0000)	(0.0000)	(0.0071)	(0.0000)	(0.5418)	(0.0781)	(0.0000)	(0.0000)	(0.0537)
β	0.7013	0.7343	0.6956	0.6916	0.6992	0.6814	0.6581	0.6671	0.4635
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.0414	1.0067	0.7663	0.7458	1.1651	1.0981	5.8461	5.3673	5.1819
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	0.0285		0.0400		0.0459		0.0174		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0111		-0.0155		-0.0110		-0.0046		
	(0.0000)		(0.0000)		(0.0050)		(0.0000)		
$large\text{-}scale\ solar \times D_{spring}$	-0.0027		-0.0039		-0.0094		0.0049		
	(0.1310)		(0.2069)		(0.0169)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.0084		-0.0037		-0.0025		-0.0010		
	(0.0000)		(0.2254)		(0.5414)		(0.3883)		
$rooftop\ solar_{winter}$		0.0151		0.0189		0.0249		0.0120	0.0846
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0047)
$rooftop\ solar \times D_{autumn}$		-0.0056		-0.0066		-0.0087		-0.0033	-0.0851
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0032)
$rooftop\ solar \times D_{spring}$		-0.0046		-0.0082		-0.0102		0.0005	0.0214
		(0.0000)		(0.0000)		(0.0000)		(0.5619)	(0.4459)
$rooftop\ solar \times D_{summer}$		-0.0063		-0.0064		-0.0084		-0.0021	-0.0868
		(0.0000)		(0.0000)		(0.0000)		(0.0079)	(0.0081)
$wind_{winter}$	0.0005	-0.0012	0.0013	0.0015	-0.0015	-0.0000	0.0007	-0.0029	0.0023
	(0.5170)	(0.0908)	(0.0283)	(0.0084)	(0.0165)	(0.9469)	(0.8172)	(0.2986)	(0.7496)
$wind \times D_{autumn}$	-0.0005	-0.0001	-0.0006	-0.0003	-0.0022	-0.0012	-0.0077	-0.0036	-0.0074
	(0.5304)	(0.8808)	(0.2405)	(0.5581)	(0.0000)	(0.0193)	(0.0222)	(0.2287)	(0.2609)
$wind \times D_{spring}$	0.0008	0.0029	0.0018	0.0041	0.0019	0.0039	-0.0163	-0.0091	0.0175
	(0.3694)	(0.0014)	(0.0045)	(0.0000)	(0.0009)	(0.0000)	(0.0001)	(0.0122)	(0.0437)
$wind \times D_{summer}$	0.0007	0.0024	0.0012	0.0037	-0.0006	0.0018	-0.0150	-0.0065	0.0095
	(0.4315)	(0.0018)	(0.0513)	(0.0000)	(0.2611)	(0.0017)	(0.0000)	(0.0506)	(0.2918)
$hydro$	0.0073	0.0085	0.0049	0.0054			0.0212	0.0208	0.0049
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0007)
$consumption\ (grid)$	0.0024		0.0020		0.0078		0.0017		
	(0.0000)		(0.0000)		(0.0000)		(0.0001)		
$consumption\ (underlying)$		0.0014		0.0017		0.0068		0.0014	0.0091
		(0.0000)		(0.0001)		(0.0000)		(0.0000)	(0.000)
$gas\ price\ price$	0.0510	0.0480	0.0462	0.0434	0.0311	0.0395	0.0616	0.0597	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
$exim_{terra}$	-0.0087	-0.0129					0.0324	0.0196	
	(0.1467)	(0.0309)					(0.0027)	(0.0606)	
$exim_{QNI}$	-0.0010	-0.0002					-0.0020	-0.0009	
	(0.1211)	(0.7858)					(0.0953)	(0.3649)	
$exim_{murray}$			-0.0145	-0.0118	-0.0139	-0.0108			
			(0.0000)	(0.0000)	(0.0001)	(0.0003)			
$exim_{heyw}$			-0.0013	-0.0023	-0.0039	-0.0006			
			(0.0027)	(0.0001)	(0.0336)	(0.4568)			
$exim_{VNI}$	0.0025	0.0023	-0.0004	-0.0014					
	(0.0000)	(0.0000)	(0.2767)	(0.0001)					
$exim_{bass}$			0.0021	0.0029					
			(0.0001)	(0.0000)					
Skew			0.0819	0.0891	0.9686	0.9682	1.0227	1.0345	1.1060
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8382	2.7699	1.0380	1.0543	2.1947	2.2177	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-230527.7	-231110.2	-235822.3	-235856.4	-242747.9	-243598.3	-206487.9	-207792.7	-239307.7
AIC	7.7412	7.7607	8.2239	8.2250	8.6092	8.6394	7.9899	8.0403	8.0357
BIC	7.7464	7.7660	8.2298	8.2310	8.6092	8.6444	7.9957	8.0462	8.0399
Q(20)	3.9487	5.3558	36.24	41.41	7.161	3.905	4.018	3.576	5.677
	(0.2337)	(0.0798)	(0.0000)	(0.0000)	(0.0000)	(0.2409)	(0.2226)	(0.3012)	(0.0612)
$Q^2(36)$	0.0018	0.0010	0.0142	0.0402	0.0007	0.0005	0.1935	0.1266	0.0396
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)
ARCH-LM Test	0.0012	0.0007	0.0017	0.0030	0.0005	0.0003	0.2201	0.1050	0.0230
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9963)	(0.9993)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and cross-border interconnector flows are scaled by 10 to clarify the results' presentation. Thus, the coefficients corresponding to these variables should be divided by 10 to recover the original values. Winter is used as a reference season. Recovering the coefficients for the other seasons (autumn, spring, and summer) requires the addition of an interaction variable to the reference variable. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table B.15 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per MWh increase in large-scale solar and wind generation for Victoria.** The subscript s denotes large-scale solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03046	0.00000	0.00000	0.00000	-0.00003	0.80876
2	0:30	0.00000	0.00000	-0.03019	0.00000	0.00000	0.00000	0.00002	0.82688
3	1:00	0.00000	0.00000	-0.02831	0.00000	0.00000	0.00000	-0.00009	0.16583
4	1:30	0.00000	0.00000	-0.02432	0.21858	0.00000	0.00000	-0.00019	0.46520
5	2:00	0.00000	0.00000	-0.02502	0.00000	0.00000	0.00000	-0.00033	0.24140
6	2:30	0.00000	0.00000	-0.02215	0.00003	0.00000	0.00000	-0.00015	0.04892
7	3:00	0.00000	0.00000	-0.02131	0.00006	0.00000	0.00000	-0.00025	0.40005
8	3:30	0.00000	0.00000	-0.02101	0.00000	0.00000	0.00000	-0.00012	0.15853
9	4:00	0.00000	0.00000	-0.01880	0.00000	0.00000	0.00000	-0.00014	0.09172
10	4:30	0.00000	0.00000	-0.01957	0.08586	0.00000	0.00000	-0.00019	0.03014
11	5:00	0.00000	0.00000	-0.02470	0.00000	0.00000	0.00000	-0.00017	0.00655
12	5:30	0.00000	0.00000	-0.02812	0.00001	0.00000	0.00000	-0.00027	0.37249
13	6:00	0.02641	0.02475	-0.02319	0.00000	-0.00185	0.26908	0.00042	0.26988
14	6:30	-0.05028	0.53538	-0.02534	0.00312	-0.00011	0.91644	-0.00056	0.12497
15	7:00	-0.05033	0.07035	-0.03082	0.00006	0.00095	0.26330	-0.00046	0.15049
16	7:30	-0.11222	0.00000	-0.04008	0.00000	-0.00069	0.49217	-0.00102	0.00232
17	8:00	-0.10690	0.31795	-0.05149	0.24404	-0.00179	0.35458	-0.00049	0.31983
18	8:30	-0.09866	0.00000	-0.05466	0.00000	-0.00125	0.30480	-0.00045	0.17544
19	9:00	-0.09192	0.00286	-0.05085	0.00000	-0.00137	0.04510	-0.00025	0.11160
20	9:30	-0.06739	0.00000	-0.04441	0.00000	-0.00140	0.03171	-0.00037	0.06042
21	10:00	-0.09448	0.00000	-0.01028	0.00000	-0.00000	0.00000	0.00000	0.00000
22	10:30	-0.04651	0.00208	-0.05263	0.00000	-0.00141	0.11332	-0.00008	0.76206
23	11:00	-0.04752	0.00004	-0.05401	0.00000	-0.00108	0.32003	-0.00013	0.77897
24	11:30	-0.05710	0.00636	-0.05197	0.00000	0.00002	0.99098	0.00072	0.04768
25	12:00	-0.02644	0.29917	-0.05509	0.00000	-0.00207	0.07179	0.00039	0.22278
26	12:30	-0.01451	0.12932	-0.05255	0.00011	-0.00083	0.79536	0.00027	0.64049
27	13:00	-0.04234	0.00000	-0.04908	0.00000	-0.00251	0.07112	0.00077	0.05217
28	13:30	-0.05420	0.07226	-0.05283	0.00000	-0.00344	0.05916	0.00070	0.10969
29	14:00	-0.04377	0.44504	-0.06341	0.00038	-0.00256	0.07041	0.00060	0.52210
30	14:30	-0.05491	0.37699	-0.06378	0.00295	-0.00137	0.30135	0.00018	0.68991
31	15:00	-0.04758	0.04584	-0.05619	0.00000	-0.00145	0.30130	0.00007	0.89398
32	15:30	-0.04220	0.06315	-0.05224	0.00000	0.00025	0.85579	0.00009	0.82340
33	16:00	-0.05702	0.00008	-0.04728	0.00000	0.00002	0.98748	0.00018	0.67185
34	16:30	-0.02736	0.31905	-0.04396	0.00000	-0.00245	0.08465	-0.00035	0.44268
35	17:00	-0.03547	0.11845	-0.04826	0.00000	-0.00056	0.75039	-0.00023	0.54362
36	17:30	-0.09882	0.06428	-0.06292	0.00000	-0.00285	0.27389	-0.00115	0.03599
37	18:00	-0.10283	0.04893	-0.08198	0.00000	-0.00451	0.00317	-0.00112	0.01856
38	18:30	0.12247	0.12315	-0.06441	0.00006	-0.00162	0.47381	-0.00098	0.02078
39	19:00	0.02671	0.85102	-0.05296	0.00001	-0.00124	0.67461	-0.00074	0.07853
40	19:30	0.00000	0.00000	-0.03902	0.00000	0.00000	0.00000	0.00031	0.41897
41	20:00	0.00000	0.00000	-0.03284	0.00000	0.00000	0.00000	0.00024	0.41233
42	20:30	0.00000	0.00000	-0.03648	0.00000	0.00000	0.00000	0.00003	0.80860
43	21:00	0.00000	0.00000	-0.03451	0.00000	0.00000	0.00000	-0.00001	0.98950
44	21:30	0.00000	0.00000	-0.03408	0.00000	0.00000	0.00000	-0.00001	0.92474
45	22:00	0.00000	0.00000	-0.02909	0.00000	0.00000	0.00000	-0.00002	0.60315
46	22:30	0.00000	0.00000	-0.05066	0.00000	0.00000	0.00000	-0.00001	0.98189
47	23:00	0.00000	0.00000	-0.03381	0.00000	0.00000	0.00000	-0.00010	0.34404
48	23:30	0.00000	0.00000	-0.03322	0.00000	0.00000	0.00000	-0.00009	0.32196

Table B.16 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in large-scale solar and wind generation for New South Wales.** The subscript s denotes large-solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.01657	0.00000	0.00000	0.00000	-0.00032	0.21172
2	0:30	0.00000	0.00000	-0.01799	0.00000	0.00000	0.00000	-0.00074	0.05522
3	1:00	0.00000	0.00000	-0.01950	0.00000	0.00000	0.00000	-0.00049	0.10473
4	1:30	0.00000	0.00000	-0.01735	0.00074	0.00000	0.00000	-0.00029	0.42765
5	2:00	0.00000	0.00000	-0.02147	0.00000	0.00000	0.00000	-0.00023	0.59615
6	2:30	0.00000	0.00000	-0.02036	0.00000	0.00000	0.00000	0.00002	0.96601
7	3:00	0.00000	0.00000	-0.02039	0.00000	0.00000	0.00000	-0.00001	0.95975
8	3:30	0.00000	0.00000	-0.01976	0.00000	0.00000	0.00000	-0.00086	0.04875
9	4:00	0.00000	0.00000	-0.02340	0.00000	0.00000	0.00000	-0.00055	0.12138
10	4:30	0.00000	0.00000	-0.01657	0.01274	0.00000	0.00000	-0.00058	0.20521
11	5:00	0.00000	0.00000	-0.01327	0.00000	0.00000	0.00000	-0.00011	0.67571
12	5:30	0.00000	0.00000	-0.01472	0.00000	0.00000	0.00000	-0.00056	0.31655
13	6:00	0.03633	0.86739	-0.01721	0.27090	-0.00093	0.67646	-0.00029	0.56622
14	6:30	0.05241	0.87379	-0.01664	0.00015	-0.00057	0.64988	-0.00039	0.47715
15	7:00	-0.01164	0.65410	-0.01785	0.02664	-0.00005	0.96183	-0.00039	0.40068
16	7:30	-0.04618	0.00028	-0.01909	0.00063	-0.00262	0.00097	-0.00111	0.02236
17	8:00	-0.04000	0.00527	-0.01860	0.00224	-0.00164	0.02436	-0.00151	0.00332
18	8:30	-0.02979	0.00042	-0.02426	0.00002	0.00006	0.93573	-0.00059	0.17350
19	9:00	-0.03810	0.00000	-0.02361	0.00000	-0.00101	0.26053	-0.00017	0.77513
20	9:30	-0.03551	0.85315	-0.02160	0.74095	-0.00050	0.86466	-0.00023	0.58788
21	10:00	-0.03452	0.00000	-0.02661	0.00000	-0.00079	0.21046	-0.00033	0.42285
22	10:30	-0.03564	0.00272	-0.02954	0.00000	-0.00131	0.06922	-0.00004	0.93061
23	11:00	-0.02912	0.00017	-0.02849	0.00000	-0.00166	0.02421	-0.00042	0.31023
24	11:30	-0.03230	0.08882	-0.03047	0.00000	-0.00184	0.01403	-0.00027	0.45824
25	12:00	-0.03828	0.06223	-0.03193	0.00016	-0.00138	0.13813	-0.00038	0.41204
26	12:30	-0.03762	0.00000	-0.02977	0.00000	-0.00169	0.02593	-0.00054	0.09517
27	13:00	-0.02831	0.00000	-0.02965	0.00000	-0.00097	0.22828	-0.00017	0.65835
28	13:30	-0.04140	0.00368	-0.02614	0.00107	-0.00094	0.40335	-0.00062	0.23390
29	14:00	-0.03690	0.00000	-0.03102	0.00000	-0.00169	0.07623	-0.00064	0.16867
30	14:30	-0.03413	0.00000	-0.02598	0.00000	0.00045	0.73999	-0.00051	0.21356
31	15:00	-0.03264	0.00046	-0.02638	0.00000	-0.00178	0.01583	-0.00095	0.01014
32	15:30	-0.02588	0.00000	-0.02076	0.00000	-0.00133	0.05264	-0.00087	0.02557
33	16:00	-0.02492	0.00000	-0.02542	0.00000	-0.00208	0.02691	-0.00028	0.60253
34	16:30	-0.02538	0.00164	-0.02284	0.00000	-0.00447	0.00002	-0.00074	0.09350
35	17:00	-0.01939	0.02115	-0.02206	0.00000	-0.00399	0.00011	-0.00089	0.06795
36	17:30	-0.01764	0.22843	-0.02608	0.00000	-0.00425	0.00016	-0.00108	0.03042
37	18:00	-0.03037	0.23160	-0.03208	0.00000	-0.00325	0.00094	-0.00069	0.28795
38	18:30	0.05282	0.00297	-0.03408	0.00002	-0.00191	0.03789	-0.00031	0.59501
39	19:00	0.05732	0.00767	-0.03997	0.00000	-0.00191	0.01633	0.00020	0.68706
40	19:30	0.00000	0.00000	-0.03629	0.00000	0.00000	0.00000	-0.00022	0.58401
41	20:00	0.00000	0.00000	-0.02812	0.00000	0.00000	0.00000	-0.00009	0.80733
42	20:30	0.00000	0.00000	-0.02860	0.00000	0.00000	0.00000	0.00005	0.96052
43	21:00	0.00000	0.00000	-0.02830	0.00000	0.00000	0.00000	-0.00027	0.42627
44	21:30	0.00000	0.00000	-0.02798	0.00000	0.00000	0.00000	-0.00045	0.29808
45	22:00	0.00000	0.00000	-0.02555	0.00000	0.00000	0.00000	-0.00021	0.40452
46	22:30	0.00000	0.00000	-0.02235	0.00000	0.00000	0.00000	-0.00028	0.31246
47	23:00	0.00000	0.00000	-0.02291	0.00000	0.00000	0.00000	-0.00038	0.24506
48	23:30	0.00000	0.00000	-0.02122	0.00000	0.00000	0.00000	-0.00041	0.38835

Table B.17 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in large-scale solar and wind generation for South Australia.** The subscript *s* denotes large-solar, and *w* denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.08762	0.00000	0.00000	0.00000	-0.00175	0.01611
2	0:30	0.00000	0.00000	-0.08010	0.00000	0.00000	0.00000	-0.00089	0.16335
3	1:00	0.00000	0.00000	-0.08663	0.00000	0.00000	0.00000	-0.00089	0.12730
4	1:30	0.00000	0.00000	-0.09499	0.00000	0.00000	0.00000	-0.00038	0.51240
5	2:00	0.00000	0.00000	-0.09262	0.00000	0.00000	0.00000	-0.00081	0.17573
6	2:30	0.00000	0.00000	-0.10004	0.00000	0.00000	0.00000	-0.00048	0.43320
7	3:00	0.00000	0.00000	-0.11788	0.00000	0.00000	0.00000	-0.00061	0.34949
8	3:30	0.00000	0.00000	-0.11929	0.00000	0.00000	0.00000	-0.00126	0.05193
9	4:00	0.00000	0.00000	-0.11054	0.11473	0.00000	0.00000	-0.00155	0.37585
10	4:30	0.00000	0.00000	-0.11203	0.04006	0.00000	0.00000	-0.00042	0.46329
11	5:00	0.00000	0.00000	-0.11154	0.00000	0.00000	0.00000	-0.00066	0.17483
12	5:30	0.00000	0.00000	-0.10847	0.00000	0.00000	0.00000	-0.00036	0.58061
13	6:00	0.00000	0.00000	-0.09554	0.13948	0.00000	0.00000	-0.00051	0.37114
14	6:30	0.00000	0.00000	-0.07876	0.00000	0.00000	0.00000	-0.00036	0.47678
15	7:00	-0.09438	0.00000	-0.11025	0.00000	-0.00013	0.96173	-0.00179	0.01546
16	7:30	-0.21698	0.00000	-0.09053	0.00000	-0.00132	0.66839	-0.00206	0.00023
17	8:00	-0.24954	0.00000	-0.10733	0.00000	-0.00103	0.46685	-0.00109	0.00150
18	8:30	-0.21570	0.00348	-0.08556	0.00000	0.00098	0.64767	-0.00093	0.02675
19	9:00	-0.11227	0.00184	-0.08228	0.00000	-0.00676	0.11266	-0.00110	0.09318
20	9:30	-0.04683	0.21357	-0.08730	0.00000	-0.01068	0.05559	-0.00080	0.16323
21	10:00	-0.03601	0.50002	-0.10030	0.00000	-0.00616	0.03041	-0.00024	0.63344
22	10:30	0.01627	0.84417	-0.10533	0.00000	-0.01372	0.00001	-0.00041	0.54892
23	11:00	0.03279	0.70077	-0.11315	0.00000	-0.01274	0.00012	-0.00080	0.25119
24	11:30	0.11136	0.31990	-0.11281	0.00038	-0.01280	0.00001	-0.00082	0.54006
25	12:00	0.13169	0.00408	-0.11563	0.00000	-0.01137	0.00025	-0.00057	0.37665
26	12:30	0.17932	0.00000	-0.10478	0.00000	-0.01460	0.00002	-0.00143	0.04148
27	13:00	0.23561	0.20671	-0.09699	0.00238	-0.01619	0.08042	-0.00118	0.24634
28	13:30	0.23765	0.00024	-0.10296	0.00000	-0.01481	0.00000	-0.00002	0.97100
29	14:00	0.20077	0.37360	-0.10021	0.18837	-0.01252	0.25414	-0.00062	0.73389
30	14:30	0.21934	0.00003	-0.09895	0.00000	-0.01900	0.00000	-0.00114	0.07415
31	15:00	0.17403	0.00026	-0.09344	0.00000	-0.01581	0.00001	-0.00177	0.00235
32	15:30	0.00903	0.99831	-0.09499	0.63194	-0.00977	0.88825	-0.00199	0.14103
33	16:00	-0.05656	0.56005	-0.08930	0.00056	-0.00693	0.00903	-0.00090	0.18287
34	16:30	0.00473	0.95832	-0.08821	0.00000	-0.00767	0.02650	-0.00135	0.01055
35	17:00	-0.12901	0.00000	-0.09938	0.00000	-0.00886	0.00036	-0.00168	0.00420
36	17:30	-0.12450	0.01808	-0.08752	0.00000	0.00156	0.58663	-0.00106	0.08250
37	18:00	-0.21247	0.00000	-0.13113	0.00000	-0.00082	0.80048	-0.00234	0.00000
38	18:30	-0.12154	0.00213	-0.13838	0.00000	0.00278	0.36428	-0.00273	0.00000
39	19:00	-0.14260	0.00014	-0.11904	0.00000	-0.00516	0.14249	-0.00267	0.00000
40	19:30	-0.22805	0.00135	-0.07600	0.00000	-0.00968	0.00285	-0.00204	0.00000
41	20:00	0.00000	0.00000	-0.06622	0.00000	0.00000	0.00000	-0.00150	0.00737
42	20:30	0.00000	0.00000	-0.07453	0.00000	0.00000	0.00000	-0.00245	0.00013
43	21:00	0.00000	0.00000	-0.07450	0.00000	0.00000	0.00000	-0.00181	0.00046
44	21:30	0.00000	0.00000	-0.07558	0.00000	0.00000	0.00000	-0.00150	0.00597
45	22:00	0.00000	0.00000	-0.07071	0.00000	0.00000	0.00000	-0.00063	0.45027
46	22:30	0.00000	0.00000	-0.08782	0.00407	0.00000	0.00000	-0.00139	0.01329
47	23:00	0.00000	0.00000	-0.08239	0.00000	0.00000	0.00000	-0.00074	0.25117
48	23:30	0.00000	0.00000	-0.07701	0.00000	0.00000	0.00000	-0.00081	0.17325

Table B.18 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in large-scale solar and wind generation for Queensland.** The subscript s denotes large-solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03630	0.02256	0.00000	0.00000	-0.00279	0.04770
2	0:30	0.00000	0.00000	-0.02880	0.00262	0.00000	0.00000	-0.00048	0.65877
3	1:00	0.00000	0.00000	-0.02766	0.00508	0.00000	0.00000	0.00001	0.92040
4	1:30	0.00000	0.00000	-0.03867	0.00051	0.00000	0.00000	-0.00198	0.15011
5	2:00	0.00000	0.00000	-0.04146	0.00001	0.00000	0.00000	-0.00129	0.27539
6	2:30	0.00000	0.00000	-0.03894	0.00001	0.00000	0.00000	-0.00131	0.12144
7	3:00	0.00000	0.00000	-0.03685	0.00002	0.00000	0.00000	-0.00207	0.00738
8	3:30	0.00000	0.00000	-0.04342	0.00000	0.00000	0.00000	-0.00169	0.01686
9	4:00	0.00000	0.00000	-0.05001	0.00000	0.00000	0.00000	-0.00135	0.06152
10	4:30	0.00000	0.00000	-0.03904	0.00066	0.00000	0.00000	-0.00121	0.16615
11	5:00	0.00000	0.00000	-0.03559	0.00157	0.00000	0.00000	-0.00184	0.05516
12	5:30	0.00000	0.00000	-0.04805	0.00108	0.00000	0.00000	-0.00071	0.49807
13	6:00	0.00000	0.00000	-0.05138	0.00000	0.00000	0.00000	-0.00072	0.52697
14	6:30	-0.10699	0.00196	-0.04916	0.00001	-0.00008	0.91557	-0.00101	0.35817
15	7:00	-0.06257	0.48948	-0.07380	0.01244	0.00023	0.87143	0.00218	0.03984
16	7:30	-0.05971	0.00000	-0.07097	0.00108	0.00012	0.78717	0.00221	0.02050
17	8:00	-0.06098	0.00000	-0.05909	0.00042	-0.00008	0.89798	0.00103	0.37538
18	8:30	-0.05448	0.00000	-0.06496	0.00000	-0.00004	0.93087	-0.00080	0.55993
19	9:00	-0.04782	0.00592	-0.05858	0.00007	-0.00027	0.56042	-0.00084	0.61668
20	9:30	-0.04728	0.00016	-0.05435	0.13336	-0.00071	0.35136	-0.00254	0.08239
21	10:00	-0.04033	0.06359	-0.04552	0.06960	-0.00082	0.11433	0.00062	0.72362
22	10:30	-0.02688	0.05271	-0.05589	0.05037	-0.00126	0.05424	-0.00188	0.14616
23	11:00	-0.00702	0.03722	-0.07591	0.00000	-0.00234	0.00229	-0.00020	0.87722
24	11:30	0.00018	0.99217	-0.08117	0.21427	-0.00179	0.00649	-0.00036	0.77178
25	12:00	-0.00324	0.55079	-0.09201	0.00000	-0.00156	0.00632	-0.00018	0.87183
26	12:30	-0.01119	0.00081	-0.09710	0.00002	-0.00138	0.01586	0.00048	0.62922
27	13:00	-0.01792	0.05761	-0.08489	0.00000	-0.00137	0.12212	0.00069	0.62008
28	13:30	-0.02753	0.01049	-0.04949	0.02421	-0.00186	0.00816	0.00253	0.11760
29	14:00	-0.02158	0.00146	-0.07078	0.00001	-0.00177	0.00164	-0.00034	0.81818
30	14:30	-0.03208	0.00019	-0.05709	0.00455	-0.00263	0.00021	-0.00086	0.68826
31	15:00	-0.03655		-0.25637		0.00000		-0.00000	
32	15:30	-0.04945	0.00126	-0.06474	0.00176	-0.00150	0.10387	-0.00182	0.39966
33	16:00	-0.06554	0.00022	-0.05186	0.02582	-0.00194	0.04184	-0.00225	0.28450
34	16:30	-0.05043	0.00000	-0.03573	0.09526	-0.00359	0.00001	-0.00030	0.85413
35	17:00	-0.04510	0.24280	-0.09080	0.10296	-0.00038	0.44069	-0.00011	0.86233
36	17:30	-0.04353	0.00567	-0.04036	0.17706	-0.00474	0.00000	-0.00701	0.00221
37	18:00	-0.08960	0.00000	-0.14035	0.00000	-0.00031	0.00727	-0.00038	0.33612
38	18:30	-0.04116	0.84038	-0.12280	0.55973	-0.00000	0.99901	0.00029	0.91658
39	19:00	0.00000	0.00000	-0.08152	0.00176	0.00000	0.00000	0.00023	0.36732
40	19:30	0.00000	0.00000	-0.06403	0.00405	0.00000	0.00000	0.00018	0.88163
41	20:00	0.00000	0.00000	-0.04872	0.02833	0.00000	0.00000	0.00104	0.20832
42	20:30	0.00000	0.00000	-0.07540	0.00002	0.00000	0.00000	0.00046	0.04815
43	21:00	0.00000	0.00000	-0.06938	0.08456	0.00000	0.00000	0.00011	0.64644
44	21:30	0.00000	0.00000	-0.05229	0.00001	0.00000	0.00000	0.00015	0.40440
45	22:00	0.00000	0.00000	-0.03199	0.17006	0.00000	0.00000	-0.00107	0.72922
46	22:30	0.00000	0.00000	-0.04067	0.13476	0.00000	0.00000	0.00021	0.71832
47	23:00	0.00000	0.00000	-0.02712	0.00333	0.00000	0.00000	0.00003	0.82671
48	23:30	0.00000	0.00000	-0.03234	0.10758	0.00000	0.00000	-0.00091	0.39678

Empty cells indicate models that failed to return the p-values. But since most of the estimated coefficients are close to ones estimated before or after the time in concern, we find it reasonable to include them in the analysis.

Table B.19 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for New South Wales.** The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.01657	0.00000	0.00000	0.00000	-0.00032	0.21172
2	0:30	0.00000	0.00000	-0.01799	0.00000	0.00000	0.00000	-0.00074	0.05522
3	1:00	0.00000	0.00000	-0.01950	0.00000	0.00000	0.00000	-0.00049	0.10473
4	1:30	0.00000	0.00000	-0.01735	0.00074	0.00000	0.00000	-0.00029	0.42765
5	2:00	0.00000	0.00000	-0.02147	0.00000	0.00000	0.00000	-0.00023	0.59615
6	2:30	0.00000	0.00000	-0.02036	0.00000	0.00000	0.00000	0.00002	0.96601
7	3:00	0.00000	0.00000	-0.02039	0.00000	0.00000	0.00000	-0.00001	0.95975
8	3:30	0.00000	0.00000	-0.01976	0.00000	0.00000	0.00000	-0.00086	0.04875
9	4:00	0.00000	0.00000	-0.02340	0.00000	0.00000	0.00000	-0.00055	0.12138
10	4:30	0.00000	0.00000	-0.01657	0.01274	0.00000	0.00000	-0.00058	0.20521
11	5:00	0.00000	0.00000	-0.01327	0.00000	0.00000	0.00000	-0.00011	0.67571
12	5:30	0.00000	0.00000	-0.01472	0.00000	0.00000	0.00000	-0.00056	0.31655
13	6:00	0.02110	0.00023	-0.01763	0.00000	-0.00050	0.30426	-0.00026	0.55792
14	6:30	0.03719	0.00009	-0.01763	0.00001	-0.00078	0.33072	-0.00037	0.48149
15	7:00	0.00266	0.93886	-0.01521	0.09089	-0.00005	0.95879	-0.00038	0.42031
16	7:30	-0.02429	0.00618	-0.01499	0.00184	-0.00246	0.00082	-0.00088	0.07518
17	8:00	-0.03483	0.00000	-0.01476	0.00034	-0.00146	0.02732	-0.00125	0.01287
18	8:30	-0.02825	0.00000	-0.02056	0.00002	-0.00071	0.21958	-0.00058	0.15485
19	9:00	-0.02971	0.00000	-0.02003	0.00074	-0.00110	0.04470	-0.00014	0.77205
20	9:30	-0.03049	0.00000	-0.01620	0.00000	-0.00073	0.05526	-0.00023	0.52078
21	10:00	-0.03188	0.00000	-0.02295	0.00000	-0.00056	0.10967	-0.00004	0.91548
22	10:30	-0.02975	0.00000	-0.02620	0.00000	-0.00060	0.05769	0.00029	0.43143
23	11:00	-0.02797	0.00000	-0.02448	0.00000	-0.00049	0.13990	-0.00008	0.81718
24	11:30	-0.03081	0.00000	-0.02686	0.00000	-0.00054	0.04690	0.00005	0.87480
25	12:00	-0.02875	0.00000	-0.02859	0.00000	-0.00018	0.51144	-0.00008	0.81612
26	12:30	-0.02694	0.00000	-0.02667	0.00000	-0.00028	0.39311	-0.00033	0.32687
27	13:00	-0.02443	0.00000	-0.02626	0.00000	-0.00020	0.51225	-0.00001	0.96974
28	13:30	-0.02417	0.00000	-0.02308	0.00000	0.00032	0.45060	-0.00045	0.40351
29	14:00	-0.02296	0.00000	-0.02847	0.00000	-0.00040	0.32322	-0.00051	0.24754
30	14:30	-0.02610	0.00008	-0.02376	0.00000	-0.00014	0.76782	-0.00032	0.42768
31	15:00	-0.02460	0.00000	-0.02597	0.00000	-0.00106	0.05562	-0.00083	0.02290
32	15:30	-0.02479	0.00000	-0.02001	0.00000	-0.00072	0.22815	-0.00070	0.07349
33	16:00	-0.02147	0.00001	-0.02346	0.00000	-0.00047	0.58365	-0.00022	0.66475
34	16:30	-0.01827	0.08321	-0.02247	0.00001	-0.00289	0.00240	-0.00025	0.64051
35	17:00	-0.02576	0.08167	-0.02116	0.00462	-0.00321	0.00245	-0.00069	0.18078
36	17:30	0.04045	0.00000	-0.02341	0.00000	-0.00205	0.01171	-0.00129	0.00718
37	18:00	0.08516	0.00003	-0.02319	0.00308	-0.00104	0.18889	-0.00073	0.21799
38	18:30	0.06140	0.23127	-0.03344	0.00909	-0.00111	0.16741	-0.00015	0.82920
39	19:00	0.00000	0.00000	-0.04063	0.00113	0.00000	0.00000	-0.00027	0.62455
40	19:30	0.00000	0.00000	-0.03629	0.00000	0.00000	0.00000	-0.00022	0.58401
41	20:00	0.00000	0.00000	-0.02812	0.00000	0.00000	0.00000	-0.00009	0.80733
42	20:30	0.00000	0.00000	-0.02860	0.00000	0.00000	0.00000	0.00005	0.96052
43	21:00	0.00000	0.00000	-0.02830	0.00000	0.00000	0.00000	-0.00027	0.42627
44	21:30	0.00000	0.00000	-0.02798	0.00000	0.00000	0.00000	-0.00045	0.29808
45	22:00	0.00000	0.00000	-0.02555	0.00000	0.00000	0.00000	-0.00021	0.40452
46	22:30	0.00000	0.00000	-0.02235	0.00000	0.00000	0.00000	-0.00028	0.31246
47	23:00	0.00000	0.00000	-0.02291	0.00000	0.00000	0.00000	-0.00038	0.24506
48	23:30	0.00000	0.00000	-0.02122	0.00000	0.00000	0.00000	-0.00041	0.38835

Table B.20 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for Victoria.** The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03046	0.00000	0.00000	0.00000	-0.00003	0.80876
2	0:30	0.00000	0.00000	-0.03019	0.00000	0.00000	0.00000	0.00002	0.82688
3	1:00	0.00000	0.00000	-0.02831	0.00000	0.00000	0.00000	-0.00009	0.16583
4	1:30	0.00000	0.00000	-0.02432	0.21858	0.00000	0.00000	-0.00019	0.46520
5	2:00	0.00000	0.00000	-0.02502	0.00000	0.00000	0.00000	-0.00033	0.24140
6	2:30	0.00000	0.00000	-0.02215	0.00003	0.00000	0.00000	-0.00015	0.04892
7	3:00	0.00000	0.00000	-0.02131	0.00006	0.00000	0.00000	-0.00025	0.40005
8	3:30	0.00000	0.00000	-0.02101	0.00000	0.00000	0.00000	-0.00012	0.15853
9	4:00	0.00000	0.00000	-0.01880	0.00000	0.00000	0.00000	-0.00014	0.09172
10	4:30	0.00000	0.00000	-0.01957	0.08586	0.00000	0.00000	-0.00019	0.03014
11	5:00	0.00000	0.00000	-0.02470	0.00000	0.00000	0.00000	-0.00017	0.00655
12	5:30	0.00000	0.00000	-0.02812	0.00001	0.00000	0.00000	-0.00027	0.37249
13	6:00	0.00746	0.96257	-0.02225	0.77938	-0.00165	0.05204	0.00029	0.61784
14	6:30	-0.01338	0.97622	-0.02298	0.72540	-0.00106	0.24139	-0.00077	0.25676
15	7:00	-0.00335	0.63204	-0.02728	0.00000	-0.00017	0.76203	-0.00056	0.08032
16	7:30	-0.04754	0.06753	-0.03250	0.00244	-0.00104	0.19438	-0.00103	0.00418
17	8:00	-0.05357	0.00000	-0.04131	0.00000	-0.00128	0.14279	-0.00036	0.36509
18	8:30	-0.06447	0.00000	-0.04677	0.00000	-0.00098	0.13879	-0.00042	0.10033
19	9:00	-0.05879	0.00000	-0.04625	0.00000	-0.00037	0.29708	-0.00021	0.16045
20	9:30	-0.05888	0.00000	-0.04404	0.00000	-0.00034	0.62729	-0.00029	0.34458
21	10:00	-0.05776	0.00000	-0.04798	0.00000	-0.00059	0.24165	-0.00033	0.11846
22	10:30	-0.05629	0.00000	-0.05405	0.00000	-0.00027	0.30596	0.00002	0.93476
23	11:00	-0.05689	0.00000	-0.05409	0.00000	-0.00037	0.27699	-0.00011	0.69105
24	11:30	-0.05937	0.00000	-0.05261	0.00000	0.00028	0.62607	0.00074	0.17823
25	12:00	-0.05456	0.00000	-0.05527	0.00000	-0.00042	0.28679	0.00022	0.57252
26	12:30	-0.05263	0.16294	-0.05295	0.00000	-0.00025	0.52030	0.00015	0.75560
27	13:00	-0.05144	0.00002	-0.04660	0.00000	0.00005	0.91602	0.00076	0.05676
28	13:30	-0.05105	0.00000	-0.04828	0.00000	-0.00000	0.98876	0.00021	0.41388
29	14:00	-0.06038	0.00000	-0.06227	0.00000	0.00029	0.73600	0.00056	0.60293
30	14:30	-0.06003	0.00000	-0.06096	0.00000	-0.00001	0.98936	0.00034	0.38765
31	15:00	-0.05168	0.00000	-0.05307	0.00000	0.00039	0.52512	0.00048	0.30441
32	15:30	-0.05318	0.00022	-0.04933	0.00000	-0.00025	0.67204	0.00014	0.69869
33	16:00	-0.03389	0.00000	-0.04159	0.00000	0.00030	0.72891	0.00039	0.38993
34	16:30	-0.02967	0.09297	-0.04137	0.03735	-0.00094	0.41939	-0.00016	0.70565
35	17:00	-0.04394	0.41256	-0.04847	0.00005	-0.00104	0.35237	-0.00020	0.74918
36	17:30	-0.02400	0.70887	-0.05370	0.00780	-0.00161	0.15382	-0.00065	0.55703
37	18:00	0.05498	0.30937	-0.06830	0.00000	-0.00006	0.95137	-0.00060	0.19234
38	18:30	-0.03381	0.00004	-0.07818	0.00000	-0.00298	0.00282	-0.00121	0.01012
39	19:00	0.23946	0.34912	-0.04494	0.10765	-0.00239	0.00401	-0.00077	0.06163
40	19:30	0.00000	0.00000	-0.03901	0.00000	0.00000	0.00000	0.00031	0.40496
41	20:00	0.00000	0.00000	-0.03284	0.00000	0.00000	0.00000	0.00024	0.41300
42	20:30	0.00000	0.00000	-0.03915	0.00000	0.00000	0.00000	0.00010	0.76323
43	21:00	0.00000	0.00000	-0.03329	0.04250	0.00000	0.00000	-0.00002	0.96910
44	21:30	0.00000	0.00000	-0.03408	0.00000	0.00000	0.00000	-0.00001	0.92474
45	22:00	0.00000	0.00000	-0.02909	0.00000	0.00000	0.00000	-0.00002	0.60315
46	22:30	0.00000	0.00000	-0.05066	0.00000	0.00000	0.00000	-0.00001	0.98189
47	23:00	0.00000	0.00000	-0.03381	0.00000	0.00000	0.00000	-0.00010	0.34404
48	23:30	0.00000	0.00000	-0.03322	0.00000	0.00000	0.00000	-0.00009	0.32196

Table B.21 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for South Australia.** The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.08761	0.00000	0.00000	0.00000	-0.00175	0.01572
2	0:30	0.00000	0.00000	-0.08010	0.00000	0.00000	0.00000	-0.00089	0.16335
3	1:00	0.00000	0.00000	-0.08663	0.00000	0.00000	0.00000	-0.00089	0.12730
4	1:30	0.00000	0.00000	-0.09499	0.00000	0.00000	0.00000	-0.00038	0.51240
5	2:00	0.00000	0.00000	-0.09262	0.00000	0.00000	0.00000	-0.00081	0.17573
6	2:30	0.00000	0.00000	-0.10004	0.00000	0.00000	0.00000	-0.00048	0.43320
7	3:00	0.00000	0.00000	-0.11788	0.00000	0.00000	0.00000	-0.00061	0.34949
8	3:30	0.00000	0.00000	-0.11929	0.00000	0.00000	0.00000	-0.00127	0.05171
9	4:00	0.00000	0.00000	-0.11056	0.00303	0.00000	0.00000	-0.00155	0.17159
10	4:30	0.00000	0.00000	-0.11203	0.04006	0.00000	0.00000	-0.00042	0.46329
11	5:00	0.00000	0.00000	-0.11154	0.00000	0.00000	0.00000	-0.00066	0.17483
12	5:30	0.00000	0.00000	-0.10847	0.00000	0.00000	0.00000	-0.00036	0.58061
13	6:00	0.00000	0.00000	-0.09554	0.13948	0.00000	0.00000	-0.00051	0.37114
14	6:30	-0.07876	0.00000	-0.07876	0.00000	-0.00189	0.04340	-0.00036	0.47716
15	7:00	-0.03020	0.21267	-0.10879	0.00000	-0.00070	0.47503	-0.00177	0.07152
16	7:30	-0.02907	0.37010	-0.08689	0.00000	-0.00285	0.10774	-0.00211	0.00036
17	8:00	-0.11185	0.00000	-0.09740	0.00000	-0.00150	0.16975	-0.00110	0.00052
18	8:30	-0.15660	0.09224	-0.07852	0.20301	-0.00150	0.24227	-0.00088	0.05046
19	9:00	-0.16159	0.00000	-0.08036	0.00000	-0.00014	0.75607	-0.00014	0.42547
20	9:30	-0.19807	0.00000	-0.09097	0.00000	0.00025	0.66622	0.00008	0.74308
21	10:00	-0.19195	0.00000	-0.10719	0.00000	0.00038	0.64725	0.00043	0.20866
22	10:30	-0.17827	0.00000	-0.11799	0.00000	0.00143	0.21279	0.00089	0.14294
23	11:00	-0.18696	0.00000	-0.12209	0.00000	0.00124	0.11089	0.00059	0.16339
24	11:30	-0.18734	0.00000	-0.13233	0.00000	0.00134	0.25195	0.00088	0.23815
25	12:00	-0.19728	0.00000	-0.13399	0.00000	0.00117	0.28832	0.00072	0.30972
26	12:30	-0.18701	0.00000	-0.13460	0.00000	-0.00033	0.71694	0.00011	0.80755
27	13:00	-0.18303	0.10590	-0.12961	0.10199	0.00105	0.67227	0.00092	0.58707
28	13:30	-0.18744	0.00000	-0.13330	0.00000	0.00142	0.13355	0.00161	0.00547
29	14:00	-0.19540	0.00000	-0.13210	0.00000	0.00175	0.10997	0.00126	0.14300
30	14:30	-0.19854	0.00000	-0.12886	0.00000	0.00051	0.65477	0.00086	0.16602
31	15:00	-0.20438	0.00000	-0.12468	0.00000	0.00023	0.83938	0.00012	0.85139
32	15:30	-0.18502	0.00000	-0.11440	0.00000	-0.00104	0.27029	-0.00039	0.41045
33	16:00	-0.19963	0.00000	-0.10437	0.00000	-0.00041	0.67688	-0.00012	0.78790
34	16:30	-0.20199	0.00000	-0.09685	0.00000	-0.00016	0.90640	-0.00051	0.31948
35	17:00	-0.22013	0.67504	-0.08956	0.68982	-0.00151	0.88016	-0.00071	0.26189
36	17:30	-0.21160	0.00000	-0.08921	0.00000	-0.00045	0.80201	-0.00070	0.15004
37	18:00	-0.15432	0.04099	-0.12248	0.00001	0.00103	0.64156	-0.00209	0.00000
38	18:30	-0.15797	0.00000	-0.13111	0.00000	-0.00305	0.01403	-0.00256	0.00000
39	19:00	-0.21868	0.01040	-0.11203	0.00001	-0.00825	0.00000	-0.00263	0.00000
40	19:30	0.39440	0.00021	-0.07205	0.00000	-0.00696	0.00001	-0.00236	0.00006
41	20:00	0.00000	0.00000	-0.06758	0.00000	0.00000	0.00000	-0.00229	0.00004
42	20:30	0.00000	0.00000	-0.07453	0.00000	0.00000	0.00000	-0.00245	0.00015
43	21:00	0.00000	0.00000	-0.07450	0.00000	0.00000	0.00000	-0.00181	0.00046
44	21:30	0.00000	0.00000	-0.07558	0.00000	0.00000	0.00000	-0.00150	0.00597
45	22:00	0.00000	0.00000	-0.07071	0.00000	0.00000	0.00000	-0.00063	0.45027
46	22:30	0.00000	0.00000	-0.08782	0.00407	0.00000	0.00000	-0.00139	0.01329
47	23:00	0.00000	0.00000	-0.08263	0.00000	0.00000	0.00000	-0.00064	0.29396
48	23:30	0.00000	0.00000	-0.07702	0.00000	0.00000	0.00000	-0.00081	0.17359

Table B.22 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for Queensland.** The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03630	0.01812	0.00000	0.00000	-0.00278	0.04850
2	0:30	0.00000	0.00000	-0.02916	0.16996	0.00000	0.00000	-0.00049	0.66268
3	1:00	0.00000	0.00000	-0.02766	0.00508	0.00000	0.00000	0.00001	0.92040
4	1:30	0.00000	0.00000	-0.03867	0.00043	0.00000	0.00000	-0.00198	0.14993
5	2:00	0.00000	0.00000	-0.04146	0.00000	0.00000	0.00000	-0.00129	0.27580
6	2:30	0.00000	0.00000	-0.03896	0.00001	0.00000	0.00000	-0.00131	0.12045
7	3:00	0.00000	0.00000	-0.03624	0.00247	0.00000	0.00000	-0.00207	0.00661
8	3:30	0.00000	0.00000	-0.04342	0.00000	0.00000	0.00000	-0.00169	0.01700
9	4:00	0.00000	0.00000	-0.05001	0.00005	0.00000	0.00000	-0.00135	0.07974
10	4:30	0.00000	0.00000	-0.03904	0.00066	0.00000	0.00000	-0.00121	0.16615
11	5:00	0.00000	0.00000	-0.03562	0.01925	0.00000	0.00000	-0.00184	0.06322
12	5:30	0.00000	0.00000	-0.04804	0.00000	0.00000	0.00000	-0.00071	0.49590
13	6:00	-0.03603	0.00000	-0.05303	0.00000	-0.00079	0.33123	-0.00090	0.43462
14	6:30	-0.02884	0.52971	-0.04969	0.00439	-0.00196	0.04532	-0.00179	0.14335
15	7:00	-0.04782	0.00996	-0.06127	0.00008	-0.00149	0.14096	0.00132	0.32320
16	7:30	-0.05399	0.00050	-0.03397	0.02732	-0.00176	0.14708	-0.00035	0.76618
17	8:00	-0.05899	0.00000	-0.06300	0.00003	-0.00138	0.07359	0.00020	0.87897
18	8:30	-0.07395	0.00000	-0.07858	0.00000	-0.00101	0.09410	-0.00214	0.10104
19	9:00	-0.07404	0.00000	-0.06649	0.00000	0.00018	0.78424	-0.00183	0.13701
20	9:30	-0.07138	0.00000	-0.06705	0.00003	-0.00044	0.46369	-0.00252	0.03773
21	10:00	-0.06667	0.00000	-0.05098	0.00035	-0.00050	0.30907	-0.00038	0.78048
22	10:30	-0.06957	0.00000	-0.06318	0.03596	-0.00063	0.20861	-0.00253	0.02275
23	11:00	-0.07482	0.00000	-0.08744	0.00000	-0.00074	0.08936	-0.00102	0.39330
24	11:30	-0.07144	0.00000	-0.09705	0.00000	-0.00031	0.06893	-0.00074	0.30253
25	12:00	-0.06470	0.00000	-0.09663	0.00001	0.00062	0.10139	0.00007	0.95144
26	12:30	-0.06408	0.00001	-0.10108	0.10573	-0.00001	0.98686	0.00049	0.65683
27	13:00	-0.05839	0.00000	-0.08945	0.00001	0.00045	0.22846	0.00048	0.70430
28	13:30	-0.05568	0.00000	-0.05452	0.00490	0.00050	0.29203	0.00202	0.17246
29	14:00	-0.05481	0.00000	-0.07564	0.00009	-0.00028	0.55644	-0.00103	0.47785
30	14:30	-0.05590	0.00000	-0.06690	0.00000	0.00070	0.17289	-0.00138	0.47633
31	15:00	-0.05113	0.00000	-0.08716	0.00003	0.00022	0.81810	0.00049	0.79733
32	15:30	-0.04334	0.08854	-0.06070	0.00557	-0.00061	0.21243	-0.00008	0.94981
33	16:00	-0.04250	0.38730	-0.06215	0.11297	-0.00064	0.76519	-0.00283	0.37384
34	16:30	-0.03508	0.04869	-0.04500	0.08837	-0.00301	0.00737	-0.00109	0.68297
35	17:00	-0.00607	0.13864	-0.05939	0.00016	-0.00196	0.09293	-0.00126	0.53730
36	17:30	0.00033	0.98338	-0.09793	0.00001	-0.00025	0.03844	-0.00069	0.04399
37	18:00	0.02722	0.00000	-0.10059	0.00373	0.00006	0.73193	0.00028	0.60449
38	18:30	0.00000	0.00000	-0.11845	0.00843	0.00000	0.00000	0.00014	0.82094
39	19:00	0.00000	0.00000	-0.08158	0.00172	0.00000	0.00000	0.00023	0.37011
40	19:30	0.00000	0.00000	-0.07830	0.00220	0.00000	0.00000	0.00015	0.89564
41	20:00	0.00000	0.00000	-0.04874	0.03521	0.00000	0.00000	0.00104	0.21224
42	20:30	0.00000	0.00000	-0.07545	0.00001	0.00000	0.00000	0.00047	0.04719
43	21:00	0.00000	0.00000	-0.06938	0.08456	0.00000	0.00000	0.00011	0.64644
44	21:30	0.00000	0.00000	-0.05231	0.29593	0.00000	0.00000	0.00015	0.47872
45	22:00	0.00000	0.00000	-0.03580	0.55965	0.00000	0.00000	-0.00019	0.59752
46	22:30	0.00000	0.00000	-0.04067	0.13476	0.00000	0.00000	0.00021	0.71832
47	23:00	0.00000	0.00000	-0.02494	0.00362	0.00000	0.00000	-0.00093	0.33549
48	23:30	0.00000	0.00000	-0.03234	0.10758	0.00000	0.00000	-0.00091	0.39678

Table B.23 : **Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for Tasmania.** The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.06030	0.00000	0.00000	0.00000	-0.00017	0.88853
2	0:30	0.00000	0.00000	-0.04340	0.00030	0.00000	0.00000	-0.00021	0.87841
3	1:00	0.00000	0.00000	-0.04626	0.01948	0.00000	0.00000	-0.00004	0.97582
4	1:30	0.00000	0.00000	-0.02649	0.00768	0.00000	0.00000	0.00036	0.83451
5	2:00	0.00000	0.00000	-0.03821	0.00237	0.00000	0.00000	0.00064	0.73389
6	2:30	0.00000	0.00000	-0.05405	0.00000	0.00000	0.00000	0.00031	0.78786
7	3:00	0.00000	0.00000	-0.06672	0.00000	0.00000	0.00000	0.00123	0.35231
8	3:30	0.00000	0.00000	-0.06481	0.00022	0.00000	0.00000	0.00138	0.28673
9	4:00	0.00000	0.00000	-0.04149	0.02834	0.00000	0.00000	0.00125	0.56738
10	4:30	0.00000	0.00000	-0.05239	0.00000	0.00000	0.00000	0.00089	0.53767
11	5:00	0.00000	0.00000	-0.05001	0.00032	0.00000	0.00000	0.00116	0.43660
12	5:30	0.00000	0.00000	-0.05120	0.00194	0.00000	0.00000	0.00069	0.65781
13	6:00	0.01599	0.99632	-0.06173	0.48881	0.00228	0.97926	0.00096	0.59817
14	6:30	-0.12669	0.71276	-0.05999	0.00107	-0.01605	0.49095	0.00062	0.70981
15	7:00	-0.07034	0.62403	-0.06450	0.00082	-0.00304	0.78134	-0.00037	0.75989
16	7:30	-0.44732	0.99086	-0.08811	0.93030	-0.01409	0.99165	-0.00121	0.98237
17	8:00	-0.25750	0.04441	-0.11146	0.00000	-0.00586	0.49593	-0.00118	0.58810
18	8:30	-0.27198	0.00000	-0.09492	0.00000	-0.00153	0.75744	-0.00161	0.10641
19	9:00	-0.16639	0.07922	-0.07239	0.00387	-0.01227	0.36247	-0.00143	0.38960
20	9:30	-0.10510	0.16201	-0.08496	0.00001	0.00005	0.98914	-0.00009	0.88359
21	10:00	-0.24452	0.00000	-0.08214	0.00000	-0.00598	0.42737	-0.00239	0.11236
22	10:30	-0.19427	0.10432	-0.08607	0.00016	-0.00557	0.63054	-0.00086	0.69136
23	11:00	-0.11046	0.39101	-0.05360	0.06270	-0.01001	0.10832	0.00174	0.20739
24	11:30	-0.17344	0.00000	-0.07055	0.00000	-0.01961	0.00069	0.00082	0.61029
25	12:00	-0.13661	0.00206	-0.05786	0.00000	-0.01267	0.07070	0.00297	0.07603
26	12:30	-0.17492	0.00974	-0.07415	0.00393	-0.01310	0.35091	0.00380	0.01581
27	13:00	-0.05969	0.12607	-0.05216	0.00386	-0.01627	0.01774	0.00396	0.00839
28	13:30	-0.12434	0.01551	-0.07788	0.00030	-0.01533	0.02404	0.00227	0.44910
29	14:00	-0.06659	0.19919	-0.07251	0.00002	-0.01659	0.01706	0.00179	0.61345
30	14:30	-0.01651	0.92239	-0.07036	0.00146	-0.01308	0.01740	0.00006	0.96975
31	15:00	-0.05983	0.00104	-0.08152	0.00000	-0.00603	0.01462	-0.00051	0.35603
32	15:30	-0.07361	0.84161	-0.08162	0.12096	-0.00726	0.63073	-0.00106	0.41411
33	16:00	-0.12053	0.00027	-0.08236	0.00000	-0.00433	0.54775	0.00091	0.47769
34	16:30	-0.20548	0.00000	-0.10133	0.00000	-0.01669	0.04008	-0.00143	0.05830
35	17:00	-0.26011	0.00000	-0.12093	0.00000	-0.01360	0.01566	-0.00145	0.01239
36	17:30	-0.16634	0.71504	-0.11758	0.02504	-0.02189	0.05537	-0.00101	0.50847
37	18:00	0.10255	0.41147	-0.09439	0.00252	-0.01708	0.10929	-0.00216	0.20379
38	18:30	-0.23451	0.73753	-0.10077	0.03853	-0.03741	0.03097	-0.00169	0.39519
39	19:00	-0.06940	0.66028	-0.11442	0.00000	-0.02797	0.03565	-0.00195	0.12323
40	19:30	0.00000	0.00000	-0.10510	0.00000	0.00000	0.00000	-0.00221	0.01012
41	20:00	0.00000	0.00000	-0.08930	0.00000	0.00000	0.00000	-0.00082	0.02286
42	20:30	0.00000	0.00000	-0.09255	0.00000	0.00000	0.00000	-0.00551	0.00606
43	21:00	0.00000	0.00000	-0.07386	0.00000	0.00000	0.00000	0.00028	0.84457
44	21:30	0.00000	0.00000	-0.09281	0.00000	0.00000	0.00000	-0.00283	0.05255
45	22:00	0.00000	0.00000	-0.06447	0.01271	0.00000	0.00000	-0.00029	0.80494
46	22:30	0.00000	0.00000	-0.06530	0.00000	0.00000	0.00000	-0.00004	0.97574
47	23:00	0.00000	0.00000	-0.05067	0.00001	0.00000	0.00000	0.00172	0.20000
48	23:30	0.00000	0.00000	-0.05632	0.00001	0.00000	0.00000	-0.00035	0.68067

Appendix C

From 30- to 5MS in the NEM: An early evaluation

C.1 Data and Preliminary Analysis

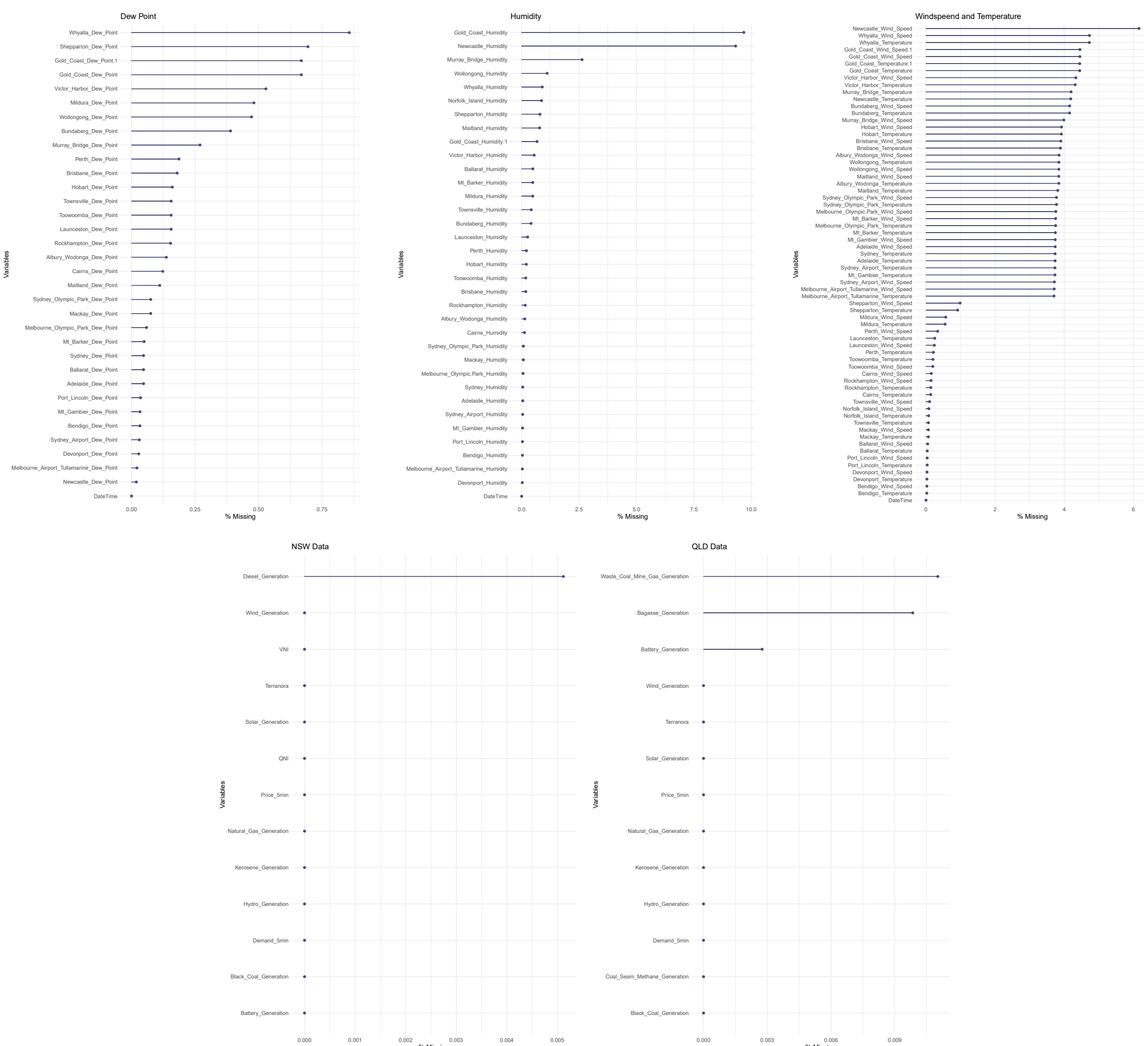

Figure C.1 : **Percentage of missing observations in the predictor variables. We apply Kalman filters to impute the missing values for all variables.** See Moritz and Bartz-Beielstein (2017) for further details about the imputation approach.

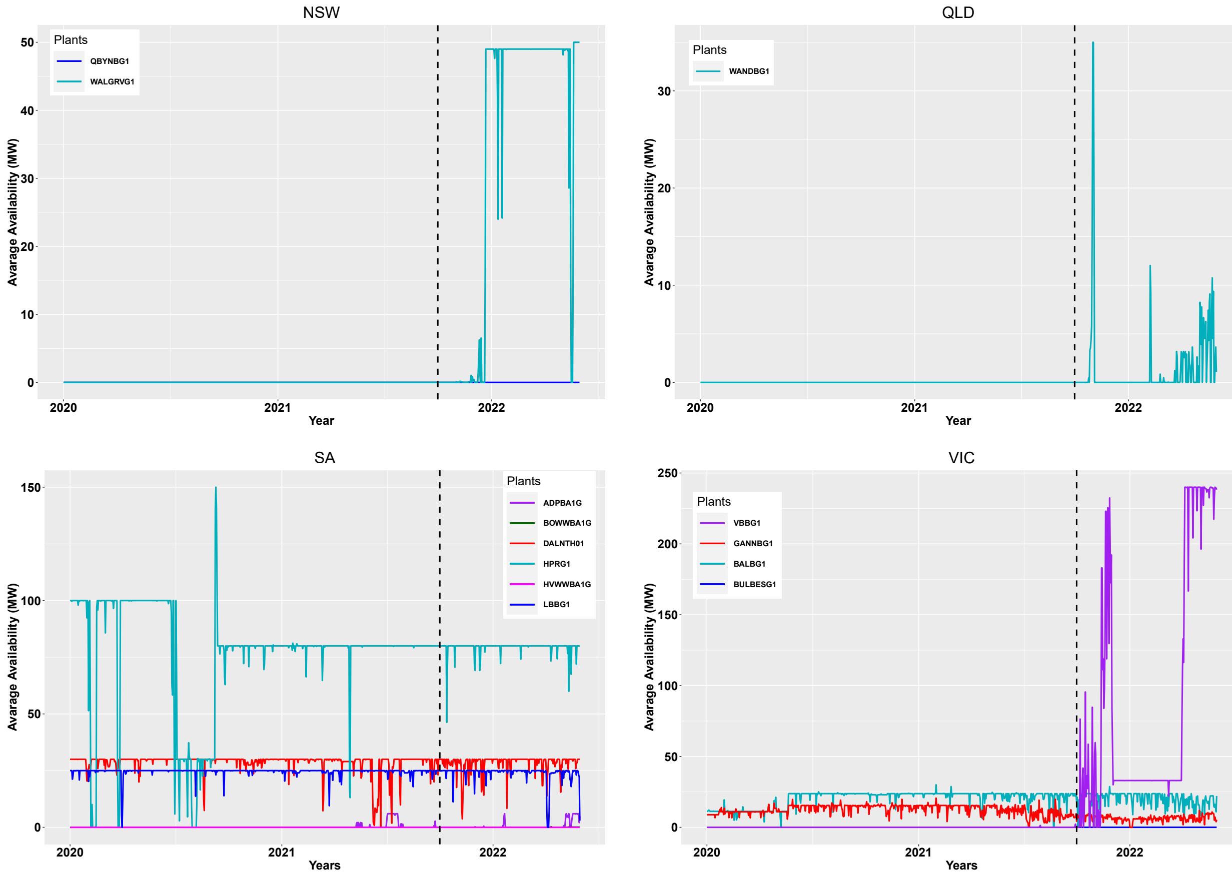

Figure C.2 : **The average available battery generation from 1st January 2020 to 31st May 2022 for NSW, QLD, SA, and VIC.** No utility-scale battery energy storage systems (BESS) are operational in TAS. The 5MS is introduced on 1st October 2021, denoted by the dashed vertical red line.

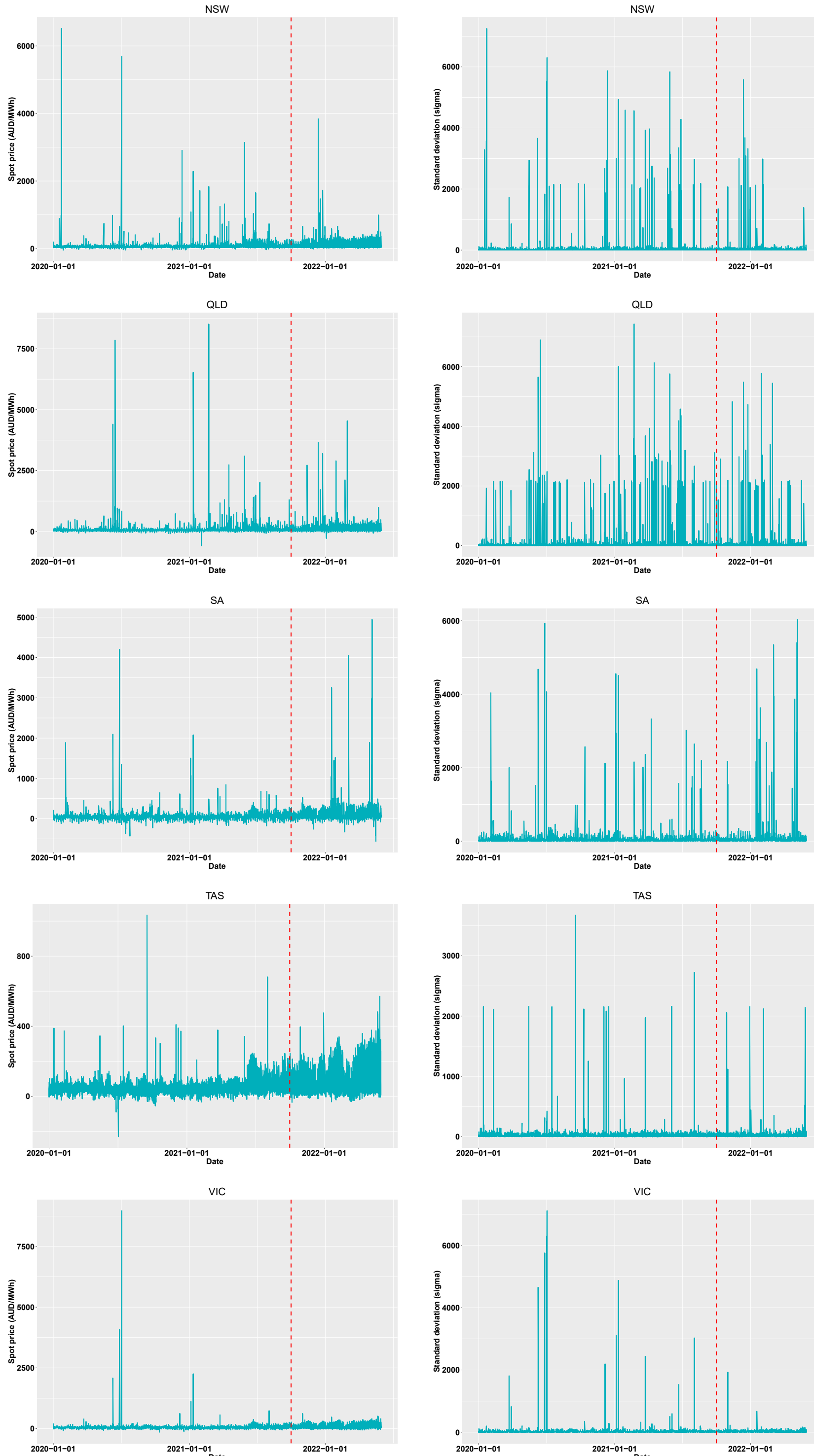

Figure C.3 : **Equally weighted 30-minute electricity spot prices (left panels) and volatility σ (right panels) from 1st January 2020 to 31st May 2022, for NSW, QLD, SA, TAS, and VIC.** The 5MS was introduced on 1st October 2021, denoted by the dashed vertical red line. Prior to 1st October 2021, 30-minute prices equal trading prices and are the average trading price (5-minute prices) from 1st October 2021.

Table C.1 : **Summary statistics for 5-minute electricity prices before and after the new settlement rule was implemented on 1st October 2021.** The first panel depicts a comparison based on one month prior to and after the 5MS. The pre-period window is from 1st to 30th September 2021 and the post-period window is from 1st to 31th October 2021. The comparison in the second panel is based on eight months before and after the 5MS. The pre-period window extends from 1st February to 30th September 2021 and the post-period window runs from 1st October 2021 to 31st May 2022.

		Mean	Std.Dev	Min	Q1	Median	Q3	Max	MAD	IQR	CV	Skewness	SE.Skewness	Kurtosis	Observations
								1 Month Comparison							
NSW	Pre	75.392	256.839	-999.999	38.33	48.52	71.725	15100	19.526	33.382	3.407	45.31	0.019	2360.665	17280
	Post	76.343	282.194	-999.986	37.966	48.5	73.028	14708.512	20.03	35.059	3.696	40.978	0.018	1903.311	17856
	% Change	1.26%	9.87%	0.00%	-0.95%	-0.04%	1.82%	-2.59%	2.58%	5.02%	8.50%	-9.56%	-1.63%	-19.37%	3.33%
QLD	Pre	85.031	494.603	-1000	33.049	44.246	74.12	15100	25.094	41.067	5.817	25.758	0.019	715.318	17280
	Post	100.049	654.863	-1000	33.16	43.989	73.955	15100	24.109	40.786	6.545	20.083	0.018	417.657	17856
	% Change	17.66%	32.40%	0.00%	0.34%	-0.58%	-0.22%	0.00%	-3.93%	-0.69%	12.53%	-22.03%	-1.63%	-41.61%	3.33%
SA	Pre	73.591	483.792	-1000	23.97	45.4	68.368	15100	33.357	44.397	6.574	25.396	0.019	684.281	17280
	Post	71.836	469.565	-1000	22.206	44.273	69	15100	35.054	46.791	6.537	25.019	0.018	673.163	17856
	% Change	-2.38%	-2.94%	0.00%	-7.36%	-2.48%	0.92%	0.00%	5.09%	5.39%	-0.57%	-1.48%	-1.63%	-1.62%	3.33%
TAS	Pre	51.605	172.059	-999.64	24.28	37.966	56.72	15000	24.961	32.44	3.334	75.987	0.019	6591.874	17280
	Post	52.161	176.392	-199.68	25.34	38.63	56.808	15000	24.575	31.468	3.382	69.888	0.018	5674.509	17856
	% Change	1.08%	2.52%	-80.02%	4.37%	1.75%	0.16%	0.00%	-1.55%	-3.00%	1.42%	-8.03%	-1.63%	-13.92%	3.33%
VIC	Pre	63.036	331.355	-125.636	24.75	42.211	65.01	14700	30.816	40.26	5.257	37.707	0.019	1498.296	17280
	Post	63.052	332.501	-1000	22.289	41.648	64.991	15100	31.582	42.692	5.273	36.959	0.018	1473.805	17856
	% Change	0.03%	0.35%	695.95%	-9.94%	-1.33%	-0.03%	2.72%	2.49%	6.04%	0.32%	-1.98%	-1.63%	-1.63%	3.33%
								8 Months Comparison							
NSW	Pre	81.17	381.80	-999.99	38.11	48.50	71.97	15100.00	19.97	33.86	4.70	35.36	0.01	1318.41	61056
	Post	80.69	387.69	-999.99	38.18	48.50	72.20	15100.00	19.82	34.03	4.80	34.61	0.01	1252.98	69984
	% Change	-0.58%	1.54%	0.00%	0.18%	0.00%	0.32%	0.00%	-0.77%	0.48%	2.14%	-2.13%	-6.60%	-4.96%	
QLD	Pre	84.66	476.66	-1000.00	32.30	43.73	72.73	15100.00	25.40	40.43	5.63	26.70	0.01	763.68	61056
	Post	88.25	543.01	-1000.00	32.85	44.70	73.07	15100.00	25.03	40.22	6.15	24.98	0.01	648.49	69984
	% Change	4.23%	13.92%	0.00%	1.69%	2.22%	0.47%	0.00%	-1.45%	-0.52%	9.29%	-6.46%	-6.60%	-15.08%	
SA	Pre	66.45	382.63	-1000.00	22.48	44.19	68.94	15100.00	34.93	46.46	5.76	31.20	0.01	1076.44	61056
	Post	59.02	301.47	-1000.00	20.92	42.68	68.00	15100.00	34.71	47.08	5.11	37.61	0.01	1613.44	69984
	% Change	-11.18%	-21.21%	0.00%	-6.92%	-3.42%	-1.36%	0.00%	-0.62%	1.33%	-11.30%	20.54%	-6.60%	49.89%	
TAS	Pre	52.06	134.87	-999.64	24.75	39.06	57.19	15100.00	24.20	32.44	2.59	79.81	0.01	8182.86	61056
	Post	50.96	126.97	-199.68	25.08	38.63	56.70	15100.00	24.45	31.62	2.49	91.85	0.01	10640.99	69984
	% Change	-2.11%	-5.85%	-80.02%	1.32%	-1.10%	-0.86%	0.00%	1.04%	-2.51%	-3.83%	15.09%	-6.60%	30.04%	
VIC	Pre	58.33	210.23	-1000.00	22.02	41.48	65.67	15000.00	31.82	43.65	3.60	59.20	0.01	4052.38	61056
	Post	56.95	197.23	-1000.00	22.11	41.16	64.66	15100.00	31.12	42.54	3.46	60.15	0.01	4165.91	69984
	% Change	-2.37%	-6.19%	0.00%	0.43%	-0.77%	-1.55%	0.67%	-2.19%	-2.56%	-3.91%	1.61%	-6.60%	2.80%	

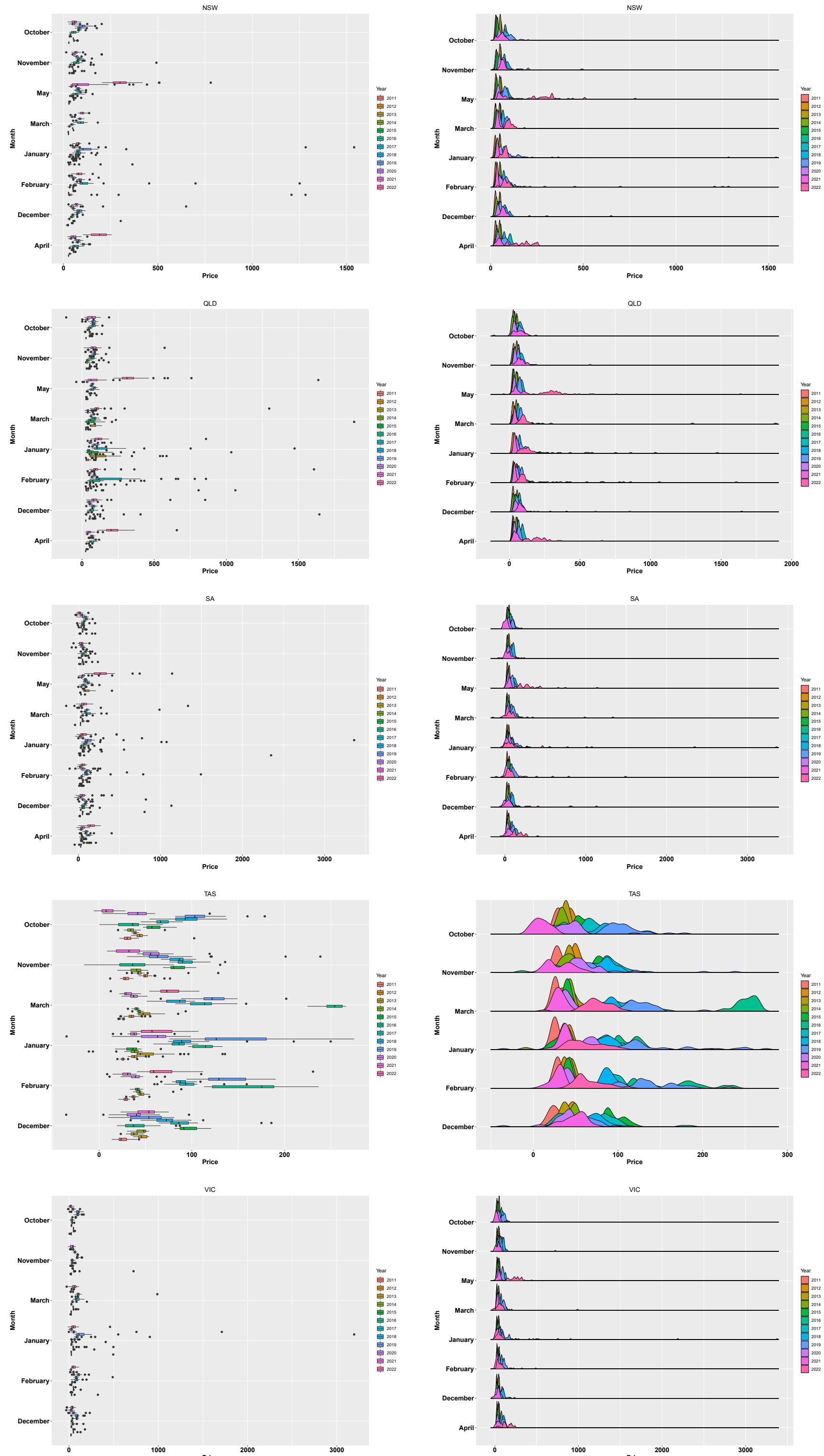

Figure C.4 : **Monthly distribution for post-period daily electricity spot prices from 2011 to 2022 for NSW, QLD, SA, TAS, and VIC.** The left panels show grouped boxplots, and the right panels show density plots.

C.2 Implementation of the Bayesian Structural Time-series Model

C.2.1 Pre-screened controls and one month post-period model predictions

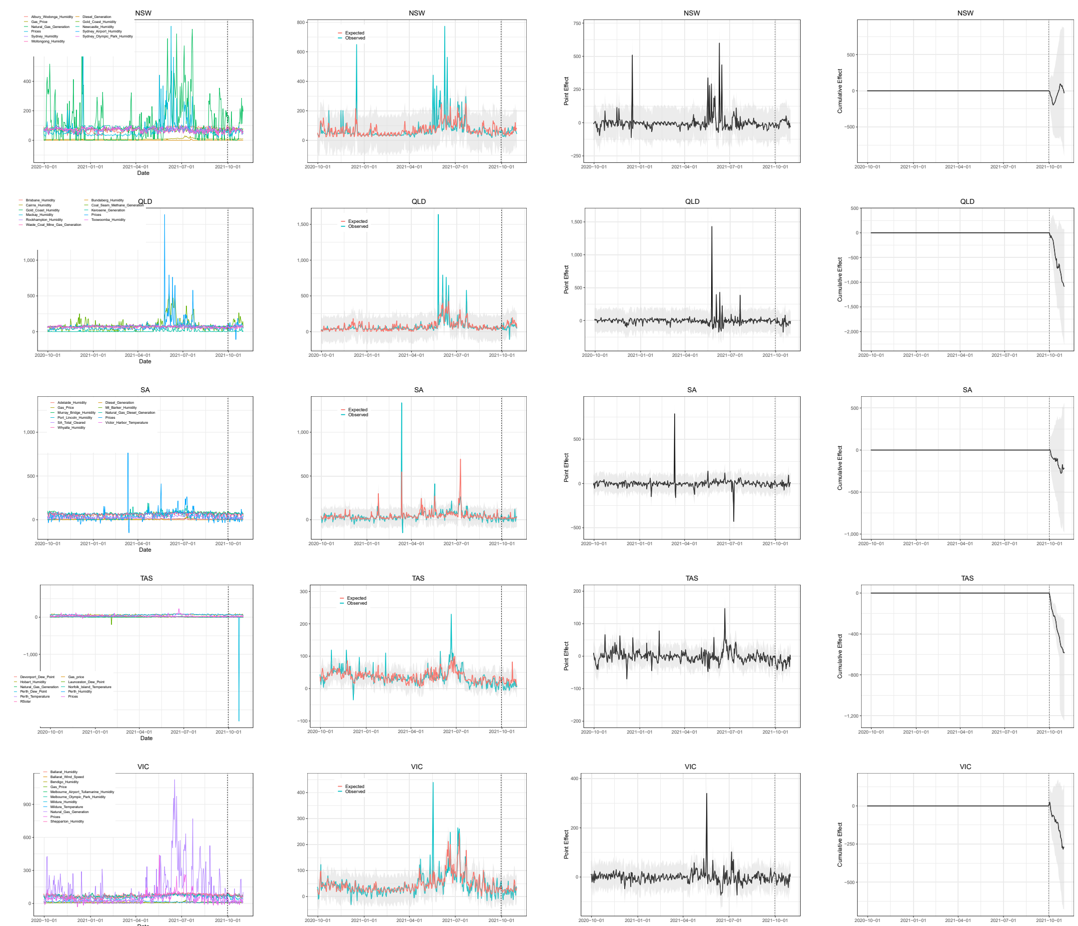

Figure C.5 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dotted vertical line) in equally daily weighted average spot price with 95% confidence intervals using pre-screened time series.** The best control time series candidates are chosen based on correlation and similarity via dynamic time warping with an emphasis of 0.5 (equal weighting). The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations). The first panels in each state show the actual equally daily weighted average spot price and the pre-screened control time series. The second panel shows the actual equally daily weighted averaged and expected spot Price. The third panels depict a pointwise causal effect. The fourth panels depict the cumulative effect.

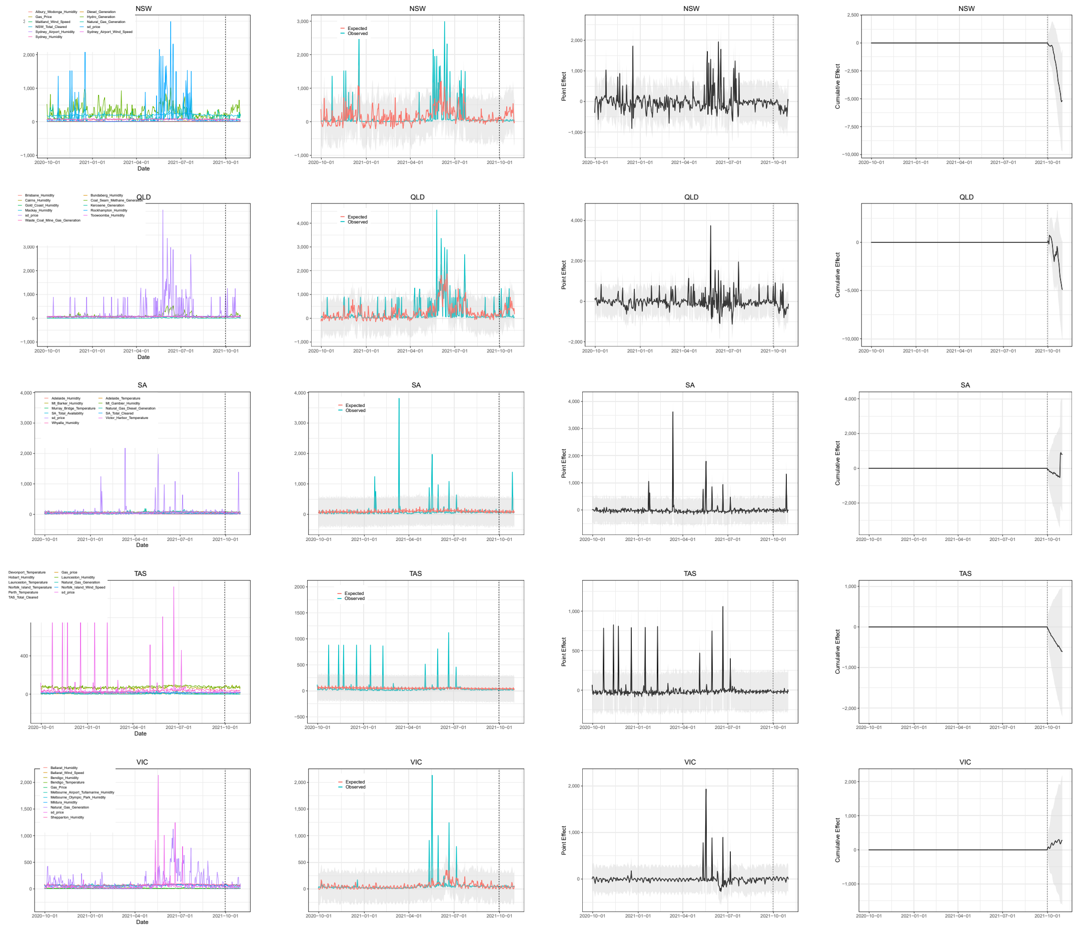

Figure C.6 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dotted vertical line) in equally daily weighted average spot price volatility with 95% confidence intervals using pre-screened time series.** The best control time series candidates are chosen based on correlation and similarity via dynamic time warping with an emphasis of 0.5 (equal weighting). The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations). The first panels in each state show the actual equally daily weighted average spot price and the pre-screened control time series. The second panel shows the actual equally daily weighted averaged and expected spot Price. The third panels depict a pointwise causal effect. The fourth panels depict the cumulative effect.

C.2.2 Pre-period's mean absolute percentage errors (MAPE)

Table C.2 : **The matching (pre) period's mean absolute percentage errors (MAPE).** The subscripts p and v denote spot price and volatility, respectively. The observation period runs from 30$^{\text{th}}$ September 2020 to 30$^{\text{th}}$ September 2021 (a total of 366 daily observations). The matching (pre) period MAPE measures the historical accuracy of the Bayesian structural time series model in predicting the observed metric during the training period, calculated as the average absolute percent error for each time period minus actual values divided by actual values. Mathematically, it is given by $MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$, where, n is the number of fitted points, A_t is the actual value, and F_t is the forecast value.

NSW			QLD			SA			TAS			VIC		
Predictors	$MAPE_p$	$MAPE_v$	Predictors	$MAPE_p$	$MAPE_v$	Predictors	$MAPE_p$	$MAPE_v$	Predictors	$MAPE_p$	$MAPE_v$	Predictors	$MAPE_p$	$MAPE_v$
10	37.98	804.81	10	44.74	379.46	10	152.66	127.91	10	51.44	191.78	10	53.83	101.92
20	49.60	781.61	20	45.23	381.04	20	152.72	128.86	20	52.50	193.38	20	38.32	101.82
30	49.74	800.06	30	45.46	381.35	30	153.41	128.55	29	48.42	194.00	30	38.05	101.73
40	50.16	802.31	40	45.50	379.16	40	109.82	128.36				39	31.82	101.79
48	45.06	720.26	50	45.38	377.94	41	110.14	128.52						

C.2.3 Using alternative distribution assumption

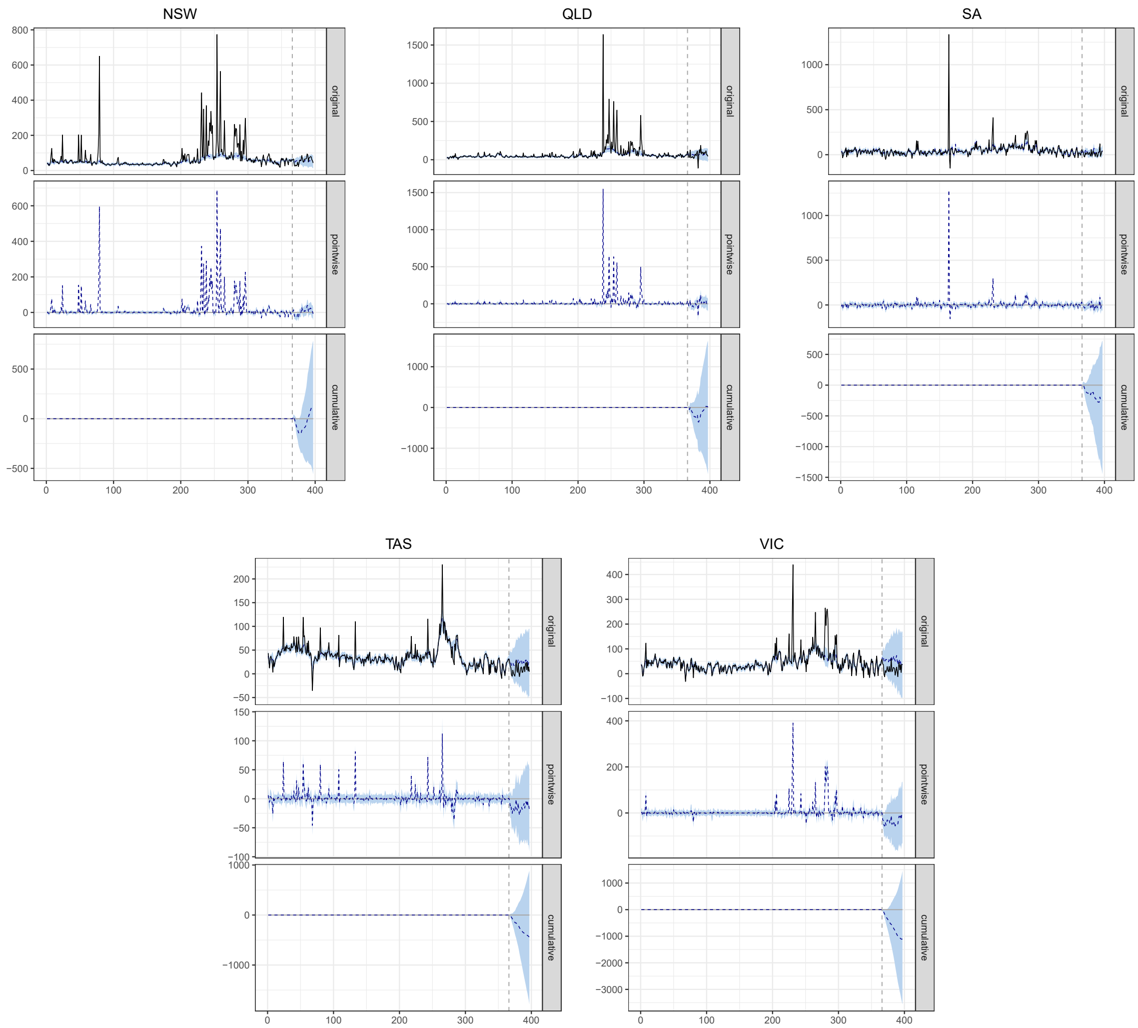

Figure C.7 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dotted vertical line) in equally daily weighted averaged spot electricity prices with 95% confidence intervals using t-distributed noise.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations). The first panel shows the actual equally daily weighted average and expected spot electricity prices. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

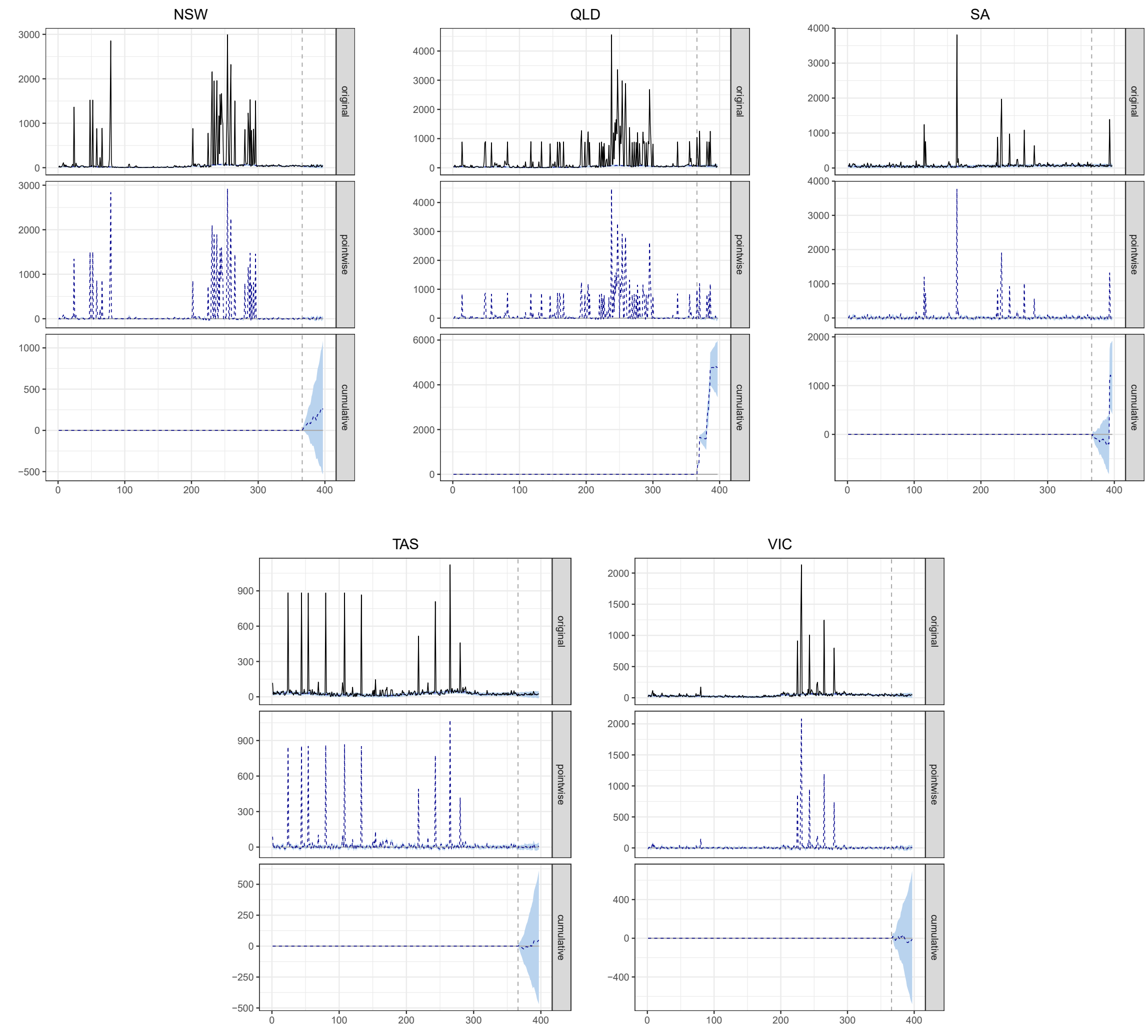

Figure C.8 : **The causal impact of introducing a five-minute settlement rule on 1$^{\text{st}}$ October 2021 (dotted vertical line) in equally daily weighted averaged spot electricity price volatility with 95% confidence intervals using t-distributed noise.** The observation period runs from 30$^{\text{th}}$ September 2020 to 30$^{\text{th}}$ September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1$^{\text{st}}$ to 31$^{\text{st}}$ October 2021 (a total of 31 daily observations). The first panel shows the actual equally daily weighted average and expected spot electricity prices. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

C.2.4 Posterior coefficients and inclusion probabilities

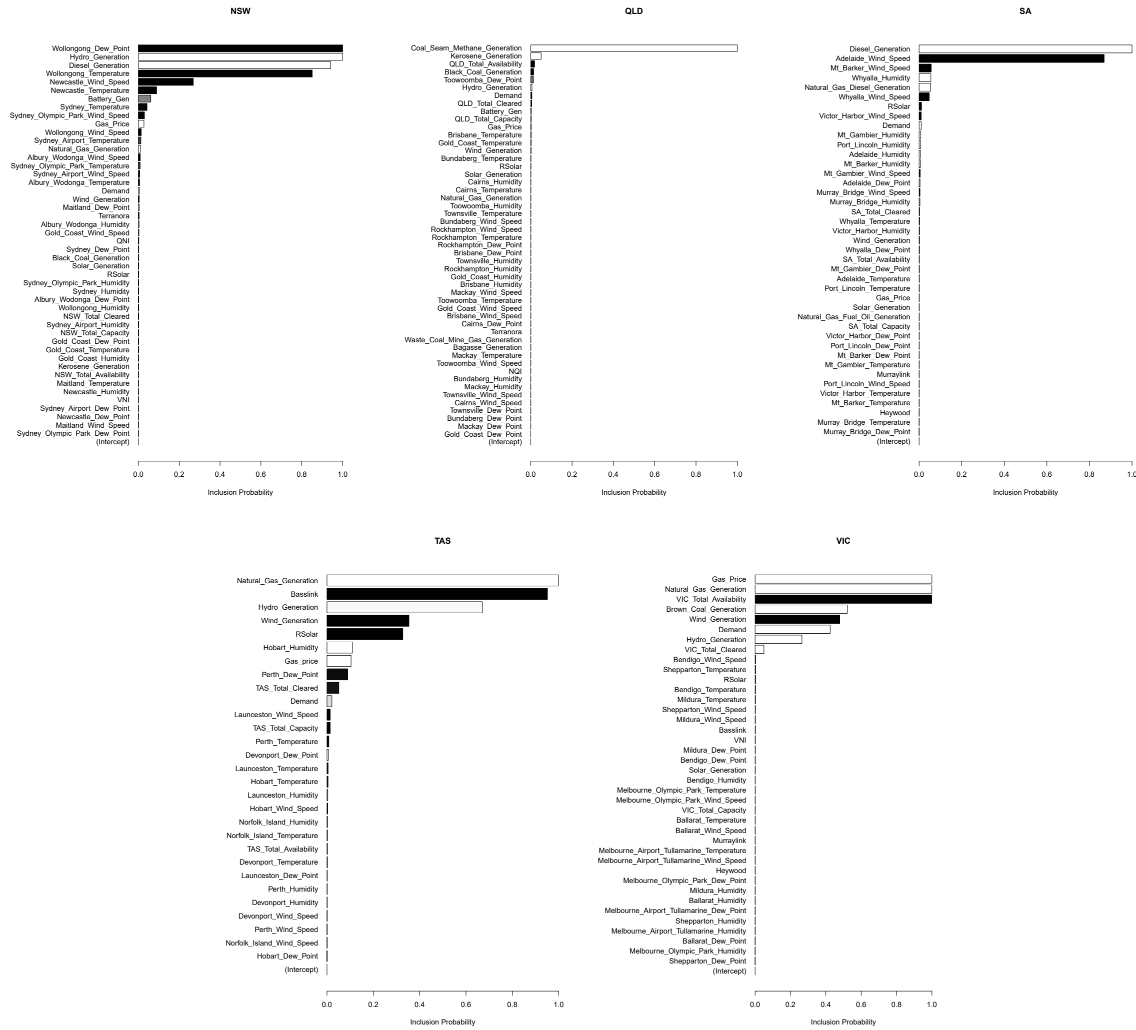

Figure C.9 : **Posterior inclusion probabilities for the most likely predictors of the daily spot price.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.3 : **Average posterior coefficients β used in the linear regression component of the structural time series model for the electricity spot price.**

NSW

Control	Average β
Market	AverageBeta
Albury Wodonga Dew Point	0.0745
Albury Wodonga Humidity	0.1130
Albury Wodonga Temperature	-0.2293
Albury Wodonga Wind Speed	-0.0981
Black Coal Generation	0.0686
Demand	0.1173
Diesel Generation	0.1755
Gas Price	0.1236
Gold Coast Dew Point	-0.0043
Gold Coast Humidity	0.0482
Gold Coast Temperature	-0.0616
Gold Coast Wind Speed	0.0772
Hydro Generation	0.4607
Kerosene Generation	-0.0004
Maitland Dew Point	0.0839
Maitland Temperature	0.0045
Maitland Wind Speed	0.0385
Natural Gas Generation	0.1231
Newcastle Dew Point	0.0285
Newcastle Humidity	0.1073
Newcastle Temperature	-0.3194
Newcastle Wind Speed	-0.1340
NSW Total Availability	-0.0051
NSW Total Capacity	-0.0472
NSW Total Cleared	0.0406
QNI	-0.0778
Solar Generation	-0.0640
Sydney Airport Dew Point	0.0517
Sydney Airport Humidity	0.0563
Sydney Airport Temperature	-0.1191
Sydney Airport Wind Speed	-0.1010
Sydney Dew Point	0.1322
Sydney Humidity	0.0708
Sydney Olympic Park Dew Point	0.0000
Sydney Olympic Park Humidity	0.0384
Sydney Olympic Park Temperature	-0.2026
Sydney Olympic Park Wind Speed	-0.1125
Sydney Temperature	-0.2951
Terrunsora	-0.0752
Wind Generation	-0.0958
Wollongong Dew Point	-0.2556
Wollongong Humidity	0.0620
Wollongong Temperature	-0.3219
Wollongong Wind Speed	-0.1019

QLD

Control	Average β
Market	AverageBeta
Bagasse Generation	-0.0647
Black Coal Generation	-0.1405
Brisbane Dew Point	-0.0666
Brisbane Humidity	-0.0058
Brisbane Temperature	-0.1274
Brisbane Wind Speed	0.0025
Bundaberg Dew Point	0.0268
Bundaberg Humidity	-0.0214
Bundaberg Temperature	-0.0528
Bundaberg Wind Speed	0.0409
Cairns Dew Point	-0.0474
Cairns Humidity	-0.0422
Cairns Temperature	-0.0401
Cairns Wind Speed	0.0286
Coal Seam Methane Generation	0.5733
Demand	-0.1242
Gas Price	-0.0533
Gold Coast Dew Point	0.0044
Gold Coast Humidity	0.0154
Gold Coast Temperature	-0.0881
Gold Coast Wind Speed	-0.0109
Hydro Generation	0.1132
Kerosene Generation	0.1624
Mackay Dew Point	-0.0423
Mackay Humidity	0.0000
Mackay Temperature	-0.0558
Mackay Wind Speed	-0.0068
Natural Gas Generation	-0.1011
NQI	-0.0185
QLD Total Availability	-0.1591
QLD Total Capacity	0.0422
QLD Total Cleared	-0.1011
Rockhampton Dew Point	-0.0508
Rockhampton Humidity	0.0077
Rockhampton Temperature	-0.0213
Rockhampton Wind Speed	0.0422
Solar Generation	-0.0413
Terrunsora	-0.0294
Toowoomba Dew Point	-0.0102
Toowoomba Humidity	0.0731
Toowoomba Temperature	0.0425
Toowoomba Wind Speed	0.0257
Townsville Dew Point	0.0218
Townsville Humidity	-0.0567
Townsville Temperature	0.0028
Townsville Wind Speed	0.0522
Waste Coal Mine Gas Generation	0.0007
Wind Generation	0.0535

SA

Control	Average β
Market	AverageBeta
Adelaide Dew Point	0.0787
Adelaide Humidity	0.0965
Adelaide Temperature	-0.0409
Adelaide Wind Speed	-0.2043
Demand	0.1045
Diesel Generation	0.6607
Gas Price	-0.0057
Heywood	0.0458
Mt Barker Dew Point	-0.0389
Mt Barker Humidity	0.1080
Mt Barker Temperature	-0.0178
Mt Barker Wind Speed	-0.1826
Mt Gambier Dew Point	0.0447
Mt Gambier Humidity	0.0884
Mt Gambier Temperature	-0.0174
Mt Gambier Wind Speed	-0.1333
Murray Bridge Dew Point	-0.0227
Murray Bridge Humidity	0.0742
Murray Bridge Temperature	-0.0343
Murray Bridge Wind Speed	-0.1383
Murraylink	-0.0442
Natural Gas Diesel Generation	0.1485
Natural Gas Fuel Oil Generation	0.0290
Port Lincoln Dew Point	0.0498
Port Lincoln Humidity	0.0863
Port Lincoln Temperature	-0.0142
Port Lincoln Wind Speed	0.0039
SA Total Availability	0.0274
SA Total Capacity	0.0124
SA Total Cleared	0.0895
Solar Generation	-0.0453
Victor Harbor Dew Point	0.0318
Victor Harbor Humidity	0.0526
Victor Harbor Temperature	-0.0650
Victor Harbor Wind Speed	-0.0985
Whyalla Dew Point	0.0576
Whyalla Humidity	0.1244
Whyalla Temperature	-0.0824
Whyalla Wind Speed	-0.1791
Wind Generation	-0.0842

TAS

Control	Average β
Market	AverageBeta
Basslink	-0.9639
Demand	1.3089
Devonport Dew Point	0.0832
Devonport Humidity	0.0698
Devonport Temperature	-0.0711
Devonport Wind Speed	-0.0439
Gas price	0.1563
Hobart Dew Point	0.0324
Hobart Humidity	0.1612
Hobart Temperature	-0.0546
Hobart Wind Speed	-0.1134
Hydro Generation	1.0303
Launceston Dew Point	0.0534
Launceston Humidity	0.1152
Launceston Temperature	-0.1418
Launceston Wind Speed	-0.0972
Natural Gas Generation	0.3841
Norfolk Island Humidity	0.0743
Norfolk Island Temperature	-0.0469
Norfolk Island Wind Speed	-0.0475
Perth Dew Point	-0.0770
Perth Humidity	0.1235
Perth Temperature	-0.1516
Perth Wind Speed	-0.0093
TAS Total Availability	-0.0674
TAS Total Capacity	-0.1359
TAS Total Cleared	-2.6999
Wind Generation	-0.3250

VIC

Control	Average β
Market	AverageBeta
Ballarat Dew Point	0.0138
Ballarat Humidity	0.0295
Ballarat Temperature	0.0019
Ballarat Wind Speed	0.0195
Basslink	0.0526
Bendigo Dew Point	0.0170
Bendigo Humidity	0.0242
Bendigo Temperature	0.0623
Bendigo Wind Speed	0.0652
Brown Coal Generation	0.2229
Demand	0.2381
Gas Price	0.3871
Heywood	0.0417
Hydro Generation	0.1521
Melbourne Airport Tullamarine Dew Point	0.0008
Melbourne Airport Tullamarine Humidity	-0.0113
Melbourne Airport Tullamarine Temperature	0.0342
Melbourne Airport Tullamarine Wind Speed	0.0144
Melbourne Olympic Park Dew Point	0.0124
Melbourne Olympic Park Humidity	0.0163
Melbourne Olympic Park Temperature	0.0148
Melbourne Olympic Park Wind Speed	0.0120
Mildura Dew Point	0.0111
Mildura Humidity	0.0450
Mildura Temperature	0.0618
Mildura Wind Speed	0.0343
Murraylink	-0.0134
Natural Gas Generation	0.3059
Shepparton Dew Point	-0.0182
Shepparton Humidity	0.0011
Shepparton Temperature	0.0821
Shepparton Wind Speed	0.0405
Solar Generation	-0.0265
VIC Total Availability	-0.3424
VIC Total Capacity	0.0340
VIC Total Cleared	0.2322
VNI	-0.0412
Wind Generation	-0.2164

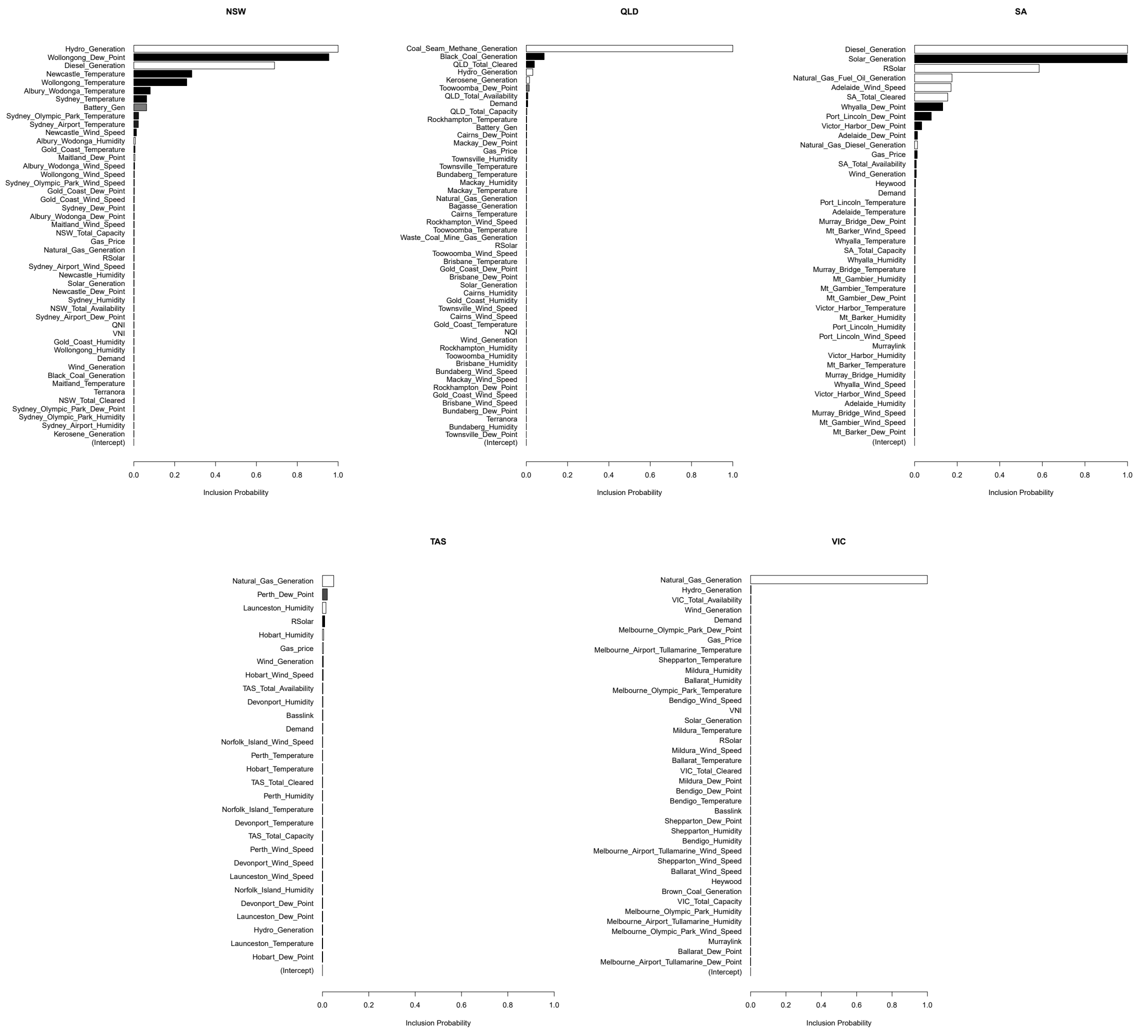

Figure C.10 : **Posterior inclusion probabilities for the most likely predictors of the daily spot price volatility.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.4 : **Average posterior coefficients β used in the linear regression component of the structural time series model for the electricity spot price volatility.**

NSW		QLD		SA		TAS		VIC	
Control	Average β	Control	Average β	Control	Average β	Control	Average β	Control	Average β
Market	AverageBeta	Market	AverageBeta	Market	AverageBeta	Market	AverageBeta	Market	AverageBeta
Albury Wodonga Dew Point	-0.0619	Bagasse Generation	-0.0602	Adelaide Dew Point	-0.0308	Basslink	-0.1068	Ballarat Dew Point	0.0315
Albury Wodonga Humidity	0.1316	Black Coal Generation	-0.1702	Adelaide Humidity	0.0000	Demand	0.0949	Ballarat Humidity	-0.0075
Albury Wodonga Temperature	-0.1973	Brisbane Dew Point	-0.0235	Adelaide Temperature	-0.0890	Devonport Dew Point	-0.0178	Ballarat Temperature	0.0193
Albury Wodonga Wind Speed	-0.1046	Brisbane Humidity	-0.0354	Adelaide Wind Speed	0.0510	Devonport Humidity	0.0444	Ballarat Wind Speed	0.0216
Black Coal Generation	0.0357	Brisbane Temperature	-0.0990	Demand	0.0716	Devonport Temperature	0.0132	Basslink	0.0845
Demand	-0.0176	Brisbane Wind Speed	-0.0565	Diesel Generation	0.6232	Devonport Wind Speed	-0.0612	Bendigo Dew Point	-0.0765
Diesel Generation	0.1798	Bundaberg Dew Point	0.0067	Gas Price	-0.2502	Gas price	0.0909	Bendigo Humidity	0.0286
Gas Price	0.0293	Bundaberg Humidity	-0.0460	Heywood	-0.0240	Hobart Dew Point	0.0076	Bendigo Temperature	0.0950
Gold Coast Dew Point	-0.0766	Bundaberg Temperature	-0.0520	Mt Barker Dew Point	-0.0210	Hobart Humidity	0.1042	Bendigo Wind Speed	-0.0008
Gold Coast Humidity	-0.0224	Bundaberg Wind Speed	0.0056	Mt Barker Humidity	0.0196	Hobart Temperature	-0.0726	Brown Coal Generation	-0.0016
Gold Coast Temperature	-0.1594	Cairns Dew Point	-0.1190	Mt Barker Temperature	-0.0373	Hobart Wind Speed	-0.0830	Demand	0.0154
Gold Coast Wind Speed	0.0912	Cairns Humidity	-0.0379	Mt Barker Wind Speed	0.0327	Hydro Generation	-0.0109	Gas Price	-0.0375
Hydro Generation	0.4532	Cairns Temperature	0.0597	Mt Gambier Dew Point	0.0197	Launceston Dew Point	-0.0154	Heywood	0.0119
Kerosene Generation	0.0031	Cairns Wind Speed	-0.0412	Mt Gambier Humidity	0.0867	Launceston Humidity	0.1381	Hydro Generation	0.1158
Maitland Dew Point	0.0989	Coal Seam Methane Generation	0.6174	Mt Gambier Temperature	-0.0210	Launceston Temperature	-0.0104	Melbourne Airport Tullamarine Dew Point	0.0394
Maitland Temperature	-0.0175	Demand	-0.1206	Mt Gambier Wind Speed	0.0229	Launceston Wind Speed	-0.0114	Melbourne Airport Tullamarine Humidity	0.0007
Maitland Wind Speed	0.0570	Gas Price	-0.0518	Murray Bridge Dew Point	0.0222	Natural Gas Generation	0.1414	Melbourne Airport Tullamarine Temperature	-0.0910
Natural Gas Generation	0.0163	Gold Coast Dew Point	-0.0234	Murray Bridge Humidity	0.0042	Norfolk Island Humidity	-0.0204	Melbourne Airport Tullamarine Wind Speed	-0.0109
Newcastle Dew Point	0.0273	Gold Coast Humidity	-0.0436	Murray Bridge Temperature	-0.0675	Norfolk Island Temperature	-0.0115	Melbourne Olympic Park Dew Point	-0.0762
Newcastle Humidity	0.0549	Gold Coast Temperature	-0.0534	Murray Bridge Wind Speed	0.0464	Norfolk Island Wind Speed	0.0430	Melbourne Olympic Park Humidity	-0.0844
Newcastle Temperature	-0.2273	Gold Coast Wind Speed	-0.0149	Murraylink	-0.0427	Perth Dew Point	-0.0264	Melbourne Olympic Park Temperature	-0.0872
Newcastle Wind Speed	-0.1062	Hydro Generation	0.1342	Natural Gas Diesel Generation	-0.0346	Perth Humidity	0.0487	Melbourne Olympic Park Wind Speed	0.0282
NSW Total Availability	-0.0606	Kerosene Generation	0.1416	Natural Gas Fuel Oil Generation	-0.0757	Perth Temperature	-0.1016	Mildura Dew Point	-0.0572
NSW Total Capacity	-0.0784	Mackay Dew Point	-0.0776	Port Lincoln Dew Point	-0.1135	Perth Wind Speed	-0.0306	Mildura Humidity	-0.0104
NSW Total Cleared	-0.0363	Mackay Humidity	-0.0529	Port Lincoln Humidity	0.0159	TAS Total Availability	-0.0982	Mildura Temperature	0.0312
QNI	0.0042	Mackay Temperature	0.0653	Port Lincoln Temperature	-0.0693	TAS Total Capacity	-0.0859	Mildura Wind Speed	0.0536
Solar Generation	-0.0489	Mackay Wind Speed	-0.0042	Port Lincoln Wind Speed	0.0326	TAS Total Cleared	-0.0298	Murraylink	-0.0322
Sydney Airport Dew Point	0.0516	Natural Gas Generation	-0.0423	SA Total Availability	0.0561	Wind Generation	-0.1008	Natural Gas Generation	0.3093
Sydney Airport Humidity	0.1428	NQI	0.0180	SA Total Capacity	-0.0577			Shepparton Dew Point	-0.0177
Sydney Airport Temperature	-0.0980	QLD Total Availability	-0.1409	SA Total Cleared	0.0820			Shepparton Humidity	-0.0219
Sydney Airport Wind Speed	-0.0525	QLD Total Capacity	0.0793	Solar Generation	-0.0845			Shepparton Temperature	0.0597
Sydney Dew Point	0.0218	QLD Total Cleared	-0.1453	Victor Harbor Dew Point	-0.0488			Shepparton Wind Speed	0.0257
Sydney Humidity	0.0619	Rockhampton Dew Point	-0.0215	Victor Harbor Humidity	0.0145			Solar Generation	0.0420
Sydney Olympic Park Dew Point	0.0391	Rockhampton Humidity	0.0080	Victor Harbor Temperature	-0.0430			VIC Total Availability	-0.1060
Sydney Olympic Park Humidity	0.0535	Rockhampton Temperature	0.1142	Victor Harbor Wind Speed	0.0238			VIC Total Capacity	0.0669
Sydney Olympic Park Temperature	-0.1314	Rockhampton Wind Speed	0.0805	Whyalla Dew Point	-0.0917			VIC Total Cleared	-0.0173
Sydney Olympic Park Wind Speed	-0.0949	Solar Generation	-0.0450	Whyalla Humidity	0.0022			VNI	-0.0074
Sydney Temperature	-0.2153	Terrunsora	-0.0012	Whyalla Temperature	-0.0958			Wind Generation	-0.0536
Terrunsora	0.0070	Toowoomba Dew Point	-0.0172	Whyalla Wind Speed	0.0134				
Wind Generation	-0.0678	Toowoomba Humidity	-0.0051	Wind Generation	0.0834				
Wollongong Dew Point	-0.2124	Toowoomba Temperature	0.0098						
Wollongong Humidity	0.0329	Toowoomba Wind Speed	0.0052						
Wollongong Temperature	-0.2090	Townsville Dew Point	-0.0536						
Wollongong Wind Speed	-0.0780	Townsville Humidity	-0.0687						
		Townsville Temperature	0.0708						
		Townsville Wind Speed	0.0214						
		Waste Coal Mine Gas Generation	0.0000						
		Wind Generation	-0.0206						

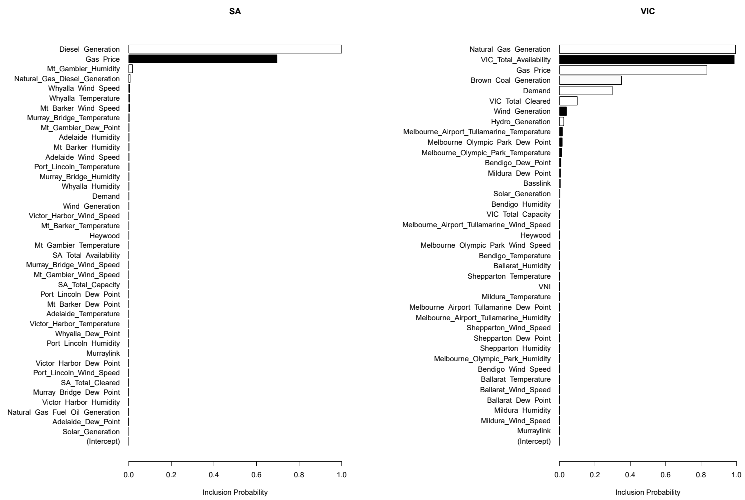

Figure C.11 : **Posterior inclusion probabilities for the most likely predictors of weighted dispatch price for battery generators.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.5 : **Average posterior coefficients β used in the linear regression component of the structural time series model for battery generators' dispatch-weighted prices.**

SA		VIC	
Control	Average β	Control	Average β
Market	AverageBeta	Market	AverageBeta
Adelaide Dew Point	-0.0178	Ballarat Dew Point	0.0127
Adelaide Humidity	0.0850	Ballarat Humidity	0.0484
Adelaide Temperature	-0.0732	Ballarat Temperature	0.0224
Adelaide Wind Speed	-0.0827	Ballarat Wind Speed	0.0590
Demand	0.0919	Basslink	0.1122
Diesel Generation	0.6669	Bendigo Dew Point	-0.1116
Gas Price	-0.2034	Bendigo Humidity	0.1659
Heywood	0.0659	Bendigo Temperature	0.0748
Mt Barker Dew Point	-0.0355	Bendigo Wind Speed	0.0513
Mt Barker Humidity	0.0692	Brown Coal Generation	0.1636
Mt Barker Temperature	-0.0464	Demand	0.2867
Mt Barker Wind Speed	-0.0847	Gas Price	0.2365
Mt Gambier Dew Point	0.0732	Heywood	0.0526
Mt Gambier Humidity	0.1194	Hydro Generation	0.1530
Mt Gambier Temperature	0.0009	Melbourne Airport Tullamarine Dew Point	-0.0001
Mt Gambier Wind Speed	-0.0485	Melbourne Airport Tullamarine Humidity	-0.0048
Murray Bridge Dew Point	-0.0062	Melbourne Airport Tullamarine Temperature	-0.1772
Murray Bridge Humidity	0.0707	Melbourne Airport Tullamarine Wind Speed	-0.0479
Murray Bridge Temperature	-0.0954	Melbourne Olympic Park Dew Point	-0.1447
Murray Bridge Wind Speed	-0.0522	Melbourne Olympic Park Humidity	0.0077
Murraylink	0.0322	Melbourne Olympic Park Temperature	-0.1657
Natural Gas Diesel Generation	0.1073	Melbourne Olympic Park Wind Speed	-0.0421
Natural Gas Fuel Oil Generation	-0.0262	Mildura Dew Point	-0.1376
Port Lincoln Dew Point	-0.0359	Mildura Humidity	0.2199
Port Lincoln Humidity	0.0579	Mildura Temperature	0.0400
Port Lincoln Temperature	-0.0801	Mildura Wind Speed	0.0327
Port Lincoln Wind Speed	0.0222	Murraylink	-0.0032
SA Total Availability	-0.0351	Natural Gas Generation	0.3425
SA Total Capacity	-0.0244	RSolar	-0.0231
SA Total Cleared	-0.0084	Shepparton Dew Point	-0.0218
Solar Generation	-0.0067	Shepparton Humidity	-0.0071
Victor Harbor Dew Point	-0.0158	Shepparton Temperature	0.0233
Victor Harbor Humidity	0.0480	Shepparton Wind Speed	-0.0093
Victor Harbor Temperature	0.0010	Solar Generation	0.0669
Victor Harbor Wind Speed	-0.0771	VIC Total Availability	-0.3340
Whyalla Dew Point	-0.0577	VIC Total Capacity	0.1145
Whyalla Humidity	0.0594	VIC Total Cleared	0.2401
Whyalla Temperature	-0.1234	VNI	0.0324
Whyalla Wind Speed	-0.0869	Wind Generation	-0.2450
Wind Generation	-0.0352		

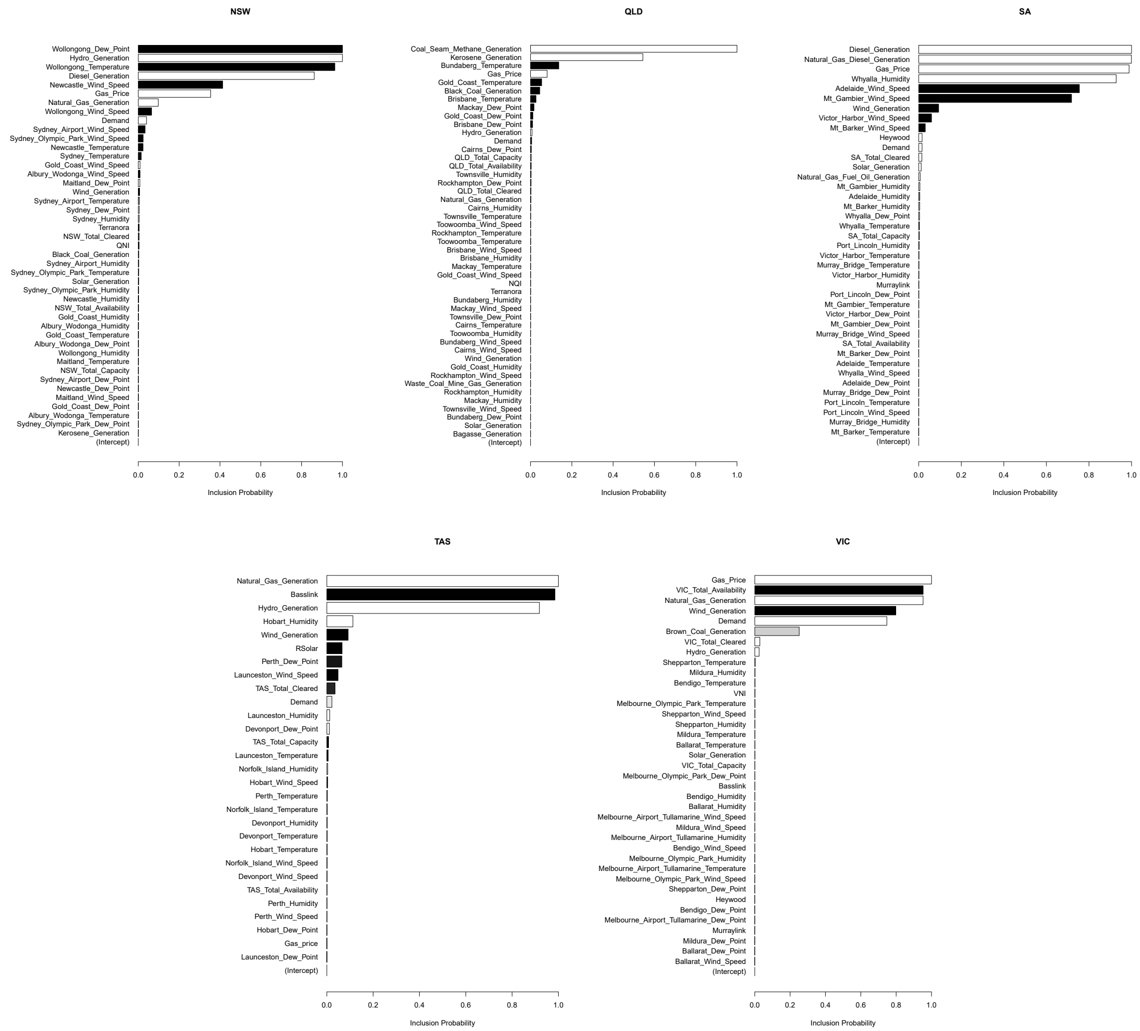

Figure C.12 : **Posterior inclusion probabilities for the most likely predictors of weighted dispatch price for wind generators.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.6 : **Average posterior coefficients β used in the linear regression component of the structural time series model for wind generators' dispatch-weighted prices.**

NSW		QLD		SA		TAS		VIC	
Control	Average β	Control	Average β	Control	Average β	Control	Average β	Control	Average β
Albury Wodonga Dew Point	0.0179	Bagasse Generation	-0.0083	Adelaide Dew Point	-0.0014	Adelaide Dew Point	-0.0958	Ballarat Dew Point	0.01914
Albury Wodonga Humidity	-0.0041	Black Coal Generation	-0.1425	Adelaide Humidity	-0.0251	Adelaide Humidity	-0.1268	Ballarat Humidity	0.03324
Albury Wodonga Temperature	-0.0477	Brisbane Dew Point	-0.1057	Adelaide Temperature	-0.02	Adelaide Temperature	0.0067	Ballarat Temperature	-0.06712
Albury Wodonga Wind Speed	-0.0974	Brisbane Humidity	-0.0596	Adelaide Wind Speed	-0.1813	Demand	0.0733	Ballarat Wind Speed	-0.00808
Black Coal Generation	0.07	Brisbane Temperature	-0.1511	Demand	0.0949	Diesel Generation	0.4579	Basslink	0.03128
Demand	0.1716	Brisbane Wind Speed	0.0369	Diesel Generation	0.4295	Gas Price	0.1379	Bendigo Dew Point	0.02521
Diesel Generation	0.16	Bundaberg Dew Point	-0.0084	Gas Price	0.1879	Heywood	0.1188	Bendigo Humidity	0.07934
Gas Price	0.1562	Bundaberg Humidity	-0.0333	Heywood	0.082	Mt Barker Dew Point	-0.0207	Bendigo Temperature	0.07898
Gold Coast Dew Point	0.0315	Bundaberg Temperature	-0.1777	Mt Barker Dew Point	-0.0416	Mt Barker Humidity	0.1629	Bendigo Wind Speed	0.04101
Gold Coast Humidity	-0.0009	Bundaberg Wind Speed	0.0345	Mt Barker Humidity	0.0746	Mt Barker Temperature	-0.1446	Brown Coal Generation	-0.0011
Gold Coast Temperature	-0.0057	Cairns Dew Point	-0.0847	Mt Barker Temperature	0.0036	Mt Gambier Dew Point	-0.0526	Demand	0.26251
Gold Coast Wind Speed	0.0834	Cairns Humidity	-0.0597	Mt Barker Wind Speed	-0.1485	Mt Gambier Humidity	0.121	Gas Price	0.42496
Hydro Generation	0.4172	Cairns Temperature	-0.0226	Mt Gambier Dew Point	0.0079	Mt Gambier Temperature	-0.1224	Heywood	0.00314
Kerosene Generation	0.0116	Cairns Wind Speed	-0.0467	Mt Gambier Humidity	0.0817	Murray Bridge Humidity	0.0373	Hydro Generation	0.13411
Maitland Dew Point	0.084	Coal Seam Methane Generation	0.6753	Mt Gambier Temperature	0.0215	Murray Bridge Temperature	0.0186	Melbourne Airport Tullamarine Dew Point	0.0153
Maitland Temperature	0.0444	Demand	-0.1071	Mt Gambier Wind Speed	-0.1605	Murraylink	0.0996	Melbourne Airport Tullamarine Humidity	0.00295
Maitland Wind Speed	0.0113	Gas Price	0.1543	Murray Bridge Dew Point	-0.0269	Natural Gas Diesel Generation	0.4109	Melbourne Airport Tullamarine Temperature	0.02476
Natural Gas Generation	0.1656	Gold Coast Dew Point	-0.1182	Murray Bridge Humidity	0.0148	Natural Gas Fuel Oil Generation	0.1698	Melbourne Airport Tullamarine Wind Speed	-0.03759
Newcastle Dew Point	0.0106	Gold Coast Humidity	-0.0169	Murray Bridge Temperature	0.0295	Port Lincoln Dew Point	0.0666	Melbourne Olympic Park Dew Point	0.04564
Newcastle Humidity	0.0471	Gold Coast Temperature	-0.1634	Murray Bridge Wind Speed	-0.0335	Port Lincoln Humidity	0.1283	Melbourne Olympic Park Humidity	0.02593
Newcastle Temperature	-0.3739	Gold Coast Wind Speed	0.0119	Murraylink	0.0445	Port Lincoln Temperature	0.0028	Melbourne Olympic Park Temperature	0.02673
Newcastle Wind Speed	-0.1301	Hydro Generation	0.0929	Natural Gas Diesel Generation	0.3168	Port Lincoln Wind Speed	0.0156	Melbourne Olympic Park Wind Speed	0.00006
NSW Total Availability	-0.0297	Kerosene Generation	0.1724	Natural Gas Fuel Oil Generation	0.0978	Victor Harbor Dew Point	-0.0571	Mildura Dew Point	0.01658
NSW Total Capacity	0.0149	Mackay Dew Point	-0.1294	Port Lincoln Dew Point	-0.0046	Victor Harbor Temperature	-0.1047	Mildura Humidity	0.06671
NSW Total Cleared	-0.1537	Mackay Humidity	-0.0303	Port Lincoln Humidity	0.0672	Whyalla Dew Point	0.0665	Mildura Temperature	0.04454
QNI	-0.0727	Mackay Temperature	-0.0427	Port Lincoln Temperature	0.0506	Whyalla Humidity	0.1656	Mildura Wind Speed	0.02711
Solar Generation	-0.0734	Mackay Wind Speed	-0.0506	Port Lincoln Wind Speed	0.0131	Whyalla Temperature	-0.1368	Murraylink	0.00224
Sydney Airport Dew Point	0.0309	Natural Gas Generation	0.0712	SA Total Availability	-0.0353			Natural Gas Generation	0.23798
Sydney Airport Humidity	0.0575	NQI	-0.0375	SA Total Capacity	0.038			Shepparton Dew Point	-0.01301
Sydney Airport Temperature	0.0754	QLD Total Availability	-0.0869	SA Total Cleared	0.2109			Shepparton Humidity	-0.03684
Sydney Airport Wind Speed	-0.1056	QLD Total Capacity	0.0623	Solar Generation	0.0865			Shepparton Temperature	0.07787
Sydney Dew Point	0.1897	QLD Total Cleared	0.0495	Victor Harbor Dew Point	-0.0317			Shepparton Wind Speed	0.03824
Sydney Humidity	0.0814	Rockhampton Dew Point	-0.0456	Victor Harbor Humidity	0.0009			Solar Generation	-0.03476
Sydney Olympic Park Dew Point	-0.0297	Rockhampton Humidity	-0.0087	Victor Harbor Temperature	-0.033			VIC Total Availability	-0.29468
Sydney Olympic Park Humidity	0.0543	Rockhampton Temperature	0.0286	Victor Harbor Wind Speed	-0.1137			VIC Total Capacity	0.02473
Sydney Olympic Park Temperature	-0.0372	Rockhampton Wind Speed	-0.0451	Whyalla Dew Point	0.0778			VIC Total Cleared	0.19768
Sydney Olympic Park Wind Speed	-0.101	Solar Generation	0.0092	Whyalla Humidity	0.131			VNI	-0.03788
Sydney Temperature	-0.3437	Terrunsora	-0.0007	Whyalla Temperature	-0.0854			Wind Generation	-0.28425
Terrunsora	-0.0794	Toowoomba Humidity	0.0381	Whyalla Wind Speed	-0.0414				
Wind Generation	-0.0761	Toowoomba Temperature	0.0658	Wind Generation	-0.1794				
Wollongong Dew Point	-0.3018	Toowoomba Wind Speed	0.0282						
Wollongong Humidity	-0.1519	Townsville Dew Point	-0.017						
Wollongong Temperature	-0.3773	Townsville Humidity	-0.069						
Wollongong Wind Speed	-0.112	Townsville Temperature	-0.0484						
		Townsville Wind Speed	0.031						
		Waste Coal Mine Gas Generation	-0.0156						
		Wind Generation	0.0093						

Table C.7 : **Average posterior coefficients β used in the linear regression component of the structural time series model for solar generators' dispatch-weighted prices.**

NSW		QLD		SA		VIC	
Control	Average β	Control	Average β	Control	Average β	Control	Average β
Albury Wodonga Dew Point	0.1380	Bagasse Generation	0.04229	Adelaide Dew Point	0.0262	Ballarat Dew Point	-0.0067
Albury Wodonga Humidity	0.1060	Black Coal Generation	0.03704	Adelaide Humidity	-0.0558	Ballarat Humidity	-0.0697
Albury Wodonga Temperature	0.0774	Brisbane Dew Point	0.25856	Adelaide Temperature	0.0939	Ballarat Temperature	0.0683
Albury Wodonga Wind Speed	-0.0435	Brisbane Humidity	0.22333	Adelaide Wind Speed	-0.2922	Ballarat Wind Speed	0.0496
Black Coal Generation	0.0888	Brisbane Temperature	-0.25708	Demand	0.2603	Basslink	-0.0237
Demand	0.0724	Brisbane Wind Speed	-0.02215	Diesel Generation	0.1954	Bendigo Dew Point	0.1018
Diesel Generation	0.1210	Bundaberg Dew Point	0.01184	Gas Price	0.2432	Bendigo Humidity	-0.0574
Gas Price	0.1488	Bundaberg Humidity	0.14907	Heywood	0.1234	Bendigo Temperature	0.1177
Gold Coast Dew Point	0.1543	Bundaberg Temperature	0.16564	Mt Barker Dew Point	-0.0788	Bendigo Wind Speed	0.1005
Gold Coast Humidity	0.1438	Bundaberg Wind Speed	0.02947	Mt Barker Humidity	0.0537	Brown Coal Generation	0.2072
Gold Coast Temperature	0.0287	Cairns Dew Point	0.06935	Mt Barker Temperature	-0.0324	Demand	0.2591
Gold Coast Wind Speed	0.0100	Cairns Humidity	0.05408	Mt Barker Wind Speed	-0.0873	Gas Price	0.4921
Hydro Generation	0.3390	Cairns Temperature	-0.08760	Mt Gambier Dew Point	0.0013	Heywood	-0.0473
Kerosene Generation	-0.0218	Cairns Wind Speed	0.08852	Mt Gambier Humidity	-0.0138	Hydro Generation	0.1551
Maitland Dew Point	0.0733	Coal Seam Methane Generation	0.54499	Mt Gambier Temperature	-0.0448	Melbourne Airport Tullamarine Dew Point	-0.0067
Maitland Temperature	0.0005	Demand	-0.00976	Mt Gambier Wind Speed	-0.1386	Melbourne Airport Tullamarine Humidity	0.0412
Maitland Wind Speed	0.0013	Gas Price	0.01520	Murray Bridge Dew Point	-0.0480	Melbourne Airport Tullamarine Temperature	0.1320
Natural Gas Generation	0.3245	Gold Coast Dew Point	0.29473	Murray Bridge Humidity	0.0284	Melbourne Airport Tullamarine Wind Speed	-0.0819
Newcastle Dew Point	0.0037	Gold Coast Humidity	0.24341	Murray Bridge Temperature	0.3882	Melbourne Olympic Park Dew Point	0.1534
Newcastle Humidity	0.1167	Gold Coast Temperature	-0.22287	Murray Bridge Wind Speed	0.0156	Melbourne Olympic Park Humidity	0.0462
Newcastle Temperature	-0.0507	Gold Coast Wind Speed	-0.03235	Murraylink	-0.1198	Melbourne Olympic Park Temperature	0.1254
Newcastle Wind Speed	-0.0883	Hydro Generation	0.01372	Natural Gas Diesel Generation	0.3132	Melbourne Olympic Park Wind Speed	-0.0849
NSW Total Availability	0.0301	Kerosene Generation	0.21635	Natural Gas Fuel Oil Generation	0.1335	Mildura Dew Point	0.0177
NSW Total Capacity	-0.1584	Mackay Dew Point	0.13983	Port Lincoln Dew Point	0.0407	Mildura Humidity	-0.0323
NSW Total Cleared	0.0719	Mackay Humidity	-0.00438	Port Lincoln Humidity	0.0403	Mildura Temperature	0.1074
QNI	-0.0145	Mackay Temperature	-0.10368	Port Lincoln Temperature	0.1077	Mildura Wind Speed	-0.0177
Solar Generation	-0.0979	Mackay Wind Speed	0.06357	Port Lincoln Wind Speed	0.0098	Murraylink	-0.0958
Sydney Airport Dew Point	0.0604	Natural Gas Generation	-0.05445	SA Total Availability	-0.0207	Natural Gas Generation	0.3149
Sydney Airport Humidity	0.0897	NQI	-0.03215	SA Total Capacity	0.1223	Shepparton Dew Point	-0.0621
Sydney Airport Temperature	-0.0070	QLD Total Availability	-0.04555	SA Total Cleared	0.1363	Shepparton Humidity	-0.0457
Sydney Airport Wind Speed	-0.0521	QLD Total Capacity	-0.03789	Solar Generation	0.0350	Shepparton Temperature	0.1187
Sydney Dew Point	0.1339	QLD Total Cleared	-0.01017	Victor Harbor Dew Point	0.0035	Shepparton Wind Speed	0.0280
Sydney Humidity	0.0990	Rockhampton Dew Point	0.28820	Victor Harbor Humidity	-0.0008	Solar Generation	-0.1466
Sydney Olympic Park Dew Point	0.0000	Rockhampton Humidity	0.12027	Victor Harbor Temperature	-0.3053	VIC Total Availability	-0.3214
Sydney Olympic Park Humidity	0.0945	Rockhampton Temperature	-0.13224	Victor Harbor Wind Speed	-0.0318	VIC Total Capacity	-0.0474
Sydney Olympic Park Temperature	0.0811	Rockhampton Wind Speed	-0.00953	Whyalla Dew Point	0.0866	VIC Total Cleared	0.2797
Sydney Olympic Park Wind Speed	-0.0701	Solar Generation	-0.08628	Whyalla Humidity	0.0704	VNI	0.0360
Sydney Temperature	0.0126	Terrunsora	0.05858	Whyalla Temperature	-0.0261	Wind Generation	-0.1993
Terrunsora	0.0015	Toowoomba Humidity	0.14521	Whyalla Wind Speed	-0.0217		
Wind Generation	0.0216	Toowoomba Temperature	-0.07176	Wind Generation	-0.1739		
Wollongong Dew Point	0.0539	Toowoomba Wind Speed	0.05184				
Wollongong Humidity	0.1295	Townsville Dew Point	0.02894				
Wollongong Temperature	-0.0301	Townsville Humidity	0.14176				
Wollongong Wind Speed	-0.0526	Townsville Temperature	-0.06873				
		Townsville Wind Speed	0.09820				
		Waste Coal Mine Gas Generation	-0.04892				
		Wind Generation	0.00414				

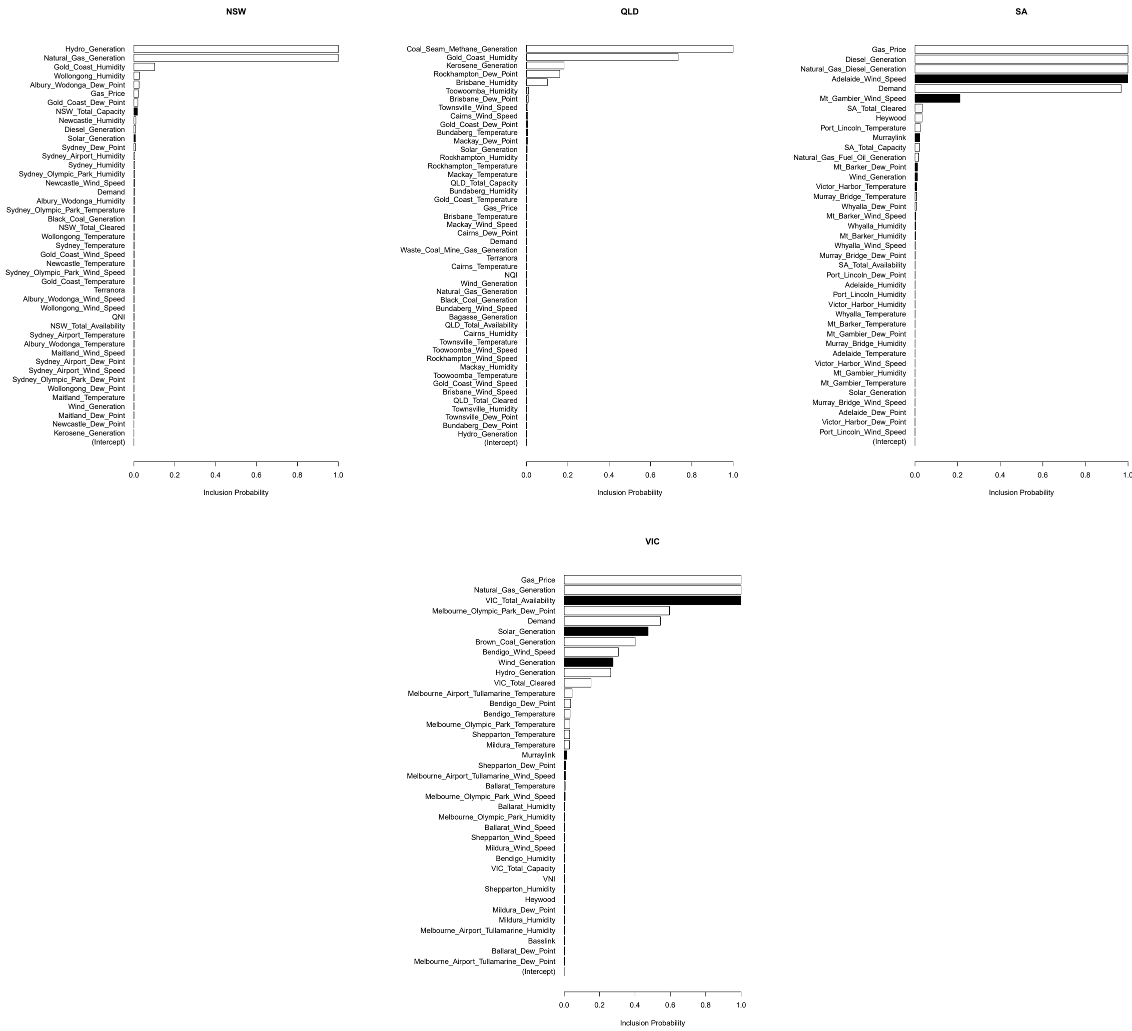

Figure C.13 : **Posterior inclusion probabilities for the most likely predictors of weighted dispatch price for solar generators.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

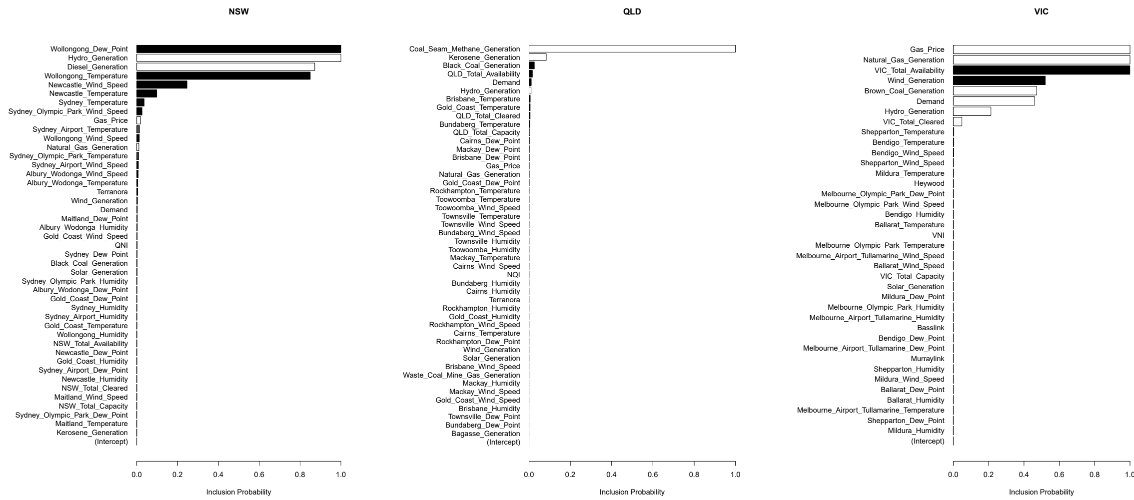

Figure C.14 : **Posterior inclusion probabilities for the most likely predictors of weighted dispatch price for coal generators.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.8 : **Average posterior coefficients β used in the linear regression component of the structural time series model for coal generators' dispatch-weighted prices.**

NSW		QLD		VIC	
Control	Average β	Control	Average β β	Control	Average β
Albury Wodonga Dew Point	0.0229	Bagasse Generation	-0.0431	Ballarat Dew Point	0.0064
Albury Wodonga Humidity	0.0601	Black Coal Generation	-0.1414	Ballarat Humidity	0.0168
Albury Wodonga Temperature	-0.3056	Brisbane Dew Point	-0.0933	Ballarat Temperature	0.0316
Albury Wodonga Wind Speed	-0.1115	Brisbane Humidity	0.0384	Ballarat Wind Speed	0.0286
Black Coal Generation	0.0325	Brisbane Temperature	-0.1233	Basslink	0.0522
Demand	0.0417	Brisbane Wind Speed	-0.0679	Bendigo Dew Point	0.0177
Diesel Generation	0.1042	Bundaberg Dew Point	0.0173	Bendigo Humidity	0.0386
Gas Price	0.0602	Bundaberg Humidity	0.0157	Bendigo Temperature	0.0711
Gold Coast Dew Point	-0.0839	Bundaberg Temperature	-0.1335	Bendigo Wind Speed	0.0576
Gold Coast Humidity	0.0109	Bundaberg Wind Speed	0.0319	Brown Coal Generation	0.2146
Gold Coast Temperature	-0.0706	Cairns Dew Point	-0.0656	Demand	0.2284
Gold Coast Wind Speed	0.0698	Cairns Humidity	-0.0533	Gas Price	0.3898
Hydro Generation	0.4079	Cairns Temperature	-0.0096	Heywood	0.0183
Kerosene Generation	-0.0356	Cairns Wind Speed	0.0478	Hydro Generation	0.1504
Maitland Dew Point	0.0977	Coal Seam Methane Generation	0.6325	Melbourne Airport Tullamarine Dew Point	0.0060
Maitland Temperature	0.0479	Demand	-0.1181	Melbourne Airport Tullamarine Humidity	0.0013
Maitland Wind Speed	0.0139	Gas Price	-0.0453	Melbourne Airport Tullamarine Temperature	0.0545
Natural Gas Generation	0.0008	Gold Coast Dew Point	-0.0349	Melbourne Airport Tullamarine Wind Speed	0.0094
Newcastle Dew Point	0.0376	Gold Coast Humidity	-0.0048	Melbourne Olympic Park Dew Point	0.0408
Newcastle Humidity	0.0184	Gold Coast Temperature	-0.1281	Melbourne Olympic Park Humidity	-0.0247
Newcastle Temperature	-0.2950	Gold Coast Wind Speed	0.0152	Melbourne Olympic Park Temperature	0.0115
Newcastle Wind Speed	-0.0758	Hydro Generation	0.1059	Melbourne Olympic Park Wind Speed	0.0169
NSW Total Availability	-0.0671	Kerosene Generation	0.1569	Mildura Dew Point	0.0021
NSW Total Capacity	0.0177	Mackay Dew Point	-0.0774	Mildura Humidity	0.0028
NSW Total Cleared	-0.0200	Mackay Humidity	-0.0078	Mildura Temperature	0.0478
QNI	-0.0832	Mackay Temperature	-0.0189	Mildura Wind Speed	0.0252
Solar Generation	0.0247	Mackay Wind Speed	-0.0148	Murraylink	0.0126
Sydney Airport Dew Point	0.0281	Natural Gas Generation	-0.0735	Natural Gas Generation	0.3136
Sydney Airport Humidity	0.0108	NQI	-0.0172	Shepparton Dew Point	-0.0173
Sydney Airport Temperature	-0.2925	QLD Total Availability	-0.1491	Shepparton Humidity	0.0174
Sydney Airport Wind Speed	-0.0865	QLD Total Capacity	0.0653	Shepparton Temperature	0.0807
Sydney Dew Point	0.0268	QLD Total Cleared	-0.1091	Shepparton Wind Speed	0.0561
Sydney Humidity	0.0210	Rockhampton Dew Point	-0.0448	Solar Generation	-0.0177
Sydney Olympic Park Dew Point	0.0170	Rockhampton Humidity	0.0135	VIC Total Availability	-0.3427
Sydney Olympic Park Humidity	0.0758	Rockhampton Temperature	0.0335	VIC Total Capacity	0.0285
Sydney Olympic Park Temperature	-0.3019	Rockhampton Wind Speed	0.0436	VIC Total Cleared	0.2143
Sydney Olympic Park Wind Speed	-0.0806	Solar Generation	-0.0463	VNI	-0.0507
Sydney Temperature	-0.3046	Terrunsora	-0.0215	Wind Generation	-0.2102
Terrunsora	-0.0919	Toowoomba Humidity	0.0465		
Wind Generation	-0.0911	Toowoomba Temperature	0.0241		
Wollongong Dew Point	-0.2627	Toowoomba Wind Speed	0.0213		
Wollongong Humidity	0.0200	Townsville Dew Point	0.0041		
Wollongong Temperature	-0.3174	Townsville Humidity	-0.0639		
Wollongong Wind Speed	-0.0802	Townsville Temperature	-0.0525		
		Townsville Wind Speed	0.0651		
		Waste Coal Mine Gas Generation	0.0190		
		Wind Generation	0.0791		

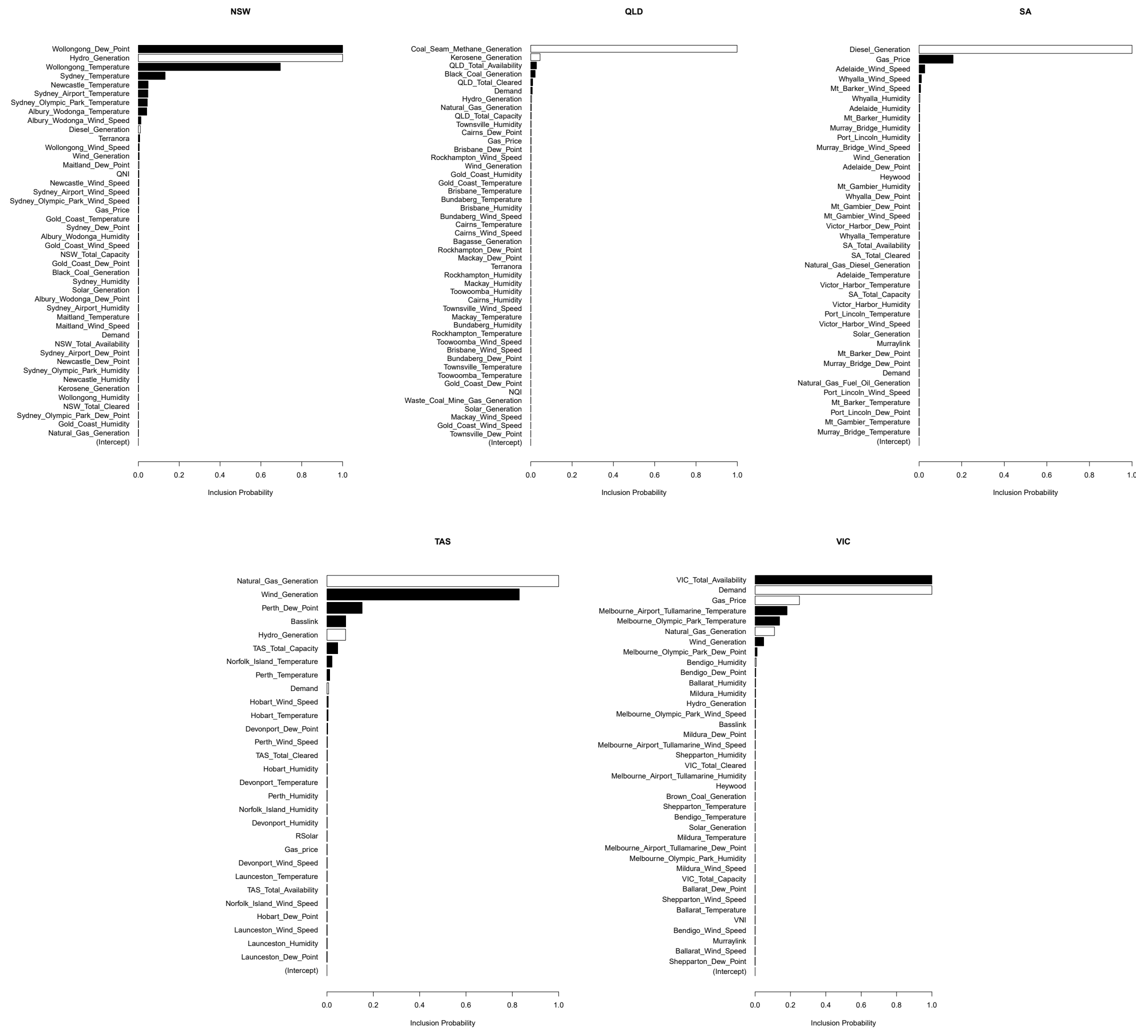

Figure C.15 : **Posterior inclusion probabilities for the most likely predictors of weighted dispatch price for gas generators.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.9 : **Average posterior coefficients β used in the linear regression component of the structural time series model for gas generators' dispatch-weighted prices.**

NSW		QLD		SA		TAS		VIC	
Control	Average β	Control	Average β	Control	Average β	Control	Average β	Control	Average β
Market	AverageBeta	Market	AverageBeta	Market	AverageBeta	Market	AverageBeta	Market	AverageBeta
Albury Wodonga Dew Point	0.0229	Bagasse Generation	-0.0248	Adelaide Dew Point	0.0661	Basslink	-0.6060	Ballarat Dew Point	-0.0039
Albury Wodonga Humidity	0.0601	Black Coal Generation	-0.1760	Adelaide Humidity	0.0815	Demand	0.1701	Ballarat Humidity	0.0858
Albury Wodonga Temperature	-0.3056	Brisbane Dew Point	-0.0992	Adelaide Temperature	-0.0172	Devonport Dew Point	-0.0867	Ballarat Temperature	-0.0777
Albury Wodonga Wind Speed	-0.1115	Brisbane Humidity	-0.0299	Adelaide Wind Speed	-0.1129	Devonport Humidity	-0.0100	Ballarat Wind Speed	0.0007
Black Coal Generation	0.0325	Brisbane Temperature	-0.1061	Demand	0.0058	Devonport Temperature	-0.0276	Basslink	0.1079
Demand	0.0417	Brisbane Wind Speed	-0.0268	Diesel Generation	0.6560	Devonport Wind Speed	0.0032	Bendigo Dew Point	-0.0731
Diesel Generation	0.1042	Bundaberg Dew Point	0.0319	Gas Price	-0.1623	Hobart Dew Point	0.0355	Bendigo Humidity	0.1345
Gas Price	0.0602	Bundaberg Humidity	-0.0254	Heywood	0.0756	Hobart Humidity	0.0716	Bendigo Temperature	0.0543
Gold Coast Dew Point	-0.0839	Bundaberg Temperature	-0.0924	Mt Barker Dew Point	-0.0054	Hobart Temperature	-0.1152	Bendigo Wind Speed	0.0206
Gold Coast Humidity	0.0109	Bundaberg Wind Speed	0.0577	Mt Barker Humidity	0.1018	Hobart Wind Speed	-0.1374	Brown Coal Generation	-0.1615
Gold Coast Temperature	-0.0706	Cairns Dew Point	-0.0877	Mt Barker Temperature	0.0152	Hydro Generation	0.6358	Demand	0.5191
Gold Coast Wind Speed	0.0698	Cairns Humidity	-0.0508	Mt Barker Wind Speed	-0.0957	Launceston Dew Point	0.0106	Gas Price	0.1775
Hydro Generation	0.4079	Cairns Temperature	0.0112	Mt Gambier Dew Point	0.0576	Launceston Humidity	-0.0119	Heywood	0.0919
Kerosene Generation	-0.0356	Cairns Wind Speed	0.0752	Mt Gambier Humidity	0.0717	Launceston Temperature	-0.0113	Hydro Generation	0.0778
Maitland Dew Point	0.0977	Coal Seam Methane Generation	0.4341	Mt Gambier Temperature	-0.0255	Launceston Wind Speed	0.0326	Melbourne Airport Tullamarine Dew Point	0.0034
Maitland Temperature	0.0479	Demand	-0.1346	Mt Gambier Wind Speed	-0.0639	Natural Gas Generation	0.3763	Melbourne Airport Tullamarine Humidity	0.0228
Maitland Wind Speed	0.0139	Gas Price	-0.0705	Murray Bridge Dew Point	-0.0129	Norfolk Island Humidity	-0.0530	Melbourne Airport Tullamarine Temperature	-0.1724
Natural Gas Generation	0.0008	Gold Coast Dew Point	-0.0555	Murray Bridge Humidity	0.0741	Norfolk Island Temperature	-0.1390	Melbourne Airport Tullamarine Wind Speed	-0.0608
Newcastle Dew Point	0.0376	Gold Coast Humidity	0.0127	Murray Bridge Temperature	-0.0050	Norfolk Island Wind Speed	-0.0175	Melbourne Olympic Park Dew Point	-0.1256
Newcastle Humidity	0.0184	Gold Coast Temperature	-0.0929	Murray Bridge Wind Speed	-0.0744	Perth Dew Point	-0.0956	Melbourne Olympic Park Humidity	0.0422
Newcastle Temperature	-0.2950	Gold Coast Wind Speed	-0.0343	Murraylink	0.0096	Perth Humidity	-0.0013	Melbourne Olympic Park Temperature	-0.1664
Newcastle Wind Speed	-0.0758	Hydro Generation	0.1138	Natural Gas Diesel Generation	0.0677	Perth Temperature	-0.1327	Melbourne Olympic Park Wind Speed	-0.0975
NSW Total Availability	-0.0671	Kerosene Generation	0.1842	Natural Gas Fuel Oil Generation	-0.0895	Perth Wind Speed	-0.0368	Mildura Dew Point	-0.1034
NSW Total Capacity	0.0177	Mackay Dew Point	-0.0734	Port Lincoln Dew Point	0.0202	TAS Total Availability	0.0298	Mildura Humidity	0.1157
NSW Total Cleared	-0.0200	Mackay Humidity	0.0027	Port Lincoln Humidity	0.0737	TAS Total Capacity	-0.1786	Mildura Temperature	0.0269
QNI	-0.0832	Mackay Temperature	-0.0439	Port Lincoln Temperature	-0.0451	TAS Total Cleared	-0.5674	Mildura Wind Speed	0.0006
Solar Generation	0.0247	Mackay Wind Speed	0.0461	Port Lincoln Wind Speed	-0.0523	Wind Generation	-0.2046	Murraylink	-0.0198
Sydney Airport Dew Point	0.0281	Natural Gas Generation	-0.1178	SA Total Availability	-0.0754			Natural Gas Generation	0.1604
Sydney Airport Humidity	0.0108	NQI	-0.0277	SA Total Capacity	-0.0273			Shepparton Dew Point	-0.0307
Sydney Airport Temperature	-0.2925	QLD Total Availability	-0.1764	SA Total Cleared	-0.0664			Shepparton Humidity	0.0848
Sydney Airport Wind Speed	-0.0865	QLD Total Capacity	0.0445	Solar Generation	-0.0051			Shepparton Temperature	0.0686
Sydney Dew Point	0.0268	QLD Total Cleared	-0.1249	Victor Harbor Dew Point	0.0755			Shepparton Wind Speed	0.0332
Sydney Humidity	0.0210	Rockhampton Dew Point	-0.0823	Victor Harbor Humidity	0.0515			Solar Generation	0.0330
Sydney Olympic Park Dew Point	0.0170	Rockhampton Humidity	-0.0284	Victor Harbor Temperature	0.0124			VIC Total Availability	-0.3772
Sydney Olympic Park Humidity	0.0758	Rockhampton Temperature	0.0216	Victor Harbor Wind Speed	-0.0442			VIC Total Capacity	0.0015
Sydney Olympic Park Temperature	-0.3019	Rockhampton Wind Speed	0.0642	Whyalla Dew Point	0.0657			VIC Total Cleared	0.0656
Sydney Olympic Park Wind Speed	-0.0806	Solar Generation	0.0000	Whyalla Humidity	0.0946			VNI	0.1003
Sydney Temperature	-0.3046	Terrunsora	-0.0164	Whyalla Temperature	-0.0551			Wind Generation	-0.1607
Terrunsora	-0.0919	Toowoomba Humidity	0.0348	Whyalla Wind Speed	-0.1071				
Wind Generation	-0.0911	Toowoomba Temperature	-0.0072	Wind Generation	-0.0742				
Wollongong Dew Point	-0.2627	Toowoomba Wind Speed	0.0076						
Wollongong Humidity	0.0200	Townsville Dew Point	-0.0216						
Wollongong Temperature	-0.3174	Townsville Humidity	-0.0845						
Wollongong Wind Speed	-0.0802	Townsville Temperature	-0.0599						
		Townsville Wind Speed	0.0823						
		Waste Coal Mine Gas Generation	0.0288						
		Wind Generation	0.0429						

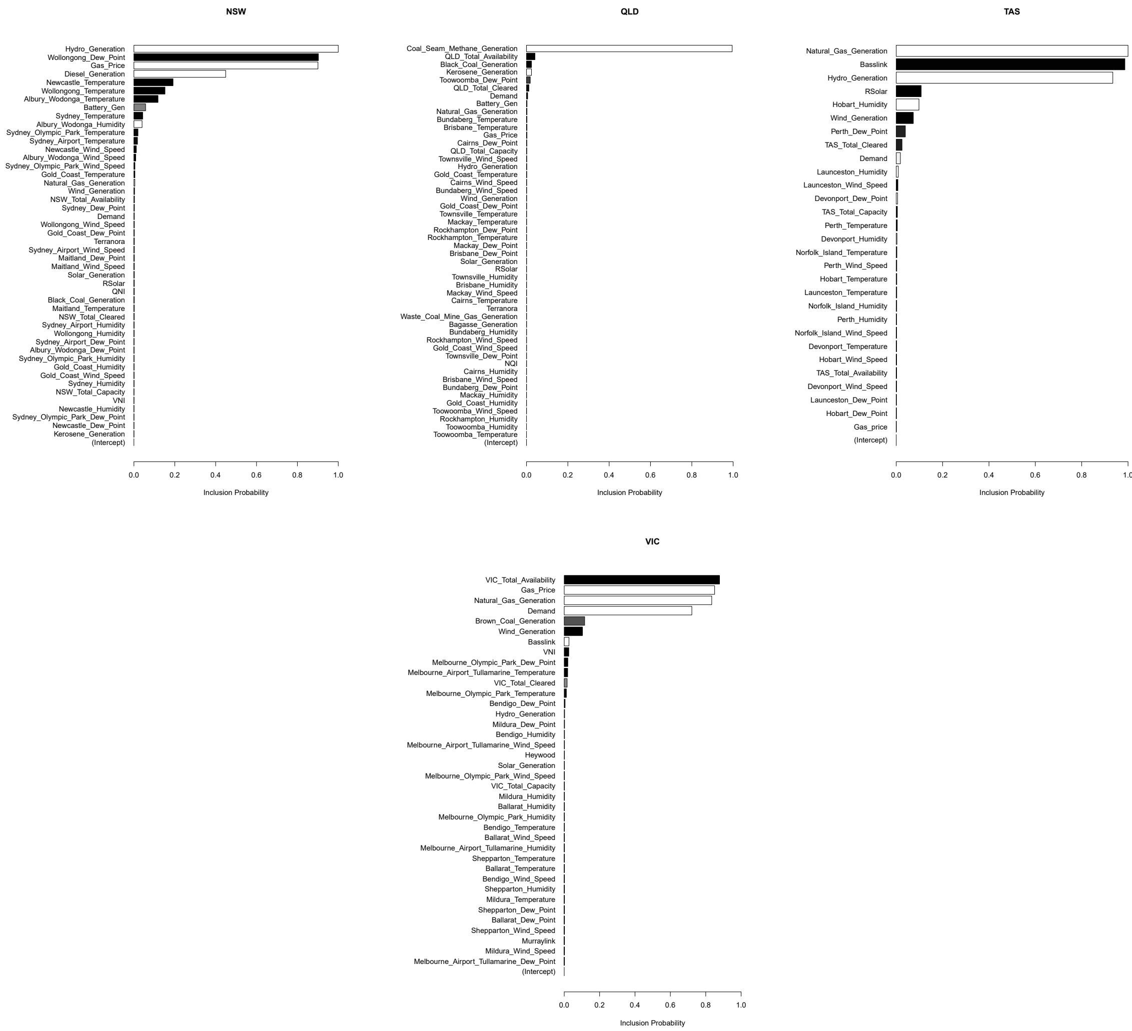

Figure C.16 : **Posterior inclusion probabilities for the most likely predictors of weighted dispatch price for hydro generators.** Bars are shaded on a continuous [0, 1] scale in proportion to the probability of a positive coefficient. Positive, negative, and indeterminate signs of the coefficients are shown in white, black, and grey colours respectively.

Table C.10 : **Average posterior coefficients β used in the linear regression component of the structural time series model for hydro generators' dispatch-weighted prices.**

NSW		QLD		SA		VIC	
Control	Average β	Control	Average β	Control	Average β	Control	Average β
Albury Wodonga Dew Point	0.0338	Bagasse Generation	0.0142	Basslink	-1.0333	Ballarat Dew Point	0.0375
Albury Wodonga Humidity	0.1202	Battery Gen	0.0283	Demand	2.7257	Ballarat Humidity	0.0851
Albury Wodonga Temperature	-0.2992	Black Coal Generation	-0.1933	Devonport Dew Point	0.0958	Ballarat Temperature	-0.0024
Albury Wodonga Wind Speed	-0.1094	Brisbane Dew Point	-0.0365	Devonport Humidity	0.0652	Ballarat Wind Speed	-0.0155
Black Coal Generation	0.0737	Brisbane Humidity	-0.0353	Devonport Temperature	-0.0721	Basslink	0.1941
Demand	0.0677	Brisbane Temperature	-0.0861	Devonport Wind Speed	-0.0584	Bendigo Dew Point	-0.082
Diesel Generation	0.1039	Brisbane Wind Speed	-0.018	Hobart Dew Point	0.0499	Bendigo Humidity	0.1513
Gas Price	0.0491	Bundaberg Dew Point	0.0007	Hobart Humidity	0.1567	Bendigo Temperature	0.0558
Gold Coast Dew Point	-0.0176	Bundaberg Humidity	0.0052	Hobart Temperature	-0.1353	Bendigo Wind Speed	0.0095
Gold Coast Humidity	0.0074	Bundaberg Temperature	-0.0794	Hobart Wind Speed	-0.0586	Brown Coal Generation	-0.2014
Gold Coast Temperature	-0.0988	Bundaberg Wind Speed	0.0726	Hydro Generation	0.9966	Demand	0.3482
Gold Coast Wind Speed	0.0969	Cairns Dew Point	-0.0674	Launceston Dew Point	0.0392	Gas Price	0.2458
Hydro Generation	0.408	Cairns Humidity	-0.019	Launceston Humidity	0.1058	Heywood	0.0615
Kerosene Generation	-0.0025	Cairns Temperature	-0.0162	Launceston Temperature	-0.0796	Hydro Generation	0.0267
Maitland Dew Point	0.0914	Cairns Wind Speed	0.0655	Launceston Wind Speed	-0.0939	Melbourne Airport Tullamarine Dew Point	-0.0096
Maitland Temperature	0.0344	Coal Seam Methane Generation	0.3894	Natural Gas Generation	0.3791	Melbourne Airport Tullamarine Humidity	-0.0246
Maitland Wind Speed	0.0212	Demand	-0.1346	Norfolk Island Humidity	0.0575	Melbourne Airport Tullamarine Temperature	-0.1969
Natural Gas Generation	-0.0707	Gas Price	-0.0294	Norfolk Island Temperature	-0.0288	Melbourne Airport Tullamarine Wind Speed	-0.0962
Newcastle Dew Point	0.0373	Gold Coast Dew Point	-0.019	Norfolk Island Wind Speed	-0.0339	Melbourne Olympic Park Dew Point	-0.1721
Newcastle Humidity	0.0148	Gold Coast Humidity	0.0153	Perth Dew Point	-0.0414	Melbourne Olympic Park Humidity	-0.0005
Newcastle Temperature	-0.2989	Gold Coast Temperature	-0.0449	Perth Humidity	0.0844	Melbourne Olympic Park Temperature	-0.1675
Newcastle Wind Speed	-0.079	Gold Coast Wind Speed	0.0281	Perth Temperature	-0.0819	Melbourne Olympic Park Wind Speed	-0.0623
NSW Total Availability	-0.0527	Hydro Generation	0.0703	Perth Wind Speed	-0.0308	Mildura Dew Point	-0.0865
NSW Total Cleared	-0.0241	Kerosene Generation	0.2031	TAS Total Availability	-0.0219	Mildura Humidity	0.1107
QNI	-0.0747	Mackay Dew Point	-0.0622	TAS Total Capacity	-0.1055	Mildura Temperature	0.0092
Rsolar	-0.0646	Mackay Humidity	0.0033	TAS Total Cleared	-6.9083	Mildura Wind Speed	0.0058
Solar Generation	0.0262	Mackay Temperature	-0.0053	Wind Generation	-0.2392	Murraylink	-0.0138
Sydney Airport Dew Point	0.0437	Mackay Wind Speed	0.048			Natural Gas Generation	0.2485
Sydney Airport Humidity	0.0551	Natural Gas Generation	-0.0945			Shepparton Dew Point	-0.0116
Sydney Airport Temperature	-0.2908	NQI	0.0025			Shepparton Humidity	-0.0267
Sydney Airport Wind Speed	-0.087	QLD Total Availability	-0.1879			Shepparton Temperature	0.003
Sydney Dew Point	0.0447	QLD Total Capacity	0.0263			Shepparton Wind Speed	-0.0059
Sydney Humidity	0.0336	QLD Total Cleared	-0.144			Solar Generation	0.0758
Sydney Olympic Park Dew Point	0.0146	Rockhampton Dew Point	-0.0313			VIC Total Availability	-0.2799
Sydney Olympic Park Humidity	0.0229	Rockhampton Humidity	-0.0225			VIC Total Capacity	0.0357
Sydney Olympic Park Temperature	-0.3005	Rockhampton Temperature	-0.0317			VIC Total Cleared	-0.0629
Sydney Olympic Park Wind Speed	-0.0945	Rockhampton Wind Speed	0.1066			VNI	-0.1606
Sydney Temperature	-0.3091	RSolar	-0.0255			Wind Generation	-0.3283
Terrunsora	-0.0837	Solar Generation	-0.0651				
VNI	0.0242	Terrunsora	-0.0393				
Wind Generation	-0.0764	Toowoomba Dew Point	-0.0312				
Wollongong Dew Point	-0.2621	Toowoomba Humidity	0.0000				
Wollongong Humidity	-0.0127	Toowoomba Temperature	-0.0295				
Wollongong Temperature	-0.3175	Toowoomba Wind Speed	0.0106				
Wollongong Wind Speed	-0.0921	Townsville Dew Point	0.0306				
		Townsville Humidity	-0.0426				
		Townsville Temperature	0.0031				
		Townsville Wind Speed	0.0686				
		Waste Coal Mine Gas Generation	0.0095				
		Wind Generation	0.0706				

C.2.5 Prior standard deviation and seasonality assumptions

The observation period in Tables C.11 and C.12 runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 31st October 2021 (a total of 31 daily observations). The posterior tail-area probability, p, indicates the probability of obtaining the estimated effect by chance.

Table C.11 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 on equally daily weighted averaged spot price equally daily weighted averaged spot price with 95% confidence intervals for the different assumptions of prior standard deviation and with a seasonality component.**

Prior sd		Actual	Pred	Pred Lo	Pred Up	Pred sd	Abs Effect	Abs Effect Lo	Abs Effect Up	Abs Effect sd	Rel Effect	Rel Effect Lo	Rel Effect.Up	Rel Effect.sd	alpha	p
									NSW							
0.001	Average	57	74.33	54.1923	94.0901	10.1463	-17.2132	-36.9748	2.9230	10.1463	-0.2316	-0.4975	0.0393	0.1365	0.0500	0.0451
	Cumulative	1771	2304.18	1679.9606	2916.7929	314.5347	-533.6097	-1146.2196	90.6126	314.5347	-0.2316	-0.4975	0.0393	0.1365	0.0500	0.0451
0.01	Average	57	72.00	48.2657	95.8503	12.0627	-14.8857	-38.7350	8.8496	12.0627	-0.2067	-0.5380	0.1229	0.1675	0.0500	0.1069
	Cumulative	1771	2232.03	1496.2361	2971.3585	373.9426	-461.4556	-1200.7852	274.3372	373.9426	-0.2067	-0.5380	0.1229	0.1675	0.0500	0.1069
0.02	Average	57	70.20	41.3586	98.4896	14.5727	-13.0847	-41.3744	15.7567	14.5727	-0.1864	-0.5894	0.2245	0.2076	0.0500	0.1861
	Cumulative	1771	2176.20	1282.1160	3053.1791	451.7530	-405.6247	-1282.6059	488.4573	451.7530	-0.1864	-0.5894	0.2245	0.2076	0.0500	0.1861
0.03	Average	57	69.46	36.5773	102.4883	16.8248	-12.3454	-45.3731	20.5380	16.8248	-0.1777	-0.6532	0.2957	0.2422	0.0500	0.2331
	Cumulative	1771	2153.28	1133.8959	3177.1382	521.5699	-382.7081	-1406.5649	636.6774	521.5699	-0.1777	-0.6532	0.2957	0.2422	0.0500	0.2331
0.04	Average	57	70.37	33.1507	109.2758	19.2599	-13.2557	-52.1606	23.9645	19.2599	-0.1884	-0.7412	0.3405	0.2737	0.0500	0.2494
	Cumulative	1771	2181.50	1027.6730	3387.5506	597.0576	-410.9261	-1616.9774	742.9002	597.0576	-0.1884	-0.7412	0.3405	0.2737	0.0500	0.2494
0.05	Average	57	71.83	29.0373	114.5246	21.7805	-14.7185	-57.4094	28.0780	21.7805	-0.2049	-0.7992	0.3909	0.3032	0.0500	0.2501
	Cumulative	1771	2226.85	900.1555	3550.2636	675.1943	-456.2728	-1779.6903	870.4178	675.1943	-0.2049	-0.7992	0.3909	0.3032	0.0500	0.2501
0.06	Average	57	72.34	25.6733	119.9259	23.9712	-15.2215	-62.8107	31.4419	23.9712	-0.2104	-0.8683	0.4347	0.3314	0.0500	0.2632
	Cumulative	1771	2242.44	795.8730	3717.7042	743.1072	-471.8680	-1947.1309	974.7002	743.1072	-0.2104	-0.8683	0.4347	0.3314	0.0500	0.2632
0.07	Average	57	73.45	22.5419	124.9132	26.0465	-16.3316	-67.7979	34.5733	26.0465	-0.2224	-0.9231	0.4707	0.3546	0.0500	0.2659
	Cumulative	1771	2276.85	698.7994	3872.3083	807.4406	-506.2792	-2101.7350	1071.7738	807.4406	-0.2224	-0.9231	0.4707	0.3546	0.0500	0.2659
0.08	Average	57	73.66	19.0536	130.0042	28.2419	-16.5402	-72.8889	38.0617	28.2419	-0.2246	-0.9896	0.5168	0.3834	0.0500	0.2767
	Cumulative	1771	2283.32	590.6619	4030.1292	875.4981	-512.7447	-2259.5559	1179.9114	875.4981	-0.2246	-0.9896	0.5168	0.3834	0.0500	0.2767
0.09	Average	57	74.12	14.1830	134.5011	30.4753	-17.0003	-77.3858	42.9323	30.4753	-0.2294	-1.0441	0.5793	0.4112	0.0500	0.2934
	Cumulative	1771	2297.58	439.6735	4169.5334	944.7354	-527.0108	-2398.9601	1330.8998	944.7354	-0.2294	-1.0441	0.5793	0.4112	0.0500	0.2934
0.10	Average	57	74.42	10.6770	138.5578	32.4958	-17.3062	-81.4426	46.4383	32.4958	-0.2325	-1.0943	0.6240	0.4366	0.0500	0.3028
	Cumulative	1771	2307.06	330.9866	4295.2927	1007.3687	-536.4914	-2524.7195	1439.5867	1007.3687	-0.2325	-1.0943	0.6240	0.4366	0.0500	0.3028
									QLD							
0.001	Average	66	98.07	64.5498	131.8176	16.9525	-31.5911	-65.3402	1.9276	16.9525	-0.3221	-0.6663	0.0197	0.1729	0.0500	0.0305
	Cumulative	2061	3040.12	2001.0438	4086.3457	525.5283	-979.3226	-2025.5455	59.7564	525.5283	-0.3221	-0.6663	0.0197	0.1729	0.0500	0.0305
0.01	Average	66	102.49	64.1977	140.5073	19.5790	-36.0099	-74.0299	2.2798	19.5790	-0.3514	-0.7223	0.0222	0.1910	0.0500	0.0338
	Cumulative	2061	3177.11	1990.1274	4355.7266	606.9478	-1116.3081	-2294.9264	70.6728	606.9478	-0.3514	-0.7223	0.0222	0.1910	0.0500	0.0338
0.02	Average	66	102.69	57.1998	146.8821	22.7851	-36.2085	-80.4047	9.2776	22.7851	-0.3526	-0.7830	0.0903	0.2219	0.0500	0.0589
	Cumulative	2061	3183.26	1773.1942	4553.3466	706.3372	-1122.4643	-2492.5464	287.6059	706.3372	-0.3526	-0.7830	0.0903	0.2219	0.0500	0.0589
0.03	Average	66	102.34	50.2941	153.8779	26.3495	-35.8597	-87.4005	16.1833	26.3495	-0.3504	-0.8540	0.1581	0.2575	0.0500	0.0860
	Cumulative	2061	3172.45	1559.1168	4770.2145	816.8351	-1111.6499	-2709.4144	501.6834	816.8351	-0.3504	-0.8540	0.1581	0.2575	0.0500	0.0860
0.04	Average	66	102.30	44.4898	160.8945	29.6062	-35.8254	-94.4171	21.9877	29.6062	-0.3502	-0.9229	0.2149	0.2894	0.0500	0.1102
	Cumulative	2061	3171.39	1379.1828	4987.7291	917.7930	-1110.5867	-2926.9289	681.6174	917.7930	-0.3502	-0.9229	0.2149	0.2894	0.0500	0.1102
0.05	Average	66	102.49	37.7402	167.2295	32.8849	-36.0156	-100.7521	28.7372	32.8849	-0.3514	-0.9830	0.2804	0.3209	0.0500	0.1341
	Cumulative	2061	3177.28	1169.9466	5184.1139	1019.4317	-1116.4833	-3123.3138	890.8535	1019.4317	-0.3514	-0.9830	0.2804	0.3209	0.0500	0.1341
0.06	Average	66	102.63	32.4553	174.0810	36.0923	-36.1494	-107.6036	34.0221	36.0923	-0.3522	-1.0485	0.3315	0.3517	0.0500	0.1553
	Cumulative	2061	3181.43	1006.1136	5396.5103	1118.8613	-1120.6308	-3335.7101	1054.6865	1118.8613	-0.3522	-1.0485	0.3315	0.3517	0.0500	0.1553
0.07	Average	66	102.91	26.5964	179.2994	39.0385	-36.4365	-112.8220	39.8811	39.0385	-0.3540	-1.0963	0.3875	0.3793	0.0500	0.1733
	Cumulative	2061	3190.33	824.4871	5558.2829	1210.1941	-1129.5322	-3497.4827	1236.3131	1210.1941	-0.3540	-1.0963	0.3875	0.3793	0.0500	0.1733
0.08	Average	66	103.40	21.3807	186.2268	42.1842	-36.9211	-119.7494	45.0967	42.1842	-0.3571	-1.1581	0.4361	0.4080	0.0500	0.1873
	Cumulative	2061	3205.36	662.8025	5773.0304	1307.7114	-1144.5552	-3712.2302	1397.9976	1307.7114	-0.3571	-1.1581	0.4361	0.4080	0.0500	0.1873
0.09	Average	66	103.55	16.1529	192.0106	45.1873	-37.0761	-125.5332	50.3245	45.1873	-0.3580	-1.2123	0.4860	0.4364	0.0500	0.2085
	Cumulative	2061	3210.16	500.7401	5952.3285	1400.8076	-1149.3601	-3891.5283	1560.0601	1400.8076	-0.3580	-1.2123	0.4860	0.4364	0.0500	0.2085
0.10	Average	66	103.76	10.2499	199.2445	48.0347	-37.2809	-132.7670	56.2275	48.0347	-0.3593	-1.2796	0.5419	0.4629	0.0500	0.2192
	Cumulative	2061	3216.51	317.7475	6176.5784	1489.0772	-1155.7066	-4115.7783	1743.0526	1489.0772	-0.3593	-1.2796	0.5419	0.4629	0.0500	0.2192
									SA							
0.001	Average	15	27.43	5.6802	48.9780	11.0176	-12.9006	-34.4475	8.8503	11.0176	-0.4703	-1.2558	0.3226	0.4016	0.0500	0.1239
	Cumulative	450	850.36	176.0851	1518.3176	341.5464	-399.9182	-1067.8731	274.3595	341.5464	-0.4703	-1.2558	0.3226	0.4016	0.0500	0.1239
0.01	Average	15	30.88	6.3995	55.4715	12.5486	-16.3445	-40.9410	8.1310	12.5486	-0.5294	-1.3260	0.2634	0.4064	0.0500	0.0974
	Cumulative	450	957.13	198.3841	1719.6163	389.0069	-506.6810	-1269.1718	252.0604	389.0069	-0.5294	-1.3260	0.2634	0.4064	0.0500	0.0974
0.02	Average	15	26.02	-2.6367	54.9183	14.8120	-11.4928	-40.3879	17.1671	14.8120	-0.4416	-1.5520	0.6597	0.5692	0.0500	0.2197
	Cumulative	450	806.72	-81.7362	1702.4685	459.1716	-356.2782	-1252.0240	532.1807	459.1716	-0.4416	-1.5520	0.6597	0.5692	0.0500	0.2197
0.03	Average	15	22.84	-10.4731	56.6259	17.1897	-8.3070	-42.0954	25.0035	17.1897	-0.3637	-1.8433	1.0948	0.7527	0.0500	0.3144
	Cumulative	450	707.96	-324.6648	1755.4029	532.8795	-257.5177	-1304.9584	775.1094	532.8795	-0.3637	-1.8433	1.0948	0.7527	0.0500	0.3144
0.04	Average	15	21.27	-17.5218	59.5348	19.6647	-6.7406	-45.0044	32.0523	19.6647	-0.3169	-2.1158	1.5068	0.9245	0.0500	0.3639
	Cumulative	450	659.40	-543.1769	1845.5801	609.6068	-208.9591	-1395.1356	993.6214	609.6068	-0.3169	-2.1158	1.5068	0.9245	0.0500	0.3639
0.05	Average	15	20.54	-22.4517	63.6318	22.0290	-6.0132	-49.1014	36.9822	22.0290	-0.2927	-2.3901	1.8002	1.0723	0.0500	0.3914
	Cumulative	450	636.85	-696.0037	1972.5866	682.8988	-186.4094	-1522.1421	1146.4482	682.8988	-0.2927	-2.3901	1.8002	1.0723	0.0500	0.3914
0.06	Average	15	20.23	-27.0024	68.2470	24.3202	-5.7045	-53.7166	41.5328	24.3202	-0.2819	-2.6546	2.0525	1.2019	0.0500	0.4073
	Cumulative	450	627.28	-837.0737	2115.6581	753.9257	-176.8389	-1665.2136	1287.5183	753.9257	-0.2819	-2.6546	2.0525	1.2019	0.0500	0.4073
0.07	Average	15	20.29	-31.6579	73.1033	26.6170	-5.7567	-58.5728	46.1884	26.6170	-0.2838	-2.8872	2.2767	1.3120	0.0500	0.4136
	Cumulative	450	628.90	-981.3956	2266.2016	825.1282	-178.4581	-1815.7571	1431.8401	825.1282	-0.2838	-2.8872	2.2767	1.3120	0.0500	0.4136
0.08	Average	15	20.40	-35.5766	77.3708	28.8734	-5.8729	-62.8404	50.1071	28.8734	-0.2878	-3.0799	2.4558	1.4151	0.0500	0.4186
	Cumulative	450	632.50	-1102.8745	2398.4962	895.0739	-182.0603	-1948.0517	1553.3191	895.0739	-0.2878	-3.0799	2.4558	1.4151	0.0500	0.4186
0.09	Average	15	20.59	-39.8312	81.8486	30.9221	-6.0605	-67.3182	54.3617	30.9221	-0.2943	-3.2693	2.6401	1.5017	0.0500	0.4217
	Cumulative	450	638.32	-1234.7686	2537.3075	958.5849	-187.8765	-2086.8629	1685.2132	958.5849	-0.2943	-3.2693	2.6401	1.5017	0.0500	0.4217
0.10	Average	15	20.84	-43.6760	86.4702	33.2684	-6.3116	-71.9398	58.2065	33.2684	-0.3028	-3.4517	2.7927	1.5962	0.0500	0.4257
	Cumulative	450	646.11	-1353.9561	2680.5775	1031.3200	-195.6611	-2230.1330	1804.4007	1031.3200	-0.3028	-3.4517	2.7927	1.5962	0.0500	0.4257
									TAS							
0.001	Average	9	34.61	20.7410	106.4042	21.3778	-25.2302	-97.0236	-11.3605	21.3778	-0.7290	-2.8033	-0.3282	0.6177	0.0500	0.0015
	Cumulative	291	1072.93	642.9725	3298.5309	662.7111	-782.1351	-3007.7325	-352.1740	662.7111	-0.7290	-2.8033	-0.3282	0.6177	0.0500	0.0015
0.01	Average	9	24.02	13.4421	61.4074	11.9139	-14.6391	-52.0268	-4.0615	11.9139	-0.6095	-2.1660	-0.1691	0.4960	0.0500	0.0047
	Cumulative	291	744.61	416.7051	1903.6294	369.3306	-453.8117	-1612.8310	-125.9066	369.3306	-0.6095	-2.1660	-0.1691	0.4960	0.0500	0.0047
0.02	Average	9	21.09	-4.3801	67.5378	16.7758	-11.7115	-58.1573	13.7607	16.7758	-0.5553	-2.7573	0.6524	0.7954	0.0500	0.1828
	Cumulative	291	653.86	-135.7837	2093.6733	520.0498	-363.0572	-1802.8749	426.5822	520.0498	-0.5553	-2.7573	0.6524	0.7954	0.0500	0.1828
0.03	Average	9	22.40	-10.3565	66.8451	18.8240	-13.0202	-57.4645	19.7371	18.8240	-0.5812	-2.5653	0.8811	0.8403	0.0500	0.2262
	Cumulative	291	694.43	-321.0516	2072.1987	583.5432	-403.6268	-1781.4002	611.8501	583.5432	-0.5812	-2.5653	0.8811	0.8403	0.0500	0.2262
0.04	Average	9	21.30	-11.8869	61.0799	18.3640	-11.9206	-51.6993	21.2675	18.3640	-0.5596	-2.4271	0.9984	0.8621	0.0500	0.2482
	Cumulative	291	660.34	-368.4944	1893.4781	569.2834	-369.5400	-1602.6797	659.2928	569.2834	-0.5596	-2.4271	0.9984	0.8621	0.0500	0.2482
0.05	Average	9	21.74	-11.5364	62.7384	18.5236	-12.3549	-53.3579	20.9170	18.5236	-0.5684	-2.4549	0.9623	0.8522	0.0500	0.2415
	Cumulative	291	673.80	-357.6284	1944.8919	574.2309	-383.0028	-1654.0934	648.4268	574.2309	-0.5684	-2.4549	0.9623	0.8522	0.0500	0.2415
0.06	Average	9	21.19	-14.4857	61.4909	19.3354	-11.8047	-52.1103	23.8663	19.3354	-0.5572	-2.4597	1.1266	0.9127	0.0500	0.2661
	Cumulative	291	656.74	-449.0578	1906.2186	599.3975	-365.9449	-1615.4201	739.8563	599.3975	-0.5572	-2.4597	1.1266	0.9127	0.0500	0.2661
0.07	Average	9	20.91	-14.8933	60.5359	19.4015	-11.5343	-51.1553	24.2739	19.4015	-0.5515	-2.4459	1.1606	0.9276	0.0500	0.2772
	Cumulative	291	648.36	-461.6926	1876.6139	601.4452	-357.5633	-1585.8155	752.4911	601.4452	-0.5515	-2.4459	1.1606	0.9276	0.0500	0.2772
0.08	Average	9	21.94	-14.7064	63.7817	20.0046	-12.5610	-54.4011	24.0870	20.0046	-0.5725	-2.4794	1.0978	0.9117	0.0500	0.2623
	Cumulative	291	680.19	-455.8973	1977.2315	620.1413	-389.3907	-1686.4330	746.6957	620.1413	-0.5725	-2.4794	1.0978	0.9117	0.0500	0.2623
0.09	Average	9	22.65	-15.2703	66.8762	20.6126	-13.2676	-57.4956	24.6509	20.6126	-0.5858	-2.5386	1.0884	0.9101	0.0500	0.2550
	Cumulative	291	702.09	-473.3805	2073.1624	638.9911	-411.2955	-1782.3639	764.1790	638.9911	-0.5858	-2.5386	1.0884	0.9101	0.0500	0.2550
0.10	Average	9	22.51	-15.4101	64.4528	20.4297	-13.1332	-55.0722	24.7907	20.4297	-0.5833	-2.4462	1.1011	0.9074	0.0500	0.2530
	Cumulative	291	697.93	-477.7139	1998.0361	633.3216	-407.1293	-1707.2376	768.5124	633.3216	-0.5833	-2.4462	1.1011	0.9074	0.0500	0.2530
									VIC							
0.001	Average	18	31.46	21.6758	41.4435	4.9923	-13.0063	-22.9910	-3.2233	4.9923	-0.4134	-0.7308	-0.1025	0.1587	0.0500	0.0041
	Cumulative	572	975.22	671.9488	1284.7481	154.7604	-403.1967	-712.7212	-99.9218	154.7604	-0.4134	-0.7308	-0.1025	0.1587	0.0500	0.0041
0.01	Average	18	27.15	15.7129	38.6500	5.8402	-8.6997	-20.1976	2.7396	5.8402	-0.3204	-0.7439	0.1009	0.2151	0.0500	0.0701
	Cumulative	572	841.72	487.0993	1198.1515	181.0457	-269.6915	-626.1245	84.9276	181.0457	-0.3204	-0.7439	0.1009	0.2151	0.0500	0.0701
0.02	Average	18	25.51	11.0944	40.0503	7.3329	-7.0543	-21.5978	7.3581	7.3329	-0.2766	-0.8467	0.2885	0.2875	0.0500	0.1633
	Cumulative	572	790.71	343.9255	1241.5582	227.3191	-218.6839	-669.5313	228.1015	227.3191	-0.2766	-0.8467	0.2885	0.2875	0.0500	0.1633
0.03	Average	18	24.83	6.9880	42.3746	8.9134	-6.3766	-23.9221	11.4645	8.9134	-0.2568	-0.9635	0.4617	0.3590	0.0500	0.2337
	Cumulative	572	769.70	216.6282	1313.6120	276.3168	-197.6752	-741.5851	355.3987	276.3168	-0.2568	-0.9635	0.4617	0.3590	0.0500	0.2337
0.04	Average	18	24.22	3.4731	44.5419	10.4752	-5.7659	-26.0894	14.9794	10.4752	-0.2381	-1.0773	0.6185	0.4325	0.0500	0.2925
	Cumulative	572	750.77	107.6663	1380.7974	324.7317	-178.7435	-808.7705	464.3606	324.7317	-0.2381	-1.0773	0.6185	0.4325	0.0500	0.2925
0.05	Average	18	23.85	0.3351	47.5016	12.0096	-5.3990	-29.0491	18.1174	12.0096	-0.2264	-1.2179	0.7596	0.5035	0.0500	0.3252
	Cumulative	572	739.40	10.3868	1472.5495	372.2991	-167.3689	-900.5226	561.6402	372.2991	-0.2264	-1.2179	0.7596	0.5035	0.0500	0.3252
0.06	Average	18	23.53	-3.0371	50.3272	13.4321	-5.0785	-31.8747	21.4896	13.4321	-0.2158	-1.3546	0.9132	0.5708	0.0500	0.3520
	Cumulative	572	729.46	-94.1513	1560.1425	416.3958	-157.4338	-988.1156	666.1783	416.3958	-0.2158	-1.3546	0.9132	0.5708	0.0500	0.3520
0.07	Average	18	23.15	-5.8488	52.3348	14.7040	-4.6928	-33.8824	24.3013	14.7040	-0.2028	-1.4639	1.0499	0.6353	0.0500	0.3740
	Cumulative	572	717.50	-181.3127	1622.3800	455.8250	-145.4764	-1050.3531	753.3396	455.8250	-0.2028	-1.4639	1.0499	0.6353	0.0500	0.3740
0.08	Average	18	23.16	-8.0265	55.0028	16.0166	-4.7111	-36.5503	26.4790	16.0166	-0.2034	-1.5779	1.1431	0.6915	0.0500	0.3873
	Cumulative	572	718.07	-248.8213	1705.0860	496.5133	-146.0448	-1133.0591	820.8482	496.5133	-0.2034	-1.5779	1.1431	0.6915	0.0500	0.3873
0.09	Average	18	23.00	-10.6763	57.1848	17.2677	-4.5516	-38.7323	29.1288	17.2677	-0.1979	-1.6837	1.2662	0.7506	0.0500	0.3978
	Cumulative	572	713.13	-330.9657	1772.7278	535.3002	-141.1008	-1200.7009	902.9927	535.3002	-0.1979	-1.6837	1.2662	0.7506	0.0500	0.3978
0.10	Average	18	23.19	-13.5822	59.8783	18.7041	-4.7354	-41.4258	32.0347	18.7041	-0.2042	-1.7865	1.3815	0.8066	0.0500	0.4036
	Cumulative	572	718.83	-421.0491	1856.2266	579.8264	-146.7983	-1284.1997	993.0760	579.8264	-0.2042	-1.7865	1.3815	0.8066	0.0500	0.4036

Table C.12 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 on equally daily weighted averaged spot price equally daily weighted averaged spot price with 95% confidence intervals for the different assumptions of prior standard deviation and without seasonality component.**

Prior sd		Actual	Pred	Pred Lo	Pred Up	Pred sd	Abs Effect	Abs Effect Lo	Abs Effect Up	Abs Effect sd	Rel Effect	Rel Effect Lo	Rel Effect.Up	Rel Effect.sd	alpha	p
NSW																
0.001	Average	57	74.07	53.8321	94.4423	10.2929	-16.9596	-37.3270	3.2832	10.2929	-0.2290	-0.5039	0.0443	0.1390	0.0500	0.0503
	Cumulative	1771	2296.32	1668.7939	2927.7105	319.0790	-525.7483	-1157.1372	101.7794	319.0790	-0.2290	-0.5039	0.0443	0.1390	0.0500	0.0503
0.01	Average	57	72.05	46.9418	96.1402	12.5049	-14.9304	-39.0249	10.1734	12.5049	-0.2072	-0.5417	0.1412	0.1736	0.0500	0.1133
	Cumulative	1771	2233.42	1455.1967	2980.3459	387.6529	-462.8429	-1209.7726	315.3765	387.6529	-0.2072	-0.5417	0.1412	0.1736	0.0500	0.1133
0.02	Average	57	70.08	41.1999	98.2517	14.6174	-12.9691	-41.1364	15.9153	14.6174	-0.1850	-0.5870	0.2271	0.2086	0.0500	0.1856
	Cumulative	1771	2172.61	1277.1980	3045.8013	453.1382	-402.0411	-1275.2280	493.3752	453.1382	-0.1850	-0.5870	0.2271	0.2086	0.0500	0.1856
0.03	Average	57	69.42	36.5489	101.9749	16.7662	-12.3097	-44.8596	20.5663	16.7662	-0.1773	-0.6462	0.2962	0.2415	0.0500	0.2292
	Cumulative	1771	2152.17	1133.0174	3161.2208	519.7535	-381.5995	-1390.6475	637.5559	519.7535	-0.1773	-0.6462	0.2962	0.2415	0.0500	0.2292
0.04	Average	57	70.42	32.0538	108.2397	19.5630	-13.3035	-51.1244	25.0615	19.5630	-0.1889	-0.7260	0.3559	0.2778	0.0500	0.2433
	Cumulative	1771	2182.98	993.6679	3355.4292	606.4533	-412.4095	-1584.8560	776.9053	606.4533	-0.1889	-0.7260	0.3559	0.2778	0.0500	0.2433
0.05	Average	57	71.82	28.4654	113.9812	21.8508	-14.7097	-56.8660	28.6498	21.8508	-0.2048	-0.7917	0.3989	0.3042	0.0500	0.2503
	Cumulative	1771	2226.57	882.4287	3533.4178	677.3755	-455.9996	-1762.8445	888.1446	677.3755	-0.2048	-0.7917	0.3989	0.3042	0.0500	0.2503
0.06	Average	57	73.07	25.8417	119.3398	23.8362	-15.9568	-62.2245	31.2736	23.8362	-0.2184	-0.8515	0.4280	0.3262	0.0500	0.2460
	Cumulative	1771	2265.23	801.0921	3699.5324	738.9222	-494.6601	-1928.9592	969.4811	738.9222	-0.2184	-0.8515	0.4280	0.3262	0.0500	0.2460
0.07	Average	57	73.90	21.9025	124.3902	26.1831	-16.7873	-67.2749	35.2128	26.1831	-0.2272	-0.9103	0.4765	0.3543	0.0500	0.2597
	Cumulative	1771	2290.98	678.9777	3856.0947	811.6754	-520.4078	-2085.5214	1091.5956	811.6754	-0.2272	-0.9103	0.4765	0.3543	0.0500	0.2597
0.08	Average	57	74.82	18.8313	129.9751	28.1831	-17.7009	-72.8599	38.2840	28.1831	-0.2366	-0.9739	0.5117	0.3767	0.0500	0.2635
	Cumulative	1771	2319.30	583.7700	4029.2295	873.6750	-548.7294	-2258.6562	1186.8032	873.6750	-0.2366	-0.9739	0.5117	0.3767	0.0500	0.2635
0.09	Average	57	75.15	15.6546	134.2514	30.0968	-18.0365	-77.1361	41.4607	30.0968	-0.2400	-1.0264	0.5517	0.4005	0.0500	0.2720
	Cumulative	1771	2329.70	485.2912	4161.7936	932.9998	-559.1313	-2391.2203	1285.2820	932.9998	-0.2400	-1.0264	0.5517	0.4005	0.0500	0.2720
0.10	Average	57	75.40	11.7443	137.5323	32.1625	-18.2859	-80.4171	45.3710	32.1625	-0.2425	-1.0665	0.6017	0.4266	0.0500	0.2843
	Cumulative	1771	2337.43	364.0726	4263.5022	997.0383	-566.8616	-2492.9290	1406.5006	997.0383	-0.2425	-1.0665	0.6017	0.4266	0.0500	0.2843
QLD																
0.001	Average	66	98.32	64.5059	131.8304	17.1144	-31.8420	-65.3530	1.9715	17.1144	-0.3239	-0.6647	0.0201	0.1741	0.0500	0.0331
	Cumulative	2061	3047.90	1999.6831	4086.7429	530.5450	-987.1018	-2025.9427	61.1171	530.5450	-0.3239	-0.6647	0.0201	0.1741	0.0500	0.0331
0.01	Average	66	102.53	64.1902	141.8657	19.7717	-36.0553	-75.3883	2.2872	19.7717	-0.3516	-0.7353	0.0223	0.1928	0.0500	0.0334
	Cumulative	2061	3178.51	1989.8977	4397.8377	612.9223	-1117.7147	-2337.0376	70.9025	612.9223	-0.3516	-0.7353	0.0223	0.1928	0.0500	0.0334
0.02	Average	66	102.88	57.3529	148.6894	22.8991	-36.3995	-82.2119	9.1245	22.8991	-0.3538	-0.7991	0.0887	0.2226	0.0500	0.0567
	Cumulative	2061	3189.19	1777.9397	4609.3699	709.8715	-1128.3859	-2548.5697	282.8604	709.8715	-0.3538	-0.7991	0.0887	0.2226	0.0500	0.0567
0.03	Average	66	102.84	51.3529	153.5341	26.1348	-36.3661	-87.0567	15.1245	26.1348	-0.3536	-0.8465	0.1471	0.2541	0.0500	0.0846
	Cumulative	2061	3188.15	1591.9413	4759.5583	810.1774	-1127.3492	-2698.7581	468.8588	810.1774	-0.3536	-0.8465	0.1471	0.2541	0.0500	0.0846
0.04	Average	66	102.81	45.1562	159.6737	29.3729	-36.3295	-93.1963	21.3213	29.3729	-0.3534	-0.9065	0.2074	0.2857	0.0500	0.1096
	Cumulative	2061	3187.01	1399.8412	4949.8862	910.5612	-1126.2131	-2889.0860	660.9590	910.5612	-0.3534	-0.9065	0.2074	0.2857	0.0500	0.1096
0.05	Average	66	102.90	38.6990	166.5437	32.8404	-36.4210	-100.0663	27.7784	32.8404	-0.3540	-0.9725	0.2700	0.3192	0.0500	0.1338
	Cumulative	2061	3189.85	1199.6691	5162.8559	1018.0516	-1129.0517	-3102.0557	861.1310	1018.0516	-0.3540	-0.9725	0.2700	0.3192	0.0500	0.1338
0.06	Average	66	103.06	33.2755	172.8589	35.6773	-36.5874	-106.3814	33.2019	35.6773	-0.3550	-1.0322	0.3221	0.3462	0.0500	0.1529
	Cumulative	2061	3195.01	1031.5419	5358.6244	1105.9952	-1134.2106	-3297.8242	1029.2583	1105.9952	-0.3550	-1.0322	0.3221	0.3462	0.0500	0.1529
0.07	Average	66	103.12	26.1617	177.8702	38.5801	-36.6396	-111.3928	40.3157	38.5801	-0.3553	-1.0803	0.3910	0.3741	0.0500	0.1672
	Cumulative	2061	3196.63	811.0129	5513.9757	1195.9842	-1135.8277	-3453.1755	1249.7872	1195.9842	-0.3553	-1.0803	0.3910	0.3741	0.0500	0.1672
0.08	Average	66	103.10	20.3135	183.6693	41.5271	-36.6181	-117.1919	46.1639	41.5271	-0.3552	-1.1367	0.4478	0.4028	0.0500	0.1850
	Cumulative	2061	3195.96	629.7194	5693.7494	1287.3405	-1135.1613	-3632.9492	1431.0807	1287.3405	-0.3552	-1.1367	0.4478	0.4028	0.0500	0.1850
0.09	Average	66	103.46	14.7954	188.4132	44.4508	-36.9823	-121.9358	51.6821	44.4508	-0.3575	-1.1786	0.4995	0.4296	0.0500	0.1985
	Cumulative	2061	3207.25	458.6563	5840.8105	1377.9753	-1146.4515	-3780.0103	1602.1438	1377.9753	-0.3575	-1.1786	0.4995	0.4296	0.0500	0.1985
0.10	Average	66	103.38	8.7120	197.1274	47.6081	-36.9063	-130.6500	57.7654	47.6081	-0.3570	-1.2637	0.5587	0.4605	0.0500	0.2176
	Cumulative	2061	3204.90	270.0732	6110.9509	1475.8517	-1144.0964	-4050.1508	1790.7270	1475.8517	-0.3570	-1.2637	0.5587	0.4605	0.0500	0.2176
SA																
0.001	Average	15	26.38	4.1773	48.3561	11.2494	-11.8529	-33.8256	10.3532	11.2494	-0.4493	-1.2821	0.3924	0.4264	0.0500	0.1477
	Cumulative	450	817.88	129.4962	1499.0391	348.7316	-367.4385	-1048.5946	320.9484	348.7316	-0.4493	-1.2821	0.3924	0.4264	0.0500	0.1477
0.01	Average	15	30.45	5.6194	55.2608	12.5966	-15.9182	-40.7303	8.9111	12.5966	-0.5228	-1.3377	0.2927	0.4137	0.0500	0.1043
	Cumulative	450	943.91	174.2004	1713.0850	390.4933	-493.4647	-1262.6405	276.2441	390.4933	-0.5228	-1.3377	0.2927	0.4137	0.0500	0.1043
0.02	Average	15	25.66	-3.2882	54.7581	14.8519	-11.1266	-40.2277	17.8186	14.8519	-0.4337	-1.5679	0.6945	0.5789	0.0500	0.2281
	Cumulative	450	795.37	-101.9336	1697.5025	460.4081	-344.9238	-1247.0579	552.3781	460.4081	-0.4337	-1.5679	0.6945	0.5789	0.0500	0.2281
0.03	Average	15	22.41	-11.0960	56.4523	17.2173	-7.8759	-41.9218	25.6265	17.2173	-0.3515	-1.8710	1.1437	0.7684	0.0500	0.3232
	Cumulative	450	694.60	-343.9755	1750.0200	533.7359	-244.1542	-1299.5755	794.4200	533.7359	-0.3515	-1.8710	1.1437	0.7684	0.0500	0.3232
0.04	Average	15	20.75	-17.3099	58.6290	19.4543	-6.2226	-44.0985	31.8404	19.4543	-0.2998	-2.1249	1.5342	0.9374	0.0500	0.3769
	Cumulative	450	643.35	-536.6081	1817.4991	603.0829	-192.9018	-1367.0546	987.0526	603.0829	-0.2998	-2.1249	1.5342	0.9374	0.0500	0.3769
0.05	Average	15	19.91	-22.6562	62.0620	21.7589	-5.3837	-47.5315	37.1866	21.7589	-0.2703	-2.3868	1.8673	1.0926	0.0500	0.4013
	Cumulative	450	617.34	-702.3407	1923.9209	674.5244	-166.8934	-1473.4764	1152.7852	674.5244	-0.2703	-2.3868	1.8673	1.0926	0.0500	0.4013
0.06	Average	15	19.61	-27.4116	66.6319	24.0311	-5.0770	-52.1014	41.9421	24.0311	-0.2589	-2.6572	2.1391	1.2256	0.0500	0.4148
	Cumulative	450	607.83	-849.7590	2065.5894	744.9633	-157.3860	-1615.1449	1300.2036	744.9633	-0.2589	-2.6572	2.1391	1.2256	0.0500	0.4148
0.07	Average	15	19.54	-32.0743	70.8701	26.2641	-5.0092	-56.3397	46.6048	26.2641	-0.2564	-2.8834	2.3851	1.3441	0.0500	0.4247
	Cumulative	450	605.73	-994.3047	2196.9746	814.1886	-155.2840	-1746.5300	1444.7493	814.1886	-0.2564	-2.8834	2.3851	1.3441	0.0500	0.4247
0.08	Average	15	19.61	-36.0089	75.4690	28.4741	-5.0823	-60.9385	50.5394	28.4741	-0.2591	-3.1071	2.5769	1.4518	0.0500	0.4261
	Cumulative	450	607.99	-1116.2755	2339.5377	882.6985	-157.5502	-1889.0932	1566.7200	882.6985	-0.2591	-3.1071	2.5769	1.4518	0.0500	0.4261
0.09	Average	15	19.80	-40.3258	80.2036	30.6510	-5.2672	-65.6731	54.8562	30.6510	-0.2661	-3.3172	2.7708	1.5482	0.0500	0.4285
	Cumulative	450	613.73	-1250.0988	2486.3120	950.1800	-163.2824	-2035.8675	1700.5433	950.1800	-0.2661	-3.3172	2.7708	1.5482	0.0500	0.4285
0.1	Average	15	19.99	-44.6006	84.2502	32.7834	-5.4566	-69.7197	59.1310	32.7834	-0.2730	-3.4882	2.9585	1.6402	0.0500	0.4296
	Cumulative	450	619.60	-1382.6177	2611.7567	1016.2861	-169.1542	-2161.3122	1833.0622	1016.2861	-0.2730	-3.4882	2.9585	1.6402	0.0500	0.4296
TAS																
0.001	Average	9	32.01	20.4845	91.6812	16.8989	-22.6302	-82.3006	-11.1039	16.8989	-0.7070	-2.5710	-0.3469	0.5279	0.0500	0.0019
	Cumulative	291	992.33	635.0185	2842.1165	523.8652	-701.5349	-2551.3180	-344.2200	523.8652	-0.7070	-2.5710	-0.3469	0.5279	0.0500	0.0019
0.01	Average	9	22.84	13.2261	43.6128	8.8467	-13.4592	-34.2322	-3.8455	8.8467	-0.5893	-1.4988	-0.1684	0.3873	0.0500	0.0045
	Cumulative	291	708.03	410.0104	1351.9969	274.2483	-417.2349	-1061.1985	-119.2120	274.2483	-0.5893	-1.4988	-0.1684	0.3873	0.0500	0.0045
0.02	Average	9	19.14	-2.6959	50.5316	13.1205	-9.7641	-41.1510	12.0765	13.1205	-0.5100	-2.1495	0.6308	0.6853	0.0500	0.1839
	Cumulative	291	593.49	-83.5733	1566.4803	406.7346	-302.6876	-1275.6818	374.3718	406.7346	-0.5100	-2.1495	0.6308	0.6853	0.0500	0.1839
0.03	Average	9	20.04	-10.0784	56.9105	16.6672	-10.6625	-47.5299	19.4590	16.6672	-0.5320	-2.3714	0.9709	0.8316	0.0500	0.2419
	Cumulative	291	621.34	-312.4315	1764.2254	516.6838	-330.5384	-1473.4269	603.2300	516.6838	-0.5320	-2.3714	0.9709	0.8316	0.0500	0.2419
0.04	Average	9	20.30	-9.4094	55.7282	16.1021	-10.9172	-46.3476	18.7900	16.1021	-0.5379	-2.2834	0.9257	0.7933	0.0500	0.2333
	Cumulative	291	629.23	-291.6908	1727.5733	499.1637	-338.4341	-1436.7748	582.4892	499.1637	-0.5379	-2.2834	0.9257	0.7933	0.0500	0.2333
0.05	Average	9	20.31	-9.6627	54.9008	16.2555	-10.9279	-45.5202	19.0433	16.2555	-0.5381	-2.2414	0.9377	0.8004	0.0500	0.2344
	Cumulative	291	629.56	-299.5442	1701.9240	503.9194	-338.7637	-1411.1255	590.3427	503.9194	-0.5381	-2.2414	0.9377	0.8004	0.0500	0.2344
0.06	Average	9	20.81	-12.0577	58.0650	17.5187	-11.4326	-48.6844	21.4383	17.5187	-0.5493	-2.3391	1.0300	0.8417	0.0500	0.2466
	Cumulative	291	645.21	-373.7890	1800.0149	543.0807	-354.4093	-1509.2164	664.5874	543.0807	-0.5493	-2.3391	1.0300	0.8417	0.0500	0.2466
0.07	Average	9	20.37	-15.7517	59.0002	18.7928	-10.9851	-49.6196	25.1323	18.7928	-0.5394	-2.4364	1.2340	0.9228	0.0500	0.2703
	Cumulative	291	631.34	-488.3013	1829.0069	582.5777	-340.5383	-1538.2084	779.0998	582.5777	-0.5394	-2.4364	1.2340	0.9228	0.0500	0.2703
0.08	Average	9	20.59	-15.9371	59.1579	19.0650	-11.2144	-49.7773	25.3177	19.0650	-0.5445	-2.4170	1.2293	0.9257	0.0500	0.2719
	Cumulative	291	638.44	-494.0493	1833.8938	591.0141	-347.6465	-1543.0953	784.8478	591.0141	-0.5445	-2.4170	1.2293	0.9257	0.0500	0.2719
0.09	Average	9	20.52	-16.5321	60.7739	19.4560	-11.1369	-51.3933	25.9127	19.4560	-0.5428	-2.5048	1.2630	0.9483	0.0500	0.2775
	Cumulative	291	636.04	-512.4952	1883.9908	603.1365	-345.2454	-1593.1923	803.2937	603.1365	-0.5428	-2.5048	1.2630	0.9483	0.0500	0.2775
0.1	Average	9	20.64	-16.6765	61.2302	19.6241	-11.2620	-51.8496	26.0571	19.6241	-0.5456	-2.5118	1.2623	0.9507	0.0500	0.2775
	Cumulative	291	639.92	-516.9712	1898.1349	608.3480	-349.1227	-1607.3364	807.7697	608.3480	-0.5456	-2.5118	1.2623	0.9507	0.0500	0.2775
VIC																
0.001	Average	18	31.33	22.0508	40.7144	4.7524	-12.8743	-22.2620	-3.5983	4.7524	-0.4110	-0.7106	-0.1149	0.1517	0.0500	0.0029
	Cumulative	572	971.13	683.5746	1262.1475	147.3242	-399.1035	-690.1205	-111.5476	147.3242	-0.4110	-0.7106	-0.1149	0.1517	0.0500	0.0029
0.01	Average	18	27.29	15.7493	38.8299	5.8734	-8.8371	-20.3775	2.7032	5.8734	-0.3238	-0.7467	0.0991	0.2152	0.0500	0.0649
	Cumulative	572	845.98	488.2290	1203.7284	182.0746	-273.9491	-631.7015	83.7979	182.0746	-0.3238	-0.7467	0.0991	0.2152	0.0500	0.0649
0.02	Average	18	25.37	11.2138	39.6393	7.2787	-6.9201	-21.1868	7.2387	7.2787	-0.2727	-0.8350	0.2853	0.2869	0.0500	0.1717
	Cumulative	572	786.55	347.6267	1228.8181	225.6409	-214.5231	-656.7912	224.4003	225.6409	-0.2727	-0.8350	0.2853	0.2869	0.0500	0.1717
0.03	Average	18	24.76	7.3213	42.1969	8.8362	-6.3047	-23.7444	11.1312	8.8362	-0.2547	-0.9591	0.4496	0.3569	0.0500	0.2342
	Cumulative	572	767.47	226.9601	1308.1027	273.9213	-195.4451	-736.0758	345.0668	273.9213	-0.2547	-0.9591	0.4496	0.3569	0.0500	0.2342
0.04	Average	18	24.20	3.5673	44.2599	10.3202	-5.7493	-25.8074	14.8852	10.3202	-0.2376	-1.0663	0.6150	0.4264	0.0500	0.2837
	Cumulative	572	750.26	110.5851	1372.0559	319.9276	-178.2284	-800.0289	461.4418	319.9276	-0.2376	-1.0663	0.6150	0.4264	0.0500	0.2837
0.05	Average	18	23.74	0.3406	46.5184	11.7807	-5.2922	-28.0659	18.1119	11.7807	-0.2229	-1.1820	0.7628	0.4961	0.0500	0.3258
	Cumulative	572	736.09	10.5586	1442.0709	365.2030	-164.0593	-870.0440	561.4684	365.2030	-0.2229	-1.1820	0.7628	0.4961	0.0500	0.3258
0.06	Average	18	23.57	-2.4662	48.9095	13.0860	-5.1177	-30.4570	20.9187	13.0860	-0.2171	-1.2922	0.8875	0.5552	0.0500	0.3429
	Cumulative	572	730.68	-76.4519	1516.1940	405.6660	-158.6483	-944.1671	648.4788	405.6660	-0.2171	-1.2922	0.8875	0.5552	0.0500	0.3429
0.07	Average	18	23.42	-5.0458	51.4716	14.4272	-4.9673	-33.0191	23.4983	14.4272	-0.2121	-1.4099	1.0034	0.6160	0.0500	0.3652
	Cumulative	572	726.01	-156.4208	1595.6186	447.2442	-153.9876	-1023.5917	728.4477	447.2442	-0.2121	-1.4099	1.0034	0.6160	0.0500	0.3652
0.08	Average	18	23.37	-7.7795	54.0840	15.6982	-4.9142	-35.6316	26.2320	15.6982	-0.2103	-1.5249	1.1226	0.6718	0.0500	0.3757
	Cumulative	572	724.37	-241.1637	1676.6055	486.6451	-152.3416	-1104.5785	813.1906	486.6451	-0.2103	-1.5249	1.1226	0.6718	0.0500	0.3757
0.09	Average	18	23.29	-10.4206	55.9534	16.9061	-4.8422	-37.5010	28.8731	16.9061	-0.2079	-1.6098	1.2395	0.7257	0.0500	0.3843
	Cumulative	572	722.14	-323.0379	1734.5568	524.0893	-150.1094	-1162.5299	895.0649	524.0893	-0.2079	-1.6098	1.2395	0.7257	0.0500	0.3843
0.1	Average	18	23.42	-13.0062	58.8294	18.1792	-4.9687	-40.3769	31.4587	18.1792	-0.2121	-1.7239	1.3432	0.7762	0.0500	0.3891
	Cumulative	572	726.06	-403.1920	1823.7114	563.5567	-154.0307	-1251.6845	975.2189	563.5567	-0.2121	-1.7239	1.3432	0.7762	0.0500	0.3891

C.3 Model Results

C.3.1 Spot price dynamics

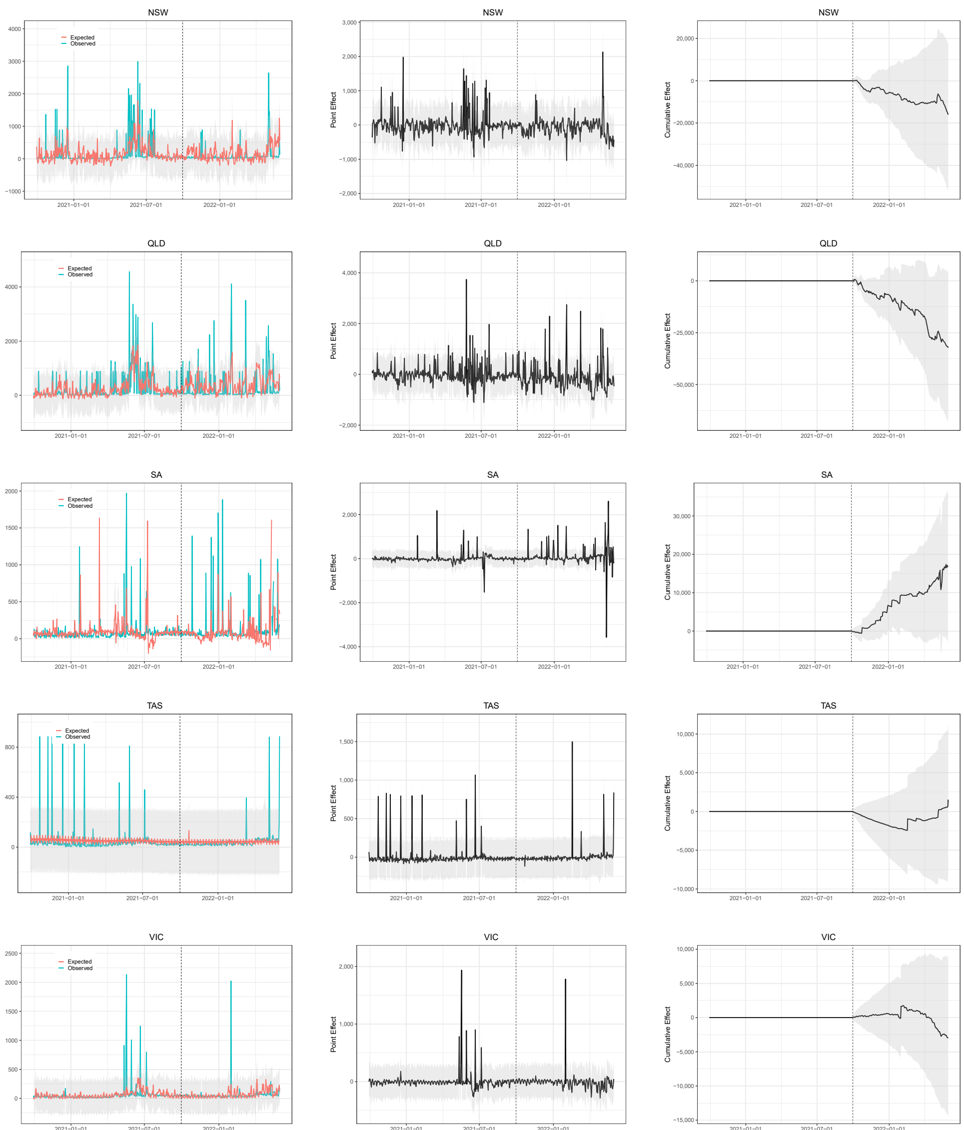

Figure C.17 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on equally daily weighted averaged spot price volatility (σ_d) with 95% confidence intervals.** The observation period run from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

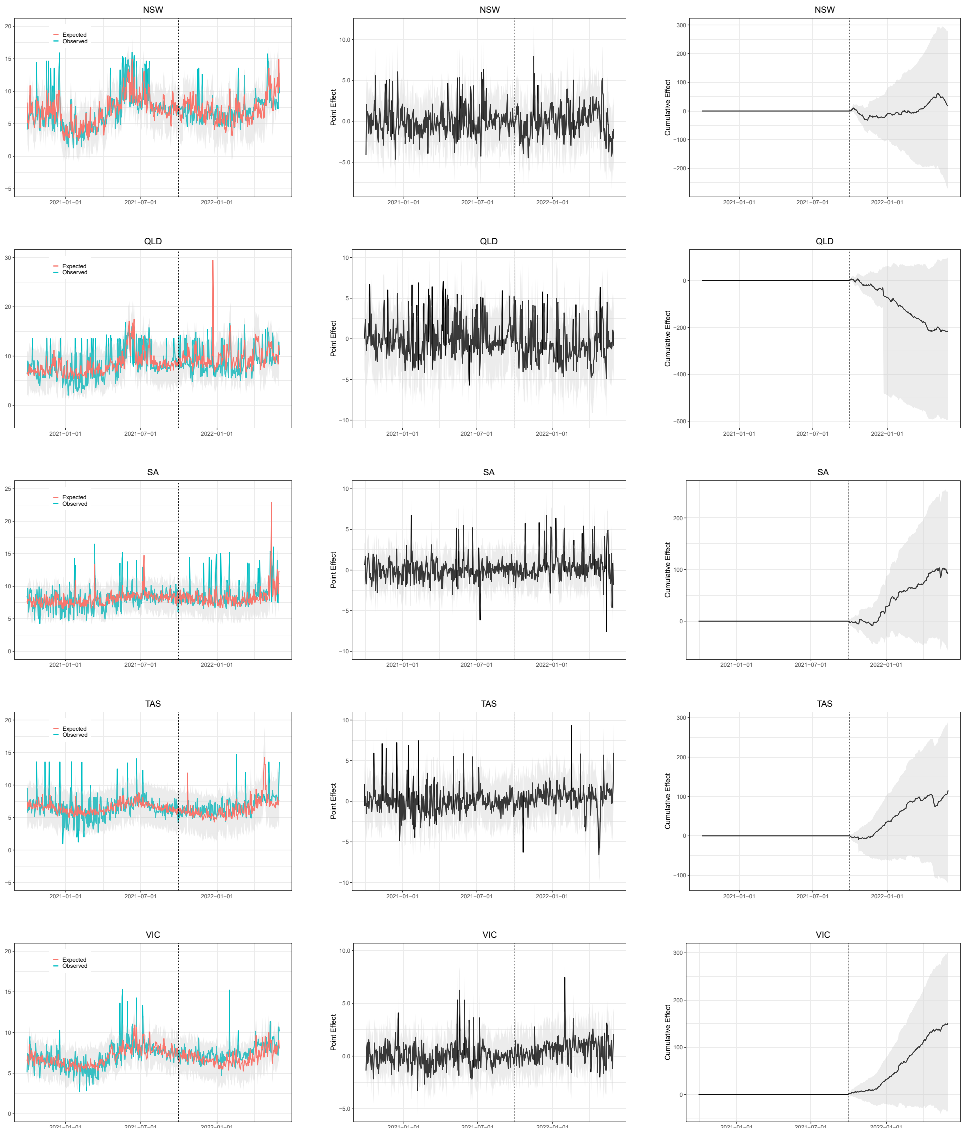

Figure C.18 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on equally daily weighted averaged spot price volatility** ($\log(\sigma_d^2)$) **with 95% confidence intervals.** The observation period run from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

Table C.13 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 on equally daily weighted averaged spot price equally daily weighted averaged spot price volatility ($\log(\sigma_d^2)$) with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative	Average	Cumulative
Actual	7.3	1762.8	9	2186	8.7	2123.0	6.8	1658.0	7.5	1834.5
Prediction (s.d.)	7.2 (0.58)	1745.4 (140.61)	9.9 (0.7)	2402.6 (170.3)	8.4 (0.32)	2031.2 (78.14)	6.3 (0.42)	1542.7 (100.88)	6.9 (0.34)	1682.7 (83.32)
95% CI	[6.1, 8.4]	[1483.5, 2034.1]	[8.6, 11]	[2089.1, 2781]	[7.7, 9]	[1873.3, 2182]	[5.6, 7.3]	[1364.0, 1772.7]	[6.3, 7.7]	[1531.1, 1868.1]
Absolute effect (s.d.)	0.071 (0.58)	17.356 (140.61)	-0.89 (0.7)	-216.47 (170.3)	0.38 (0.32)	91.84 (78.14)	0.47 (0.42)	115.32 (100.88)	0.62 (0.34)	151.83 (83.32)
95% CI	[-1.1, 1.1]	[-271.3, 279.3]	[-2.4, 0.4]	[-595.0, 97.0]	[-0.24, 1]	[-58.52, 250]	[-0.47, 1.2]	[-114.68, 294.0]	[-0.14, 1.2]	[-33.60, 303.4]
Relative effect (s.d.)	0.99% (8.1%)	0.99% (8.1%)	-9% (7.1%)	-9% (7.1%)	4.5% (3.8%)	4.5% (3.8%)	7.5% (6.5%)	7.5% (6.5%)	9% (5%)	9% (5%)
95% CI	[-16%, 16%]	[-16%, 16%]	[-25%, 4%]	[-25%, 4%]	[-2.9%, 12%]	[-2.9%, 12%]	[-7.4%, 19%]	[-7.4%, 19%]	[-2%, 18%]	[-2%, 18%]
Posterior tail-area probability p:	0.4330	0.4330	0.0948	0.0948	0.1134	0.1134	0.1126	0.1126	0.0421	0.0421
Posterior prob. of a causal effect:	57%	57%	91%	91%	89.00%	89.00%	89.00%	89.00%	95.79%	95.79%

C.3.2 Spot market revenues

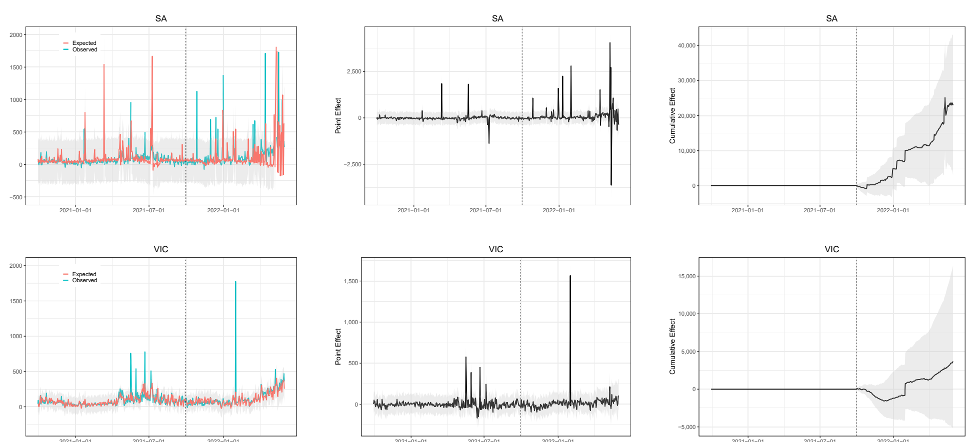

Figure C.19 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on the daily dispatch-weighted prices for battery generation with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022(a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

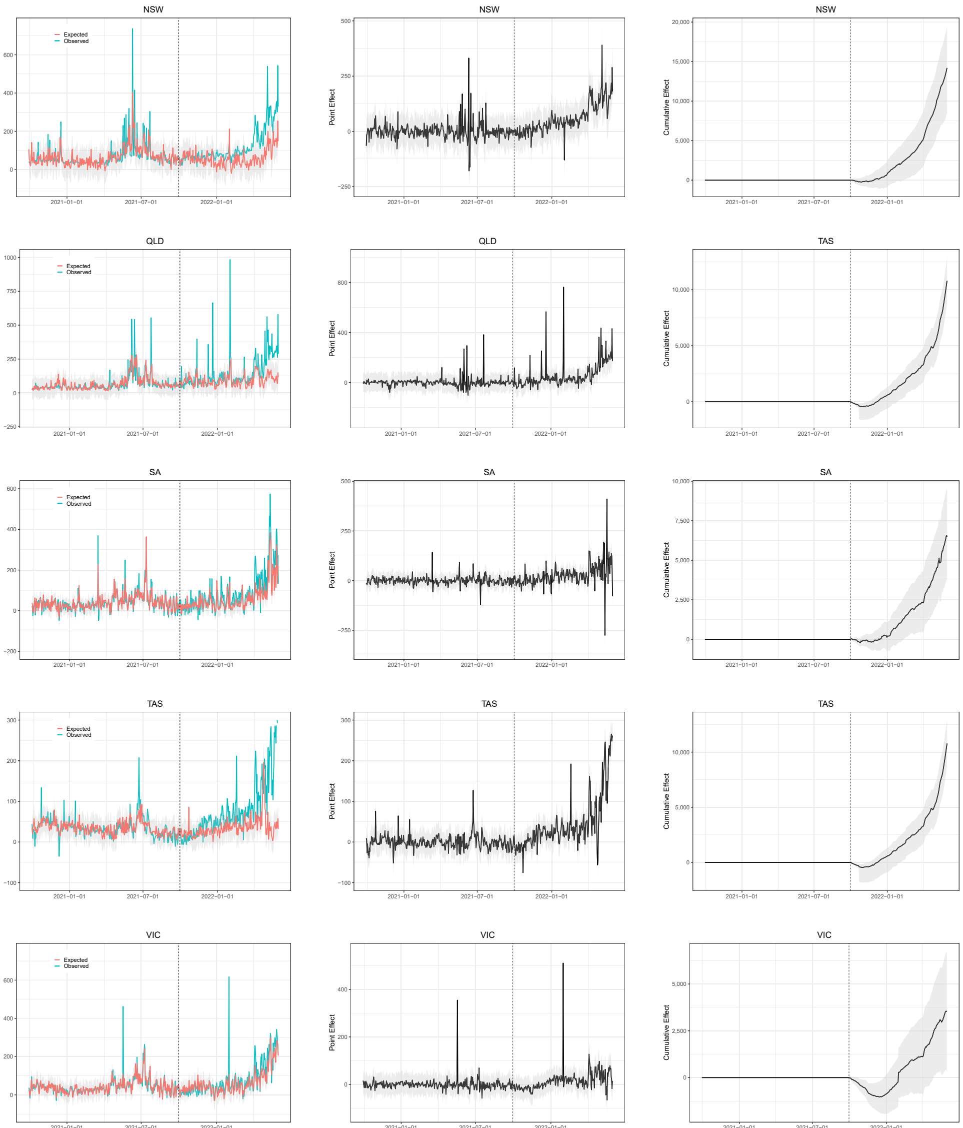

Figure C.20 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on the daily dispatch-weighted prices for wind generation with 95% confidence intervals using pre-screened time series.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

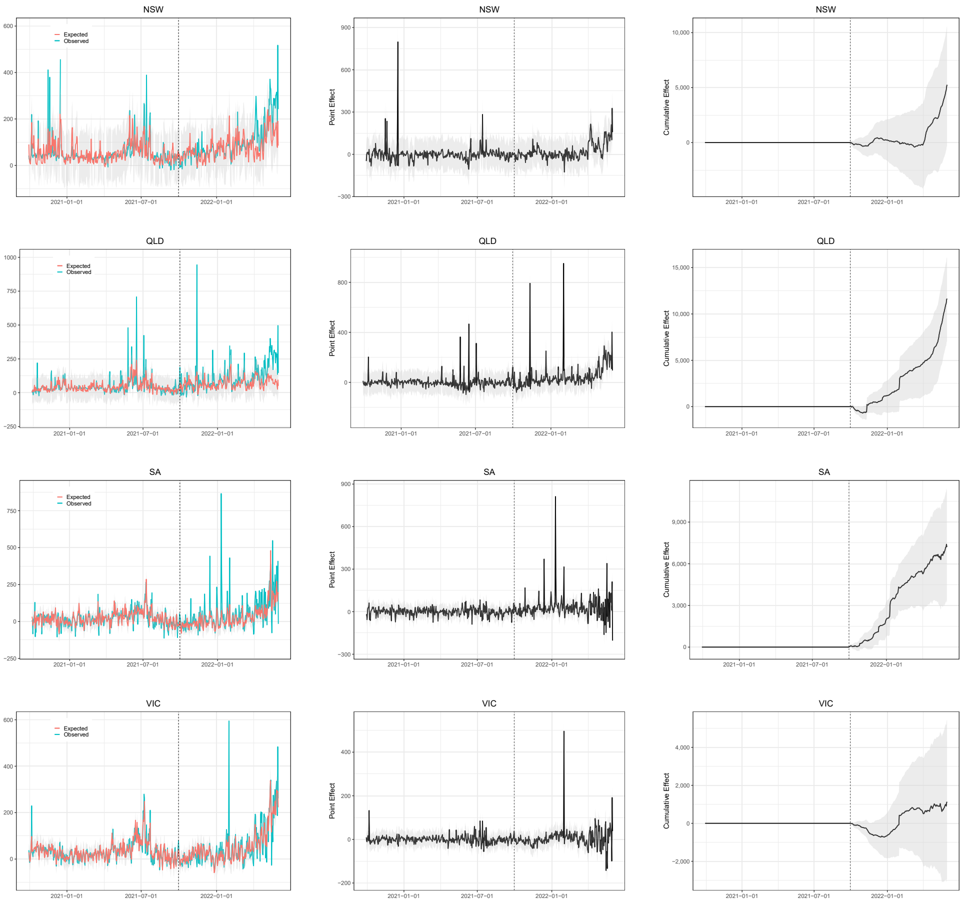

Figure C.21 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on the daily dispatch-weighted prices for solar generation with 95% confidence intervals using pre-screened time series.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

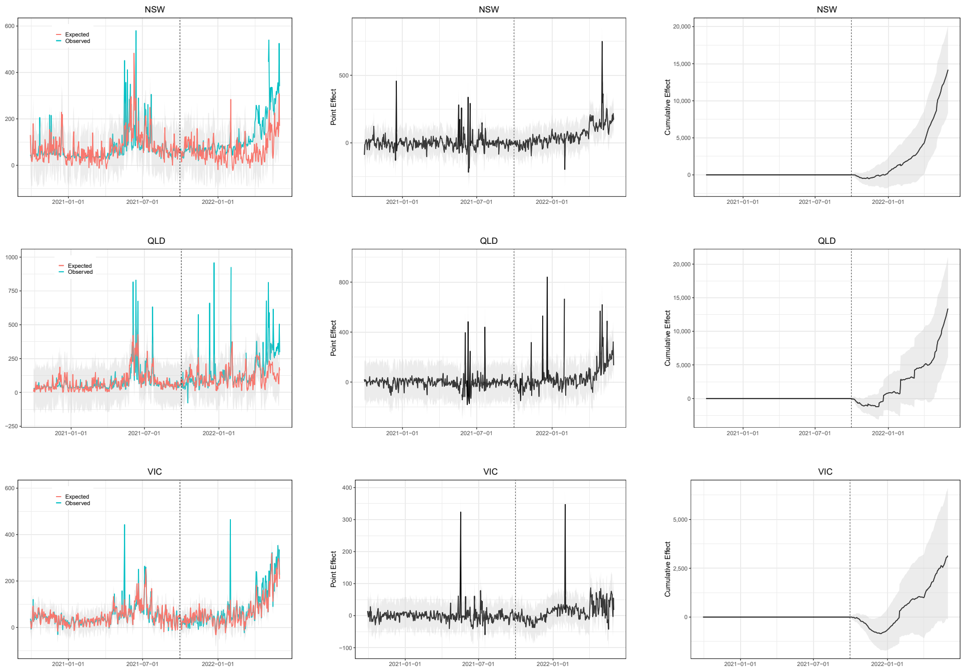

Figure C.22 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on the daily dispatch-weighted prices for coal-fired generation with 95% confidence intervals using pre-screened time series.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022(a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

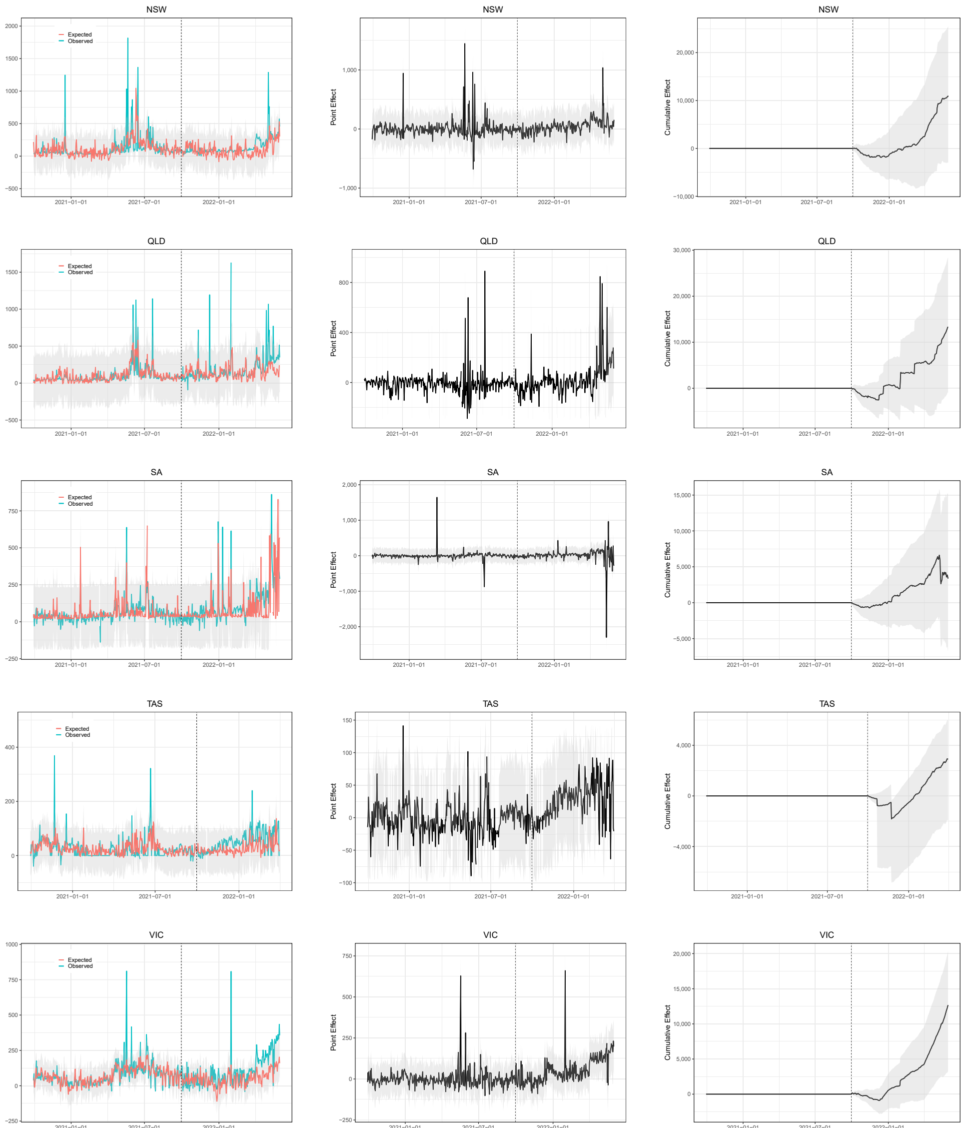

Figure C.23 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on the daily dispatch-weighted prices for natural gas generation with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2022 (a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

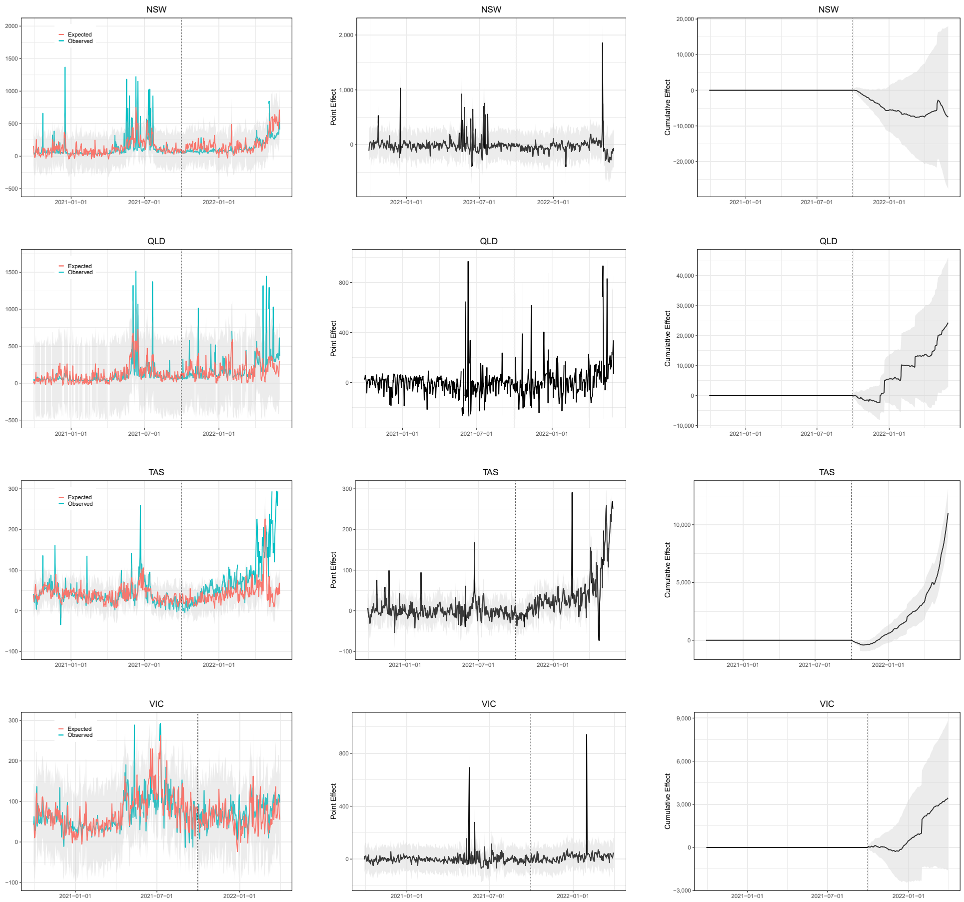

Figure C.24 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 (dashed vertical line) on the daily dispatch-weighted prices for hydro generation with 95% confidence intervals using pre-screened time series.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October 2021 to 31st May 2021 (a total of 243 daily observations). The first panel shows the actual equally daily weighted average and expected spot price. The second panels depict a pointwise causal effect. The third panels depict the cumulative effect.

C.3.3 Estimating the immediate impact of 5MS on price dynamics using different post-period windows

Table C.14 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 on equally daily weighted averaged spot price equally daily weighted averaged spot price dynamics with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st to 21st October 2021 (a total of 21 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	spot price									
Actual	51	1070	59	1245	11	226	7.4	156.0	16	346
Prediction (s.d.)	69 (14)	1450 (289)	92 (22)	1928 (472)	30 (14)	625 (299)	23 (4.8)	474 (101.6)	22 (6.5)	452 (137.2)
95% CI	[42, 96]	[874, 2014]	[49, 137]	[1027, 2870]	[2.2, 58]	[46.0, 1225]	[13, 32]	[277, 674]	[8.6, 34]	[181.4, 722]
Absolute effect (s.d.)	-18 (14)	-380 (289)	-33 (22)	-683 (472)	-19 (14)	-399 (299)	-15 (4.8)	-318 (101.6)	-5 (6.5)	-106 (137.2)
95% CI	[-45, 9.3]	[-944, 195.3]	[-77, 10]	[-1625, 218]	[-48, 8.6]	[-999, 180.3]	[-25, -5.7]	[-518, -120.6]	[-18, 7.8]	[-376, 164.3]
Relative effect (s.d.)	-26% (20%)	-26% (20%)	-35% (24%)	-35% (24%)	-64% (48%)	-64% (48%)	-67% (21%)	-67% (21%)	-23% (30%)	-23% (30%)
95% CI	[-65%, 13%]	[-65%, 13%]	[-84%, 11%]	[-84%, 11%]	[-160%, 29%]	[-160%, 29%]	[-109%, -25%]	[-109%, -25%]	[-83%, 36%]	[-83%, 36%]
Posterior tail-area probability p:	0.0911	0.0911	0.0697	0.0697	0.0892	0.0892	0.0007	0.0007	0.2195	0.2195
Posterior prob. of a causal effect:	91.00%	91.00%	93.00%	93.00%	91.00%	91.00%	99.93%	99.93%	78.00%	78.00%
	spot price volatility									
Actual	36	756	289	6062	63	1326	20	415	41	857
Prediction (s.d.)	143 (81)	3012 (1704)	327 (96)	6865 (2025)	86 (50)	1797 (1055)	41 (31)	863 (655)	29 (37)	607 (776)
95% CI	[-12, 305]	[-252, 6402]	[141, 517]	[2955, 10848]	[-13, 186]	[-270, 3896]	[-19, 103]	[-390, 2165]	[-41, 103]	[-868, 2158]
Absolute effect (s.d.)	-107 (81)	-2256 (1704)	-38 (96)	-803 (2025)	-22 (50)	-471 (1055)	-21 (31)	-449 (655)	12 (37)	250 (776)
95% CI	[-269, 48]	[-5646, 1008]	[-228, 148]	[-4786, 3107]	[-122, 76]	[-2569, 1597]	[-83, 38]	[-1751, 805]	[-62, 82]	[-1301, 1724]
Relative effect (s.d.)	-75% (57%)	-75% (57%)	-12% (29%)	-12% (29%)	-26% (59%)	-26% (59%)	-52% (76%)	-52% (76%)	41% (128%)	41% (128%)
95% CI	[-187%, 33%]	[-187%, 33%]	[-70%, 45%]	[-70%, 45%]	[-143%, 89%]	[-143%, 89%]	[-203%, 93%]	[-203%, 93%]	[-214%, 284%]	[-214%, 284%]
Posterior tail-area probability p:	0.0922	0.0922	0.3419	0.3419	0.3249	0.3249	0.2467	0.2467	0.3718	0.3718
Posterior prob. of a causal effect:	91.00%	91.00%	66.00%	66.00%	68.00%	68.00%	75.00%	75.00%	0.3718	0.3718

Table C.15 : **The causal impact of introducing a five-minute settlement rule on 1st October 2021 on equally daily weighted averaged spot price equally daily weighted averaged spot price dynamics with 95% confidence intervals.** The observation period runs from 30th September 2020 to 30th September 2021 (a total of 366 daily observations), and the post-treatment period runs from 1st October to 7th November 2021 (a total of 38 daily observations). The posterior tail-area probability p indicates the probability of obtaining the estimated effect by chance. The posterior probability of a causal effect indicates a statistical hypothesis test for whether or not the causal effect is valid.

	NSW		QLD		SA		TAS		VIC	
	spot price									
Actual	59	2250	66	2508	19	714	11	424	19	714
Prediction (s.d.)	70 (12)	2677 (437)	93 (18)	3528 (697)	31 (12)	1189 (455)	24 (14)	901 (517)	31 (12)	1189 (455)
95% CI	[48, 93]	[1806, 3537]	[57, 129]	[2168, 4899]	[7.6, 55]	[288.4, 2081]	[12, 73]	[464, 2783]	[7.6, 55]	[288.4, 2081]
Absolute effect (s.d.)	-11 (12)	-427 (437)	-27 (18)	-1020 (697)	-12 (12)	-475 (455)	-13 (14)	-477 (517)	-12 (12)	-475 (455)
95% CI	[-34, 12]	[-1287, 444]	[-63, 8.9]	[-2391, 340.0]	[-36, 11]	[-1367, 426]	[-62, -1.1]	[-2360, -40.9]	[-36, 11]	[-1367, 426]
Relative effect (s.d.)	-16% (16%)	-16% (16%)	-29% (20%)	-29% (20%)	-40% (38%)	-40% (38%)	-53% (57%)	-53% (57%)	-40% (38%)	-40% (38%)
95% CI	[-48%, 17%]	[-48%, 17%]	[-68%, 9.6%]	[-68%, 9.6%]	[-115%, 36%]	[-115%, 36%]	[-262%, -4.5%]	[-262%, -4.5%]	[-115%, 36%]	[-115%, 36%]
Posterior tail-area probability p:	0.1639	0.1639	0.0686	0.0686	0.1417	0.1417	0.0143	0.0143	0.1417	0.1417
Posterior prob. of a causal effect:	84.00%	84.00%	93.00%	93.00%	86.00%	86.00%	98.57%	98.57%	86.00%	86.00%
	spot price volatility									
Actual	35	1340	201	7631	97	3677	20	771	97	3677
Prediction (s.d.)	160 (71)	6089 (2715)	332 (80)	12615 (3033)	77 (42)	2922 (1583)	43 (37)	1619 (1405)	77 (42)	2922 (1583)
95% CI	[22, 301]	[838, 11452]	[172, 491]	[6529, 18673]	[-5.5, 158]	[-207.1, 5992]	[-10, 97]	[-389, 3699]	[-5.5, 158]	[-207.1, 5992]
Absolute effect (s.d.)	-125 (71)	-4749 (2715)	-131 (80)	-4984 (3033)	20 (42)	755 (1583)	-22 (37)	-848 (1405)	20 (42)	755 (1583)
95% CI	[-266, 13]	[-10112, 502]	[-291, 29]	[-11042, 1102]	[-61, 102]	[-2315, 3884]	[-77, 31]	[-2928, 1160]	[-61, 102]	[-2315, 3884]
Relative effect (s.d.)	-78% (45%)	-78% (45%)	-40% (24%)	-40% (24%)	26% (54%)	26% (54%)	-52% (87%)	-52% (87%)	26% (54%)	26% (54%)
95% CI	[-166%, 8.2%]	[-166%, 8.2%]	[-88%, 8.7%]	[-88%, 8.7%]	[-79%, 133%]	[-79%, 133%]	[-181%, 72%]	[-181%, 72%]	[-79%, 133%]	[-79%, 133%]
Posterior tail-area probability p:	0.0423	0.0423	0.0526	0.0526	0.3179	0.3179	0.2015	0.2015	0.3179	0.3179
Posterior prob. of a causal effect:	95.77%	95.77%	95.00%	95.00%	68.00%	68.00%	80.00%	80.00%	68.00%	68.00%

C.3.4 Estimating the impact of 5MS using ARX-eGARCHX models

Table C.16 : **The impact of introducing a five-minute settlement rule on 1st October 2021, in the equally daily weighted average spot price dynamics.** The effect on price levels is given by the mean equation and on price volatility by the variance equation. Dummy = 0 and 1 during the pre- and post-5MS period, respectively. The pre-period run from 1st January 2020 to 30th September, 2021. The post-period run from 1st to 31st October 2021.

	NSW	QLD	SA	TAS	VIC
	Mean Equation				
μ	−13.2952	−146.0134***	−75.8585***	11.8657***	−66.5446***
	(0.1752)	(0.0000)	(0.0000)	(0.0006)	(0.0000)
ϕ_1	0.7277***	0.3933***	0.3725***	0.7816***	0.6287***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dummy	−2.3107	−2.1727	−6.2570*	−8.7767***	−6.6183
	(0.6928)	(0.8172)	(0.0144)	(0.0000)	(0.1479)
Wind	−0.1282***	−0.9013***	−0.5990***	−0.3538***	−0.2115***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Solar	−0.1718	0.1665	1.1645***	−2.1048***	−0.0934
	(0.0617)	(0.2295)	(0.0000)	(0.0000)	(0.2332)
Hydro	0.2437**	2.1073***		0.0362***	0.0771
	(0.0082)	(0.0000)		(0.0000)	(0.0763)
Demand	0.0887***	0.2272***	0.8992***	0.3566***	0.2065***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Gas price	1.3633	9.1132***	5.7052***		3.9216***
	(0.4820)	(0.0000)	(0.0000)		(0.0000)
Terranora	−0.1156	1.1785			
	(0.7548)	(0.0687)			
QNI	0.0055	−0.1632*			
	(0.9040)	(0.0239)			
VNI	−0.0516*				0.0464
	(0.0223)				(0.0674)
Murraylink			−0.5472**		0.0322
			(0.0010)		(0.8247)
Heywood			−0.3191***		0.1198**
			(0.0000)		(0.0094)
Basslink				0.0126	0.0424
				(0.1124)	(0.2787)
	Variance Equation				
ω	−3.9255*	0.3047	2.5365**	0.7665	1.2405
	(0.0189)	(0.4995)	(0.0083)	(0.5992)	(0.2977)
α	0.3778*	−0.0531	0.0172	0.1285	−0.0571
	(0.0178)	(0.1459)	(0.8254)	(0.1228)	(0.4247)
β	0.1718*	0.9519***	0.3395**	0.4151***	0.5210***
	(0.0157)	(0.0000)	(0.0077)	(0.0000)	(0.0000)
γ	0.6661***	0.1811**	0.2035*	0.6330***	0.6218***
	(0.0008)	(0.0023)	(0.0290)	(0.0000)	(0.0000)
Dummy	−0.4735	0.0505	−0.0677	−0.3346	−0.0642
	(0.2442)	(0.4235)	(0.8141)	(0.1766)	(0.7930)
Wind	−0.0027	−0.0031	−0.0081*	−0.0035	0.0008
	(0.3919)	(0.3141)	(0.0121)	(0.7964)	(0.6989)
Solar	−0.0111	−0.0029	−0.0552	−0.3518***	−0.0051
	(0.3181)	(0.2122)	(0.0923)	(0.0002)	(0.7561)
Hydro	0.0120*	0.0060	0.0169***	−0.0125	0.0069
	(0.0435)	(0.1834)	(0.0010)	(0.3445)	(0.1309)
Demand	0.0112***	0.0001	0.0980**	0.0386***	0.0016
	(0.0000)	(0.8624)	(0.0041)	(0.0000)	(0.4735)
Gas price	0.1080**	0.0033	−0.0219		0.0928**
	(0.0061)	(0.6682)	(0.2292)		(0.0031)
Terrunsora	−0.0821	0.0050			
	(0.0979)	(0.6260)			
QNI	0.0049	−0.0016			
	(0.3874)	(0.1853)			
VNI	0.0070*				−0.0022
	(0.0285)				(0.3781)
Murraylink			−0.0124*		−0.0154
			(0.0476)		(0.3808)
Heywood			1.0338***		0.0020
			(0.0000)		(0.6609)
Basslink				0.0142	0.0015
				(0.3185)	(0.6686)
skew		1.1133***		1.3443***	
		(0.0000)		(0.0000)	
shape	2.4763***	4.3277***	3.0560***	3.5073***	3.8748***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log likelihood	−2944.7625	−3210.5968	−3024.9197	−2511.8630	−2793.9423
AIC	8.8650	9.6555	9.0953	7.5578	8.4207
BIC	9.0331	9.8170	9.2433	7.6923	8.6024

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