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

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Abstract

Solar generation has set a world record by supplying 100% of electricity demand in (a region of) Australia's National Electricity Market. Solar output variability coupled with the impact of rooftop solar on demand as a behind-the-meter resource poses challenges to electricity price stability. Using 30-minute intraday data from 2015 to 2021, we find that, on average, large-scale and rooftop solar generation depress the level of spot prices and positively impact volatility. Further, solar generation increases electricity prices in the early morning and in the evening due to the high cost of fossil fuel generators used during off-peak solar generation periods. While large-scale solar generation typically smooths volatility, rooftop solar tends to increase it, reflecting the dominance of axis-tracking systems in the former and north-facing systems in the latter. Solar generation's impact on electricity prices differs substantially across seasons. These results stress the need for policy adjustment to increase the correlation between solar output and electricity demand through small-scale renewable energy schemes and state-based policies, rooftop solar curtailment, dynamic feed-in tariffs, and two-sided market reform.

Keywords: large-scale solar generation, rooftop solar generation, electricity spot price volatility, merit order effect

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1 Introduction

The uptake of variable renewable energy (VRE) at the grid-scale and individual customer levels continues to surge, imposing significant stress on aging coal-fired and gas-powered generation in Australia's National Electricity Market (NEM). About 18 Gigawatts (GW) of new solar and wind energy, equivalent to 250 Watts per person per year, were installed during the three-year period from 2018 to 2020 (Blakers et al., 2021).[1,2] Although wind generation currently is the dominant weather-dependent renewable generation system in the NEM, rooftop solar photovoltaic (PV) systems have experienced the most rapid growth. Australia has one of the highest per-capita rates of rooftop solar PV installation in the world. Rooftop solar partially meets the electricity needs of around 24% of customers in the NEM who, in turn, sell their excess generation back to the grid (AER, 2021). Moreover, investment in large-scale solar generation has increased significantly in the NEM since 2018, as this system became the cheapest form of new power-generation technology.[3] On October 11, 2020, a combination of large-scale and rooftop solar generation alone set a record in South Australia, which has the highest solar penetration in the NEM by supplying more than 100% of the region's electricity demand. Rooftop solar generation supplied 77% of demand on several occasions and more than 70% for around four hours (AEMO, 2020; AER, 2021).

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

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

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

[3]Between 2010 and 2020, the global weighted-average levelized cost of electricity (LCOE) of utility-scale solar PV for newly commissioned projects declined by 85%, from USD 0.381/kWh to USD 0.057/kWh (IRENA, 2021).

putting the economics and operating capability of coal-fired generators to the test. The operator, in some instances, is forced to intervene and requires rooftop solar owners to draw power from the grid to ensure the security of the power system.

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

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

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

tends to increase spot price volatility. Although states with moderate generation levels experience a relatively large MOE, this benefit comes at the cost of high price variability. When comparing the average effect of large-scale and rooftop solar generation, we find that the former exhibits a more substantial negative impact on the price level and a positive impact on volatility dynamics compared to the latter.

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

Important implications and policy recommendations can be drawn from these findings to maximize the benefits derived from the rapid uptake of solar generation, especially rooftop solar. We propose four courses of action to increase the correlation between rooftop generation and electricity demand,[5] which, in turn, would increase the MOE and reduce electricity price volatility. First, small-scale renewable energy schemes (SRESs) and state-based policies should allocate their support to PV-plus battery systems to enable owners of rooftop solar generation to store extra generation during the day and export later in the evening to meet the peak demand. Secondly,

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

the Australian Energy Market Operator (AEMO) should design appropriate measures to curtail rooftop solar generation, especially via dynamic/flexible export management, to effectively absorb all excess rooftop generation and maintain system security. Thirdly, state governments and retailers should transition to dynamic feed-in tariffs (FiTs), which are lower during the day and higher in the morning and evening peak hours, to incentivize rooftop owners to inject their electricity into the grid in the morning and evening when it is more valuable. Finally, the findings stress the importance of transitioning to a two-sided market to increase market flexibility by allowing demand-side participation. Demand-side participation is the cheaper option for providing flexibility compared to peaking (gas-fired or hydro) generation, and is expected to shape the future of clean energy.

The remaining sections proceed as follows: In section 3, we detail the data and methodology. Section 4 presents the average impact of both large-scale and rooftop solar generation on the spot price dynamics over the whole sample period, while section 5 discusses these effects based on half-hourly time intervals and seasons of the year. In section 6, we present policy implications of the findings, and in section 7, we conclude.

2 Literature Review

Most previous work examining the impact of VRE on electricity price dynamics in the NEM was restricted to large-scale wind and to a much smaller extent, on solar generation (Forrest and MacGill, 2013; Cludius et al., 2014; Csereklyei et al., 2019; Mwampashi et al., 2021). Csereklyei et al. (2019) investigated the impact of large-scale wind and solar generation on NEM electricity prices. The application of econometric models on high-frequency (30 minutes) and daily data from 2010 to 2018 demonstrated the MOE of wind and solar generation. Solar generation exhibited a much stronger impact than the former, reducing the price level by around 14 AUD/MWh, which is 3 AUD/MWh more than that exhibited by wind generation. Furthermore, these authors found that the impact of solar and wind generation on a daily window was relatively small. Recently, Abban and Hasan (2021) investigated the impact of solar generation and volatility transmission in the NEM. To this end, the authors applied the Autoregressive-Generalized Autoregressive Conditional Heteroskedasticity model with exogenous variables (ARX-GARCHX) to daily solar generation data from April 1, 2014, to February 28, 2019. In line with Csereklyei et al. (2019), Abban and Hasan (2021) observed the MOE of solar generation in the NEM and found it was more pronounced in QLD, SA, and TAS. These authors also found that solar power penetration increased price volatility in TAS, NSW, and VIC. Jha and Leslie (2020) examined the extent to which the development of rooftop solar generation impacted fossil fuel–based generation in West Australia from 2015 to 2018. Their results suggested that higher solar generation during the day displaced fossil fuel generators, exposing them to significant start-up and shutdown costs. The authors also demonstrated that the increase in solar capacity translated into increased market power, operating profits, and wholesale prices during the evening.

Several works, including Kyritsis et al. (2017), Rintamäki et al. (2017), and Rintamäki et al. (2017), have examined the impact of wind and solar generation on price dynamics in European markets. These studies applied GARCH-in-Mean models, seasonally adjusted autoregressive moving average (SARMA) models, quantile regression models, and the inter-quantile range (IQR) to investigate the impact of solar and wind generation on the level and volatility of electricity prices in Germany. Several observations follow from this literature. First, there is an apparent pertinent negative contribution of wind and solar generation to the level of electricity prices. Secondly, wind and solar generation have different impacts on the volatility of electricity prices. For instance, Kyritsis et al. (2017) showed that the former increased price volatility and the latter reduced it. Rintamäki et al. (2017) demonstrated that wind generation reduced price volatility in Denmark and increased it in Germany. Furthermore, solar generation had a negative impact on Germany's daily price volatility during peak hours. Maciejowska (2020) showed that the effect of solar and wind generation on price volatility depends on the level of total demand. Thirdly, the impact of solar and wind generation varies throughout the day, especially during peak and off-peak hours. For instance, Rintamäki et al. (2017) found that the MOE of wind generation was more pronounced during off-peak hours in Germany due to high wind generation during this period.

The other stream of related literature considers the issues arising when modeling electricity price dynamics with high-frequency data. In a review of modeling of spot prices in deregulated wholesale electricity markets, Higgs and Worthington (2010) recommended using high-frequency data to improve the robustness of the GARCH, regime-switching, and market efficiency models. High-frequency data contain rich information which can significantly improve modeling and forecasting accuracy (Narsoo, 2016). Yet despite the availability of high-frequency data in recent years, studies based on daily analysis continue to dominate (Ketterer, 2014; Rintamäki et al., 2017; Kyritsis et al., 2017; Maciejowska, 2020; Mwampashi et al., 2021; Abban and Hasan, 2021).[6] However, several have leveraged the availability of high-frequency data to examine the behavior of electricity prices and volatility in the NEM (Higgs and Worthington, 2005; Thomas and Mitchell, 2005). Higgs and Worthington (2005) found the skewed Student apARCH specification best accounts for the right-skewed and fat-tailed characteristics of NEM electricity prices compared to the other models. Thomas and Mitchell (2005) suggested that volatility in the NEM could be effectively captured by the eGARCH specification. Mauritzen (2010), Woo et al. (2011), and Pineau et al. (2020) applied intraday data in the cause-and-effect context. The last two studies demonstrated the MOE of wind generation and its positive impact on price volatility using the ARX-GARCHX and AR(1) regressions approaches. However, the former study showed that the effect of wind power depends

[6] We are aware that some researchers employ low-frequency data in their analyses to cope with financial contract settlements or cope with the difference in the data frequency of the variables included in the analysis.

on the time windows over which electricity price movements are examined. Specifically, wind power reduced the short-term (intraday) price volatility, whereas it increased the average price movements over longer time windows, i.e., weekly and monthly periods. These results underscore the importance of exploring the effect of VRE not only on a low-frequency, but also on a high-frequency basis.

This study makes original contributions to several important areas. First, we treat large-scale and rooftop solar generation as two separate variables. We are the first to consider the effects of both large-scale and rooftop solar generation separately on the level and volatility of spot prices. We extend Csereklyei et al. (2019), who studied only the MOE of large-scale solar generation, and using only the sparse observations available at the time. We also extend Abban and Hasan (2021), who combined large-scale and rooftop solar generation and thus, obscured the individual contributions of these two variables to the price dynamics. This study also likely suffered from endogeneity problems.[7]

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

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

Fourthly, we thoroughly examine the intraday relationships between solar generation, spot price dynamics, and electricity generation mixes. We, therefore, extend earlier studies, such as that of

[7] Abban and Hasan (2021) run their analysis by including only penetration of wind and solar generation, electricity demand, and gas prices, ignoring other important price determinants such as hydro generation and cross-border interconnector flows. Therefore, it is likely that their analysis suffered from omitted variable bias (Csereklyei et al., 2019; Mwampashi et al., 2021).

Forrest and MacGill (2013) who investigated the impact of wind generation on spot prices as well as gas and coal-fired generation in SA and VIC and demonstrated the potential of wind generation in reducing electricity prices and displacing gas and brown coal generation.

3 Data and Methodology

3.1 Data and preliminary analysis

Our analysis considers five NEM markets: NSW, VIC, QLD, SA, and TAS. We use high-frequency NEM data based on 30-minute trading intervals obtained from **?**. The sample period is from March 2015 to July 2021. The data include wholesale electricity prices,[8] large-scale solar generation, rooftop solar generation, large-scale wind generation, hydro generation, electricity consumption, and cross-border interconnector flows. The daily gas price data for NSW, SA, and VIC were obtained from the Short Term Trading Market (STTM) (AEMO, 2021b) and the four-hour gas price data for VIC from the Declared Wholesale Gas Market (DWGM) (AEMO, 2021a). While most of the control variables are available for many years, the main variables, large-scale solar generation and rooftop solar generation, are available for recent years only.[9] To match the sample periods of the data available for large-scale and rooftop solar generation, we base most of the analysis on data from 2018 onward.

In Figure 1, the annual growth of rooftop and large-scale solar generation per state is compared in terms of their generation levels and penetration rates.[10] It is apparent from this figure that large-scale solar generation increased substantially across states in the NEM following the decline in the cost of VRE and government policy incentives, especially since 2018 (de Atholia et al., 2020). NSW was the initial focus for solar farm development, accounting for the significant generation in NSW since 2015. Efforts to promote solar generation in QLD, VIC, and SA recently triggered a considerable uptake of large-scale solar generation in these regions, making QLD the leader across the NEM.[11] Although investment in large-scale solar generation has been slow in Australia, the uptake of rooftop solar generation has been dramatic. From Figure 1 we see that rooftop generation has increased substantially since 2018 across the NEM with the slight exception of TAS, where generation remained fairly constant. SA and QLD exhibit high rooftop solar penetration compared

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

[9]In Appendix A, we discuss the challenges associated with data availability, assumptions, and adjustments.

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

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

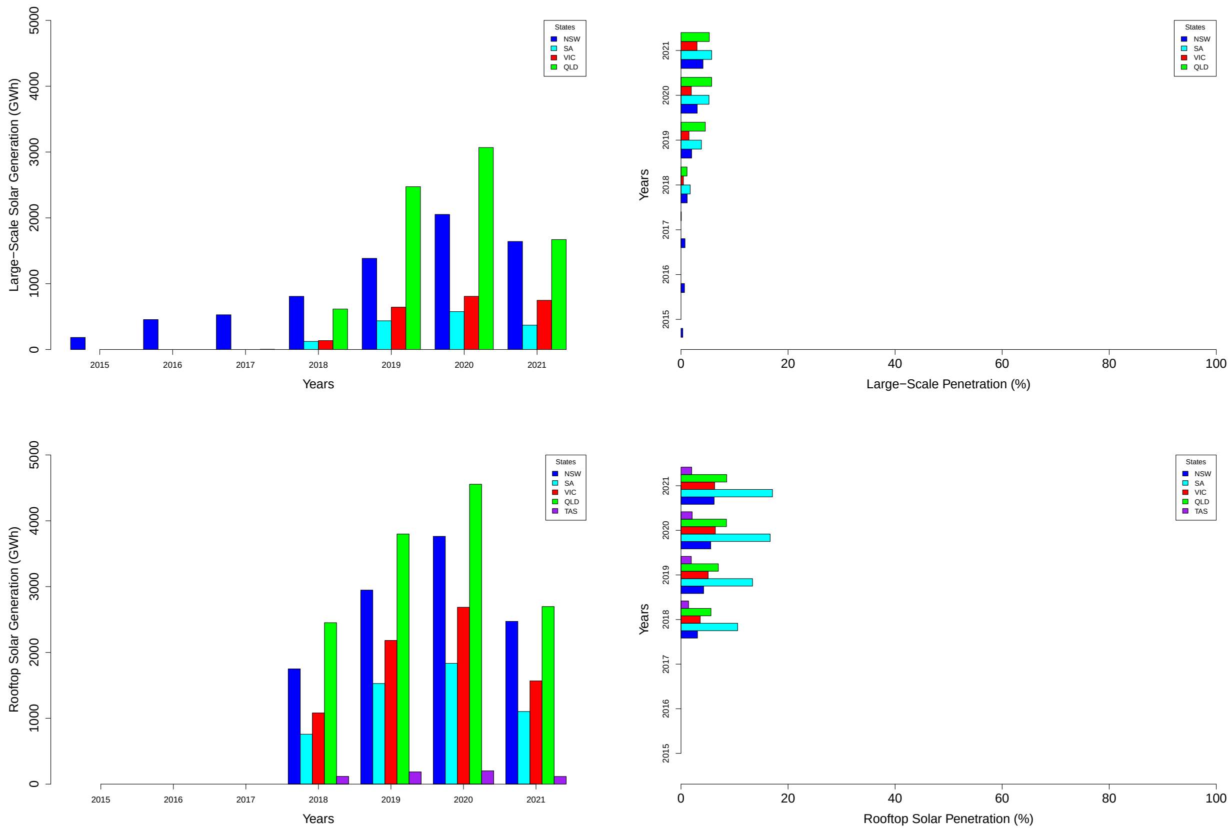

Figure 1: Large-scale solar (first row) and rooftop solar (second row) for NSW, SA, VIC, QLD, and TAS, between March 2015 and July 2021. The first panel in each row shows the generation, and the second panel shows penetration. Note that data for rooftop solar generation are available only from 2018 onward (i.e., the zeros for 2017 and previous years do not reflect a lack of solar PV system installations). The generation levels and penetration rates for both large-scale and rooftop solar generation for the year 2021 capture electricity generated up until July 2021, not the entire 2021 year.

to other states.

Figure 2 displays average hourly electricity prices per state and per season. It is evident that electricity prices vary over different hours of the day and the seasons for all five states, corresponding to variation in electricity demand. Although the peaks and troughs differ slightly between regions, roughly speaking, the peak period lasts from 16:00 to 21:00. Electricity demand fluctuates depending on the time of day, season, and ambient temperature. Demand often increases in the early evening, when many businesses are at their peak operations, and a large quantity of electricity is required for domestic purposes. This period overlaps with the decrease in rooftop PV generation. Seasonal peaks occur in the summer due to increased air conditioning and in the winter due to heating needs. High-marginal-cost generators, such as gas, set the price at peak periods. In contrast, low-marginal-cost generators, such as wind, solar, hydro, and coal, are typically sufficient at low-load times. It is worth mentioning that electricity prices in the past were lower overnight and early in the morning when demand is lower and relatively higher during other times.

However, the dramatic increase in rooftop generation exerted substantial downward pressure on grid electricity prices in the middle of the day. Figure 3, showing the average hourly electricity consumption per state and season, depicts the hollowing out of the demand during the middle of the day, often termed the "duck curve". Furthermore, we observe a clear variation in electricity prices over four seasons in Figure 2, with the average higher prices occurring in the summer and the winter.

The generation profiles over time and seasons for rooftop solar and large-scale solar generation are plotted in Figures 4 and 5, respectively. Generation starts gradually at around 05:00 and decreases around 20:00. However, peak generation period differs across states. The differences in orientation may explain the differences in generation profiles between rooftop PV and large-scale PV systems. The former are largely north-facing fixed-panel systems, which typically give the greatest energy output, in turn, producing the characteristic "bell-shaped" intraday generation profile. The latter has a higher share of axis-tracking systems, which maximize electricity output by moving the panels to track the sun throughout the day, making their generation profile flatter/less peaky. Solar trackers are usually used in utility-scale and commercial/industrial solar projects, such as ground-mounted solar panels, and rarely in residential solar projects. The availability of government policy incentives such as SRES and high FiTs triggered the dominance of north-facing rooftop solar panels. Northerly orientation guarantees household owners high solar generation during the day and, in turn, high FiTs payments. On average, days are longer in the spring and summer, resulting in more sunlight. This explains why there are more output and longer generation periods during these seasons. Comparing the variation in solar generation to that of wind (Figure 6), it is apparent that the two are negatively correlated. NSW, QLD, and SA attain peak wind generation at night, whereas VIC and TAS exhibit higher wind generation during daytime hours. Other states attain higher generation during spring and winter except QLD, which exhibits higher outputs during autumn and spring. Based on these observations, the present study raises the possibility that solar generation may exhibit a varying impact on the dynamics of spot prices based on the time of day.[12] Table 2 summarizes descriptive statistics for all variables used in our analysis.

3.2 Seasonality adjustments and time-series tests

From the previous discussion, it is evident that demand and supply exhibit seasonal fluctuations. These variations result in seasonal behavior in spot electricity prices over daily, weekday, month, and yearly periods. The use of high-frequency data necessitates modification of the Ketterer (2014)

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

and Mwampashi et al. (2021) approaches to include an intraday seasonality term in the OLS model. Thus, we decompose the time series of the dependent and independent variables, π_t, as the sum of a stochastic component y_t and a seasonal component s_t; that is, $\pi_t = y_t + s_t$, $t > 0$. The seasonality component is then specified as

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

where $\hat{c}$ is the intercept; p, q, r, and s are the total number of half-hourly trading intervals in a day, days in a week, months, and years, respectively; and $\hat{\psi}$, $\hat{\phi}$, $\hat{\zeta}$, $\hat{\chi}$ are the corresponding estimated coefficients. We run the regressions for each of the dependent and independent variables and extract the seasonality-free time series from the estimated residuals, which is then aligned to the original series by adding the mean (Ketterer, 2014; Mwampashi et al., 2021). As the same adjustment process is applied to all variables in the model, we measure the long-term effect of independent variables in spot electricity dynamics without seasonal noise, which may otherwise lead to false cause-and-effect conclusions.[13] Moreover, spot electricity prices tend to exhibit significant short-run upside and downside (low or negative prices) spikes, causing significant price deviations from the short-run marginal costs.[14,15] As these observations are valid, we include them in the analysis to better capture the volatility of spot electricity prices (Kyritsis et al., 2017; Mwampashi et al., 2021). Before specifying the models, we confirmed the stationarity of the time series using the augmented Dickey-Fuller (ADF) test, the presence of autocorrelation using the Ljung-Box test, conditional heteroscedasticity using Engle (1982) ARCH-LM test, and the absence of multicollinearity between explanatory variables using the variance inflation factors (VIFs). We provide further details in Appendix A.

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

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

[15] Typically, the former spikes reflect the shortage of supply due to inter alia unplanned generator outages, network outages, and lower-than-forecast VRE. The last occurs due to a combination of minimum electricity demand, high output from VRE, and unrestricted imports or restricted exports via cross-border interconnectors.

3.3 Model specification for the mean and volatility process

Using high-frequency data requires a robust approach to capture the intraday volatility process effectively. To this end, we considered three ARCH models: the eGARCH, the apARCH, and the mscGARCH. ARCH models can potentially capture the volatility observed in electricity markets by allowing volatility shocks to cluster and persist over time and revert to more normal levels (Higgs and Worthington, 2005; Frömmel et al., 2014). Comparing the performance of the above models (see Appendix B), we find that the eGARCH produces the most robust results not only when modeling daily volatility, as shown by Pereira and Rodrigues (2015), Macedo et al. (2020), and Mwampashi et al. (2021), but also when modeling high-frequency volatility. On this basis, we chose to employ eGARCH in the analysis. Before specifying a eGARCH equation for the variance, a primary requirement is to remove the predictable component of the electricity price to produce price innovations, ε_t, with a conditional mean of zero (Higgs and Worthington, 2005). Following inter alia Ketterer (2014) and Mwampashi et al. (2021), we generate an uncorrelated process by assuming the half-hourly price follows an autoregressive AR(m) process with exogenous variables given by

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

where p_t is the half-hour electricity price for each regional electricity market in the current period, p_{t-i} is the half-hour electricity price lagged i periods, μ is the long-term drift coefficient, ϕ_i is the degree of the mean spillover effect across time, $\boldsymbol{v}_t$ is the vector of n external regressors, which are passed pre-lagged, and ε_t is the random error or innovation at time t. The variance of the half-hour spot price innovation process is then modeled using the Nelson (1991) eGARCH specification, which allows for the leverage effect to better capture temporal variations in market volatility. The eGARCH(p, q) process for the random error term, ε_t, is specified as $\varepsilon_t = z_t \sigma_t$ and $z_t \sim \mathrm{iid}(0, 1)$ is a standardized innovation that follows a specific distribution,[16] with

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

where σ_t is the latent conditional standard deviation of volatility of ε_t at time t, ω is a variance intercept parameter, α_i and γ_i are coefficients that are associated with the sign and size effects

[16] Instead of assuming that z_t is Gaussian by default, we chose the best conditional distribution of the standardized residuals by jointly estimating equations (1) and (2) under a range of univariate distributions; that is, normal distribution, skew normal distribution, generalized error distribution, skew generalized error distribution, Student-t distribution, skew Student-t distribution, normal inverse Gaussian distribution, and Johnson's reparametrized SU distribution. The best-performing model is the one that minimizes the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria denoted as AIC, BIC, HQIC, and SIC, respectively.

of the standardized innovation from the previous period, respectively, and β_j is the coefficient associated with the degree of the previous period's volatility spillover effects. We refer to equations (1) and (2) as the mean and variance equations, respectively. The mean and variance equations and thus the parameters $(\mu, \phi, \zeta, \omega, \alpha, \gamma, \beta, \psi)$ are estimated concurrently by maximizing the log-likelihood.[17] Furthermore, the expected value of the absolute standardized innovation is defined by $\mathbb{E}|z_t| = \int_{-\infty}^{\infty} |z| f(z, 0, 1, \dots)\, dz$. The stationarity of the eGARCH(p, q) model is achieved when the roots of $\beta(z) = 1 - \sum_{i=1}^{p} \beta_i z^i$ lie outside the unit circle. For eGARCH(1,1), the stationarity condition requires that $|\beta_i| < 1$. One advantage of the eGARCH model is that it requires no restriction on the parameters, as it models the log variance instead of variance itself. This means the positivity of the variance is guaranteed regardless of the sign of the estimated coefficient. Thus, the likelihood maximization yields faster and more reliable optimizations. Existing research also suggests that compared to other GARCH specifications, the eGARCH is better at capturing the volatility persistence and asymmetry effect found in power markets (Thomas and Mitchell, 2005; Bowden and Payne, 2008; Hickey et al., 2012; Frömmel et al., 2014; Mwampashi et al., 2021). It is also worth noting that our method allows investigation of the impact of exogenous variables on the level and volatility of spot prices while also accounting for downward and upward spikes and mean reversion.

The exogenous variables used in this analysis are defined in Table 1. One argument against using rooftop solar generation as a regressor on the spot price is that it is not channeled through the NEM bidding process (Csereklyei et al., 2019) and is only visible to the market through reduced demand and dispatch targets during periods of rooftop PV generation. We postulate that, irrespective of whether rooftop PV generation is considered 'negative demand' or 'positive supply', the marginal generator (i.e., the price setter) is the same in both cases. If rooftop PV were to bid into the market, would effectively bid in its capacity at (close to) the spot price floor – this is the logical outcome of its automatic netting off from demand.[18] In practice, bidding would differ by price band due to minimum stable loadings (MSL) (e.g., in Footnote 18, the coal plant might bid its MSL at the spot price floor and then its excess capacity at 10 AUD/MWh) and other real-world considerations. Thus, our assumption that spot price outcomes remain unchanged would still be correct. Our argument in relation to rooftop PV bidding in its capacity at (close to) the spot

[17] We jointly estimated the AR-eGARCH and ARX-eGARCHX models in R programming language using the `rugarch` package (R Core Team, 2019; Ghalanos, 2021).

[18] To justify this, lets consider, the following highly stylized situation: there are two utility-scale generators – one black coal, the other solar PV (both of 50MW available capacity). Coal bids in all its capacity at 10 AUD/MWh, while the utility-scale solar PV plant bids in all its capacity at 0 AUD/MWh. In a given interval, demand (excluding rooftop PV) is 100MW, and rooftop PV generation is 50MW. Case 1 - rooftop PV generation is netted off demand: Here, operational/grid-sourced demand is 50MW. This is fully met by utility-scale solar PV with the market clearing at the spot price of 0 AUD/MWh. Case 2 - rooftop PV generation is NOT netted off demand and rooftop PV bids into the spot market: In this situation, operational/grid-sourced demand remains at 100MW. Rooftop PV generation would be dispatched first – since it bids in at (close to) the floor. The market clears at the spot price of 0 AUD/MWh, with the marginal generator being the utility-scale solar PV plant. In both cases, the spot price is the same: 0 AUD/MWh.

Table 1: Exogenous variables

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

price floor, if rooftop PV were to bid into the market, reflects AEMO's approach to generator curtailment.[19] As thermal plants bid in their MSL at the spot price floor, this curtailment order means rooftop PV effectively bids in its capacity at (close to) the spot price floor. We say "close to" as we understand AEMO prefers to curtail rooftop PV ahead of tripping off the thermal plant in order to maintain system security. We note that oversupply problems in the NEM have, to date, not required the last step, but the first three steps have been utilized in recent times in SA.[20]

[19]That is, at times of oversupply, AEMO's order of curtailment is as follows: thermal plant are curtailed down to their MSL. If this doesn't resolve the oversupply problem, AEMO then curtails utility-scale solar and wind down. If oversupply still exists despite AEMO curtailing utility-scale solar and wind output down to zero, AEMO then curtails rooftop PV output. If oversupply still exists, AEMO would then be forced to curtail thermal down below their MSL – effectively tripping off the power plant.

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

4 Impact of Solar Generation

Tables 3 to 7 present the estimated coefficients and the corresponding p-values for the conditional mean and conditional variance equations of the estimated ARX-eGARCHX models for each spot electricity market for the whole sample period. Because the starting points of the data series for NSW and QLD are different from those for the other states, we include more models than for the other states. Models A and B capture the impact of solar generation and penetration in the spot electricity price dynamics for both states using data from 2015 and 2017 for NSW and QLD, respectively. Models C and D for QLD capture the impact of rooftop solar generation and penetration on electricity price dynamics using rooftop solar generation data without controlling for wind generation. Models E to J capture the impact of large-scale solar generation, rooftop solar generation, and wind generation from 2018 onward.[21]

4.1 The intraday mean and volatility dynamics

We observe significant mean and volatility spillovers in all five markets. From the mean equation in Tables 3 to 7; Models A to J, the magnitude of the mean spillovers effect is positive and is strongly pronounced in QLD, VIC, TAS, and NSW and ranges from 0.9302 to 0.9681; it is relatively less pronounced in SA (0.9147 to 0.9191). From the variance equation, we observe strong and statistically significant ARCH spillovers across all five markets. QLD, TAS, SA, and NSW exhibit a far higher effect, ranging from 1.0311 to 6.0482, compared to VIC (0.7538 to 0.7817). These results suggest that shocks from the previous period tend to affect future volatility to a lesser extent in VIC compared to the other markets. Similarly, the effect of positive and negative shocks is not consistent across all five markets. While we find that positive shocks tend to exert a larger impact on electricity price volatility than negative shocks of the same magnitude in VIC, SA, and TAS, the effect in NSW and QLD is the reverse. Moreover, we observe pronounced GARCH spillovers in which VIC, NSW, SA, and QLD experience a larger effect ranging from 0.6491 to 0.7359. TAS display a relatively small effect ranging from 0.4755 to 0.4827. Therefore, we infer that the last period's volatility shocks tend to affect future spot price volatility more strongly in VIC, NSW, SA, and QLD than in TAS.

[21]We run the ARX-eGARCHX models by assuming the standardized residuals follow skew Student distribution in SA, QLD, and TAS, Student distribution in NSW, and Johnson's reparametrized SU distribution in TAS. A detailed analysis of the choice of these distributions is given in Appendix B. Tables 4 to 7 also present the corresponding skew and shape parameters of these distributions. The adequacy of the model fit is assessed using the weighted Ljung-Box test and the weighted Lagrange multiplier test (ARCH-LM tests), with the null adequate fitted autoregressive–moving-average (ARMA) models and the ARCH process (Ghalanos, 2021). In most cases, we fail to reject both hypotheses, and the models seem to account for a fair amount of the autocorrelation. The autocorrelation function (ACF) and the partial autocorrelation (PACF) of the standardized residuals and the squared standardized residuals, respectively, also indicate low autocorrelation and the absence of a specific pattern due to a non-stationary or seasonal time series.

The present findings suggest that at high frequency, the estimated ARCH and GARCH spillovers exhibited by spot prices are relatively large compared to those of the average (daily) spot prices, as examined by Mwampashi et al. (2021). In the following sections, we present the impacts of large-scale and rooftop solar generation, among other variables, on spot electricity price dynamics. The top and bottom panels of Tables 3 to 7 present the impact of large-scale and rooftop solar generation, among other variables, on the level (mean equation) and volatility (variance equation) of electricity spot prices, respectively. A detailed discussion of the findings follows.

4.2 Large-scale solar generation

4.2.1 Impact on spot electricity prices

The findings in the mean equation (Tables 3 to 6; Model E) confirm the MOE of large-scale solar generation in all four regional markets. This effect appears more substantial in VIC and SA, which have moderate large-scale solar generation levels. A 1 MWh increase in large-scale solar generation decreases prices by around 0.15 AUD/MWh and 0.08 AUD/MWh in SA and VIC, respectively.[22] In contrast, QLD and NSW, which experience higher large-scale solar generation during the sample period, exhibit a relatively moderate effect of around 0.03 AUD/MWh for each 1 MWh increase in solar generation.[23] These results are expected because solar generation has a low short-run marginal cost and is prioritized in the dispatch process, allowing it to push higher-marginal-cost thermal units out in the dispatch process and lower spot prices. The higher magnitude of the MOE in SA may be accounted for by the state's significant reliance on expensive gas-powered generation and limited interconnector capacity with other regions. Under these conditions, the market tends to experience high average electricity prices. Thus, an increase in large-scale solar generation displaces expensive gas-powered generators and lowers electricity prices. A link between the impact of large scale solar generation and the average electricity prices is evident from Table 2 and Figure 2. In particular, regions experiencing higher average electricity prices tend to exhibit higher MOE for an increase in large-scale solar generation.

The results in Model F further suggest that states with the highest solar penetration in the NEM, namely, SA and QLD, experience relatively lower price reductions for an increase in large-

[22] All supply and demand variables in Tables 3 to 7 are scaled by a factor of 10 to ease the presentation of the estimated coefficients. This adjustment means that the coefficients in these tables are ten times larger than the original coefficients. Thus, to recover the original values, one needs to divide the estimated coefficients by 10. Upon recovering the original values, our interpretation of the variables in the mean equation (1) is that a 1 unit increase in a jth independent variable is associated with a ζ_j AUD/MWh change in spot prices, where ζ_j, is the coefficient of the jth independent variable.

[23] We observe a slight difference between the MOE obtained by running the analysis using 2015 and 2017 data and that of 2018 for NSW and QLD. The estimated coefficients are lower and higher by 0.01 AUD/MWh for a 1 MWh increase in large-scale solar generation in QLD and NSW, respectively (see Models A and E in Tables 3 and 6).

scale solar penetration. In particular, a 1 percentage point increase in large-scale solar penetration is associated with a 1 AUD/MWh decrease in electricity prices in NSW and VIC.[24] The decrease in QLD and SA is relatively small and is 0.9 AUD/MWh and 0.6 AUD/MWh, respectively. The results concur with those of Csereklyei et al. (2019), who found a strong contemporaneous MOE of large-scale solar generation in SA and VIC, a relatively lower MOE in QLD, and the absence of the MOE in NSW.

4.2.2 Impact on the volatility of electricity prices

The results in the variance equation (Tables 3 to 6; Model E) suggest that the impact of large-scale solar generation on price volatility is notable and consistent across four states in the NEM. An increase in large-scale solar generation is associated with an increase in price volatility in states with moderate generation levels. Specifically, for each 1 MWh increase in large-scale solar generation, volatility increases by 0.4% and 0.3% in SA and VIC, and only 0.2% in NSW and QLD.[25,26] Furthermore, large-scale solar penetration exhibits the same sign effect with statistical evidence observed for all states in the NEM (see Model F). A 1 percentage point increase in large-scale solar penetration is associated with a volatility increase of around 8% in NSW and VIC, 5% in QLD, and only 2% in SA.[27]

When solar PV generation is disrupted due to a lack of sunlight, market prices spike to balance the price-inelastic demand and fossil fuel generation required to meet the lost output (Milstein and Tishler, 2011). Specifically, the decrease in sunlight can increase spot prices significantly due to the higher marginal costs of generation associated with fast start-up and flexible plants and ramping costs associated with coal-fired power plants (Jha and Leslie, 2020). Despite the relatively higher penetration of solar generation, the positive impact on price volatility in SA is relatively lower than in other states. The lower magnitude of the estimated coefficient may be accounted for by the presence of more fast-start and flexible generating capacity, such as gas in SA's generation mix, which tends to smooth price volatility. Moreover, solar generation tends to

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

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

[26] We find a marginal difference between the coefficients in the variance equation estimated using 2018 data and 2015 and 2017 data for NSW and QLD (see Model A and E in Tables 3 and 6).

[27] We follow a similar interpretation of the coefficients as in Footnote 25 with a minor modification to account for the fact that penetration variables are expressed in ratios. In particular, a 1 percentage point increase in a kth penetration variable is associated with a $\zeta_k \times 0.01 \times 100\% = \zeta_k\%$ change in spot price volatility, where ζ_k, is the coefficient of the kth penetration variable.

have low variability during the day compared to wind generation, allowing mid-load power plants to efficiently adjust their power production to residual demand and stave off large and frequent price spikes (Kyritsis et al., 2017). Furthermore, large-scale solar generation tends to exhibit a substantial MOE compared to wind generation for the same marginal increase in the generation levels for all states except QLD. Although wind penetration in QLD is still modest, it has greater potential to lower spot prices and reduce price volatility compared to large-scale solar generation.

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

4.3 Rooftop solar generation

4.3.1 Impact on electricity spot prices

We observe in the mean equation (see Tables 3 to 7; Model G) that rooftop solar generation contributes to depressing spot prices in the NEM. Similar to large-scale solar generation, this effect is more pronounced in states with moderate and low rooftop solar generation levels. We find that a 1 MWh increase in rooftop solar generation decreases electricity prices in NSW, VIC, SA, and TAS in a range of 0.01 AUD/MWh (NSW) to 0.04 AUD/MWh (TAS). The effect in QLD is marginal. Moreover, incorporating the effect of consumption via the rooftop solar penetration in Model H reveals a consistently negative impact on electricity prices for all states in the NEM. In this respect, a 1 percentage point increase in rooftop solar penetration decreases prices substantially in states with moderate penetration rates by 0.84 AUD/MWh and 0.43 AUD/MWh in VIC and NSW, respectively. The effect in other states is lower, including in SA, which has the highest penetration of rooftop solar generation. In particular, prices decrease by 0.28 AUD/MWh, 0.22 AUD/MWh, and 0.17 AUD/MWh in QLD, SA, and TAS, respectively, for a 1 percentage point increase in rooftop penetration.

4.3.2 Impact on the volatility of electricity prices

Turning to price volatility (see the variance equation in Tables 3 to 7; Model G), we observe a considerable positive impact of increasing rooftop generation on the volatility dynamics in the

NEM. Numerically, an increase in rooftop solar generation by 1 MWh increases price volatility by 0.4% in TAS and by almost half in SA and VIC. The effect in NSW and QLD is marginal, approximately 0.1% for each 1 MWh increase in rooftop generation.[28] Considering rooftop solar penetration in Model H, we observe a similar sign effect. For each 1 percentage point increase in rooftop solar penetration, volatility increase by 5%, 4%, 4%, and 2% in NSW, VIC, QLD, and TAS, respectively. A much lower effect of around 1% is found for SA. As noted, this lower positive impact on price volatility may result from the richness of flexible energy sources, especially gas generation, which contributes to smoothing price volatility resulting from the rooftop solar generation.

Large-scale solar and rooftop solar generation generally impact electricity spot prices in a similar manner. The main difference is that the magnitude of this effect is lower for rooftop solar generation. This may be due to network restrictions caused by the recent influx of rooftop solar PV power, which forces several networks to cap the amount of excess electricity that customers can export to the grid. Moreover, the results observed in sections 4.2 and 4.3 underscore the importance of examining the impact of large-scale and rooftop solar generation separately. We note that combining large-scale and rooftop solar generation undercuts the MOE of large-scale solar generation, likely due to the opposing effects observed during the day. For instance, while the MOE of large-scale solar generation in SA is 0.15 AUD/MWh, adding rooftop solar generation reduces it to 0.03 AUD/MWh. Overall, these results for the MOE are in line with those of Abban and Hasan (2021). However, those authors combined large-scale and rooftop solar generation and observed a positive correlation between daily solar penetration and electricity prices in NSW and VIC.[29]

4.4 Other factors

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

[28] Using data from 2017 without controlling for wind generation in QLD suggests a marginal difference in the estimated coefficients (see Models C and D, as well as Models G and H in Table 6).

[29] There are several reasons for this effect. First, the authors considered the sample period from 1 April 2014 to 28 February 2019, when solar generation, especially large-scale solar generation, was at the lowest levels. Second, their study did not account for the impact of hydro and cross-border interconnectors flow, signaling the potential omitted variable bias in their model estimation.

4.4.1 Impact on spot electricity prices

We observe in the mean equation of Tables 3 to 7; Models A, C, E, G, and I, that wind generation exhibits a negative impact on the level of electricity prices in all states across the NEM. TAS and SA exhibit a far higher impact, in which a 1 MWh increase in wind output lowers spot prices by a maximum of around 0.14 AUD/MWh and 0.12 AUD/MWh, respectively. VIC and QLD follow with the effect ranging from 0.05 AUD/MWh to 0.06 AUD/MWh. The impact in NSW is small, approximately 0.02 AUD/MWh for the same increase in wind generation. When we factor in the effect of consumption via wind penetration in Models B, D, F, H, and J, we get the opposite result. In states with intermediate penetration rates, such as VIC and QLD, increasing wind penetration by 1 percentage point decreases electricity prices by 1 AUD/MWh, followed by NSW with a maximum of 0.72 AUD/MWh. TAS and SA exhibit a price reduction of up to 0.67 AUD/MWh and 0.66 AUD/MWh, respectively.

Results in Tables 3 to 7; Models A to J demonstrate that an increase in consumption and gas prices tend to impact electricity prices positively. In particular, increasing electricity consumption by 1 MWh tends to raise prices more in states with low demand profiles, i.e., TAS and SA, by a maximum of 0.16 AUD/MWh.[30] The increase in NSW, VIC, and QLD is moderate, ranging from 0.03 AUD/MWh to 0.07 AUD/MWh. Increasing gas generation by 1 AUD/GJ is associated with substantial upward pressure on the level of electricity prices in states that rely more on gas generation, such as SA, by a maximum of 3.2 AUD/MWh, followed by QLD, by a maximum of around 1.9 AUD/MWh. The lowest effect is observed in VIC, which has the least amount of gas in its generation mix. Hydro generation negatively impacts electricity prices in TAS and QLD, with a 1 MWh increase in hydro generation exerting negative pressure on electricity prices by around 0.01 AUD/MWh. In NSW, an increase in hydropower has the opposite effect, with electricity prices rising by 0.02 AUD/MWh to 0.03 AUD/MWh for each 1 MWh increase in hydro generation. The impact of the interconnectors on the level of spot electricity prices varies. In NSW, the Terranora interconnector and the QNI tend to impact electricity prices negatively. The latter interconnector exhibits the same effect in QLD, whereas the former shows the reverse effect. The interconnectors to VIC: Heywood, Basslink, and VNI impact electricity prices negatively, whereas the Murraylink interconnector impacts electricity prices positively. The Heywood and Murraylink interconnectors show similar effects in SA, and the Basslink interconnector shows the same impact in TAS.

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

4.4.2 *Impact on the volatility of electricity prices*

Models A, C, E, G, and I in the variance equation in Tables 3 to 7 show that wind generation tends to negatively and positively impact electricity volatility. A 1 MWh increase in wind generation is related to a maximum of 0.06%, 0.03%, and 0.01% increase in price volatility in TAS, VIC, and NSW, respectively. In contrast, the same increase in wind generation tends to smooth price variability in QLD by a maximum of 0.08%. Similarly, we observe in Models B, D, F, H, and J that an increase in wind penetration by 1 percentage point is linked to a maximum of 0.6% and 0.8% volatility increase in NSW and VIC, respectively, and a maximum of a 3% volatility decrease in QLD. Although wind generation appears to increase price volatility in TAS, adjusting for consumption via wind penetration produces a statistically insignificant effect.

The findings in Tables 3 to 7; Models A to J show that electricity consumption, hydro generation, and gas prices impact spot price volatility in a positive direction. For each 1 MWh of electricity consumed, price volatility increases substantially in low-demand-profile states such as TAS and SA by a maximum of 0.13% and 0.10%, respectively. The magnitude of this effect is marginal in other states, zero percent in one decimal point. The effect of hydro generation is more pronounced in QLD, whereby a 1 MWh increase impacts price volatility positively by a maximum of 0.19%. The effect observed in NSW, VIC, and TAS do not exceed 0.09% for the same increase in hydro generation. Gas prices appear to increase price volatility more substantially in QLD, in which a 1 AUD/GJ increase impacts price volatility by a maximum of 6%, followed by NSW (5%). VIC and SA exhibit the same effect of up to 4%, although, in more than two decimals, SA exhibits the lowest impact in the NEM. Most interconnectors tends to decrease price variability. We observe this effect for the Terranora interconnector and the QNI in NSW and the Murraylink and Heywood interconnectors in SA. The latter two interconnectors, in conjunction with the VNI, also exhibit a similar effect in VIC. In contrast, the Basslink interconnector positively impacts VIC and TAS spot price volatility. The same effect is true for the Terranora interconnector in QLD.

Collectively, the results of this analysis concur with previous findings regarding the impact of wind generation and other determinants such as gas prices and consumption on price dynamics in the NEM (Forrest and MacGill, 2013; Cludius et al., 2014; Csereklyei et al., 2019; Abban and Hasan, 2021; Mwampashi et al., 2021). As the present study bears a resemblance to that by Mwampashi et al. (2021), we compare the findings and highlight points of divergence. First, the intraday (half-hourly) MOE of wind generation and its impact on price volatility are higher than the average (daily) effects reported by Mwampashi et al. (2021). Second, while Mwampashi et al. (2021) observed a consistently positive impact of hydro generation across all states in the NEM, the present study demonstrates the potential for hydro generation in reducing the level of electricity prices. The differences in the observed results are accounted for mainly by the difference in the sample period under investigation, the present findings being fueled by low implicit fuel cost (water). The years 2018 to 2021 experienced relatively high rainfall compared to, for instance, 2015 and 2016, which witnessed significant drought conditions affecting water storage and hydro generating capacity. Moreover, the reduction in the bidding levels of coal and gas generators following relatively low coal and gas prices may also have been a factor. Third, Mwampashi et al. (2021) found that all interconnectors to NSW contribute to lowering electricity prices, reflecting the import position of the region, but the present analysis shows that this is no longer the case for the VNI. This is most likely due to the huge reduction in inexpensive imports from VIC following the closure of the Hazelwood power plant in 2017, which removed roughly 5% of the NEM's total capacity. Finally, we include QLD, which Mwampashi et al. (2021) excluded. We find that wind generation has a potential to reducing QLD's electricity prices and smoothing price volatility although wind generation began only in 2018.

5 Further Considerations of Solar Generation in the NEM

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

5.1 The intraday dynamics

To understand how solar generation impacts spot prices throughout the day, we run separate regressions for each half-hour interval resulting in a total of 48 estimated coefficients.[31] Figures 7 and 8 plot these coefficients for large-scale solar generation, rooftop solar generation, and wind generation only for easy presentation of the results. We provide the corresponding p-values in Appendix C.

5.1.1 Intraday MOE

We observe in Figures 7 and 8 that although the negative impact of wind generation on spot prices appears about the same throughout the day, the impact of solar generation varies and can be positive during some hours. The MOE is most pronounced during the middle of the day. High solar generation supplants expensive fossil fuel power generation during these times, translating

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

into a substantial decline in electricity prices. In addition, the effect may be more pronounced due to the inability or unwillingness of incumbent coal-fired power plants to reduce their output during the day (Rai and Nunn, 2020). Pereira and Rodrigues (2015), Rintamäki et al. (2017), Kyritsis et al. (2017), and Maciejowska (2020) noted that increasing solar power production tends to have a more pronounced negative impact on electricity prices during peak hours than during off-peak hours in Germany. The peak period aligns with the highest solar generation levels. A striking observation from Figure 7 and 8 is that large-scale and rooftop solar generation (especially for NSW and VIC) tend to impact electricity prices positively early in the morning and in the evening when the sun is about to set. Specifically, the price coefficients are positive in the morning (06:00 and 6:30) and evening (18:00 to 19:30). Moreover, we observe a positive correlation between large-scale solar generation and spot prices in SA, which can be seen for most of the day. There is also evidence of a drop in the MOE of large-scale solar generation during the middle of the day in QLD.

5.1.2 Intraday volatility

In contrast to wind generation, which appears to impact price volatility positively for most of the time, the impact of large-scale and rooftop solar generation during the day varies (see Figures 7 and 8). An increase in large-scale solar generation tends to reduce price volatility across all states in the NEM. This effect is more apparent and pronounced in three states, SA, NSW, and VIC, and relatively less pronounced in QLD. The availability of flexible generation and interconnection capacities is a possible explanation as to why the increase in large-scale solar generation decreases volatility prominently in SA, especially during the shoulder hours. These findings are in line with those of Maciejowska (2020), who showed that solar power tends to stabilize price variability when demand is moderate. Moreover, adding rooftop generation to the systems tends to impact spot prices differently from large-scale solar generation. Generally, an increase in rooftop solar generation is associated with an increase in price volatility during most of the day. A likely explanation is that rooftop PV systems are largely north-facing, which means they have a higher impact on price volatility than large-scale systems, which typically tend to be axis-tracking. TAS behaves slightly differently in that an increase in rooftop solar generation appears to decrease price volatility most of the time compared to the other states. The availability of flexible generation sources, such as hydro and gas, could account for this effect.

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

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

5.2 Why does solar generation drive up electricity spot prices?

To further explore why solar generation may increase electricity prices, we run separate regressions with the same explanatory variables. However, this time we set the dependent variable to be the generation sources available in a particular state rather than spot electricity prices.[32] We plot the results for the estimated coefficients in Figures 9 and 10.

We find that the increase in both large-scale and rooftop solar generation displaces incumbent coal-fired generators during the middle of the day when the sun is at the maximum. We observe similar behavior for other sources of generation, such as hydro and gas generation, although not as consistently as for coal-fired power plants. Interestingly, these figures clearly link the impact of solar generation to spot price dynamics.[33] While wind generation displacement effect is visible throughout the day, solar generation has the opposite effect during some hours. The increase in solar generation during the daytime is negatively associated with spot prices. However, the requirement to ramp up generation quickly in the evening to replace the lost output and the increase in demand can result in a rapid upsurge of the spot prices. Because solar generation is at its lowest during these hours, prices will equal the dispatch cost of the marginal generators (natural gas or coal). This then results in higher prices that solar generators benefit from, resulting

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

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

in a positive coefficient of solar PV. These dispatch costs tend to be higher in a system with a lot of solar than they would be otherwise. This is because switching coal-fired plants on and off frequently is more expensive than maintaining continuous production. We observe that increasing solar generation in NSW during the evening is associated with an increase in natural gas generation. These hours align with the time when the increase in solar generation impacts electricity prices positively; that is, morning hours (6:00 to 6:30) and evening hours (18:00 to 19:00). We conclude that solar generation tends to increase electricity prices in NSW due to the high marginal costs associated with the natural gas generation required to replace the lost output when the sun is about to set. In VIC, the increase in large-scale solar generation is associated with an increase in brown coal generation in the early morning. In the evening, an increase in large-scale and rooftop solar generation is linked to an increase in brown coal and natural gas generation. This means that solar generation is more likely to impact electricity prices positively in VIC due to the high start-up and shutdown costs associated with brown coal-fired generation and the high marginal costs associated with natural gas generation.[34]

Solar generation tends to positively impact electricity prices in QLD in the morning via natural gas generation and in the evening via black coal-fired generation. There is no clearer link between the impact of large-scale solar generation on the electricity generation mix and its effect on spot prices in SA. However, the curtailment of large-scale solar generation very likely drives the results.[35] AEMO curtails utility-scale (semi-scheduled) generators before rooftop generation (non-scheduled). In the middle of the day, when rooftop solar generation is at its peak, AEMO is likely to curtail utility-scale solar to maintain system security. However, as there is an excess supply of zero-short-run marginal cost (SRMC) generation at this time, prices are also low. Therefore, as prices fall, and coal generators' output is increasingly pushed down toward the minimum stable levels, AEMO curtails large-scale solar generation as prices fall. This then translates to a positive correlation between prices and large-scale solar, as shown in Figure 7. Rooftop penetration is especially high in SA and QLD, which is why we do not see the same phenomenon in the other NEM regions.[36] Evidence from rooftop solar generation suggests that natural gas/diesel generation is

[34]It is also worth mentioning that high prices during these periods could also result from strategic bidding behaviors of generators in the NEM (Clements et al., 2016; Hurn et al., 2016; Dungey et al., 2018). Although such behaviors remain challenging in the market, recent studies demonstrate that their role in influencing prices has declined over time, especially after the AEMC introduced the Bidding in Good Faith Rule in July 2016 (Han et al., 2022). This rule is aimed at addressing generators' strategic and misleading bidding behaviors. The AEMC also noted in the Gaming in Rebidding Assessment report of 2018 that the cost of gaming related to rebidding decreased in 2017 compared to the previous three years (AEMC, 2018).

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

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

responsible for driving prices up. Peaker plants are primarily gas turbines or gas engines that use natural gas or a liquid fuel, such as diesel. Although both types of plants have the highest SRMC of generation, diesel peaking plants have the highest marginal cost of generation, roughly 500 AUD/MWh. Finally, the absence of statistical evidence for the positive effect of rooftop solar generation in TAS can be accounted for by the dominance of hydro generation and the negligible proportion of gas generation in the state's generation mix. Overall, the present findings are in line with those of Bushnell and Novan (2021), who found that the increase in solar generation increased electricity prices in California due to the higher use of less fuel-efficient and higher marginal cost gas turbine (GT) production required to meet the evening peak when solar power is not available.

These results provide important insights into the varying impact of solar generation throughout the day. In general, adding solar capacity to the system may not result in lower spot electricity prices. Although studies that consider the average effect over the whole sample period, as in sections 4.2 and 4.3, may indicate this occurs, the intraday profile of the impact of solar generation suggests the opposite effect often happens throughout the day.[37] These findings underscore the importance of interconnectors and battery storage technologies to store surplus energy from solar PV systems to meet peak demand. Investment in storage technologies and interconnectors is increasingly important given the increasing incidence of solar generation curtailment during the day (AER, 2021). Moreover, the fact that energy resources are dispatched based on the costs of running the plant today, not the costs of keeping them running tomorrow, makes it hard for coal-fired generators to recover their high fixed costs. In turn, high penetration of both large-scale and rooftop solar generation renders coal generation commercially unviable to operate, hastening retirement in advance of planned dates and placing the system in jeopardy of blackout. The rapid increase of VRE would significantly impact numerous coal-fired generators by 2025, making shutdown a desirable or even unavoidable alternative for at least one power plant owner in the NEM (Edis and Bowyer, 2021). Gas generation, unlike coal, is more flexible, allowing it to quickly ramp up and down to manage fluctuations in solar generation or offer frequency control ancillary services. It often generates at the margin, making it at less financial stress compared to coal-fired units.

[37] To further demonstrate how the average analysis may obscure the positive impact of solar generation, we run an additional analysis by applying the typical approaches of dividing the data into peak and off-peak hours. We define hours associated with the highest average electricity consumption as the "peak period" from 16:00 to 21:00 and hours with low and moderate average electricity consumption as the "off-peak period" from 00:00 to 07:00 and 21:00 to 00:00. We provide technical details and the corresponding results in Appendix B.5 and Appendix C, respectively. We find the depressing price effect of solar generation and its positive impact on price volatility during peak and off-peak hours. However, results in this section show that solar generation has great potential to smooth price volatility compared to wind.

5.3 Seasonal effects

Table 8 presents the impact of large-scale and rooftop solar generation on the level and volatility of electricity spot prices during the four seasons of the year, i.e., summer, autumn, winter, and spring.[38] The results suggest that solar generation impacts the level of electricity prices differently over the four seasons. We observe that adding large-scale solar generation and, to a lesser extent, rooftop solar generation into the mix tend to substantially decrease electricity prices during the summer followed by the spring, autumn, and winter. For instance, for each 1 MWh increase in large-scale solar generation, spot prices in SA decrease by 0.25 AUD/MWh and 0.11 AUD/MWh in the summer and winter, respectively.[39] However, the effect of rooftop solar generation is relatively small compared to that of large-scale solar generation. For instance, an increase in rooftop solar generation negatively impacts the level of electricity prices in SA by 0.10 AUD/MWh and 0.02 AUD/MWh during the summer and winter, respectively. The impact of rooftop solar generation in QLD is evident only in the winter and spring.

As Figures 5 and 4 demonstrate, the spring and summer seasons coincide with high solar generation in the NEM, except for QLD. One possible explanation for the substantial reduction in prices, especially in the summer, is that the days are longer than in the winter. Thus, the amount of electricity produced by a solar generation system in the summer at the same location could be twice that produced in the winter. Given a relatively higher correlation between solar generation and demand (both peak in the summer), an increase in large-scale solar generation significantly impacts electricity prices. In SA, this effect is enhanced further by the rapid uptake of domestic rooftop solar generation, which lowers demand during the middle of the day, leading to the occurrence of near-zero or negative prices. In contrast to other states, QLD does not experience high solar generation in the summer, which explains why rooftop solar generation shows an insignificant MOE during this season. Also, low rooftop solar generation in TAS may explain the lack of statistical evidence for its effect during the four seasons of the year. The findings for the MOE of large-scale solar generation agree with those of Mountain et al. (2018).[40]

[38] Table 8 presents the estimated coefficients for large-scale solar generation, rooftop solar generation, and wind generation only for easy presentation of the results. However, we control for all determinants of electricity prices and provide the complete results in Appendix C.

[39] In Table 8, winter is used as a reference (base), and no adjustment is required to the estimated coefficients for this season. However, the adjustment is required for coefficients in the other remaining seasons. For example, since the coefficient of large-scale solar generation in NSW (Model M) in winter is -0.1924 and *large-scale solar* $\times$ D_{spring} is -0.1159, then the coefficient for spring season is recovered by summing the two coefficients, i.e., $(-0.1924) + (-0.1159) = -0.3083$. The same adjustment applies to other seasons and to both solar and wind generation coefficients. Once these coefficients are adjusted, the same scaling and interpretations as in Footnotes 22 and 25 apply. The seasonality approach is discussed in greater depth in Appendix B.5.

[40] Mountain et al. (2018) showed that a 100 MW increase in average solar PV production in SA leads to a higher reduction in spot prices during the summer by around 11 AUD/MWh compared to 31 AUD/MWh in the winter. The authors argued that although the marginal impact of solar generation tends to be higher in the winter, the total impact tends to be lower. Moreover, they found an increase in solar generation increases spot prices in the late afternoon in the summer. As we consider the average over the whole summer season, the negative effect of solar

Large-scale and rooftop solar generation have a consistent positive impact on the volatility of spot prices, an effect that is more pronounced in the winter than in the other seasons. The output from solar generation varies substantially in the winter because the days are shorter, there is more cloud cover, and the sun is lower in the sky. Fluctuations in solar generation force the electricity system to respond to significant and unexpected changes in output and plant operators' dispatch decisions. This means more fast starts and flexible, and fossil fuel–based generation is required to replace the lost power output from solar generation compared to other seasons. As stated in section 4.2, this can result in extreme price spikes when the market attempts to balance the price-inelastic demand and fossil fuel generation when solar PV output falls. The tendency of coal-fired generators to withdraw from the market for maintenance during this season is likely to trigger further price variability (AER, 2021). The lack of statistical evidence for the impact of large-scale solar generation on spot price volatility during the summer reflects the relatively higher correlation between demand and solar generation during this season. This correlation tends to minimize the probability of high price spikes. Solar generation profile is best aligned to the heat waves that typically occur during summer, causing price spikes. Having solar generation reaching its maximum during most hours of this season means that both large-scale and rooftop solar generation can significantly reduce the frequency and severity of scarcity prices. Furthermore, the results show that large-scale solar generation has a greater positive impact on spot price volatility over all four seasons than rooftop solar generation. This difference can be partly explained by the smaller volume of excess rooftop solar generation exported back in the grid due to export limits.

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

6 Policy Implications

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

generation likely outweighs its positive effect, as explained in subsection 5.1. The difference in the estimated results between the present and the Mountain et al. (2018) study may also be accounted for primarily by the difference in the sample period and the methodological approach employed in the analysis. We consider a period from 2018 to 2021 but Mountain et al. (2018) covered a period from 2012 to 2018. Furthermore, their approach did not adjust for the yearly variations or include lagged electricity prices.

of the market. We provide next a number of courses of action to ensure an effective transition to clean energy.

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

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

6.2 Rooftop solar curtailment

Evidence from this study suggests that the rapid uptake of rooftop solar generation is imposing significant challenges during the middle of the day by pushing demand down to levels where system security is threatened and, on some occasions, pushing spot prices into negative territory. Most generators in the electricity grid are controlled by AEMO, which allows dispatch by stacking the offer bids of all generators depending on the price offers and supply limitations, such as transmission network constraints. Unlike these generators, rooftop solar generation has long been unregulated by AEMO, which prioritized it over other types of generators (Reddaway, 2020). Lack of controllability not only cuts the share of large-scale solar generators when their capacities are curtailed but also causes significant distress to coal-fired generators, which are not designed to operate at low output levels. As we have demonstrated, the impact of rooftop solar generation is increasingly pronounced in SA and QLD, with the highest penetration of rooftop solar generation in the NEM to date. In response, and for the first time, in March 2021, AEMO instructed network operators in SA to turn off rooftop solar generators and draw power from the grid to ensure the security of the power system (AER, 2021). This incident occurred during a low-demand period with excess supply from rooftop solar systems. Given the increasing uptake of rooftop solar generation at around 3,000 MW a year, and given that the battery storage capacity is still insufficient to enable extensive decarbonization at a cost-effective level, there is little doubt that curtailing rooftop solar generation is becoming increasingly important in the NEM. As QLD, VIC, and NSW are also witnessing high increases in rooftop solar generation, this is not exclusive to SA, and curtailment of rooftop solar generation may be required across the NEM in the not-too-distant future. However, one important question still remains, namely, identifying the best mechanism with which to curtail rooftop solar generation. The dynamic/flexible solar export mechanism being considered in SA, QLD, and VIC would probably provide a more robust solution to the increasing penetration of rooftop solar generation compared to current static or arbitrary limits.[41] This curtailment mechanism involves a central computer system instructing solar inverters on how much and when to export power to the main grid depending on the on-network conditions. This would allow absorption of all households' excess solar power, by varying the export amount from time to time based on the supply and demand conditions and other network constraints.[42] Effective management of rooftop exports via flexible export limits in conjunction with other planned mechanisms to support the penetration of solar generation, such as increased interconnections, would eliminate the need to switch off rooftop solar systems completely to maintain grid stability.

6.3 Feed-in tariffs (FiTs)

Rooftop solar generators often receive FiTs for the excess generation exported back into the grid as a means of encouraging renewable energy adoption (Li et al., 2020). These rates vary significantly across the NEM. For instance, the NSW and VIC governments recommend FiTs of at least 4.6 c/kWh to 5.5 c/kWh and 6.7 c/kWh, respectively (NSWGov, 2021; VICGov, 2021a). State governments and retailers should move from offering flat-rate FiTs to FiTs that vary throughout the day (dynamic FiTs). These rates should be set in such a way that they are lower during the day when demand, especially at the residential level, is typically low and higher during morning and evening demand peaks. This will trigger owners of solar generators to export their excess electricity to the grid when it is most valuable, in this case, the morning and evening. This reform has several potential benefits. First, it might incentivize north-facing PV systems to invest in batteries to store

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

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

surplus energy and draw on it when needed in the evening. Second, it may attract owners to place their solar panels in other orientations, such as an east/west split, to maximize generation in the morning and evening hours. Victoria offers a typical example of the proposed reform. Beginning 1 July 2020, all retailers were required by law to offer either a single-rate rate FiT, a time-varying FiT, or both. The time-varying rates depend on whether excess electricity is exported during off-peak, shoulder, or peak hours. The FiT rates currently stand at 9.1 c/kWh during off-peak hours, 9.8 c/kWh during shoulder hours, and 12.5 c/kWh during peak hours (VICGov, 2021b). However, per our findings, the rates during morning and evening hours should be substantially higher than daytime rates. Third, consumers would be encouraged to shift some of their electricity use from peak to solar generation hours, reducing peak-hour electricity demands.

6.4 Two-sided market reform

The increase in solar generation is pushing out traditional coal and gas-generating businesses during the day. However, these generators are required to complement the variability of solar power output because of the ramping up and down of solar plants, adding more costs to the system. As demonstrated in this study, the benefits derived by increasing solar generation depend substantially on the cost associated with dispatchable and flexible capacities. High flexibility costs are likely to undermine the merit order effect for solar generation. Therefore, the market needs cheap firming technologies to allow the benefits of renewables to translate to low electricity prices. A two-sided market that allows the supply and demand sides to participate in the dispatch and price-setting process is a potential solution. Since the inception of the NEM, electricity has generally been flowing one way, from large-scale centralized generators to homes and businesses. However, the advent of automation, digitalization, and the Internet of Things means that the market can allow for the effective participation of the demand side. This advancement in technology will enable the demand side to respond directly to price signals similar to the supply side without being energy traders and physically or consciously controlling their demand (Rai et al., 2021). In line with these transitions, the market will move from two-part structures with fixed daily charges and volumetric tariffs to more dynamic/time-varying retail pricing (time-of-use (ToU)) rates such as "solar-sponge" tariffs. The solar sponge aims at encouraging the "soaking up" of cheaper power during the day, when there is extra electricity generation, typically between 10:00 and 15:00, particularly in SA and QLD, and setting high prices during peak periods. Thus, allowing for effective demand-side participation can be a more cost-effective mechanism for dealing with peak demand than peaking generation, such as gas and pumped hydro. The October 2021 reform, namely Wholesale Demand Response (WDR) mechanism, which allows customers to offer demand response to the wholesale market directly,[43] will likely translate into a potentially lower volatility effect for solar generation

[43]For more details on the WDR mechanism see the Quarterly Energy Dynamics Q4 2021 AEMO's report on https://aemo.com.au/-/media/files/major-publications/qed/2021/q4-report.pdf?la=en.

than currently observed in the market but may also reduce the MOE of solar PV. A two-sided market provides the potential for maximizing CO_2-e emission reduction by substituting thermal generation with demand-side resources and allowing for maximum generation from VRE, which would otherwise be curtailed to allow the thermal generators to run.

7 Conclusion

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

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

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

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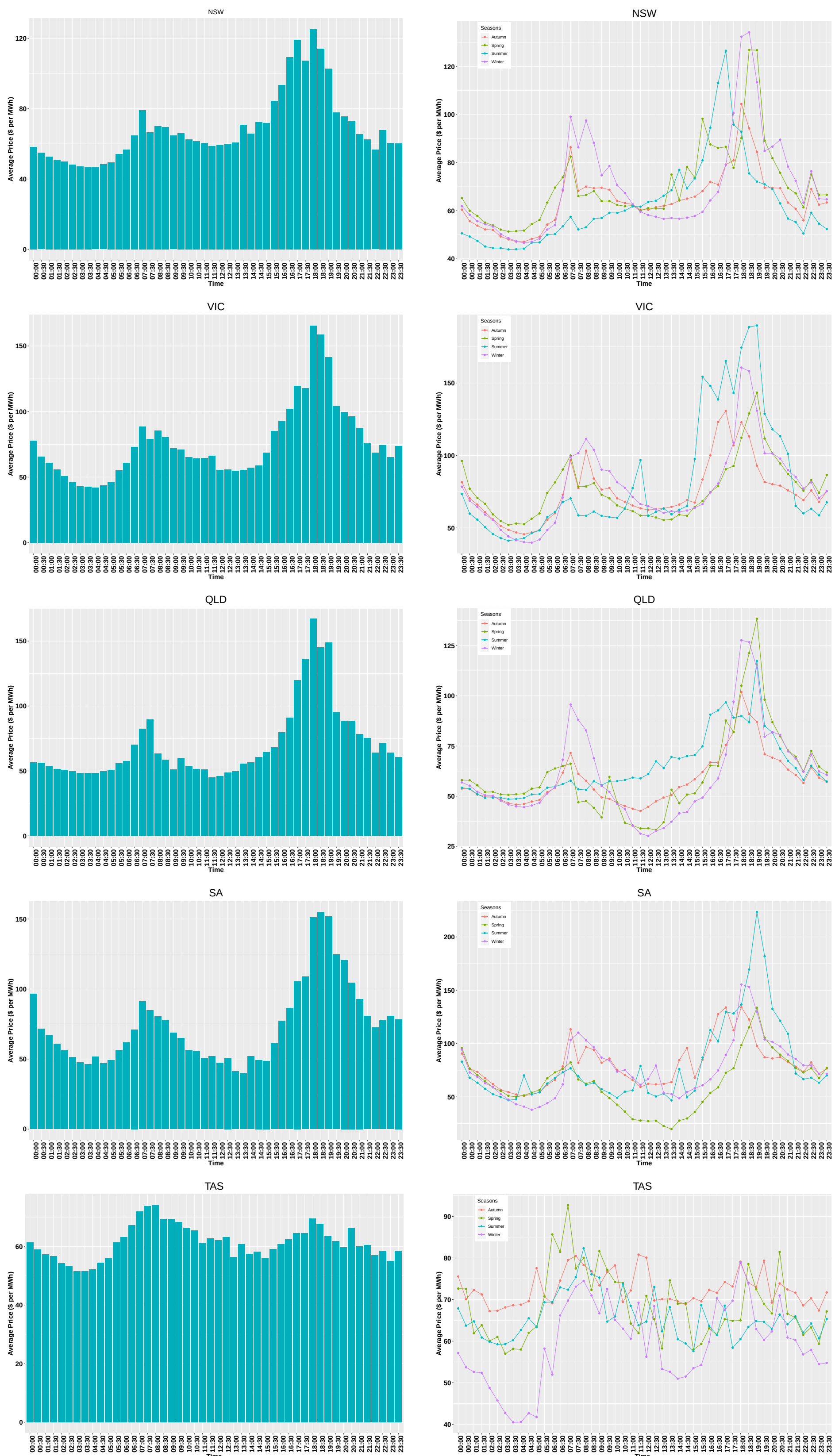

Figure 2: Average hourly electricity prices for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021). The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of electricity spot prices over four seasons of the year.

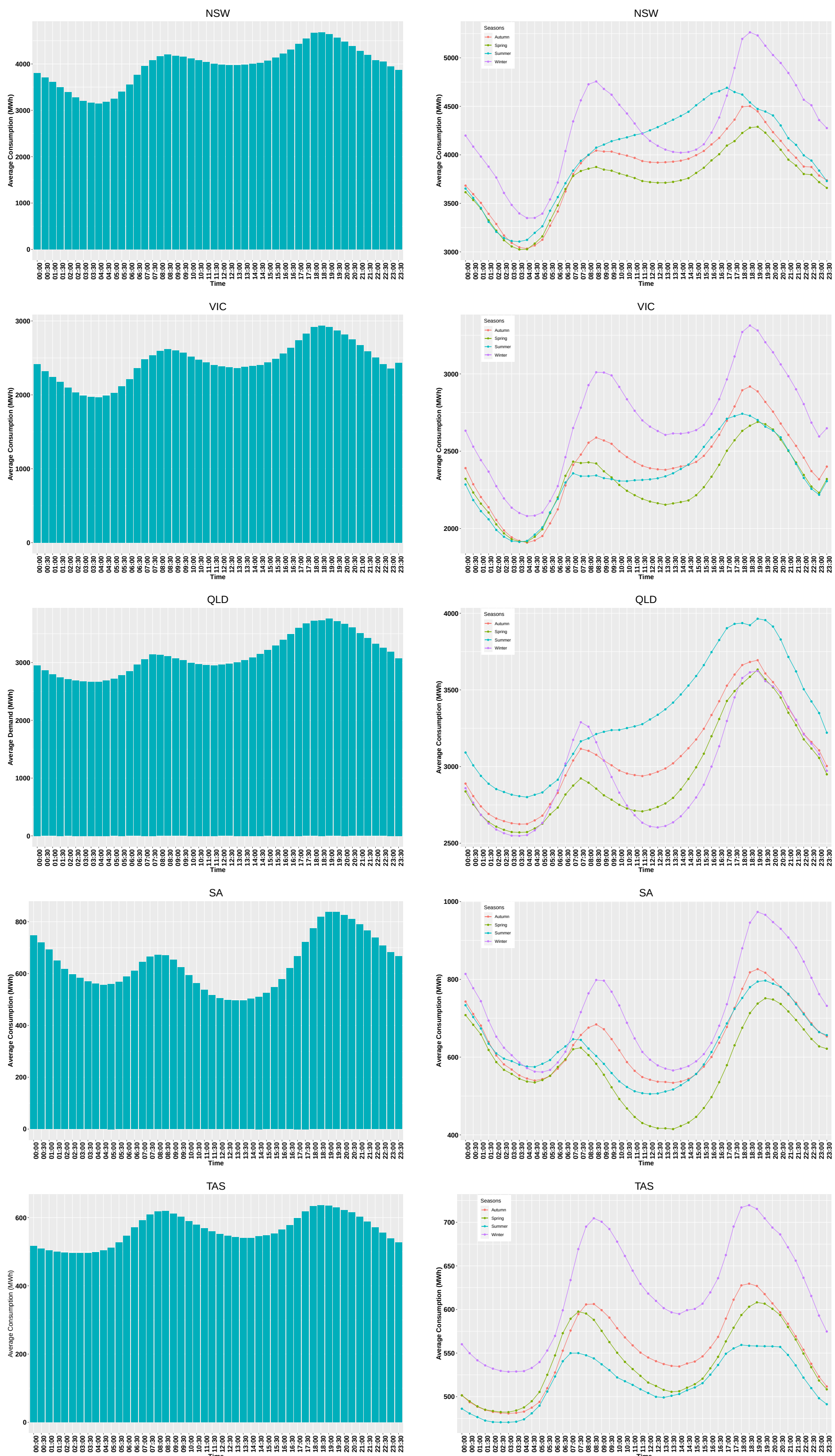

Figure 3: Average hourly electricity consumption for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021). The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of electricity consumption over four seasons of the year and, most importantly, the duck curve.

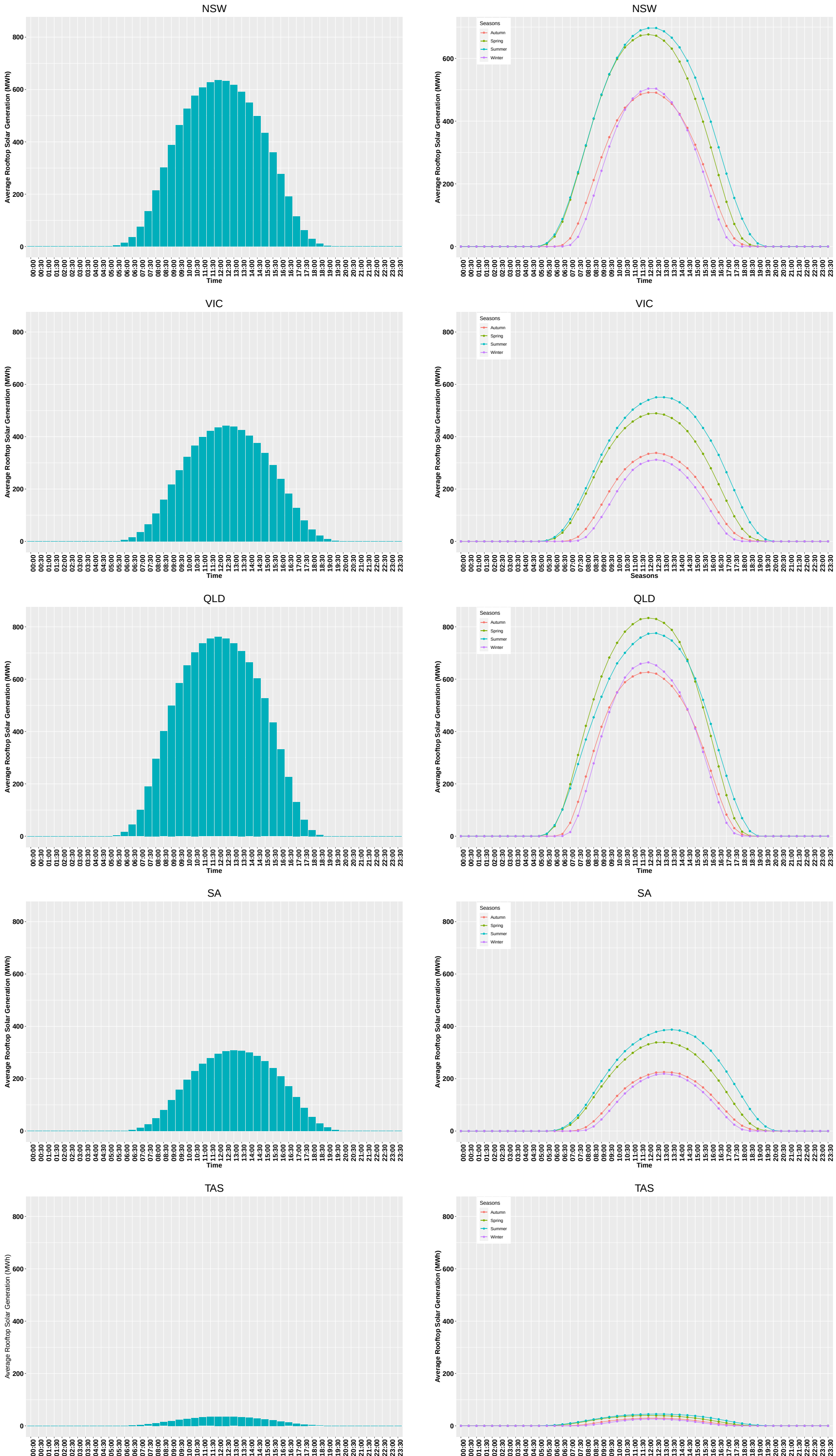

Figure 4: Average hourly rooftop solar generation for NSW, SA, VIC, TAS, and QLD from 2018 to 2021.

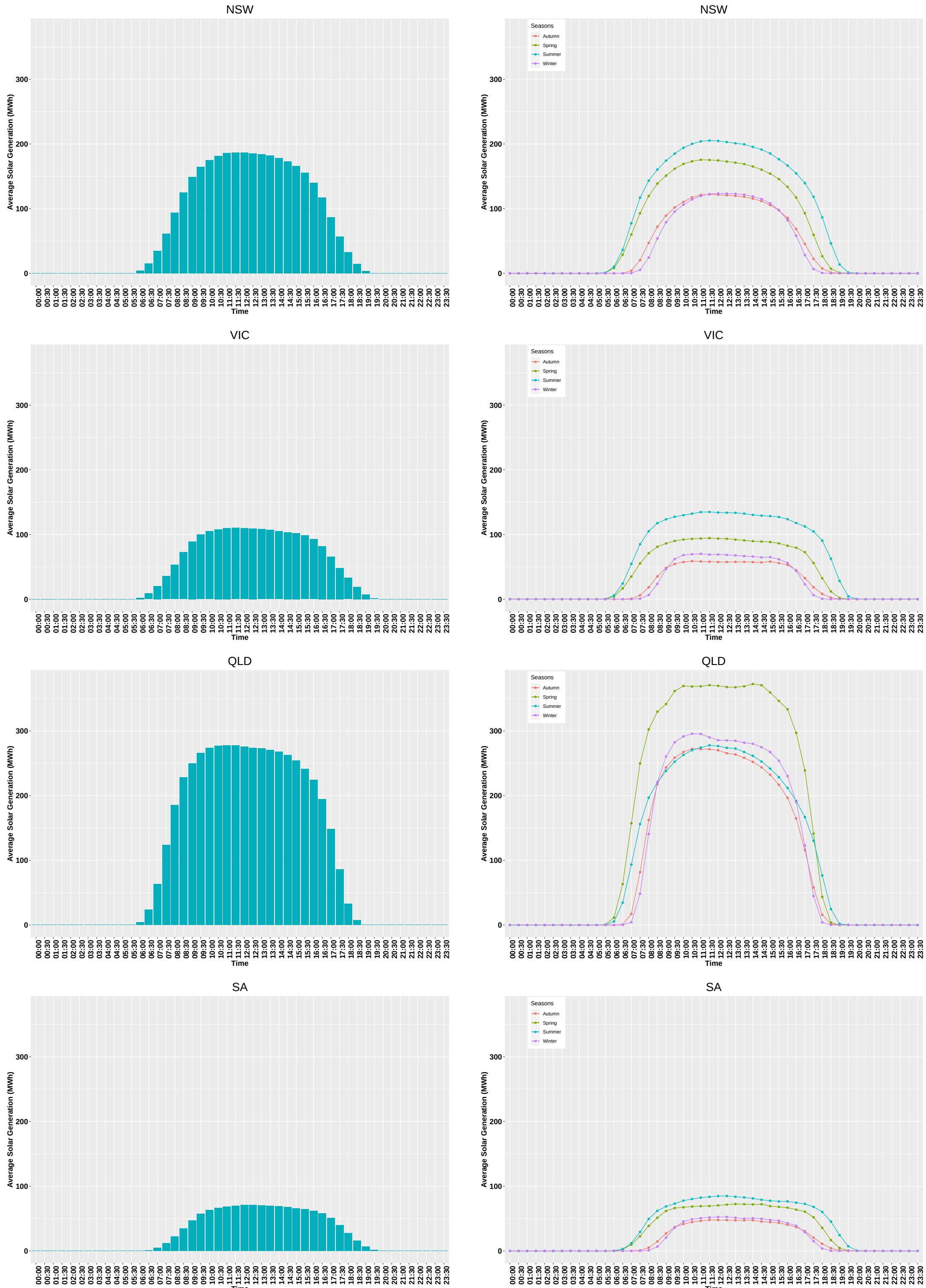

Figure 5: Average hourly large-scale solar generation for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021).

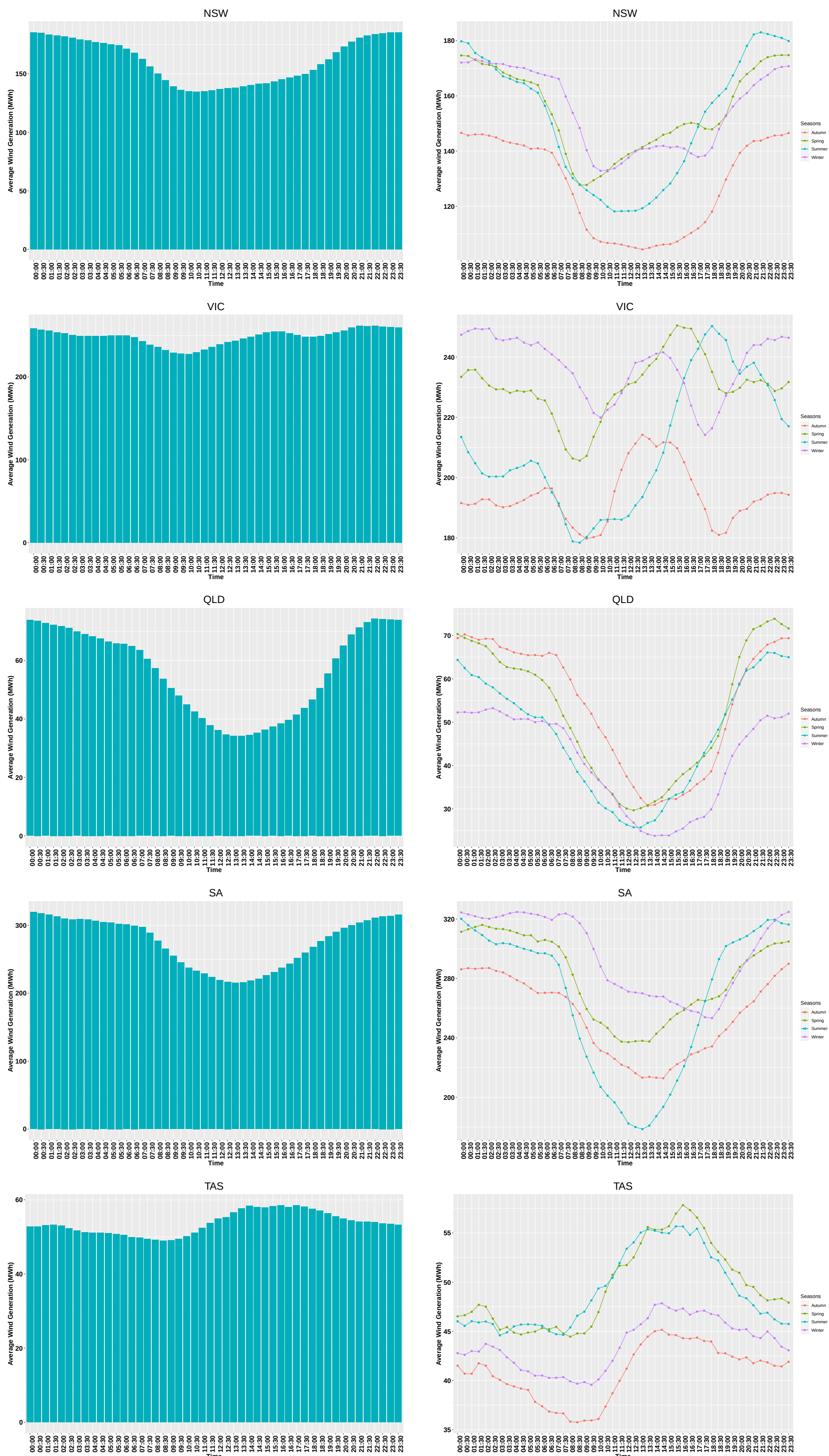

Figure 6: Average hourly large-scale wind generation for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021). The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of wind generations over four seasons of the year.

Table 2: Summary statistics of the intraday (half-hourly) variables employed in the analysis.

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

Table 3: The effect of large-scale and rooftop solar generation 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. The dependent variable is electricity spot prices in 30-minute trading intervals.

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

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

Table 4: The effect of large-scale and rooftop solar generation 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. The dependent variable is electricity spot prices in 30-minute trading intervals.

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

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

Table 5: The effect of large-scale and rooftop solar generation 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. The dependent variable is electricity spot prices in 30-minute trading intervals.

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

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

Table 6: The effect of large-scale and rooftop solar generation on Queensland's electricity price behavior. The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

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

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

Table 7: The effect of large-scale and rooftop solar generation 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. The dependent variable is electricity spot prices in 30-minute trading intervals.

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

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

Figure 7: Change in spot electricity prices (left panels) and volatility (right panels) per MWh increase in large-scale solar and wind generation for NSW, SA, VIC, and QLD

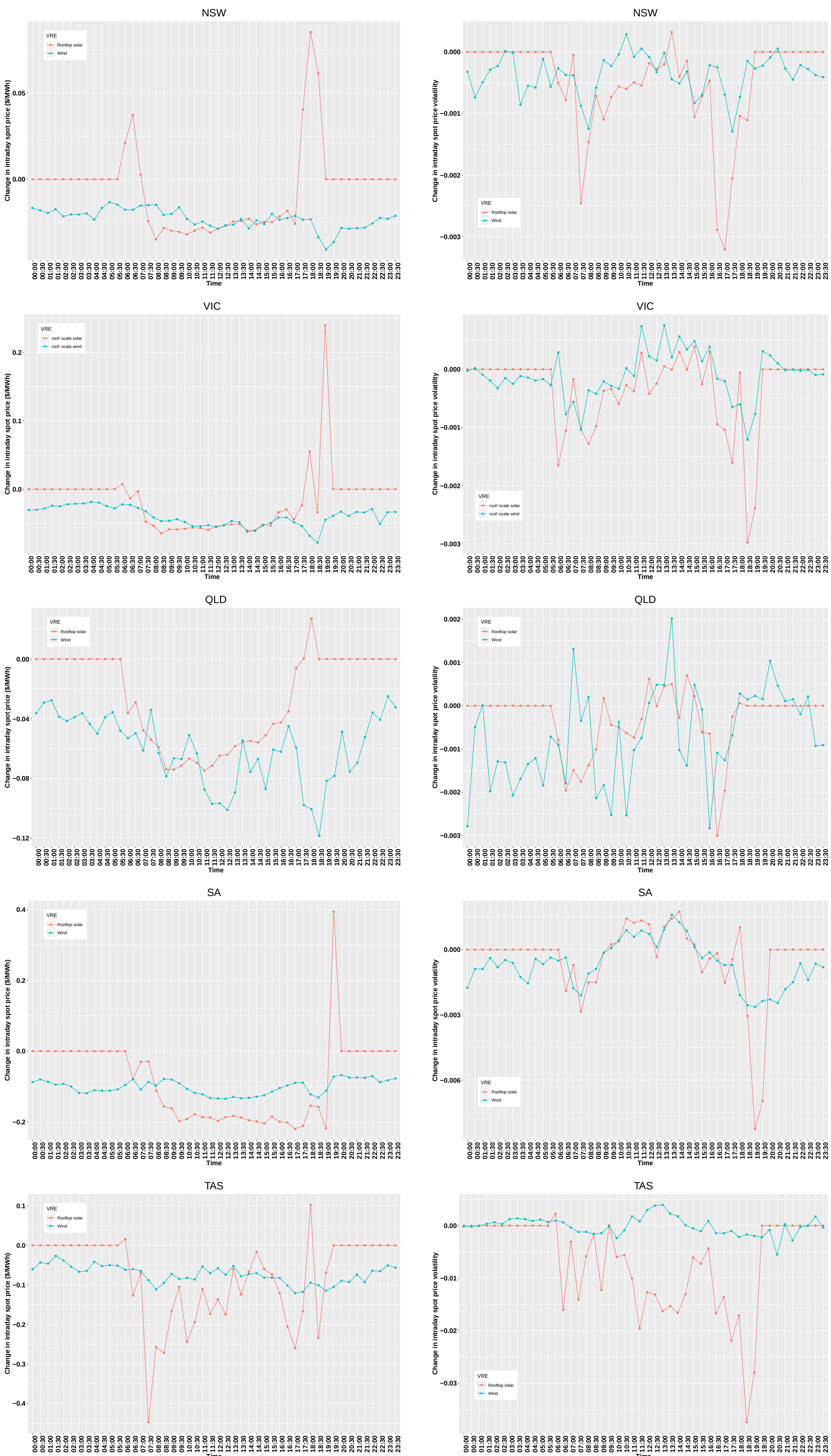

Figure 8: Change in spot electricity prices (left panels) and volatility (right panels) per MWh increase in rooftop solar and wind generation for NSW, SA, VIC, QLD, and TAS.

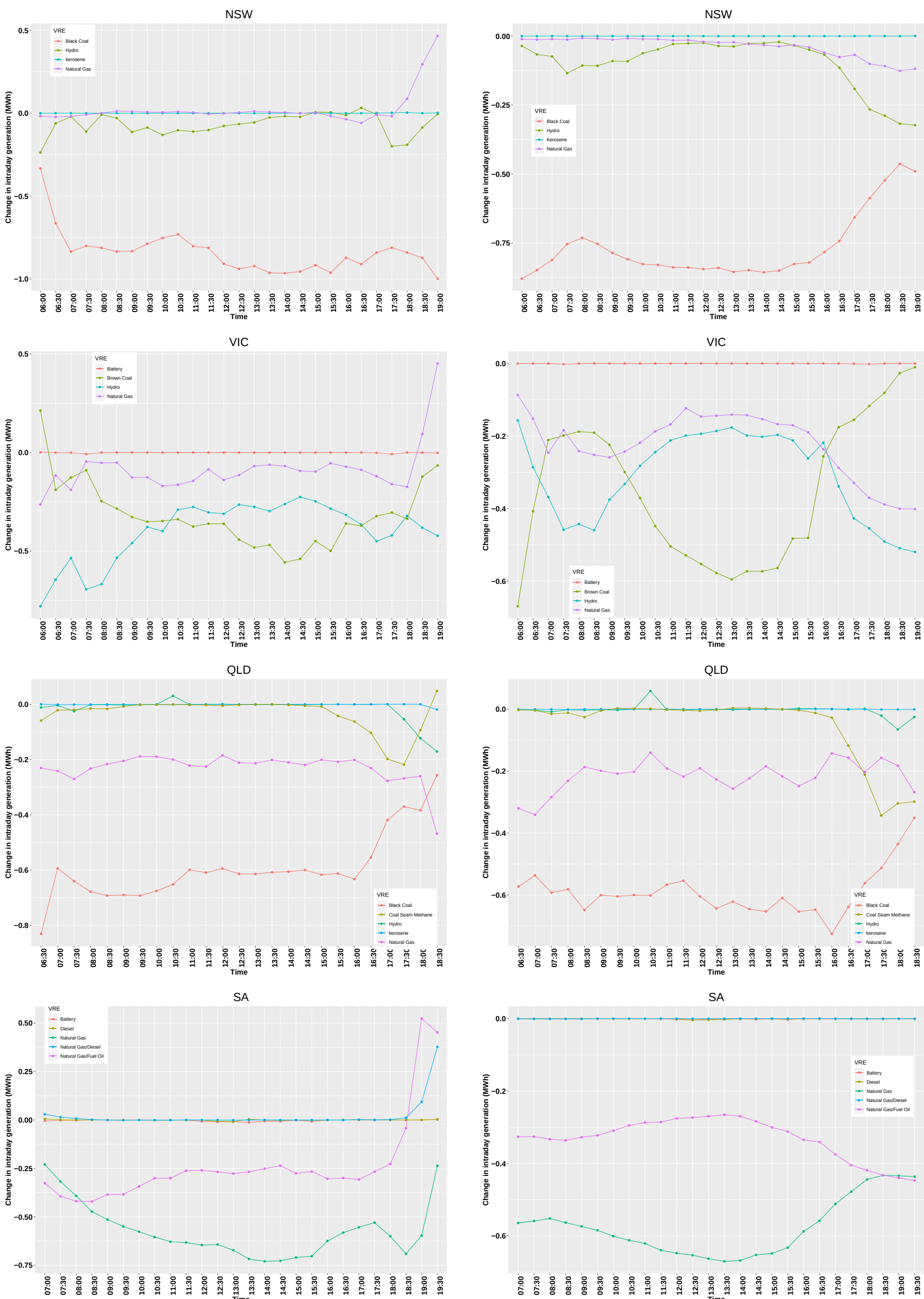

Figure 9: Change in generation by a source per MWh increase in large-scale solar (left panels) and wind generation (right panels) for NSW, SA, VIC, and QLD.

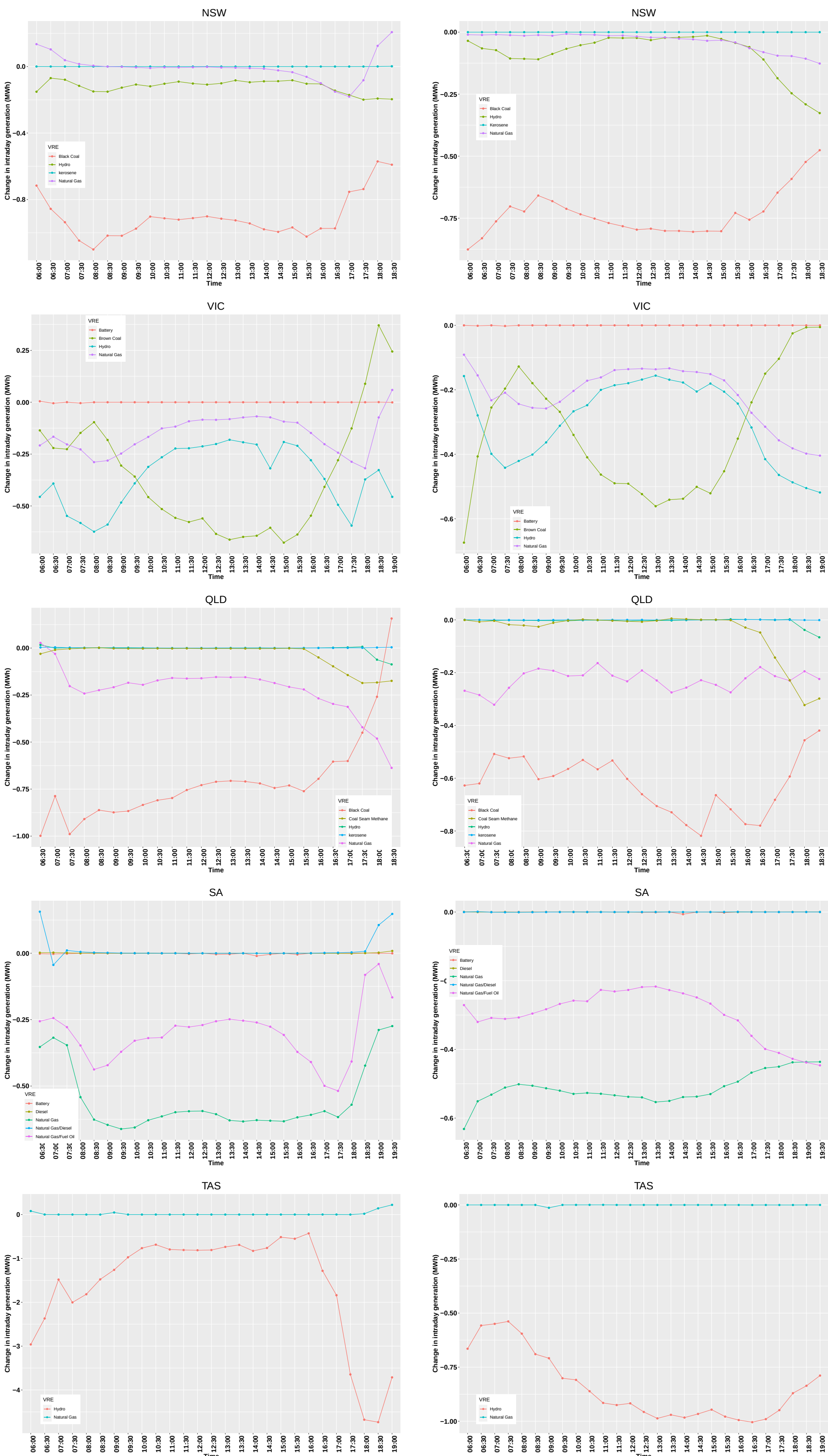

Figure 10: Change in generation by a source per MWh increase in rooftop solar (left panels) and wind generation (right panels) for NSW, SA, VIC, QLD, and TAS.

Table 8: The effect of large-scale and rooftop solar generation on spot price behavior during summer, autumn, winter and spring. The effect on price levels is given by the mean equation and on price volatility by the variance equation. The dependent variable is electricity spot prices in 30-minute trading intervals.

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

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

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