Wind generation and the dynamics of electricity prices in Australia

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Abstract

Australia's National Electricity Market (NEM) is experiencing one of the world's fastest and marked transitions toward variable renewable energy generation. This transformation poses challenges to system security and reliability and has triggered increased variability and uncertainty in electricity prices. By employing an exponential generalized autoregressive conditional heteroskedasticity (eGARCH) model, we gauge the effects of wind power generation on the dynamics of electricity prices in the NEM. We find that a 1 GWh increase in wind generation decreases daily prices up to 1.3 AUD/MWh and typically increases price volatility up to 2%. Beyond consumption and gas prices, hydro generation also contributes to an increase in electricity prices and their volatility. The cross-border interconnectors play a significant role in determining price levels and volatility dynamics. This underscores the important role of strategic provisions and investment in the connectivity within the NEM to ensure the reliable and effective delivery of renewable energy generation. Regulatory interventions, such as the carbon pricing mechanism and nationwide lockdown restrictions due to COVID-19 pandemic, also had a measurable impact on electricity price dynamics.

Keywords: wind generation, electricity price volatility, merit order effect, hydro generation, interconnectors, carbon pricing mechanism, COVID-19
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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 incentivizes 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, 2018). 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 been associated with a marked reduction in greenhouse gas, electricity prices, and sustainability of the electricity energy sector. 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, 2020; Kelley et al., 2020). The cyclic nature of demand and constraints in supply due to outages in transmission networks, strategic bidding practices, ramping up 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

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[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).

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. South Australia, with more than 50% wind penetration, the highest in the NEM, is second only to Denmark in the world.[2] Wind generation has been the main contributor to this increasing variation and negative prices. Therefore, it would be useful to focus on the effect of wind generation in the NEM and to comprehensively analyze 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 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 liquified 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. To the best of our knowledge, 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, 2019; Rai and Nunn, 2020). 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

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[2]South Australia is on track to meet its target to be self-sufficient in renewables by 2030 (AEMO, 2019c; 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 LRTE scheme.

[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.

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 heteroskedasticity (eGARCH) model proposed by Nelson (1991) to study the electricity price and volatility dynamics. The main advantage of this approach is that both prices and volatility are modeled simultaneously while taking into account heteroskedasticity 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 behaviors 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 the high average exports to 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 good news increases volatility more than bad news in NSW. 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 5%. Wind penetration exhibits a significant effect of

the same sign for states with moderate penetration levels (around 13% in 2020); i.e., increasing wind penetration by 1% reduces and amplifies price volatility by the same magnitude 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 July 1, 2012, to July 1, 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. To our knowledge, 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 marginal 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 rest of the paper is structured as follows. In Section 2, we provide a review of relevant literature. In Section 3, we describe the data and the model for the dynamics of electricity prices. In Section 4, we discuss the effects of wind generation on electricity prices and volatility. In Section 5, we analyze the impact of federal regulatory measures on electricity dynamics. In Section 6, we provide concluding remarks and policy implications.

2   Literature review

The growth and increased investment in renewable energies have attracted theoretical and empirical interest in the MOE in renewables-rich countries, such as Germany, Denmark, and Australia. The literature has shown that near-zero marginal cost characteristics of wind generation manifest through the decrease in the level of electricity prices (Forrest and MacGill, 2013; Cludius et al., 2014a; Ketterer, 2014; Clò et al., 2015; Csereklyei et al., 2019). These findings are unlikely to be due to chance, as most authors came to the same conclusion.[4] Although research on the subject has been mostly restricted to the MOE, several researchers investigated the impact of VRE on price volatility as either a stand-alone or integrated study with the MOE (Tveten et al., 2013; Pereira and Rodrigues, 2015; Ketterer, 2014; Rintamäki et al., 2017; Kyritsis et al., 2017; Maciejowska, 2020). In contrast, 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 at establishing this relationship in the NEM. This study makes

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[4]Several divergent accounts of the merit order have been observed. For instance, Bublitz et al. (2017) employed agent-based modeling and a regression approach to study the main price drivers in Germany from 2011 and 2015. In contrast to other studies, the findings indicate that fuel and carbon prices are still dominant, and reductions in their prices rather than the increase in renewable energy generation (wind and solar Photovoltaics (PV)) are responsible for the downward pressure on the electricity prices.

contributions to the current literature in three major dimensions:

First, we conduct a comprehensive analysis of the impact of wind generation on the volatility of electricity prices in the NEM. To our knowledge, this is the first study of substantial duration (2011–2020) to examine the variability of electricity prices in Australia. Moreover, we add to previous empirical studies on the MOE by including recent years that witnessed large-scale VRE investments in the NEM (Simshauser and Gilmore, 2020). In particular, the share of electricity generation from VRE increased rapidly since 2018, breaking NEM records (de Atholia et al., 2020). One aspect overlooked by previous studies is cross-border interconnector flow and hydro generation. By controlling for these variables, this study provides a deeper understanding of the impact of VRE generation on prices and volatility. Existing literature in this area includes Woo et al. (2011), who investigated the four zone of Texas. Using an econometric analysis of high-frequency electricity prices, these authors found that an increase in wind generation results in a reduction in spot electricity prices, however, at the cost of increasing price volatility. Ketterer (2014) reached the same conclusion using GARCH modeling with daily electricity data in Germany. Kyritsis et al. (2017) applied GARCH-in-mean models to the German electricity market, grouping data into peak and off-peak periods. These authors confirmed the merit order effect and the negative and positive effects of solar and wind, respectively, in the volatility of electricity prices. In a similar context, Rintamäki et al. (2017) divided data into off-peak and peak hours and estimated the impact of renewable generation on electricity price levels in Germany and Denmark. Using an autoregressive moving average (SARMA) model, these authors found that wind power reduces the volatility of daily day-ahead electricity prices in Denmark, whereas it increases such volatility in Germany. Nonetheless, the authors found consistent increase in weekly volatility when wind generation increased. Maciejowska (2020) applied quantile regression and examined the inter-quantile range (IQR) variability, to examine the impact of wind and solar generation. The author found that during low demand for electricity, wind tends to increase price variability and reduces it during high demand. In contrast, when electricity demand is moderate, solar power tends to stabilize price variance. Similar studies are scant in the NEM. There are, however, a considerable number of studies that investigated the intra- and inter-relationships of wholesale electricity prices and price volatility between regional electricity markets (Worthington et al., 2005; Higgs, 2009; Ignatieva and Trück, 2016; Han et al., 2020). Most of these studies apply GARCH-based models finding the presence of significant own-mean spillovers and means spillovers from other lagged markets. The occurrence of shocks in one market affects the price volatility of not only that market but also other markets in the region, especially between adjoining and physically connected markets. We build on these findings with a somewhat similar methodological approach based on an eGARCH-type model to investigate prices and volatility. Where this analysis differs from other analyses, however, is by accounting for seasonality, electricity spikes, and explicit incorporation rather than removal of negative electricity prices.

We provide a deeper insight into negative electricity prices in Australia, which appear far more frequently following the upsurge in VRE penetration in the NEM. To capture the volatility of electricity prices effectively, we include negative prices and price spikes in the empirical analysis without applying any truncation or transformation. This contrasts with much of the literature (Cutler et al., 2011; Forrest and MacGill, 2013; Cludius et al., 2014b; Ketterer, 2014), which applies statistical approaches to adjust prices spikes or truncates electricity prices based on the marginal cost of generation.

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 in optimizing the total generation supply through the transfer of energy between the major generation and demand centers. Denny et al. (2010) investigated the impacts of interconnectors in Ireland, which has one of the highest penetrations of wind generation in the world. The empirical findings suggest that the increase in interconnectors has the potential for reducing the level and variability of electricity prices. Similarly, Rai and Nunn (2020) examined the role of interconnectors in offsetting the challenges associated with higher penetration of wind generation specifically 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 potential to lower price levels and smooth out price volatility. The GARCH modeling with copulae by Ignatieva and Trück (2016) found a significant interdependence between markets that are well connected via interconnector transmission. This conclusion concurs with that of Han et al. (2020), who used more recent NEM data and found pronounced volatility spillovers between physically interconnected markets.

Third, 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. Existing research has been unable to confirm either the MOE of wind generation or its impact on volatility dynamics during the CPM period. However, several researchers demonstrated substantial changes in prices, demand, and emission intensity. Nazifi (2016) carried out an investigation in the NEM from 2010 to 2013 and concluded that carbon costs resulted in higher wholesale spot electricity prices and windfall profits for some generators. Beyond these effects, O'Gorman and Jotzo (2014) showed that electricity demand decreased by 3.8% and overall emission by 8.2%, relative to the two-year period before its introduction. Han et al. (2020), in contrast, found that the CPM had an impact on dampening volatility spillover across the NEM. A recent analysis by the Australian Energy Market Operator (AEMO) also suggested a moderate reduction in electricity demand during the implementation of COVID-19 restrictions and lockdowns (AEMO, 2020e,f). A substantial reduction was observed in QLD and NSW due to the decrease in commercial demand and a limited increase in residential demand (due to mild weather conditions).

3 Data and methodology

3.1 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 January 1, 2011, to May 31, 2020. The main datasets for this analysis were obtained from the NEM via NEOpoint (2020). We use daily data, aggregated from high-frequency (5- and 30-minute) wholesale electricity prices (depicted in Figure 1), electricity consumption, wind electricity generation,[5] 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, 2020g). The four-hourly gas price data for VIC were obtained from the Declared Wholesale Gas Market (DWGM) (AEMO, 2020c).

Wind generation in the NEM has increased significantly since 2010. As shown in Figure 2a, large-scale wind generation has grown exponentially across all states. The 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, NSW, VIC, and SA made approximately equal contributions 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 (2020) for the NEM, we infer that states with higher wind generation such as SA will exhibit a significant impact 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

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[5]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).
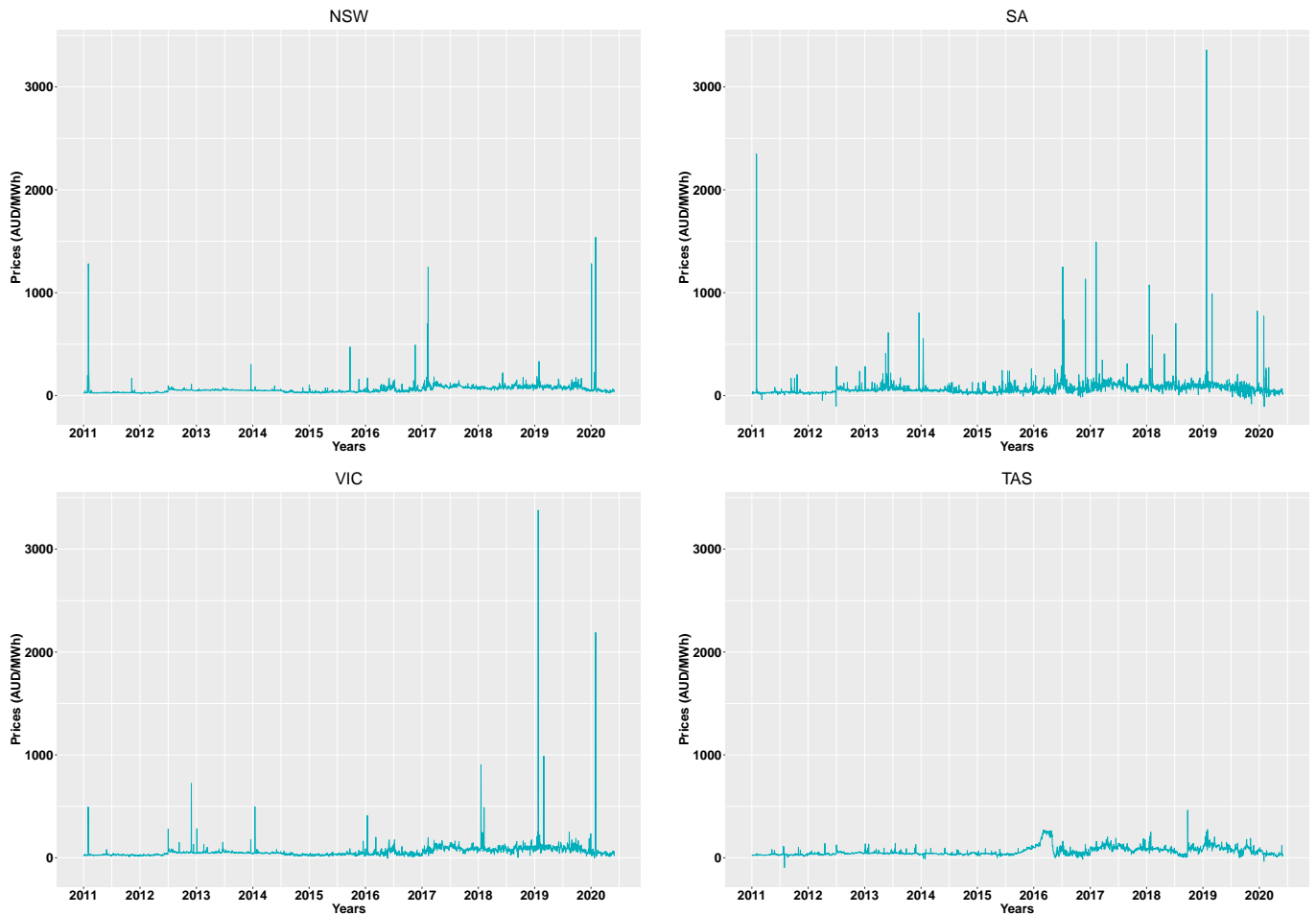
Figure 1: The equally weighted daily average spot price (regional reference price (RRP)) for NSW, SA, VIC, and TAS from January 1, 2011, to May 31, 2020. The RRP is estimated on a half-hour basis by averaging six dispatch electricity prices.

the second half of 2019 (see Figure 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 2a.[6] The uptake of rooftop solar PV generation contributed significantly to reducing consumption by meeting more than 5.5% of Australia's energy demand.[7] In the last three months of the sample period, the implementation of tighter pandemic restrictions due to COVID-19 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 computed as the ratio between wind generation and consumption, and

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

[7]Australia is a global leader in solar PV generation, originating mainly from household rooftop installations. 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.

(a) Wind generation
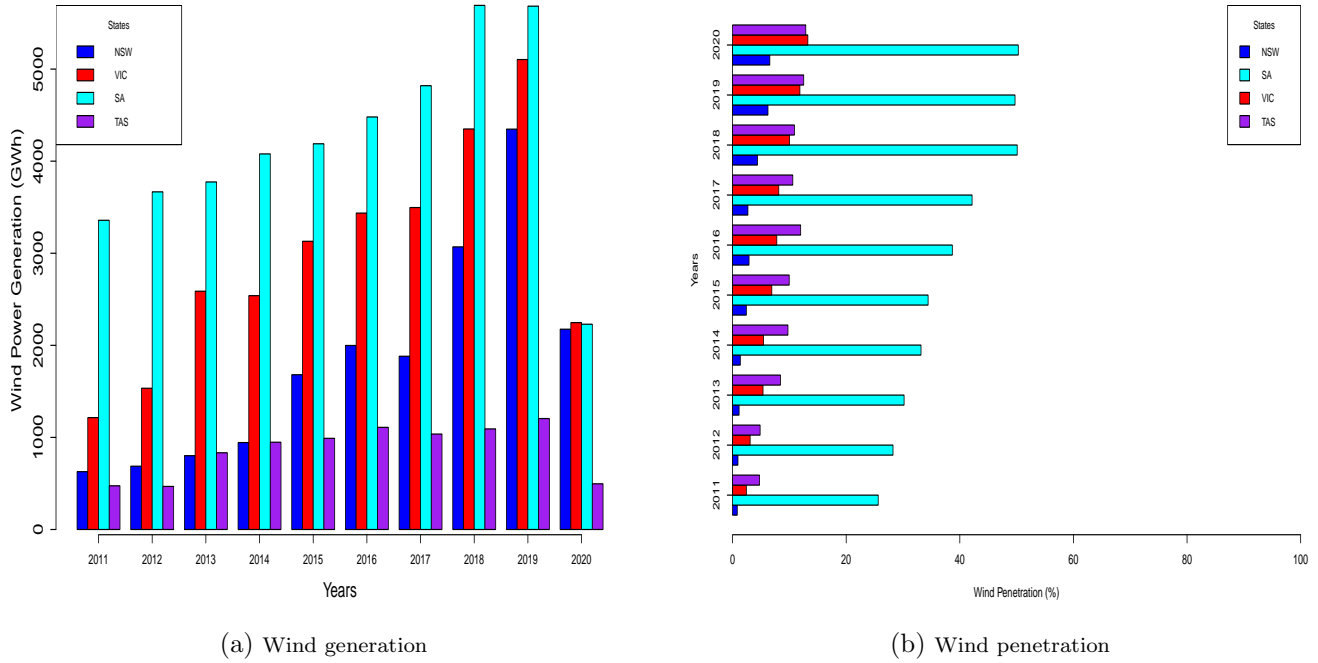
(b) Wind penetration

Figure 2: Large-scale wind generation (left panel) and wind penetration (right panel) for NSW, SA, VIC, and TAS, from 2011 to 2020. The year 2020 covers the sample period from January 1, 2020, to May 31, 2020.

captures the correlation between the two variables.[8] 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 2a and 2b show the significant increase in wind generation and penetration from 2011 to 2019. This increase varies significantly between states. SA is the leader in the uptake of wind energy. Its penetration was approximately 50.1% in 2018 and 49.7% in 2019, which are the highest levels across the NEM and the second highest worldwide following Denmark. The drop in penetration between 2018 and 2019 reflects increasing 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 9 in Appendix A) 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

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[8]Denoting the wind penetration by w_p, then if $w_p < 1$, it implies that wind generation meets only a proportion of consumption, and $w_p = 1$ indicates that wind generation meets the entire electricity consumption. If wind generation exceeds electricity consumption, then $w_p > 1$. Generally, the higher the wind penetration, the higher the negative impact on the level of electricity prices. This stems from the fact that the inverse of consumption and wind generation are negatively correlated with prices.

(a) Consumption
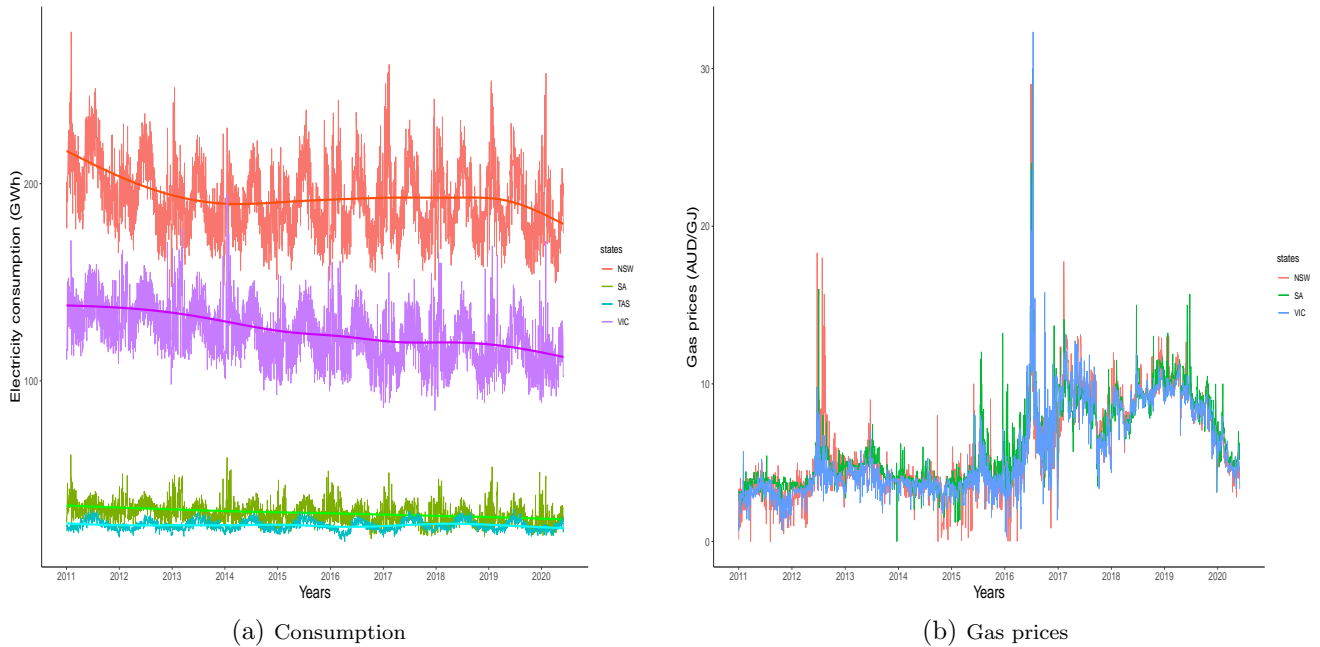
(b) Gas prices

Figure 3: The daily electricity consumption and gas for NSW, SA, VIC, and TAS from January 1, 2011, to May 31, 2020. The daily electricity consumption and daily gas prices are depicted in the left and right graphs, respectively.

(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.[9] Rai and Nunn (2020) noted further that through the interconnectors, demand and supply between states with imperfectly correlated demand are equalized and thus, reduce price volatility. Figure 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.[10] 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 behavior 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 6 in Appendix A) (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

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[9]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.

[10]The closure of the Hazelwood power station caused a decrease of around 5% in the NEM's capacity (Burke et al., 2019; Mountain and Percy, 2019)
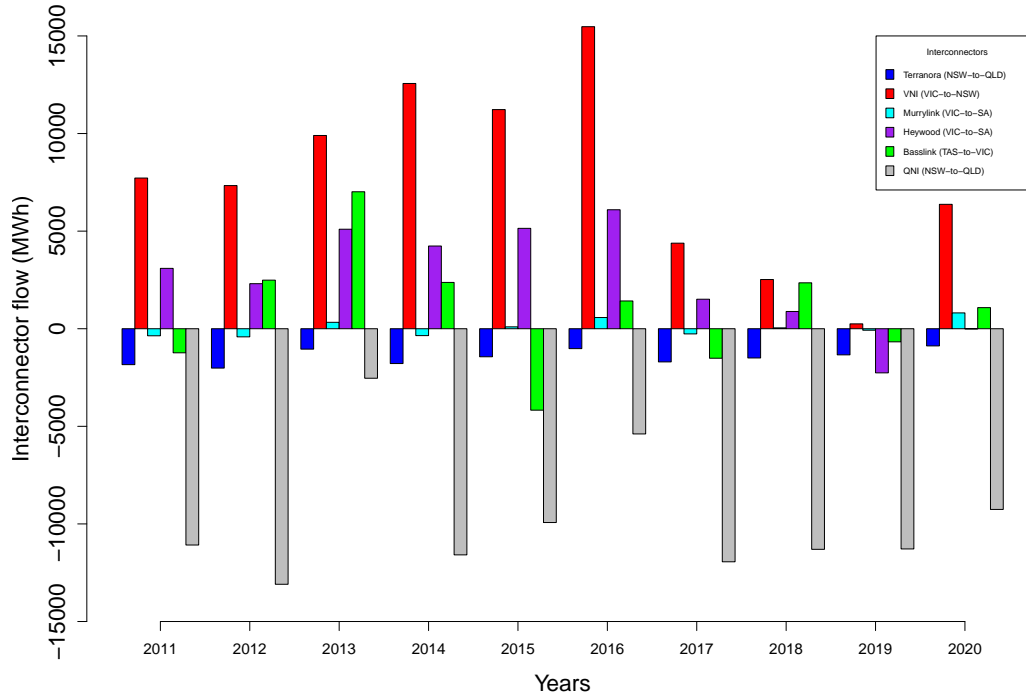
Figure 4: The average annual net interconnector flow for NSW, SA, VIC, and TAS. The year 2020 covers the sample period from January 1, 2020, to May 31, 2020. The positive sign indicates a forward flow (export to), and the negative sign indicates a backward flow (import from).

and contributed an approximate 36% output rise in the NEM during 2012–13. This effect is evident in Figure 4 by the increase in exports from TAS to VIC from increased hydro generation. To the best of our knowledge, 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).[11] 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.[12] 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,

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[11]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).

[12]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.

Table 1: Summary statistics of daily data (aggregated from high-frequency data) from January 1, 2011, to May 31, 2020.

	Unit	Mean	Standard Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile
					NSW					
Electricity Prices	AUD/MWh	60.29	58.31	15.71	334.19	51.60	18.54	1539.50	35.77	74.30
Gas Prices	AUD/GJ	5.89	2.93	0.90	5.25	4.96	29.00	3.70	8.35	
Wind Generation	MWh	5214.39	4964.22	1.56	5.63	3528.29	-1.54	29825.40	1524.28	7448.58
Hydro Generation	MWh	6515.69	4681.00	1.08	4.06	5349.38	-0.27	29509.67	2833.44	9246.30
Electricity Consumption	MWh	193819.00	18360.32	0.37	3.19	192326.00	147701.00	276893.00	181415.00	205921.00
					SA					
Electricity Prices	AUD/MWh	69.85	99.64	17.41	460.48	54.36	-107.16	3359.82	35.30	3359.82
Gas Prices	AUD/GJ	6.16	2.67	1.17	6.28	5.15	0.00	29.99	3.95	8.38
Wind Generation	MWh	12259.89	7343.318	0.73	2.80	10653.94	57.68	34363.58	6530.24	16956.66
Electricity Consumption	MWh	33079.00	5372.77	0.79	4.50	32617.00	19907.00	62493.00	29377.00	36107.00
					VIC					
Electricity Prices	AUD/MWh	60.24	82.23	25.68	915.22	47.96	-6.35	3377.97	31.645	76.388
Gas Prices	AUD/GJ	5.64	2.88	1.38	10.29	4.5	0.00	44.86	3.52	8.12
Wind Generation	MWh	8647.77	6783.99	1.19	3.99	6597.15	30.54	35916.26	3467.95	12334.22
Hydro Generation	MWh	7240.65	5338.39	0.92	3.18	5892.44	-7.96	28751.15	2913.00	10515.92
Electricity Consumption	MWh	125578.00	15168.02	0.11	2.81	125616.00	85021.00	194849.00	114356.00	136511.00
					TAS					
Electricity Prices	AUD/MWh	61.79	43.22	2.25	10.70	44.97	-94.67	461.64	34.78	82.02
Wind Generation	MWh	2524.43	1764.81	0.71	2.55	2127.88	-14.85	7436.14	1116.11	3686.50
Hydro Generation	MWh	25429.00	8362.80	-0.02	2.05	25565.00	5820.00	45120.00	18502.00	32332.00
Electricity Consumption	MWh	26758.00	2471.89	0.35	2.79	26425.00	18558.00	35097.00	25001.00	28433.00
					Interconnector Flow					
Terranora (NSW-QLD)	MWh	-1491.50	716.83	-0.13	2.94	-1477.50	-3852.80	926.10	-1981.20	-991.50
QNI (NSW-QLD)	MWh	-9769.00	6920.51	0.04	2.27	-9604.00	-25216.00	8617.00	-15178 .00	-4694.00
VNI (VIC-NSW)	MWh	7863.30	9079.41	-0.04	2.27	8102.40	-15983.40	30337.50	896.30	14764.40
Basslink (T-V-MNSP1)	MWh	904.50	6466.18	-0.19	2.09	390.50	-11472.00	14149.3 0	-3631.50	6404.10
Heywood (VIC-SA)	MWh	2772.90	4868.45	-0.30	2.58	3038.00	-11668.90	14142.20	-562.10	6474.40
Murraylink (VIC-SA)	MWh	-9.47	1173.49	0.57	4.31	-77.71	-3611.30	5040.13	-720.07	573.44

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, i.e., merchant or economically unregulated.

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. We recognize that coal 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 neighboring 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 our 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 1. We observe a considerable 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 9% of the total exports from SA and TAS via the Murraylink and Basslink interconnector.

Figure 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.[13] We do not truncate the series and include all the observations to capture the volatility of prices more effectively.[14] Furthermore, we apply a two-stage method similar to

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[13]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; Ward et al., 2019; Yan and Trück, 2020).

[14]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 section A.2 of Appendix A. We will present the results of this approach and show how the two treatments of price spikes affect the empirical analysis.

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.[15] 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 sections A.3 and A.4 in Appendix A.

3.2 Negative prices in the NEM

Negative prices may occur when periods of relatively low demand coincide with a high supply of 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 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 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.

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[15] Our 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. Second, we adjust for the trend effect in all variables and on either side of the equation.

These low or negative price periods occur more regularly and last longer, e.g., on July 21, 2019, the spot prices in SA remained in negative territory for 4.5 hours and in VIC for 1.5 hours.[16]

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).[17] 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.[18] Similar to Kyritsis et al. (2017) and 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.

3.3 Modeling 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[19] model specification:

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

[17]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).

[18]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). 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.

[19]Few researchers on the subject have been able to investigate the impact on price behaviors 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.

$$P_t = \mu + \sum_{i=1}^{m} \phi_i P_{t-i} + \sum_{j=1}^{n} \xi_j' \boldsymbol{v}_{t-j} + \epsilon_t, \tag{1}$$

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

where equation (1) is the autoregressive (AR) structure of the conditional expectation, and equation (2) is the eGARCH model of the conditional variance with exogenous variables.[20] P_{t-i}, $i = 1, \ldots, k$, are lags of the electricity prices, $\boldsymbol{v}_t$ is an $m \times 1$ vector of variables, and ξ and δ are the $m \times 1$ vector of positive coefficients. σ_t represents a time-dependent standard deviation, 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, 2020). 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 heteroskedasticity, provides a more accurate tool of the heteroskedasticity 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 market.[21] 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.

4 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. The technical details regarding the optimal ARMA structure and the distribution of

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[20]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.

[21]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).

the standardized residuals are given in Appendix B. Tables 2 to 5 present the regression estimates for the four states, namely, NSW, SA, VIC, and TAS, respectively.[22]

4.1 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 2–5). 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 (0.6 AUD/MWh), and NSW (0.5 AUD/MWh). The pronounced effect in SA, the second in the world 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 (2018), 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 turbines, being statistically significantly larger in SA and lower in VIC with no firm evidence in NSW. Numerically, our estimated coefficients exceed the daily merit order from this study by 0.3 AUD/MWh for NSW and VIC, and by 0.4 AUD/MWh for SA. We account for the difference in the magnitude and statistically significance of our results to the sample period under the analysis and the fact that our model includes 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 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

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[22]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 the ARCH process (Ghalanos, 2020). Overall, the weighted Ljung-Box test and the weighted ARCH-LM test 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, 2020)

that increasing the daily gas price by 1 AUD/GJ raises electricity prices in the range 6 AUD/MWh to 7 AUD/MWh for SA. We find less evidence to support the positive effect in NSW. SA is the state most affected by gas prices, exceeding VIC by approximately 5 AUD/MWh to 6 AUD/MWh as SA relies more on gas-powered generation than any other region across the NEM.[23] Between 2014 and 2018, Australia witnessed a threefold increase in gas prices (see Figure 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. We account for this effect by the reduced availability of lower-priced hydro generation due to persistent drought periods (Csereklyei et al., 2019). 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 cross-border interconnectors flow exhibits a differential effect on the level of electricity prices across the NEM. Our 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, 2019). 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, 2018). 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,

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[23]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 (2018), 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, 2017).

however, has made SA more self-sufficient. 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. Favorable conditions such as the resumption of the Basslink interconnector to VIC and favorable 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 analyze the impact of these factors on the volatility of electricity prices.

4.2 Volatility dynamics

The bottom panels of Tables 2–5 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 0.5875, 0.5079, 0.4225, and 1.4055, 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 (0.8284). The impact is almost half this in other regions, i.e., VIC (0.4708), SA (0.4440), and NSW (0.3697).[24] Considering Models I and J, we find the estimated innovation spillovers exceed the volatility spillovers in NSW only. The opposite effect is observed in VIC and TAS; the results for SA are inconclusive. The estimated innovation spillovers exceed those observed in the German market (Ketterer, 2014; Kyritsis et al., 2017). Kyritsis et al. (2017), for

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[24]These results are generally in keeping with the previous study by Higgs and Worthington (2005), who found the ARCH and GARCH effects 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.

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) and Thomas and Mitchell (2005). In addition to the Australian market, Knittel and Roberts (2005) found similar behavior for California electricity prices in the US. Contrary to these studies, however, we find the estimated coefficients for the other states are not statistically significant (at the 5% level). Positive and negative shocks have marginal differential effects on price volatility in all of the Australian states except NSW.

4.3 Effects on volatility of electricity prices

In the second panel in Tables 2–5 (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 10% 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%. The increase in VIC differs moderately and is 1% lower. In contrast, we find strong evidence for the opposite effect in TAS, with a 5% 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, 2020). 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 the daily 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 11% in SA and marginally in NSW and VIC, i.e., around 6%. 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. Our 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 no evidence of a positive 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. Nevertheless, we find less evidence for the Murraylink interconnector. These results also suggest the impact 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 interconnector 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 output introduce volatility in NEM electricity prices.[25] 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, 2020). This range is above the market cap on prices typically excluded in studies after treatment for outliers. In Appendix C, 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 SA. 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.

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

4.4 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 8. 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 to 5 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 1% 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. The magnitude of this reduction is relatively lower in SA and TAS, where the same increase in wind penetration reduces prices 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 the same percentage increase in wind penetration. We observe a similar 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 less evidence that increasing wind penetration by 1% in VIC increases price volatility by the same magnitude. 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 experiences the largest price reduction and volatility, 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 50%. This also explains 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.

4.5 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.[26] 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 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 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 LRTE (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, 2019).[27] 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, 2020). 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.[28] 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 4.4 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. One explanation is that incumbent thermal plants remain online up to a certain penetration rate

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

[27]According to AER (2018) 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.

[28]The p values from Figure 14 in Appendix C indicate, however, the estimated coefficients for all states are generally not statistically significant, especially between 2016 and 2019, with the slight exception of SA.

Figure 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.

(50% to 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 behaviors 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 less than 15%, i.e., NSW and VIC, tends to result in price swings, which are currently biased below zero. States with high wind penetration, i.e., SA and TAS, tend to exhibit a marginal reduction in price volatility.

5   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 analyze the impact of these two regulatory shocks on the NEM and then discuss their implications.

5.1 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 (AER, 2015). These changes, combined with the reduction in demand, reduced carbon emissions from electricity sector by 10.3% during the two years the CPM was implemented.

Table 6 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 July 1, 2012, until it was repealed on July 1, 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 intensification 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.[29] The results show that increasing wind generation by 1 GWh during the CPM period reduced prices by 0.9 AUD/MWh and 0.5 AUD/MWh in SA and TAS and approximately 0.1 AUD/MWh and 0.2 AUD/MWh in NSW and VIC, respectively. Likewise, wind penetration had a dampening effect on the level of electricity prices with a greater reduction observed in VIC and moderate reduction in SA and TAS. We find no statistical evidence for this effect in NSW, likely reflecting the smallest

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

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 found 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. Further, we find statistically significant evidence that gas contributed to increasing electricity prices during the CPM period in VIC.[30] Last, it is evident that in virtually all states in the NEM the competitiveness of hydro was enhanced. We find statistically significant evidence that increasing hydro generation by 1 GWh during the CPM period reduced prices by 0.2 AUD/MWh in TAS and evidence of a more moderate reduction in NSW (0.1 AUD/MWh). The effect in VIC was not statistically significant, particularly after controlling for other variables (see Model Q).

We find a statistically significant decrease in price volatility during the CPM period (see Model K). The coefficients, however, are not statistically significant after controlling for other variables (see Model Q). This suggests the possibility of omitted variable bias, namely, the effect attributed to volatility in the regression may have been due to the effects of the omitted variables. The influence of wind generation on price volatility during the CPM period is marginal and evident in only 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 0.2%. The imposition of carbon pricing stimulated investment in wind generation and supplied about 28%, 30%, and 33% of the output in SA in the years 2012, 2013, and 2014, respectively. Furthermore, we find statistically significant evidence that volatility increased during the CPM period, specifically 1% for each 1 GWh increase in hydro generation for NSW. Although there is less statistical evidence for the coefficient of the interaction term in TAS and not statistically significant during the non-CPM period, higher prices in other regions during the CPM period increased the competitiveness of hydro generation making TAS a net exporter of electricity in 2012–13. 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,

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[30]The impact in NSW and SA is not statistically significant.

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 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.[31] 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, 2017). Future climate change policies, therefore, must operate in a broader spectrum of considerations for energy policies to maintain safe and reliable energy systems.

5.2   COVID-19 and the NEM

A significant discussion of immediate interest is centered on the novel coronavirus (COVID-19) and its socioeconomic impacts. In Australia, the first person tested positive in VIC on January 25, 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 March 23, 2020, to May 31, 2020, after which the tightest restrictions were lifted in all states, and zero otherwise. The results obtained are summarized in Table 7.

The results provide evidence of a statistically significant difference in the average levels of prices between the lockdown and non-lockdown period. Looking at Model W, which includes all the variables, we find strong evidence that prices decreased substantially in NSW 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, 2020e,f). Focusing on the latter factor, we find statistically significant evidence that wind generation reduced electricity prices in SA and VIC during the lockdown period. Wind penetration

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[31]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).

has the same sign effect, although the interaction term is statistically significant only in SA. From the beginning of 2020 until the end of the sample period, SA and VIC lead in terms of wind penetration with around 50.29% and 13.24%, 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, 2020f). Despite the observed reductions, we find strong evidence that consumption increased electricity prices during the lockdown period in NSW. The impact of consumption in other regions was not statistically significant. Overall, VIC experienced a moderate operational demand reduction,[32] 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 3a suggests further that the trend of consumption reduction after the imposition of a strict nationwide lockdown on March 23, 2020, to May 31, 2020, did not diverge substantially from the pre-lockdown period. The impact of gas during the lockdown period is not evident in any state, including SA and VIC, both of which have a large proportion of gas in their generation mix. Since the start of 2020, gas prices have been offered in the markets at increasingly lower prices and reached the historically lowest levels in all markets across the NEM (AEMO, 2020f). The lower gas prices have been associated with falling gas prices in the international market and increased gas production in QLD. Although high rainfall allowed increased output from hydro, we find some evidence that the marginal increase is associated with higher electricity prices in NSW. We find no statistical evidence to back up the positive and negative impacts in VIC and TAS, respectively.

These results suggest further that price volatility during the lockdown period was higher in SA.[33] As pointed out previously, SA is characterized by extreme and volatile prices compared with other markets in the NEM. The effect of wind generation and penetration during the lockdown period was not evident across the markets. Similarly, we find no evidence for the impact of electricity consumption. The marginal increase in hydro generation in VIC reduced volatility (see Model W); nonetheless, the interaction term is not statistically significant after controlling for other electricity price determinants. Moreover, we find modest evidence for the effect of gas prices in NSW and SA. In both states, the results reveal that the marginal increase in gas prices during the lockdown period was associated with 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.

Overall, we find that the COVID-19 pandemic and the associated restrictions had a moderate

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[32]The imposition of the second statewide restrictions due to the second wave of infections in VIC in early July is expected to have an additional impact on the demand.

[33]The effects in other markets are not statistically significant.

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. Therefore, the system architecture, regulation, and governance should be designed so that they are flexible enough to accommodate a range of 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.

6   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.[34] 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 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 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,

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[34]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.

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 our 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.[35] The level and volatility of wholesale electricity prices impact end-consumer prices and electricity bills. Evidence suggests that the costs 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, 2019), 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 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, i.e., NSW and VIC, to meet the lost output from wind generation.[36] 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

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[35]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).

[36]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).

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 inter-state, 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,[37] 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 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.[38] 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 windfarm (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 modeling. 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

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[37]Denmark, which leads with the highest penetration of wind generation, is strongly interconnected with central European and Scandinavian power systems, which offers strong support for balancing the system (AEMO, 2020d)

[38]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)

NEM.

Table 2: The effect of wind generation, electricity consumption, gas prices, hydro generation, and interconnectors flow on New South Wales' electricity price behavior. 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	54.3343	57.1014	-8.2404	-2.9146	56.6694	50.5466	49.4523	50.3224	2.2736	47.1826
	(0.0000)	(0.0000)	(0.1214)	(0.0992)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5702)	(0.0000)
ϕ_1	0.8385	0.8445	0.8488	0.8556	0.8456	0.8349	0.8414	0.8535	0.8607	0.8539
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-5.8979		-5.5736					-4.5167	
		(0.0000)		(0.0000)					(0.0000)	
$consumption$			3.2269	3.0795					2.4622	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-100.0000					-92.4660
					(0.0000)					(0.0000)
gas						0.63661			0.2021	0.3489
						(0.0000)			(0.1513)	(0.0164)
$hydro$							7.6019		4.0481	6.6880
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-11.7043	-11.0483	-11.4251
								(0.0178)	(0.0143)	(0.0107)
$exim_{QNI}$								-3.4987	-1.6940	-2.1430
								(0.0000)	(0.0143)	(0.0146)
$exim_{VNI}$								-1.2123	-0.7607	-0.8209
								(0.0000)	(0.0007)	(0.0014)
					Variance Equation					
ω	2.5631	2.6162	-1.1792	-1.3694	2.6427	2.2504	2.18344	2.3460	-0.8407	1.7301
	(0.0000)	(0.0000)	(0.0210)	(0.0091)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1252)	(0.0000)
α	0.1470	0.1404	0.1585	0.1479	0.1402	0.1356	0.14700	0.1537	0.1364	0.1233
	(0.0001)	(0.0003)	(0.0000)	(0.0001)	(0.00037)	(0.0005)	(0.0000)	(0.0000)	(0.0001)	(0.0006)
β	0.4819	0.4707	0.4235	0.4113	0.4696	0.4685	0.45716	0.4575	0.3697	0.3961
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.5553	0.5791	0.5801	0.5944	0.5812	0.5623	0.6012	0.5073	0.5875	0.5926
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.0143		0.0004					-0.0238	
		(0.8583)		(0.9960)					(0.7892)	
$consumption$			0.2028	0.2147					0.1388	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-1.2349					-1.3381
					(0.4163)					(0.4252)
gas						0.0620			0.0639	0.0676
						(0.0003)			(0.0010)	(0.0004)
$hydro$							0.6120		0.4857	0.5909
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-0.83015	-1.0180	-0.9218
								(0.2384)	(0.1931)	(0.2248)
$exim_{QNI}$								-0.0759	-0.0892	-0.1038
								(0.2813)	(0.2607)	(0.1763)
$exim_{VNI}$								0.1082	0.1378	0.1039
								(0.0027)	(0.0008)	(0.0086)
Shape	2.7368	2.6903	2.8627	2.8229	2.6902	2.7712	2.9984	2.8153	3.1373	3.0807
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log Likelihood	-12615.46	-12522.92	-12423.65	-12330.16	-12507.30	-12600.20	-12493.69	-12519.98	-12231.91	-12323.42
AIC	7.3408	7.2881	7.2304	7.1772	7.2790	7.3331	7.2711	7.2887	7.1259	7.1779
BIC	7.3533	7.3042	7.2465	7.1968	7.2951	7.3491	7.2872	7.3120	7.1634	7.2119
$Q(20)$	1.35009	1.4802	4.4455	4.5792	1.4659	1.2747	1.2306	1.2688	3.8520	1.4159
	(0.8815)	(0.8515)	(0.1630)	(0.1474)	(0.8549)	(0.8977)	(0.9066)	(0.8989)	(0.2500)	(0.8667)
$Q^2(36)$	0.0051	0.0052	0.0131	0.0134	0.0052	0.0051	0.0034	0.0046	0.0057	0.0035
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0027	0.0028	0.0066	0.0075	0.0028	0.0025	0.0021	0.0025	0.0035	0.0022
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	3439	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 3: The effect of wind generation, electricity consumption, gas prices, and interconnectors flow on South Australia's electricity price behavior. 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	61.2996	80.0152	-36.9771	14.2491	79.6139	10.955	59.8263	-15.2729	38.9298
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1289)	(0.0000)
ϕ_1	0.5842	0.6290	0.6023	0.6400	0.6311	0.47087	0.6105	0.5474	0.5114
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-15.1445		-12.5028				-12.7961	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			30.1136	19.0979				17.8255	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-47.5034				-45.6440
					(0.0000)				(0.0000)
gas						8.3650		6.1472	7.0736
						(0.0000)		(0.0000)	(0.0000)
$exim_{heyw}$							6.3609	-11.1388	-10.0847
							(0.0000)	(0.0000)	(0.0000)
$exim_{murry}$							83.4109	44.4606	46.0293
							(0.0000)	(0.0000)	(0.0000)
					Variance Equation				
ω	3.2552	3.7145	1.1663	1.1381	4.6687	1.99188	3.4616	0.6852	2.6630
	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0234)	(0.0000)
α	-0.0792	-0.0117	-0.0371	0.0166	0.0609	-0.1642	-0.0306	-0.0353	-0.1067
	(0.0768)	(0.8154)	(0.3172)	(0.6854)	(0.0000)	(0.0000)	(0.5237)	(0.3722)	(0.0185)
β	0.5587	0.4903	0.4515	0.4455	0.3610	0.63140	0.5145	0.4440	0.4883
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.5016	0.4881	0.5864	0.5568	0.5597	0.45263	0.5099	0.5079	0.4737
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.0134		0.1025				0.1893	
		(0.7470)		(0.0222)				(0.0013)	
$consumption$			0.7805	0.7555				0.6329	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-0.2684				0.1095
					(0.0277)				(0.5157)
gas						0.10863		0.1061	0.1333
						(0.0000)		(0.0000)	(0.0000)
$exim_{heyw}$							0.1301	0.0990	0.1245
							(0.1386)	(0.2998)	(0.1721)
$exim_{murry}$							0.8512	0.6424	0.6636
							(0.0162)	(0.1009)	(0.0741)
$Shape$	2.3979	2.3159	2.7174	2.5587	2.3492	2.4694	2.3487	2.6372	2.4139
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log\ likelihood$	-16092.81	-15629.53	-15746.19	-15438.66	-15574.91	-15966.86	-15648.23	-15297.49	-15394.90
AIC	9.3631	9.0948	9.1627	8.9850	9.0630	9.2910	9.1069	8.9064	8.9618
BIC	9.3756	9.1109	9.1787	9.0046	9.0791	9.3071	9.1265	8.9367	8.9886
$Q(20)$	0.0366	0.4685	6.5090	5.7500	0.4493	0.6080	0.6111	5.8930	0.8018
	(0.9978)	(0.9949)	(0.0299)	(0.0576)	(0.9955)	(0.9881)	(0.9879)	(0.0510)	(0.9720)
$Q^2(36)$	0.0367	0.0347	0.0668	0.0743	0.0315	0.0389	0.03403	0.1023	0.03706
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$ARCH\text{-}LM\ Test$	0.0307	0.0282	0.0417	0.0476	0.0232	0.0326	0.0273	0.0694	0.0288
	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(1.0000)	(1.0000)	(1.0000)	(0.9997)	(1.0000)
$Observations$	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 4: The effect of wind generation, electricity consumption, gas prices, hydro generation, and interconnectors flow on Victoria's electricity price behavior. 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	55.5357	62.4618	-26.2933	1.2561	61.2108	44.3530	46.5494	59.0653	31.0060	50.3037
	(0.0000)	(0.0000)	(0.0000)	(0.7517)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.7670	0.7952	0.7903	0.81200	0.7980	0.7596	0.7989	0.7967	0.8059	0.8046
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-9.3468		-7.9024					-5.6644	
		(0.0000)		(0.0000)					(0.0000)	
$consumption$			6.4743	4.7584					1.6063	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-100.0000					-69.5166
					(0.0000)					(0.0000)
gas						1.9743			1.3077	1.3776
						(0.0000)			(0.0000)	(0.0000)
$hydro$							11.7813		5.1931	6.2821
							(0.0000)		(0.0000)	(0.0000)
$exim_{bass}$								8.4499	5.2680	5.8647
								(0.0000)	(0.0000)	(0.0000)
$exim_{heyw}$								0.1553	-2.3095	-2.4988
								(0.8318)	(0.0008)	(0.0038)
$exim_{VNI}$								-7.2068	-3.7079	-4.2282
								(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$								5.1647	0.2273	-0.7486
								(0.0338)	(0.9231)	(0.7894)
					Variance Equation					
ω	1.42613	2.4699	-0.4104	-0.3431	2.3883	1.6114	1.9076	2.4215	0.0529	2.1460
	(0.0000)	(0.0000)	(0.2793)	(0.4155)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9126)	(0.0000)
α	-0.1506	-0.1363	-0.1202	-0.0619	-0.1505	-0.1697	-0.1133	-0.1359	-0.0430	-0.0574
	(0.0000)	(0.0004)	(0.0005)	(0.0909)	(0.0001)	(0.0000)	(0.0012)	(0.0003)	(0.2383)	(0.1242)
β	0.7571	0.5701	0.5409	0.4709	0.5929	0.6763	0.6079	0.5747	0.4708	0.4821
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.40652	0.4543	0.4949	0.4558	0.4628	0.4574	0.4631	0.4482	0.4225	0.4143
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.0097		0.0734					0.1225	
		(0.8340)		(0.1570)					(0.0455)	
$consumption$			0.2354	0.2511					0.1745	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-0.6921					1.43069
					(0.2043)					(0.0579)
gas						0.0496			0.05745	0.0566
						(0.0015)			(0.0014)	(0.0015)
$hydro$							0.4186		0.2199	0.3849
							(0.0000)		(0.0055)	(0.0000)
$exim_{bass}$								0.0845	-0.0151	0.0418
								(0.0469)	(0.7659)	(0.3841)
$exim_{heyw}$								0.1891	0.1666	0.1572
								(0.0148)	(0.0606)	(0.0718)
$exim_{VNI}$								-0.0757	-0.0472	-0.0969
								(0.0163)	(0.2421)	(0.0115)
$exim_{murr}$								-0.8094	-0.7001	-0.7616
								(0.0125)	(0.0519)	(0.0325)
Shape	2.5984	2.5377	2.8571	2.7783	2.51015	2.6134	2.7310	2.5434	2.7651	2.6808
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-13925.35	-13564.78	-13662.80	-13398.21	-13539.68	-13887.69	-13699.24	-13521.06	-13278.52	-13296.37
AIC	8.1026	7.8940	7.9510	7.7983	7.8794	8.0818	7.9722	7.8721	7.7357	7.7449
BIC	8.1151	7.9101	7.9671	7.8180	7.8955	8.0979	7.9883	7.8989	7.7768	7.7824
Q(20)	1.5874	1.6186	7.1600	7.1560	1.8130	1.7525	5.1500	2.364 0	8.1030	5.1800
	(0.8248)	(0.8168)	(0.0167)	(0.0167)	(0.7645)	(0.7811)	(0.0943)	(0.6053)	(0.0069)	(0.0921)
$Q^2(36)$	0.0331	0.0211	0.0203	0.0128	0.02433	0.0366	0.0277	0.0241	0.0137	0.0138
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0326	0.0195	0.01995	0.0125	0.0228	0.0354	0.0243	0.0222	0.0132	0.0127
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	3439	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 5: The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on Tasmania's electricity price behavior. 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	59.7511	62.1004	20.9592	33.1653	62.0528	58.5080	59.4424	33.0415	61.3706
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9569	0.9634	0.9631	0.9642	0.9639	0.9576	0.9572	0.9643	0.9648
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-10.5035		-5.7509				-5.8390	
		(0.0000)		(0.0000)				(0.0000)	
$consumption$			14.6485	10.4509				10.1070	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$					-27.6488				-28.3447
					(0.0000)				(0.0000)
gas									
$hydro$						1.4388		1.1169	
						(0.0042)		(0.0028)	
$exim_{bass}$							1.8034		2.3559
							(0.0000)		(0.0000)
					Variance Equation				
ω	0.9585	1.19689	0.5208	1.0607	1.1939	0.9182	1.0341	1.0414	1.2614
	(0.0000)	(0.0000)	(0.1670)	(0.0116)	(0.0000)	(0.0000)	(0.0000)	(0.0123)	(0.0000)
α	0.0443	0.0102	0.0245	0.0072	0.0090	0.0388	0.0370	0.0053	-0.0012
	(0.3139)	(0.8328)	(0.6562)	(0.8927)	(0.8553)	(0.3743)	(0.4130)	(0.9210)	(0.9824)
β	0.8393	0.8212	0.8296	0.8247	0.8214	0.8431	0.8293	0.8284	0.8129
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.1081	1.2804	1.4478	1.4148	1.2978	1.1035	1.1548	1.4055	1.3963
	(0.0000)	(0.0000)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
$wind$		-0.4278		-0.4689				-0.4580	
		(0.0022)		(0.0014)				(0.002)	
$consumption$			0.2109	0.0592				0.0502	
			(0.1059)	(0.6703)				(0.7175)	
$wind_{pen}$					-1.0598				-0.9282
					(0.0031)				(0.0114)
$hydro$						0.0267		0.0252	
						(0.5531)		(0.5995)	
$exim_{bass}$							-0.0799		-0.0642
							(0.0130)		(0.0569)
$Shape$	2.2463	2.1931	2.1387	2.1502	2.18611	2.2457	2.2280	2.1512	2.1590
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log\ likelihood$	-12907.05	-12777.51	-12756.38	-12724.31	-12768.23	-12900.76	-12893.77	-12719.80	-12748.20
AIC	7.5104	7.4362	7.4239	7.4064	7.4308	7.5079	7.5038	7.4049	7.4203
BIC	7.5229	7.4523	7.4400	7.4261	7.4469	7.5239	7.5199	7.4282	7.4399
$Q(20)$	58.2400	57.6400	56.7400	58.8500	57.4000	58.9100	55.8200	59.0600	54.1700
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	2.4107	3.0359	3.1623	3.4111	3.0462	2.3314	2.5383	3.3242	3.3007
	(0.8507)	(0.7530)	(0.7319)	(0.6896)	(0.7513)	(0.8620)	(0.8320)	(0.7045)	(0.7084)
$ARCH\text{-}LM\ Test$	1.6395	1.9827	2.0895	2.2262	1.9853	1.5842	1.7353	2.1572	2.1791
	(0.7930)	(0.7210)	(0.6984)	(0.6695)	(0.7204)	(0.8043)	(0.7731)	(0.6840)	(0.6794)
$Observations$	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 6: The effect of wind generation, electricity consumption, and hydro generation during the implementation of the Carbon Pricing Mechanism (CPM) on electricity price behavior. The effect on price levels is given by the mean equation and on price volatility by the variance equation.

NSW

	Model K	Model L	Model M	Model N	Model O	Model P	Model Q
Mean Equation							
D_{cu}	10.6334 (0.0000)	8.8335 (0.0000)	53.2534 (0.0000)	9.8298 (0.0000)	8.8334 (0.0001)	17.6555 (0.0000)	30.2206 (0.0000)
wind	-6.0733 (0.0000)						-4.4324 (0.0000)
$D_{cu}\times wind$	3.1969 (0.0375)						3.7487 (0.0038)
consumption			3.8609 (0.0000)				2.6807 (0.0000)
$D_{cu}\times consumption$			-2.2056 (0.0000)				-0.9088 (0.0000)
$wind_{pen}$				-100.0000 (0.0000)			
$D_{cu}\times wind_{pen}$				24.9161 (0.3610)			
gas					0.6254 (0.001)		0.1425 (0.1755)
$D_{cu}\times gas$					0.2228 (0.4911)		0.2747 (0.2898)
hydro						11.5091 (0.0000)	6.7710 (0.0000)
$D_{cu}\times hydro$						-11.6139 (0.0000)	-8.0265 (0.0000)
Variance Equation							
D_{cu}	-0.4338 (0.0000)	-0.4080 (0.0499)	-0.0332 (0.9782)	-0.3637 (0.0722)	-0.4167 (0.2222)	-0.1011 (0.43623)	-1.2984 (0.3641)
wind		-0.0139 (0.9855)					-0.0510 (0.5872)
$D_{cu}\times wind$		0.0199 (0.9584)					0.1191 (0.7786)
consumption			0.2191 (0.0000)				0.1267 (0.0002)
$D_{cu}\times consumption$			-0.0216 (0.7308)				0.0673 (0.3733)
$wind_{pen}$				-1.1489 (0.4629)			
$D_{cu}\times wind_{pen}$				-1.2645 (0.8586)			
gas					0.0859 (0.0000)		0.0892 (0.0000)
$D_{cu}\times gas$					-0.0166 (0.7565)		-0.0362 (0.5542)
hydro						0.7750 (0.0000)	0.6571 (0.0000)
$D_{cu}\times hydro$						-0.5369 (0.0014)	-0.5510 (0.0072)
log likelihood	-12555.67	-12468.89	-12345.23	-12454.99	-12534.28	-12379.11	-12117.30
AIC	7.3072	7.2590	7.1871	7.2509	7.2971	7.2068	7.0650
BIC	7.3232	7.2822	7.2203	7.2742	7.3203	7.2300	7.1204
Q(20)	1.3656	1.4259	4.3437	1.4139	1.3052	1.1738	3.7210
$Q^2(36)$	0.0054 (0.8781)	0.0165 (0.8644)	0.0165 (0.1758)	0.0055 (0.8671)	0.0059 (0.8913)	0.0036 (0.9175)	0.0056 (0.2733)
ARCH-LM Test	0.0028 (1.0000)	0.003 (1.0000)	0.0095 (1.0000)	0.0030 (1.0000)	0.0029 (1.0000)	0.0023 (1.0000)	0.0033 (1.0000)
Observations	3439	3439	3439	3439	3439	3439	3439

SA

	Model K	Model L	Model M	Model N	Model O	Model Q
Mean Equation						
D_{cu}	10.9901 (0.0000)	6.0048 (0.0514)	39.3319 (0.0000)	5.9563 (0.0449)	11.1851 (0.4619)	19.8901 (0.0018)
wind	-15.8420 (0.0000)					-13.5691 (0.0000)
$D_{cu}\times wind$	4.5167 (0.0006)					4.4822 (0.0007)
consumption			32.228 (0.0000)			18.8938 (0.0000)
$D_{cu}\times consumption$			-8.3980 (0.0000)			-3.9816 (0.0126)
$wind_{pen}$				-49.8149 (0.0000)		
$D_{cu}\times wind_{pen}$				15.3732 (0.0003)		
gas					8.6319 (0.0941)	5.9800 (0.0000)
$D_{cu}\times gas$					-0.4337 (0.7353)	-0.4368 (0.2024)
Variance Equation						
D_{cu}	-0.2069 (0.0002)	0.0827 (0.6336)	0.4302 (0.4080)	0.0460 (0.7436)	-0.2266 (0.5427)	0.7072 (0.3160)
wind		-0.0021 (0.9659)				0.1900 (0.0021)
$D_{cu}\times wind$		-0.2074 (0.1135)				-0.2114 (0.1023)
consumption			0.8489 (0.0000)			0.6775 (0.0000)
$D_{cu}\times consumption$			-0.2000 (0.2020)			-0.1401 (0.4093)
$wind_{pen}$				-0.3161 (0.0146)		
$D_{cu}\times wind_{pen}$				-0.4362 (0.2008)		
gas					0.1232 (0.0126)	0.1097 (0.0000)
$D_{cu}\times gas$					0.0056 (0.9224)	-0.0270 (0.7085)
log likelihood	-16066.83	-15603.54	-15708.35	-15536.75	-15942.27	-15258.65
AIC	9.3491	9.0820	9.1430	9.0432	9.2790	8.8884
BIC	9.3652	9.1052	9.1662	9.0664	9.3022	8.9331
Q(20)	4.0667	0.35884	6.2944	0.4326	0.7275	5.5867
$Q^2(36)$	0.0373 (0.9968)	0.0278 (0.9979)	0.0370 (0.03904)	0.0373 (0.9961)	0.04206 (0.9791)	0.0682 (0.0660)
ARCH-LM Test	0.0312 (1.0000)	0.0203 (1.0000)	0.0415 (0.9999)	0.0302 (1.0000)	0.0355 (0.9999)	0.0750 (0.9997)
Observations	3439	3439	3439	3439	3439	3439

VIC

	Model K	Model L	Model M	Model N	Model O	Model P	Model Q
Mean Equation							
D_{cu}	8.5311 (0.0000)	3.6748 (0.0491)	52.0962 (0.0000)	5.778 (0.0015)	12.2875 (0.0003)	12.6754 (0.0000)	24.2449 (0.0004)
wind	-10.1840 (0.0000)						-6.1944 (0.0000)
$D_{cu}\times wind$	5.4468 (0.0000)						4.6584 (0.0000)
consumption			7.4568 (0.0000)				2.1327 (0.0000)
$D_{cu}\times consumption$			-3.5369 (0.0000)				-1.4205 (0.0305)
$wind_{pen}$				-100.0000 (0.0000)			
$D_{cu}\times wind_{pen}$				37.4303 (0.0010)			
gas					2.0834 (0.0000)		1.3104 (0.0000)
$D_{cu}\times gas$					-0.7401 (0.0816)		-0.4923 (0.0000)
hydro						13.7976 (0.0000)	5.7151 (0.0000)
$D_{cu}\times hydro$						-6.2734 (0.0000)	-1.6154 (0.3574)
Variance Equation							
D_{cu}	-0.2236 (0.0007)	-0.2012 (0.1598)	-1.2976 (0.1294)	-0.1135 (0.3861)	-0.2521 (0.4963)	-0.4809 (0.0002)	-1.4894 (0.1509)
wind		-0.0138 (0.7791)					0.0795 (0.2140)
$D_{cu}\times wind$		-0.0073 (0.9614)					0.2288 (0.1804)
consumption			0.2254 (0.0000)				0.1411 (0.0012)
$D_{cu}\times consumption$			0.0799 (0.2384)				0.1181 (0.1694)
$wind_{pen}$				-0.6353 (0.2779)			
$D_{cu}\times wind_{pen}$				-1.005 (0.5596)			
gas					0.0638 (0.0002)		0.0684 (0.0003)
$D_{cu}\times gas$					-0.0023 (0.9718)		-0.1115 (0.1725)
hydro						0.3917 (0.0002)	0.1075 (0.0271)
$D_{cu}\times hydro$						0.2964 (0.0509)	0.2253 (0.2547)
log likelihood	-13889.43	-13529.36	-13624.13	-13514.06	-13859.49	-13657.18	-13228.71
AIC	8.0886	7.8758	7.9309	7.8669	8.0677	7.9501	7.7125
BIC	8.1047	7.8990	7.9541	7.8901	8.0910	7.9733	7.7715
Q(20)	1.3451	1.4639	1.6219	1.6219	1.5848	4.9630	7.3410
$Q^2(36)$	0.0277 (0.8826)	0.0166 (1.0000)	0.0144 (1.0000)	0.0210 (1.0000)	0.0297 (0.8255)	0.0179 (1.0000)	0.1092 (0.01413)
ARCH-LM Test	0.0259 (1.0000)	0.0151 (1.0000)	0.0014 (1.0000)	0.0195 (1.0000)	0.0277 (1.0000)	0.0158 (1.0000)	0.0750 (0.9997)
Observations	3439	3439	3439	3439	3439	3439	3439

TAS

	Model K	Model L	Model M	Model N	Model P	Model Q
Mean Equation						
D_{cu}	-0.2713 (0.9909)	-2.1106 (0.3437)	22.9799 (0.0000)	-2.0802 (0.3863)	14.8384 (0.0000)	19.9908 (0.0000)
wind		-12.9729 (0.0000)				-6.4178 (0.0000)
$D_{cu}\times wind$		5.9192 (0.0000)				1.8215 (0.0001)
consumption			18.1472 (0.0000)			9.1875 (0.0000)
$D_{cu}\times consumption$			-8.7412 (0.0000)			-1.3476 (0.0000)
$wind_{pen}$				-33.7269 (0.0000)		
$D_{cu}\times wind_{pen}$				14.7054 (0.0221)		
hydro					6.2713 (0.0000)	3.6200 (0.0000)
$D_{cu}\times hydro$					-5.2336 (0.0000)	-5.3903 (0.0000)
Variance Equation						
D_{cu}	-0.3010 (0.0000)	-0.3629 (0.0003)	0.4500 (0.6213)	-0.3687 (0.0002)	0.2305 (0.3370)	-0.2795 (0.7793)
wind		-0.4735 (0.0028)				-0.4485 (0.0075)
$D_{cu}\times wind$		0.1554 (0.6775)				0.2546 (0.5119)
consumption			0.3150 (0.0470)			0.0102 (0.9537)
$D_{cu}\times consumption$			-0.2856 (0.4020)			0.1693 (0.6521)
$wind_{pen}$				-1.2034 (0.0032)		
$D_{cu}\times wind_{pen}$				0.4697 (0.6248)		
hydro					0.0315 (0.0899)	0.0325 (0.3995)
$D_{cu}\times hydro$					-0.1919 (0.0332)	-0.1993 (0.0301)
log likelihood	-12870.66	-12731.10	-12708.06	-12721.81	-12763.94	-12636.90
AIC	7.4904	7.4115	7.3981	7.4061	7.4306	7.3614
BIC	7.5064	7.4347	7.4213	7.4293	7.4538	7.3989
Q(20)	54.8400	53.5700	53.2600	53.2500	50.9500	52.6300
$Q^2(36)$	6.7573 (0.2353)	6.7654 (0.2196)	6.7303 (0.1780)	6.6573 (0.2203)	7.1155 (0.1897)	7.2388 (0.1800)
ARCH-LM Test	6.5359 (0.1091)	6.6347 (0.1040)	7.3619 (0.0725)	6.6571 (0.1028)	6.8390 (0.09404)	7.1324 (0.0813)
Observations	3439	3439	3439	3439	3439	3439

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 7: The effect of wind generation, electricity consumption, and hydro generation during the implementation of nationwide restrictions due COVID-19 on electricity price behavior. The effect on price levels is given by the mean equation and on price volatility by the variance equation.

NSW

	Model R	Model S	Model T	Model U	Model V	Model W	Model X
Mean Equation							
D_{co}	-10.3086 (0.0165)	-8.4105 (0.0516)	2.1101 (0.9628)	-7.6757 (0.0754)	-21.7722 (0.0003)	-15.4581 (0.0034)	-84.5834 (0.0000)
$wind$		-5.9078 (0.0000)					-4.5077 (0.0000)
$D_{co} \times wind$		0.5858 (0.7150)					1.1326 (0.3547)
$consumption$			3.2314 (0.0000)				2.4673 (0.0000)
$D_{co} \times consumption$			-0.5767 (0.8086)				2.9431 (0.0011)
$wind_{gen}$				-100.0000 (0.0000)			
$D_{co} \times wind_{gen}$				-8.3813 (0.7821)			
gas					0.6215 (0.0000)		0.1902 (0.1751)
$D_{co} \times gas$					2.2640 (0.0187)		3.1074 (0.0002)
$hydro$						7.5285 (0.0000)	3.9724 (0.0000)
$D_{co} \times hydro$						7.4525 (0.1810)	10.0652 (0.0209)
Variance Equation							
D_{co}	-0.0018 (0.9907)	-0.2334 (0.3183)	3.7775 (0.3687)	-0.2534 (0.2769)	-1.1467 (0.5133)	0.3054 (0.3981)	-10.7977 (0.1641)
$wind$		-0.0383 (0.6417)					-0.0388 (0.6747)
$D_{co} \times wind$		0.4288 (0.1678)					0.0137 (0.9704)
$consumption$			0.2048 (0.0000)				0.1382 (0.0000)
$D_{co} \times consumption$			-0.1932 (0.3768)				0.2447 (0.4333)
$wind_{gen}$				-1.7303 (0.2692)			
$D_{co} \times wind_{gen}$				8.8010 (0.1360)			
gas					0.0619 (0.0004)		0.0642 (0.0010)
$D_{co} \times gas$					0.2214 (0.5122)		1.2121 (0.0644)
$hydro$						0.6209 (0.0000)	0.4924 (0.0000)
$D_{co} \times hydro$						-0.4896 (0.4200)	-0.5980 (0.5174)
log likelihood	-12611.48	-12520.08	-12420.61	-12504.31	-12594.95	-12488.07	-12225.72
AIC	7.3396	7.2888	7.2309	7.2796	7.3323	7.2702	7.1281
BIC	7.3557	7.3120	7.2542	7.3028	7.3556	7.2934	7.1834
Q(20)	1.33763	1.4592	4.3718	1.4402	1.2767	1.2087	3.7510
Q^2(36)	0.0051 (0.8843)	0.0052 (0.8565)	0.0130 (0.1722)	0.0052 (0.8610)	0.0051 (0.8973)	0.0034 (0.9109)	0.0057 (0.2678)
ARCH-LM Test	0.0026 (1.0000)	0.0028 (1.0000)	0.0065 (1.0000)	0.0028 (1.0000)	0.0025 (1.0000)	0.0021 (1.0000)	0.0034 (1.0000)
Observations	3439	3439	3439	3439	3439	3439	3439

SA

	Model R	Model S	Model T	Model U	Model V	Model X
Mean Equation						
D_{co}	-0.3187 (0.3376)	-6.1253 (0.1078)	-3.3307 (0.8248)	-5.2293 (0.1484)	19.0547 (0.0000)	-11.5560 (0.2108)
$wind$		-15.5142 (0.0000)				-12.9711 (0.0000)
$D_{co} \times wind$		4.4725 (0.0014)				4.8723 (0.0015)
$consumption$			30.3641 (0.0000)			17.6988 (0.0000)
$D_{co} \times consumption$			-0.5410 (0.8435)			0.7905 (0.8497)
$wind_{gen}$				-48.1500 (0.0000)		
$D_{co} \times wind_{gen}$				10.4479 (0.0189)		
gas					8.4115 (0.0000)	6.1769 (0.0000)
$D_{co} \times gas$					-2.6728 (0.0001)	0.7255 (0.7638)
Variance Equation						
D_{co}	-0.2730 (0.05513)	-0.5106 (0.1207)	3.9454 (0.0775)	-0.6165 (0.0563)	2.3784 (0.1219)	3.5535 (0.0194)
$wind$		-0.0125 (0.7679)				0.1858 (0.0055)
$D_{co} \times wind$		0.0536 (0.8189)				0.1143 (0.4911)
$consumption$			0.8027 (0.0000)			0.6519 (0.0000)
$D_{co} \times consumption$			-1.2940 (0.0442)			-0.3970 (0.3652)
$wind_{gen}$				-0.3126 (0.0100)		
$D_{co} \times wind_{gen}$				0.4361 (0.5745)		
gas					0.1117 (0.0000)	0.1024 (0.0097)
$D_{co} \times gas$					-0.4617 (0.0986)	-0.5162 (0.0495)
log likelihood	-16090.74	-15621.54	-15738.45	-15563.21	-15963.80	-15287.86
AIC	9.3630	9.0925	9.1605	9.0586	9.2915	8.9054
BIC	9.3791	9.1157	9.1837	9.0818	9.3148	8.9501
Q(20)	0.0036	0.4535	6.7410	0.5186	0.6178	6.0020
Q^2(36)	0.0365 (0.9980)	0.0341 (0.9954)	0.0641 (0.0243)	0.0368 (0.9928)	0.0390 (0.9875)	0.1027 (0.0465)
ARCH-LM Test	0.0305 (1.0000)	0.0277 (1.0000)	0.0411 (0.9999)	0.0298 (1.0000)	0.0326 (1.0000)	0.0706 (0.9997)
Observations	3439	3439	3439	3439	3439	3439

VIC

	Model R	Model S	Model T	Model U	Model V	Model W	Model X
Mean Equation							
D_{co}	-10.0977 (0.0451)	-12.6614 (0.0006)	-80.1369 (0.0626)	-11.2769 (0.0032)	-5.6873 (0.8122)	-20.3283 (0.0002)	0.5577 (0.8730)
$wind$		-9.6708 (0.0000)					-5.8757 (0.0000)
$D_{co} \times wind$		2.0371 (0.0250)					3.8289 (0.0000)
$consumption$			6.4429 (0.0000)				1.5683 (0.0008)
$D_{co} \times consumption$			5.5143 (0.0964)				-0.4265 (0.4903)
$wind_{gen}$				-100.0000 (0.0000)			
$D_{co} \times wind_{gen}$				4.3929 (0.6973)			
gas					1.9705 (0.0000)		1.3043 (0.0000)
$D_{co} \times gas$					-0.6883 (0.8811)		-2.1812 (0.3405)
$hydro$						11.6088 (0.0000)	5.1301 (0.0000)
$D_{co} \times hydro$						7.8946 (0.0016)	4.2085 (0.2488)
Variance Equation							
D_{co}	0.0034 (0.9661)	-0.4425 (0.1003)	5.1012 (0.1690)	-0.3823 (0.0933)	0.3966 (0.7625)	0.4758 (0.110089)	2.0680 (0.6837)
$wind$		0.0404 (0.4564)					0.1282 (0.0403)
$D_{co} \times wind$		0.0790 (0.7281)					-0.0949 (0.6937)
$consumption$			0.2364 (0.0000)				0.1788 (0.0000)
$D_{co} \times consumption$			-0.4111 (0.1616)				-0.1300 (0.7943)
$wind_{gen}$				-0.6990 (0.2096)			
$D_{co} \times wind_{gen}$				1.9179 (0.4541)			
gas					0.0493 (0.0016)		0.0544 (0.0027)
$D_{co} \times gas$					-0.0719 (0.7840)		-0.0259 (0.9469)
$hydro$						0.4441 (0.0000)	0.2396 (0.0029)
$D_{co} \times hydro$						-0.8997 (0.0082)	-0.6281 (0.3032)
log likelihood	-13923.06	-13562.98	-13658.74	-13533.56	-13885.54	-13688.62	-13267.54
AIC	8.1024	7.8953	7.9510	7.8782	8.0829	7.9684	7.7351
BIC	8.1185	7.9185	7.9742	7.9014	8.1061	7.9916	7.7941
Q(20)	1.5585	1.0685	7.1340	1.7790	1.7242	5.2780	8.1910
Q^2(36)	0.03303 (0.8322)	0.0100 (1.0000)	0.0207 (1.0000)	0.0243 (1.0000)	0.0368 (1.0000)	0.0276 (1.0000)	0.0140 (1.0000)
ARCH-LM Test	0.0325 (1.0000)	0.0074 (1.0000)	0.0203 (1.0000)	0.0228 (1.0000)	0.0356 (0.9999)	0.0242 (1.0000)	0.0133 (1.0000)
Observations	3439	3439	3439	3439	3439	3439	3439

TAS

	Model R	Model S	Model T	Model U	Model W	Model X
Mean Equation						
D_{co}	5.2015 (0.1996)	1.7347 (0.6975)	-0.8496 (0.9686)	2.5212 (0.5766)	16.4108 (0.3758)	5.6648 (0.8544)
$wind$		-0.5359 (0.0000)				-6.1606 (0.0000)
$D_{co} \times wind$		3.2203 (0.4900)				0.1518 (0.9814)
$consumption$			14.6328 (0.0000)			10.1884 (0.0000)
$D_{co} \times consumption$			1.2682 (0.8774)			-1.0067 (0.9316)
$wind_{gen}$				-27.7265 (0.0000)		
$D_{co} \times wind_{gen}$				9.1795 (0.4448)		
$hydro$					4.6657 (0.0000)	
$D_{co} \times hydro$					-5.4709 (0.2957)	
Variance Equation						
D_{co}	0.0193 (0.8563)	-0.0048 (0.9851)	-2.0625 (0.6035)	0.0032 (0.9900)	0.6600 (0.5578)	-0.9017 (0.8389)
$wind$		-0.4393 (0.0029)				-0.4286 (0.0055)
$D_{co} \times wind$		0.2204 (0.7876)				0.3527 (0.0890)
$consumption$			0.2011 (0.1258)			0.0680 (0.6418)
$D_{co} \times consumption$			0.7717 (0.5960)			0.3312 (0.8354)
$wind_{gen}$				-1.0835 (0.0029)		
$D_{co} \times wind_{gen}$				0.4883 (0.8241)		
$hydro$					-0.0580 (0.0766)	
$D_{co} \times hydro$					-0.2155 (0.5884)	
log likelihood	-12906.60	-12777.08	-12755.94	-12767.77	-12815.27	-12706.88
AIC	7.5113	7.4383	7.4260	7.4328	7.4605	7.4009
BIC	7.5273	7.4615	7.4492	7.4561	7.4837	7.4349
Q(20)	58.2500	57.8800	57.0900	57.6100	52.8000	55.4300
Q^2(36)	2.4136 (0.8503)	3.0260 (0.7547)	3.1500 (0.7324)	3.0334 (0.7534)	3.4132 (0.6892)	3.6210 (0.6536)
ARCH-LM Test	1.6438 (0.7921)	1.9723 (0.7232)	2.0970 (0.6968)	1.9732 (0.7230)	2.3231 (0.6491)	2.3681 (0.6397)
Observations	3439	3439	3439	3439	3439	3439

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 8: Price distribution properties for different wind penetration levels.

Wind Penetration	< 5%	5% − 15%		< 5%	5% − 10%	10% − 15%	15% − 30%		< 5%	5% − 10%	10% − 15%	15% − 20%	20% − 35%
		NSW				VIC					TAS		
Mean	61.39	50.48		66.68	63.06	49.27	34.40		70.20	62.74	59.45	54.21	48.85
Standard Deviation	56.73	15.88		36.15	113.38	20.35	20.54		37.73	28.43	27.44	34.08	32.74
Skewness	18.11	0.89		8.32	21.82	0.10	-0.19		2.56	1.73	1.45	1.42	1.47
Kurtosis	389.69	3.98		120.21	554.18	5.58	0.18		16.56	7.42	6.78	5.15	5.66
Observations	3092	347		1259	1405	535	240		890	1081	776	421	271

Wind Penetration	< 5%	5% − 10%	10% − 15%	15% − 20%	20% − 25%	25% − 30%	30% − 35%	35% − 40%	40% − 45%	45% − 50%	> 50%
						SA					
Mean	112.38	89.81	99.92	82.12	69.49	85.58	67.98	64.78	61.83	58.90	44.91
Standard Deviation	124.29	63.16	104.86	53.41	149.58	197.77	49.95	27.96	38.32	27.77	29.78
Skewness	6.41	6.32	6.09	6.87	11.75	12.92	9.08	2.76	3.10	0.24	1.78
Kurtosis	47.53	51.49	46.52	73.27	162.08	192.26	117.24	19.19	24.02	6.18	21.91
Observations	131	161	201	305	332	368	296	242	224	201	978

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Appendices

A Data

A.1 Preliminary analysis

Table 9: 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
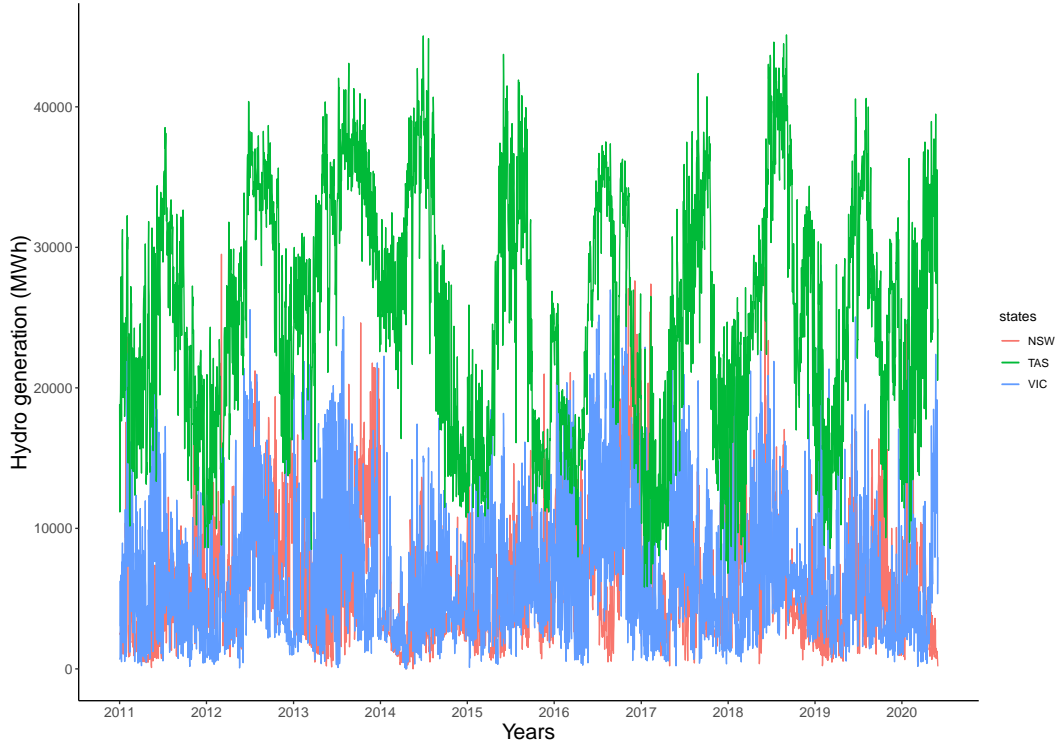
Figure 6: The daily hydro generation for NSW, SA, VIC, and TAS from January 1, 2020, to May 31, 2020.

A.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[39] is defined as

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

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 10. The total number of outliers in the NEM during the sample period is 599. TAS accounts for more than half of the

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[39]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).

Table 10: Occurrences of extreme spikes in prices by region and Weekday.

Weekday	NSW	SA	VIC	TAS	TOTAL
Monday	9	19	11	43	82
Tuesday	13	17	13	41	84
Wednesday	10	24	20	49	103
Thursday	17	23	22	48	110
Friday	12	23	15	49	99
Saturday	4	13	9 3	8	64
Sunday	2	10	7	38	57
TOTAL	67	129	97	306	599
	11.19%	21.54%	16.19%	51.09%	100%

total spikes, and NSW has the lowest number of instances where prices exceeded the limit (11.19% of the total sample spikes). Furthermore, price spikes are more pronounced during business days than at the weekends. All values in Table 10 are then replaced by the median of the respective weekday (Ketterer, 2014; Kyritsis et al., 2017).

A.3 Deseasonalizing and detrending the data

We assume that the time series p_t can be decomposed as a sum of the stochastic component y_t and the seasonal component s_t, that is, $p_t = y_t + s_t$, $t > 0$ (Bierbrauer et al., 2007; Trueck et al., 2007; Ketterer, 2014; Pereira and Rodrigues, 2015).[40] We then apply the ordinary least squares (OLS) approach by creating dummy variables for the days ($day_i, i = 1, 2, \ldots, 7$) corresponding to Monday to Sunday, months ($month_j, j = 1, 2, \ldots, 12$) corresponding to January to December and years ($year_k, k = 1, 2, \ldots, 10$) corresponding to 2011 to 2020, and specify the OLS as

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

where p_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 weekly, monthly and yearly regressors. The deseasonalized time series of electricity prices and other explanatory variables is captured by the

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[40]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 deseasonalized 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, 2014; Auer, 2014).

regression residuals ϵ_t. Similar to Ketterer (2014) we then 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. The reason for the two-stage approach is because 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, 2020). The results for the deseasonalized and detrended time series are presented in Tables 11 to 18.

We specify Monday, January, and the year 2011 in Table 11 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, prices 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 behavior where prices in autumn, especially March and April, exceed summer month prices.

After accounting for price spikes in Table 12, 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 winter months. Further, 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.[41] This is mostly accounted for by the repeal of the carbon pricing mechanism on July, 1 2014.

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[41]The year 2020 dummy does not cover the whole year but the sample period from January 1, 2020, to May 31, 2020.

Table 11: 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)	46.8946	4.7001	9.977	< 2e − 16	***	66.508	8.262	8.050	1.14e − 15	***
Tuesday	2.4696	3.4676	0.712	0.476387		-5.175	6.096	-0.849	0.395953	
Wednesday	2.7243	3.4677	0.786	0.432143		-1.253	6.096	-0.205	0.837210	
Thursday	1.9126	3.4677	0.552	0.581297		12.925	6.096	2.120	0.034051	*
Friday	5.3469	3.4678	1.542	0.123195		-1.710	6.096	-0.280	0.779144	
Saturday	-3.6419	3.4659	-1.051	0.293433		-18.318	6.093	-3.007	0.002661	**
Sunday	-9.0805	3.4658	-2.620	0.008831	**	-20.991	6.092	-3.445	0.000577	***
February	4.7119	4.4668	1.055	0.291557		-20.690	7.852	-2.635	0.008453	**
March	-16.4177	4.3640	-3.762	0.000171	***	-30.679	7.671	-3.999	6.49e − 05	***
April	-12.1218	4.4001	-2.755	0.005903	**	-31.091	7.735	-4.020	5.96e − 05	***
May	-13.2085	4.3639	-3.027	0.002490	**	-26.694	7.671	-3.480	0.000508	***
June	-3.3494	4.5465	-0.737	0.461355		-15.482	7.992	-1.937	0.052817	.
July	-7.9612	4.5076	-1.766	0.077453	.	-2.384	7.924	-0.301	0.763551	
August	-7.7437	4.5075	-1.718	0.085899	.	-28.954	7.924	-3.654	0.000262	***
September	-6.3475	4.5465	-1.396	0.162771		-33.491	7.992	-4.190	2.86e − 05	***
October	-8.6893	4.5075	-1.928	0.053971	.	-37.566	7.924	-4.741	2.21e − 06	***
November	-7.6952	4.5465	-1.693	0.090633	.	-35.970	7.992	-4.501	7.00e − 06	***
December	-15.1619	4.5076	-3.364	0.000778	***	-26.869	7.924	-3.391	0.000705	***
2012	4.1253	4.0189	1.026	0.304749		6.789	7.065	0.961	0.336650	
2013	14.9803	4.0217	3.725	0.000199	***	34.240	7.070	4.843	1.33e − 06	***
2014	3.8526	4.0217	0.958	0.338150		10.673	7.070	1.510	0.131227	
2015	0.2348	4.0217	0.058	0.953449		12.083	7.070	1.709	0.087516	.
2016	20.0209	4.0189	4.982	6.62e − 07	***	43.163	7.065	6.110	1.11e − 09	***
2017	56.5887	4.0217	14.071	< 2e − 16	***	67.926	7.070	9.608	< 2e − 16	***
2018	43.4131	4.0217	10.795	< 2e − 16	***	62.431	7.070	8.831	< 2e − 16	***
2019	45.9243	4.0217	11.419	< 2e − 16	***	61.485	7.070	8.697	< 2e − 16	***
2020	28.6670	5.3646	5.344	9.70e − 08	***	13.241	9.430	1.404	0.160402	
Multiple R-squared		0.1383					0.0882			
Adjusted R-squared		0.1317					0.0812			
		VIC					TAS			
Intercept (c)	53.908	6.673	8.078	9.02e − 16	***	41.3443	2.8247	14.637	< 2e − 16	***
Tuesday	1.357	4.923	0.276	0.782818		0.1746	2.0839	0.084	0.9332	
Wednesday	2.683	4.923	0.545	0.585863		-0.3671	2.0840	-0.176	0.8602	
Thursday	11.764	4.923	2.389	0.016935	*	-0.9230	2.0840	-0.443	0.6579	
Friday	7.754	4.924	1.575	0.115362		-2.8644	2.0841	-1.374	0.1694	
Saturday	-8.234	4.921	-1.673	0.094360	.	-5.1073	2.0829	-2.452	0.0143	*
Sunday	-11.068	4.921	-2.249	0.024563	*	-4.6960	2.0829	-2.255	0.0242	*
February	-27.834	6.342	-4.389	1.17e − 05	***	2.8378	2.6845	1.057	0.2905	
March	-29.312	6.196	-4.731	2.33e − 06	***	11.2428	2.6227	4.287	1.86e − 05	***
April	-31.058	6.247	-4.971	6.98e − 07	***	6.8530	2.6444	2.591	0.0096	**
May	-28.790	6.196	-4.647	3.50e − 06	***	-15.6316	2.6226	-5.960	2.77e − 09	***
June	-19.045	6.455	-2.950	0.003196	**	-13.4544	2.7324	-4.924	8.88e − 07	***
July	-21.558	6.400	-3.368	0.000764	***	-15.7293	2.7090	-5.806	6.97e − 09	***
August	-25.537	6.400	-3.990	6.74e − 05	***	-25.8588	2.7090	-9.546	< 2e − 16	***
September	-26.472	6.455	-4.101	4.21e − 05	***	-25.1761	2.7324	-9.214	< 2e − 16	***
October	-30.492	6.400	-4.765	1.97e − 06	***	-15.9627	2.7089	-5.893	4.17e − 09	***
November	-28.551	6.455	-4.423	1.00e − 05	***	-13.2618	2.7324	-4.854	1.27e − 06	***
December	-33.241	6.400	-5.194	2.18e − 07	***	-16.5307	2.7090	-6.102	1.16e − 09	***
2012	15.044	5.706	2.636	0.008416	**	12.6772	2.4153	5.249	1.63e − 07	***
2013	23.463	5.710	4.109	4.06e − 05	***	17.0519	2.4170	7.055	2.08e − 12	***
2014	12.219	5.710	2.140	0.032433	*	9.7926	2.4170	4.052	5.20e − 05	***
2015	4.438	5.710	0.777	0.437094		18.3135	2.4170	7.577	4.52e − 14	***
2016	18.048	5.706	3.163	0.001575	**	66.6363	2.4153	27.589	< 2e − 16	***
2017	62.858	5.710	11.008	< 2e − 16	***	68.9337	2.4170	28.521	< 2e − 16	***
2018	61.067	5.710	10.695	< 2e − 16	***	44.4992	2.4170	18.411	< 2e − 16	***
2019	79.968	5.710	14.005	< 2e − 16	***	64.8003	2.4170	26.811	< 2e − 16	***
2020	30.663	7.617	4.026	5.80e − 05	***	-1.9709	3.2240	-0.611	0.5410	
Multiple R-squared		0.1267					0.4335			
Adjusted R-squared		0.1200					0.4292			

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$, $p < 1$

Table 12: Seasonal and trend adjustment of daily electricity prices adjusted for the outliers effect. The threshold is set at $3\times$MAD.

	Estimate	Std. Error	t value	$\Pr(>|t|)$		Estimate	Std. Error	t value	$\Pr(>|t|)$	
		NSW					SA			
Intercept (c)	27.44988	1.17291	23.403	$< 2e-16$	***	29.30708	2.02722	14.457	$< 2e-16$	***
Tuesday	0.46801	0.86533	0.541	0.58864		0.53909	1.49561	0.360	0.718533	
Wednesday	1.16181	0.86535	1.343	0.17950		-0.83688	1.49565	-0.560	0.575830	
Thursday	0.48761	0.86537	0.563	0.57315		-0.35234	1.49568	-0.236	0.813780	
Friday	0.02506	0.86538	0.029	0.97690		-1.86234	1.49570	-1.245	0.213170	
Saturday	-3.54185	0.86491	-4.095	$4.32e-05$	***	-9.05673	1.49488	-6.058	$1.52e-09$	***
Sunday	-6.07831	0.86489	-7.028	$2.52e-12$	***	-10.81304	1.49486	-7.233	$5.78e-13$	***
February	1.22860	1.11470	1.102	0.27046		3.03549	1.92661	1.576	0.115219	
March	-0.83418	1.08902	-0.766	0.44374		-1.02483	1.88224	-0.544	0.586150	
April	3.53910	1.09805	3.223	0.00128	**	3.68740	1.89785	1.943	0.052106	.
May	2.73904	1.08901	2.515	0.01194	*	6.12862	1.88221	3.256	0.001141	**
June	6.97931	1.13459	6.151	$8.57e-10$	***	14.25939	1.96099	7.272	$4.39e-13$	***
July	5.79924	1.12486	5.156	$2.67e-07$	***	11.42628	1.94417	5.877	$4.57e-09$	***
August	6.05115	1.12486	5.379	$7.97e-08$	***	7.17426	1.94417	3.690	0.000228	***
September	5.38983	1.13459	4.750	$2.11e-06$	***	3.94292	1.96099	2.011	0.044438	*
October	4.82532	1.12485	4.290	$1.84e-05$	***	-1.10023	1.94415	-0.566	0.571486	
November	3.59369	1.13458	3.167	0.00155	**	0.82835	1.96097	0.422	0.672748	
December	-1.34481	1.12488	-1.196	0.23197		0.04488	1.94420	0.023	0.981585	
2012	13.52476	1.00293	13.485	$< 2e-16$	***	13.70430	1.73343	7.906	$3.56e-15$	***
2013	23.66874	1.00361	23.584	$< 2e-16$	***	32.94324	1.73461	18.992	$< 2e-16$	***
2014	13.22754	1.00361	13.180	$< 2e-16$	***	15.43573	1.73461	8.899	$< 2e-16$	***
2015	7.91299	1.00361	7.885	$4.21e-15$	***	16.66478	1.73461	9.607	$< 2e-16$	***
2016	25.46557	1.00292	25.391	$< 2e-16$	***	28.36201	1.73343	16.362	$< 2e-16$	***
2017	56.91209	1.00361	56.707	$< 2e-16$	***	60.52080	1.73461	34.890	$< 2e-16$	***
2018	50.18483	1.00361	50.004	$< 2e-16$	***	56.46360	1.73461	32.551	$< 2e-16$	***
2019	49.67861	1.00361	49.500	$< 2e-16$	***	49.25717	1.73461	28.397	$< 2e-16$	***
2020	19.49527	1.33874	14.562	$< 2e-16$	***	13.47634	2.31384	5.824	$6.27e-09$	***
Multiple R-squared		0.6759					0.4435			
Adjusted R-squared		0.6734					0.4392			
		VIC					TAS			
Intercept (c)	23.263909	1.457538	15.961	$< 2e-16$	***	35.6563	1.6176	22.043	$< 2e-16$	***
Tuesday	1.294187	1.075319	1.204	0.228852		0.7119	1.1934	0.597	0.550877	
Wednesday	0.115687	1.075352	0.108	0.914335		-0.8263	1.1934	-0.692	0.488759	
Thursday	-0.001834	1.075370	-0.002	0.998640		-1.1672	1.1935	-0.978	0.328147	
Friday	-0.142540	1.075383	-0.133	0.894558		-2.8070	1.1935	-2.352	0.018734	*
Saturday	-6.603647	1.074799	-6.144	$8.97e-10$	***	-3.6022	1.1928	-3.020	0.002548	**
Sunday	-9.149048	1.074779	-8.512	$< 2e-16$	***	-3.2630	1.1928	-2.736	0.006260	**
February	4.299361	1.385202	3.104	0.001926	**	-2.5420	1.5373	-1.653	0.098322	.
March	3.494963	1.353301	2.583	0.009849	**	-5.0036	1.5019	-3.331	0.000873	***
April	5.918268	1.364523	4.337	$1.48e-05$	***	-8.7109	1.5144	-5.752	$9.59e-09$	***
May	7.635450	1.353279	5.642	$1.82e-08$	***	-5.7597	1.5019	-3.835	0.000128	***
June	14.152060	1.409925	10.037	$< 2e-16$	***	-0.8454	1.5648	-0.540	0.589032	
July	11.731422	1.397831	8.393	$< 2e-16$	***	-5.2629	1.5513	-3.392	0.000701	***
August	8.907235	1.397831	6.372	$2.11e-10$	***	-10.4975	1.5513	-6.767	$1.54e-11$	***
September	7.148357	1.409923	5.070	4.19e-07	***	-11.3172	1.5648	-7.233	$5.82e-13$	***
October	4.968516	1.397817	3.554	0.000384	***	-3.1881	1.5513	-2.055	0.039949	*
November	5.649593	1.409910	4.007	$6.28e-05$	***	1.0644	1.5647	0.680	0.496391	
December	0.779054	1.397852	0.557	0.577344		-1.6799	1.5514	-1.083	0.278945	
2012	14.261363	1.246310	11.443	$< 2e-16$	***	11.8581	1.3832	8.573	$< 2e-16$	***
2013	24.163109	1.247158	19.375	$< 2e-16$	***	15.6919	1.3841	11.337	$< 2e-16$	***
2014	12.231857	1.247158	9.808	$< 2e-16$	***	9.4193	1.3841	6.805	$1.19e-11$	***
2015	6.137143	1.247158	4.921	$9.02e-07$	***	17.3408	1.3841	12.528	$< 2e-16$	***
2016	17.041951	1.246307	13.674	$< 2e-16$	***	19.2404	1.3832	13.910	$< 2e-16$	***
2017	59.124508	1.247158	47.407	$< 2e-16$	***	49.0737	1.3841	35.455	$< 2e-16$	***
2018	55.354707	1.247158	44.385	$< 2e-16$	***	39.3860	1.3841	28.456	$< 2e-16$	***
2019	55.798515	1.247158	44.741	$< 2e-16$	***	38.6620	1.3841	27.933	$< 2e-16$	***
2020	17.740404	1.663615	10.664	$< 2e-16$	***	9.2253	1.8463	4.997	$6.13e-07$	***
Multiple R-squared		0.6364					0.4189			
Adjusted R-squared		0.6337					0.4144			

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

Table 13: 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)	2.682386	0.137194	19.552	$< 2e-16$	***	3.314618	0.122276	27.108	$< 2e-16$	***
Tuesday	0.066038	0.101217	0.652	0.514163		0.090871	0.090211	1.007	0.313849	
Wednesday	0.066213	0.101220	0.654	0.513057		0.162038	0.090213	1.796	0.072557	.
Thursday	0.105067	0.101222	1.038	0.299348		0.097351	0.090215	1.079	0.280617	
Friday	0.001449	0.101223	0.014	0.988576		0.063885	0.090216	0.708	0.478913	
Saturday	-0.338332	0.101168	-3.344	0.000834	***	-0.140990	0.090167	-1.564	0.117991	
Sunday	-0.375369	0.101166	-3.710	0.000210	***	-0.198720	0.090165	-2.204	0.027594	*
February	0.311066	0.130385	2.386	0.017099	*	0.302527	0.116207	2.603	0.009272	**
March	0.118234	0.127383	0.928	0.353380		0.031653	0.113531	0.279	0.780411	
April	-0.120826	0.128439	-0.941	0.346910		-0.118950	0.114472	-1.039	0.298823	
May	0.224483	0.127380	1.762	0.078108	.	0.158881	0.113529	1.399	0.161761	
June	1.433802	0.132712	10.804	$< 2e-16$	***	0.991946	0.118281	8.386	$< 2e-16$	***
July	1.260491	0.131574	9.580	$< 2e-16$	***	1.728652	0.117267	14.741	$< 2e-16$	***
August	0.741515	0.131574	5.636	$1.88e-08$	***	0.617861	0.117267	5.269	$1.46e-07$	***
September	0.180591	0.132712	1.361	0.173676		-0.006927	0.118281	-0.059	0.953304	
October	-0.217470	0.131573	-1.653	0.098454	.	-0.287699	0.117265	-2.453	0.014201	*
November	-0.290538	0.132711	-2.189	0.028646	*	-0.115781	0.118280	-0.979	0.327712	
December	-0.333300	0.131576	-2.533	0.011349	*	0.427164	0.117268	3.643	0.000274	***
2012	1.883377	0.117312	16.054	$< 2e-16$	***	0.878632	0.104555	8.404	$< 2e-16$	***
2013	1.579485	0.117392	13.455	$< 2e-16$	***	1.090517	0.104626	10.423	$< 2e-16$	***
2014	0.559875	0.117392	4.769	$1.93e-06$	***	0.130494	0.104626	1.247	0.212395	
2015	1.211213	0.117392	10.318	$< 2e-16$	***	0.949109	0.104626	9.071	$< 2e-16$	***
2016	3.228080	0.117311	27.517	$< 2e-16$	***	3.700175	0.104555	35.390	$< 2e-16$	***
2017	6.168645	0.117392	52.548	$< 2e-16$	***	4.796865	0.104626	45.848	$< 2e-16$	***
2018	6.573598	0.117392	55.997	$< 2e-16$	***	5.451738	0.104626	52.107	$< 2e-16$	***
2019	6.119757	0.117392	52.131	$< 2e-16$	***	5.814598	0.104626	55.575	$< 2e-16$	***
2020	2.453538	0.156592	15.668	$< 2e-16$	***	2.406839	0.139564	17.245	$< 2e-16$	***
Multiple R-squared			0.7093					0.7209		
Adjusted R-squared			0.7071					0.7188		

	Estimate	Std. Error	t value	$\Pr(> |t|)$	
			VIC		
Intercept (c)	2.602386	0.125845	20.679	$< 2e-16$	***
Tuesday	0.050901	0.092844	0.548	0.583562	
Wednesday	0.081623	0.092847	0.879	0.379405	
Thursday	0.111339	0.092849	1.199	0.230557	
Friday	-0.092926	0.092850	-1.001	0.316982	
Saturday	-0.147995	0.092799	-1.595	0.110854	
Sunday	-0.161113	0.092798	-1.736	0.082623	.
February	0.312189	0.119600	2.610	0.009086	**
March	0.016374	0.116845	0.140	0.888563	
April	0.003677	0.117814	0.031	0.975103	
May	0.446090	0.116844	3.818	0.000137	***
June	1.166584	0.121734	9.583	$< 2e-16$	***
July	1.439296	0.120690	11.926	$< 2e-16$	***
August	0.533250	0.120690	4.418	$1.03e-05$	***
September	0.050989	0.121734	0.419	0.675350	
October	-0.050287	0.120689	-0.417	0.676950	
November	-0.189792	0.121733	-1.559	0.119070	
December	-0.049226	0.120692	-0.408	0.683398	
2012	1.067093	0.107608	9.917	$< 2e-16$	***
2013	1.154799	0.107681	10.724	$< 2e-16$	***
2014	0.579988	0.107681	5.386	$7.68e-08$	***
2015	0.958527	0.107681	8.902	$< 2e-16$	***
2016	3.574431	0.107607	33.217	$< 2e-16$	***
2017	5.677707	0.107681	52.727	$< 2e-16$	***
2018	6.066366	0.107681	56.336	$< 2e-16$	***
2019	5.869392	0.107681	54.507	$< 2e-16$	***
2020	2.505682	0.143638	17.444	$< 2e-16$	***
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 14: 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)	220035.5	970.3	226.768	$< 2e-16$	***	38962.0	358.6	108.657	$< 2e-16$	***
Tuesday	2986.5	715.9	4.172	$3.10e-05$	***	698.1	264.5	2.639	0.008359	**
Wednesday	2061.0	715.9	2.879	0.004015	**	848.7	264.6	3.208	0.001349	**
Thursday	2692.8	715.9	3.761	0.000172	***	973.5	264.6	3.680	0.000237	***
Friday	1476.8	715.9	2.063	0.039196	*	307.7	264.6	1.163	0.244952	
Saturday	-12850.0	715.5	-17.959	$< 2e-16$	***	-3172.5	264.4	-11.998	$< 2e-16$	***
Sunday	-17955.6	715.5	-25.095	$< 2e-16$	***	-4106.7	264.4	-15.531	$< 2e-16$	***
February	-727.1	922.2	-0.789	0.430448		101.7	340.8	0.298	0.765353	
March	-10456.3	900.9	-11.606	$< 2e-16$	***	-2674.2	332.9	-8.032	$1.31e-15$	***
April	-20063.5	908.4	-22.087	$< 2e-16$	***	-4419.3	335.7	-13.165	$< 2e-16$	***
May	-6742.5	900.9	-7.484	$9.11e-14$	***	-2423.9	332.9	-7.280	$4.11e-13$	***
June	8419.6	938.6	8.970	$< 2e-16$	***	317.0	346.9	0.914	0.360838	
July	10210.9	930.6	10.973	$< 2e-16$	***	167.1	343.9	0.486	0.626985	
August	1328.6	930.6	1.428	0.153456		-1078.2	343.9	-3.135	0.001731	**
September	-16116.4	938.6	-17.170	$< 2e-16$	***	-4756.7	346.9	-13.714	$< 2e-16$	***
October	-22610.6	930.6	-24.298	$< 2e-16$	***	-6244.	1 343.9	-18.157	$< 2e-16$	***
November	-17654.1	938.6	-18.809	$< 2e-16$	***	-4870.6	346.9	-14.042	$< 2e-16$	***
December	-14804.0	930.6	-15.908	$< 2e-16$	***	-3373.2	343.9	-9.809	$< 2e-16$	***
2012	-11411.4	829.7	-13.754	$< 2e-16$	***	-420.1	306.6	-1.370	0.170737	
2013	-17963.5	830.3	-21.636	$< 2e-16$	***	-1644.5	306.8	-5.360	$8.89e-08$	***
2014	-19491.4	830.3	-23.476	$< 2e-16$	***	-2203.3	306.8	-7.181	$8.45e-13$	***
2015	-18006.2	830.3	-21.688	$< 2e-16$	***	-2318.7	306.8	-7.557	$5.26e-14$	***
2016	-18037.0	829.7	-21.740	$< 2e-16$	***	-3660.7	306.6	-11.939	$< 2e-16$	***
2017	-16171.4	830.3	-19.478	$< 2e-16$	***	-4141.2	306.8	-13.497	$< 2e-16$	***
2018	-17515.0	830.3	-21.096	$< 2e-16$	***	-4757.9	306.8	-15.507	$< 2e-16$	***
2019	-18372.4	830.3	-22.129	$< 2e-16$	***	-4562.0	306.8	-14.869	$< 2e-16$	***
2020	-25563.5	1107.5	-23.082	$< 2e-16$	***	-6932.5	409.3	-16.938	$< 2e-16$	***
Multiple R-squared			0.6296					0.6268		
Adjusted R-squared			0.4093					0.4048		
			VIC					TAS		
Intercept (c)	140518.2	777.1	180.819	$< 2e-16$	***	26306.24	123.60	212.839	$< 2e-16$	***
Tuesday	2524.0	573.3	4.402	$1.10e-05$	***	-57.27	91.19	-0.628	0.529989	
Wednesday	2927.0	573.3	5.105	$3.49e-07$	***	-238.45	91.19	-2.615	0.008963	**
Thursday	3541.2	573.4	6.176	$7.34e-10$	***	-161.52	91.19	-1.771	0.076600	.
Friday	1667.9	573.4	2.909	0.00365	**	-302.66	91.19	-3.319	0.000913	***
Saturday	-11926.6	573.1	-20.812	$< 2e-16$	***	-1203.57	91.14	-13.206	$< 2e-16$	***
Sunday	-15954.2	573.0	-27.841	$< 2e-16$	***	-1231.13	91.14	-13.508	$< 2e-16$	***
February	2099.8	738.6	2.843	0.00449	**	-87.95	117.46	-0.749	0.454047	
March	-2903.0	721.5	-4.023	$5.86e-05$	***	-499.80	114.76	-4.355	$1.37e-05$	***
April	-7065.6	727.5	-9.712	$< 2e-16$	***	749.23	115.71	6.475	$1.08e-10$	***
May	1847.6	721.5	2.561	0.01049	*	2683.41	114.76	23.384	$< 2e-16$	***
June	9709.8	751.7	12.917	$< 2e-16$	***	4559.91	119.56	38.139	$< 2e-16$	***
July	9485.4	745.3	12.727	$< 2e-16$	***	4709.67	118.53	39.733	$< 2e-16$	***
August	6060.3	745.3	8.131	$5.87e-16$	***	3990.67	118.53	33.667	$< 2e-16$	***
September	-3059.6	751.7	-4.070	$4.81e-05$	***	2151.91	119.56	17.999	$< 2e-16$	***
October	-7923.3	745.3	-10.631	$< 2e-16$	***	720.72	118.53	6.080	$1.33e-09$	***
November	-7616.8	751.7	-10.132	$< 2e-16$	***	605.78	119.56	5.067	$4.26e-07$	***
December	-8427.8	745.3	-11.308	$< 2e-16$	***	-469.86	118.54	-3.964	$7.53e-05$	***
2012	-1603.8	664.5	-2.414	0.01585	*	-1071.92	105.69	-10.143	$< 2e-16$	***
2013	-5132.1	664.9	-7.718	$1.54e-14$	***	-350.52	105.76	-3.314	0.000928	***
2014	-9629.9	664.9	-14.482	$< 2e-16$	***	-818.70	105.76	-7.741	$1.29e-14$	***
2015	-12747.8	664.9	-19.171	$< 2e-16$	***	-136.16	105.76	-1.287	0.198026	
2016	-15405.7	664.5	-23.184	$< 2e-16$	***	-1880.05	105.68	-17.789	$< 2e-16$	***
2017	-18410.8	664.9	-27.688	$< 2e-16$	***	-421.94	105.76	-3.990	$6.75e-05$	***
2018	-18597.1	664.9	-27.968	$< 2e-16$	***	38.72	105.76	0.366	0.714318	
2019	-19475.1	664.9	-29.288	$< 2e-16$	***	-1096.73	105.76	-10.370	$< 2e-16$	***
2020	-24182.4	887.0	-27.263	$< 2e-16$	***	-849.28	141.07	-6.020	$1.93e-09$	***
Multiple R-squared			0.6519					0.6685		
Adjusted R-squared			0.6493					0.6659		

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$, $p < 1$

Table 15: 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)	518.945	297.807	1.743	0.08150	.	8910.947	596.586	14.937	$< 2e-16$	***
Tuesday	103.379	219.711	0.471	0.63801		3.067	440.139	0.007	0.994441	
Wednesday	-5.124	219.718	-0.023	0.98139		223.418	440.153	0.508	0.611773	
Thursday	-61.861	219.722	-0.282	0.77831		26.107	440.160	0.059	0.952707	
Friday	213.505	219.724	0.972	0.33127		-51.750	440.166	-0.118	0.906417	
Saturday	189.357	219.605	0.862	0.38860		-297.917	439.926	-0.677	0.498326	
Sunday	-53.193	219.601	-0.242	0.80862		-141.553	439.918	-0.322	0.747646	
February	414.918	283.027	1.466	0.14274		-961.439	566.978	-1.696	0.090029	.
March	138.663	276.509	0.501	0.61607		-1043.075	553.920	-1.883	0.059775	.
April	-133.539	278.802	-0.479	0.63199		-1897.138	558.513	-3.397	0.000690	***
May	1081.833	276.504	3.913	$9.31e-05$	***	355.412	553.911	0.642	0.521149	
June	758.929	288.078	2.634	0.00847	**	-446.529	577.097	-0.774	0.439132	
July	2415.231	285.607	8.456	$< 2e-16$	***	3118.416	572.147	5.450	$5.38e-08$	***
August	2405.825	285.607	8.424	$< 2e-16$	***	2211.721	572.147	3.866	0.000113	***
September	1992.295	288.078	6.916	$5.53e-12$	***	1523.121	577.096	2.639	0.008346	**
October	1439.187	285.605	5.039	$4.92e-07$	***	805.808	572.141	1.408	0.159102	
November	1627.597	288.075	5.650	$1.74e-08$	***	-197.576	577.091	-0.342	0.732096	
December	1522.535	285.612	5.331	$1.04e-07$	***	163.039	572.155	0.285	0.775695	
2012	160.412	254.648	0.630	0.52878		820.376	510.128	1.608	0.107889	
2013	474.258	254.822	1.861	0.06281	.	1140.676	510.475	2.235	0.025512	*
2014	864.492	254.822	3.393	0.00070	***	1974.621	510.475	3.868	0.000112	***
2015	2912.945	254.822	11.431	$< 2e-16$	***	2355.695	510.475	4.615	$4.08e-06$	***
2016	3826.350	254.648	15.026	$< 2e-16$	***	3270.596	510.126	6.411	$1.64e-10$	***
2017	3501.339	254.822	13.740	$< 2e-16$	***	4180.024	510.475	8.189	$3.70e-16$	***
2018	6688.913	254.822	26.249	$< 2e-16$	***	6396.801	510.475	12.531	$< 2e-16$	***
2019	10192.236	254.822	39.998	$< 2e-16$	***	6379.013	510.475	12.496	$< 2e-16$	***
2020	11170.534	339.913	32.863	$< 2e-16$	***	6652.503	680.935	9.770	$< 2e-16$	***
Multiple R-squared		0.5228					0.1248			
Adjusted R-squared		0.5191					0.1181			
		VIC					TAS			
Intercept (c)	2013.71	494.57	4.072	$4.77e-05$	***	1022.953	138.393	7.392	$1.81e-13$	***
Tuesday	-88.23	364.88	-0.242	0.8089		64.277	102.102	0.630	0.529039	
Wednesday	-161.97	364.89	-0.444	0.6571		6.491	102.105	0.064	0.949317	
Thursday	149.58	364.89	0.410	0.6819		90.801	102.106	0.889	0.373917	
Friday	11.53	364.90	0.032	0.9748		114.602	102.108	1.122	0.261784	
Saturday	31.67	364.70	0.087	0.9308		198.086	102.052	1.941	0.052337	.
Sunday	-102.66	364.69	-0.281	0.7783		102.278	102.050	1.002	0.316302	
February	-135.84	470.02	-0.289	0.7726		14.029	131.525	0.107	0.915060	
March	215.16	459.20	0.469	0.6394		-233.330	128.496	-1.816	0.069480	.
April	-674.56	463.01	-1.457	0.1452		-327.817	129.561	-2.530	0.011444	*
May	1920.45	459.19	4.182	$2.96e-05$	***	140.178	128.494	1.091	0.275381	
June	721.59	478.41	1.508	0.1316		31.343	133.872	0.234	0.814903	
July	4163.88	474.31	8.779	$< 2e-16$	***	589.327	132.724	4.440	$9.27e-06$	***
August	3071.29	474.31	6.475	$1.08e-10$	***	380.244	132.724	2.865	0.004197	**
September	2295.18	478.41	4.797	$1.68e-06$	***	435.289	133.872	3.252	0.001159	**
October	1961.82	474.31	4.136	$3.62e-05$	***	436.832	132.723	3.291	0.001007	**
November	1207.66	478.41	2.524	0.0116	*	444.150	133.871	3.318	0.000917	***
December	1093.98	474.32	2.306	0.0211	*	403.187	132.726	3.038	0.002402	**
2012	866.20	422.90	2.048	0.0406	*	-21.521	118.337	-0.182	0.855701	
2013	3760.67	423.18	8.887	$< 2e-16$	***	981.055	118.418	8.285	$< 2e-16$	***
2014	3628.63	423.18	8.575	$< 2e-16$	***	1296.474	118.418	10.948	$< 2e-16$	***
2015	5279.46	423.18	12.476	$< 2e-16$	***	1422.898	118.418	12.016	$< 2e-16$	***
2016	6170.19	422.90	14.590	$< 2e-16$	***	1764.059	118.337	14.907	$< 2e-16$	***
2017	6347.32	423.18	14.999	$< 2e-16$	***	1565.316	118.418	13.219	$< 2e-16$	***
2018	8583.49	423.18	20.283	$< 2e-16$	***	1692.083	118.418	14.289	$< 2e-16$	***
2019	10651.35	423.18	25.170	$< 2e-16$	***	2000.780	118.418	16.896	$< 2e-16$	***
2020	12653.26	564.50	22.415	$< 2e-16$	***	2269.684	157.960	14.369	$< 2e-16$	***
Multiple R-squared		0.2952					0.1845			
Adjusted R-squared		0.2899					0.1783			

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

Table 16: 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)	4701.827	335.049	14.033	$< 2e-16$	***	6622.82	364.86	18.152	$< 2e-16$	***
Tuesday	146.680	247.187	0.593	0.552957		636.08	269.18	2.363	0.0182	*
Wednesday	-9.126	247.195	-0.037	0.970554		473.25	269.19	1.758	0.0788	.
Thursday	180.082	247.199	0.728	0.466364		493.23	269.19	1.832	0.0670	.
Friday	-90.137	247.202	-0.365	0.715411		-169.65	269.19	-0.630	0.5286	
Saturday	-2495.496	247.068	-10.100	$< 2e-16$	***	-4701.08	269.05	-17.473	$< 2e-16$	***
Sunday	-2830.194	247.063	-11.455	$< 2e-16$	***	-5156.63	269.04	-19.167	$< 2e-16$	***
February	-116.574	318.421	-0.366	0.714313		684.98	346.75	1.975	0.0483	*
March	-899.776	311.088	-2.892	0.003848	**	-398.27	338.76	-1.176	0.2398	
April	-1782.617	313.667	-5.683	$1.43e-08$	***	-784.58	341.57	-2.297	0.0217	*
May	-1078.081	311.083	-3.466	0.000536	***	2317.75	338.76	6.842	$9.22e-12$	***
June	2040.351	324.104	6.295	$3.46e-10$	***	4028.52	352.94	11.414	$< 2e-16$	***
July	992.672	321.324	3.089	0.002022	**	3383.18	349.91	9.669	$< 2e-16$	***
August	596.084	321.324	1.855	0.063670	.	2687.87	349.91	7.682	$2.04e-14$	***
September	320.571	324.104	0.989	0.322685		1633.72	352.94	4.629	$3.81e-06$	***
October	1587.021	321.321	4.939	$8.23e-07$	***	476.79	349.91	1.363	0.1731	
November	1325.619	324.101	4.090	$4.41e-05$	***	-659.51	352.93	-1.869	0.0618	.
December	1462.310	321.329	4.551	$5.53e-06$	***	-849.12	349.91	-2.427	0.0153	*
2012	4771.066	286.494	16.653	$< 2e-16$	***	420.49	311.98	1.348	0.1778	
2013	3725.389	286.688	12.995	$< 2e-16$	***	2484.37	312.19	7.958	$2.36e-15$	***
2014	-497.410	286.688	-1.735	0.082828	.	-1292.24	312.19	-4.139	$3.57e-05$	***
2015	782.154	286.688	2.728	0.006400	**	658.96	312.19	2.111	0.0349	*
2016	5616.309	286.493	19.604	$< 2e-16$	***	4400.54	311.98	14.105	$< 2e-16$	***
2017	1070.645	286.688	3.735	0.000191	***	86.49	312.19	0.277	0.7818	
2018	3582.641	286.688	12.497	$< 2e-16$	***	1220.15	312.19	3.908	$9.47e-05$	***
2019	852.048	286.688	2.972	0.002979	**	-609.17	312.19	-1.951	0.0511	.
2020	2388.153	382.421	6.245	$4.77e-10$	***	541.02	416.44	1.299	0.1940	

Multiple R-squared		0.3206				0.3806	
Adjusted R-squared		0.3155				0.3759	

	Estimate	Std. Error	t value	Pr($> |t|$)	
			TAS		
Intercept (c)	18021.4	469.3	38.403	$< 2e-16$	***
Tuesday	144.6	346.2	0.418	0.676194	
Wednesday	115.0	346.2	0.332	0.739686	
Thursday	471.5	346.2	1.362	0.173299	
Friday	257.4	346.2	0.743	0.457260	
Saturday	-2428.8	346.0	-7.019	$2.69e-12$	***
Sunday	-3206.4	346.0	-9.266	$< 2e-16$	***
February	-462.2	446.0	-1.036	0.300115	
March	-1326.0	435.7	-3.043	0.002358	**
April	3141.7	439.3	7.151	$1.05e-12$	***
May	7786.2	435.7	17.871	$< 2e-16$	***
June	12189.9	453.9	26.854	$< 2e-16$	***
July	14393.7	450.0	31.983	$< 2e-16$	***
August	14450.4	450.0	32.109	$< 2e-16$	***
September	10300.8	453.9	22.692	$< 2e-16$	***
October	5668.7	450.0	12.596	$< 2e-16$	***
November	2947.5	453.9	6.493	$9.62e-11$	***
December	1045.8	450.0	2.324	0.020201	*
2012	2705.6	401.3	6.743	$1.82e-11$	***
2013	8657.6	401.5	21.561	$< 2e-16$	***
2014	3564.6	401.5	8.878	$< 2e-16$	***
2015	-235.6	401.5	-0.587	0.557412	
2016	1213.8	401.3	3.025	0.002505	**
2017	-1484.2	401.5	-3.696	0.000222	***
2018	4782.3	401.5	11.910	$< 2e-16$	***
2019	540.7	401.5	1.347	0.178180	
2020	6244.2	535.6	11.658	$< 2e-16$	***

Multiple R-squared		0.5825
Adjusted R-squared		0.5793

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$, $p < 1$

Table 17: 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)	-3929.4	430.7	-9.124	$< 2e-16$	***	3698.181	355.443	10.404	$< 2e-16$	***
Tuesday	283.0	317.7	0.891	0.373190		-75.339	262.233	-0.287	0.773903	
Wednesday	370.5	317.7	1.166	0.243697		-248.992	262.241	-0.949	0.342445	
Thursday	688.5	317.7	2.167	0.030304	*	-89.794	262.246	-0.342	0.732068	
Friday	583.6	317.7	1.837	0.066330	.	-209.086	262.249	-0.797	0.425343	
Saturday	-1170.0	317.6	-3.684	0.000233	***	-233.379	262.106	-0.890	0.373314	
Sunday	-1987.1	317.6	-6.258	$4.40e-10$	***	-277.434	262.102	-1.058	0.289903	
February	297.4	409.3	0.727	0.467474		-8.867	337.803	-0.026	0.979060	
March	-553.5	399.9	-1.384	0.166353		-48.543	330.024	-0.147	0.883069	
April	2245.8	403.2	5.570	$2.74e-08$	***	720.962	332.760	2.167	0.030333	*
May	3781.3	399.8	9.457	$< 2e-16$	***	123.700	330.018	0.375	0.707811	
June	5457.4	416.6	13.100	$< 2e-16$	***	823.502	343.832	2.395	0.016671	*
July	7171.1	413.0	17.363	$< 2e-16$	***	-1092.988	340.883	-3.206	0.001357	**
August	7371.6	413.0	17.848	$< 2e-16$	***	-239.662	340.883	-0.703	0.482065	
September	5416.3	416.6	13.002	$< 2e-16$	***	-1142.807	343.832	-3.324	0.000898	***
October	2341.0	413.0	5.668	$1.56e-08$	***	-2112.728	340.879	-6.198	$6.41e-10$	***
November	597.9	416.6	1.435	0.151286		-1801.794	343.828	-5.240	$1.70e-07$	***
December	183.4	413.0	0.444	0.657097		-489.178	340.888	-1.435	0.151375	
2012	3731.9	368.2	10.135	$< 2e-16$	***	-786.363	303.932	-2.587	0.009714	**
2013	8246.4	368.5	22.379	$< 2e-16$	***	2004.670	304.139	6.591	$5.03e-11$	***
2014	3601.9	368.5	9.775	$< 2e-16$	***	1145.025	304.139	3.765	0.000169	***
2015	-2943.6	368.5	-7.988	$1.85e-15$	***	2049.797	304.139	6.740	$1.86e-11$	***
2016	2661.7	368.2	7.228	$6.01e-13$	***	3001.316	303.931	9.875	$< 2e-16$	***
2017	-275.6	368.5	-0.748	0.454642		-1580.376	304.139	-5.196	$2.15e-07$	***
2018	3582.2	368.5	9.721	$< 2e-16$	***	-2209.189	304.139	-7.264	$4.64e-13$	***
2019	558.7	368.5	1.516	0.129568		-5353.895	304.139	-17.603	$< 2e-16$	***
2020	4032.3	491.5	8.203	$3.28e-16$	***	-3701.436	405.698	-9.124	$< 2e-16$	***
Multiple R-squared		0.4118					0.2932			
Adjusted R-squared		0.4073					0.2878			
		VNI					Murrylink			
Intercept (c)	9545.7	653.7	14.602	$< 2e-16$	***	-548.215	95.328	-5.751	$9.66e-09$	***
Tuesday	-513.1	482.3	-1.064	0.287430		-13.329	70.330	-0.190	0.849699	
Wednesday	-778.1	482.3	-1.613	0.106762		23.507	70.332	0.334	0.738228	
Thursday	-779.6	482.3	-1.616	0.106079		8.775	70.333	0.125	0.900718	
Friday	-439.5	482.3	-0.911	0.362236		36.838	70.334	0.524	0.600479	
Saturday	1505.9	482.1	3.124	0.001799	**	-136.081	70.296	-1.936	0.052971	.
Sunday	2691.2	482.0	5.583	$2.55e-08$	***	-175.316	70.294	-2.494	0.012677	*
February	-1058.2	621.3	-1.703	0.088604	.	-20.276	90.597	-0.224	0.822923	
March	-1330.4	607.0	-2.192	0.028449	*	98.930	88.511	1.118	0.263767	
April	-402.4	612.0	-0.657	0.510907		181.915	89.245	2.038	0.041588	*
May	-4256.8	607.0	-7.013	$2.79e-12$	***	84.900	88.509	0.959	0.337514	
June	-6002.1	632.4	-9.492	$< 2e-16$	***	449.118	92.214	4.870	$1.16e-06$	***
July	-4457.4	626.9	-7.110	$1.41e-12$	***	616.111	91.423	6.739	$1.86e-11$	***
August	-2805.5	626.9	-4.475	$7.89e-06$	***	453.830	91.423	4.964	$7.24e-07$	***
September	-1743.7	632.4	-2.757	0.005857	**	350.948	92.214	3.806	0.000144	***
October	258.9	626.9	0.413	0.679630		160.891	91.422	1.760	0.078520	.
November	-2220.0	632.3	-3.511	0.000453	***	73.989	92.213	0.802	0.422397	
December	-799.0	626.9	-1.274	0.202614		215.268	91.425	2.355	0.018599	*
2012	-391.1	559.0	-0.700	0.484212		-53.895	81.513	-0.661	0.508542	
2013	2186.1	559.4	3.908	$9.48e-05$	***	689.708	81.569	8.456	$< 2e-16$	***
2014	4851.4	559.4	8.673	$< 2e-16$	***	8.423	81.569	0.103	0.917757	
2015	3513.4	559.4	6.281	$3.79e-10$	***	457.485	81.569	5.609	$2.20e-08$	***
2016	7753.5	559.0	13.871	$< 2e-16$	***	936.150	81.513	11.485	$< 2e-16$	***
2017	-3339.8	559.4	-5.971	$2.60e-09$	***	96.588	81.569	1.184	0.236445	
2018	-5194.5	559.4	-9.287	$< 2e-16$	***	405.154	81.569	4.967	$7.13e-07$	***
2019	-7465.1	559.4	-13.346	$< 2e-16$	***	284.582	81.569	3.489	0.000491	***
2020	-1999.3	746.1	-2.679	0.007409	**	1326.159	108.806	12.188	$< 2e-16$	***
Multiple R-squared		0.3126					0.1249			
Adjusted R-squared		0.3073					0.1182			

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

Table 18: 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)	-7521.34	504.02	-14.923	$< 2e-16$	***	-1516.928	52.251	-29.032	$< 2e-16$	***
Tuesday	-286.86	371.84	-0.771	0.44049		-26.593	38.549	-0.690	0.490332	
Wednesday	-62.32	371.86	-0.168	0.86692		-15.449	38.550	-0.401	0.688634	
Thursday	-244.22	371.86	-0.657	0.51139		-38.010	38.550	-0.986	0.324211	
Friday	-334.79	371.87	-0.900	0.36803		-38.445	38.551	-0.997	0.318708	
Saturday	-907.17	371.66	-2.441	0.01470	*	-131.548	38.530	-3.414	0.000647	***
Sunday	-1028.23	371.66	-2.767	0.00569	**	-97.883	38.529	-2.540	0.011114	*
February	-1088.72	479.00	-2.273	0.02309	*	-8.238	49.657	-0.166	0.868252	
March	-1531.16	467.97	-3.272	0.00108	**	-184.474	48.514	-3.803	0.000146	***
April	-4783.79	471.85	-10.138	$< 2e-16$	***	-535.918	48.916	-10.956	$< 2e-16$	***
May	-3206.04	467.96	-6.851	$8.66e-12$	***	-461.333	48.513	-9.509	$< 2e-16$	***
June	-5588.93	487.55	-11.463	$< 2e-16$	***	-451.847	50.544	-8.940	$< 2e-16$	***
July	-5396.01	483.37	-11.163	$< 2e-16$	***	-293.507	50.110	-5.857	$5.15e-09$	***
August	-5804.77	483.37	-12.009	$< 2e-16$	***	-404.124	50.110	-8.065	$1.01e-15$	***
September	-4270.08	487.55	-8.758	$< 2e-16$	***	-289.311	50.544	-5.724	$1.13e-08$	***
October	-2843.94	483.36	-5.884	$4.40e-09$	***	-292.928	50.110	-5.846	$5.52e-09$	***
November	-2583.59	487.55	-5.299	$1.24e-07$	***	-275.456	50.543	-5.450	$5.40e-08$	***
December	-638.40	483.38	-1.321	0.18669		-65.280	50.111	-1.303	0.192761	
2012	-2018.13	430.97	-4.683	$2.94e-06$	***	-177.215	44.678	-3.966	$7.44e-05$	***
2013	8541.96	431.27	19.807	$< 2e-16$	***	-177.215	44.678	-3.966	$7.44e-05$	***
2014	-507.35	431.27	-1.176	0.23951		55.202	44.709	1.235	0.217026	
2015	1149.83	431.27	2.666	0.00771	**	402.844	44.709	9.010	$< 2e-16$	***
2016	5684.77	430.97	13.191	$< 2e-16$	***	819.372	44.678	18.339	$< 2e-16$	***
2017	-859.47	431.27	-1.993	0.04635	*	139.706	44.709	3.125	0.001794	**
2018	-223.89	431.27	-0.519	0.60369		341.283	44.709	7.633	$2.95e-14$	***
2019	-202.69	431.27	-0.470	0.63839		500.302	44.709	11.190	$< 2e-16$	***
2020	793.98	575.28	1.380	0.16762		925.931	59.638	15.526	$< 2e-16$	***
Multiple R-squared			0.2991					0.2954		
Adjusted R-squared			0.2913					0.2901		

$***p < 0.001, **p < 0.01, *p < 0.05, .p < 0.1, p < 1$

A.4 Summary statistics and time-series tests of the data series

The summary statistics and time-series tests of the deseasonalized and detrended electricity prices are given in Table 19. In Table 20, we apply the augmented 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 19 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

Table 19: 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	60.29	158.96	64.51	4856.46	50.42	-147.03	14700.00	34.45	68.76	1.62×10^{11}
Daily	60.29	58.31	15.70	331.00	51.60	18.54	1539.50	35.77	74.30	15858700
Prices adjusted for outliers	55.86	23.73	0.75	-0.09	51.58	18.54	136.30	35.77	72.02	326.7
Deseasonalized actual prices	60.29	54.12	18.79	424.60	55.73	0.14	1518.88	47.09	66.23	26066236
Deseasonalized outliers-adjusted prices	55.86	13.51	0.89	2.39	54.63	17.40	125.21	47.86	62.33	1276.70
SA										
30-min prices	69.85	242.478	40.25	2006.12	50.86	-996.70	14700.00	33.94	79.81	2.7726×10^{10}
Daily	69.85	99.64	17.40	457.21	54.36	-107.16	3359.82	35.30	84.79	30162390
Prices adjusted for outliers	59.67	31.29	0.71	0.190	53.91	-45.74	162.15	35.39	78.94	293.04
Deseasonalized actual prices	69.85	95.14	18.70	509.80	62.46	-103.27	3288.75	45.80	78.91	37484939
Deseasonalized outliers-adjusted prices	59.67	23.34	0.51	2.55	57.85	-54.92	163.24	46.19	70.39	1087.2
VIC										
30-min prices	60.24	191.32	58.39	3880.15	46.61	-554.62	14700.00	30.54	72.11	1.0365×10^{11}
Daily	60.24	82.23	25.67	911.68	47.96	-6.354	3377.971	31.65	76.39	119616255
Prices adjusted for outliers	54.02	27.84	0.86	-0.11	47.72	-6.35	142.270	31.65	71.80	421.38
Deseasonalized actual prices	60.24	76.85	29.06	1082.25	57.79	-38.19	3292.57	45.44	68.41	168512140
Deseasonalized outliers-adjusted prices	54.02	16.78	0.33	1.94	53.40	-22.16	144.76	44.98	62.48	605.55
TAS										
30-min prices	61.79	73.22	20.03	765.61	44.97	-956.35	4928.30	32.53	80.03	4042758292
Daily	61.79	43.22	2.24	7.69	44.97	-94.67	461.64	34.78	82.02	11378
Prices adjusted for outliers	51.32	24.44	0.87	-0.10	43.80	-16.42	122.69	34.81	66.61	436.72
Deseasonalized actual prices	61.79	32.53	1.98	12.05	60.42	-53.80	462.77	44.26	73.58	23086
Deseasonalized outliers-adjusted prices	51.32	18.63	0.37	1.18	50.27	-17.80	132.82	41.86	132.82	280.8

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.

of both values once the outliers are accounted for. However, the distribution of prices remains non-normal even after removal of outliers. This 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 7 and 8. 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 21. 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 20: The ADF and KPSS tests of stationarity.

	NSW	SA	VIC	TAS	Interconnector	NSW	SA	VIC	TAS	Interconnector
	ADF test					KPSS test				
Actual prices	-9.7678	-45.2304	-44.7075	-6.9362		0.0418	0.0476	0.0527	0.0649	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
Outlier adjusted prices	-12.5325	-16.8068	-11.1450	-10.9649		0.0568	0.0791	0.0555	0.0428	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
wind	-31.6960	-37.9793	-28.8997	-32.2349		0.0351	0.0178	0.0228	0.0447	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
consumption	-21.7395	-25.4845	-24.6776	-17.7464		0.0238	0.0401	0.0462	0.0421	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.1000)	(0.1000)	(0.1000)	(0.1000)	
gas	-10.5226	-8.3073	-6.9306			0.0598	0.0531	0.0623		
	(0.0000)	(0.0000)	(0.0000)			(0.1000)	(0.1000)	(0.1000)		
hydro	-10.9311		-13.6130	-10.3220		0.0462		0.0328	0.0597	
	(0.0000)		(0.0000)	(0.0000)		(0.1000)		(0.1000)	(0.1000)	
Basslink					-9.3500					0.0669
					(0.0000)					(0.1000)
Heywood					-11.9008					0.0795
					(0.0000)					(0.1000)
Murrylink					-14.9799					0.0508
					(0.0000)					(0.1000)
Terranora					-15.6676					0.0328
					(0.0000)					(0.1000)
QNI					-16.2289					0.0409
					(0.0000)					(0.1000)
VNI					-14.5019					0.0365
					(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.

Table 21: 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	492.46	685.61	804.77	221.16	286.13	327.37	240.49	267.84	293.67	2346.7	12620	33456
p−value	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$
ARCH-LM Test	148.12	154.85	403.97	4.4592	4.5278	4.7178	9.4109	9.4093	9.4316	1650.9	1843.8	1882.5
p−value	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	(0.0347)	(0.4788)	(1.0000)	(0.0022)	(0.0938)	(0.9999)	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$
	Adjusted Prices											
Ljung-Box statistic	1280.5	4432.1	9135.4	525.93	1081.4	2449.6	926.27	3094.1	6306.2	1257.9	5116.7	9987.4
p−value	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$
ARCH-LM Test	1142.7	1276.8	1328.6	394.22	448.51	551.51	907.94	1071.6	1154.9	1077.5	1279.4	1320.7
p−value	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$	$(< 2.2 \times 10^{-16})$

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).
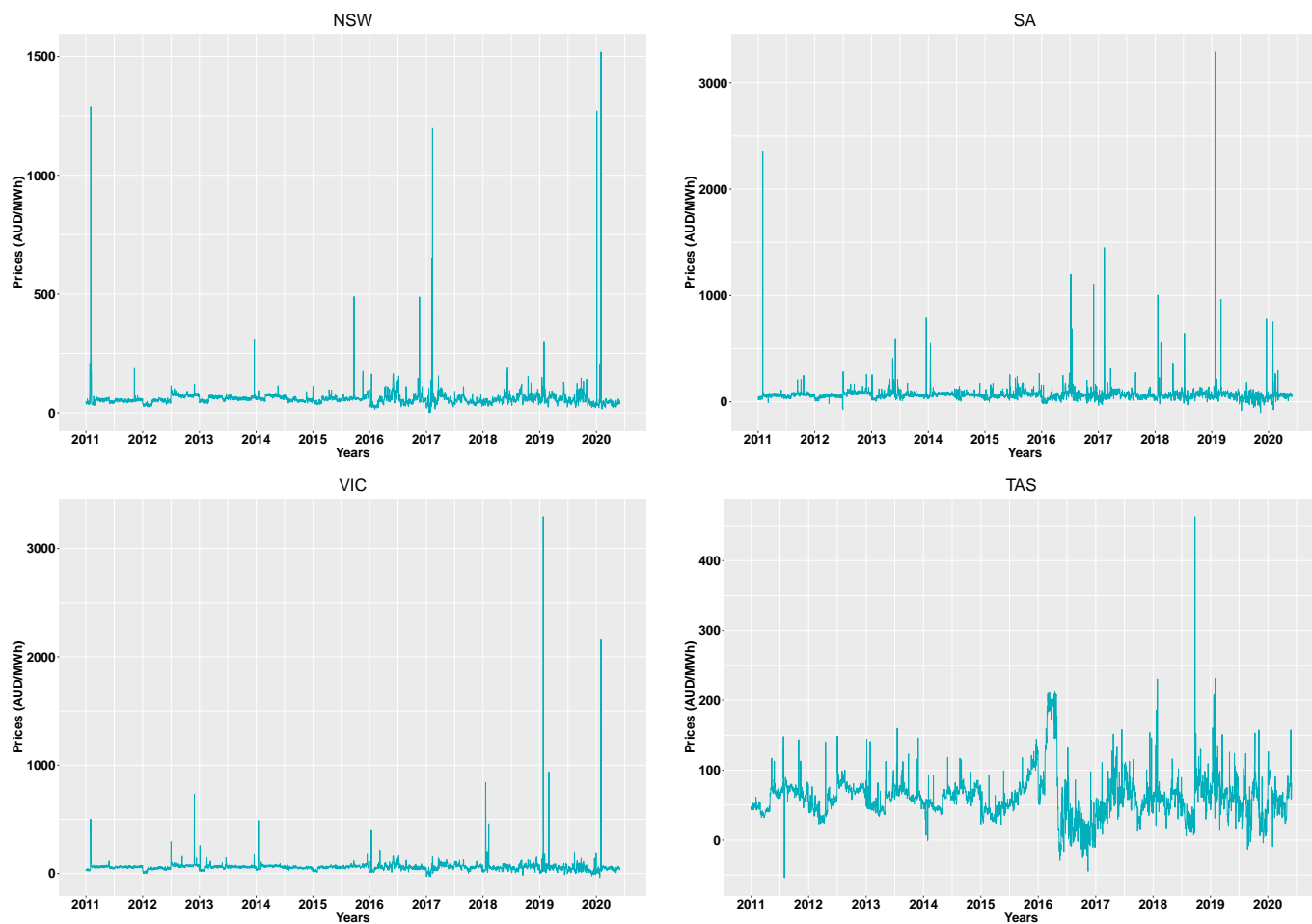
Figure 7: The daily average actual spot price adjusted for both the seasonal and trend effects for NSW, SA, VIC, and TAS from January 1, 2020, to May 31, 2020.
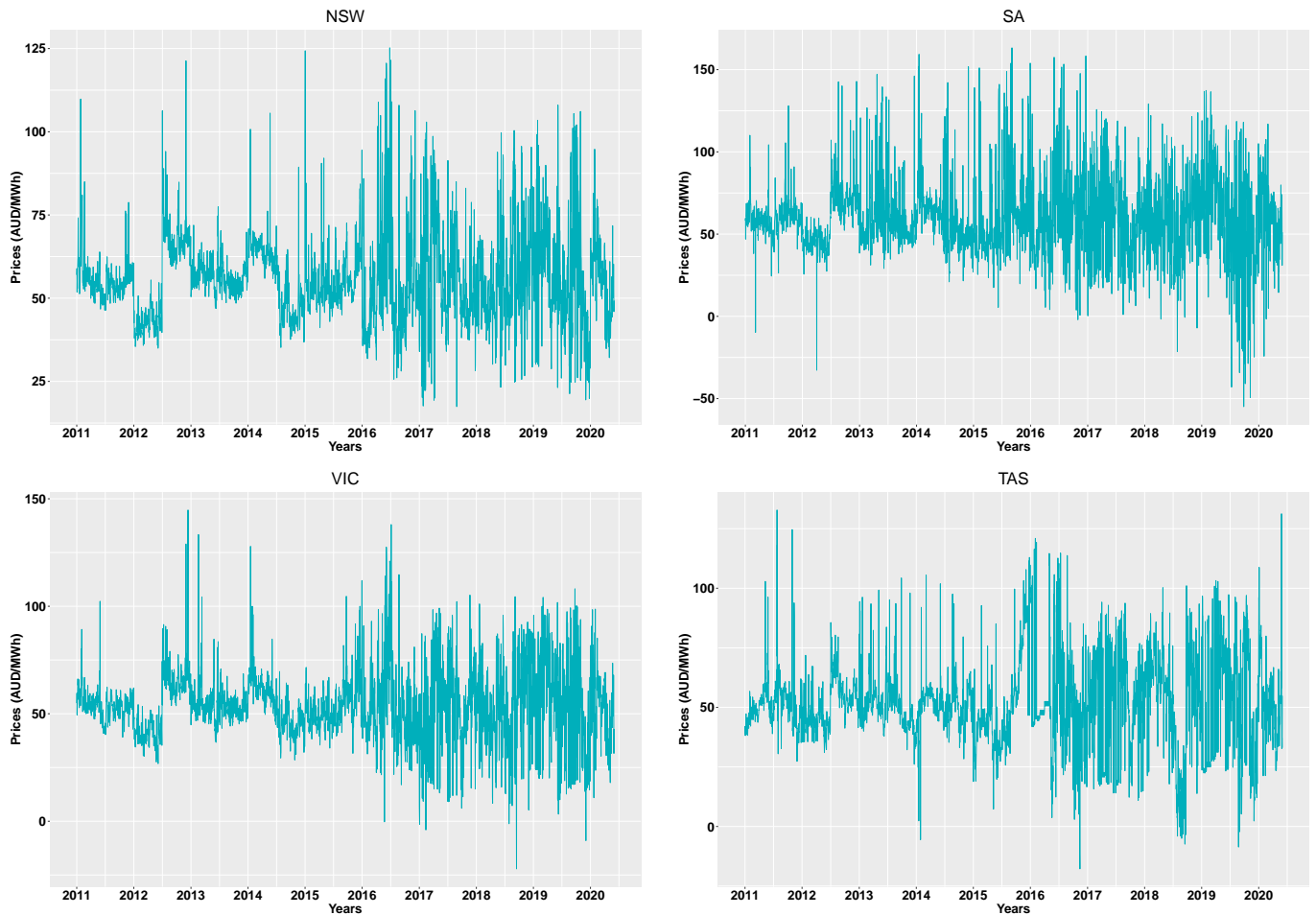
Figure 8: The daily average actual spot price adjusted for price spikes, seasonal and trend effects for NSW, SA, VIC, and TAS from January 1, 2020, to May 31, 2020.

Finally, we examined the regressors for collinearity using the correlation coefficient matrix (Figure 9 and 10) and variance inflation factors (VIF) in Table 22. 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.

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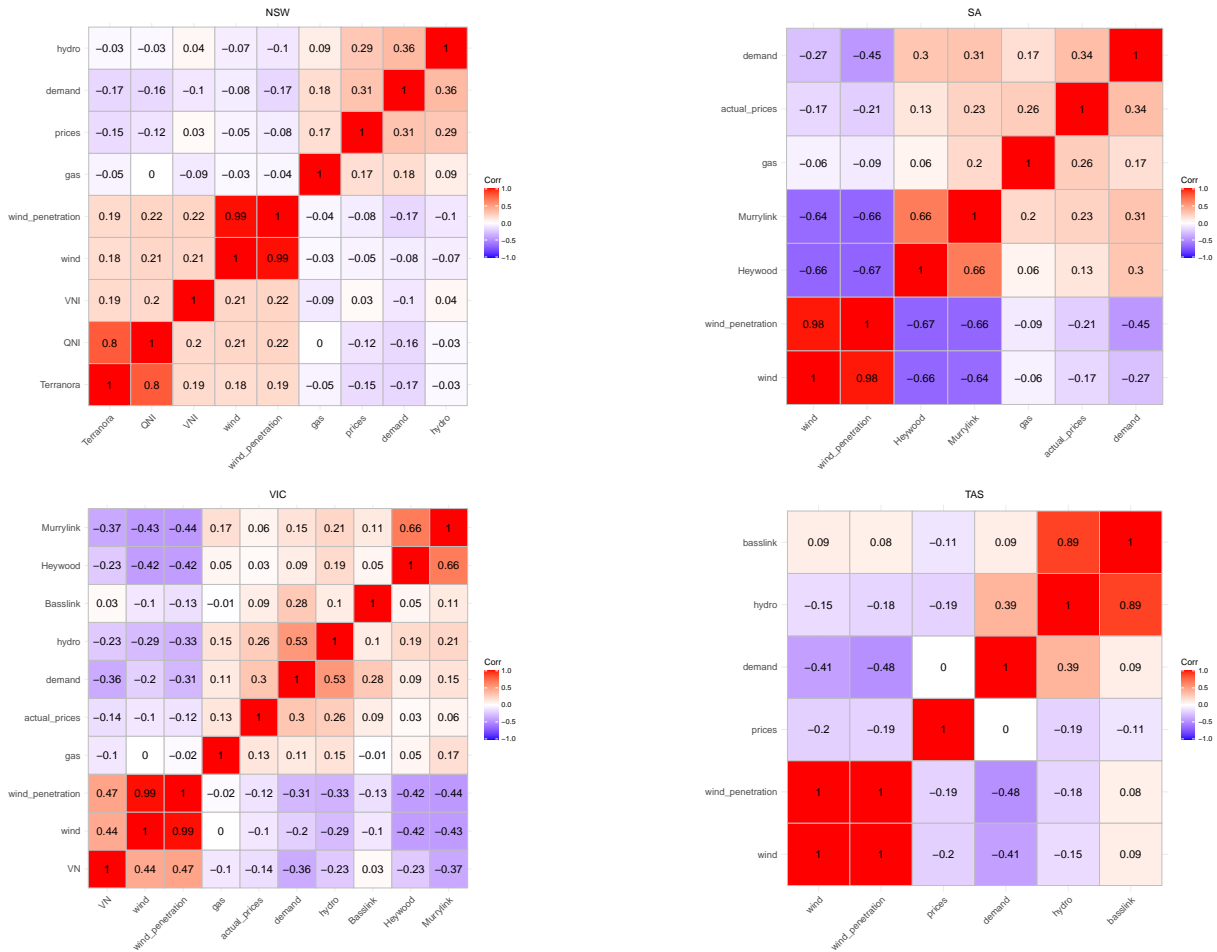
Figure 9: Correlation coefficient matrix of the variables. Prices stands for daily averaged prices adjusted for the seasonality and trend effects.
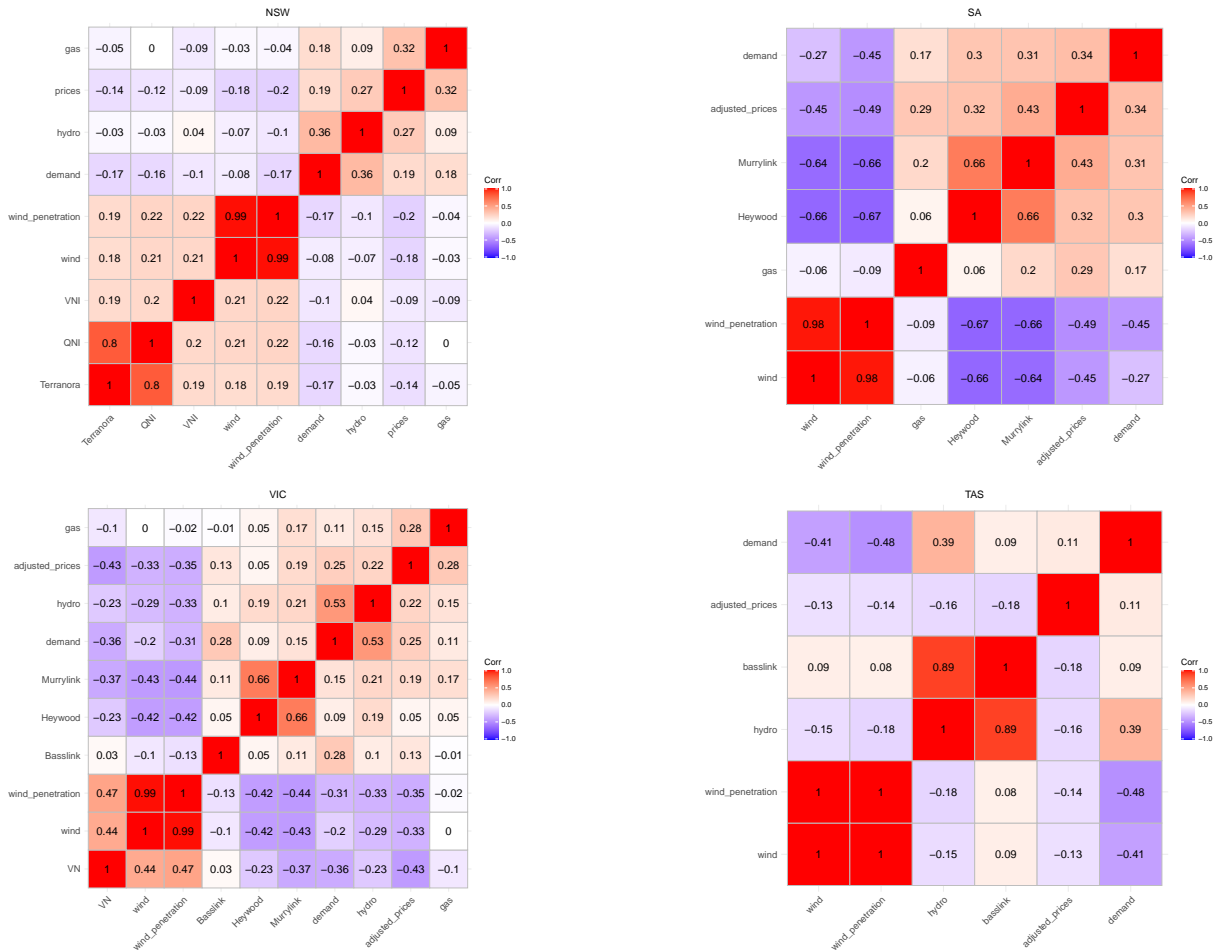
Figure 10: Correlation coefficient matrix of the variables. Prices stands for daily averaged prices adjusted for price spikes, seasonality and trend effects.

Table 22: VIF collinearity diagnostic measure.

	NSW	SA	VIC	TAS		NSW	SA	VIC	TAS
		Actual Prices					Adjusted Prices		
wind	379.5179	67.6639	229.6587	297.7076		379.5179	67.6639	229.6587	297.7076
wind pen	387.9440	77.8989	243.1950	321.5999		387.9440	77.8989	243.1950	321.5999
consumption	4.3269	4.1418	4.6484	4.1458		4.3269	4.1418	4.6484	4.1458
gas	1.0504	1.0728	1.0670			1.0504	1.0728	1.0670	
hydro	1.1704		1.5242	10.6125		1.1704		1.5242	10.6125
QNI	2.7879					2.7879			
VNI	1.0966		1.5193			1.0957		1.5193	
Terranora	2.7589					2.7589			
Heywood		2.1895	1.9058				2.1868	1.9058	
Murrylink		2.1794	2.0920				2.1783	2.0920	
Basslink			1.1436	9.2441				1.1436	9.2441

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B 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, 2020). 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 23 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 11) 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 12), 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 13, Table 24 and Table 25). Based on the BIC information criterion, the Student distribution outperforms the Normal Distribution (see Table 24 and 26) reflecting the non-normality characteristics of the Australian electricity market, and Nelson (1991) generalized error distribution (GED).

Table 23: 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.

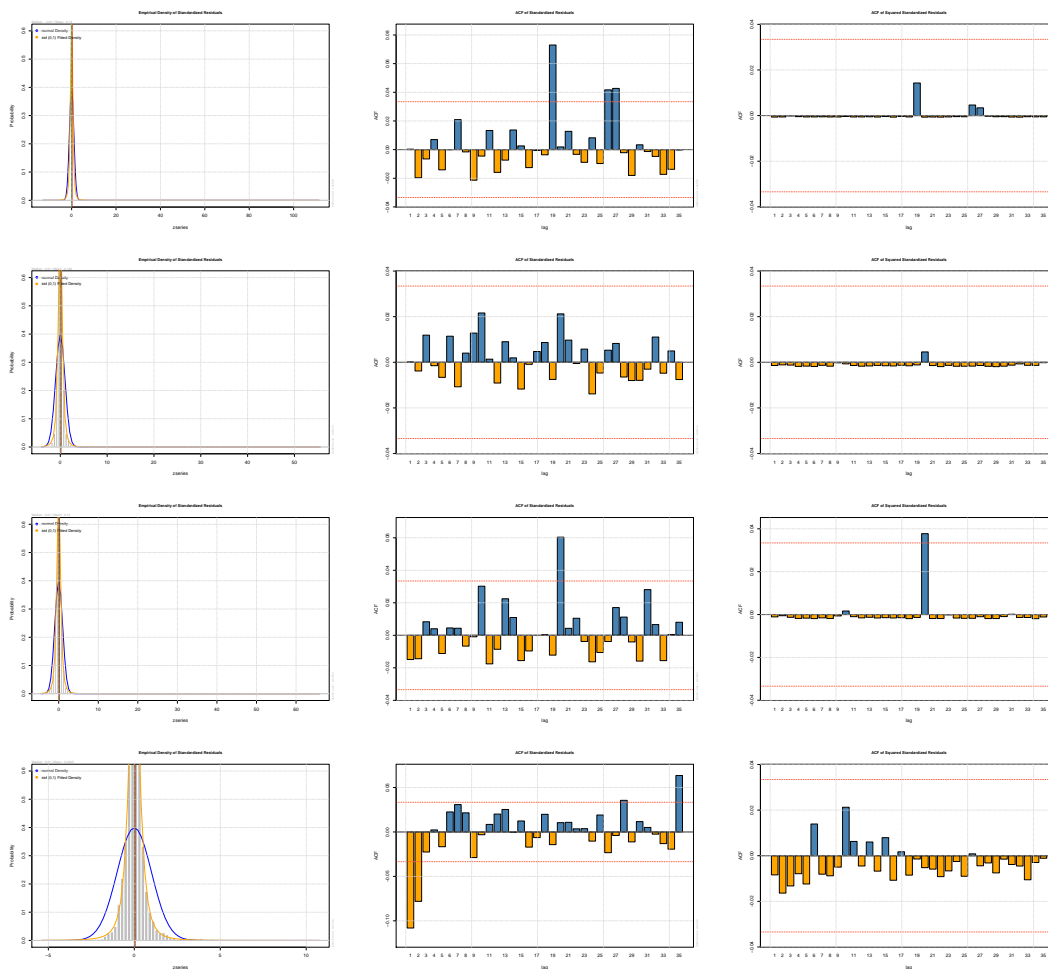|	Lag 1	Lag 4	Lag 20	Lag 1	Lag 20	Lag 36	Lag 3	Lag 5	Lag 7
	Ljung-Box on $\hat{z}_t$			Ljung-Box on $\hat{z}_t^2$			ARCH LM Tests		
NSW	0.0003	0.6612	1.35012	0.0015	0.0030	0.0051	0.0000	0.0013	0.0027
	(0.9857)	(0.9136)	(0.8815)	(0.9693)	(1.0000)	(1.0000)	(0.9941)	(1.0000)	(1.0000)
SA	0.0000	0.0250	0.3655	0.0067	0.0196	0.0367	0.0052	0.0197	0.0307
	(0.9959)	(1.0000)	(0.9978)	(0.9347)	(0.9999)	(1.0000)	(0.9427)	(0.9987)	(1.0000)
VIC	0.7636	1.1207	1.5872	0.0041	0.0146	0.0332	0.0056	0.0203	0.0326
	(0.3822)	(0.6658)	(0.8249)	(0.9490)	(1.0000)	(1.0000)	(0.9403)	(0.9986)	(1.0000)
TAS	40.2000	50.7000	58.2400	0.2426	1.5357	2.4107	0.6028	1.0905	1.6395
	(0.0000)	(0.0000)	(0.0000)	(0.6223)	(0.7311)	(0.8507)	(0.4375)	(0.7063)	(0.7930)

Figure 11: 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.
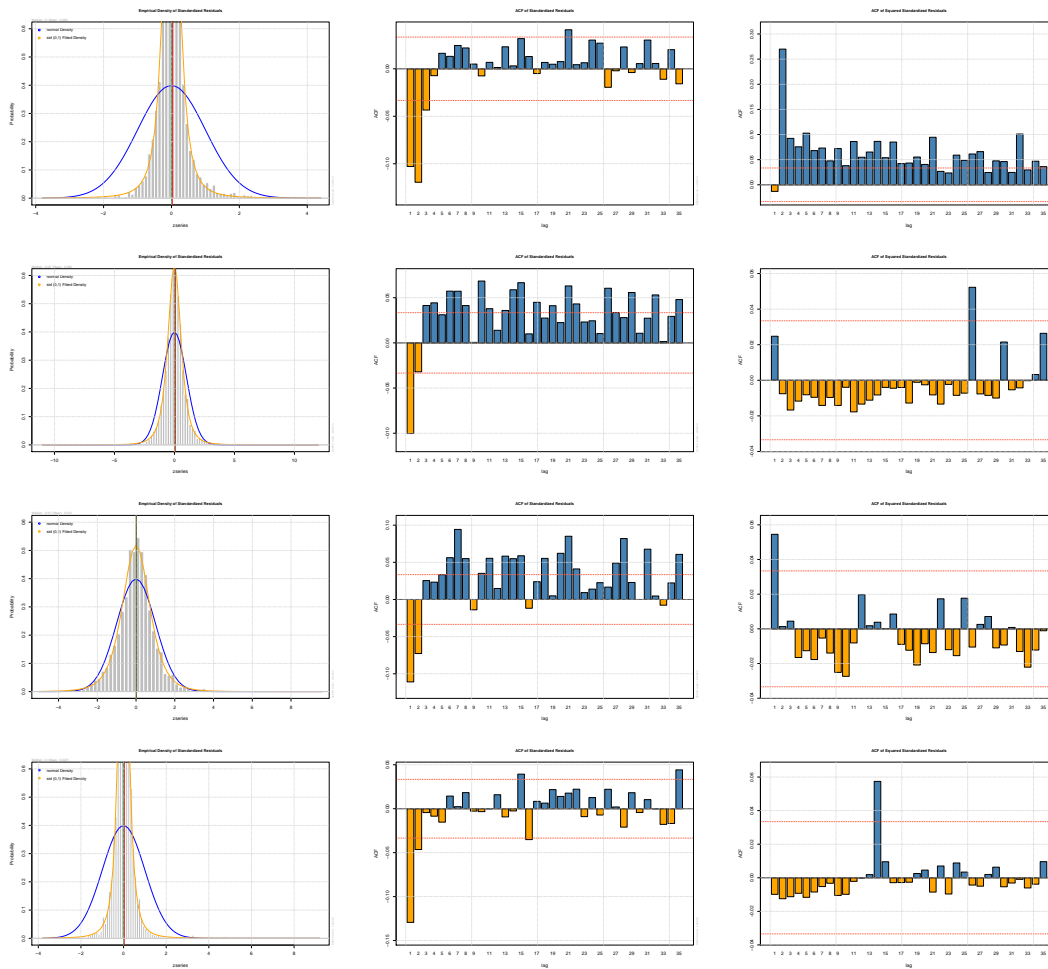
Figure 12: The empirical density of standardized residuals, ACF of standardized residuals, and ACF of standardized squared residuals of the AR-eGARCH models for NSW (first row), SA (second row), VIC (third row), and TAS (fourth row). All models estimated using prices adjusted for outliers, seasonality, and trend effect, one autoregressive component, and Student distribution.

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Table 24: 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	-11808.51	-11385.1	-11421.08	-15060.92	-14636.01	-14678.55	-12862.98	-12665.44	-12678.95	-13451.38	-12521.7	-12828.05
AIC	6.8709	6.6252	6.6462	8.7624	8.5159	8.5406	7.4841	7.3698	7.3777	7.8263	7.2862	7.4644
BIC	6.8816	6.6377	6.6587	8.7731	8.5284	8.5531	7.4949	7.3823	7.3902	7.8370	7.2987	7.4769
2												
Log-Likelihood	-11783.85	-11367.78	-11406.58	-15049.51	-14620.73	-14669.63	-12847.22	-12656.28	-12671.91	-13413.35	-12472.98	-12539.25
AIC	6.8571	6.6158	6.6383	8.7563	8.5075	8.5360	7.4756	7.3651	7.3742	7.8048	7.2585	7.2970
BIC	6.8696	6.6300	6.6526	8.7688	8.5218	8.5503	7.4881	7.3794	7.3885	7.8173	7.2728	7.3113
3												
Log-Likelihood	-11761.46	-11345.17	-11390.03	-15030.46	-14579.41	-14630.29	-12791.46	-12604.84	-12621.62	-13396.54	-12450.57	-12545.77
AIC	6.8447	6.6032	6.6293	8.7458	8.4841	8.5137	7.4437	7.3358	7.3455	7.7956	7.2460	7.3014
BIC	6.8590	6.6193	6.6453	8.7601	8.5002	8.5298	7.4580	7.3518	7.3616	7.8099	7.2621	7.3175
4												
Log-Likelihood	-11734.03	-11318.86	-11363.41	-15020.22	-14560.68	-14613.48	-12778.03	-12590.5	-12607.08	-13388.71	-12438.79	-12525.47
AIC	6.8293	6.5885	6.6144	8.7405	8.4738	8.5045	7.4365	7.3280	7.3376	7.7916	7.2398	7.2902
BIC	6.8454	6.6063	6.6322	8.7565	8.4917	8.5224	7.4526	7.3459	7.3555	7.8077	7.2576	7.3080
5												
Log-Likelihood	-11703.72	-11288.06	-11334.61	-15013.17	-14540.45	-14594.52	-12760.64	-12570.63	-12587.18	-13381.83	-12426.67	-12525.15
AIC	6.8123	6.5711	6.5982	8.7369	8.4626	8.4941	7.4270	7.3170	7.3267	7.7882	7.2333	7.2906
BIC	6.8301	6.5908	6.6179	8.7548	8.4823	8.5137	7.4448	7.3367	7.3463	7.8061	7.2530	7.3102
6												
Log-Likelihood	-11690.24	-11260.98	-11310.71	-15001.97	-14512.6	-14568.29	-12725.94	-12533.75	-12550.03	-13370.38	-12413.71	-12513.85
AIC	6.8050	6.5560	6.5849	8.7310	8.4470	8.4794	7.4073	7.2962	7.3056	7.7821	7.2264	7.2846
BIC	6.8247	6.5774	6.6063	8.7507	8.4684	8.5008	7.4270	7.3176	7.3271	7.8018	7.2478	7.3060
7												
Log-Likelihood	-11679.77	-11242.95	-11290.42	-14995.3	-14494.17	-14551.34	-12710.27	-12517.22	-12534.23	-13361.62	-12407.61	-12516.61
AIC	6.7995	6.5461	6.5737	8.7277	8.4369	8.4701	7.3988	7.2871	7.2970	7.7776	7.2234	7.2868
BIC	6.8210	$\boxed{6.5693}$	6.5969	8.7491	$\boxed{8.4601}$	8.4933	7.4203	$\boxed{7.3104}$	7.3202	7.7991	$\boxed{7.2466}$	7.3100
8												
Log-Likelihood	-11679.33	-11241.86	-11290.98	-14994.28	-14492.03	-14548.55	-12710.57	-12516.84	-12533.85	-13359.41	-12406.67	-12509.44
AIC	6.7998	6.5460	6.5746	8.7277	8.4362	8.4691	7.3996	7.2875	7.2974	7.7769	7.2234	7.2832
BIC	6.8231	6.5710	6.5996	8.7509	8.4612	8.4941	7.4228	7.3125	7.3224	7.8001	7.2484	7.3082
9												
Log-Likelihood	-11678.67	-11242.34	-11291.28	-14993.36	-14490.54	-14546.6	-12710.76	-12517.43	-12534.33	-13359.46	-12407.13	-12522.74
AIC	6.800	6.5469	6.5753	8.7277	8.4359	8.4685	7.4003	7.2884	7.2982	7.7775	7.2243	7.2915
BIC	6.825	6.5737	6.6021	8.7528	8.4627	8.4953	7.4253	7.3152	7.3250	7.8025	7.2511	7.3183
10												
Log-Likelihood	-11677.93	-11243.61	-11293.06	-14986.22	-14483.05	-14541.04	-12710.76	-12515.37	-12531.79	-13354.84	-12407.63	-12525.61
AIC	6.8002	6.5482	6.5769	8.7242	8.4321	9 8.4659	7.4008	7.2878	7.2973	7.7754	7.2251	7.2938
BIC	6.8270	6.5768	6.6055	8.7510	8.4607	8.4944	7.4276	7.3164	7.3259	7.8022	7.2537	7.3223

Table 25: 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.

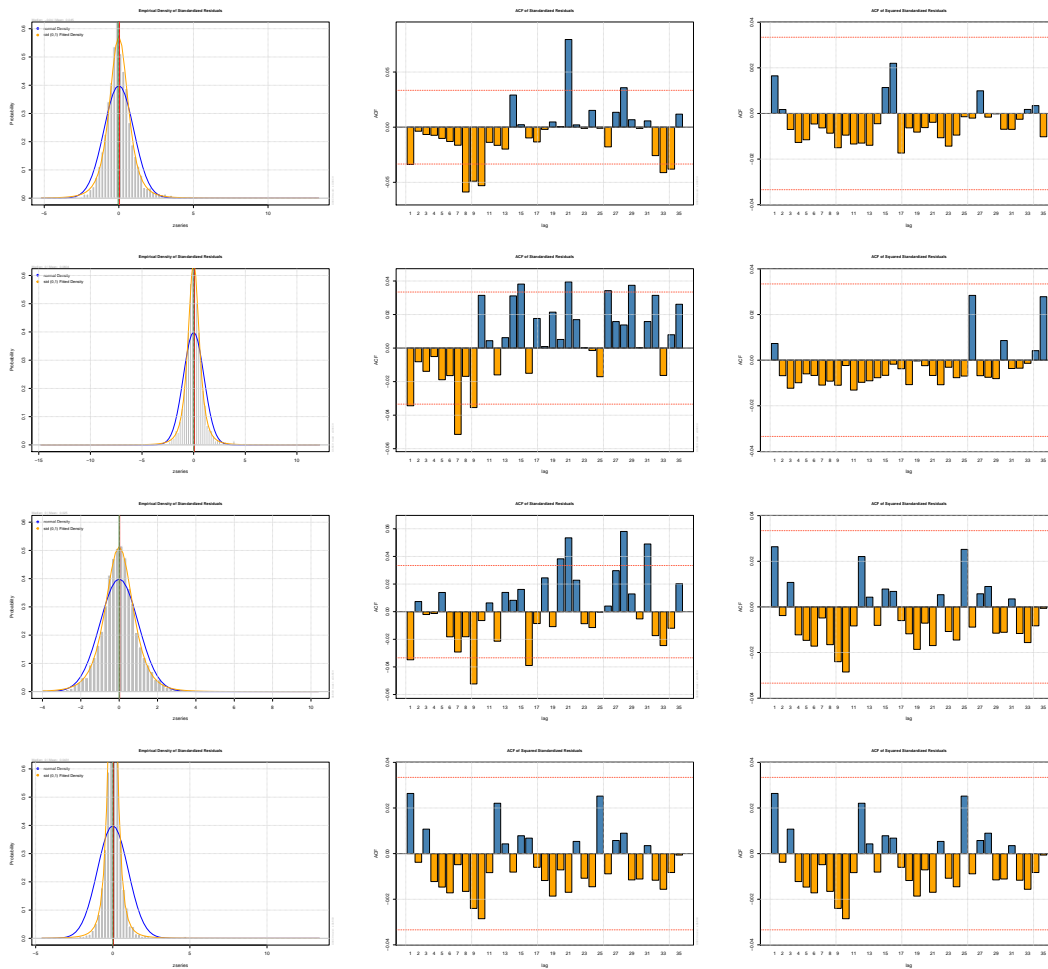|	Lag 1	Lag 4	Lag 20	Lag 1	Lag 20	Lag 36	Lag 3	Lag 5	Lag 7
		Ljung-Box on $\hat{z}_t$			Ljung-Box on $\hat{z}_t^2$			ARCH LM Tests	
NSW	3.9320	26.2310	44.5160	0.9366	1.3602	1.9242	0.1691	0.8870	1.0714
	(0.0474)	(0.0000)	(0.0000)	(0.3332)	(0.7742)	(0.9139)	(0.6809)	(0.7668)	(0.9017)
SA	4.0650	21.8900	34.1920	0.1840	0.7826	1.3393	0.5199	0.8626	1.1593
	0.0438	(0.0000)	(0.0000)	(0.6680)	(0.9066)	(0.9677)	(0.4709)	(0.7741)	(0.8863)
VIC	4.2350	17.6790	34.8630	2.4020	3.0340	4.4230	0.3960	1.2530	1.9830
	(0.0396)	(0.0000)	(0.0000)	(0.1212)	(0.4008)	(0.5188)	(0.5292)	(0.6597)	(0.7209)
TAS	11.2000	21.5000	28.1800	0.2453	0.9051	1.4111	0.3211	0.7053	0.9676
	(0.0008)	(0.0000)	(0.0015)	(0.6204)	(0.8808)	(0.9625)	(0.5709)	(0.8219)	(0.9188)

Figure 13: 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 26: 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	-15074.39	-12615.46	-12859.51	-18685.1	-16092.81	-16360.03	-13925.35	-15829.69	-14148.84	-13803.76	-12907.05	-12954.15
	AIC	8.7702	7.3408	7.4827	10.870	9.3631	9.5185	9.2095	8.1026	8.2325	8.0313	7.5104	7.5377
	BIC	8.7809	7.3533	7.4952	10.881	9.3756	9.5310	9.2202	8.1151	8.2450	8.0420	7.5229	7.5502

C   Model Results

Table 27: The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on New South Wales' electricity price behavior. 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	54.4671	56.7646	16.4629	18.4053	57.0256	52.6879	51.5705	54.3879	22.8198	52.4369
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.7231	0.7077	0.6815	0.6711	0.7033	0.7156	0.6836	0.73173	0.6671	0.6703
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	0.0023	0.0192	0.0075	0.0185	0.0055	0.0176	0.0104	0.0104	0.0327	0.0423
	(0.6661)	(0.0171)	(0.6356)	(0.2066)	(0.0774)	(0.1694)	(0.1167)	(0.1517)	(0.0000)	(0.0004)
ϕ_3	0.0132	0.0190	0.0267	0.0272	0.0186	0.0132	0.0168	0.0080	0.0228	0.0173
	(0.5525)	(0.2587)	(0.0000)	(0.0184)	(0.1002)	(0.1520)	(0.6138)	(0.6138)	(0.0001)	(0.1847)
ϕ_4	0.0215	0.0246	0.0262	0.0346	0.0249	0.0215	0.0283	0.0204	0.0307	0.0321
	(0.3697)	(0.0591)	(0.0000)	(0.0387)	(0.0000)	(0.2349)	(0.0059)	(0.4410)	(0.0025)	(0.0019)
ϕ_5	0.0463	0.0395	0.0558	0.0559	0.0410	0.0437	0.0448	0.0381	0.0492	0.0371
	(0.0000)	(0.0292)	(0.0000)	(0.0000)	(0.0006)	(0.0118)	(0.0002)	(0.0581)	(0.0000)	(0.0008)
ϕ_6	0.0558	0.0548	0.0688	0.0567	0.0540	0.0602	0.0633	0.0570	0.0595	0.0622
	(0.0000)	(0.0558)	(0.0000)	(0.0000)	(0.0040)	(0.0001)	(0.0000)	(0.0003)	(0.0024)	(0.0000)
ϕ_7	0.0912	0.0900	0.1015	0.1020	0.0908	0.0916	0.1008	0.0930	0.1032	0.0989
	(0.0000)	(0.0039)	(0.0000)	(0.0000)	(0.0000)	(0.0166)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-4.6439		-4.4180					-3.7232	
		(0.0000)		(0.0000)					(0.0000)	
$demand$			2.0378	2.0087					1.6472	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-98.6784					-82.9010
					(0.0000)					(0.0000)
gas						0.3170			0.1755	0.2473
						(0.0021)			(0.0507)	(0.0012)
$hydro$							3.9882		1.6997	3.5790
							(0.0000)		(0.0000)	(0.0000)
$exim_{terra}$								-1.7394	-2.0088	-1.7976
								(0.0238)	(0.1630)	(0.3410)
$exim_{QNI}$								-1.2378	-0.7030	-0.8221
								(0.0000)	(0.0000)	(0.0010)
$exim_{VNI}$								-1.3227	-0.9320	-0.9937
								(0.0000)	(0.0000)	(0.0000)
Variance Equation										
ω	0.1032	0.1439	-0.3264	-0.2773	0.1547	0.1153	0.1102	0.0947	-0.2880	0.1232
	(0.0000)	(0.0000)	(0.0348)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.1228	0.1314	0.1003	0.1018	0.1309	0.1212	0.0978	0.1286	0.0969	0.1067
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.9725	0.9656	0.9685	0.9598	0.9647	0.9728	0.9666	0.9705	0.9495	0.9535
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.3150	0.3323	0.3296	0.3571	0.3343	0.3174	0.3638	0.3157	0.4075	0.3942
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.0311		-0.0451					-0.0396	
		(0.3657)		(0.2177)					(0.3211)	
$demand$			0.0229	0.0231					0.0236	
			(0.0040)	(0.0000)					(0.0031)	
$wind_{pen}$					-0.8859					-0.6894
					(0.1768)					(0.3651)
gas						-0.0023			0.0015	0.0034
						(0.5819)			(0.7866)	(0.4909)
$hydro$							0.0221		0.0155	0.031
							(0.2535)		(0.5162)	(0.1300)
$exim_{terra}$								0.0307	0.1254	0.0723
								(0.8761)	(0.6149)	(0.7675)
$exim_{QNI}$								-0.0182	-0.0316	-0.0330
								(0.3583)	(0.2063)	(0.1743)
$exim_{VNI}$								0.0028	0.0070	0.0052
								(0.7662)	(0.5602)	(0.6624)
$Shape$	3.4368	3.3929	3.4182	3.3359	3.3722	3.4476	3.6069	3.3588	3.3574	3.4859
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-11242.95	-11148.33	-11054.17	-10957.75	-11122.25	-11235.37	-11175.04	-11166.32	-10902.65	-11008.81
AIC	6.5461	6.4922	6.4374	6.3825	6.4770	6.5428	6.5077	6.5050	6.3563	6.4169
BIC	6.5693	6.5190	6.4642	6.4129	6.5038	6.5696	6.5345	6.5389	6.4045	6.4615
Q(40)	27.5400	27.5930	26.5570	27.4930	27.8320	25.6490	27.5780	29.2200	50.4120	30.4650
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q^2(36)	1.9236	1.5490	1.9610	1.4263	1.4587	1.7955	2.1241	1.9506	1.4449	1.5353
	(0.9139)	(0.9515)	(0.9096)	(0.9614)	(0.9589)	(0.9280)	(0.8897)	(0.9108)	(0.9599)	(0.9526)
ARCH-LM Test	1.0712	1.2162	1.3015	1.3158	1.2072	0.9922	1.5474	1.2131	1.5726	1.6648
	(0.9017)	(0.8760)	(0.8602)	(0.8574)	(0.8777)	(0.9148)	(0.8118)	(0.8766)	(0.8067)	(0.7878)
Observations	3439	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 28: The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on Victoria's electricity price behavior. 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	55.1197	67.1999	5.3721	32.8670	66.4943	31.8707	53.7617	23.3024	50.0306
	(0.0000)	(0.0000)	(0.0011)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.4724	0.4950	0.4626	0.4899	0.4813	0.4311	0.4984	0.4702	0.4351
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	0.0002	0.0487	0.0193	0.0439	0.04703	0.0001	0.0503	0.0498	0.0527
	(0.9888)	(0.0134)	(0.0483)	(0.0008)	(0.0007)	(0.9956)	(0.0000)	(0.0000)	(0.0003)
ϕ_3	0.0772	0.0743	0.0835	0.0910	0.0827	0.0747	0.0833	0.0880	0.0845
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_4	0.0402	0.0372	0.0475	0.0425	0.0400	0.0484	0.0313	0.0522	0.0515
	(0.0000)	(0.0806)	(0.0004)	(0.1034)	(0.0041)	(0.0060)	(0.0000)	(0.0000)	(0.0000)
ϕ_5	0.0430	0.0287	0.0506	0.0376	0.0339	0.0421	0.0348	0.0318	0.0356
	(0.0000)	(0.1076)	(0.0001)	(0.0002)	(0.0089)	(0.0171)	(0.0007)	(0.0000)	(0.0000)
ϕ_6	0.0686	0.0785	0.0882	0.0880	0.0833	0.0674	0.0706	0.0768	0.0731
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0888	0.0920	0.0992	0.0923	0.1001	0.0794	0.0771	0.0889	0.0978
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-10.6577		-8.8833				-9.6585	
		(0.0000)		(0.0000)				(0.0000)	
$demand$			15.4630	9.8898				9.1916	
			(0.0000)	(0.0000)				(0.0000)	
$wind_{pen}$				-32.5214					-33.4935
				(0.0000)					(0.0000)
gas						3.9141		2.5838	3.2324
						(0.0000)		(0.0000)	(0.0000)
$exim_{heyw}$							4.9820	-8.7858	-8.5536
							(0.0000)	(0.0000)	(0.0000)
$exim_{murry}$							57.1023	32.3190	34.1883
							(0.0000)	(0.0000)	(0.0000)
					Variance Equation				
ω	0.0653	0.2358	-0.0994	-0.0712	0.3292	0.0486	0.2561	-0.1838	0.3563
	(0.0000)	(0.0000)	(0.2480)	(0.6109)	(0.0000)	(0.0201)	(0.0000)	(0.2904)	(0.0000)
α	0.0330	0.0449	0.0190	-0.0251	0.0199	0.0257	0.0560	-0.0815	-0.0337
	(0.0227)	(0.0568)	(0.3476)	(0.5053)	(0.5504)	(0.0832)	(0.0367)	(0.1354)	(0.3936)
β	0.9890	0.9688	0.9665	0.9133	0.9581	0.9869	0.9578	0.8871	0.9387
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.2498	0.4955	0.4059	0.8126	0.5894	0.2568	0.4746	1.1483	0.7824
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0018)	(0.0000)
$wind$		-0.0253		-0.0144				0.0158	
		(0.2136)		(0.6075)				(0.6811)	
$demand$			0.0904	0.1978				0.2255	
			(0.0004)	(0.0000)				(0.0000)	
$wind_{pen}$				-0.1379					-0.1537
				(0.0282)					(0.0648)
gas						0.0047		0.0305	0.0191
						(0.1625)		(0.0067)	(0.0093)
$exim_{heyw}$							0.0251	0.0383	0.0050
							(0.4182)	(0.4725)	(0.8967)
$exim_{murry}$							0.0499	0.0635	-0.0093
							(0.7117)	(0.7893)	(0.9575)
$Shape$	2.9253	2.2375	2.7439	2.2281	2.2195	2.9588	2.3619	2.1361	2.1644
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log\ likelihood$	-14494.17	-13828.63	-14147.35	-13657.95	-13736.69	-14445.33	-13893.22	-13505.79	-13576.28
AIC	8.4369	8.0510	8.2363	7.9529	7.9975	8.4096	8.0897	7.8679	7.9077
BIC	8.4601	8.0778	8.2631	7.9832	8.0243	8.4364	8.1201	7.9089	7.9452
$Q(40)$	34.1820	29.6300	38.6910	30.97	30.4900	18.913	31.4100	30.1700	25.1240
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.00000)	(0.0000)	(0.00000)
$Q^2(36)$	1.3395	2.34108	2.5699	3.7866	2.2379	1.2951	2.1677	4.8113	2.2706
	(0.9676)	(0.8606)	(0.8273)	(0.6252)	(0.8748)	(1.2951)	(0.8841)	(0.4576)	(0.8704)
$ARCH\text{-}LM\ Test$	1.1601	2.1946	2.3690	2.7862	1.9588	1.1162	1.9720	3.3550	1.8090
	(0.8862)	(0.6761)	(0.6395)	(0.5548)	(0.7260)	(0.8939)	(0.7233)	(0.4491)	(0.7577)
$Observations$	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 29: The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on South Australia's electricity price behavior. 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	52.3733	57.6046	3.7017	20.5258	57.4160	45.2958	47.0058	55.2372	39.9271	48.8940
	(0.0000)	(0.0000)	(0.0032)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.6389	0.6481	0.5999	0.6135	0.6368	0.6215	0.6137	0.6233	0.5736	0.5751
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	-0.0578	-0.0323	-0.0350	-0.0222	-0.0249	-0.0463	-0.0481	-0.0429	-0.0276	-0.0252
	(0.0003)	(0.8079)	(0.0047)	(0.4908)	(0.0018)	(0.0051)	(0.0000)	(0.0068)	(0.0212)	(0.1486)
ϕ_3	0.0990	0.0857	0.1116	0.0984	0.0824	0.0966	0.1002	0.0796	0.0919	0.0858
	(0.0000)	(0.5303)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_4	0.0142	0.0222	0.0183	0.0262	0.0274	0.0158	0.0252	0.0093	0.0338	0.0348
	(0.1661)	(0.8851)	(0.0494)	(0.3330)	(0.0002)	(0.0142)	(0.0142)	(0.4510)	(0.0000)	(0.0008)
ϕ_5	0.0226	0.0078	0.0113	-0.0019	0.0064	0.0205	0.0247	-0.0026	-0.0118	-0.0104
	(0.0796)	(0.8400)	(0.0969)	(0.9642)	(0.0540)	(0.1077)	(0.0001)	(0.6595)	(0.0205)	(0.1891)
ϕ_6	0.0828	0.0901	0.0977	0.1004	0.0914	0.0842	0.0990	0.0921	0.1049	0.1048
	(0.0000)	(0.0887)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_7	0.0974	0.0951	0.1158	0.1106	0.0973	0.1004	0.1016	0.1398	0.1483	0.1471
	(0.0000)	(0.3142)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-6.7633		-5.5992					-3.9581	
		(0.0000)		(0.0000)					(0.0000)	
$demand$			3.8937	2.8274					0.7467	
			(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$					-84.5162					-48.9434
					(0.0000)					(0.0000)
gas						1.2524			1.0410	1.0593
						(0.0000)			(0.0000)	(0.0000)
$hydro$							7.6591		3.4482	3.8860
							(0.0000)		(0.0000)	(0.0000)
$exim_{bass}$								5.4234	3.5435	3.6762
								(0.0000)	(0.0000)	(0.0000)
$exim_{heyw}$								-0.2851	-2.4048	-2.4072
								(0.4763)	(0.0000)	(0.0000)
$exim_{VNI}$								-5.0591	-3.1865	-3.3607
								(0.0000)	(0.0000)	(0.0000)
$exim_{murr}$								3.6669	1.4308	1.0712
								(0.0014)	(0.2597)	(0.3191)
					Variance Equation					
ω	0.1018	0.2277	-0.4748	-0.5004	0.2443	0.1126	0.0798	0.1180	-0.4061	0.1173
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0612)	(0.0492)
α	0.0562	0.0345	0.0388	0.0158	0.0254	0.0559	0.0317	0.0183	-0.0018	-0.0084
	(0.0019)	(0.0130)	(0.0333)	(0.4660)	(0.2163)	(0.0025)	(0.1041)	(0.3292)	(0.9326)	(0.6869)
β	0.9777	0.9634	0.9724	0.9546	0.9623	0.9773	0.9642	0.9710	0.9522	0.9537
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.3691	0.4537	0.4085	0.5056	0.4600	0.3705	0.4688	0.3983	0.5121	0.5068
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.0753		-0.0750					-0.0575	
		(0.0027)		(0.0051)					(0.0740)	
$demand$			0.0477	0.0607					0.0426	
			(0.0000)	(0.0000)					(0.0230)	
$wind_{pen}$					-1.1093					-0.7805
					(0.0000)					(0.0443)
gas						-0.0016			0.0061	0.0061
						(0.7276)			(0.4037)	(0.4041)
$hydro$							0.1137		0.0937	0.1173
							(0.0004)		(0.0032)	(0.0003)
$exim_{bass}$								0.0237	0.0121	0.0250
								(0.0792)	(0.5083)	(0.1367)
$exim_{heyw}$								0.0837	0.0874	0.0815
								(0.0058)	(0.0270)	(0.0364)
$exim_{VNI}$								-0.0202	-0.0058	-0.0137
								(0.0973)	(0.7248)	(0.4034)
$exim_{murr}$								-0.2703	-0.3346	-0.3545
								(0.0394)	(0.0505)	(0.0384)
$Shape$	4.3361	3.5155	3.9659	3.5518	3.5114	4.2910	3.9738	3.3547	3.4325	3.4263
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-12517.22	-12108.07	-12236.63	-11935.77	-12060.8 0	-12493.68	-12263.25	-11964.87	-11692.29	-11702.40
AIC	7.2871	7.0503	7.1251	6.9513	7.0229	7.2746	7.1406	6.9706	6.8167	6.8214
BIC	7.3104	7.0771	7.1519	6.9817	7.0496	7.3014	7.1674	7.0081	6.8685	6.8696
Q(40)	17.6610	18.794	20.543	18.1550	18.0700	17.7610	22.1480	25.5500	21.4390	22.6700
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Q^2(36)$	4.4210	2.6504	9.1040	4.0244	2.3855	4.3300	5.6070	1.1140	3.2740	3.0125
	(0.5190)	(0.8150)	(0.0774)	(0.5847)	(0.8543)	(0.5338)	(0.3459)	(0.9810)	(0.7130)	(0.7569)
ARCH-LM Test	1.9836	1.7143	5.3290	3.1130	1.6288	2.1935	2.9195	0.8132	2.2460	2.0653
	(0.7208)	(0.7775)	(0.1934)	(0.4924)	(0.7952)	(0.6764)	(0.5289)	(0.9419)	(0.6652)	(0.7035)
Observations	3439	3439	3439	3439	3439	3439	3439	3439	3439	3439

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 30: The effect of wind generation, electricity consumption, hydro generation, and interconnectors flow on Tasmania's electricity price behavior. 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	47.0315	46.5598	11.3323	18.6648	46.2901	46.2105	46.9814	18.7611	45.8133
	(0.0000)	(0.0000)	(0.0162)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.6666	0.6728	0.6782	0.6757	0.6738	0.6623	0.6708	0.6713	0.6835
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_2	0.0849	0.0816	0.0819	0.0797	0.0816	0.0847	0.0853	0.0800	0.0777
	(0.0061)	(0.0000)	(0.0094)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0021)
ϕ_3	0.0489	0.0449	0.0481	0.0487	0.0446	0.0508	0.0484	0.0498	0.0452
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0048)	(0.0000)	(0.0002)	(0.0028)	(0.0289)
ϕ_4	0.0266	0.0266	0.0306	0.0280	0.0259	0.0273	0.0235	0.0297	0.0243
	(0.0000)	(0.0258)	(0.0000)	(0.0123)	(0.0000)	(0.0295)	(0.0000)	(0.0368)	(0.0027)
ϕ_5	0.0320	0.0368	0.0377	0.0400	0.0381	0.0331	0.0338	0.0416	0.0384
	(0.0358)	(0.0000)	(0.0000)	(0.0012)	(0.0074)	(0.0104)	(0.0000)	(0.0349)	(0.0000)
ϕ_6	0.0446	0.0522	0.0408	0.0447	0.0512	0.0454	0.0434	0.0423	0.0489
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0001)	(0.0012)
ϕ_7	0.0402	0.0425	0.0418	0.0434	0.0427	0.0409	0.0387	0.0449	0.0411
	(0.0093)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0002)	(0.0016)	(0.0000)
$wind$		-8.1098		-3.8676				-4.0573	
		(0.0000)		(0.0000)				(0.0000)	
$demand$		12.2871	9.7754					9.5098	
		(0.0000)	(0.0000)					(0.0000)	
$wind_{pen}$				-21.5690					-22.1955
				(0.0000)					(0.0000)
$hydro$						0.8854		1.11433	
						(0.0000)		(0.0020)	
$exim_{bass}$							1.0686		1.4303
							(0.0000)		(0.0000)
					Variance Equation				
ω	0.6014	0.7769	0.5400	0.8031	0.7841	0.5972	0.6224	0.7994	0.8150
	(0.0000)	(0.0000)	(0.0426)	(0.0056)	(0.0000)	(0.0000)	(0.0000)	(0.0060)	(0.0000)
α	-0.0957	-0.1312	-0.1413	-0.1437	-0.1355	-0.0974	-0.1014	-0.1502	-0.1452
	(0.0398)	(0.0199)	(0.0076)	(0.0069)	(0.0104)	(0.0259)	(0.0214)	(0.0047)	(0.0061)
β	0.8973	0.8882	0.8866	0.8856	0.8875	0.8995	0.8938	0.8866	0.8825
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.0338	1.3613	1.4363	1.4619	1.4058	1.0264	1.0247	1.4671	1.4696
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$wind$		-0.2768		-0.3009				-0.2953	
		(0.0210)		(0.0149)				(0.0171)	
$demand$		0.0697	0.0023					0.0013	
		(0.4754)	(0.9824)					(0.9901)	
$wind_{pen}$				-0.6763					-0.5472
				(0.0283)					(0.0825)
$hydro$						-0.0151		-0.0014	
						(0.6787)		(0.9713)	
$exim_{bass}$							-0.0684		-0.0578
							(0.0053)		(0.0286)
$Shape$	2.1983	2.1152	2.1000	2.10000	2.1074	2.2031	2.2074	2.1000	2.1000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log\ likelihood$	-12407.61	-12321.76	-12281.24	-12262.56	-12315.69	-12402.36	-12398.72	-12256.61	-12305.23
AIC	7.2234	7.1746	7.1511	7.1414	7.1711	7.2215	7.2194	7.1391	7.1662
BIC	7.2466	7.2014	7.1778	7.1717	7.1979	7.2483	7.2462	7.1730	7.1965
$Q(40)$	21.5000	22.0400	23.0100	23.1000	22.3000	21.3200	21.5200	22.7100	22.3600
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.0000)	(0.00000)	(0.0000)
$Q^2(36)$	1.4111	2.8414	3.1730	3.7720	3.0038	1.6117	1.4689	3.8835	3.1583
	(0.9625)	(0.7848)	(0.7301)	(0.6277)	(0.7583)	(0.9459)	(0.9581)	(0.6086)	(0.7326)
$ARCH\text{-}LM\ Test$	0.9676	1.7973	2.0451	2.3442	1.8820	1.1097	0.9903	2.4419	1.9494
	(0.9188)	(0.7601)	(0.7078)	(0.6447)	(0.7424)	(0.8951)	(0.9151)	(0.6244)	(0.7280)
$Observations$	3439	3439	3439	3439	3439	3439	3439	3439	3439

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.
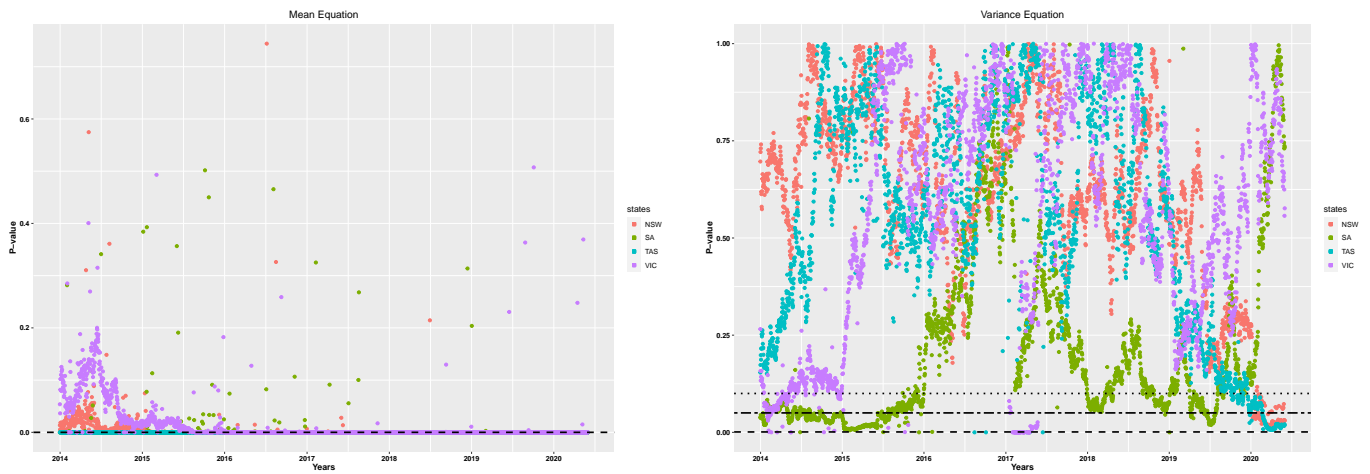
Figure 14: Estimated p-values for the volution of the impact of wind penetration from 2014 - May 2020 for NSW, SA, VIC, and TAS. The coefficients estimated using the rolling regression with three years windows while controlling for gas prices, hydro generation and the interconnectors. The effect on price level is given by the figures on the left and on price volatility by the figures on the right panel.