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

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Abstract

Solar generation has increased dramatically over recent years, breaking world records for meeting 100% of the electricity demand on occasion in Australia's National Electricity Market (NEM). Solar output variability coupled with the rooftop solar impact on demand as a behind-the-meter resource poses challenges to electricity price stability. Using 30-minute intraday data, we investigate how electricity spot prices are impacted by the rapid uptake of large-scale and rooftop solar generation in the NEM. We find that, on average, both large-scale and rooftop solar generation depress the level of spot prices and positively impact price volatility. However, over 30-minute intervals, solar generation tends to increase electricity prices in the early morning and the evening due to the high cost of traditional fossil fuel generators required to meet the lost output when the sun is down. While large-scale solar generation typically smooths spot price volatility, rooftop solar tends to increase it, reflecting the dominance of axis-tracking systems in the former and north-facing systems in the latter. The increasing incidences of variable renewable energy curtailment undermine the merit order effect in the middle of the day but with the benefit of reducing price variability. Moreover, 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, variable renewable energy curtailment
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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. On several occasions, rooftop solar generation supplied 77% of the demand and more than 70% for four hours (AEMO, 2020; AER, 2021).

In a market with yet-to-grow firming capacities, such as fast-start generation, demand response, and battery storage, the VRE increases are not without challenges. The weather dependence of wind and solar generation has resulted in more volatile supply and demand conditions than conventional sources. Wind and solar generation is characterized by the variability of output reflecting changes in weather patterns. Output from wind tends to be high during windy periods,[4] and solar generation depends on available light, implying low generation during cloudy days and in the winter. As the NEM is a real-time energy-only market in which demand and supply must be met instantaneously, VRE generators sometimes offer capacity at floor prices to increase the chances of their dispatch. Although some generators can still profit by selling renewable energy certificates, the more frequent instances of negative prices have increased the occasions of VRE curtailment for economic or system security reasons.[5]

[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 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).

[4] In addition to being variable, wind output is poorly correlated with demand, exhibiting zero or even negative correlation (Rai and Nunn, 2020).

[5] 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 Queensland

A recent comprehensive analysis of the NEM showed that the high penetration of wind generation exerts negative pressure on the level of electricity prices at the cost of increasing their variability (Mwampashi et al., 2021).[6] Although the influence of wind generation in the NEM has been 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).[7] Widespread consumer installation of rooftop solar PV panels began as early as 2010. Despite this, rooftop solar generation data for the NEM were not available until 2018. Recently, however, Abban and Hasan (2021) demonstrated the contradictory impact of solar generation on daily electricity price dynamics in the NEM. The authors found the MOE was present in Queensland, South Australia, and Tasmania, whereas New South Wales and Victoria experienced the reverse effect. The latter effect is unusual when considering low-marginal-cost generation sources, although consistent with the findings of Milstein and Tishler (2011) and Jha and Leslie (2020). In the presence of such contradictions, which diverge from observations in other markets, particularly in Europe, we contend that an in-depth analysis of the way solar generation affects electricity price dynamics in the NEM is of critical importance.

Although the Abban and Hasan (2021) study bears a close resemblance to the present analysis, the effect of solar generation on spot price dynamics in the NEM is still understudied. The authors combined large-scale and rooftop solar generation and used a sample of daily data from 2014 to 2020. As stated previously, large-scale solar generation in the NEM is relatively new. Thus, it is important to separate the impact of the large-scale and rooftop solar generation, given that they are affected by different government policy incentives, differences in entrance periods, and different uptake rates.[8] Moreover, 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 fast. Second, evidence suggests that the new solar PV entrants quickly outpaced their respective markets due to the near-perfect correlation between fleets (Simshauser, 2021). Third, the rapid uptake of rooftop solar PV output lowers the grid demand in the middle of the day when generation is high, pushing

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).

[6] On the other hand, the authors showed that wind generation tends to negatively affect the price level and volatility in Tasmania, which is by far the top renewable-rich state in the NEM.

[7] Given the difference in the generation profiles between wind and solar generation, the latter tends to exhibit a far higher magnitude of the MOE than the former due to relatively higher correlation with demand and co-incident output, especially in the summer (Csereklyei et al., 2019; Rai and Nunn, 2020).

[8] 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 the omitted variable bias (Csereklyei et al., 2019; Mwampashi et al., 2021). Running the analysis using daily data is also likely to underestimate the merit order effect and the impact of weather-dependent sources on price variability.

prices down and putting the economics and operating capability of coal-fired generators to the test.

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. The rapid uptake of rooftop solar PV in the NEM is becoming increasingly critical. 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. 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. Motivated by the variation in electricity spot prices and their determinants throughout the day and over the four seasons of the year, we also assess how the impact of VRE on spot prices varies throughout the day and over seasons (summer, autumn, winter, and spring). Similar studies in the European market found that peak and off-peak variations are pronounced and worth establishing (Kyritsis et al., 2017; Rintamäki et al., 2017; Maciejowska, 2020). We thoroughly examine the intraday profile of the impact of solar generation on electricity spot prices and generation mixes during each time interval. This contrasts with estimating the average impacts of solar generation, as in these previous studies. Moreover, to date, studies have overlooked the impact of VRE over the yearly seasons. However, solar generation varies appreciably over the seasons, with the maximum output reached during the summer and lower output in the winter, when the days are shorter, and the sun is lower in the sky. Owing to the recent increase in VRE curtailment in the NEM, this is the first study to investigate the extent to which large-scale solar and wind curtailment impacts the dynamics of electricity prices in the NEM.

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.[9] 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). We capture the intraday dynamics of large-scale and rooftop solar generation on spot prices using Nelson (1991) exponential generalized autoregressive conditional heteroskedasticity (eGARCH) model. We also account for changes in spot prices due to other factors, such as wind generation, hydro generation, gas prices, electricity consumption, and cross-border interconnector flows (Mwampashi et al., 2021).

[9] A dispatch price is 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.

We find that large-scale and rooftop solar generation impact spot prices and volatility in the NEM. However, these effects differ across regional markets depending on several factors, such as solar penetration rates, prevailing weather condition, and system flexibility. The MOE of large-scale 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. Solar generation has a low short-run marginal cost of generation. As a result, solar generation is prioritized in the dispatch process, displacing more expensive thermal generators such as coal and gas and lower spot prices in hours they operate. 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. The MOE of large-scale solar generation remains apparent even after adjusting for the impact of electricity consumption. However, states with high penetration of large-scale 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 solar generation to the system tends to increase spot price volatility. We postulate that scarcity prices[10] and volatility may result from the lack of sunlight during the day, forcing the market to balance the price-inelastic demand and expensive fossil fuel generation required to replace the lost output. The results show that although states with moderate generation levels experience a relatively large MOE, this benefit comes at the cost of amplifying price variability. Similarly, states with lower penetration rates, such as NSW and VIC, tend to experience a pronounced impact on price volatility compared to states with high penetration rates, such as QLD and SA. The availability of a large proportion of fast-start and flexible generating capacity in the latter states helps to smooth price variability, resulting in lower average volatility than in other states.

Similarly, rooftop solar generation exhibits a negative impact on electricity spot prices. We observe substantial effects in states with low and moderate generation levels, such as SA, VIC, and TAS. A 1 MWh increase in rooftop solar generation in these states exhibits negative pressure on electricity spot prices of 0.02 AUD/MWh. The impact of rooftop solar penetration moves in the same direction, with a substantial impact observed in states with moderate penetration rates, such as NSW and VIC. Furthermore, adding rooftop solar generation to the system amplifies the volatility in electricity spot prices more substantially in states with low and moderate rooftop solar generation. Similarly, states with low and moderate rooftop solar penetration rates, such as TAS, NSW, and VIC, tend to exhibit a much higher impact on price volatility than states with high penetration rates, such as SA. When comparing the average effect of large-scale and rooftop solar generation, we find that the former exhibits a more substantial impact on the MOE and the volatility dynamics compared to the latter. This finding reflects, among other factors, a small average proportion of rooftop solar generation injected back in the grid due to solar export limits,

[10] The frequency and severity of price spikes are referred to as scarcity prices.

typically around 5 KW.

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 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.[11] High solar generation means that additional generation from coal-fired and fast-start and flexible generators is required to fill the gaps when solar generation ramps up and down. An inelastic demand curve allows these generators to exercise their monopoly power and raise electricity spot prices.[12] The empirical analysis of the intraday profile of the impact of large-scale and rooftop solar generation in the states' generation mix is in line with these findings. In most cases, the increase in solar generation displaces fossil fuels during the middle of the day but increases fossil fuels generation in the early morning and the evening. This is a period coinciding with the period in which increases in solar generation drive up spot prices. We demonstrate that high prices resulting from high 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, 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 wind generation, especially in SA, NSW, and VIC. In contrast, rooftop solar generation appears to positively impact price volatility in NSW, QLD, and SA most of the time. Large-scale solar generation is dominated by a large share of axis-tracking systems, which maximize solar output by using moving panels that follow the sun throughout the day. Rooftop solar generation is dominated by north-facing fixed-panel systems, which typically produce their maximum output during the middle parts of the day leading to a low MOE and a higher impact on price volatility than axis-tracking systems. Moreover, 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. States dominated by flexible generation sources, such as SA and TAS, experience more occasions when an increase in large-scale and rooftop solar generation reduces price variability than other states.

[11] 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.

[12] These reasons also provide a better account of why previous studies in the NEM observed a positive impact on the average level of electricity prices in NSW (Csereklyei et al., 2019) and NSW and VIC (Abban and Hasan, 2021) for a marginal increase in solar generation. Increased prices in the morning and evening hours likely offset the negative effect in the middle of the day, causing an increase in solar power to have an average positive effect on electricity prices.

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. Typically, the same solar plant may produce twice as much output in the summer compared to the winter. The higher MOE of solar generation is triggered further by the higher correlation between solar generation and electricity demand during the summer. We show that adding large-scale and rooftop solar generation leads to a more pronounced positive impact on price volatility during the winter than in other seasons. Solar panels become more efficient at converting the sun's rays into electricity when the weather is cool. However, cloud cover and shorter sun hours in the winter mean that additional output from fast-start and flexible as well as coal-fired power plants is required to replace the varying levels of solar generation. In turn, this translates into price spikes and volatility when the market attempts to balance the price-inelastic demand and the required fossil fuel generators. Furthermore, the results suggest that, on average, if the curtailed generation had been injected into the grid, it would have a marginal impact on electricity price dynamics in the NEM. However, when considering the intraday profiles of the impact of VRE on spot prices, this is not the case for all time intervals. In states with high penetration of solar generation, such as SA and QLD, curtailment undercuts the MOE of VRE during the middle of the day when the sun is at the highest point. In the same vein, the results suggest that increasing VRE generation without curtailment would result in more price variability than currently observed in the market, especially in SA and QLD.

The present findings have important implications for policymakers and suggest several actions 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, which, in turn, increases the MOE and reduces electricity price volatility. First, small-scale renewable energy schemes (SRESs) and state-based policies should allocate their support to PV-plus battery systems to enable owners of rooftop solar generation to store extra generation during the day and export later in the evening to meet the peak demand. Second, the Australian Energy Market Operator (AEMO) should design appropriate measures to curtail rooftop solar generation, especially via dynamic/flexible export management, to effectively absorb all excess rooftop generation and maintain system security. Third, state governments and retailers should transition to dynamic feed-in tariffs (FiTs), which are lower during the day and higher in the morning and evening peak hours, to 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 2, we review existing studies on the impact

of VRE on spot price dynamics and high-frequency data-based analysis. In section 3, we detail the data and methodology used in the empirical analysis. In section 4, we present the average impact of solar generation on spot price dynamics over the whole sample period. In section 5, we explore the impact of solar generation on electricity price dynamics over half-hourly time intervals throughout the day and the seasons of the year and the effect of increased incidences of VRE curtailment. In section 6, we present policy implications of the findings, and in section 7, we provide concluding remarks.

2 Literature Review

2.1 Solar generation impact on electricity price dynamics

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). One early study on photovoltaic generation often cited in the Australian context is that of McConnell et al. (2013). In this study, the researchers applied PV generation and price-demand models demonstrating the MOE of photovoltaic energy generation from 2009 and 2010 on the four largest NEM capitals, Brisbane (QLD), Sydney (NSW), Melbourne (VIC), and Adelaide (SA). Csereklyei et al. (2019) investigated the impact of large-scale wind and solar generation on NEM electricity prices. The application of econometrics models on high-frequency (30 minutes) and daily data from 2010 to 2018 showed 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. Regionally, SA and VIC exhibited a larger impact, whereas QLD and NSW exhibited a relatively smaller impact. 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) the researchers observed the MOE of solar generation in the NEM and found it was more pronounced in QLD, SA, and TAS. The authors also found that solar power penetration increased price volatility in TAS, NSW, and VIC. TAS exhibited the largest magnitude. Relatively few researchers have explored the role of small-scale solar generation in Australia. These researchers include Jha and Leslie (2020) who examined the extent to which the development of rooftop solar panels 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 showed that the increase in solar capacity translated into increased market power, operating profits, and wholesale prices during the evening.

Several scholars, including Kyritsis et al. (2017), Rintamäki et al. (2017), and Rintamäki et al. (2017), 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. Second, 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.[13] Maciejowska (2020) showed that the effect of solar and wind generation on price volatility depends on the level of total demand. Wind generation increased volatility when demand was low and decreased volatility when demand was high. On the other hand, solar generation stabilized price volatility when the demand volume was moderate. Third, the impact of solar and wind generation varies throughout the day, especially during peak and off-peak hours.[14] 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.

2.2 Analysis based on 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,

[13]The authors accounted for the negative effect of wind generation in Denmark with the role of hydropower reservoirs and cross-border transmission systems, which tend to smooth the price variability.

[14]The definitions of peak and off-peak hours vary slightly across studies. For instance, Kyritsis et al. (2017) grouped the data into peak hours (09:00–20:00) and off-peak hours (01:00-–08:00 and 21:00-–00:00). Rintamäki et al. (2017) defined off-peak hours from 00:00 to 09:00 and 21:00 to 00:00 and peak hours from 09:00 to 21:00. Maciejowska (2020) defined peak hours from 09:00 to 20:00 and off-peak hours from 00:00 to 08:00 and 21:00 to 23:00.

2020; Mwampashi et al., 2021; Abban and Hasan, 2021).[15] 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) were among the first to investigate the intraday price volatility process in the NEM. Using half-hourly electricity prices and demand volumes from January 1, 2002, to June 1, 2003, the authors modeled time-varying volatility using standard GARCH, RiskMetrics, normal asymmetric power ARCH (apARCH), Student apARCH, and skewed Student apARCH models. The authors found the apARCH specification best accounts for the right-skewed and fat-tailed characteristics of electricity prices in the NEM compared to the other models. Similarly, Thomas and Mitchell (2005) investigated the volatility of electricity prices in the NEM using 30-minute prices from December 7, 1998, 02:00 to April 1, 2005, 00:00 . In this analysis, various GARCH specifications were tested and compared, i.e., the standard GARCH, threshold ARCH (tARCH), exponential GARCH (eGARCH), and power ARCH (pARCH) specifications. Moreover, these authors applied the ordinary least squares (OLS) framework to account for the negative prices, seasonality, and outlier effects before fitting the GARCH models.[16] Their empirical findings suggested that volatility in the NEM could be effectively captured by the pARCH specification with a generalized error distribution (GED). However, the restrictions underlying this model failed to hold for all five states. For this reason, the eGARCH emerged as the best-performing model in their analysis.

Several researchers, such as Mauritzen (2010), Woo et al. (2011), and Pineau et al. (2020) applied intraday data in the cause-and-effect context. The latter two 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 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.

The present study makes original contributions to several important areas. First, we treat large-scale and rooftop solar generation as two separate variables, so we are the first to separate and explore the effects of both large-scale and rooftop solar generation individually on the level and volatility of spot prices. To this end, we extend previous studies by Csereklyei et al. (2019), who studied only the MOE of large-scale solar generation and who noted the unreliability of their estimates due to the sparse observations used in their analysis. We also extend the work of Abban and Hasan (2021), who combined large-scale and rooftop solar generation and thus, obscured the

[15] 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.

[16] The authors applied this approach to tackle the complexity associated with the addition of dummy variables in the variance equation to capture these effects, which resulted in the failure of the fitted models to converge.

individual contributions of these two variables to the price dynamics. As noted, that study also likely suffered from endogeneity problems.

Second, we are the first to apply high-frequency data based on 30-minute trading intervals to concurrently investigate the intraday merit order effect and intraday volatility. This analysis adds to recent NEM studies such as those by Mwampashi et al. (2021) and Abban and Hasan (2021) that suggested the increase in VRE tends to impact the average (daily) price level and volatility negatively and positively, respectively. Moreover, to test robustness, we assess the impact of solar generation on intraday (half-hourly) prices and volatility using the multiplicative component GARCH (mcsGARCH) in electricity markets.

Third, 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), but our proposed approach allows one to capture this effect directly from the high-frequency data. This study is the first to employ this approach in this context. 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). Recently, Bushnell and Novan (2021) investigated the effect of the growth of solar capacity on wholesale prices in California's electricity market. Using hourly data from 1 January 2013 through 31 May 2017, the authors explored the intraday effect and potential impacts over the seasons of the year. Solar generation appeared to have a substantial impact in the two analyses. Most importantly, the study demonstrated the negative impact of solar energy generation during the middle of the day and its positive effect during the early morning and evening. In the same vein, Mountain et al. (2018) demonstrated the variation in the impact of solar and wind generation on the level of spot prices over different times during the day and underscored their varying effects throughout two seasons of the year (winter and summer) in SA. Therefore, we add to the literature by analyzing the impact of VRE on spot price dynamics over all four seasons of the year based on high-frequency data in the NEM.

Fourth, we thoroughly examine the association among solar generation, spot price dynamics, and electricity generation mixes. Although in previous NEM studies analyses were run by ignoring the impact of curtailment (Csereklyei et al., 2019; Abban and Hasan, 2021; Mwampashi et al., 2021), in the present study, we assess the impact of VRE curtailment on price dynamics in the NEM.

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 NEOpoint (2021). The sample period is from March 2015 to July 2021. The data include wholesale electricity prices, 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 a significant number of years, the main variables, large-scale solar generation and rooftop solar generation, are available for recent years only. The data presented two challenges. First, large-scale solar generation data for NSW and QLD are available since 2015 and 2017, respectively, and for SA and VIC since 2018. These years correspond to the construction of the first large-scale solar plants; that is, the lack of a longer-run large-scale PV output time series reflects the relatively short period large-scale solar generation has contributed to the NEM. There are no large-scale solar farms in TAS. Large-scale wind farms have historically had a lower LCOE than large-scale solar PV plants, resulting in more wind farms than solar PV plants being built to meet the large-scale renewable energy target (LRET) at the lowest cost. In contrast, and on a small scale, solar PV has been the cheapest means of meeting the SRES (Rai and Nunn, 2020). Second, although rooftop solar generation has been available in Australia for the last decade, rooftop solar generation data are available only since 2018. 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.[17] 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.[18] Although investment in large-scale solar generation has been slow in Australia, the uptake of rooftop solar generation has been dramatic. Many customers meet their electricity needs

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

[18] 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).

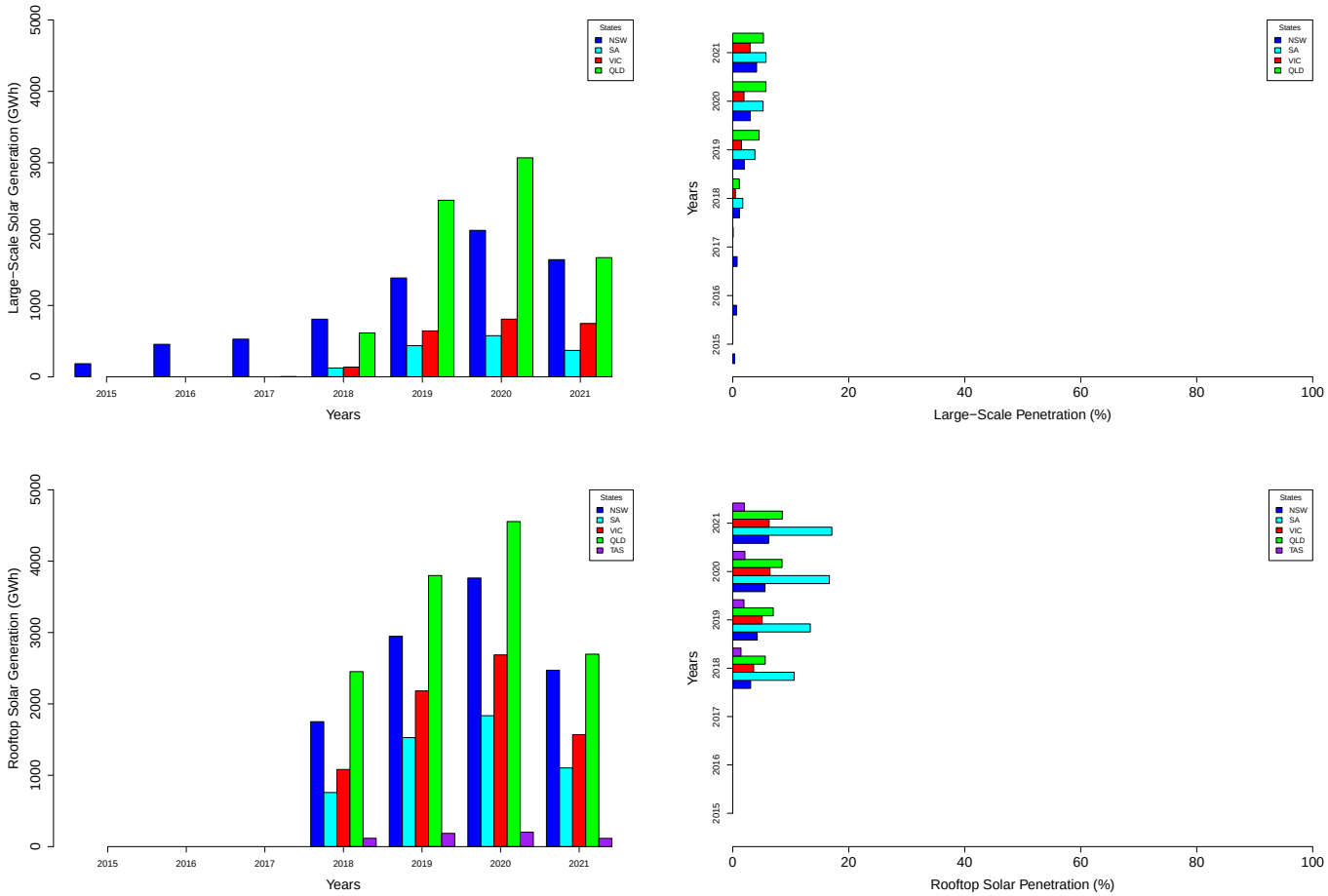

Figure 1: Large-scale solar generation (first row) and rooftop solar generation (second row) for NSW, SA, VIC, QLD, and TAS. The first panel in each row shows the generation, and the second panel shows penetration. Note that data for rooftop solar generation are available only since 2018 onward (i.e., the zeros for 2017 and previous years do not reflect a lack of solar PV system installations).

through rooftop solar generation and feed their excess generation back to the grid.[19] Figure 1 shows that rooftop generation has increased substantially since 2018 across the NEM with the slight exception of TAS, where generation remained fairly constant. SA and QLD exhibit high rooftop solar penetration compared to other states in the NEM.

McConnell et al. (2013) and Csereklyei et al. (2019) demonstrated the MOE of large-scale solar generation in the NEM. The latter found that large-scale solar generation exhibits a much bigger impact than wind generation. Abban and Hasan (2021) found the MOE of the combined impact of rooftop and large-scale solar generation, and positive impact on electricity price volatility. The present study is likely to observe a similar effect on the dynamics of electricity prices. As the generation profile of rooftop solar power is relatively small, as seen in Figure 2, its impact may be smaller and less significant compared to large-scale solar power, as seen in Figure 3. As noted in

[19] A larger proportion of rooftop solar generation is consumed domestically, exerting substantial downward pressure on demand for grid electricity during the middle of the day when the sun is at the maximum.

section 2, combining large-scale and rooftop solar generation hides the individual contributions of the two given their difference in output levels and uptake rates. Ultimately, this may overestimate or underestimate the impact of solar generation and wrongly inform VRE policies that provide incentives to large-scale and rooftop solar generation. Therefore, we analyze large-scale solar generation and rooftop solar generation as two separate variables. We also account for variations in spot prices caused by demand or non-renewable supply movements that could be correlated with solar generation and wind generation. They include hydro generation, gas prices, and the interconnector flow, to avoid potential endogeneity bias in the estimated models[20] (see Forrest and MacGill (2013), Csereklyei et al. (2019) and Mwampashi et al. (2021) for further discussion).

One of the things that previous studies in the NEM have overlooked is the variation in electricity prices over different times during the day and seasons due to the changing level of electricity demand. Figure 4 displays average hourly electricity prices per state and per season. It is evident that electricity prices vary over different hours of the day and seasons for all five states, corresponding to variation in electricity demand. Although the peaks and troughs differ slightly from one region to another, 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, resulting in very low and negative prices. Figure 5, 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 of the year in Figure 4, with the average higher prices occurring in the summer and the winter.

The generation profiles over time and seasons for large-scale and rooftop solar generation are

[20]One of the key econometric assumptions that we make in this analysis is that solar and wind generation are exogenously determined. This allows us to establish a one-way causal relationship between the level of generator output and the spot price. We believe that this is a plausible assumption for two reasons: (i) Solar and wind generation are driven by natural phenomena. (ii) Their low marginal cost of generation allows them to be dispatched under the vast majority of market conditions (Bell et al., 2017). The data employed in this analysis are actual real-time data obtained from the NEM, not estimates or measurements. Therefore, unless there are reporting errors, there will be no measurement error in the dependent variable. Moreover, using a sufficiently large number of observations in the model ensures the estimators are unbiased, and the standard errors are correct. Put differently, the robust standard errors asymptotically converge to the correct standard errors.

plotted in Figure 3 and Figure 2, respectively. Generation starts gradually at around 05:00 and decreases around 20:00 pm. However, the 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 "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 guaranteed the 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 (see 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 the day. Furthermore, 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 coincident output. Therefore, it is likely that the impact of solar generation on spot price dynamics is not evenly distributed across seasons, underscoring the importance of establishing this effect in the NEM.

Finally, in recent years, instances of solar and wind curtailment in the NEM have increased due to network constraints and economic reasons, such as the increasing incidence of negative spot prices. Table 1 summarizes descriptive statistics for all variables we employed in the analysis.[21] We see a relatively substantial curtailment of VRE in SA followed by VIC and QLD during the sample period. Other states experienced marginal curtailed generation. Existing studies in the

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

NEM assume curtailed VRE has a negligible effect in the analysis (Csereklyei et al., 2019; Abban and Hasan, 2021; Mwampashi et al., 2021). In contrast, we find it important to investigate this assumption for two main reasons. First, the rising incidence of curtailment across the NEM, particularly since 2018, following the rapid uptake in VRE, is likely to have affected underlying dynamics. Second, curtailment may impose potential bias on the estimated coefficients, especially when the timing and level of curtailments are correlated with spot electricity prices (Bushnell and Novan, 2021). Typically, the system operator curtails output during low-demand periods and low spot electricity prices to prevent oversupply. This may cause the negative impact of large-scale solar generation on spot prices to be biased toward zero.

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 during daily, weekday, month, and year. The use of high-frequency data necessitates modification of Ketterer (2014) and Mwampashi et al. (2021) approach 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 $\hat{\phi}$, $\hat{\zeta}$, $\hat{\psi}$, $\hat{\chi}$ 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).[22] 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. Moreover, spot electricity prices tend to exhibit significant short-run

[22]The typical approach for dealing with seasonality effects is to add dummy variables in the mean equation, variance equation, or both depending on the study objective (Taylor and Buizza, 2004; Byström, 2005; Higgs and Worthington, 2005; Black, 2006; Hickey et al., 2012; Tang et al., 2014; Castagneto Gissey, 2015; Auer, 2014; Pereira da Silva and Horta, 2019). However, two reasons motivate the approach used in the present analysis: First, the `rugarch` package employed in this analysis supports only to only ARFIMA-GARCH-type models. Therefore, it is not well-suited for incorporating seasonal dummies in the regression models. Second, the chosen approach avoids the complexity associated with the inclusion of many explanatory variables in the regression models, which are likely to result in convergence problems. Technically, the deseasonalization approach applied in this analysis resembles adding the seasonality dummy variable in the regression equations to account for the seasonality effect (Pineau et al., 2020).

upside and downside (low or negative prices) spikes, causing significant price deviations from the short-run marginal costs.[23] Typically, the former spikes reflect the shortage of supply due to inter alia unplanned generator outages, network outages, and lower-than-forecast VRE. The last occurs due to a combination of minimum electricity demand, high output from VRE, and unrestricted imports or restricted exports via cross-border interconnectors. As these observations are valid, we include them in the analysis to better capture the volatility of spot electricity prices (Kyritsis et al., 2017; Mwampashi et al., 2021).

Before specifying the model, we confirmed the stationarity of the electricity spot price series and explanatory variables by rejecting the null hypothesis for the presence of the unit root at the 1% significance level for all the variables and for all five regional markets using the augmented Dickey-Fuller (ADF) test. The Jarque-Bera test for normality indicates that the distribution of prices is non-normal with positive skewness and pronounced positive kurtosis. Moreover, we confirmed the presence of autocorrelation and conditional heteroscedasticity in spot electricity prices after rejecting the null hypotheses for the Ljung-Box and Engle (1982) ARCH-LM tests at the 1% significance level for all lags and in all regional markets. The clustering of price volatility suggests further that the ARCH-type models are appropriate for capturing the volatility dynamics in electricity markets. To isolate the relationship between each explanatory variable and the dependent variable and to avoid collinearity problem, we specify the models by examining the correlation coefficient matrix and variance inflation factors (VIFs). The results for these tests are presented in Section A.1 of Appendix A.

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[24]. Existing studies suggest that 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 models above in Appendix B, we find that the eGARCH produces the most robust results among the competing models 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 (Thomas and Mitchell, 2005; Pereira da Silva and

[23]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.

[24]The existing literature (Singh et al., 2013; Zhang et al., 2014; Diao and Tong, 2015; Narsoo, 2016; Summinga-Sonagadu and Narsoo, 2019) applies the mscGARCH to model and forecast the intraday Value at Risk (VaR) and expected shortfall (ES). In contrast, we adopt the Engle and Sokalska (2012) approach to examine the price dynamics and measure high-frequency cause-and-effect between price dynamics and their determinants.

Horta, 2019). 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. We then modeled the variance of the half-hour spot price innovation process using Nelson (1991) eGARCH specification, which allows for the leverage effect to better capture temporal variations in market volatility. The eGARCH(p, q) process for the random error term, ε_t, is specified as $\varepsilon_t = z_t \sigma_t$ and $z_t \sim \text{iid}(0, 1)$ is a standardized innovation that follows a specific distribution[25], 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 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.[26] 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

[25] 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 (norm) distribution, skew normal (snorm) distribution, generalized error distribution (ged), skew generalized error distribution (sged), Student-t distribution (std), skew Student-t distribution (sstd), normal inverse Gaussian (nig) distribution, and Johnson's reparametrized SU (jsu) distribution. 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.

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

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.

4 Impact of Solar Generation

Tables 3 to 6 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.[27]

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 2 to 6, 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 0.9672; it is relatively less pronounced in SA (0.9098 to 0.9156). 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,

[27] We run the ARX-eGARCHX models by assuming the standardized residuals follow skew Student distribution (sstd) in SA, QLD, and TAS, Student distribution (std) in NSW, and Johnson's reparametrized SU (jsu) distribution in TAS. A detailed analysis of the choice of these distributions is given in Appendix B. Tables 3 to 6 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.

ranging from 0.9979 to 6.0482, compared to VIC (0.7389 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 0.7592. QLD and TAS display a relatively small effect ranging from 0.4728 to 0.4735. Therefore, we infer that the last period's volatility shocks tend to affect future spot price volatility more strongly in VIC, NSW, SA, and QLD than in TAS.

The present findings suggest that at high frequency, the estimated ARCH and GARCH spillovers exhibited by spot prices are relatively large compared to those of the average (daily) spot prices, 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 2 to 6 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 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 lowers prices by approximately 0.15 AUD/MWh and 0.08 AUD/MWh in SA and VIC, respectively. 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.[28] 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

[28] 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.

generators and lowers electricity prices. Looking at Table 1 and Figure 4, we observe an apparent link between the impact of large-scale solar generation and the average electricity prices. In particular, the regions experiencing higher average electricity prices tend to exhibit higher MOEs for an increase in large-scale solar generation.

The results further suggest that states with the highest solar penetration in the NEM, namely, SA and QLD, experience relatively lower price reductions for increased large-scale solar penetration. In particular, a 1% increase in large-scale solar penetration leads to an approximately 1 AUD/MWh drop in spot electricity prices in NSW and VIC. 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. These authors observed the MOE of approximately 0.14 AUD/MWh, 0.12 AUD/MWh, and 0.03 AUD/MWh in SA, VIC, and QLD, respectively, for each 1 MW increase in large-scale solar generation.[29] These results are consistent with results from previous studies in European and U.S. markets that demonstrated a strong and consistent negative association between solar generation and the level of electricity prices (Tveten et al., 2013; Pereira and Rodrigues, 2015; Kyritsis et al., 2017; Rintamäki et al., 2017; Maciejowska, 2020; Bushnell and Novan, 2021).

4.2.2 Impact on the volatility of electricity prices

The impact of large-scale solar generation on price volatility is notable and consistent across four states in the NEM. We find statistical evidence that an increase in large-scale solar generation is associated with relatively higher 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.[30] Large-scale solar penetration exhibits the same sign effect with statistical evidence observed for all states in the NEM. A 1% increase in large-scale solar penetration increases volatility by 8% in NSW and VIC, 5% in QLD, and only 2% in SA.

The observed impact of solar penetration concurs with that of Abban and Hasan (2021), who showed that increasing solar penetration amplifies volatility in the NEM, especially in NSW, VIC, and TAS. Their study observed no effect in QLD and SA. 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

[29] The authors argued that these results are less reliable because of the small number of observations used in the model estimation. Specifically, the analysis considered a sample period from 2010 to 2018, whereas large-scale data for SA and VIC, for instance, started around January and May 2018, respectively.

[30] 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).

generation associated with fast start-up and flexible plants and ramping costs associated with coal-fired power plants (Jha and Leslie, 2020). Despite the relatively higher penetration of solar generation, the positive impact on price volatility in SA is relatively lower than in other states. The lower magnitude of the estimated coefficient may be accounted for by the presence of more fast-start and flexible generating capacity, such as gas in SA's generation mix, which tends to smooth price volatility. Moreover, solar generation tends to have low variability during the day compared to wind generation, allowing mid-load power plants to efficiently adjust their power production to residual demand and stave off large and frequent price spikes (Kyritsis et al., 2017).

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. The increase in large-scale solar generation in states with relatively higher penetration rates and flexible and fast-start generation capacity, such as SA, helps smooth volatility dynamics and lower the overall price variability. Moreover, the results suggest that 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.

4.3 Rooftop solar generation

4.3.1 Impact on electricity spot prices

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 contributes to lowering electricity prices in VIC, SA, and TAS by 0.02 AUD/MWh. The effect in NSW and QLD is marginal. Moreover, incorporating the effect of consumption via the rooftop solar penetration reveals a consistently negative impact on electricity prices for all states in the NEM. In this respect, a 1% increase in rooftop solar penetration lowers prices substantially in states with moderate penetration rates by 0.40 AUD/MWh and 0.24 AUD/MWh in VIC and NSW, respectively. The effect in other states is lower, approximately 0.12 AUD/MWh in QLD and 0.07 AUD/MWh in TAS. SA, which has the highest penetration of rooftop solar generation, exhibits the lowest reduction in spot prices, approximately 0.05 AUD/MWh.

4.3.2 Impact on the volatility of electricity prices

Turning to price volatility, 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 0.5% 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.[31] Considering rooftop solar penetration, we observe a similar sign effect. For each 1% increase in rooftop solar penetration, volatility increases by 4%, 3%, and 2% in NSW, VIC and QLD, and TAS, respectively. A much lower effect of around 0.7% 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 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 noted that combining large-scale and rooftop solar generation undercuts the MOE of large-scale solar generation, likely due to the opposing effects observed during the day. For instance, while the MOE of large-scale solar generation in SA is 0.15 AUD/MWh, adding rooftop solar generation reduces it to 0.01 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.[32]

The findings of Csereklyei et al. (2019) and Abban and Hasan (2021) suggest that solar generation may positively affect electricity spot prices. In section 5, we explore the intraday effect rather than averaging over the whole sample period.

4.4 Other factors

In addition to large-scale and rooftop solar generation, there are several other important determinants of electricity spot prices. They are wind generation, electricity consumption, hydro

[31] Using data from 2017 without controlling for wind generation in QLD suggests a marginal difference in the estimated coefficients.

[32] 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.

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.

4.4.1 Impact on spot electricity prices

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 for each 1 MWh increase in wind generation. 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, we get the opposite result. In states with intermediate penetration rates, such as VIC and QLD, increasing wind penetration by 1% resulted in price reductions of roughly 1 AUD/MWh, followed by NSW with a maximum of 0.72 AUD/MWh. TAS and SA, however, exhibit a price reduction of up to 0.67 AUD/MWh and 0.65 AUD/MWh, respectively.

Consumption and gas prices tend to positively impact electricity price levels. Increasing electricity consumption by 1 MWh tends to raise prices more in states with low demand profiles, i.e., TAS and SA, by approximately 0.13 AUD/MWh to 0.17 AUD/MWh. The increase in VIC and QLD is moderate, ranging from 0.06 AUD/MWh to 0.07 AUD/MWh, and the increase in NSW is small, ranging from 0.03 AUD/MWh to 0.04 AUD/MWh. The effect of gas prices depends on their proportionality in the generation mix. Increasing gas generation by 1 AUD/GJ exerts substantial upward pressure on the level of electricity prices in states that rely more on gas generation, such as SA, by a maximum of 0.31 AUD/MWh, followed by QLD, by a maximum of around 0.18 AUD/MWh. The effect is relatively lower in NSW, in which the same increase in gas prices increases electricity prices by 0.07 AUD/MWh to 0.15 AUD/MWh, with no evidence of an effect in VIC, which has the lowest proportion of gas in the generation mix. Hydro generation negatively influences power pricing in TAS and QLD, with a 1 MWh increase in hydro generation depressing prices by around 0.01 AUD/MWh. In VIC, the negative effect is negligible. In NSW, an increase in hydropower has the opposite impact, 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 contribute to lowering spot electricity prices. The latter interconnector exhibits the same effect in QLD, whereas the former shows the reverse effect. The Heywood and Basslink interconnectors contribute to lowering prices in VIC, while the VNI and the Murraylink interconnector account for the region's increase in spot prices. The Heywood and Murraylink interconnectors show similar effects in SA, and the Basslink interconnector shows the same impact in TAS.

4.4.2 Impact on the volatility of electricity prices

Wind generation exhibits negative and positive effects on spot price volatility. A 1 MWh increase in wind generation increases price volatility in TAS, VIC, and NSW by a maximum of 0.07%, 0.02%, and 0.01%, respectively. In contrast, the same increase in wind generation contributes to smoothing price variability in QLD and SA by a maximum of 0.08% and 0.02%, respectively. These two states have higher gas generation in their generation mix, which can operate flexibly and contribute to smoothing volatility resulting from high wind generation. Similarly, increasing wind penetration by 1% increases price volatility by a maximum of 0.6% and 0.7% in NSW and VIC, respectively, and lowers it by a maximum of 3% in QLD. Although wind generation accounts for a substantial increase in TAS price volatility, adjusting it for consumption shows a statistically insignificant effect on price variability.

Electricity consumption, hydro generation, and gas prices impact spot prices 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 0.16% and 0.13%, 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, with a 1 MWh increase leading to a maximum 0.19% increase in price volatility. The effect observed in NSW, VIC, and TAS do not exceed 0.08% for the same increase in hydro generation. The effects of gas prices on increasing price volatility appears more pronounced in QLD, in which a 1 AUD/GJ increases volatility by 0.6% followed by 0.5% in NSW. VIC and SA exhibit the same effect of up to 0.4%, although, in more than two decimals, SA exhibits the lowest impact in the NEM. Most interconnectors contribute to smoothing 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 affects 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 in all states except NSW. 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 contributes substantially 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. Finally, we examine the potential impact of VRE curtailment on the behavior of spot prices. More details about the seasonality and intraday analysis and the interpretation of the estimated coefficients are provided in Appendix B.6.

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. 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

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 of the hours. The MOE is strongly pronounced during the middle of the day. This implies that high solar generation supplants expensive fossil fuel power generation during these times, translating into a substantial decline in electricity prices. In addition, the effect may be more pronounced due to

the inability or unwillingness of incumbent coal-fired power plants to reduce their output during the day (Rai and Nunn, 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 Figure 8 is that large-scale and rooftop solar generation (especially for NSW and VIC) tend to increase the level of electricity prices early in the morning and in the evening when the sun is about to set. Specifically, prices increase 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 energy, which appears to mostly enhance price volatility, the impact of large-scale and rooftop solar generation during the day varies. 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 explains 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 tends to increase price volatility in NSW, QLD, and SA. 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. In the same vein, TAS and VIC behave slightly differently, in which an increase in rooftop solar generation tends to mostly reduce price volatility compared to the other. The effect observed in the former could be accounted for by the availability of flexible generation sources; that is, hydro and gas, which have a moderating effect on the variability of electricity prices.

The findings in this subsection agree with observations by Bushnell and Novan (2021) in California's electricity market. The authors showed that an increase in the daily level of 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. The present study results also reflect those of Jha and Leslie (2020), who demonstrated that an increase in solar capacity triggers an increase in the exercise of market power, operating profits, and wholesale prices in Western Australia. The phenomenon observed in the present analysis occurs for two reasons: First, high solar genera-

tion 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. Moreover, Milstein and Tishler (2011) showed that an increase in PV capacity triggers higher electricity price spikes when the sun is not shining, and the entire demand must be met by conventional fossil fuel technology. An inelastic demand curve allows producers to exercise their monopoly power and raise average electricity prices. 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 explains why the 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.[33] We plot the results for the estimated coefficients in Figures 9 and 10.

It is apparent from these figures 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.[34] 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 lowers spot prices. However, the requirement to ramp up generation quickly in the evening to replace the lost output and the

[33]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.

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

increase in demand can result in a rapid upsurge of the spot prices. Because solar generation is at its lowest during these hours, prices will equal the dispatch cost of the marginal generators (natural gas or coal). This then results in higher prices that solar generators benefit from, resulting in a positive coefficient of solar PV. These dispatch costs tend to be higher in a system with a lot of solar than they would be otherwise. This is because switching coal-fired plants on and off frequently is more expensive than maintaining continuous production. We observe that increasing solar generation in NSW during the evening leads to an increase in natural gas generation. These hours align with the time when the increase in solar generation drives electricity prices high; 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 and rooftop solar generation leads to an increase in brown coal generation in the early morning. In the evening, large-scale solar generation increases natural gas generation, whereas rooftop solar generation increases brown coal and natural gas generation. This means that solar generation increases electricity prices 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.

Rooftop solar generation also contributes to higher electricity prices in QLD in the evening via higher 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. 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 sees 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. Evidence from rooftop solar generation suggests that natural gas/diesel and natural gas/fuel oil generation are 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 does not necessarily 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.[35] 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 by the system operator and for economic reasons to avoid solar generators' exposure to negative prices (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.

5.3 The impact of VRE curtailment

Table 7 presents the impact of curtailment on spot price dynamics. In Model K, we estimate the impact of the observed VRE generation (VRE generation). In Model L, we estimate the impact of the observed VRE generation plus the curtailed generation (VREC generation) on spot price dynamics. This means the difference between the two coefficients measures how curtailment affects the dynamics of spot prices.[36]

[35] 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.6.1 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.

[36] As the present analysis is more inclined to study the impact of solar generation on spot prices, we aimed at investigating the impact of solar curtailment rather than VRE curtailment. However, this analysis is limited by the

We observe the MOE of VRE generation and VREC generation for all states in the NEM. Although there is an apparent difference between the estimated coefficients, the magnitude of this difference is, in general, very small. The difference is relatively larger in VIC and QLD. In this respect, increasing VREC generation in VIC by 1 MWh depresses electricity prices by around 0.006 AUD/MWh, whereas increasing VRE generation by the same magnitude lowers the prices by around 0.005 AUD/MWh. In QLD, the estimated coefficients are 0.005 AUD/MWh and 0.004 AUD/MWh for VREC generation and VRE generation, respectively. The difference in other states is marginal and is almost zero in three decimal places. Looking at the variance equation, we also observe the marginal difference of the estimated coefficients.[37] To explore further how curtailment impacts spot price dynamics, we estimate the intraday profile of the impact of VRE and VREC generation on spot price dynamics and plot the estimated coefficients over 48 time intervals in Figure 11.[38] These figures show that curtailment does not substantially affect spot price dynamics throughout the day, especially in NSW, VIC, and TAS. However, the findings for states with higher penetration of solar generation, such as QLD and SA, suggest a notable difference between VRE generation and VREC generation during the middle of the day. In QLD, we observe that curtailment undermines the MOE between 07:30 and 15:00. In the same vein, the MOE of VREC generation exceeds that of VRE generation in SA between 08:30 and 16:00. As these hours coincide with higher solar generation, it suggests that the increase in curtailment associated with solar generation contributes to undercutting its MOE. Moreover, these findings suggest that in the absence of curtailment in QLD and SA, the price variability in the middle of the day would have been higher than what is currently observed in the market.

Overall, these results indicate that although the frequency with which the operator curtails renewable generation has risen markedly in the NEM, allowing the curtailed generation to enter the system would not have significantly changed the dynamics of the electricity prices observed in the market. Nonetheless, 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. Moreover, the marginal difference between the VRE generation and VREC generation estimates observed in this analysis indicates that the estimates are less likely to be biased by curtailments.

fact that data on curtailment are available as the sum of wind and solar generation, not separate. As there are no large-scale solar farms in TAS, the curtailed generation referred to in this analysis is large-scale wind generation instead of large-scale solar generation plus wind generation in other states.

[37] It is worth mentioning that combining solar and wind generation accounts for the reduction in price volatility in QLD and SA; the effect in VIC is the opposite.

[38] We provide the complete results and the corresponding p-values in Appendix C.

5.4 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.[39] 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 contributes substantially to reducing electricity prices during the summer followed by the spring, autumn, and winter. However, the effect of rooftop solar generation is relatively small compared to that of large-scale solar generation. Specifically, 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. VIC similarly exhibits a larger magnitude in the summer, around 0.21 AUD/MWh, and a lower magnitude in the winter, around 0.05 AUD/MWh. The effects in other states are marginal; that is, increasing large-scale solar generation in NSW and QLD, which has the highest solar generation in the NEM, lowers prices by 0.09 AUD/MWh and 0.05 AUD/MWh in the summer and 0.02 AUD/MWh and 0.01 AUD/MWh in the winter, respectively. On the other hand, an increase in rooftop solar generation exerts negative pressure on the level of electricity prices in VIC by 0.06 AUD/MWh and 0.02 AUD/MWh, in SA by 0.05 AUD/MWh and 0.01 AUD/MWh, and in NSW by 0.02 AUD/MWh and 0.01 AUD/MWh during the summer and winter, respectively. The impact of rooftop solar generation in QLD is evident only in the winter and spring.

As Figures 3 and 2 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. In the same context, low rooftop solar generation in TAS explains 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). However, their study 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

[39] 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.

in the winter.[40] 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, these authors found an increase in solar generation increases spot prices in the late afternoon in the summer. This is because solar generation drives out more efficient output during the day, increasing the need for less efficient generation to meet the nighttime peak when solar generation is unavailable. However, as the present analysis considers the average over the whole summer season, the negative effect of solar generation likely outweighs its positive effect, as explained in subsection 5.1.

Large-scale and rooftop solar generation appear to have a consistent impact on the volatility of electricity spot prices. Specifically, adding solar generation to the system tends to impact price volatility positively. This effect is more pronounced in the winter than in the other seasons. A possible explanation for this finding is that 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 due to a lack of sunshine (Milstein and Tishler, 2011; Jha and Leslie, 2020). 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, therefore, 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 via readily-dispatchable natural gas generation, energy storage, interconnectors, and demand-side resources required to balance the

[40]The difference in the estimated results between the present study and the Mountain et al. (2018) study may 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. Moreover, their approach did not adjust for the yearly variations or include lagged electricity prices.

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 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, our findings stress the need for unlocking relatively cheap options for market flexibility, such as allowing participation from the demand side of the market. Our findings provide a number of courses of action to ensure an effective transition to clean energy, as detailed below.

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, consequently, 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.

[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).

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 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, which allows customers to offer demand response to the wholesale market directly, will likely translate into a potentially lower volatility effect for solar generation than currently observed in the market but may also reduce the MOE of solar PV. In the same vein, 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 generation, is the leading installed capacity, its effect on electricity spot electricity 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 also examined the impact of increased incidences of VRE curtailment over the past three years on the electricity spot price dynamics.

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. In particular, 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 of generation associated with fossil fuel generation. In addition, large-scale solar generation has great potential to reduce spot price volatility, while rooftop solar generation has the reverse effect most of the time. Rooftop solar generation is dominated by north-facing fixed-panel systems, which produce the "bell-shaped" intraday generation profile, whereas large-scale solar generation is based on axis-tracking systems, which produce a flatter intraday generation profile. Thus, 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 also experiences high price volatility for the increase in solar generation. Finally, we find that allowing VRE curtailed generation to enter the system would have a marginal impact on spot price dynamics compared to the effect observed in the market. However, according to the intraday profiles, curtailment undermines the MOE in states experiencing high penetration of solar generation, such as South Australia and Queensland, but, reducing price volatility during the middle of the day.

The present findings have important implications for the current transition to renewable energy in the NEM, which aims at ensuring reliable, secure, and affordable energy supply while cutting CO_2-e emissions. We recommend several policy adjustments aimed at increasing the correlation between rooftop solar generation by directing federal and states' local policies to support PV-plus-battery systems. The dynamic export management of rooftop solar generation, which allows flexibility of exports over time, can be a robust measure for dealing with the negative effects of rooftop solar generation on system security. In addition, policymakers should transition to dynamic FiTs to increase the contribution of rooftop solar generation to meet the early morning and evening demand peaks. To maximize electricity consumption during the middle of the day and reduce incidences of VRE curtailment, demand-side participation via the two-sided market reforms is essential. This reform would ensure the system's flexibility, by soaking up extra solar power during the day, lowering pressure on energy and grid costs, and reducing the need for peaking generators.

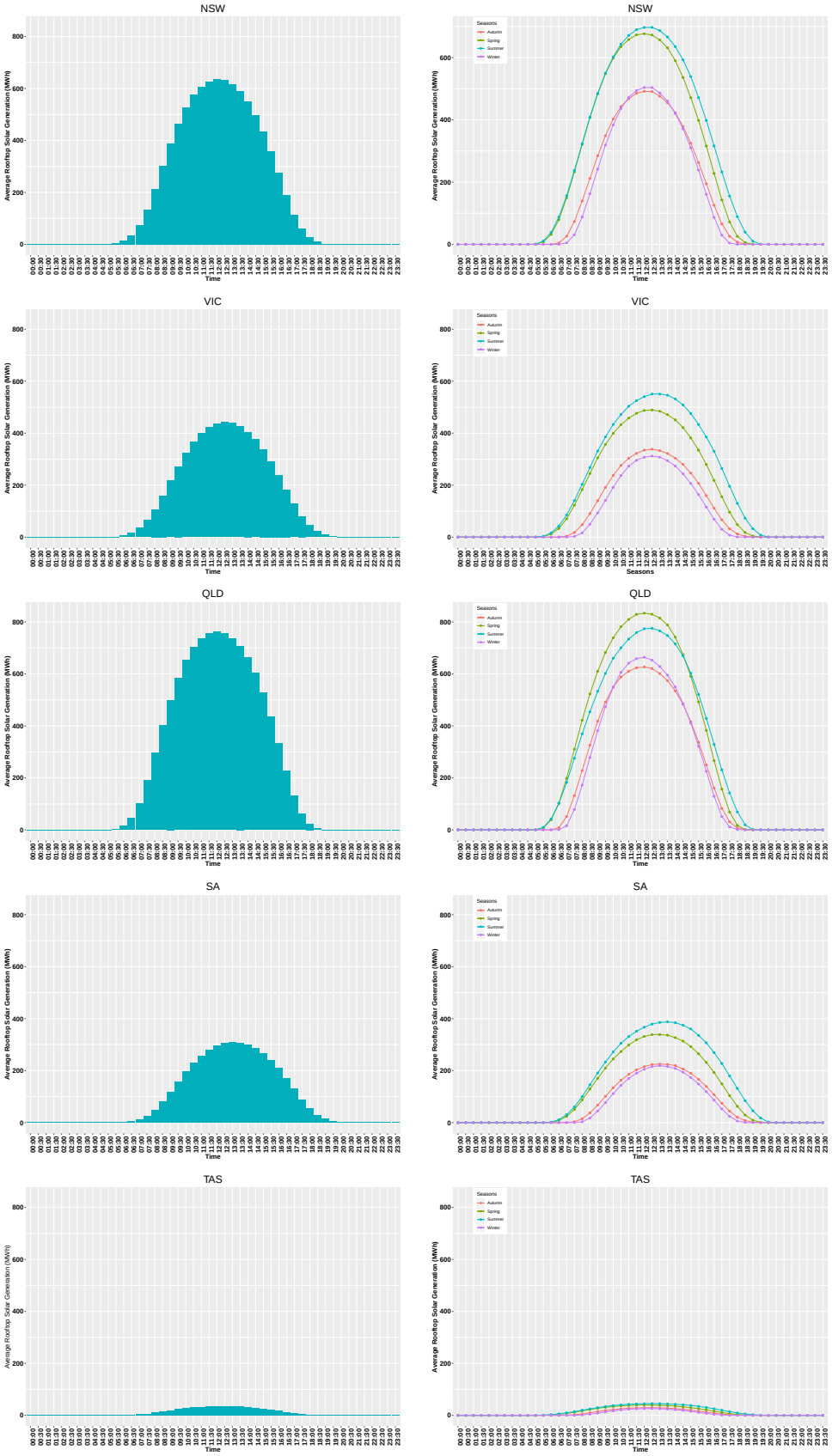

Figure 2: Average hourly rooftop solar generation for NSW, SA, VIC, TAS, and QLD from 2018 to 2021.

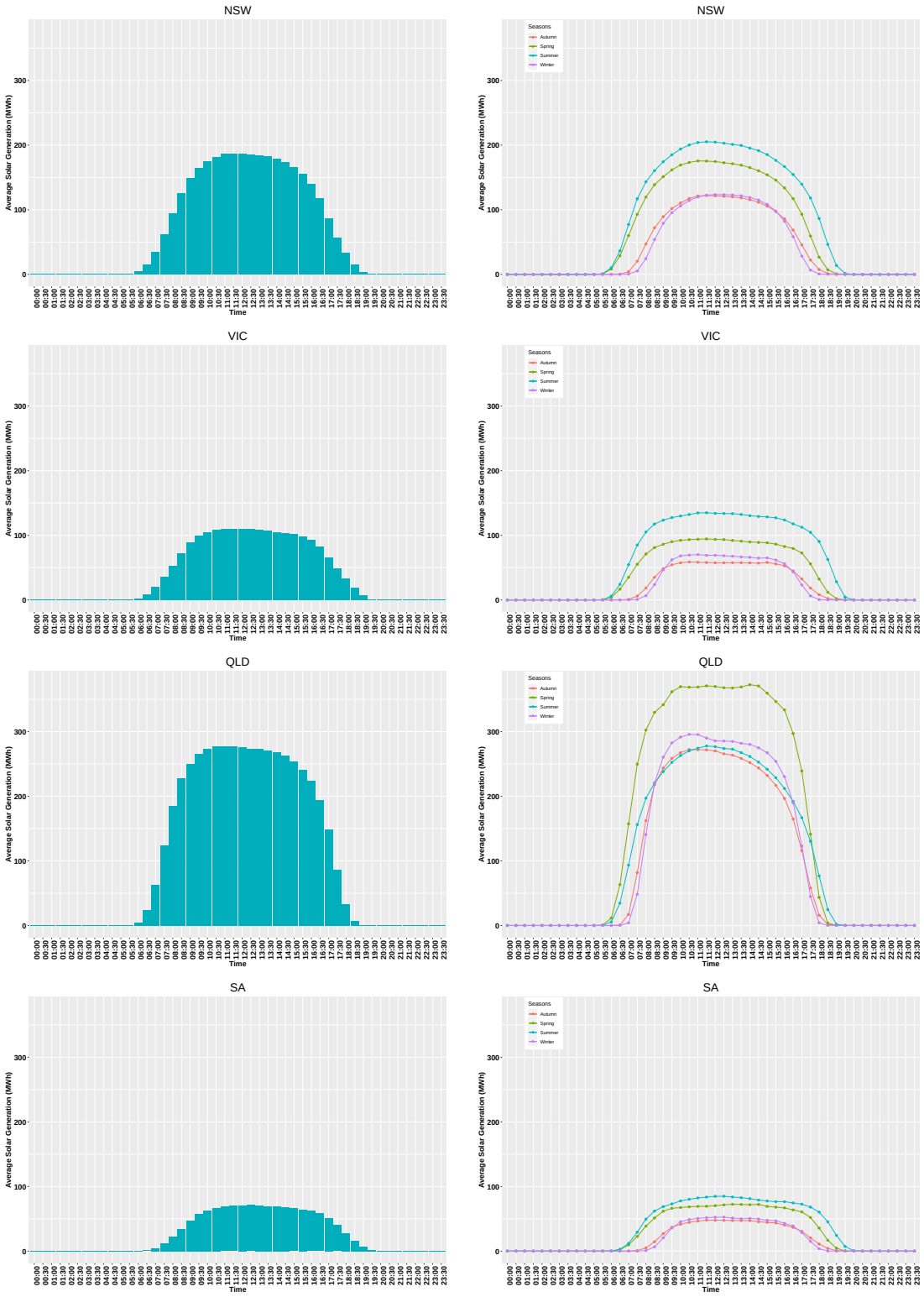

Figure 3: Average hourly large-scale solar generation for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021).

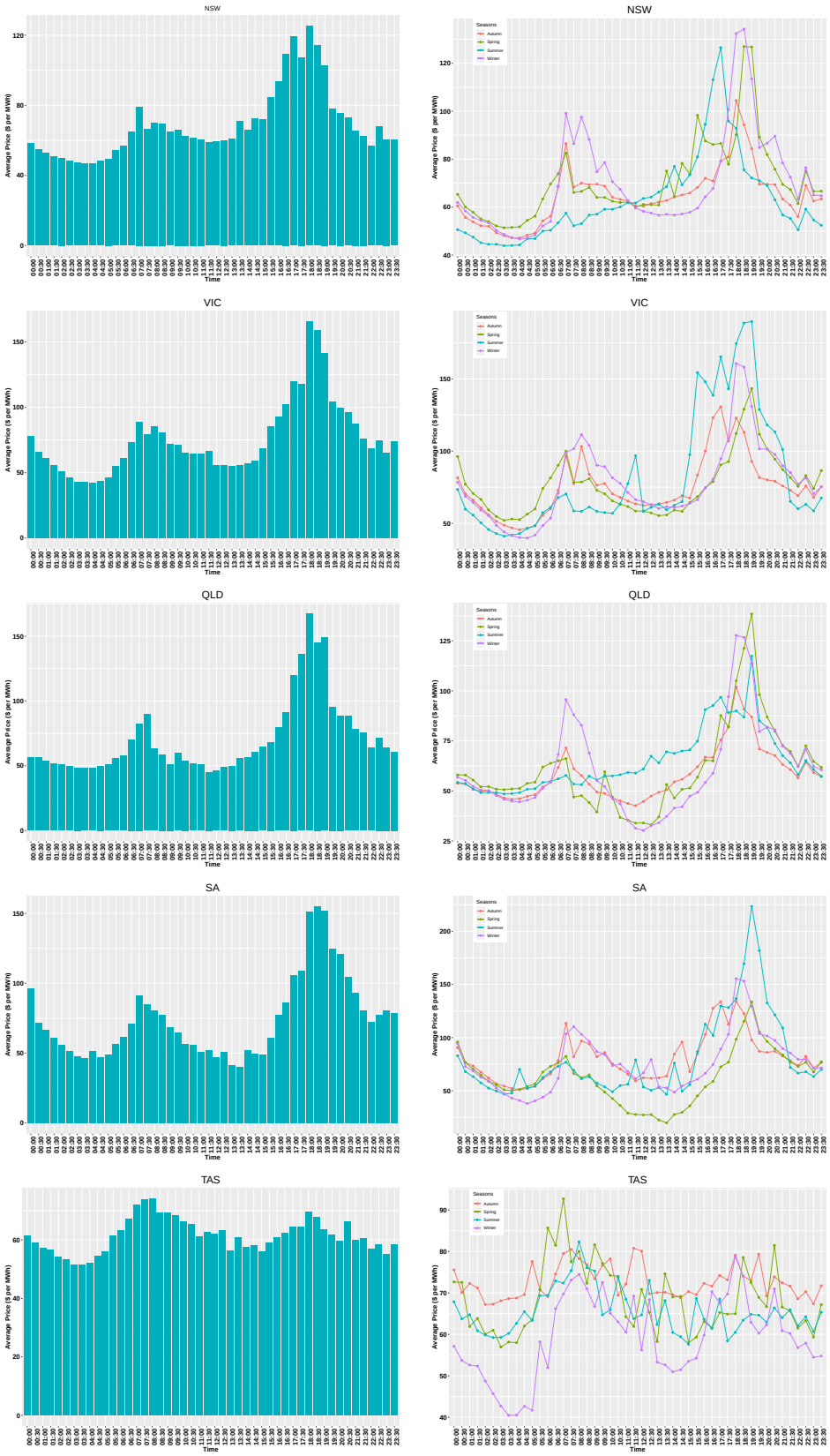

Figure 4: Average hourly electricity prices for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021). The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of electricity spot prices over four seasons of the year.

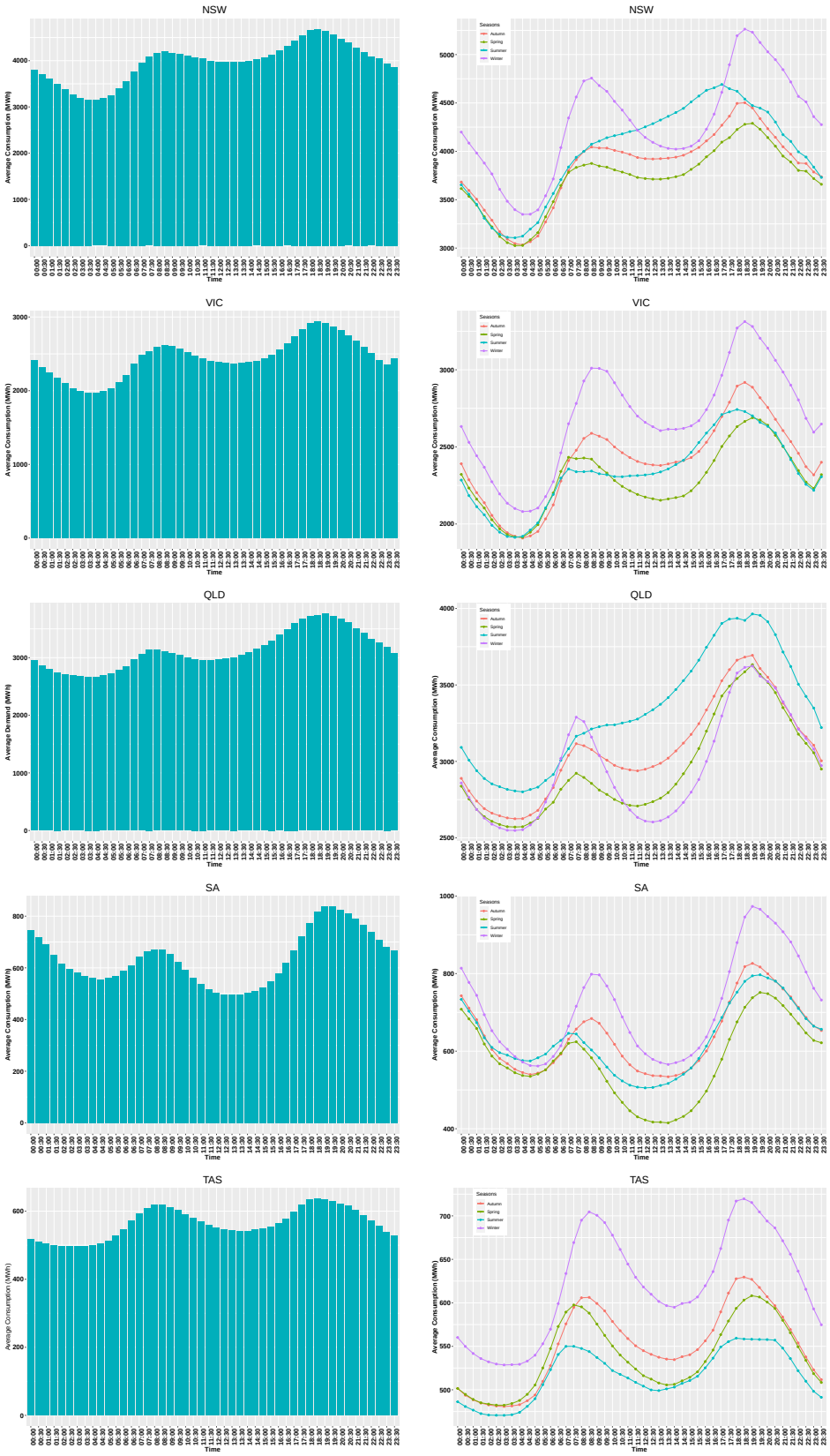

Figure 5: Average hourly electricity consumption for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021). The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of electricity consumption over four seasons of the year and, most importantly, the duck curve.

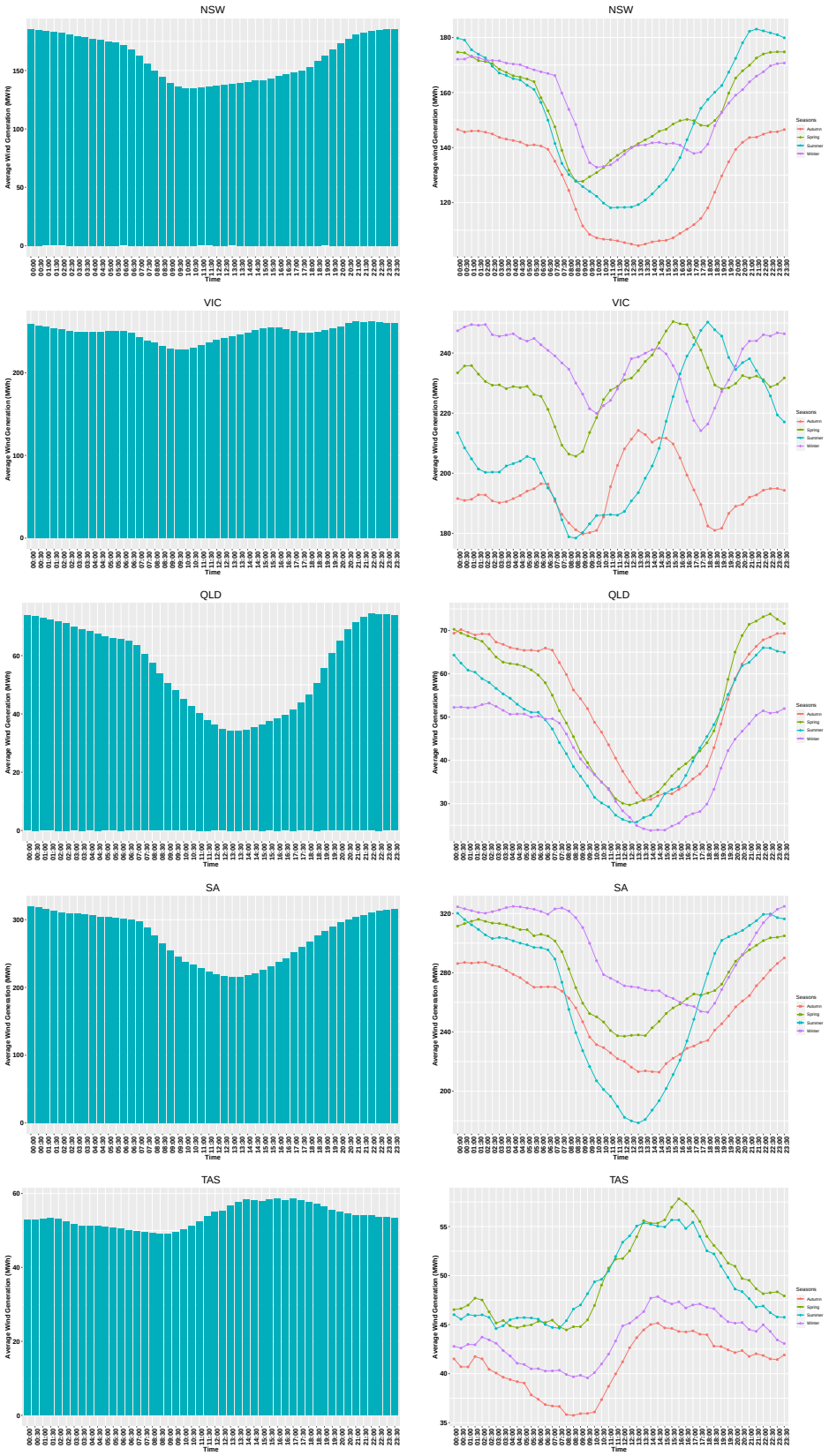

Figure 6: Average hourly large-scale wind generation for NSW (2015 to 2021), SA (2018 to 2021), VIC (2018 to 2021), TAS (2018 to 2021), and QLD (2017 to 2021). The y-axis scale for the left panel figures is not the same as the right panel figures to ensure the clarity of the pattern of wind generations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

Table 1: Summary statistics of the intraday (half-hourly) variables employed in the analysis.

	Unit	Mean	Standard Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile
						NSW				
Electricity Prices	AUD/MWh	72.40	191.61	49.15	3010.44	58.94	-139.93	14700.00	38.81	83.14
Large-scale Solar Generation	MWh	63.19	111.07	2.36	8.68	0.46	0.00	645.74	0.00	83.13
Rooftop Solar Generation	MWh	183.56	266.76	1.43	4.17	1.38	0.00	1270.98	0.00	335.73
Wind Generation	MWh	156.66	128.67	1.12	4.02	125.47	0.00	798.39	55.01	223.21
Natural Gas Generation	MWh	122.4	140.69	1.36	4.79	80.00	0.00	938.30	0.00	206.00
Black Coal Generation	MWh	3152.00	577.57	0.01	2.49	3162	1293.00	4844.00	2728.00	3559.00
Kerosene Generation	MWh	0.07	0.91	16.21	293.94	0.00	0.00	0.00	0.00	0.00
Gas Prices	AUD/GJ	7.40	2.98	1.41	10.64	7.30	0.02	29.78	5.05	9.40
Hydro Generation	MWh	143.7	158.33	1.95	8.66	86.00	0.00	1366.6	26.5	219.4
Electricity Consumption	MWh	3969.00	629.15	0.64	3.50	3922.00	2585.00	6993.00	3515.00	4331.00
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
VRE	MWh	1900.72	1074.44	0.85	3.68	1736.17	4.55	7494.75	1091.62	2496.85
Curtailed Generation	MWh	18.36	65.83	6.24	53.81	0.00	0.00	1174.47	0.00	2.96
VRE + Curtailed Generation	MWh	1919.08	1094.69	0.88	3.74	1747.00	4.55	7498.64	1095.38	2524.93
						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 Prices	AUD/GJ	7.53	2.69	2.32	28.77	7.77	0.00	58.44	5.35	9.35
Electricity Consumption	MWh	2440.00	430.88	0.73	3.63	2382.00	1154.00	4754.00	2118.00	2698.00
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
VRE	MWh	1759.57	1234.21	0.86	3.39	1527.43	1.09	6738.51	775.62	2519.77
Curtailed Generation	MWh	56.21	184.36	6.52	11.50	0.00	0.00	3677.39	0.00	11.50
VRE + Curtailed Generation	MWh	1815.78	1307.47	0.96	3.67	1551.64	2.14	7708.69	785.80	2579.85
						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 Prices	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
Electricity Consumption	MWh	3098.00	447.87	0.57	3.00	3039.00	1874.00	4994.00	2741.00	3407.00
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
VRE	MWh	1246.9	1139.18	0.86	2.48	843.90	0.00	5080.10	310.90	2072.60
Curtailed Generation	MWh	59.95	204.46	6.88	66.67	0.00	0.00	3573.79	0.00	18.80
VRE + Curtailed Generation	MWh	1306.80	1203.06	0.86	2.45	869.60	0.00	5375.00	315.80	2204.00
						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 Prices	AUD/GJ	8.18	2.74	1.68	10.77	8.34	3.15	28.01	5.99	9.83
Electricity Consumption	MWh	639.50	168.89	0.57	4.43	625.40	142.30	1553.90	540.00	728.60
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
VRE	MWh	1807.10	1076.54	0.19	1.85	1685.80	0.10	4909.80	878.80	2816.10
Curtailed Generation	MWh	112.09	313.31	3.61	17.22	0.62	0.00	2951.94	0.00	11.56
VRE + Curtailed Generation	MWh	1919.20	1213.14	0.40	2.12	1728.20	0.10	5348.60	895.30	2921.10
						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
Electricity Consumption	MWh	560.80	75.96	0.62	3.04	548.80	338.70	863.50	505.20	606.30
Basslink (T-V-MNSP1)	MWh	10.27	153.31	-0.09	1.68	0.00	-239.00	239.00	-127.14	151.95
VRE	MWh	307.13	269.23	1.01	3.70	254.41	0.00	1220.95	76.12	474.17
Curtailed Generation	MWh	4.91	25.02	9.38	121.33	0.00	0.00	621.00	0.00	0.00
VRE + Curtailed Generation	MWh	312.04	274.99	1.02	3.67	257.21	0.00	480.54	76.45	1236.65

Table 2: 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.

	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	-87.0762	-83.2937	-86.1117	-81.5735
	(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	0.9305	0.9315	0.9309	0.9315
	(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					-0.0770			
					(0.0000)			
rooftop solar$_{pen}$						-24.2550		
						(0.0001)		
solar total							-0.0569	
							(0.0000)	
solar total$_{pen}$								-19.1624
								(0.0000)
wind	-0.2374		-0.2286		-0.2234		-0.2256	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
wind$_{pen}$		-72.3117		-67.1832		-65.1705		-64.5715
		(0.0000)		(0.0000)		(0.0000)		(0.0000)
hydro	0.1529	0.1597	0.2443	0.2489	0.2556	0.2613	0.2493	0.2576
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
consumption	0.3099	0.2997	0.3627	0.3493	0.3676	0.3553	0.3668	0.3527
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	0.7962	0.7207	1.5246	1.4635	1.4839	1.4204	1.4784	1.3818
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0241)	(0.0000)	(0.0000)	(0.0000)
exim$_{terrs}$	-0.5302	-0.5332	-0.7419	-0.7488	-0.8003	-0.7831	-0.7890	-0.7697
	(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	-0.1937	-0.1983	-0.1938	-0.2000
	(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	0.0466	0.0488	0.0441	0.0468
	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
				Variance Equation				
ω	0.0324	-0.1201	-0.0814	-0.3581	-0.0456	-0.2935	-0.1025	-0.3303
	(0.7069)	(0.1613)	(0.0570)	(0.0019)	(0.6888)	(0.0000)	(0.3739)	(0.2154)
α	-0.0907	-0.1073	-0.1408	-0.1396	-0.1616	-0.1561	-0.1389	-0.1467
	(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	0.7402	0.7316	0.7276	0.7265
	(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	0.9979	1.0410	1.0299	1.0522
	(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					0.0112			
					(0.0000)			
rooftop solar$_{pen}$						4.0000		
						(0.0000)		
solar total							0.0077	
							(0.0000)	
solar total$_{pen}$								2.6891
								(0.0000)
wind	0.0014		0.0007		-0.0003		0.0002	
	(0.0096)		(0.2535)		(0.6154)		(0.7173)	
wind$_{pen}$		0.5769		0.3953		0.1167		0.2386
		(0.0035)		(0.0514)		(0.5074)		(0.3125)
hydro	0.0056	0.0054	0.0069	0.0062	0.0075	0.0065	0.0065	0.0059
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1302)	(0.0025)
consumption	0.0023	0.0027	0.0023	0.0030	0.0019	0.0027	0.0022	0.0028
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0015)
gas	0.0427	0.0422	0.0498	0.0497	0.0437	0.0435	0.0442	0.0446
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0205)	(0.0000)
exim$_{terra}$	-0.0113	-0.0115	-0.0104	-0.0109	-0.0101	-0.0131	-0.0118	-0.0142
	(0.0277)	(0.0218)	(0.0944)	(0.0728)	(0.0894)	(0.0409)	(0.3262)	(0.0128)
exim$_{QNI}$	-0.0012	-0.0012	-0.0006	-0.0006	0.0001	0.0001	-0.0001	0.00004
	(0.0265)	(0.0326)	(0.3631)	(0.3633)	(0.8514)	(0.8464)	(0.9121)	(0.9536)
exim$_{VNI}$	0.0022	0.0022	0.0024	0.0023	0.0019	0.0018	0.0021	0.0019
	(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	2.7918	2.7772	2.7747	2.7626
	(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	-231182.3	-231317.7	-231178.7	-231305
AIC	7.4555	7.4604	7.7537	7.7585	7.7627	7.7673	7.7626	7.7669
BIC	7.4575	7.4624	7.7572	7.7620	7.7662	7.7708	7.7661	7.7703
Q(40)	3.5107	2.8530	3.7751	3.0926	6.5613	4.9795	5.8369	4.3280
	(0.3144)	(0.4692)	(0.2635)	(0.4083)	(0.0286)	(0.1081)	(0.05349)	(0.1779)
$Q^2(36)$	0.0026	0.0020	0.0020	0.0017	0.0019	0.0018	0.0024	0.0019
	(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	0.0014	0.0013	0.0017	0.0013
	(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

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 3: 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.

	Model E	Model F	Model G	Model H	Model I	Model J
			Mean Equation			
μ	-79.5598	-61.8610	-71.9529	-54.8414	-71.7445	-54.2069
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9449	0.9458	0.9436	0.9441	0.9436	0.9434
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-0.8473					
	(0.0000)					
large-scale solar$_{pen}$		-99.9994				
		(0.0000)				
rooftop solar			-0.2116			
			(0.0000)			
rooftop solar$_{pen}$				-39.6935		
				(0.0000)		
solar total					-0.1941	
					(0.0000)	
solar total$_{pen}$						-36.3768
						(0.0000)
wind	-0.5842		-0.5433		-0.5527	
	(0.0000)		(0.0000)		(0.0000)	
wind$_{pen}$		-99.9990		-99.9945		-99.9905
		(0.0000)		(0.0000)		(0.0000)
hydro	-0.0624	0.0266	-0.0074	0.0514	-0.0197	0.0447
	(0.0003)	(0.1534)	(0.5773)	(0.5743)	(0.7437)	(0.1248)
consumption	0.7294	0.6308	0.6918	0.6063	0.6957	0.6064
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	0.3670	0.2864	0.3950	0.3364	0.4106	0.3320
	(0.1756)	(0.1339)	(0.6874)	(0.2219)	(0.4012)	(0.1897)
exim$_{murr}$	0.6864	0.5942	0.6404	0.5693	0.6490	0.5766
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
exim$_{hey}$	-0.0856	-0.1559	-0.1221	-0.1676	-0.1140	-0.1645
	(0.0041)	(0.0000)	(0.0000)	(0.0081)	(0.0175)	(0.0001)
exim$_{VNI}$	0.0592	-0.0080	0.0186	-0.0223	0.0273	-0.0190
	(0.0000)	(0.6069)	(0.5885)	(0.7432)	(0.5755)	(0.5538)
exim$_{bass}$	-0.1398	-0.0590	-0.0821	-0.0405	-0.0950	-0.0479
	(0.0000)	(0.3247)	(0.0284)	(0.5359)	(0.1696)	(0.2093)
			Variance Equation			
ω	0.7074	0.4101	0.3944	0.0770	0.4222	0.1017
	(0.0000)	(0.0001)	(0.0000)	(0.0974)	(0.0000)	(0.3222)
α	0.0418	0.0305	0.0502	0.0452	0.0587	0.0500
	(0.4037)	(0.0705)	(0.0026)	(0.0046)	(0.0028)	(0.0120)
β	0.6999	0.7048	0.7017	0.7012	0.6984	0.6986
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	0.7817	0.7796	0.7389	0.7554	0.7458	0.7558
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0337					
	(0.0000)					
large-scale solar$_{pen}$		7.5344				
		(0.0000)				
rooftop solar			0.0143			
			(0.0000)			
rooftop solar$_{pen}$				2.9762		
				(0.0000)		
solar total					0.0110	
					(0.0000)	
solar total$_{pen}$						2.3345
						(0.0000)
wind	0.0019		0.0019		0.0020	
	(0.0096)		(0.0000)		(0.0000)	
wind$_{pen}$		0.6308		0.6463		0.6736
		(0.0000)		(0.0000)		(0.0000)
hydro	0.0051	0.0044	0.0040	0.0031	0.0042	0.0034
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0021)
consumption	0.0018	0.0029	0.0030	0.0044	0.0029	0.0042
	(0.0099)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
gas	0.0445	0.0449	0.0402	0.0405	0.0421	0.0423
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
exim$_{murr}$	-0.0145	-0.0160	-0.0113	-0.0121	-0.0128	-0.0138
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
exim$_{hey}$	-0.0014	-0.0009	-0.0019	-0.0014	-0.0017	-0.0013
	(0.1217)	(0.1362)	(0.0012)	(0.0166)	(0.0050)	(0.0463)
exim$_{VNI}$	-0.0005	-0.0009	-0.0006	-0.0009	-0.0005	-0.0009
	(0.3622)	(0.0128)	(0.0823)	(0.0095)	(0.1697)	(0.0166)
exim$_{bass}$	0.0023	0.0026	0.0021	0.0023	0.0022	0.0025
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Skew	0.0797	0.0798	0.0898	0.0899	0.0927	0.0916
	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	1.0387	1.0318	1.0476	1.0423	1.0498	1.0438
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-236110.6	-236293.2	-236075.5	-236221	-236001.3	-236154.2
AIC	8.2335	8.2399	8.2323	8.2373	8.2297	8.2350
BIC	8.2376	8.2439	8.2363	8.2414	8.2337	8.2350
Q(40)	38.69	34.99	46.10	42.30	45.23	42.17
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(1.0000)
$Q^2(36)$	0.0412	0.02776	0.0330	0.0352	0.0450	0.0453
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0038	0.0038	0.0045	0.0044	0.0045	0.0046
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	57360	57360	57360	57360	57360	57360

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 4: 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.

	Model E	Model F	Model G	Model H	Model I	Model J
			Mean Equation			
μ	-18.3237	16.4111	-25.7305	4.6176	-23.1524	7.8919
	(0.0000)	(0.0000)	(0.0003)	(0.0288)	(0.0000)	(0.1657)
ϕ_1	0.9156	0.9147	0.9098	0.9097	0.9104	0.9102
	(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			-0.1609			
			(0.0000)			
rooftop solar$_{pen}$				-5.0498		
				(0.0000)		
solar total					-0.1487	
					(0.0000)	
solar total$_{pen}$						-4.7401
						(0.0000)
wind	-1.2272		-1.1673		-1.1716	
	(0.0000)		(0.0000)		(0.0000)	
wind$_{pen}$		-67.1991		-62.0123		-62.2506
		(0.0000)		(0.0000)		(0.0000)
consumption	1.6203	1.0280	1.6513	1.1245	1.6388	1.1072
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	2.8529	2.7298	3.1234	2.9456	2.9401	2.7185
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
exim$_{murr}$	0.6393	0.5938	0.7038	0.6711	0.7013	0.6680
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
exim$_{hey}$	-0.8213	-0.8091	-0.7711	-0.7338	-0.7744	-0.7368
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
			Variance Equation			
ω	1.3335	1.0827	1.1880	0.9757	1.1719	0.9742
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.0165	0.0248	0.0363	0.0428	0.0329	0.0428
	(0.5147)	(0.3346)	(0.1564)	(0.0763)	(0.1195)	(0.0658)
β	0.7072	0.7081	0.6766	0.6769	0.6847	0.6813
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.2126	1.1947	1.0751	1.1467	1.0625	1.1682
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0396					
	(0.0000)					
large-scale solar$_{pen}$		1.6603				
		(0.0000)				
rooftop solar			0.0206			
			(0.0000)			
rooftop solar$_{pen}$				0.6794		
				(0.0000)		
solar total					0.0150	
					(0.0000)	
solar total$_{pen}$						0.5243
						(0.0000)
wind	-0.0016		-0.0010		-0.0010	
	(0.0047)		(0.0553)		(0.0863)	
wind$_{pen}$		0.1253		0.1484		0.1608
		(0.0001)		(0.0000)		(0.0000)
consumption	0.0080	0.0098	0.0105	0.0133	0.0100	0.0130
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	0.0284	0.0323	0.0318	0.0353	0.0313	0.0353
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
exim$_{murr}$	-0.0132	-0.0083	-0.0134	-0.0095	-0.0133	-0.0090
	(0.0001)	(0.0064)	(0.0000)	(0.0034)	(0.0000)	(0.0036)
exim$_{hey}$	-0.0038	-0.0008	-0.0037	-0.0005	-0.0036	-0.0004
	(0.0001)	(0.3290)	(0.0001)	(0.5427)	(0.0002)	(0.6628)
Skew	0.9711	0.9757	0.9698	0.9723	0.9690	0.9728
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.1779	2.1822	2.2386	2.2080	2.2437	2.1988
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-242961.9	-243236.4	-243030.8	-243346.9	-243069.5	-243363.7
AIC	8.6164	8.6261	8.6188	8.6300	8.6202	8.6306
BIC	8.6196	8.6293	8.6220	8.6332	8.6234	8.6338
Q(40)	7.258	6.425	6.190	6.255	6.417	6.270
	(0.0153)	(0.0322)	(0.0395)	(0.0374)	(0.0324)	(0.0369)
$Q^2(36)$	0.0006	0.0007	0.0008	0.0006	0.0006	0.0006
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0005	0.0005	0.0004	0.0004	0.0004	0.0004
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	56400	56400	56400	56400	56400	56400

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 5: 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.

	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	-162.3970	-152.1689	-158.6972	-153.8876	-167.4497	-155.7497	-157.9398	-155.1205
	(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	0.9616	0.9625	0.9671	0.9672	0.9659	0.9666	0.9665	0.9664
	(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			-0.0367				-0.0353			
			(0.0000)				(0.0000)			
rooftop solar$_{pen}$				-11.5306				-11.7956		
				(0.0000)				(0.0000)		
solar total									-0.0306	
									(0.0000)	
solar total$_{pen}$										-8.4465
										(0.0000)
wind					-0.5361		-0.5430		-0.5395	
					(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	-0.0080	-0.0343	-0.1202	-0.1246	-0.0643	-0.0765	-0.0811	-0.0840
	(0.6229)	(0.5784)	(0.9032)	(0.6149)	(0.0040)	(0.0554)	(0.3384)	(0.2545)	(0.5937)	(0.2606)
consumption	0.6531	0.6454	0.6827	0.6605	0.6858	0.6667	0.7102	0.6797	0.6931	0.6800
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	1.4728	1.4160	1.3930	1.5420	1.6887	1.7572	1.4554	1.6396	1.6061	1.6303
	(0.0000)	(0.0029)	(0.2709)	(0.0032)	(0.0000)	(0.0098)	(0.0002)	(0.2158)	(0.0000)	(0.0000)
exim$_{terra}$	0.0755	0.0982	0.1773	0.1556	0.1042	0.1510	0.1984	0.1933	0.1428	0.1886
	(0.4156)	(0.2548)	(0.0551)	(0.2152)	(0.3170)	(0.3997)	(0.0393)	(0.3342)	(0.1199)	(0.1321)
exim$_{QNI}$	-0.2505	-0.2533	-0.2810	-0.2720	-0.3238	-0.3169	-0.3195	-0.3036	-0.3109	-0.3050
	(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	1.1140	1.2571	2.1076	1.7195	1.0299	1.1009	1.6573	1.2876
	(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	-2.1383	-1.6700	-1.8471	-1.8414	-1.8621	-1.8220	-1.7743	-1.7758
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
β	0.6491	0.6566	0.7501	0.6688	0.6575	0.6558	0.7592	0.6718	0.6720	0.6700
	(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	3.5109	5.6933	6.0079	6.0301	2.9839	5.5206	5.5321	5.5560
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0086)	(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			0.0084				0.0085			
			(0.0000)				(0.0000)			
rooftop solar$_{pen}$				2.9367				3.0586		
				(0.0000)				(0.0000)		
solar total									0.0067	
									(0.0000)	
solar total$_{pen}$										1.9079
										(0.0000)
wind					-0.0081		-0.0063		-0.0070	
					(0.0000)		(0.0000)		(0.1427)	
wind$_{pen}$						-2.5146		-2.2611		-2.2434
						(0.0000)		(0.0000)		(0.0000)
hydro	0.0152	0.0176	0.0094	0.0124	0.0190	0.0188	0.0089	0.0143	0.0157	0.0152
	(0.0005)	(0.0000)	(0.0041)	(0.0045)	(0.0000)	(0.0000)	(0.0021)	(0.0003)	(0.0000)	(0.0034)
consumption	0.0017	0.0027	0.0021	0.0038	0.0013	0.0027	0.0021	0.0043	0.0024	0.0038
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0812)	(0.0000)	(0.0000)	(0.0000)	(0.0058)	(0.0000)
gas	0.0553	0.0542	0.0440	0.0530	0.0638	0.0617	0.0391	0.0520	0.0550	0.0522
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0030)	(0.1087)	(0.0002)
exim$_{terra}$	0.0266	0.0217	0.0142	0.0131	0.0262	0.0259	0.0127	0.0173	0.0253	0.0202
	(0.0117)	(0.0293)	(0.0522)	(0.2044)	(0.0168)	(0.0724)	(0.0862)	(0.1122)	(0.5170)	(0.0854)
exim$_{QNI}$	-0.0013	-0.0007	-0.0011	-0.0007	-0.0011	-0.0011	-0.0013	-0.0017	-0.0019	-0.0015
	(0.2371)	(0.5045)	(0.1851)	(0.5321)	(0.3736)	(0.4843)	(0.1100)	(0.1236)	(0.4751)	(0.1706)
Skew	1.0212	1.0183	1.0013	1.0268	1.0226	1.0245	1.0086	1.0313	1.0331	1.0329
	(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	2.0135	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	-235132.1	-234998.6	-206724.5	-206796.5	-207069.7	-207179.4	-207143.1	-207189.6
AIC	7.7994	7.7999	7.8952	7.8908	7.9986	8.0013	8.0119	8.0161	8.0147	8.0165
BIC	7.8023	7.8027	7.8983	7.8938	8.0023	8.0051	8.0157	8.0199	8.0185	8.0203
Q(40)	3.466	3.646	12.607	5.033	3.887	3.817	11.846	4.694	4.390	4.318
	(0.3236)	(0.2876)	(0.0000)	(0.1035)	(0.2440)	(0.2561)	(0.0002)	(0.1350)	(0.1699)	(0.1791)
$Q^2(36)$	0.18226	0.2014	0.0944	0.2049	0.1901	0.2016	0.1059	0.1902	0.1621	0.1928
	(0.9999)	(0.9999)	(1.0000)	(0.9999)	(0.9999)	(0.9999)	(1.0000)	(0.9999)	(1.0000)	(0.9999)
ARCH-LM Test	0.2004	0.2272	0.0645	0.2166	0.2030	0.2211	0.0778	0.1940	0.1640	0.2000
	(0.9970)	(0.9961)	(0.9998)	(0.9965)	(0.9969)	(0.9963)	(0.9996)	(0.9972)	(0.9981)	(0.9970)
Observations	64272	64272	59568	59568	51696	51696	51696	51696	51696	51696

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table 6: 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.

	Model C	Model D
	Mean Equation	
μ	12.7981	18.2487
	(0.0000)	(0.0210)
ϕ_1	0.9421	0.9420
	(0.0000)	(0.0000)
rooftop solar	-0.1630	
	(0.0329)	
$rooftop\ solar_{pen}$		-6.8575
		(0.0937)
wind	-1.3926	
	(0.0000)	
$wind_{pen}$		-65.2465
		(0.0000)
hydro	-0.1267	
	(0.0000)	
consumption	1.3470	1.1158
	(0.0000)	(0.0000)
$exim_{bass}$		-0.1319
		(0.0000)
	Variance Equation	
ω	3.9125	3.9243
	(0.0000)	(0.0000)
α	0.8982	0.8979
	(0.0000)	(0.0000)
β	0.4735	0.4728
	(0.0000)	(0.0000)
γ	5.2137	5.2026
	(0.0000)	(0.0000)
rooftop solar	0.0463	
	(0.0000)	
$rooftop\ solar_{pen}$		2.3311
		(0.0000)
wind	0.0065	
	(0.0303)	
$wind_{pen}$		0.1263
		(0.4339)
hydro	0.0045	
	(0.0000)	
consumption	0.0118	0.0161
	(0.0000)	(0.0000)
$exim_{bass}$		0.0059
		(0.0000)
Skew	1.1061	1.1058
	(0.0000)	(0.0000)
Shape	2.0100	2.0100
	(0.0000)	(0.0000)
log likelihood	-239421.2	-239407.5
AIC	8.0391	8.0387
BIC	8.0415	8.0411
Q(40)	5.644	5.579
	(0.0629)	(0.0664)
$Q^2(36)$	0.0392	0.0395
	(1.0000)	(1.0000)
ARCH-LM Test	0.0216	0.0219
	(1.0000)	(1.0000)
Observations	59568	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

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.

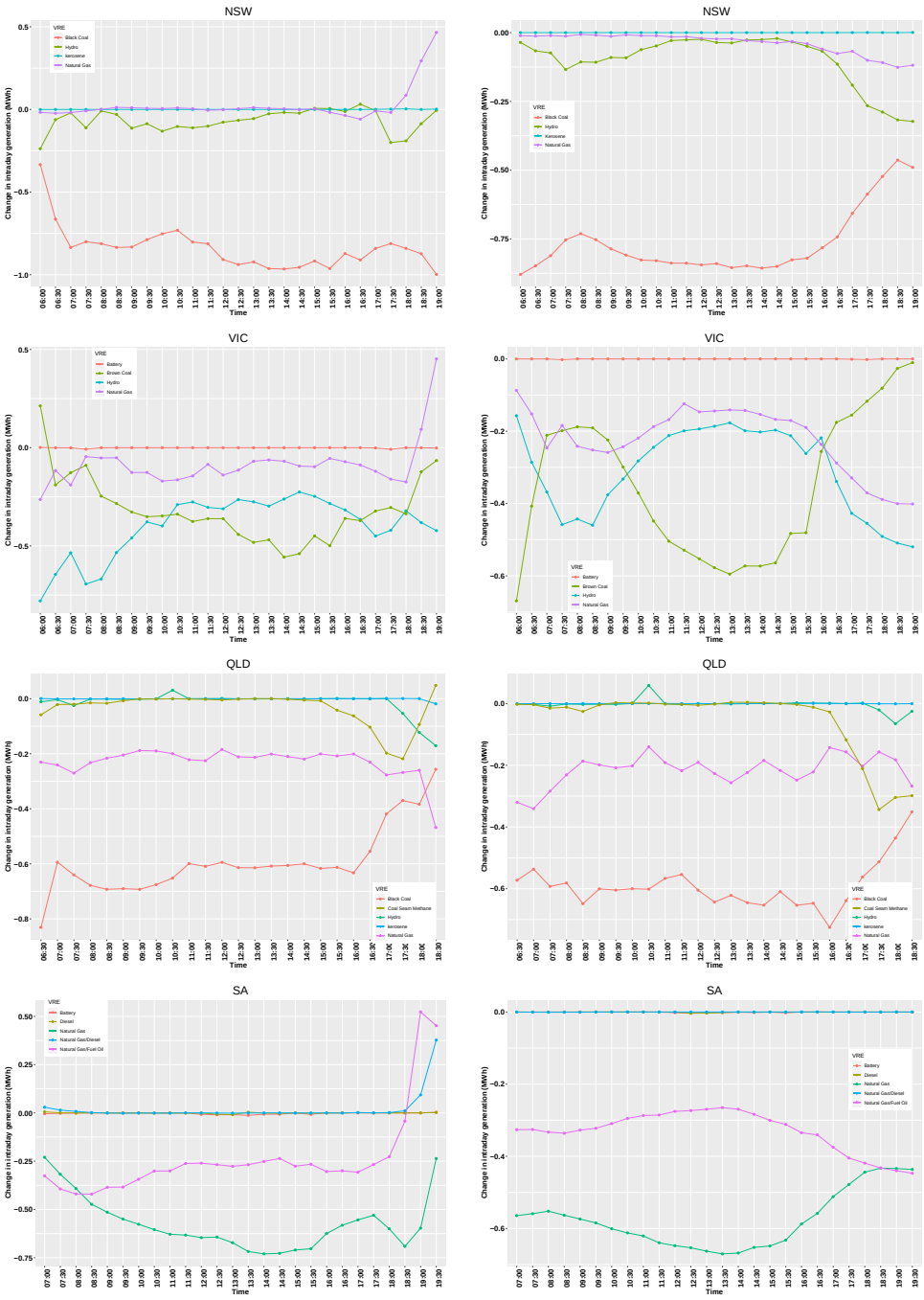

Figure 9: Change in generation by a source per MWh increase in large-scale solar (left panels) and wind generation (right panels) for NSW, SA, VIC, and QLD.

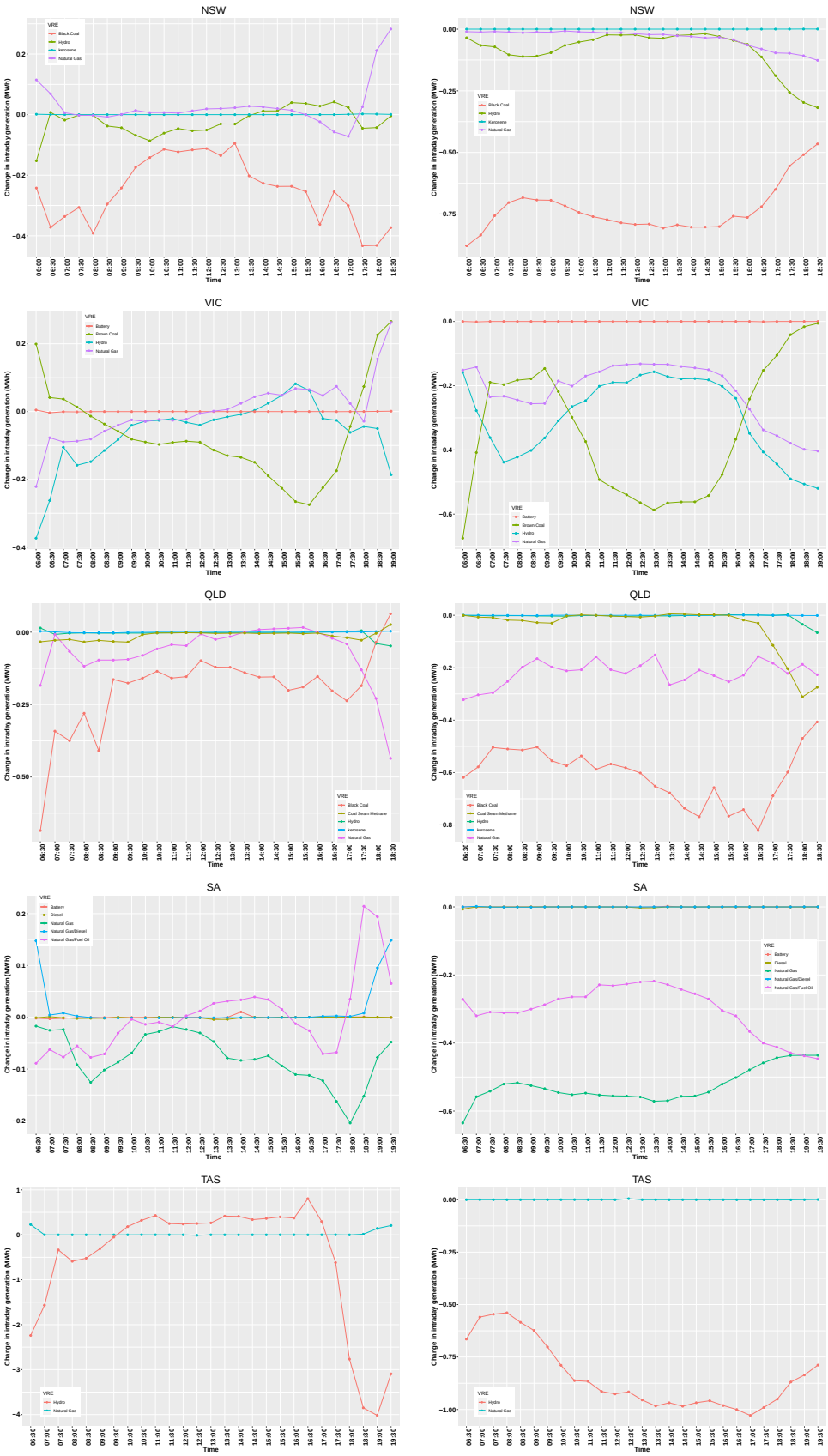

Figure 10: Change in generation by a source per MWh increase in rooftop solar (left panels) and wind generation (right panels) for NSW, SA, VIC, QLD, and TAS.

Table 7: The effect of VRE generation and observed VRE generation plus curtailed generation on spot price behavior. The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	NSW		VIC		SA		QLD		TAS	
	Model K	Model L	Model K	Model L	Model K	Model L	Model K	Model L	Model K	Model L
					Mean Equation					
μ	-85.9076	-85.9554	-65.2537	-64.6074	-23.0524	-21.6156	-179.2125	-176.9389	11.6530	9.1506
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0000)
ϕ_1	0.9307	0.9305	0.9452	0.9451	0.9057	0.9057	0.9622	0.9626	0.9430	0.9398
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
vre	-0.0365		-0.0533		-0.1103		-0.0397		-0.0936	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
vre_{curt}		-0.0367		-0.0621		-0.1134		-0.0484		-0.0938
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
$hydro$	0.2666	0.2645	0.1186	0.1109			0.0234	0.0264	-0.0385	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.3931)	(0.7585)	(0.0751)	
$consumption$	0.3633	0.3634	0.6099	0.6135	1.3606	1.3369	0.7046	0.6993	1.2134	1.2234
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	1.3762	1.3786	0.3082	0.3578	3.1023	3.2697	1.0408	1.0052		
	(0.0000)	(0.0000)	(0.0118)	(0.3704)	(0.0000)	(0.0000)	(0.0049)	(0.2903)		
$exim_{terra}$	-0.7981	-0.7974					0.1543	0.1491		
	(0.0000)	(0.0000)					(0.2596)	(0.4801)		
$exim_{QNI}$	-0.1959	-0.1962					-0.2911	-0.2893		
	(0.0000)	(0.0000)					(0.0000)	(0.0000)		
$exim_{murray}$			0.5214	0.5213	1.1831	1.1500				
			(0.0000)	(0.0000)	(0.0000)	(0.0000)				
$exim_{heyw}$			-0.2312	-0.2259	-0.3609	-0.3697				
			(0.0000)	(0.0000)	(0.0000)	(0.0000)				
$exim_{VNI}$	0.0515	0.0526	-0.1026	-0.0918						
	(0.0000)	(0.0001)	(0.0000)	(0.0000)						
$exim_{bass}$			0.0434	0.0287						-0.1750
			(0.0595)	(0.2284)						(0.0000)
					Variance Equation					
ω	0.6201	0.6328	0.8769	0.8909	1.6563	2.2878	1.8038	1.7517	3.9675	4.0725
	(0.0000)	(0.9035)	(0.0000)	(0.0000)	(0.0312)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	-0.2620	-0.2561	-0.0380	-0.0369	-0.0099	-0.0090	-2.7179	-2.7213	0.8208	0.9080
	(0.0000)	(0.0000)	(0.0154)	(0.0189)	(0.7144)	(0.9276)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.7418	0.7370	0.7182	0.7181	0.7038	0.7091	0.7516	0.7513	0.4838	0.4709
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	1.1609	1.1771	0.8359	0.8349	1.2704	4.1919	3.9701	3.9358	5.2508	5.2291
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5086)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
vre	-0.0001		0.0001		-0.0006		-0.0004		0.0017	
	(0.6288)		(0.1723)		(0.0000)		(0.0080)		(0.0009)	
vre_{curt}		-0.0001		0.0002		-0.0002		-0.0001		0.0010
		(0.9599)		(0.0089)		(0.0105)		(0.5786)		(0.0034)
$hydro$	0.0075	0.0072	0.0040	0.0043			0.0079	0.0085	0.0044	
	(0.0097)	(0.3340)	(0.0000)	(0.0000)			(0.0138)	(0.0065)	(0.0000)	
$consumption$	0.0009	0.0009	0.0016	0.0015	0.0068	0.0061	0.0007	0.0008	0.0099	0.0144
	(0.0037)	(0.9357)	(0.0000)	(0.0002)	(0.0000)	(0.0077)	(0.0310)	(0.0000)	(0.0000)	(0.0000)
gas	0.0439	0.0422	0.0397	0.0399	0.0273	0.0289	0.0446	0.0447		
	(0.0000)	(0.4866)	(0.0000)	(0.0000)	(0.0206)	(0.0000)	(0.0000)	(0.0000)		
$exim_{terra}$	-0.0044	-0.0081					0.0235	0.0243		
	(0.6281)	(0.3964)					(0.0136)	(0.0043)		
$exim_{QNI}$	-0.0005	-0.0003					-0.0026	-0.0025		
	(0.7286)	(0.9498)					(0.0312)	(0.0054)		
$exim_{murray}$			-0.0076	-0.0074	-0.0138	-0.0092				
			(0.0006)	(0.0010)	(0.0001)	(0.0030)				
$exim_{heyw}$			-0.0016	-0.0016	-0.0059	-0.0038				
			(0.0115)	(0.0087)	(0.0000)	(0.0001)				
$exim_{VNI}$	0.0020	0.0020	0.0001	-0.0001						
	(0.0021)	(0.0000)	(0.7172)	(0.7467)						
$exim_{bass}$			0.0008	0.0010						0.0054
			(0.1250)	(0.0351)						(0.0000)
Skew			0.0423	0.0422	0.9514	0.9544	0.9496	0.9473	1.1067	1.1106
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.6539	2.6503	1.0011	1.0003	2.1620	2.0129	2.0100	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-232358.2	-232357	-237278.1	-237199.5	-244538.3	-244479.8	-208444.3	-208418.4	-239873	-239774.6
AIC	7.8021	7.8021	8.2741	8.2714	8.6722	8.6701	8.0650	8.0640	8.0542	8.0509
BIC	7.8053	7.8053	8.2779	8.2751	8.6751	8.6730	8.0684	8.0674	8.0563	8.0530
Q(20)	2.38294	2.1699	25.20	26.90	6.519	7.011	6.695	6.801	6.230	6.100
	(0.6000)	(0.6620)	(0.0000)	(0.0000)	(0.0297)	(0.0000)	(0.0254)	(0.0231)	(0.03819)	(0.04273)
$Q^2(36)$	0.0007	0.0008	0.0024	0.0026	0.0009	0.0008	0.0579	0.0581	0.0426	0.0439
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0005	0.0005	0.0011	0.0012	0.0007	0.0006	0.0435	0.0435	0.0229	0.0233
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(1.0000)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Figure 11: The effect of observed VRE generation and observed VRE generation plus curtailed generation on spot price (left panels) and volatility (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.

	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	-87.0655	-76.7986	-70.8963	-17.8313	-23.1743	-158.1378	-160.2840	12.8975
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7891)
ϕ_1	0.9292	0.9290	0.9413	0.9389	0.9091	0.9047	0.9670	0.9658	0.9410
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	-0.1924		-0.5174		-1.0723		-0.1170		
	(0.0000)		(0.0000)		(0.0000)		(0.0051)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0238		-0.1254		-0.1760		-0.0947		
	(0.0898)		(0.0067)		(0.0626)		(0.0697)		
$large\text{-}scale\ solar \times D_{spring}$	-0.1159		-0.3501		-0.4480		-0.2780		
	(0.0000)		(0.0000)		(0.0001)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.6794		-1.5917		-1.4067		-0.3573		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$rooftop\ solar_{winter}$		-0.0670		-0.1737		-0.1165		-0.0525	0.0942
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.7703)
$rooftop\ solar \times D_{autumn}$		0.0234		-0.0166		-0.0052		0.0288	-0.3881
		(0.0021)		(0.4972)		(0.8925)		(0.0004)	(0.4183)
$rooftop\ solar \times D_{spring}$		-0.0315		0.0071		-0.0136		-0.0024	-0.3354
		(0.0050)		(0.7910)		(0.7824)		(0.7891)	(0.6213)
$rooftop\ solar \times D_{summer}$		-0.1274		-0.3863		-0.3447		0.0119	-0.5530
		(0.0000)		(0.0000)		(0.0000)		(0.1635)	(0.7253)
$wind_{winter}$	-0.1859	-0.1597	-0.5544	-0.5227	-1.1915	-1.1247	-0.7041	-0.6768	-1.7660
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
$wind \times D_{autumn}$	0.0094	-0.0144	0.0545	0.0680	0.0031	-0.0020	0.1610	0.1395	0.5348
	(0.8386)	(0.5978)	(0.1023)	(0.0036)	(0.9423)	(0.9808)	(0.1547)	(0.0240)	(0.1830)
$wind \times D_{spring}$	-0.1095	-0.1174	-0.0650	-0.0700	0.0878	0.1000	0.2935	0.2741	0.1802
	(0.0218)	(0.0006)	(0.0559)	(0.1130)	(0.0294)	(0.0172)	(0.4061)	(0.0000)	(0.3306)
$wind \times D_{summer}$	-0.1231	-0.1480	-0.2079	-0.1717	-0.3168	-0.2948	0.1418	0.1163	0.6383
	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.4038)	(0.0000)	(0.0000)
					Variance Equation				
ω	-0.1591	-0.1517	0.6579	0.3639	1.3583	2.2916	1.9702	1.3405	3.9886
	(0.2693)	(0.4765)	(0.0000)	(0.0815)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)
α	-0.1469	-0.1523	0.0438	0.0576	0.0148	0.1330	-1.8804	-1.8706	0.8878
	(0.0000)	(0.0000)	(0.0071)	(0.0001)	(0.5418)	(0.1738)	(0.0000)	(0.0000)	(0.0006)
β	0.7013	0.7335	0.6956	0.6963	0.6992	0.6642	0.6581	0.6730	0.4623
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
γ	1.0414	0.9891	0.7663	0.7326	1.1651	4.7402	5.8461	5.3821	5.2056
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	0.0285		0.0400		0.0459		0.0174		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0111		-0.0155		-0.0110		-0.0046		
	(0.0000)		(0.0000)		(0.0050)		(0.0000)		
$large\text{-}scale\ solar \times D_{spring}$	-0.0027		-0.0039		-0.0094		0.0049		
	(0.1310)		(0.2069)		(0.0169)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.0084		-0.0037		-0.0025		-0.0010		
	(0.0000)		(0.2254)		(0.5414)		(0.3883)		
$rooftop\ solar_{winter}$		0.0156		0.0191		0.0242		0.0127	0.0845
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0010)
$rooftop\ solar \times D_{autumn}$		-0.0055		-0.0057		-0.0054		-0.0039	-0.0819
		(0.0000)		(0.0000)		(0.0001)		(0.0000)	(0.0101)
$rooftop\ solar \times D_{spring}$		-0.0040		-0.0072		-0.0048		0.0003	0.0286
		(0.0000)		(0.0000)		(0.0011)		(0.7029)	(0.2753)
$rooftop\ solar \times D_{summer}$		-0.0062		-0.0053		-0.0026		-0.0030	-0.0785
		(0.0000)		(0.0000)		(0.0958)		(0.0000)	(0.0420)
$wind_{winter}$	0.0005	-0.0011	0.0013	0.0008	-0.0015	-0.0012	0.0007	-0.0027	0.0031
	(0.5170)	(0.0816)	(0.0283)	(0.2369)	(0.0165)	(0.0432)	(0.8172)	(0.3094)	(0.5616)
$wind \times D_{autumn}$	-0.0005	-0.0004	-0.0006	-0.0005	-0.0022	-0.0021	-0.0077	-0.0046	-0.0080
	(0.5304)	(0.5561)	(0.2405)	(0.3418)	(0.0000)	(0.0001)	(0.0222)	(0.1348)	(0.1735)
$wind \times D_{spring}$	0.0008	0.0022	0.0018	0.0037	0.0019	0.0026	-0.0163	-0.0101	0.0165
	(0.3694)	(0.0116)	(0.0045)	(0.0000)	(0.0009)	(0.0000)	(0.0001)	(0.0045)	(0.0217)
$wind \times D_{summer}$	0.0007	0.0021	0.0012	0.0033	-0.0006	0.0004	-0.0150	-0.0072	0.0083
	(0.4315)	(0.0037)	(0.0513)	(0.0000)	(0.2611)	(0.5215)	(0.0000)	(0.0249)	(0.3470)
Skew			0.0819	0.0915	0.9686	0.9671	1.0227	1.0310	1.1045
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8382	2.8217	1.0380	1.0552	2.1947	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)
log likelihood	-230527.7	-231003.5	-235822.3	-235887.2	-242747.9	-242864.7	-206487.9	-207034.7	-239265.5
AIC	7.7412	7.7571	8.2239	8.2261	8.6092	8.6134	7.9899	8.0110	8.0343
BIC	7.7464	7.7624	8.2298	8.2321	8.6092	8.6184	7.9957	8.0168	8.0385
Q(20)	3.9487	6.9743	36.24	42.20	7.161	6.319	4.018	5.052	5.744
	(0.2337)	(0.0197)	(0.0000)	(0.0000)	(0.0000)	(0.0353)	(0.2226)	(0.1020)	(0.0578)
$Q^2(36)$	0.0018	0.0018	0.0142	0.0193	0.0007	0.0006	0.1935	0.1764	0.0397
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)
ARCH-LM Test	0.0012	0.0012	0.0017	0.0027	0.0005	0.0004	0.2201	0.1987	0.0230
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9963)	(0.9971)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

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

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Online Appendix

A Data

Table A.1: Available data for large-scale solar, rooftop solar, and wind generation. The date indicates the starting point of the datasets in each state.

	NSW	VIC	QLD	SA	TAS
Rooftop Solar	2018-03-09 00:00:00	2018-03-09 00:00:00	2018-03-09 00:00:00	2018-03-09 00:00:00	2018-03-09 00:00:00
Large-scale Solar	2015-03-21 00:00:00	2018-04-24 00:00:00	2017-12-01 00:00:00	2018-05-14 00:00:00	No large-scale plants
Large-scale wind	More than a decade	More than a decade	2018-08-20 00:00:00	More than a decade	More than a decade

A.1 Summary statistics and time-series tests of the adjusted data series

Table A.2: Summary statistics of the original and adjusted electricity prices and the corresponding JB tests.

	Unit	Mean	Standard Dev	Skewness	Kurtosis	Median	Minimum	Maximum	1st Quartile	3rd Quartile	JB test
						NSW					
Electricity Prices 2015	AUD/MWh	72.40	191.61	49.15	3010.44	58.94	-139.93	14700.00	38.81	83.14	4.2103e+10
Electricity Prices 2018	AUD/MWh	76.84	213.52	41.31	2202.72	60.15	-139.93	14700.00	41.29	83.83	1.2027e+10
Adjusted Electricity Prices 2015	AUD/MWh	72.40	189.32	50.23	3109.01	65.17	-179.55	14664.29	49.27	80.51	4.4907e+10
Adjusted Electricity Prices 2018	AUD/MWh	76.84	210.76	42.10	2272.64	68.57	-199.91	14641.42	50.34	86.86	1.2803e+10
						VIC					
Electricity Prices	AUD/MWh	77.40	286.26	42.36	1958.69	61.44	-676.37	14700.00	37.58	95.29	9158204713
Adjusted Electricity Prices	AUD/MWh	77.40	282.61	42.65	1977.74	70.76	-621.28	14626.65	44.32	93.36	9337388164
						QLD					
Electricity Prices 2017	AUD/MWh	67.56	172.60	46.79	3330.20	56.51	-859.85	15000.00	38.16	75.89	2.967e+10
Electricity Prices 2018 rooftop	AUD/MWh	67.17	178.76	45.40	3122.65	54.89	-859.85	15000.00	37.29	74.91	2.4176e+10
Electricity Prices 2018 wind	AUD/MWh	66.87	191.09	42.77	2755.24	51.81	-859.85	15000.00	35.81	74.51	1.6332e+10
Adjusted Electricity Prices 2017	AUD/MWh	67.56	168.95	48.21	3505.23	64.36	-849.02	14918.73	40.42	82.03	3.2872e+10
Adjusted Electricity Prices 2018 rooftop	AUD/MWh	67.17	174.87	46.78	3289.72	63.40	-851.87	14916.35	38.68	82.15	2.6834e+10
Adjusted Electricity Prices 2018 wind	AUD/MWh	66.87	186.80	44.05	2902.00	62.42	-848.63	14907.64	36.16	83.05	1.8119e+10
						SA					
Electricity Prices	AUD/MWh	77.40	286.26	42.36	1958.69	61.44	-676.37	14700.00	37.58	95.29	9158204713
Adjusted Electricity Prices	AUD/MWh	77.40	282.61	42.65	1977.74	70.76	-621.28	14626.65	44.32	93.36	9337388164
						TAS					
Electricity Prices	AUD/MWh	63.64	81.52	21.90	738.86	53.91	-844.65	4551.39	32.33	85.83	1348739321
Adjusted Electricity Prices	AUD/MWh	63.64	77.19	25.36	901.74	59.08	-847.71	4516.49	42.76	76.57	2011190775

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

Table A.3: Tests for the autocorrelation and the conditional heteroscedasticity (ARCH effects) in the adjusted prices series.

	NSW (2015)				VIC				QLD (2017)			
Lag	1	7	24	48	1	7	24	48	1	7	24	48
Ljung-Box test	45017	75621	76585	80674	38386	112959	115589	124420	28135	59273	60826	64639
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
ARCH-LM test	36012	37503	37546	37650	34644	35541	35858	36717	40549	44229	44403	44424
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
	NSW (2018)								QLD (2018 - roof)			
Ljung-Box test	23110	44439	44889	46745					26291	55353	5678	60284
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)					(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
ARCH-LM test	20905	23494	23777	23778					37597	41019	41183	41201
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)					(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
	SA				TAS				QLD (2018 - wind)			
Ljung-Box test	31495	83206	86518	89432	4265.8	16292	28130	43169	23029	48267	49429	52317
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
ARCH-LM test	29942	30866	31184	31609	324.66	717.93	846.80	955.95	32637	35615	35758	35771
	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)

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

Table A.4: The augmented Dickey-Fuller (ADF) tests of stationarity. We assume a constant (no visible trend) and choose optimal lag lengths based on the Bayesian information criterion (BIC).

	NSW (2015)	NSW (2018)	SA	VIC	QLD (2017)	QLD (2018 - rooftop)	QLD (2018 - wind)	TAS
					ADF test			
intraday prices	-34.9874	-26.4923	-31.6286	-25.0221	-26.7923	-25.8289	-24.2561	-16.7065
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	-20.7275	-17.3524	-19.7240	-19.3157	-15.2161		-13.2079	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	
large-scale solar pen	-20.2462	-16.0736	-19.6811	-17.9223	-16.3456		-14.6473	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	
rooftop solar		-18.8419	-21.8044	-20.5349		-18.7314	-18.2223	-24.2790
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
rooftop solar pen		-18.4750	-20.5752	-20.8984		-18.2334	-17.1574	-24.0473
		(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)
solar total		-17.3532	-20.5188	-20.1126			-16.2464	
		(0.0000)	(0.0000)	(0.0000)			(0.0000)	
solar total pen		-16.8626	-20.0162	-19.9770			-15.9810	
		(0.0000)	(0.0000)	(0.0000)			(0.0000)	
wind	-29.2005	-20.7268	-33.0654	-25.7079			-13.7774	-24.4109
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)
wind pen	-29.7822	-21.5150	-33.9346	-27.7088			-13.8648	-25.2239
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	(0.0000)
consumption	-22.2513	-15.9641	-17.1399	-17.7405	-13.6983	-13.2551	-12.2678	-19.8793
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hydro	-20.6285	-15.8939		-18.6644	-10.3422	-10.3195	-9.2985	-16.9282
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	-10.0696	-15.8939	-6.3108	-7.6258	-6.9247	-6.5921	-6.1975	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Basslink				-15.5687				-15.7429
				(0.0000)				(0.0000)
Heywood			-21.6460	-21.8392				
			(0.0000)	(0.0000)				
Murrylink			-21.1390	-21.3795				
			(0.0000)	(0.0000)				
Terranora	-19.1589	-15.0073			-15.5351	-15.0073	-14.1811	
	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	
QNI	-18.1018	-14.9023			-15.2865	-14.9023	-14.1366	
	(0.0000)	(0.0000)			(0.0000)	(0.0000)	(0.0000)	
VNI	-22.2530	-17.7476		-17.3851				
	(0.0000)	(0.0000)		(0.0000)				

Hypothesis for ADF test: H_0: unit root (non-stationary); H_1: no unit root (stationary).

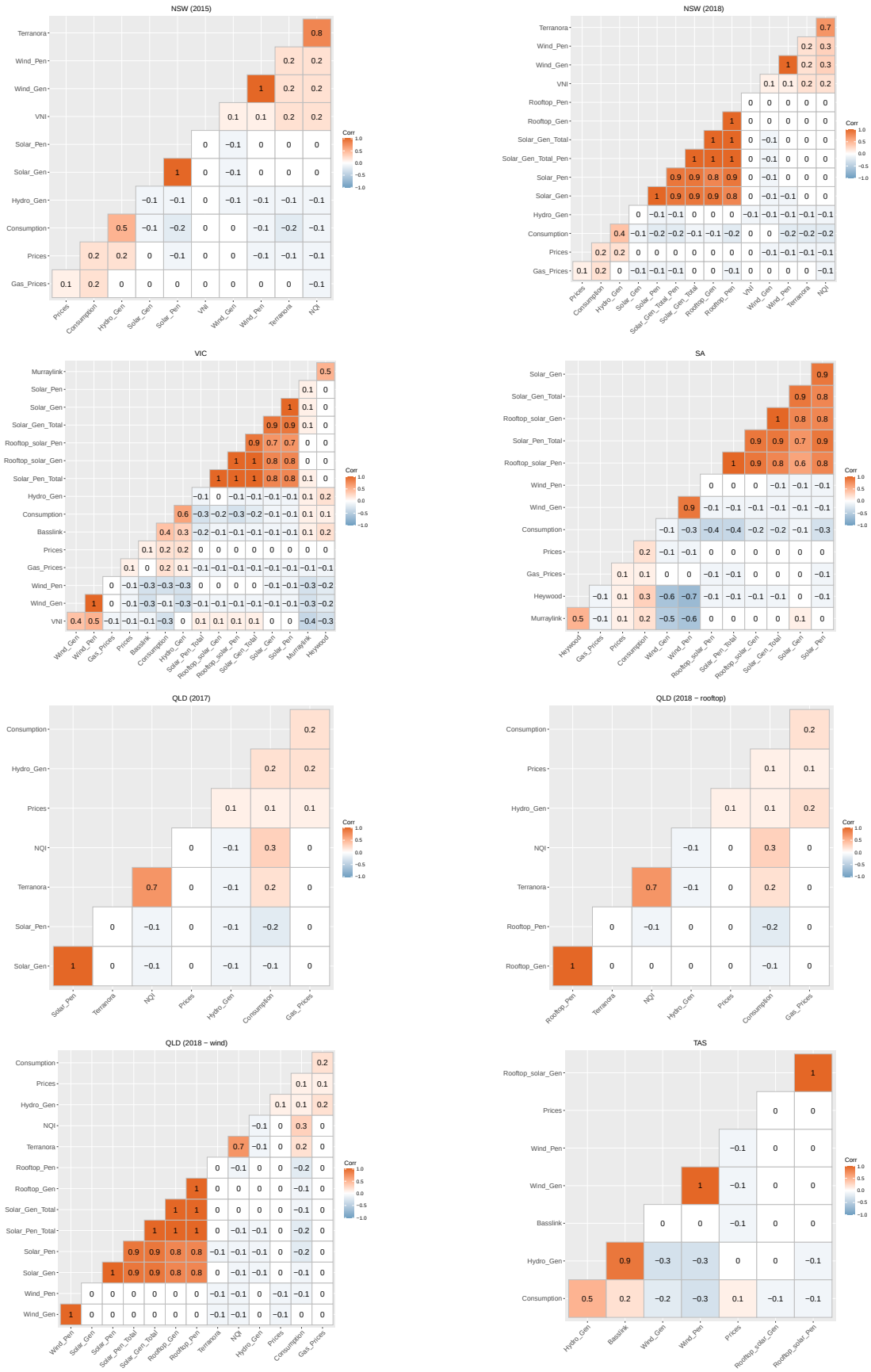

Figure A.1: Correlation coefficient matrix of the variables.

Table A.5: The variance inflation factors (VIF) collinearity diagnostic measure according to model specifications

	NSW (2015)						NSW (2018)					
	Model A	Model B					Model E	Model F	Model G	Model H	Model I	Model J
Solar Gen	1.3567						1.0256					
Solar Pen		1.0592						1.0602				
Rooftop Gen									1.0144			
Rooftop Pen										1.0479		
Solar Gen Total											1.0181	
Solar Pen Total												1.0531
Wind Gen	1.0681						1.0844		1.0786		1.0802	
Wind Pen		1.0829						1.1056		1.0998		1.1014
Consumption	1.3567	1.3968					1.3543	1.4041	1.3520	1.4002	1.3534	1.4035
Hydro Gen	1.2828	1.2816					1.2243	1.2211	1.2249	1.2223	1.2246	1.2219
Gas	1.0326	1.0325					1.0580	1.0579	1.0568	1.0566	1.0571	1.0569
QNI	2.4824	2.4850					2.3699	2.3655	2.3714	2.3675	2.3703	2.3662
VNI	1.0608	1.0604					1.0779	1.0791	1.0781	1.0794	1.0780	1.0793
Terranora	2.4114	2.4113					2.2319	2.2319	2.2328	2.2332	2.2323	2.2325

	VIC						SA					
	Model E	Model F	Model G	Model H	Model I	Model J	Model E	Model F	Model G	Model H	Model I	Model J
Solar Gen	1.0634						1.0493					
Solar Pen		1.0595						1.1914				
Rooftop Gen			1.0531						1.0684			
Rooftop Pen				1.1298						1.2139		
Solar Gen Total					1.0567						1.0688	
Solar Pen Total						1.1335						1.2244
Wind Gen	1.6228		1.6173		1.6207		2.0285		2.0235		2.0290	
Wind Pen		1.6856		1.6864		1.6896		2.3404		2.2733		2.2917
Consumption	2.3322	2.1731	2.3494	2.2724	2.3425	2.2573	1.2081	1.3079	1.2296	1.3568	1.2263	1.3609
Gas Prices	1.0484	1.0484	1.0442	1.0441	1.0449	1.0448	1.0539	1.0592	1.0530	1.0574	1.0533	1.0579
Hydro Gen	2.0693	1.9651	2.0610	1.9667	2.0611	1.9631						
QNI												
VNI	1.8693	1.8827	1.8668	1.8865	1.8686	1.8884						
Terranora												
Heywood	1.4408	1.4408	1.4410	1.4404	1.4406	1.4407	1.9753	2.0001	1.9746	1.9819	1.9764	1.9882
Murraylink	1.4493	1.4525	1.4286	1.4351	1.4328	1.4409	1.5124	1.5469	1.5123	1.5469	1.5122	1.5469
Basslink	1.4668	1.4722	1.4551	1.4638	1.4585	1.4675						

	QLD (2017)		QLD (2018 - roof)	
	Model A	Model B	Model C	Model D
Solar Gen	1.0164			
Solar Pen		1.0448		
Rooftop Gen			1.0142	
Rooftop Pen				1.0522
Solar Gen Total				
Solar Pen Total				
Wind Gen				
Wind Pen				
Consumption	1.1453	1.1682	1.1420	1.1787
Hydro Gen	1.0885	1.0883	1.0728	1.0728
Gas	1.0495	1.0494	1.0518	1.0521
QNI	2.3769	2.3771	2.3391	2.3398
VNI				
Terranora	2.2666	2.2667	2.2411	2.2425
Heywood				
Murrylink				
Basslink				

	QLD (2018 - wind)						TAS	
	Model E	Model F	Model G	Model H	Model I	Model J	Model G	Model H
Solar Gen	1.0107							
Solar Pen		1.0345						
Rooftop Gen			1.0142				1.0141	
Rooftop Pen				1.0527				1.0257
Solar Gen Total					1.0113			
Solar Pen Total						1.0453		
Wind Gen	1.0198		1.0202		1.0200		1.1140	
Wind Pen		1.0224		1.0226		1.0226		1.1108
Consumption	1.1435	1.1640	1.1530	1.1920	1.1484	1.1816	1.3044	1.1638
Hydro Gen	1.0861	1.0854	1.0826	1.0822	1.0833	1.0828	1.3362	1.0342
Gas	1.0648	1.0643	1.0642	1.0648	1.0641	1.0643		
QNI	2.2470	2.2466	2.2466	2.2465	2.2469	2.2468		
VNI								
Terranora	2.1380	2.1386	2.1397	2.1417	2.1387	2.1399		
Heywood								
Murrylink								
Basslink								

B Modeling Approaches

We considered the multiplicative component GARCH (mscGARCH) model for high-frequency data, which has not been previously employed to study the dynamics of electricity prices. Moreover, we tested two models that have been shown to perform better in electricity markets, the exponential GARCH model (eGARCH) (Frömmel et al., 2014; Mwampashi et al., 2021; Thomas and Mitchell, 2005) and the asymmetric power ARCH model (apARCH). Thomas and Mitchell (2005) and Higgs and Worthington (2005) showed that the power ARCH (apARCH) and the apARCH specification outperformed other GARCH-specifications and can better account for the right-skewed and fat-tailed characteristics of electricity prices in the NEM. To this end, we find it important to include them in the analysis.

B.1 The Multiplicative Component GARCH (mcsGARCH)

Our understanding of high-frequency volatility is constrained by data availabilty (Higgs and Worthington, 2010), and also is largely based on the standard GARCH models. However, conventional GARCH approach arguably produces unsatisfactory results when applied to high-frequency data due to the seasonality effects characterizing the intraday time series (Zhang et al., 2014). Although such models can explain well the exponential decay in the autocorrelation structure of the returns, they cannot accommodate the intraday seasonality pattern observed in high-frequency financial returns (Andersen and Bollerslev, 1997, 1998). Following the two-stage approach proposed by Thomas and Mitchell (2005) and most notably Ketterer (2014), it has been a custom to bypass this issue in the Energy and related literatures by deseasonalizing the time series prior to applying the GARCH-based models (Ketterer, 2014; Pereira and Rodrigues, 2015; Mwampashi et al., 2021) or to include dummy variables in the mean or variance equations (or both) to account for these effects. Engle and Sokalska (2012) proposed a robust approach, the mscGARCH for modeling and forecasting intraday volatility. In this approach, the conditional variance is expressed as a product of daily, diurnal, and stochastic intraday volatility components, which can be easily estimated and interpreted. These authors found that this model produced better volatility forecasts than benchmark models when applied to a sample of more than 2500, 10-minute returns.

A considerable number of studies have used the mscGARCH to model and forecast volatility of high-frequency returns. Singh et al. (2013) used the intraday prices spaced over 1, 5, and 10 minutes from the S&P/ASX-50 stock market from January 4, 2012, to March 31, 2012, to forecast the intraday volatility of Australia's stock market and the intraday Value at Risk (VaR). This analysis suggested that the mscGARCH provides a good fit for the dynamics of intraday returns, producing the best forecast results. Diao and Tong (2015) reached a similar conclusion when applying mcsGARCH to forecast intraday volatility and VaR for 5-minute returns of the

CSI 300 index. Zhang et al. (2014) argued that the typical GARCH models do not consider the trend and seasonality in data, thus providing inadequate results when applied to high-frequency data. The authors studied travel time prediction using three GARCH specifications, the standard GARCH (sGARCH), component GARCH (cGARCH), and the mscGARCH models. Using the high-frequency travel-time data obtained along a freeway corridor in Houston, TX, USA, the study concluded that the mscGARCH outperformed sGARCH and cGARCH models and that cGARCH and mscGARCH models could produce better results with data having trend and cyclical components. Narsoo (2016) in studying the intraday volatility of EUR/USD exchange rates for 2015 using the mscGARCH demonstrated that the mscGARCH could accurately forecast volatility and VaR of intraday EUR/USD exchange rates. Summinga-Sonagadu and Narsoo (2019) analyzed the mscGARCH model's performance in forecasting the intraday risk metrics, VaR, and the Expected Shortfall (ES). Using intraday 1-min EUR/USD exchange rate prices for February 2016, the study demonstrated that the mscGARCH produced the best forecast results for VaR and ES under the generalised error distribution (ged) and the asymmetric Skewed Student's-t innovation assumption, respectively.

Based on the observation that mscGARCH had proven suitable for forecasting intraday volatility in many different contexts, we conjecture that this model could also be applied in electricity markets to study intraday price dynamics. To this end, this is the first study to comprehensively assess the intraday prices and volatility using the mscGARCH model. In contrast to existing literature, which applied the mscGARCH to model and forecast the intraday VaR and ES, we adopt the Engle and Sokalska (2012) approach to measure high-frequency cause-and-effect between price dynamics and their determinants.[1] Using a modified version of the Engle and Sokalska (2012) allows us to add the exogenous variables and to study the intra-day impact of solar generation (large-scale and rooftop solar) on price dynamics. This is another contribution of this study.

Formally, let $p_{t,i}$ denote electricity prices, where $t, (t = 1, 2, 3, \ldots, T)$ is the day and $i, (i = 1, 2, 3, \ldots, N)$ is the regularly spaced time interval. Define the conditional mean and variance of the price series as $\mathbb{E}(p_{t,i}|\mathscr{F}_{t,i-1}) = \mu_{t,i}$ and $\mathrm{Var}(p_{t,i}|\mathscr{F}_{t,i-1}) = u_{t,i}$, respectively. The sigma field $\mathscr{F}_{t,i-1}$ denotes publicly available information at the time $(t, t-1)$ (Diao and Tong, 2015). We employ the mcsGARCH of Engle and Sokalska (2012) with some modifications (Ghalanos, 2021). Our first assumption and modification is the inclusion of the ARMAX dynamics in the conditional mean ($\mu_{t,i}$). Following the Engle and Sokalska (2012) approach, we then express the conditional variance as a product of daily, diurnal, and stochastic intraday volatility components. The intraday

[1] The diversions from Engle and Sokalska (2012) approach are detailed in the methodology section.

prices are therefore described by the following process:

$$p_{t,i} = \mu + \sum_{j=1}^{m} \phi_j p_{t,i-j} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{t,ij} + \varepsilon_{t,i},$$
$$\varepsilon_{t,i} = u_{t,i} z_{t,i}, \quad u_{t,i} = \sqrt{h_t s_i q_{t,i}}, \tag{B.1}$$

where h_t is a daily exogenously determined forecast volatility, s_i the diurnal/calendar volatility in each regularly spaced interval i, $q_{t,i}$ is the stochastic intraday volatility, and $z_{t,i}$ is the i.i.d $(0, 1)$ standardized innovation which follows a certain specified distribution. $\boldsymbol{v}_t$ is a vector of exogenous explanatory variables.

The daily variance component (h_t) can be estimated in various ways. Engle and Sokalska (2012) pointed out that the daily sGARCH and realized volatility are alternative estimation approaches for estimating the daily volatility component. Many recent studies leverage GARCH based models to estimate the daily volatility component. Diao and Tong (2015), Narsoo (2016) and Summinga-Sonagadu and Narsoo (2019) compared the performance of sGARCH and eGARCH models under several innovations distributions, concluding that eGARCH outperformed sGARCH under the Student-t distribution (std), skew Student-t distribution (sstd), and ged assumptions, respectively. In contrast, Singh et al. (2013) and (Zhang et al., 2014) employed the sGARCH model.

In this study, we test the sGARCH, apARCH, and eGARCH models chosen based on performance under the normal distribution (norm), skew normal distribution (snorm), generalized error distribution (ged), skew generalized error distribution (sged), Student-t distribution (std), skew Student-t distribution (sstd), normal inverse Gaussian (nig) distribution, and Johnson's reparametrized SU (jsu) distribution. We choose the best distribution assumption based on four information criteria methods, the Akaike (AIC), Bayesian (BIC), Hannan-Quinn (HQIC), and Shibata (SIC) information criteria. We use daily electricity prices from January 2010 to July 2021 to forecast the daily volatility component.[2] From Table B.1, the AR(1)-apARCH(1,1) outperforms the competing models under the sstd distribution assumption for NSW, SA, VIC, and QLD and jsu distribution assumption for TAS. Therefore, the AR(1)-apARCH(1,1) is employed in forecasting the daily volatility component.

[2]There is no established criterion for the choice of the length of the sample period. We use a long period to enhance the model performance. Chanda et al. (2005), for instance, estimated the intraday volatility using tick data spaced in the 10-minutes interval from January 2, 1998, to June 30, 1999, and forecasted the daily component using daily data from August 1985 to June 1999. Singh et al. (2013) used the intraday prices from the ASX-50 stock market for three months from January 4, 2012, to March 31, 2012, and forecasted the daily volatility component using daily data from February 4, 2004, to March 31, 2012 (2062 days). Diao and Tong (2015) used intraday data for the CSI 300 stock price index covering a period from January 4, 2011, to December 31, 2013, and estimated the daily variance component from April 16, 2010, to December 31, 2013. Summinga-Sonagadu and Narsoo (2019) applied the intraday 1-min EUR/USD exchange rate price for February 2016 and estimated the daily variance component using daily EUR/USD exchange rate prices data from December 2, 2003, to February 29, 2016.

The seasonal (diurnal) part of the process represents the regular intraday variations and is estimated from equation (B.1) for each time index scaled by its corresponding variance for each day as follows:

$$\hat{s}_i = \frac{1}{T}\sum_{t=1}^{T}\frac{\varepsilon_{t,i}^2}{h_t}.$$

The remaining component in the variance part, the stochastic intraday component is then modeled as a sGARCH(p,q) process, where the normalized residuals ($\bar{\varepsilon}$) are obtained by dividing residuals by the diurnal and daily volatility components, leading to the following expressions:

$$\bar{\varepsilon}_{t,i} = \frac{\varepsilon_{t,i}}{\sqrt{h_t s_i}} = \sqrt{q_{t,i}} z_{t,i},$$
$$q_{t,i} = \omega + \sum_{j=1}^{p}\alpha_j \bar{\varepsilon}_{t,i-j}^2 + \sum_{j=1}^{q}\beta_j q_{t,i-j} + \sum_{j=1}^{m}\psi \boldsymbol{v}_{t,ij},$$

where $q_{t,i}$ denotes the conditional variance, ω the intercept and α_j $(j = 1, \ldots p)$ and β_j $(j = 1, \ldots q)$ are coefficients that are associated with the degree of innovation from previous period, ε_{t-j}^2 (ARCH term) and previous period's volatility spillover effects, σ_{t-j}^2 (GARCH term), respectively. The conditions $\omega > 0$, $\alpha_j \geq 0$, $\beta_j \geq 0$, and $\alpha_j + \beta_j < 1$ ensure positivity of the variance, stability and covariance stationarity. $\boldsymbol{v}_t$ is a vector of m exogenous explanatory variables which are passed pre-lagged.

Based on the information criteria in Table B.2, the best AR(1)-mscGARCH(1,1) model is attained by the nig distribution assumption for NSW, SA, VIC, and TAS, and jsu for QLD. The estimated daily, diurnal, and stochastic intraday volatility components of the AR(1)-mscGARCH(1,1) are presented in Figure B.1 to Figure B.5. The estimated model results for AR-mscGARCH are given in Table B.5 and for ARX-mscGARCHx in Table B.6.

Table B.1: The performance of the AR(1)-sGARCH(1,1), AR(1)-apARCH(1,1) and AR(1)-eGARCH(1,1) models under a range of univariate distributions, i.e., Normal (norm), skew Normal (snorm), Student-t (std), skew Student-t (sstd), Generalized Error (ged), skew Generalized Error (sged), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution. Daily data extends from January 2010 to July 2021.

	norm	snorm	std	sstd	ged	sged	nig	jsu
NSW								
sGARCH								
AIC	8.7342	8.5849	7.5304	7.5056	12.0408	12.0413	7.5559	7.5194
BIC	8.7417	8.5939	7.5394	7.5161	12.0498	12.0518	7.5664	7.5299
SIC	8.7342	8.5849	7.5304	7.5056	12.0408	12.0413	7.5559	7.5194
HQIC	8.7368	8.5881	7.5336	7.5093	12.0440	12.0450	7.5596	7.5231
eGARCH								
AIC	8.6249	8.2691	7.5082	7.4522	12.0033	12.0037	7.4917	7.4624
BIC	8.6354	8.2811	7.5202	7.4657	12.0153	12.0172	7.5052	7.4759
SIC	8.6249	8.2691	7.5082	7.4522	12.0033	12.0037	7.4917	7.4624
HQIC	8.6287	8.2734	7.5125	7.4570	12.0075	12.0085	7.4965	7.4671
apARCH								
AIC	8.8248	8.3614	7.5622	7.5328	7.6918	7.6483	7.5762	7.5478
BIC	8.8338	8.3719	7.5728	7.5448	7.7023	7.6603	7.5882	7.5598
SIC	8.8248	8.3614	7.5622	7.5328	7.6918	7.6483	7.5762	7.5478
HQIC	8.8280	8.3651	7.5660	7.5370	7.6955	7.6525	7.5804	7.5520
VIC								
sGARCH								
AIC	9.4746	9.2403	8.1421	8.1419	Failed	Failed	8.2091	8.1617
BIC	9.4821	9.2493	8.1512	8.1524	Failed	Failed	8.2196	8.1722
SIC	9.4746	9.2403	8.1421	8.1419	Failed	Failed	8.2091	8.1617
HQIC	9.4773	9.2435	8.1453	8.1456	Failed	Failed	8.2128	8.1654
eGARCH								
AIC	9.4734	9.5762	8.1706	8.1681	8.3038	8.3037	8.2356	8.1889
BIC	9.4824	9.5867	8.1811	8.1801	8.3143	8.3157	8.2476	8.2010
SIC	9.4734	9.5762	8.1706	8.1681	8.3038	8.3037	8.2356	8.1889
HQIC	9.4766	9.5799	8.1743	8.1724	8.3075	8.3079	8.2398	8.1932
apARCH								
AIC	9.0725	9.0886	8.1315	8.1295	Failed	Failed	8.1912	8.1479
BIC	9.0830	9.1006	8.1435	8.1431	Failed	Failed	8.2047	8.1614
SIC	9.0725	9.0886	8.1315	8.1295	Failed	Failed	8.1912	8.1479
HQIC	9.0763	9.0929	8.1357	8.1343	Failed	Failed	8.1959	8.1526
TAS								
sGARCH								
AIC	8.6827	8.4522	7.4954	7.4930	9.8820	9.8824	7.4964	7.4838
BIC	8.6902	8.4612	7.5044	7.5035	9.8910	9.8929	7.5069	7.4943
SIC	8.6827	8.4522	7.4954	7.4930	9.8820	9.8824	7.4964	7.4838
HQIC	8.6854	8.4554	7.4986	7.4967	9.8851	9.8861	7.5001	7.4875
eGARCH								
AIC	8.5600	8.3349	7.4899	7.4896	Failed	Failed	7.4961	7.4876
BIC	8.5690	8.3455	7.5004	7.5016	Failed	Failed	7.5081	7.4996
SIC	8.5600	8.3349	7.4899	7.4896	Failed	Failed	7.4961	7.4876
HQIC	8.5632	8.3387	7.4936	7.4939	Failed	Failed	7.5003	7.4919
apARCH								
AIC	8.4864	8.4220	7.4272	7.4220	9.9109	9.9114	7.4273	7.4173
BIC	8.4970	8.4340	7.4392	7.4355	9.9229	9.9249	7.4408	7.4308
SIC	8.4864	8.4220	7.4272	7.4220	9.9109	9.9114	7.4273	7.4173
HQIC	8.4902	8.4262	7.4315	7.4267	9.9151	9.9162	7.4320	7.4220

	norm	snorm	std	sstd	ged	sged	nig	jsu
SA								
sGARCH								
AIC	10.9531	10.6938	9.3153	9.3114	9.4592	9.4544	9.3565	9.3281
BIC	10.9621	10.7043	9.3258	9.3234	9.4698	9.4664	9.3686	9.3401
SIC	10.9621	10.7043	9.3258	9.3234	9.4698	9.4664	9.3686	9.3401
HQIC	10.9563	10.6975	9.3190	9.3156	9.4630	9.4586	9.3608	9.3324
eGARCH								
AIC	10.7638	10.4802	9.2713	9.2640	13.7205	13.5923	9.3136	9.2808
BIC	10.7713	10.4893	9.2803	9.2745	13.7295	13.6028	9.3241	9.2913
SIC	10.7638	10.4802	9.2713	9.2640	13.7205	13.5923	9.3136	9.2808
HQIC	10.7665	10.4834	9.2745	9.2677	13.7237	13.5960	9.3173	9.2845
apARCH								
AIC	10.5806	10.5596	9.2610	9.2487	13.7367	13.5535	9.2906	9.2635
BIC	10.5911	10.5716	9.2730	9.2622	13.7487	13.5670	9.3041	9.2770
SIC	10.5806	10.5596	9.2610	9.2487	13.7367	13.5535	9.2906	9.2635
HQIC	10.5843	10.5638	9.2652	9.2534	13.7409	13.5583	9.2953	9.2683
QLD								
sGARCH								
AIC	9.2650	8.8852	7.8784	7.8695	12.4080	12.4085	7.9244	7.8829
BIC	9.2725	8.8942	7.8874	7.8800	12.4170	12.4190	7.9349	7.8934
SIC	9.2650	8.8852	7.8784	7.8695	12.4080	12.4085	7.9244	7.8829
HQIC	9.2677	8.8884	7.8816	7.8732	12.4112	12.4122	7.9281	7.8866
eGARCH								
AIC	8.9929	9.1217	7.9316	7.9149	8.1883	8.0573	8.0498	7.9321
BIC	9.0019	9.1322	7.9421	7.9269	8.1988	8.0693	8.0618	7.9442
SIC	8.9929	9.1217	7.9316	7.9149	8.1883	8.0573	8.0498	7.9321
HQIC	8.9961	9.1254	7.9353	7.9192	8.1920	8.0616	8.0540	7.9364
apARCH								
AIC	8.8496	8.8011	7.8320	7.8063	12.3695	12.3700	7.8483	7.8179
BIC	8.8601	8.8131	7.8440	7.8198	12.3815	12.3835	7.8618	7.8314
SIC	8.8496	8.8011	7.8320	7.8062	12.3695	12.3700	7.8483	7.8179
HQIC	8.8533	8.8054	7.8362	7.8110	12.3738	12.3748	7.8531	7.8227

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria. "Failed" denotes modes that failed to converge.

Table B.2: The performance of the AR(1)-mscGARCH(1,1) models under a range of univariate distributions, i.e., Normal (norm), skew Normal (snorm), Student-t (std), skew Student-t (sstd), Generalized Error (ged), skew Generalized Error (sged), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.

	norm	snorm	std	sstd	ged	sged	nig	jsu	norm	snorm	std	sstd	ged	sged	nig	jsu
	NSW								**SA**							
AIC	10.5664	8.6376	7.8187	7.8184	12.5846	10.6872	7.7743	7.7820	10.1815	10.1423	8.8866	8.8857	14.3683	14.3684	8.8039	8.8129
BIC	10.5671	8.6385	7.8196	7.8194	12.5855	10.6883	7.7754	7.7830	10.1823	10.1433	8.8875	8.8868	14.3693	14.3695	8.8050	8.8140
SIC	10.5664	8.6376	7.8187	7.8184	12.5846	10.6872	7.7743	7.7820	10.1815	10.1423	8.8866	8.8857	14.3683	14.3684	8.8039	8.8129
HQIC	10.5666	8.6379	7.8190	7.8187	12.5848	10.6875	7.7747	7.7823	10.1818	10.1426	8.8869	8.8860	14.3686	14.3687	8.8042	8.8133
	VIC								**QLD**							
AIC	9.0757	9.0752	8.3071	8.3070	10.9603	10.5248	8.2643	8.2720	8.9440	9.1242	7.7399	7.7394	7.7201	7.7188	7.7336	7.7151
BIC	9.0764	9.0762	8.3081	8.3081	10.9612	10.5259	8.2654	8.2731	8.9449	9.1252	7.7409	7.7406	7.7212	7.7200	7.7348	7.7163
SIC	9.0757	9.0752	8.3071	8.3070	10.9603	10.5248	8.2643	8.2720	8.9440	9.1242	7.7399	7.7394	7.7201	7.7188	7.7336	7.7151
HQIC	9.0759	9.0755	8.3074	8.3074	10.9606	10.5252	8.2647	8.2723	8.9443	9.1245	7.7402	7.7398	7.7205	7.7191	7.7339	7.7154
	TAS															
AIC	9.8984	9.6597	8.1696	8.1666	12.0140	11.6115	8.0794	8.0828								
BIC	9.8991	9.6606	8.1705	8.1677	12.0149	11.6126	8.0805	8.0838								
SIC	9.8984	9.6597	8.1696	8.1666	12.0140	11.6115	8.0794	8.0828								
HQIC	9.8986	9.6600	8.1698	8.1669	12.0143	11.6118	8.0797	8.0831								

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria.

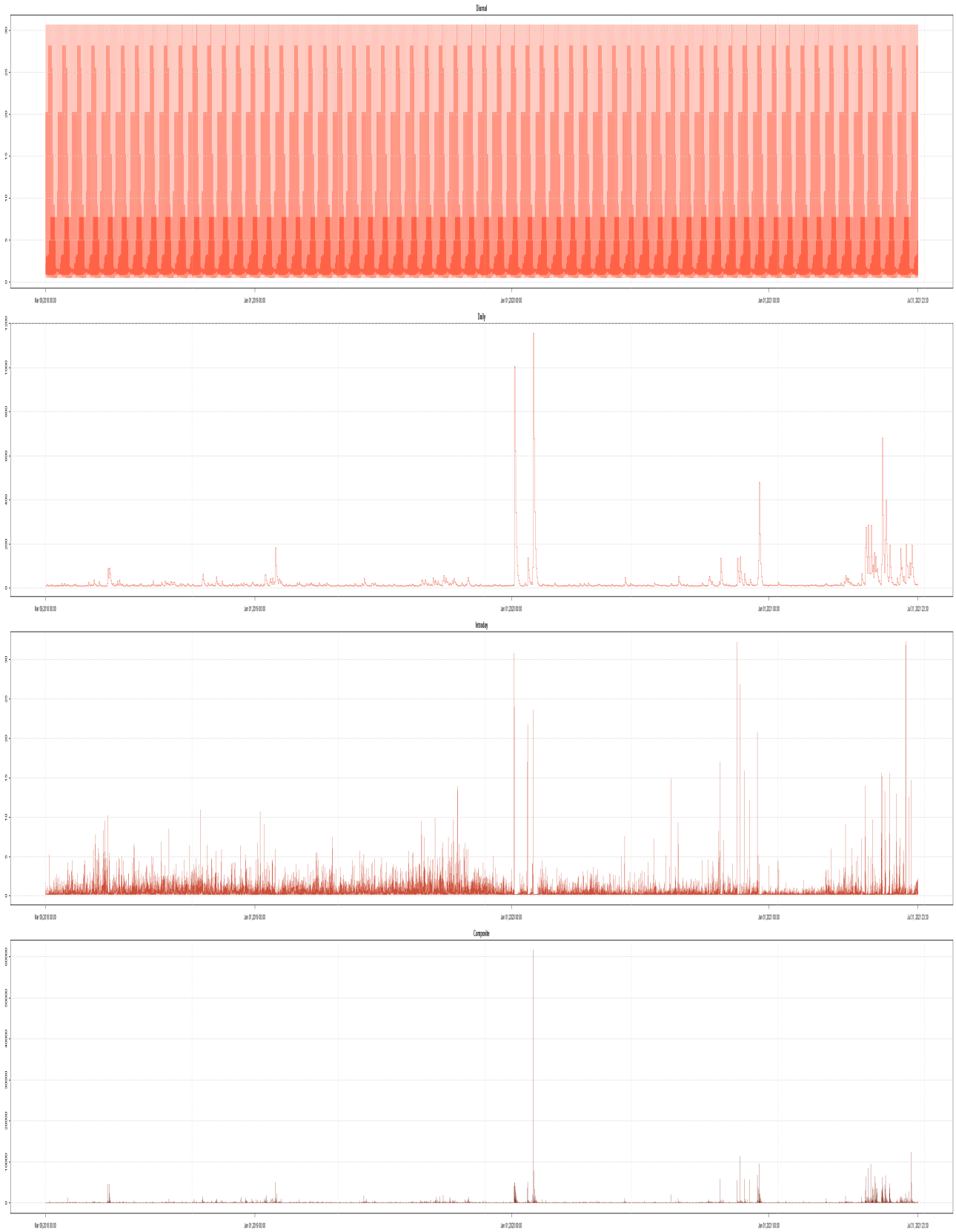

Figure B.1: The diurnal, daily, intraday, and total composite volatility components for NSW from 2018 to 2021.

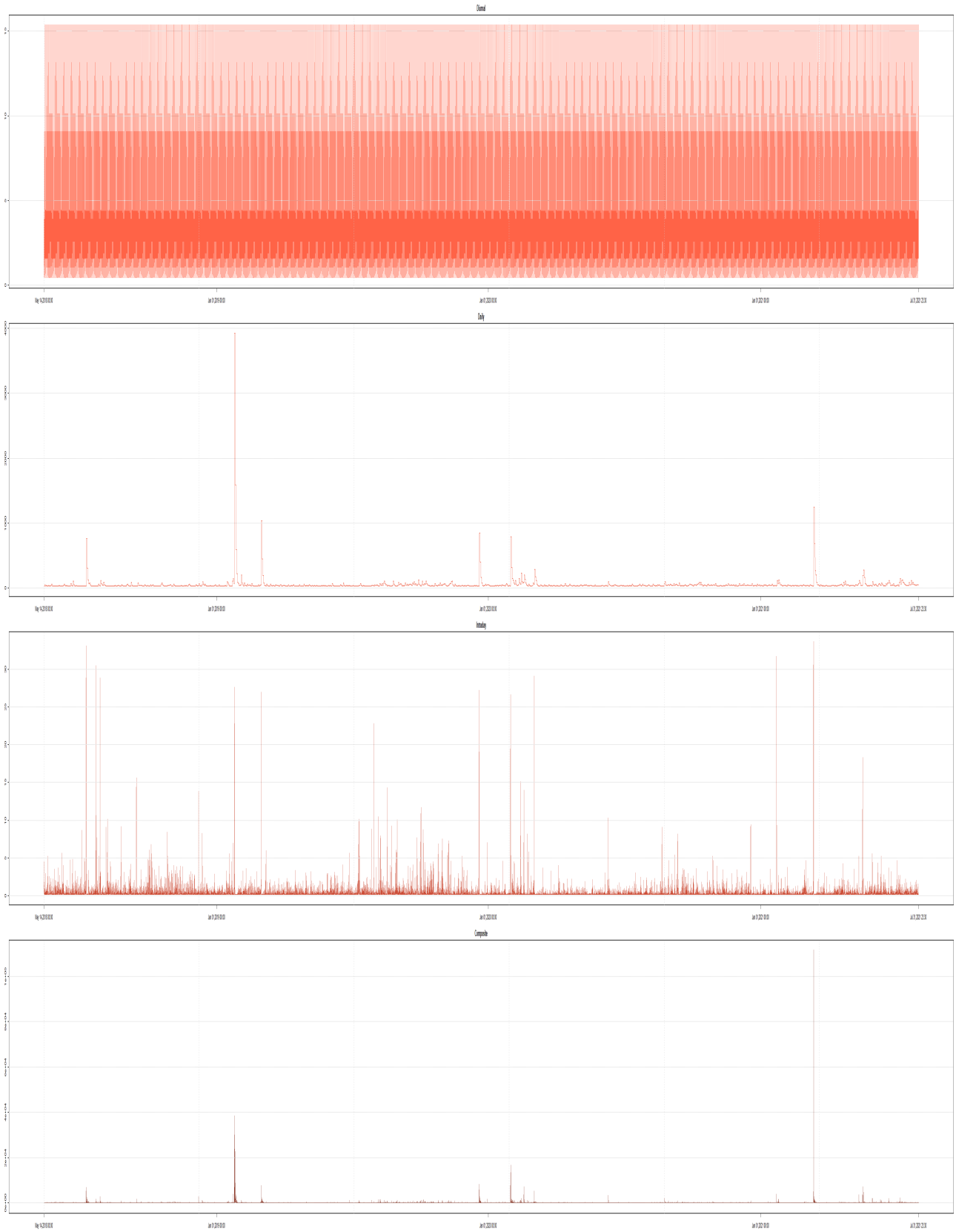

Figure B.2: The diurnal, daily, intraday, and total composite volatility components for SA from 2018 to 2021.

Figure B.3: The diurnal, daily, intraday, and total composite volatility components for VIC from 2018 to 2021.

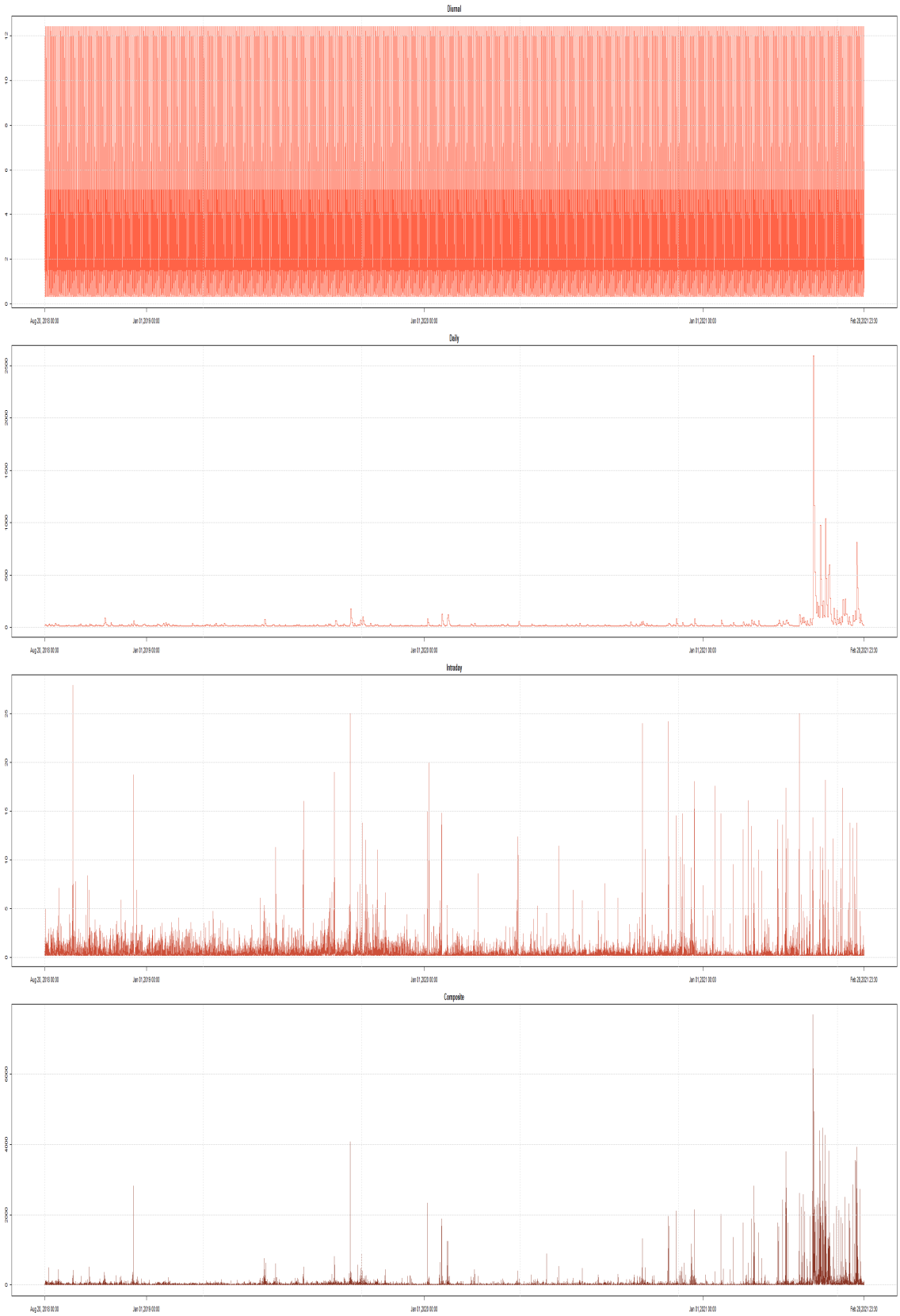

Figure B.4: The diurnal, daily, intraday, and total composite volatility components for QLD from 2018 to 2021.

Figure B.5: The diurnal, daily, intraday, and total composite volatility components for TAS from 2018 to 2021.

B.2 The exponential GARCH model (eGARCH)

The exponential GARCH model of Nelson (1991) with ARMA dynamics and exogenous variables may be written as

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{tj} + \varepsilon_t, \tag{B.2}$$

$$\epsilon_t = z_t \sigma_t \quad \text{with} \quad \log_e(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - \mathbb{E}|z_{t-i}|\right)\right) + \sum_{j=1}^{q} \beta_j \log_e(\sigma_{t-j}^2) + \sum_{k=1}^{r} \psi_k \boldsymbol{v}_{tk}, \tag{B.3}$$

Where p_{t-i}, $i = 1, \ldots, k$ are lags of the electricity prices, α_i and γ_j capture the sign and size effect of the standardized innovations on volatility. We choose the best distribution assumption based on four information criteria methods, AIC, BIC, HQIC, and SIC information criteria. According to the estimated AR(1)-eGARCH(1,1) model in Table B.3, the best performing distribution assumption is sstd for SA, QLD, and TAS electricity prices, std for NSW, and jsu for VIC. We estimate both the AR-eGARCH and ARX-eGARCHX. The results obtained from running these models are presented in Table B.5 and Table B.6, respectively.

Table B.3: The performance of the AR(1)-eGARCH(1,1) model under a range of univariate distributions, i.e., Normal (norm), skew Normal (snorm), Generalized Error (ged), skew Generalized Error (sged), Student-t (std), skew Student-t (sstd), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.

	norm	snorm	std	sstd	ged	sged	nig	jsu	norm	snorm	std	sstd	ged	sged	nig	jsu
	NSW								VIC							
AIC	9.3259	9.0747	7.9578	7.9578	8.0404	8.1569	8.5750	7.9666	8.9869	9.5085	8.4807	8.4651	8.4277	8.4277	8.3986	8.3919
BIC	9.3268	9.0758	7.9588	7.9590	8.0414	8.1581	8.5762	7.9678	8.9878	9.5096	8.4818	8.4663	8.4288	8.4289	8.3998	8.3931
SIC	9.3259	9.0747	7.9578	7.9578	8.0404	8.1569	8.5750	7.9666	8.9869	9.5085	8.4807	8.4651	8.4277	8.4277	8.3986	8.3919
HQIC	9.3262	9.0750	7.9581	7.9582	8.0407	8.1573	8.5753	7.9670	8.9872	9.5089	8.4810	8.4655	8.4280	8.4281	8.3990	8.3923
	SA								QLD							
AIC	10.1589	10.1233	8.8694	8.7625	8.8385	8.9257	8.8644	8.7708	9.5828	9.7640	8.1776	8.1721	8.2816	8.2816	8.2300	8.1904
BIC	10.1598	10.1244	8.8705	8.7638	8.8396	8.9270	8.8657	8.7720	9.5838	9.7652	8.1788	8.1735	8.2828	8.2830	8.2314	8.1917
SIC	10.1589	10.1233	8.8694	8.7625	8.8385	8.9257	8.8644	8.7708	9.5828	9.7640	8.1776	8.1721	8.2816	8.2816	8.2300	8.1904
HQIC	10.1592	10.1237	8.8698	8.7629	8.8388	8.9261	8.8648	8.7712	9.5831	9.7644	8.1779	8.1726	8.2819	8.2821	8.2305	8.1908
	TAS															
AIC	9.1594	9.3703	8.0948	8.0450	8.1453	8.1411	8.0846	8.0740								
BIC	9.1603	9.3713	8.0959	8.0469	8.1464	8.1423	8.0858	8.0752								
SIC	9.1594	9.3703	8.0948	8.0450	8.1453	8.1411	8.0846	8.0740								
HQIC	9.1597	9.3706	8.0952	8.0456	8.1456	8.1415	8.0850	8.0743								

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria.

B.3 The asymmetric power ARCH model (apARCH)

The GARCH types models are built assuming a squared power term, which may not always hold. The apARCH model of Ding et al. (1993) accounts for the leverage and the Taylor effect, and it also allows the power parameter (δ) to be estimated rather than imposed. The apARCH model with exogenous variables and ARMAX dynamics is given by

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

$$\varepsilon_t = z_t \sigma_t \quad \text{with} \quad \sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_j (|z_{t-j}| - \gamma_j z_{t-j})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum_{k=1}^{r} \psi_k \boldsymbol{v}_{tk},$$

$\omega > 0$, $\delta \geq 0$, $\alpha_i \geq 0$ $(i = 1, \ldots, p)$, $\beta_j \geq 0$ $(j = 1, \ldots, q)$, $-1 < \gamma_i < 1$ $(i = 1, \ldots, p)$. Positive γ_i values indicate that negative shocks have a deeper impact on conditional volatility, whereas a negative γ_i indicate that positive shocks have a larger impact on the current conditional variance. δ plays the role of a Box-Cox transformation of the conditional standard deviation σ_t. The persistence of the model is given by $\sum_{j=1}^{p} \beta_j + \sum_{j=1}^{q} \alpha_j \kappa_j$, where κ_j is the expected value of the standardized residuals z_t under the Box-Cox transformation of the term which includes the leverage coefficient γ_j, $\kappa_j = E(|z| - \gamma_j z)^{\delta} = \int_{-\infty}^{\infty} (|z| - \gamma_j z)^{\delta} f(z, 0, 1, ...)\, dz$. The results obtained after running this model presented in Table B.4 indicate that the best AR(1)-apARCH(1,1) model is obtained by assuming the sstd distribution assumption for SA, std for NSW, and jsu for VIC and TAS. We employ these distributions while running the AR-apARCH and ARX-apaRCHX models.

Table B.4: The performance of the AR(1)-apARCH(1,1) model under a range of univariate distributions, i.e., Normal (norm), skew Normal (snorm), Generalized Error (ged), skew Generalized Error (sged), Student-t (std), skew Student-t (sstd), Normal Inverse Gaussian (nig), and Johnson's reparametrized SU (jsu) distribution.

	norm	snorm	std	sstd	nig	jsu	norm	snorm	std	sstd	nig	jsu
	NSW						**VIC**					
AIC	8.9320	8.5824	7.9057	7.9057	7.9581	7.9142	9.1381	8.8948	8.3683	8.3671	8.3784	8.3664
BIC	8.9330	8.5837	7.9070	7.9071	7.9595	7.9155	9.1392	8.8961	8.3695	8.3685	8.3798	8.3678
SIC	8.9320	8.5824	7.9057	7.9057	7.9581	7.9142	9.1381	8.8948	8.3683	8.3671	8.3784	8.3664
HQIC	8.9323	8.5828	7.9061	7.9061	7.9586	7.9146	9.1385	8.8952	8.3686	8.3675	8.3788	8.3668
	SA						**QLD**					
AIC	9.8012	9.7973	8.7387	8.7383	8.7712	8.7448	9.6338	9.6043	8.0802	8.0802	8.1328	8.0905
BIC	9.8023	9.7986	8.7400	8.7397	8.7726	8.7462	9.6350	9.6056	8.0815	8.0818	8.1343	8.0920
SIC	9.8012	9.7973	8.7387	8.7383	8.7712	8.7448	9.6338	9.6043	8.0802	8.0802	8.1328	8.0905
HQIC	9.8016	9.7977	8.7391	8.7387	8.7716	8.7452	9.6342	9.6047	8.0806	8.0807	8.1333	8.0909
	TAS											
AIC	9.1763	11.1368	8.0391	8.0175	8.0137	8.0047						
BIC	9.1773	11.1380	8.0403	8.0189	8.0151	8.0061						
SIC	9.1763	11.1368	8.0391	8.0175	8.0137	8.0047						
HQIC	9.1766	11.1372	8.0394	8.0179	8.0141	8.0052						

AIC, BIC, HQIC, and SIC denote the Akaike, Bayesian, Hannan-Quinn, and Shibata information criteria. We have not included "ged" and "sged" distributions assumptions because their application causes convergence problems.

B.4 Comparison of Models Performance

Table B.5 compares the performance of the mscGARCH, eGARCH, and apARCH models with a single autoregressive component. According to the AIC and BIC, the apARCH model outperforms the competing models in SA and TAS, the mscGARCH outperforms the competing models in VIC and QLD, and the eGARCH outperforms the competing models in NSW. Of these three models, however, the eGARCH appears best capture the autocorrelation and the ARCH effect as evidenced by the weighted Ljung-Box and the weighted Lagrange multiplier tests. In Table B.6 we extend our comparison and include exogenous variables to the mscGARCH, apARCH, and eGARCH models. To easily illustrate the performance of the models, we run a single model only that includes solar generation along with other control variable. The results are similar to other combinations of the exogenous variables. One observation from this analysis is that the estimated coefficients of the variance equation are very small in magnitude, especially for the mscGARCH. We observe similar behavior for the apARCH model though not for all estimated coefficients. Moreover, the estimated

own innovation coefficient in the mscGARCH is 1 for all states. For the apARCH, it is less than 1 in NSW and VIC; in general however, the sum of α and β exceeds 1, suggesting that the proposed models are unstable and that the volatility process is highly persistent. As a robustness test, we add more autoregressive, moving average, and the two together in the ARMAX dynamics slightly improves the model fit in terms of AIC and BIC but no notable changes in the estimated coefficients and the conclusion.[3] In addition to the tiny magnitude and statistical significance of $p = 1$ for all models in the variance equation, we conclude that the proposed models may not be the appropriate choice given our objective of studying the impact of exogenous variables on the price level and volatility. Our results contrast with Higgs and Worthington (2005) who found that the apARCH model performed better when employed to model price volatility in the NEM. We account for the poor performance of the apARCH model in the present analysis for two reasons. First, Higgs and Worthington (2005) modeled the log-returns rather than price levels employed in this analysis. Secondly, the researchers' analysis and conclusion were solely based on the performance of AR-GARCH type models without exogenous variables being included. Moreover, the results for the mscGARCH from Table B.5 and B.6 potentially suggest the model may be well suited for modeling or forecasting volatility alone rather than for studying the cause-effect, making it unsuitable for this analysis.

Following these challenges, we also considered the eGARCH model with exogenous variables. In contrast to the mscGARCH and the apARCH models, the eGARCH yields sound results in both the mean and variance equation. In contrast to other GARCH type models, the eGARCH does not require any restriction on the parameters. Since the logarithm of variance rather than variance itself is modeled, the positivity of the variance is automatically satisfied. Normally, likelihood maximization with no restrictions leads to faster and more reliable optimizations. These results concur with that of Thomas and Mitchell (2005) who found that although the AIC and SBC favored a pARCH specification, the restriction governing the pARCH model failed to hold for all states making the eGARCH the best model. Indeed, existing literature suggests that the eGARCH model has the ability to capture the asymmetry and complexity of price volatility in electricity markets (Bowden and Payne, 2008; Hickey et al., 2012; Frömmel et al., 2014; Mwampashi et al., 2021). Moreover, we see that $\beta < 1$ for all models suggesting that the stationarity condition is satisfied. To further investigate the model performance, we add more autoregressive structures up to 48 lags corresponding to a complete day and also by choosing the optimal ARMA structure using the `auto.arima` package in R (Hyndman et al., 2021). We observe only a slight improvement in the AIC and BIC but no significant changes in the estimated coefficients, especially when approximated to two decimal points. To avoid creating complex models due to the number of exogenous variables under investigation, we, therefore, run the analysis using ARX-eGARCHX with a single autoregressive structure for all models and states based on the distribution assumptions provided

[3]The results for this analysis are available upon request.

Table B.5: The estimated AR(1)-mscGARCH(1,1), AR(1)-apARCH(1,1), and AR(1)-eGARCH(1,1) for New South Wales, Victoria, South Australia, Queensland, and Tasmania.

	NSW			VIC			SA			QLD			TAS		
	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH
	Mean Equation														
μ	42.2542	72.6544	64.9387	48.3535	82.7843	74.0262	46.4770	78.1082	73.1549	29.7595	58.2548	60.5476	72.1060	106.7956	58.9070
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ϕ_1	0.9609	0.9432	0.9476	0.9455	0.9536	0.9329	0.9554	0.9276	0.9324	0.9822	0.9709	0.9648	0.9915	0.95938	0.9463
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Variance Equation														
ω	0.0154	3.0119	1.4979	0.0290	5.9508	1.8148	0.0136	21.3770	2.9503	0.0146	1.9330	3.1325	0.0180	7.4232	3.4448
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.6063	0.8602	-0.1741	0.5482	0.6188	0.0350	0.6346	1.0000	0.3109	0.6165	1.0000	-1.8740	0.7709	1.0000	0.0844
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1512)	(0.0000)	(0.0000)	(0.0093)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0043)
β	0.3926	0.3636	0.7464	0.4508	0.4158	0.7188	0.3644	0.3990	0.7115	0.3825	0.4416	0.6663	0.2281	0.2477	0.5098
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ		0.0838	1.3885		-0.0745	0.78113		-0.0578	5.1072		0.3232	6.3972		-0.6299	1.7821
		(0.0000)	(0.0000)		(0.0003)	(0.0000)		(0.0001)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
δ		0.9421			1.0671			1.2805			0.6472			0.9423	
		(0.0000)			(0.0000)			(0.0000)			(0.0000)			(0.0000)	
Skew	-0.0192			-0.0136	0.0850	-0.0396	-0.0558		0.9710	-0.0297		1.0087	0.1221	0.2294	
	(0.0004)			(0.0414)	(0.0000)	(0.0002)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Shape	0.2044	2.5967	2.3062	0.1892	0.9895	0.9089	0.0928	2.3005	2.0100	0.9618	2.1052	2.0100	0.0751	0.7874	2.1000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-231543.5	-235456.8	-425163.6	-237014.1	-239939.6	-247327.5	-248262.7	-246423.7	-247095.2	-199412.1	-208847.9	-255673.8	-240630.2	-238404.4	-241089.8
AIC	7.7743	7.9057	7.6195	8.2643	8.3664	8.7708	8.8039	8.7387	8.7625	7.7151	8.0802	7.9562	8.0794	8.0047	8.0948
BIC	7.7754	7.9070	7.6201	8.2654	8.3678	8.7720	8.8050	8.7400	8.7638	7.7163	8.0815	7.9574	8.0805	8.0061	8.0959
Q(20)	8.129	1.1749	0.8542	43.9670	21.40	2.325	33.129	7.957	2.090	15.89	25.24	1.1447	86.30	10.911	7.065
	(0.0000)	(0.9173)	(0.9662)	(0.0000)	(0.0000)	(0.6167)	(0.0000)	(0.0080)	(0.6853)	(0.0000)	(0.0000)	(0.9229)	(0.0000)	(0.0001)	(0.0182)
$Q^2(36)$	0.1354	0.0006	0.0003	0.3746	0.0225	0.0013	0.0256	0.0009	0.0013	0.1314	0.0416	0.0963	0.0858	0.0331	0.0425
	(1.0000)	(1.0000)	(1.0000)	(0.9994)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0947	0.0004	0.0003	0.1854	0.0065	0.0009	0.0163	0.0008	0.0009	0.0801	0.0432	0.0560	0.0623	0.0219	0.0233
	(0.9994)	(1.0000)	(1.0000)	(0.9975)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9996)	(0.9999)	(0.9998)	(0.9998)	(1.0000)	(1.0000)
Observations	59568	59568	59568	57360	57360	57360	56400	56400	56400	51696	51696	51696	56400	56400	56400

AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

in Table B.3.

Table B.6: The effect of large-scale and rooftop solar generation on electricity price behavior for New South Wales, Victoria, South Australia, Queensland, and Tasmania. The models are estimated using the ARX-mscGARCHX, ARX-apARCHX, and ARX-eGARCHX. The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	NSW			**VIC**			**SA**			**QLD**			**TAS**		
	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH	mscGARCH	apARCH	eGARCH
							Mean Equation								
μ	-13.5161	-79.4664	-83.2652	14.8972	-71.4141	-79.5598	-6.2029	-11.6603	-18.3237	-34.5787	-162.0577	-158.6972	48.76289	47.9164	12.7981
	(0.0008)	(0.0000)	(0.0000)	(0.0041)	(0.0000)	(0.0000)	(0.1710)	(0.9948)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0019)	(0.0000)	(0.0000)
ϕ_1	0.9377	0.9303	0.9302	0.9210	0.9435	0.9449	0.9242	0.9123	0.9156	0.9794	0.9729	0.9671	0.9890	0.9562	0.9421
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar	0.0292	-0.2682	-0.3061	0.0969	-0.9052	-0.8473	-0.2008	-1.4759	-1.4898	-0.0666	-0.3293	-0.3052			
	(0.0011)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.5635)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
rooftopsolar													0.1074	-0.2121	-0.1630
													(0.1074)	(0.0001)	(0.0329)
wind	-0.1713	-0.2354	-0.2286	-0.1912	-0.6114	-0.5842	-0.6213	-1.2339	-1.2272	-0.2596	-0.5465	-0.5361	-0.7206	-1.2048	-1.3926
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3630)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
hydro	-0.0085	0.2340	0.2443	0.1123	-0.0778	-0.0624				-0.3573	-0.1406	-0.1202	-0.1373	-0.0367	-0.1267
	(0.4843)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)				(0.0000)	(0.0000)	(0.0040)	(0.0000)	(0.0014)	(0.0000)
consumption	0.0982	0.3544	0.3627	0.1254	0.7096	0.7294	0.6819	1.5544	1.6203	0.2230	0.6850	0.6858	0.6109	1.1558	1.3470
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7304)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
gas	3.1283	1.5831	1.5246	1.5060	0.2358	0.3670	3.6761	2.8823	2.8529	0.4747	1.6374	1.6887			
	(0.0000)	(0.0006)	(0.0000)	(0.0008)	(0.0856)	(0.1756)	(0.0000)	(0.9868)	(0.0000)	(0.0583)	(0.0000)	(0.0000)			
$exim_{terra}$	-0.3346	-0.7177	-0.7419							0.4220	-0.0065	0.1042			
	(0.0000)	(0.0257)	(0.0000)							(0.0035)	(0.9231)	(0.3170)			
$exim_{QNI}$	-0.0599	-0.1766	-0.1879							-0.1032	-0.3237	-0.3238			
	(0.0000)	(0.0000)	(0.0000)							(0.0000)	(0.0000)	(0.0000)			
$exim_{murray}$				0.3396	0.6817	0.6864	1.0699	0.5993	0.6393						
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8026)	(0.0000)						
$exim_{heyw}$				-0.0817	-0.0704	-0.0856	-0.2267	-0.8082	-0.8213						
				(0.0007)	(0.0035)	(0.0041)	(0.0000)	(0.0020)	(0.0000)						
$exim_{VNI}$	-0.0735	0.0366	0.0401	-0.2478	0.0722	0.0592									
	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)									
$exim_{bass}$				0.0330	-0.1611	-0.1398									
				(0.0852)	(0.0000)	(0.0000)									
							Variance Equation								
ω	0.0062	3.3118	-0.0814	0.0163	5.1976	0.7074	0.0086	16.6967	1.3335	0.0079	2.0330	2.1076	0.0002	5.8485	3.9125
	(0.0062)	(0.0000)	(0.0570)	(0.0005)	(0.0000)	(0.0000)	(0.0519)	(0.1633)	(0.0000)	(0.2911)	(0.0010)	(0.0000)	(0.9877)	(0.0000)	(0.0000)
α	1.0000	0.9331	-0.1408	1.0000	0.6389	0.0418	1.0000	1.0000	0.0165	1.0000	1.0000	-1.8471	1.0000	1.0000	0.8982
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0418	(0.0000)	(0.0000)	(0.5147)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.4519	0.3463	0.7038	0.4770	0.4136	0.6999	0.4273	0.4091	0.7072	0.4372	0.3981	0.6575	0.3727	0.2413	0.4735
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0477)	(0.0000)	(0.0000)
γ		0.1093	1.0629		-0.0779	0.7817		-0.0097	1.2126		0.2404	6.0079		-0.6563	5.2137
		(0.0000)	(0.0000)		(0.0003)	(0.0000)		(0.9864)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
δ		1.0351			1.0654			1.2466			0.8495			0.9457	
		(0.0000)			(0.0000)			(0.0001)			(0.0000)			(0.0000)	
large-scale solar	1.8188e-11	9.5686e-08	0.0221	5.1292e-12	2.2397e-06	0.0337	3.2448e-09	4.0474e-08	0.0396	2.5397e-10	0.0990	0.0171			
	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(0.9997)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)	(0.0000)			
rooftopsolar													4.5849e-16	4.3012e-08	0.0463
													(1.0000)	(1.0000)	(0.0000)
wind	8.5561e-09	1.0475e-08	0.0007	7.0043e-09	2.7960e-08	0.0019	1.0997e-08	7.2430e-09	-0.0016	9.1958e-09	9.1025e-19	-0.0081	1.3006e-08	1.8521e-07	0.0065
	(0.9999)	(1.0000)	(0.2535)	(1.0000)	(1.0000)	(0.0096)	(0.9998)	(1.0000)	(0.0047)	(0.9999)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0303)
hydro	1.6055e-08	1.1984e-08	0.0069	4.9282e-08	5.6761e-08	0.0051				1.0739e-08	1.1248e-08	0.0190	1.9678e-04	0.0355	0.0045
	(0.9996)	(1.0000)	(0.0000)	(0.9998)	(1.0000)	(0.0001)				(1.0000)	(1.0000)	(0.0000)	(0.3462)	(0.0000)	(0.0000)
consumption	2.3070e-08	3.13980e-08	0.0023	1.0786e-07	3.0017e-07	0.0018	2.1060e-08	2.2434e-08	0.0080	1.5159e-08	1.1509e-08	0.0013	3.0055e-08	4.3196e-06	0.0118
	(0.5961)	(1.0000)	(0.0000)	(0.9922)	(1.0000)	(0.0099)	(0.9997)	(1.0000)	(0.0000)	(0.9867)	(1.0000)	(0.0812)	(0.9999)	(0.9998)	(0.0000)
gas	9.5583e-09	1.2182e-08	0.0498	1.1065e-08	1.7084e-08	0.0445	1.1453e-08	1.4908e-08	0.0284	9.9206e-09	1.7280e-08	0.0638			
	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0000)			
$exim_{terra}$	9.4228e-09	1.0042e-08	-0.0104							9.9751e-09	1.1966e-08	0.0262			
	(1.0000)	(1.0000)	(0.0944)							(1.0000)	(1.0000)	(0.0168)			
$exim_{QNI}$	5.5085e-09	9.7312e-09	-0.0006							9.6602e-09	2.9704e-08	-0.0011			
	(0.9999)	(1.0000)	(0.3631)							(0.9999)	(1.0000)	(0.3736)			
$exim_{murray}$				9.4685e-09	5.4105e-09	-0.0145	7.6305e-09	7.2349e-09	-0.0132						
				(1.0000)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.0001)						
$exim_{heyw}$				5.1970e-09	1.1247e-12	-0.0014	4.2610e-09	1.8412e-09	-0.0038						
				(1.0000)	(1.0000)	(0.1217)	(1.0000)	(1.0000)	(0.0001)						
$exim_{VNI}$	1.2383e-08	2.1588e-08	0.0024	9.4217e-09	1.7905e-08	-0.0005									
	(0.9998)	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(0.3622)									
$exim_{bass}$				1.8373e-08	1.4461e-08	0.0023									
				(0.9999)	(1.0000)	(0.0000)									
Skew	-0.0317			-0.0254	0.0818	0.0797	-0.0854	0.9809	0.9711	-0.0258		1.0226	0.1268	0.2355	1.1061
	(0.0002)			(0.2253)	(0.0000)	(0.0004)	(0.0000)	(0.0050)	(0.0000)	(0.0000)		(0.0000)	(0.0161)	(0.0000)	(0.0000)
Shape	0.1623	2.6514	2.8276	0.1373	1.0084	1.0387	0.0761	2.2962	2.1779	0.8900	2.2159	2.0100	0.0667	0.78638	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0756)	(0.0000)	(0.0000)
log likelihood	-228170.9	-230718	-230912.9	-233623.1	-236373	-236110.6	-244331.6	-242839.6	-242961.9	-197094.3	-204364.2	-206724.5	-238827.6	-237196.4	-239421.2
AIC	7.6616	7.7472	7.7537	8.1467	8.2427	8.2335	8.6649	8.6121	8.6164	7.6259	7.9072	7.9986	8.0192	7.9645	8.0391
BIC	7.6651	7.7508	7.7572	8.1506	8.2469	8.2376	8.6679	8.6154	8.6196	7.6295	7.9110	8.0023	8.0214	7.9670	8.0415
Q(20)	7.583	0.9201	3.7751	29.0159	42.04	38.69	23.3775	13.39	7.258	8.730	23.49	3.887	56.37	11.40	5.644
	(0.0113)	(0.9581)	(0.2635)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0153)	(0.0038)	(0.0000)	(0.2440)	(0.0000)	(0.0003)	(0.0629)
$Q^2(36)$	0.1270	0.0005	0.0020	0.3116	0.0064	0.0412	0.0298	0.0011	0.0006	0.0466	0.0373	0.1901	0.0413	0.0317	0.0392
	(1.0000)	(1.0000)	(1.0000)	(0.9997)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0916	0.0003	0.0013	0.2495	0.0037	0.0038	0.0213	0.0009	0.0005	0.0353	0.0347	0.2030	0.0317	0.0206	0.0216
	(0.9995)	(1.0000)	(1.0000)	(0.9952)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(0.9999)	(0.9969)	(1.0000)	(1.0000)	(1.0000)
Observations	59568	59568	59568	57360	57360	57360	56400	56400	56400	51696	51696	51696	59568	59568	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

B.5 The interpretation of the estimated ARX-eGARCH coefficients

Interpretation of the estimated coefficients in the mean equation is direct, i.e., a 1 unit increase in an independent variable leads to a ζ AUD/MWh change in spot prices. For the variance equation (B.5), since we are modeling the logarithm of σ_t^2, we treated the second equation as a *log-linear* equation, $\ln Y = \psi_0 + \psi_1 X$, so that a 1 unit increase in X (i.e., $\Delta X = 1$) leads to a $100 \times \psi_1\%$ change in Y. In the present analysis, the interpretation of the variance equation is, therefore, a 1 unit increase in the independent variable leads to a $100 \times \psi\%$ change in the spot price volatility.

$$p_t = \mu + \sum_{i=1}^{m} \phi_i p_{t-i} + \sum_{j=1}^{n} \zeta_j \boldsymbol{v}_{jt} + \varepsilon_t, \tag{B.4}$$

$$\varepsilon_t = z_t \sigma_t \quad \text{with} \quad \log_e(\sigma_t^2) = \omega + \sum_{i=1}^{p} \left(\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - \mathbb{E}|z_{t-i}|\right)\right) + \sum_{j=1}^{q} \beta_j \log_e(\sigma_{t-j}^2) + \sum_{k=1}^{r} \psi_k \boldsymbol{v}_{kt}, \tag{B.5}$$

B.6 Intraday and Seasonality Analysis

In existing literature on peak and off-peak analysis (Pereira and Rodrigues, 2015; Rintamäki et al., 2017; Kyritsis et al., 2017; Maciejowska, 2020), the authors simply aggregate the daily peak/off-peak periods onto one (average) value to avoid the non-contiguous time problem and then compare statistics on these (now daily) time-series. However, there is little literature based on the seasons, probably reflecting the challenges associated with data partitioning and the resulting non-contiguous time problem between seasons of the year. We propose an alternative approach based on intraday and seasonal dummies to capture these effects while retaining the high-frequency data. Following the objective of the study which is to examine the impact of VRE on the spot prices dynamics, we base the intraday and seasonality analysis on the two variables of interest, solar and wind generation while controlling for other price determinants.

B.6.1 Intraday effects

Denote solar generation by S_t, wind generation by W_t, hydro generation H_t, electricity consumption C_t, gas prices G_t and interconnectors I_t, then the AR(1)-eGARCH(1,1) with these exogenous

variables can be expressed mathematically as

$$p_t = \mu + \phi p_{t-1} + \zeta_1 S_t + \zeta_2 W_t + \zeta_3 H_t + \zeta_4 C_t + \zeta_5 I_t + \varepsilon_t, \quad \varepsilon_t = z_t \sigma_t \quad \text{with} \tag{B.6}$$

$$\log_e(\sigma_t^2) = \omega + \tau(z_{t-1}) + \beta \log_e(\sigma_{t-1}^2) + \psi_1 S_t + \psi_2 W_t + \psi_3 H_t + \psi_4 C_t + \psi_5 I_t, \tag{B.7}$$

the leverage function, $\tau(\cdot)$, is given by $\tau(z_{t-1}) = (\tau_1 z_{t-1} + \tau_2 (|z_{t-1}| - \mathbb{E}|z_{t-1}|)$. Now assume that one is interested in examining coefficients and the statistical differences of the impact of solar and wind generation within the day, namely off-peak and peak hours. To capture this effect, we introduce one dummy variable for solar and wind generation, D_1, corresponding peak hours, with the reference level being off-peak hours, when $D_1 = 0$. We then add the variables $D_1 \times S_t$, and $D_1 \times W_t$ as extra terms in the regression to capture the intraday effect. Since we are not interested in investigating the variation of the other variables, we include them in the regression as controls to avoid endogeneity problems. Equations (B.6) and (B.7) becomes

$$\begin{aligned} p_t &= \mu + \phi p_{t-1} + \zeta_1 S_t + \zeta_{1,1}(D_1 S_t) + \zeta_2 W_t + \zeta_{2,1}(D_1 W_t) + \zeta_3 H_t + \zeta_4 C_t + \zeta_5 I_t + \varepsilon_t, \\ \varepsilon_t &= z_t \sigma_t \quad \text{with} \end{aligned} \tag{B.8}$$

$$\begin{aligned} \log_e(\sigma_t^2) &= \omega + \tau(z_{t-1}) + \beta \log_e(\sigma_{t-1}^2) + \psi_1 S_t + \psi_{1,1}(D_1 S_t) + \psi_2 W_t + \psi_{2,1}(D_1 W_t) + \\ &+ \psi_3 H_t + \psi_4 C_t + \psi_5 I_t, \end{aligned} \tag{B.9}$$

equation equation (B.8) and (B.9) simplifies to

$$p_t = \mu + \phi p_{t-1} + (\zeta_1 + \zeta_{1,1} D_1) S_t + (\zeta_2 + \zeta_{2,1} D_1) W_t + \zeta_3 H_t + \zeta_4 C_t + \zeta_5 I_t + \varepsilon_t, \quad \varepsilon_t = z_t \sigma_t \quad \text{with}$$

$$\log_e(\sigma_t^2) = \omega + \tau(z_{t-1}) + \beta \log_e(\sigma_{t-1}^2) + (\psi_1 + \psi_{1,1} D_1) S_t + (\psi_2 + \psi_{2,1} D_1) W_t + \psi_3 H_t + \psi_4 C_t + \psi_5 I_t.$$

Then, the estimated coefficients for the peak and off-peak hours in the mean and variance equation are given by

	Solar Generation	Wind Generation	
Mean Equation	$\zeta_1 + \zeta_{1,1} D_1$,	$\zeta_2 + \zeta_{2,1} D_1$	(B.10)
Variance Equation	$\psi_1 + \psi_{1,1} D_1$,	$\psi_2 + \psi_{2,1} D_1$	(B.11)

The estimated coefficients for peak and off-peak hours are recovered as follows:

When $D_1 = 0$, we have the (base) off-peak coefficient of S_t and W_t, namely ζ_1 and ζ_2 in the mean equation and ψ_1 and ψ_2 in the variance equation.

The peak coefficient for solar and wind generation are recovered when $D_1 = 1$, i.e., $\zeta_1 + \zeta_{1,1}$ and $\zeta_2 + \zeta_{2,1}$ in the mean equation and $\psi_1 + \psi_{1,1}$ and $\psi_2 + \psi_{2,1}$ in the variance equation.

B.6.2 Seasonal effects

We estimate the effect of wind and solar generation on spot prices over four seasons using the same approach as in the intraday analysis. The only difference is that here we introduce three dummy variables for solar generation and wind generation, D'_1, D'_2, D'_3, corresponding to autumn, spring, and summer, with the reference level being winter, when all $D_i = 0$. Following the same approach one can show that the estimated coefficients for wind and solar generation are given by

	Solar Generation	Wind Generation	
Mean Equation	$\zeta'_1 + \sum_{i=1}^{3} \zeta'_{1,i} D_i,$	$\zeta'_2 + \sum_{i=1}^{3} \zeta'_{2,i} D'_i$	(B.12)
Variance Equation	$\psi'_1 + \sum_{i=1}^{3} \psi'_{1,i} D_i,$	$\psi'_2 + \sum_{i=1}^{3} \psi'_{2,i} D'_i$	(B.13)

Then the estimated coefficients for the four seasons of the year are recovered as follows:

When all the $D'_i = 0$, we have the (base) winter coefficient of S_t and W_t, namely ζ_1 and ζ'_2 in the mean equation and ψ'_1 and ψ'_2 in the variance equation.

The autumn coefficient for solar and wind generation is recovered when $D'_1 = 1$ and the other $D'_i = 0$, i.e., $\zeta'_1 + \zeta'_{1,1}$ and $\zeta'_2 + \zeta'_{2,1}$ in the mean equation and $\psi_1 + \psi'_{1,1}$ and $\psi'_2 + \psi'_{2,1}$ in the variance equation.

The spring coefficient for solar and wind generation is recovered when $D_2 = 1'$ and the other $D'_i = 0$, i.e., $\zeta'_1 + \zeta'_{1,2}$ and $\zeta'_2 + \zeta'_{2,2}$ in the mean equation and $\psi_1 + \psi'_{1,2}$ and $\psi'_2 + \psi'_{2,2}$ in the variance equation.

The autumn coefficient for solar and wind generation is recovered when $D'_3 = 1$ and the other $D'_i = 0$, i.e., $\zeta'_1 + \zeta'_{1,3}$ and $\zeta'_2 + \zeta'_{2,3}$ in the mean equation and $\psi'_1 + \psi'_{1,3}$ and $\psi'_2 + \psi'_{2,3}$ in the variance equation.

C Results

Table C.1: The effect of large-scale and rooftop solar generation on spot price behavior during off-peak and peak hours. The effect on price levels is given by the mean equation and on price volatility by the variance equation.

	NSW		VIC		SA		QLD		TAS
	Model A	Model B	Model A	Model B	Model A	Model B	Model A	Model B	Model B
				Mean Equation					
μ	-81.3859	-83.8177	-77.2630	-71.3544	-15.2661	-23.5878	-155.2346	-156.1860	12.1986
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2693)
ϕ_1	0.9304	0.9296	0.9445	0.9420	0.9197	0.9143	0.9690	0.9680	0.9424
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
large-scale solar$_{off-peak}$	-0.1842		-0.6465		-1.3178		-0.2961		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
large-scale solar $\times D_{peak}$	-0.7533		-0.9282		-0.6527		-0.1412		
	(0.0000)		(0.0000)		(0.0000)		(0.0013)		
rooftop solar$_{off-peak}$		-0.0559		-0.1605		-0.0440		-0.0215	-0.0794
		(0.0000)		(0.0000)		(0.0206)		(0.0000)	(0.4772)
rooftop solar $\times D_{peak}$		-0.3236		-0.3527		-0.3585		-0.2180	-0.2648
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.1202)
wind$_{off-peak}$	-0.2304	-0.2295	-0.5419	-0.5037	-1.1670	-1.0912	-0.5393	-0.5456	-1.3948
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
wind $\times D_{peak}$	-0.0334	-0.0458	-0.1928	-0.1857	-0.2507	-0.2374	-0.2771	-0.1174	-0.0003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9915)
hydro	0.2328	0.2443	-0.0439	-0.0016			-0.1026	-0.0745	-0.1297
	(0.0000)	(0.0000)	(0.2311)	(0.9837)			(0.1228)	(0.3737)	(0.0000)
consumption	0.3568	0.3585	0.7081	0.6807	1.5493	1.5967	0.6903	0.6999	1.3596
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
gas	1.7481	1.8062	0.3875	0.4971	3.0773	3.2118	1.9266	1.7231	
	(0.1526)	(0.0000)	(0.0791)	(0.2858)	(0.0000)	(0.0000)	(0.0215)	(0.0100)	
$exim_{terra}$	-0.7681	-0.7713					0.0622	0.1366	
	(0.0000)	(0.0000)					(0.6491)	(0.2450)	
$exim_{QN1}$	-0.1802	-0.1850					-0.3008	-0.2956	
	(0.0000)	(0.0000)					(0.0000)	(0.0000)	
$exim_{murray}$			0.6716	0.6255	0.6901	0.7779			
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			
$exim_{heyw}$			-0.0925	-0.1233	-0.7721	-0.7141			
			(0.0010)	(0.0052)	(0.0000)	(0.0000)			
$exim_{VN1}$	0.0343	0.0402	0.0361	0.0043					
	(0.0020)	(0.0000)	(0.2516)	(0.9293)					
$exim_{bass}$			-0.1221	-0.0737					
			(0.0027)	(0.0103)					
				Variance Equation					
ω	0.0666	0.1533	0.7007	0.5146	1.4541	1.3118	1.7048	1.2358	3.9673
	(0.5137)	(0.0556)	(0.0000)	(0.0000)	(0.0000)	(0.0154)	(0.2934)	(0.0000)	(0.0042)
α	0.0071	0.0080	0.0677	0.0905	0.0718	0.0749	-1.2684	-1.3088	0.8892
	(0.6047)	(0.6082)	(0.0000)	(0.0000)	(0.0056)	(0.0312)	(0.0000)	(0.0108)	(0.1994)
β	0.6271	0.6980	0.6528	0.6713	0.6677	0.6493	0.6999	0.7373	0.4738
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
γ	0.8808	0.7466	0.7169	0.6519	1.1453	1.0455	3.5278	2.8514	5.2039
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0225)	(0.0000)
large-scale solar$_{off-peak}$	0.0160		0.0248		0.0196		0.0109		
	(0.0000)		(0.0000)		(0.0000)		(0.0016)		
large-scale solar $\times D_{peak}$	0.0459		0.0650		0.0912		0.0264		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
rooftop solar$_{off-peak}$		0.0080		0.0099		0.0143		0.0075	0.0295
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0011)
rooftop solar $\times D_{peak}$		0.0263		0.0300		0.0342		0.0157	0.0567
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0069)
wind$_{off-peak}$	-0.0014	-0.0017	0.0007	0.0016	-0.0035	-0.0020	-0.0173	-0.0153	0.0020
	(0.0367)	(0.0009)	(0.1451)	(0.0004)	(0.0000)	(0.0014)	(0.0648)	(0.0000)	(0.5307)
wind $\times D_{peak}$	0.0078	0.0070	0.0029	-0.0026	0.0006	-0.0020	0.0460	0.0420	0.0172
	(0.0000)	(0.0000)	(0.0004)	(0.0002)	(0.3820)	(0.0158)	(0.1670)	(0.0000)	(0.0001)
hydro	0.0085	0.0062	0.0061	0.0040			0.0126	0.0092	0.0044
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0126)	(0.0005)	(0.0875)
consumption	0.0023	0.0017	0.0024	0.0028	0.0099	0.0110	0.0014	0.0021	0.0109
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.4740)	(0.0000)	(0.0681)
gas	0.0620	0.0470	0.0515	0.0451	0.0321	0.0355	0.0533	0.0381	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0014)	(0.0000)	
$exim_{terra}$	-0.0114	-0.0118					0.0149	0.0090	
	(0.0721)	(0.0169)					(0.0917)	(0.4568)	
$exim_{QN1}$	-0.0018	-0.0007					-0.0017	-0.0012	
	(0.0116)	(0.2485)					(0.1698)	(0.1809)	
$exim_{murray}$			-0.0176	-0.0125	-0.0165	-0.0159			
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			
$exim_{heyw}$			-0.0017	-0.0023	-0.0055	-0.0046			
			(0.0142)	(0.0002)	(0.0000)	(0.0007)			
$exim_{VN1}$	0.0033	0.0023	-0.0004	-0.0003					
	(0.0000)	(0.0000)	(0.3993)	(0.4370)					
$exim_{bass}$			0.0027	0.0023					
			(0.0000)	(0.0000)					
Skew			0.0585	0.0826	0.9789	0.9785	1.0462	1.0433	1.1061
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8315	2.8449	1.0756	1.1031	2.1936	2.2310	2.0100	2.0100	2.0100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
log likelihood	-227871.7	-228175.8	-234725.8	-234338.5	-241664.9	-241554.4	-204591.5	-204452.7	-239357.7
AIC	7.6517	7.6619	8.1853	8.1718	8.5705	8.5666	7.9162	7.9108	8.0371
BIC	7.6558	7.6660	8.1900	8.1765	8.5743	8.5704	7.9206	7.9153	8.0401
Q(20)	8.062	11.473	52.85	63.14	9.609	8.381	8.051	16.95	5.582
	(0.0072)	(0.0003)	(0.0000)	(0.0000)	(0.0016)	(0.0053)	(0.0073)	(0.0000)	(0.0663)
$Q^2(36)$	0.0019	0.0021	0.0417	0.0483	0.0007	0.0006	0.0225	0.0321	0.0389
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
ARCH-LM Test	0.0010	0.0015	0.0019	0.0017	0.0005	0.0004	0.0154	0.0203	0.0213
	(1.0000)	(1.0000)	(1.000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table C.2: 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.

	NSW		VIC		SA		QLD		TAS
	Model A	Model B	Model A	Model B	Model A	Model B	Model A	Model B	Model B
					Mean Equation				
μ	-82.4669	-87.0655	-76.7986	-70.8963	-17.8313	-23.1743	-158.1378	-160.2840	12.8975
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7891)
ϕ_1	0.9292	0.9290	0.9413	0.9389	0.9091	0.9047	0.9670	0.9658	0.9410
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	-0.1924		-0.5174		-1.0723		-0.1170		
	(0.0000)		(0.0000)		(0.0000)		(0.0051)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0238		-0.1254		-0.1760		-0.0947		
	(0.0898)		(0.0067)		(0.0626)		(0.0697)		
$large\text{-}scale\ solar \times D_{spring}$	-0.1159		-0.3501		-0.4480		-0.2780		
	(0.0000)		(0.0000)		(0.0001)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.6794		-1.5917		-1.4067		-0.3573		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$rooftop\ solar_{winter}$		-0.0670		-0.1737		-0.1165		-0.0525	0.0942
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.7703)
$rooftop\ solar \times D_{autumn}$		0.0234		-0.0166		-0.0052		0.0288	-0.3881
		(0.0021)		(0.4972)		(0.8925)		(0.0004)	(0.4183)
$rooftop\ solar \times D_{spring}$		-0.0315		0.0071		-0.0136		-0.0024	-0.3354
		(0.0050)		(0.7910)		(0.7824)		(0.7891)	(0.6213)
$rooftop\ solar \times D_{summer}$		-0.1274		-0.3863		-0.3447		0.0119	-0.5530
		(0.0000)		(0.0000)		(0.0000)		(0.1635)	(0.7253)
$wind_{winter}$	-0.1859	-0.1597	-0.5544	-0.5227	-1.1915	-1.1247	-0.7041	-0.6768	-1.7660
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
$wind \times D_{autumn}$	0.0094	-0.0144	0.0545	0.0680	0.0031	-0.0020	0.1610	0.1395	0.5348
	(0.8386)	(0.5978)	(0.1023)	(0.0036)	(0.9423)	(0.9808)	(0.1547)	(0.0240)	(0.1830)
$wind \times D_{spring}$	-0.1095	-0.1174	-0.0650	-0.0700	0.0878	0.1000	0.2935	0.2741	0.1802
	(0.0218)	(0.0006)	(0.0559)	(0.1130)	(0.0294)	(0.0172)	(0.4061)	(0.0000)	(0.3306)
$wind \times D_{summer}$	-0.1231	-0.1480	-0.2079	-0.1717	-0.3168	-0.2948	0.1418	0.1163	0.6383
	(0.0003)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.4038)	(0.0000)	(0.0000)
$hydro$	0.2426	0.2561	-0.0637	0.0014			-0.1187	-0.0768	-0.1208
	(0.0000)	(0.0000)	(0.0001)	(0.9591)			(0.0329)	(0.0944)	(0.0935)
$consumption$	0.3587	0.3670	0.7140	0.6846	1.6065	1.6106	0.6806	0.6961	1.3306
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0685)
gas	1.6647	1.5397	0.4927	0.5051	2.8961	3.0580	1.8722	1.7072	
	(0.0000)	(0.0000)	(0.0247)	(0.0190)	(0.0000)	(0.0000)	(0.0005)	(0.0000)	
$exim_{terra}$	-0.7844	-0.8099					0.0810	0.1361	
	(0.0000)	(0.0000)					(0.5732)	(0.3318)	
$exim_{QNI}$	-0.1927	-0.1980					-0.3279	-0.3090	
	(0.0000)	(0.0000)					(0.0000)	(0.0000)	
$exim_{murray}$			0.7122	0.6543	0.6045	0.6704			
			(0.0000)	(0.0000)	(0.0000)	(0.0000)			
$exim_{heyu}$			-0.0863	-0.1210	-0.8336	-0.7673			
			(0.0001)	(0.0000)	(0.0000)	(0.0000)			
$exim_{VNI}$	0.0401	0.0472	0.0574	0.0172					
	(0.0004)	(0.0000)	(0.0000)	(0.4703)					
$exim_{bass}$			-0.1392	-0.0819					
			(0.0000)	(0.0019)					
					Variance Equation				
ω	-0.1591	-0.1517	0.6579	0.3639	1.3583	2.2916	1.9702	1.3405	3.9886
	(0.2693)	(0.4765)	(0.0000)	(0.0815)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)
α	-0.1469	-0.1523	0.0438	0.0576	0.0148	0.1330	-1.8804	-1.8706	0.8878
	(0.0000)	(0.0000)	(0.0071)	(0.0001)	(0.5418)	(0.1738)	(0.0000)	(0.0000)	(0.0006)
β	0.7013	0.7335	0.6956	0.6963	0.6992	0.6642	0.6581	0.6730	0.4623
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
γ	1.0414	0.9891	0.7663	0.7326	1.1651	4.7402	5.8461	5.3821	5.2056
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$large\text{-}scale\ solar_{winter}$	0.0285		0.0400		0.0459		0.0174		
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		
$large\text{-}scale\ solar \times D_{autumn}$	-0.0111		-0.0155		-0.0110		-0.0046		
	(0.0000)		(0.0000)		(0.0050)		(0.0000)		
$large\text{-}scale\ solar \times D_{spring}$	-0.0027		-0.0039		-0.0094		0.0049		
	(0.1310)		(0.2069)		(0.0169)		(0.0000)		
$large\text{-}scale\ solar \times D_{summer}$	-0.0084		-0.0037		-0.0025		-0.0010		
	(0.0000)		(0.2254)		(0.5414)		(0.3883)		
$rooftop\ solar_{winter}$		0.0156		0.0191		0.0242		0.0127	0.0845
		(0.0000)		(0.0000)		(0.0000)		(0.0000)	(0.0010)
$rooftop\ solar \times D_{autumn}$		-0.0055		-0.0057		-0.0054		-0.0039	-0.0819
		(0.0000)		(0.0000)		(0.0001)		(0.0000)	(0.0101)
$rooftop\ solar \times D_{spring}$		-0.0040		-0.0072		-0.0048		0.0003	0.0286
		(0.0000)		(0.0000)		(0.0011)		(0.7029)	(0.2753)
$rooftop\ solar \times D_{summer}$		-0.0062		-0.0053		-0.0026		-0.0030	-0.0785
		(0.0000)		(0.0000)		(0.0958)		(0.0000)	(0.0420)
$wind_{winter}$	0.0005	-0.0011	0.0013	0.0008	-0.0015	-0.0012	0.0007	-0.0027	0.0031
	(0.5170)	(0.0816)	(0.0283)	(0.2369)	(0.0165)	(0.0432)	(0.8172)	(0.3094)	(0.5616)
$wind \times D_{autumn}$	-0.0005	-0.0004	-0.0006	-0.0005	-0.0022	-0.0021	-0.0077	-0.0046	-0.0080
	(0.5304)	(0.5561)	(0.2405)	(0.3418)	(0.0000)	(0.0001)	(0.0222)	(0.1348)	(0.1735)
$wind \times D_{spring}$	0.0008	0.0022	0.0018	0.0037	0.0019	0.0026	-0.0163	-0.0101	0.0165
	(0.3694)	(0.0116)	(0.0045)	(0.0000)	(0.0009)	(0.0000)	(0.0001)	(0.0045)	(0.0217)
$wind \times D_{summer}$	0.0007	0.0021	0.0012	0.0033	-0.0006	0.0004	-0.0150	-0.0072	0.0083
	(0.4315)	(0.0037)	(0.0513)	(0.0000)	(0.2611)	(0.5215)	(0.0000)	(0.0249)	(0.3470)
$hydro$	0.0073	0.0072	0.0049	0.0034			0.0212	0.0175	0.0046
	(0.0000)	(0.0000)	(0.0000)	(0.0160)			(0.0000)	(0.0000)	(0.0004)
$consumption$	0.0024	0.0022	0.0020	0.0032	0.0078	0.0103	0.0017	0.0034	0.0122
	(0.0000)	(0.0009)	(0.0000)	(0.0007)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
gas	0.0510	0.0443	0.0462	0.0410	0.0311	0.0350	0.0616	0.0532	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
$exim_{terra}$	-0.0087	-0.0103	-0.0145	-0.0105			0.0324	0.0220	
	(0.1467)	(0.0776)	(0.0000)	(0.0000)			(0.0027)	(0.0243)	
$exim_{QNI}$	-0.0010	-0.0002	-0.0013	-0.0019			-0.0020	-0.0023	
	(0.1211)	(0.7835)	(0.0336)	(0.0039)			(0.0953)	(0.0191)	
$exim_{murray}$					-0.0139	-0.0138			
					(0.0001)	(0.0000)			
$exim_{heyu}$					-0.0039	-0.0036			
					(0.0001)	(0.0001)			
$exim_{VNI}$	0.0025	0.0022	-0.0004	-0.0004					
	(0.0000)	(0.0000)	(0.2767)	(0.5174)					
$exim_{bass}$			0.0021	0.0018					
			(0.0001)	(0.0189)					
Skew			0.0819	0.0915	0.9686	0.9671	1.0227	1.0310	1.1045
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shape	2.8382	2.8217	1.0380	1.0552	2.1947	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)
log likelihood	-230527.7	-231003.5	-235822.3	-235887.2	-242747.9	-242864.7	-206487.9	-207034.7	-239265.5
AIC	7.7412	7.7571	8.2239	8.2261	8.6092	8.6134	7.9899	8.0110	8.0343
BIC	7.7464	7.7624	8.2298	8.2321	8.6092	8.6184	7.9957	8.0168	8.0385
Q(20)	3.9487	6.9743	36.24	42.20	7.161	6.319	4.018	5.052	5.744
	(0.2337)	(0.0197)	(0.0000)	(0.0000)	(0.0000)	(0.0353)	(0.2226)	(0.1020)	(0.0578)
$Q^2(36)$	0.0018	0.0018	0.0142	0.0193	0.0007	0.0006	0.1935	0.1764	0.0397
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9999)	(1.0000)	(1.0000)
ARCH-LM Test	0.0012	0.0012	0.0017	0.0027	0.0005	0.0004	0.2201	0.1987	0.0230
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9963)	(0.9971)	(1.0000)
Observations	59568	59568	57360	57360	56400	56400	51696	51696	59568

Large-scale solar, rooftop solar, wind generation, electricity consumption, hydro generation, and the cross-border interconnector flows are scaled by 10 to clarify the results' presentation. AIC denotes the Akaike information criterion, BIC is the Bayesian information criterion, and ARCH LM is the Lagrange multiplier test for the ARCH effect. The p values are in parentheses.

Table C.3: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per MWh increase in large-scale solar and wind generation for Victoria. The subscript s denotes large-scale solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03046	0.00000	0.00000	0.00000	-0.00003	0.80876
2	0:30	0.00000	0.00000	-0.03019	0.00000	0.00000	0.00000	0.00002	0.82688
3	1:00	0.00000	0.00000	-0.02831	0.00000	0.00000	0.00000	-0.00009	0.16583
4	1:30	0.00000	0.00000	-0.02432	0.21858	0.00000	0.00000	-0.00019	0.46520
5	2:00	0.00000	0.00000	-0.02502	0.00000	0.00000	0.00000	-0.00033	0.24140
6	2:30	0.00000	0.00000	-0.02215	0.00003	0.00000	0.00000	-0.00015	0.04892
7	3:00	0.00000	0.00000	-0.02131	0.00006	0.00000	0.00000	-0.00025	0.40005
8	3:30	0.00000	0.00000	-0.02101	0.00000	0.00000	0.00000	-0.00012	0.15853
9	4:00	0.00000	0.00000	-0.01880	0.00000	0.00000	0.00000	-0.00014	0.09172
10	4:30	0.00000	0.00000	-0.01957	0.08586	0.00000	0.00000	-0.00019	0.03014
11	5:00	0.00000	0.00000	-0.02470	0.00000	0.00000	0.00000	-0.00017	0.00655
12	5:30	0.00000	0.00000	-0.02812	0.00001	0.00000	0.00000	-0.00027	0.37249
13	6:00	0.02641	0.02475	-0.02319	0.00000	-0.00185	0.26908	0.00042	0.26988
14	6:30	-0.05028	0.53538	-0.02534	0.00312	-0.00011	0.91644	-0.00056	0.12497
15	7:00	-0.05033	0.07035	-0.03082	0.00006	0.00095	0.26330	-0.00046	0.15049
16	7:30	-0.11222	0.00000	-0.04008	0.00000	-0.00069	0.49217	-0.00102	0.00232
17	8:00	-0.10690	0.31795	-0.05149	0.24404	-0.00179	0.35458	-0.00049	0.31983
18	8:30	-0.09866	0.00000	-0.05466	0.00000	-0.00125	0.30480	-0.00045	0.17544
19	9:00	-0.09192	0.00286	-0.05085	0.00000	-0.00137	0.04510	-0.00025	0.11160
20	9:30	-0.06739	0.00000	-0.04441	0.00000	-0.00140	0.03171	-0.00037	0.06042
21	10:00	-0.09448	0.00000	-0.01028	0.00000	-0.00000	0.00000	0.00000	0.00000
22	10:30	-0.04651	0.00208	-0.05263	0.00000	-0.00141	0.11332	-0.00008	0.76206
23	11:00	-0.04752	0.00004	-0.05401	0.00000	-0.00108	0.32003	-0.00013	0.77897
24	11:30	-0.05710	0.00636	-0.05197	0.00000	0.00002	0.99098	0.00072	0.04768
25	12:00	-0.02644	0.29917	-0.05509	0.00000	-0.00207	0.07179	0.00039	0.22278
26	12:30	-0.01451	0.12932	-0.05255	0.00011	-0.00083	0.79536	0.00027	0.64049
27	13:00	-0.04234	0.00000	-0.04908	0.00000	-0.00251	0.07112	0.00077	0.05217
28	13:30	-0.05420	0.07226	-0.05283	0.00000	-0.00344	0.05916	0.00070	0.10969
29	14:00	-0.04377	0.44504	-0.06341	0.00038	-0.00256	0.07041	0.00060	0.52210
30	14:30	-0.05491	0.37699	-0.06378	0.00295	-0.00137	0.30135	0.00018	0.68991
31	15:00	-0.04758	0.04584	-0.05619	0.00000	-0.00145	0.30130	0.00007	0.89398
32	15:30	-0.04220	0.06315	-0.05224	0.00000	0.00025	0.85579	0.00009	0.82340
33	16:00	-0.05702	0.00008	-0.04728	0.00000	0.00002	0.98748	0.00018	0.67185
34	16:30	-0.02736	0.31905	-0.04396	0.00000	-0.00245	0.08465	-0.00035	0.44268
35	17:00	-0.03547	0.11845	-0.04826	0.00000	-0.00056	0.75039	-0.00023	0.54362
36	17:30	-0.09882	0.06428	-0.06292	0.00000	-0.00285	0.27389	-0.00115	0.03599
37	18:00	-0.10283	0.04893	-0.08198	0.00000	-0.00451	0.00317	-0.00112	0.01856
38	18:30	0.12247	0.12315	-0.06441	0.00006	-0.00162	0.47381	-0.00098	0.02078
39	19:00	0.02671	0.85102	-0.05296	0.00001	-0.00124	0.67461	-0.00074	0.07853
40	19:30	0.00000	0.00000	-0.03902	0.00000	0.00000	0.00000	0.00031	0.41897
41	20:00	0.00000	0.00000	-0.03284	0.00000	0.00000	0.00000	0.00024	0.41233
42	20:30	0.00000	0.00000	-0.03648	0.00000	0.00000	0.00000	0.00003	0.80860
43	21:00	0.00000	0.00000	-0.03451	0.00000	0.00000	0.00000	-0.00001	0.98950
44	21:30	0.00000	0.00000	-0.03408	0.00000	0.00000	0.00000	-0.00001	0.92474
45	22:00	0.00000	0.00000	-0.02909	0.00000	0.00000	0.00000	-0.00002	0.60315
46	22:30	0.00000	0.00000	-0.05066	0.00000	0.00000	0.00000	-0.00001	0.98189
47	23:00	0.00000	0.00000	-0.03381	0.00000	0.00000	0.00000	-0.00010	0.34404
48	23:30	0.00000	0.00000	-0.03322	0.00000	0.00000	0.00000	-0.00009	0.32196

Table C.4: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in large-scale solar and wind generation for New South Wales. The subscript s denotes large-solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.01657	0.00000	0.00000	0.00000	-0.00032	0.21172
2	0:30	0.00000	0.00000	-0.01799	0.00000	0.00000	0.00000	-0.00074	0.05522
3	1:00	0.00000	0.00000	-0.01950	0.00000	0.00000	0.00000	-0.00049	0.10473
4	1:30	0.00000	0.00000	-0.01735	0.00074	0.00000	0.00000	-0.00029	0.42765
5	2:00	0.00000	0.00000	-0.02147	0.00000	0.00000	0.00000	-0.00023	0.59615
6	2:30	0.00000	0.00000	-0.02036	0.00000	0.00000	0.00000	0.00002	0.96601
7	3:00	0.00000	0.00000	-0.02039	0.00000	0.00000	0.00000	-0.00001	0.95975
8	3:30	0.00000	0.00000	-0.01976	0.00000	0.00000	0.00000	-0.00086	0.04875
9	4:00	0.00000	0.00000	-0.02340	0.00000	0.00000	0.00000	-0.00055	0.12138
10	4:30	0.00000	0.00000	-0.01657	0.01274	0.00000	0.00000	-0.00058	0.20521
11	5:00	0.00000	0.00000	-0.01327	0.00000	0.00000	0.00000	-0.00011	0.67571
12	5:30	0.00000	0.00000	-0.01472	0.00000	0.00000	0.00000	-0.00056	0.31655
13	6:00	0.03633	0.86739	-0.01721	0.27090	-0.00093	0.67646	-0.00029	0.56622
14	6:30	0.05241	0.87379	-0.01664	0.00015	-0.00057	0.64988	-0.00039	0.47715
15	7:00	-0.01164	0.65410	-0.01785	0.02664	-0.00005	0.96183	-0.00039	0.40068
16	7:30	-0.04618	0.00028	-0.01909	0.00063	-0.00262	0.00097	-0.00111	0.02236
17	8:00	-0.04000	0.00527	-0.01860	0.00224	-0.00164	0.02436	-0.00151	0.00332
18	8:30	-0.02979	0.00042	-0.02426	0.00002	0.00006	0.93573	-0.00059	0.17350
19	9:00	-0.03810	0.00000	-0.02361	0.00000	-0.00101	0.26053	-0.00017	0.77513
20	9:30	-0.03551	0.85315	-0.02160	0.74095	-0.00050	0.86466	-0.00023	0.58788
21	10:00	-0.03452	0.00000	-0.02661	0.00000	-0.00079	0.21046	-0.00033	0.42285
22	10:30	-0.03564	0.00272	-0.02954	0.00000	-0.00131	0.06922	-0.00004	0.93061
23	11:00	-0.02912	0.00017	-0.02849	0.00000	-0.00166	0.02421	-0.00042	0.31023
24	11:30	-0.03230	0.08882	-0.03047	0.00000	-0.00184	0.01403	-0.00027	0.45824
25	12:00	-0.03828	0.06223	-0.03193	0.00016	-0.00138	0.13813	-0.00038	0.41204
26	12:30	-0.03762	0.00000	-0.02977	0.00000	-0.00169	0.02593	-0.00054	0.09517
27	13:00	-0.02831	0.00000	-0.02965	0.00000	-0.00097	0.22828	-0.00017	0.65835
28	13:30	-0.04140	0.00368	-0.02614	0.00107	-0.00094	0.40335	-0.00062	0.23390
29	14:00	-0.03690	0.00000	-0.03102	0.00000	-0.00169	0.07623	-0.00064	0.16867
30	14:30	-0.03413	0.00000	-0.02598	0.00000	0.00045	0.73999	-0.00051	0.21356
31	15:00	-0.03264	0.00046	-0.02638	0.00000	-0.00178	0.01583	-0.00095	0.01014
32	15:30	-0.02588	0.00000	-0.02076	0.00000	-0.00133	0.05264	-0.00087	0.02557
33	16:00	-0.02492	0.00000	-0.02542	0.00000	-0.00208	0.02691	-0.00028	0.60253
34	16:30	-0.02538	0.00164	-0.02284	0.00000	-0.00447	0.00002	-0.00074	0.09350
35	17:00	-0.01939	0.02115	-0.02206	0.00000	-0.00399	0.00011	-0.00089	0.06795
36	17:30	-0.01764	0.22843	-0.02608	0.00000	-0.00425	0.00016	-0.00108	0.03042
37	18:00	-0.03037	0.23160	-0.03208	0.00000	-0.00325	0.00094	-0.00069	0.28795
38	18:30	0.05282	0.00297	-0.03408	0.00002	-0.00191	0.03789	-0.00031	0.59501
39	19:00	0.05732	0.00767	-0.03997	0.00000	-0.00191	0.01633	0.00020	0.68706
40	19:30	0.00000	0.00000	-0.03629	0.00000	0.00000	0.00000	-0.00022	0.58401
41	20:00	0.00000	0.00000	-0.02812	0.00000	0.00000	0.00000	-0.00009	0.80733
42	20:30	0.00000	0.00000	-0.02860	0.00000	0.00000	0.00000	0.00005	0.96052
43	21:00	0.00000	0.00000	-0.02830	0.00000	0.00000	0.00000	-0.00027	0.42627
44	21:30	0.00000	0.00000	-0.02798	0.00000	0.00000	0.00000	-0.00045	0.29808
45	22:00	0.00000	0.00000	-0.02555	0.00000	0.00000	0.00000	-0.00021	0.40452
46	22:30	0.00000	0.00000	-0.02235	0.00000	0.00000	0.00000	-0.00028	0.31246
47	23:00	0.00000	0.00000	-0.02291	0.00000	0.00000	0.00000	-0.00038	0.24506
48	23:30	0.00000	0.00000	-0.02122	0.00000	0.00000	0.00000	-0.00041	0.38835

Table C.5: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in large-scale solar and wind generation for South Australia. The subscript s denotes large-solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.08762	0.00000	0.00000	0.00000	-0.00175	0.01611
2	0:30	0.00000	0.00000	-0.08010	0.00000	0.00000	0.00000	-0.00089	0.16335
3	1:00	0.00000	0.00000	-0.08663	0.00000	0.00000	0.00000	-0.00089	0.12730
4	1:30	0.00000	0.00000	-0.09499	0.00000	0.00000	0.00000	-0.00038	0.51240
5	2:00	0.00000	0.00000	-0.09262	0.00000	0.00000	0.00000	-0.00081	0.17573
6	2:30	0.00000	0.00000	-0.10004	0.00000	0.00000	0.00000	-0.00048	0.43320
7	3:00	0.00000	0.00000	-0.11788	0.00000	0.00000	0.00000	-0.00061	0.34949
8	3:30	0.00000	0.00000	-0.11929	0.00000	0.00000	0.00000	-0.00126	0.05193
9	4:00	0.00000	0.00000	-0.11054	0.11473	0.00000	0.00000	-0.00155	0.37585
10	4:30	0.00000	0.00000	-0.11203	0.04006	0.00000	0.00000	-0.00042	0.46329
11	5:00	0.00000	0.00000	-0.11154	0.00000	0.00000	0.00000	-0.00066	0.17483
12	5:30	0.00000	0.00000	-0.10847	0.00000	0.00000	0.00000	-0.00036	0.58061
13	6:00	0.00000	0.00000	-0.09554	0.13948	0.00000	0.00000	-0.00051	0.37114
14	6:30	0.00000	0.00000	-0.07876	0.00000	0.00000	0.00000	-0.00036	0.47678
15	7:00	-0.09438	0.00000	-0.11025	0.00000	-0.00013	0.96173	-0.00179	0.01546
16	7:30	-0.21698	0.00000	-0.09053	0.00000	-0.00132	0.66839	-0.00206	0.00023
17	8:00	-0.24954	0.00000	-0.10733	0.00000	-0.00103	0.46685	-0.00109	0.00150
18	8:30	-0.21570	0.00348	-0.08556	0.00000	0.00098	0.64767	-0.00093	0.02675
19	9:00	-0.11227	0.00184	-0.08228	0.00000	-0.00676	0.11266	-0.00110	0.09318
20	9:30	-0.04683	0.21357	-0.08730	0.00000	-0.01068	0.05559	-0.00080	0.16323
21	10:00	-0.03601	0.50002	-0.10030	0.00000	-0.00616	0.03041	-0.00024	0.63344
22	10:30	0.01627	0.84417	-0.10533	0.00000	-0.01372	0.00001	-0.00041	0.54892
23	11:00	0.03279	0.70077	-0.11315	0.00000	-0.01274	0.00012	-0.00080	0.25119
24	11:30	0.11136	0.31990	-0.11281	0.00038	-0.01280	0.00001	-0.00082	0.54006
25	12:00	0.13169	0.00408	-0.11563	0.00000	-0.01137	0.00025	-0.00057	0.37665
26	12:30	0.17932	0.00000	-0.10478	0.00000	-0.01460	0.00002	-0.00143	0.04148
27	13:00	0.23561	0.20671	-0.09699	0.00238	-0.01619	0.08042	-0.00118	0.24634
28	13:30	0.23765	0.00024	-0.10296	0.00000	-0.01481	0.00000	-0.00002	0.97100
29	14:00	0.20077	0.37360	-0.10021	0.18837	-0.01252	0.25414	-0.00062	0.73389
30	14:30	0.21934	0.00003	-0.09895	0.00000	-0.01900	0.00000	-0.00114	0.07415
31	15:00	0.17403	0.00026	-0.09344	0.00000	-0.01581	0.00001	-0.00177	0.00235
32	15:30	0.00903	0.99831	-0.09499	0.63194	-0.00977	0.88825	-0.00199	0.14103
33	16:00	-0.05656	0.56005	-0.08930	0.00056	-0.00693	0.00903	-0.00090	0.18287
34	16:30	0.00473	0.95832	-0.08821	0.00000	-0.00767	0.02650	-0.00135	0.01055
35	17:00	-0.12901	0.00000	-0.09938	0.00000	-0.00886	0.00036	-0.00168	0.00420
36	17:30	-0.12450	0.01808	-0.08752	0.00000	0.00156	0.58663	-0.00106	0.08250
37	18:00	-0.21247	0.00000	-0.13113	0.00000	-0.00082	0.80048	-0.00234	0.00000
38	18:30	-0.12154	0.00213	-0.13838	0.00000	0.00278	0.36428	-0.00273	0.00000
39	19:00	-0.14260	0.00014	-0.11904	0.00000	-0.00516	0.14249	-0.00267	0.00000
40	19:30	-0.22805	0.00135	-0.07600	0.00000	-0.00968	0.00285	-0.00204	0.00000
41	20:00	0.00000	0.00000	-0.06622	0.00000	0.00000	0.00000	-0.00150	0.00737
42	20:30	0.00000	0.00000	-0.07453	0.00000	0.00000	0.00000	-0.00245	0.00013
43	21:00	0.00000	0.00000	-0.07450	0.00000	0.00000	0.00000	-0.00181	0.00046
44	21:30	0.00000	0.00000	-0.07558	0.00000	0.00000	0.00000	-0.00150	0.00597
45	22:00	0.00000	0.00000	-0.07071	0.00000	0.00000	0.00000	-0.00063	0.45027
46	22:30	0.00000	0.00000	-0.08782	0.00407	0.00000	0.00000	-0.00139	0.01329
47	23:00	0.00000	0.00000	-0.08239	0.00000	0.00000	0.00000	-0.00074	0.25117
48	23:30	0.00000	0.00000	-0.07701	0.00000	0.00000	0.00000	-0.00081	0.17325

Table C.6: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in large-scale solar and wind generation for Queensland. The subscript s denotes large-solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03630	0.02256	0.00000	0.00000	-0.00279	0.04770
2	0:30	0.00000	0.00000	-0.02880	0.00262	0.00000	0.00000	-0.00048	0.65877
3	1:00	0.00000	0.00000	-0.02766	0.00508	0.00000	0.00000	0.00001	0.92040
4	1:30	0.00000	0.00000	-0.03867	0.00051	0.00000	0.00000	-0.00198	0.15011
5	2:00	0.00000	0.00000	-0.04146	0.00001	0.00000	0.00000	-0.00129	0.27539
6	2:30	0.00000	0.00000	-0.03894	0.00001	0.00000	0.00000	-0.00131	0.12144
7	3:00	0.00000	0.00000	-0.03685	0.00002	0.00000	0.00000	-0.00207	0.00738
8	3:30	0.00000	0.00000	-0.04342	0.00000	0.00000	0.00000	-0.00169	0.01686
9	4:00	0.00000	0.00000	-0.05001	0.00000	0.00000	0.00000	-0.00135	0.06152
10	4:30	0.00000	0.00000	-0.03904	0.00066	0.00000	0.00000	-0.00121	0.16615
11	5:00	0.00000	0.00000	-0.03559	0.00157	0.00000	0.00000	-0.00184	0.05516
12	5:30	0.00000	0.00000	-0.04805	0.00108	0.00000	0.00000	-0.00071	0.49807
13	6:00	0.00000	0.00000	-0.05138	0.00000	0.00000	0.00000	-0.00072	0.52697
14	6:30	-0.10699	0.00196	-0.04916	0.00001	-0.00008	0.91557	-0.00101	0.35817
15	7:00	-0.06257	0.48948	-0.07380	0.01244	0.00023	0.87143	0.00218	0.03984
16	7:30	-0.05971	0.00000	-0.07097	0.00108	0.00012	0.78717	0.00221	0.02050
17	8:00	-0.06098	0.00000	-0.05909	0.00042	-0.00008	0.89798	0.00103	0.37538
18	8:30	-0.05448	0.00000	-0.06496	0.00000	-0.00004	0.93087	-0.00080	0.55993
19	9:00	-0.04782	0.00592	-0.05858	0.00007	-0.00027	0.56042	-0.00084	0.61668
20	9:30	-0.04728	0.00016	-0.05435	0.13336	-0.00071	0.35136	-0.00254	0.08239
21	10:00	-0.04033	0.06359	-0.04552	0.06960	-0.00082	0.11433	0.00062	0.72362
22	10:30	-0.02688	0.05271	-0.05589	0.05037	-0.00126	0.05424	-0.00188	0.14616
23	11:00	-0.00702	0.03722	-0.07591	0.00000	-0.00234	0.00229	-0.00020	0.87722
24	11:30	0.00018	0.99217	-0.08117	0.21427	-0.00179	0.00649	-0.00036	0.77178
25	12:00	-0.00324	0.55079	-0.09201	0.00000	-0.00156	0.00632	-0.00018	0.87183
26	12:30	-0.01119	0.00081	-0.09710	0.00002	-0.00138	0.01586	0.00048	0.62922
27	13:00	-0.01792	0.05761	-0.08489	0.00000	-0.00137	0.12212	0.00069	0.62008
28	13:30	-0.02753	0.01049	-0.04949	0.02421	-0.00186	0.00816	0.00253	0.11760
29	14:00	-0.02158	0.00146	-0.07078	0.00001	-0.00177	0.00164	-0.00034	0.81818
30	14:30	-0.03208	0.00019	-0.05709	0.00455	-0.00263	0.00021	-0.00086	0.68826
31	15:00	-0.03655		-0.25637		0.00000		-0.00000	
32	15:30	-0.04945	0.00126	-0.06474	0.00176	-0.00150	0.10387	-0.00182	0.39966
33	16:00	-0.06554	0.00022	-0.05186	0.02582	-0.00194	0.04184	-0.00225	0.28450
34	16:30	-0.05043	0.00000	-0.03573	0.09526	-0.00359	0.00001	-0.00030	0.85413
35	17:00	-0.04510	0.24280	-0.09080	0.10296	-0.00038	0.44069	-0.00011	0.86233
36	17:30	-0.04353	0.00567	-0.04036	0.17706	-0.00474	0.00000	-0.00701	0.00221
37	18:00	-0.08960	0.00000	-0.14035	0.00000	-0.00031	0.00727	-0.00038	0.33612
38	18:30	-0.04116	0.84038	-0.12280	0.55973	-0.00000	0.99901	0.00029	0.91658
39	19:00	0.00000	0.00000	-0.08152	0.00176	0.00000	0.00000	0.00023	0.36732
40	19:30	0.00000	0.00000	-0.06403	0.00405	0.00000	0.00000	0.00018	0.88163
41	20:00	0.00000	0.00000	-0.04872	0.02833	0.00000	0.00000	0.00104	0.20832
42	20:30	0.00000	0.00000	-0.07540	0.00002	0.00000	0.00000	0.00046	0.04815
43	21:00	0.00000	0.00000	-0.06938	0.08456	0.00000	0.00000	0.00011	0.64644
44	21:30	0.00000	0.00000	-0.05229	0.00001	0.00000	0.00000	0.00015	0.40440
45	22:00	0.00000	0.00000	-0.03199	0.17006	0.00000	0.00000	-0.00107	0.72922
46	22:30	0.00000	0.00000	-0.04067	0.13476	0.00000	0.00000	0.00021	0.71832
47	23:00	0.00000	0.00000	-0.02712	0.00333	0.00000	0.00000	0.00003	0.82671
48	23:30	0.00000	0.00000	-0.03234	0.10758	0.00000	0.00000	-0.00091	0.39678

Empty cells indicate models that failed to return the p-values. But since most of the estimated coefficients are close to ones estimated before or after the time in concern, we find it reasonable to include them in the analysis.

Table C.7: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for New South Wales. The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.01657	0.00000	0.00000	0.00000	-0.00032	0.21172
2	0:30	0.00000	0.00000	-0.01799	0.00000	0.00000	0.00000	-0.00074	0.05522
3	1:00	0.00000	0.00000	-0.01950	0.00000	0.00000	0.00000	-0.00049	0.10473
4	1:30	0.00000	0.00000	-0.01735	0.00074	0.00000	0.00000	-0.00029	0.42765
5	2:00	0.00000	0.00000	-0.02147	0.00000	0.00000	0.00000	-0.00023	0.59615
6	2:30	0.00000	0.00000	-0.02036	0.00000	0.00000	0.00000	0.00002	0.96601
7	3:00	0.00000	0.00000	-0.02039	0.00000	0.00000	0.00000	-0.00001	0.95975
8	3:30	0.00000	0.00000	-0.01976	0.00000	0.00000	0.00000	-0.00086	0.04875
9	4:00	0.00000	0.00000	-0.02340	0.00000	0.00000	0.00000	-0.00055	0.12138
10	4:30	0.00000	0.00000	-0.01657	0.01274	0.00000	0.00000	-0.00058	0.20521
11	5:00	0.00000	0.00000	-0.01327	0.00000	0.00000	0.00000	-0.00011	0.67571
12	5:30	0.00000	0.00000	-0.01472	0.00000	0.00000	0.00000	-0.00056	0.31655
13	6:00	0.02762	0.13557	-0.01762	0.00005	-0.00039	0.39615	-0.00026	0.57025
14	6:30	0.05131	0.20411	-0.01763	0.00439	-0.00027	0.74424	-0.00037	0.48366
15	7:00	-0.01710	0.60867	-0.01473	0.09764	0.00082	0.15906	-0.00035	0.35756
16	7:30	-0.00784	0.48355	-0.01486	0.00613	-0.00201	0.00688	-0.00092	0.06278
17	8:00	-0.01592	0.00058	-0.01444	0.00064	-0.00112	0.06588	-0.00132	0.01001
18	8:30	-0.00963	0.06949	-0.02048	0.00004	-0.00007	0.91340	-0.00059	0.15132
19	9:00	-0.01462	0.00007	-0.02019	0.00001	-0.00052	0.32977	-0.00014	0.77386
20	9:30	-0.01125	0.00594	-0.01639	0.00099	-0.00018	0.63106	-0.00024	0.49355
21	10:00	-0.01306	0.00000	-0.02341	0.00000	-0.00014	0.67682	-0.00005	0.88525
22	10:30	-0.01183	0.00083	-0.02614	0.00000	-0.00016	0.65467	0.00029	0.43805
23	11:00	-0.01247	0.00201	-0.02472	0.00000	-0.00013	0.73046	-0.00008	0.80852
24	11:30	-0.01290	0.00066	-0.02733	0.00000	-0.00014	0.66418	0.00004	0.90444
25	12:00	-0.00995	0.00000	-0.02910	0.00000	0.00022	0.48639	-0.00009	0.78931
26	12:30	-0.00856	0.21115	-0.02688	0.00000	0.00012	0.75771	-0.00034	0.30893
27	13:00	-0.00735	0.89520	-0.02668	0.00000	0.00030	0.38137	-0.00003	0.94820
28	13:30	-0.00837	0.00000	-0.02366	0.00000	0.00071	0.10062	-0.00047	0.37366
29	14:00	-0.00695	0.07237	-0.02917	0.00098	0.00004	0.92091	-0.00051	0.25227
30	14:30	-0.01003	0.05257	-0.02465	0.00000	0.00089	0.11045	-0.00053	0.19863
31	15:00	-0.00839	0.49030	-0.02622	0.00012	-0.00041	0.45982	-0.00083	0.02582
32	15:30	-0.00868	0.09002	-0.02030	0.00000	-0.00012	0.84744	-0.00072	0.06913
33	16:00	-0.00309	0.63690	-0.02358	0.00000	-0.00006	0.94731	-0.00001	0.98380
34	16:30	-0.01448	0.05759	-0.02453	0.00000	-0.00267	0.00797	-0.00025	0.60447
35	17:00	-0.01048	0.24447	-0.02143	0.00000	-0.00285	0.00645	-0.00071	0.16715
36	17:30	0.04889	0.45953	-0.02410	0.00134	-0.00186	0.05566	-0.00128	0.01049
37	18:00	0.09413	0.00000	-0.02403	0.00028	-0.00055	0.45760	-0.00075	0.20462
38	18:30	0.07046	0.50535	-0.03366	0.38725	-0.00085	0.55461	-0.00015	0.90457
39	19:00	0.00000	0.00000	-0.04063	0.00113	0.00000	0.00000	-0.00027	0.62455
40	19:30	0.00000	0.00000	-0.03629	0.00000	0.00000	0.00000	-0.00022	0.58401
41	20:00	0.00000	0.00000	-0.02812	0.00000	0.00000	0.00000	-0.00009	0.80733
42	20:30	0.00000	0.00000	-0.02860	0.00000	0.00000	0.00000	0.00005	0.96052
43	21:00	0.00000	0.00000	-0.02830	0.00000	0.00000	0.00000	-0.00027	0.42627
44	21:30	0.00000	0.00000	-0.02798	0.00000	0.00000	0.00000	-0.00045	0.29808
45	22:00	0.00000	0.00000	-0.02555	0.00000	0.00000	0.00000	-0.00021	0.40452
46	22:30	0.00000	0.00000	-0.02235	0.00000	0.00000	0.00000	-0.00028	0.31246
47	23:00	0.00000	0.00000	-0.02291	0.00000	0.00000	0.00000	-0.00038	0.24506
48	23:30	0.00000	0.00000	-0.02122	0.00000	0.00000	0.00000	-0.00041	0.38835

Table C.8: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for Victoria. The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03046	0.00000	0.00000	0.00000	-0.00003	0.80876
2	0:30	0.00000	0.00000	-0.03019	0.00000	0.00000	0.00000	0.00002	0.82688
3	1:00	0.00000	0.00000	-0.02831	0.00000	0.00000	0.00000	-0.00009	0.16583
4	1:30	0.00000	0.00000	-0.02432	0.21858	0.00000	0.00000	-0.00019	0.46520
5	2:00	0.00000	0.00000	-0.02502	0.00000	0.00000	0.00000	-0.00033	0.24140
6	2:30	0.00000	0.00000	-0.02215	0.00003	0.00000	0.00000	-0.00015	0.04892
7	3:00	0.00000	0.00000	-0.02131	0.00006	0.00000	0.00000	-0.00025	0.40005
8	3:30	0.00000	0.00000	-0.02101	0.00000	0.00000	0.00000	-0.00012	0.15853
9	4:00	0.00000	0.00000	-0.01880	0.00000	0.00000	0.00000	-0.00014	0.09172
10	4:30	0.00000	0.00000	-0.01957	0.08586	0.00000	0.00000	-0.00019	0.03014
11	5:00	0.00000	0.00000	-0.02470	0.00000	0.00000	0.00000	-0.00017	0.00655
12	5:30	0.00000	0.00000	-0.02812	0.00001	0.00000	0.00000	-0.00027	0.37249
13	6:00	0.03657	0.02603	-0.02235	0.00087	-0.00196	0.03005	0.00030	0.44858
14	6:30	0.00462	0.70390	-0.02353	0.00114	-0.00103	0.25309	-0.00077	0.02925
15	7:00	0.01287	0.00753	-0.02838	0.00000	-0.00008	0.89513	-0.00056	0.07891
16	7:30	-0.03996	0.49695	-0.03513	0.25509	-0.00085	0.49617	-0.00103	0.02301
17	8:00	-0.00031	0.00000	-0.04930	0.00000	0.00000	0.00000	0.00000	0.00000
18	8:30	-0.04470	0.00000	-0.04911	0.00000	-0.00081	0.28124	-0.00038	0.13014
19	9:00	-0.04764	0.00000	-0.04709	0.00000	-0.00030	0.28859	-0.00019	0.19287
20	9:30	-0.04440	0.01475	-0.04715	0.00000	-0.00057	0.87528	-0.00043	0.46262
21	10:00	-0.03549	0.00126	-0.04941	0.00000	-0.00029	0.61688	-0.00031	0.14751
22	10:30	-0.03223	0.00957	-0.05491	0.00000	0.00001	0.96575	0.00003	0.88696
23	11:00	-0.02838	0.00000	-0.05485	0.00000	0.00009	0.83095	-0.00007	0.85048
24	11:30	-0.02306	0.00096	-0.05493	0.00000	0.00087	0.22042	0.00083	0.03989
25	12:00	-0.01507	0.34728	-0.05604	0.00001	-0.00068	0.20492	0.00039	0.24800
26	12:30	-0.01223	0.00615	-0.05330	0.00000	-0.00024	0.71214	0.00030	0.48536
27	13:00	-0.01366	0.54381	-0.04737	0.00001	-0.00009	0.88594	0.00093	0.02019
28	13:30	-0.01730	0.26099	-0.04901	0.00000	0.00031	0.35475	0.00028	0.35905
29	14:00	-0.01621	0.05952	-0.06268	0.00000	0.00050	0.24371	0.00091	0.08015
30	14:30	-0.01722	0.13839	-0.06144	0.00000	0.00040	0.33552	0.00045	0.26847
31	15:00	-0.00698	0.35766	-0.05066	0.00000	0.00149	0.00572	0.00084	0.03302
32	15:30	-0.01294	0.14869	-0.04917	0.00000	0.00083	0.14131	0.00024	0.51127
33	16:00	-0.00103	0.99913	-0.04213	0.91712	0.00126	0.94492	0.00045	0.95643
34	16:30	-0.00310	0.63505	-0.04142	0.00000	0.00034	0.76453	-0.00008	0.86867
35	17:00	-0.00640	0.90205	-0.04949	0.00180	0.00021	0.84771	-0.00014	0.74894
36	17:30	-0.00106	0.96516	-0.05627	0.00000	-0.00087	0.30035	-0.00068	0.16874
37	18:00	0.08586	0.61522	-0.07290	0.06125	0.00067	0.76006	-0.00063	0.27719
38	18:30	-0.00407	0.99258	-0.07999	0.29599	-0.00204	0.77369	-0.00124	0.01032
39	19:00	0.25400	0.01098	-0.04327	0.00044	-0.00141	0.41123	-0.00038	0.50329
40	19:30	0.00000	0.00000	-0.03902	0.00000	0.00000	0.00000	0.00031	0.41897
41	20:00	0.00000	0.00000	-0.03284	0.00000	0.00000	0.00000	0.00024	0.41233
42	20:30	0.00000	0.00000	-0.03648	0.00000	0.00000	0.00000	0.00003	0.80860
43	21:00	0.00000	0.00000	-0.03451	0.00000	0.00000	0.00000	-0.00001	0.98950
44	21:30	0.00000	0.00000	-0.03408	0.00000	0.00000	0.00000	-0.00001	0.92474
45	22:00	0.00000	0.00000	-0.02909	0.00000	0.00000	0.00000	-0.00002	0.60315
46	22:30	0.00000	0.00000	-0.05066	0.00000	0.00000	0.00000	-0.00001	0.98189
47	23:00	0.00000	0.00000	-0.03381	0.00000	0.00000	0.00000	-0.00010	0.34404
48	23:30	0.00000	0.00000	-0.03322	0.00000	0.00000	0.00000	-0.00009	0.32196

Table C.9: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for South Australia. The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.08762	0.00000	0.00000	0.00000	-0.00175	0.01611
2	0:30	0.00000	0.00000	-0.08010	0.00000	0.00000	0.00000	-0.00089	0.16335
3	1:00	0.00000	0.00000	-0.08663	0.00000	0.00000	0.00000	-0.00089	0.12730
4	1:30	0.00000	0.00000	-0.09499	0.00000	0.00000	0.00000	-0.00038	0.51240
5	2:00	0.00000	0.00000	-0.09262	0.00000	0.00000	0.00000	-0.00081	0.17573
6	2:30	0.00000	0.00000	-0.10004	0.00000	0.00000	0.00000	-0.00048	0.43320
7	3:00	0.00000	0.00000	-0.11788	0.00000	0.00000	0.00000	-0.00061	0.34949
8	3:30	0.00000	0.00000	-0.11929	0.00000	0.00000	0.00000	-0.00126	0.05193
9	4:00	0.00000	0.00000	-0.11054	0.11473	0.00000	0.00000	-0.00155	0.37585
10	4:30	0.00000	0.00000	-0.11203	0.04006	0.00000	0.00000	-0.00042	0.46329
11	5:00	0.00000	0.00000	-0.11154	0.00000	0.00000	0.00000	-0.00066	0.17483
12	5:30	0.00000	0.00000	-0.10847	0.00000	0.00000	0.00000	-0.00036	0.58061
13	6:00	0.00000	0.00000	-0.09554	0.13948	0.00000	0.00000	-0.00051	0.37114
14	6:30	0.00137	0.95257	-0.07870	0.00000	-0.00143	0.13484	-0.00055	0.27748
15	7:00	0.03954	0.33405	-0.10863	0.00000	-0.00033	0.81627	-0.00180	0.01458
16	7:30	0.04898	0.50934	-0.08744	0.00294	-0.00493	0.72487	-0.00219	0.03479
17	8:00	-0.02981	0.12483	-0.09639	0.00000	-0.00134	0.20478	-0.00108	0.00152
18	8:30	-0.05712	0.01807	-0.07966	0.00000	-0.00056	0.66504	-0.00096	0.01067
19	9:00	-0.07782	0.01374	-0.08275	0.00000	-0.00027	0.85914	-0.00033	0.61932
20	9:30	-0.10664	0.00009	-0.09419	0.00000	0.00113	0.11919	0.00003	0.92921
21	10:00	-0.09062	0.00002	-0.10995	0.00000	0.00111	0.28863	0.00039	0.33656
22	10:30	-0.08842	0.01451	-0.12034	0.00000	0.00192	0.25671	0.00100	0.32225
23	11:00	-0.08225	0.00000	-0.12603	0.00000	0.00240	0.00111	0.00065	0.15432
24	11:30	-0.07922	0.09418	-0.13643	0.00001	0.00289	0.00691	0.00085	0.51003
25	12:00	-0.08155	0.00131	-0.14056	0.00000	0.00199	0.05424	0.00071	0.34408
26	12:30	-0.08266	0.06768	-0.14215	0.00000	0.00130	0.20148	0.00009	0.84464
27	13:00	-0.07792	0.00000	-0.13363	0.00000	0.00221	0.00186	0.00087	0.05424
28	13:30	-0.06368	0.00000	-0.13805	0.00000	0.00171	0.03312	0.00165	0.00719
29	14:00	-0.08925	0.00000	-0.13641	0.00000	0.00305	0.00144	0.00124	0.06199
30	14:30	-0.09101	0.00003	-0.13183	0.00000	0.00211	0.15855	0.00077	0.33420
31	15:00	-0.10717	0.01348	-0.12955	0.00000	0.00233	0.06298	0.00011	0.87828
32	15:30	-0.09657	0.00000	-0.11690	0.00000	0.00209	0.03348	-0.00047	0.30219
33	16:00	-0.13260	0.00000	-0.10686	0.00000	0.00285	0.00501	-0.00009	0.86275
34	16:30	-0.12240	0.00000	-0.10005	0.00000	0.00274	0.05177	-0.00050	0.33660
35	17:00	-0.11654	0.80110	-0.09162	0.00703	0.00177	0.81647	-0.00073	0.40007
36	17:30	-0.11601	0.28391	-0.09149	0.01853	0.00225	0.27863	-0.00090	0.10175
37	18:00	-0.02723	0.52806	-0.12613	0.00000	0.00300	0.13082	-0.00224	0.00000
38	18:30	-0.06726	0.31863	-0.13468	0.00000	-0.00127	0.52772	-0.00266	0.00000
39	19:00	0.27542	0.02905	-0.10745	0.00000	-0.00494	0.00302	-0.00177	0.00017
40	19:30	-0.12344	0.00000	-0.07563	0.00000	-0.00555	0.00001	-0.00214	0.00000
41	20:00	0.00000	0.00000	-0.06622	0.00000	0.00000	0.00000	-0.00150	0.00737
42	20:30	0.00000	0.00000	-0.07453	0.00000	0.00000	0.00000	-0.00245	0.00013
43	21:00	0.00000	0.00000	-0.07450	0.00000	0.00000	0.00000	-0.00181	0.00046
44	21:30	0.00000	0.00000	-0.07558	0.00000	0.00000	0.00000	-0.00150	0.00597
45	22:00	0.00000	0.00000	-0.07071	0.00000	0.00000	0.00000	-0.00063	0.45027
46	22:30	0.00000	0.00000	-0.08782	0.00407	0.00000	0.00000	-0.00139	0.01329
47	23:00	0.00000	0.00000	-0.08239	0.00000	0.00000	0.00000	-0.00074	0.25117
48	23:30	0.00000	0.00000	-0.07701	0.00000	0.00000	0.00000	-0.00081	0.17325

Table C.10: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for Queensland. The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.03630	0.01812	0.00000	0.00000	-0.00278	0.04850
2	0:30	0.00000	0.00000	-0.02916	0.16996	0.00000	0.00000	-0.00049	0.66268
3	1:00	0.00000	0.00000	-0.02766	0.00508	0.00000	0.00000	0.00001	0.92040
4	1:30	0.00000	0.00000	-0.03867	0.00043	0.00000	0.00000	-0.00198	0.14993
5	2:00	0.00000	0.00000	-0.04146	0.00000	0.00000	0.00000	-0.00129	0.27580
6	2:30	0.00000	0.00000	-0.03896	0.00001	0.00000	0.00000	-0.00131	0.12045
7	3:00	0.00000	0.00000	-0.03624	0.00247	0.00000	0.00000	-0.00207	0.00661
8	3:30	0.00000	0.00000	-0.04342	0.00000	0.00000	0.00000	-0.00169	0.01700
9	4:00	0.00000	0.00000	-0.05001	0.00005	0.00000	0.00000	-0.00135	0.07974
10	4:30	0.00000	0.00000	-0.03904	0.00066	0.00000	0.00000	-0.00121	0.16615
11	5:00	0.00000	0.00000	-0.03562	0.01925	0.00000	0.00000	-0.00184	0.06322
12	5:30	0.00000	0.00000	-0.04804	0.00000	0.00000	0.00000	-0.00071	0.49590
13	6:00	-0.01074	0.00002	-0.05251	0.00000	-0.00034	0.63774	-0.00091	0.44737
14	6:30	0.00560	0.17150	-0.04902	0.00000	-0.00093	0.13986	-0.00164	0.11364
15	7:00	-0.00172	0.02399	-0.05802	0.00000	-0.00164	0.27716	-0.00069	0.73618
16	7:30	-0.02345	0.01142	-0.06251	0.00089	-0.00038	0.56916	0.00177	0.10948
17	8:00	-0.03470	0.01108	-0.06282	0.80932	-0.00006	0.97499	0.00065	0.62687
18	8:30	-0.05202	0.00000	-0.07781	0.00095	0.00003	0.96490	-0.00178	0.18767
19	9:00	-0.04474	0.00000	-0.06642	0.00000	0.00050	0.43955	-0.00166	0.20569
20	9:30	-0.03246	0.02986	-0.06658	0.00117	-0.00043	0.56775	-0.00282	0.03297
21	10:00	-0.02442	0.00000	-0.04972	0.00001	-0.00036	0.45105	-0.00017	0.89751
22	10:30	-0.02093	0.00000	-0.06188	0.00000	-0.00085	0.09775	-0.00242	0.02831
23	11:00	-0.02161	0.00000	-0.08455	0.00000	-0.00081	0.10155	-0.00092	0.47951
24	11:30	-0.01037	0.00173	-0.08387	0.00001	-0.00032	0.39552	-0.00054	0.64717
25	12:00	-0.00854	0.11664	-0.09381	0.00000	-0.00001	0.97202	-0.00013	0.90509
26	12:30	-0.01034	0.10456	-0.09888	0.00069	-0.00020	0.45424	0.00045	0.66122
27	13:00	-0.01082	0.01916	-0.08699	0.00000	0.00027	0.43023	0.00043	0.75858
28	13:30	-0.01181	0.00004	-0.05203	0.00000	0.00100	0.01645	0.00159	0.26939
29	14:00	-0.01091	0.00282	-0.07288	0.02724	-0.00013	0.79115	-0.00093	0.59486
30	14:30	-0.01209	0.00918	-0.06384	0.00114	0.00014	0.77105	-0.00151	0.46040
31	15:00	-0.01474	0.00015	-0.08592	0.00000	0.00044	0.60861	0.00062	0.73167
32	15:30	-0.00104	0.97551	-0.05734	0.06986	-0.00028	0.47693	0.00027	0.83239
33	16:00	-0.00639	0.58255	-0.06049	0.03079	0.00021	0.81768	-0.00232	0.22020
34	16:30	-0.00562	0.64146	-0.04222	0.06036	-0.00261	0.01062	-0.00096	0.70951
35	17:00	0.02656	0.00000	-0.08165	0.04957	-0.00044	0.00788	-0.00053	0.25943
36	17:30	0.06367	0.00000	0.02203	0.00000	0.00041	0.00000	-0.00733	0.00000
37	18:00	0.04242	0.00000	-0.09987	0.00024	0.00016	0.33628	0.00031	0.53083
38	18:30	0.00000	0.00000	-0.11845	0.00843	0.00000	0.00000	0.00014	0.82094
39	19:00	0.00000	0.00000	-0.08158	0.00172	0.00000	0.00000	0.00023	0.37011
40	19:30	0.00000	0.00000	-0.07830	0.00220	0.00000	0.00000	0.00015	0.89564
41	20:00	0.00000	0.00000	-0.04874	0.03521	0.00000	0.00000	0.00104	0.21224
42	20:30	0.00000	0.00000	-0.07545	0.00001	0.00000	0.00000	0.00047	0.04719
43	21:00	0.00000	0.00000	-0.06938	0.08456	0.00000	0.00000	0.00011	0.64644
44	21:30	0.00000	0.00000	-0.05231	0.29593	0.00000	0.00000	0.00015	0.47872
45	22:00	0.00000	0.00000	-0.03580	0.55965	0.00000	0.00000	-0.00019	0.59752
46	22:30	0.00000	0.00000	-0.04067	0.13476	0.00000	0.00000	0.00021	0.71832
47	23:00	0.00000	0.00000	-0.02494	0.00362	0.00000	0.00000	-0.00093	0.33549
48	23:30	0.00000	0.00000	-0.03234	0.10758	0.00000	0.00000	-0.00091	0.39678

Table C.11: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in rooftop solar and wind generation for Tasmania. The subscript s denotes rooftop solar, and w denotes wind generation.

	Time	MOEs	pMOEs	MOEw	pMOEw	VOLs	pVOLs	VOLw	pVOLw
1	0:00	0.00000	0.00000	-0.06030	0.00000	0.00000	0.00000	-0.00017	0.88853
2	0:30	0.00000	0.00000	-0.04340	0.00030	0.00000	0.00000	-0.00021	0.87841
3	1:00	0.00000	0.00000	-0.04626	0.01948	0.00000	0.00000	-0.00004	0.97582
4	1:30	0.00000	0.00000	-0.02649	0.00768	0.00000	0.00000	0.00036	0.83451
5	2:00	0.00000	0.00000	-0.03821	0.00237	0.00000	0.00000	0.00064	0.73389
6	2:30	0.00000	0.00000	-0.05405	0.00000	0.00000	0.00000	0.00031	0.78786
7	3:00	0.00000	0.00000	-0.06672	0.00000	0.00000	0.00000	0.00123	0.35231
8	3:30	0.00000	0.00000	-0.06481	0.00022	0.00000	0.00000	0.00138	0.28673
9	4:00	0.00000	0.00000	-0.04149	0.02834	0.00000	0.00000	0.00125	0.56738
10	4:30	0.00000	0.00000	-0.05239	0.00000	0.00000	0.00000	0.00089	0.53767
11	5:00	0.00000	0.00000	-0.05001	0.00032	0.00000	0.00000	0.00116	0.43660
12	5:30	0.00000	0.00000	-0.05120	0.00194	0.00000	0.00000	0.00069	0.65781
13	6:00	0.08436	0.92495	-0.06166	0.37459	0.00244	0.94332	0.00098	0.63004
14	6:30	-0.07057	0.95415	-0.05995	0.08709	-0.01679	0.67839	0.00061	0.78953
15	7:00	0.02862	0.93779	-0.06462	0.00639	-0.00209	0.87920	-0.00035	0.76924
16	7:30	-0.33039	0.18816	-0.08878	0.00000	-0.01202	0.59296	-0.00129	0.53166
17	8:00	-0.14273	0.03773	-0.11256	0.00000	-0.00692	0.42860	-0.00130	0.53683
18	8:30	-0.17046	0.00468	-0.09440	0.00000	-0.00225	0.68654	-0.00163	0.14478
19	9:00	-0.06691	0.35020	-0.07307	0.00013	-0.01563	0.25006	-0.00132	0.41769
20	9:30	0.01192	0.90402	-0.08392	0.00003	-0.00054	0.88965	-0.00007	0.91054
21	10:00	-0.15744	0.00001	-0.08245	0.00000	-0.01242	0.08022	-0.00230	0.12408
22	10:30	-0.10220	0.03145	-0.06892	0.00001	-0.01553	0.00542	-0.00077	0.66962
23	11:00	-0.03445	0.55919	-0.05363	0.06434	-0.01203	0.05625	0.00176	0.21714
24	11:30	-0.07421	0.22511	-0.08926	0.00000	-0.02548	0.00012	-0.00045	0.82491
25	12:00	-0.05880	0.49479	-0.07419	0.00087	-0.02211	0.01278	0.00079	0.68329
26	12:30	-0.06599	0.24132	-0.07416	0.00024	-0.01279	0.38577	0.00382	0.01499
27	13:00	0.06316	0.41787	-0.05125	0.00014	-0.01784	0.02311	0.00392	0.00906
28	13:30	-0.01861	0.77584	-0.07767	0.00017	-0.01427	0.03062	0.00234	0.40695
29	14:00	0.03967	0.22254	-0.07240	0.00000	-0.01740	0.02691	0.00177	0.60991
30	14:30	0.06867	0.25326	-0.07022	0.00000	-0.01437	0.00993	0.00007	0.96365
31	15:00	-0.00437	0.01395	-0.08089	0.00000	-0.00512	0.02714	-0.00049	0.37707
32	15:30	0.01828	0.74560	-0.08098	0.00000	-0.00554	0.47553	-0.00105	0.30373
33	16:00	-0.01896	0.53220	-0.08216	0.00000	-0.00235	0.73171	0.00094	0.46303
34	16:30	-0.08834	0.00003	-0.10201	0.00000	-0.01543	0.09071	-0.00141	0.07659
35	17:00	-0.18400	0.09369	-0.12086	0.03027	-0.01266	0.05422	-0.00142	0.02554
36	17:30	-0.06627	0.96200	-0.11835	0.16786	-0.02119	0.46406	-0.00098	0.62123
37	18:00	0.20256	0.01089	-0.09503	0.00000	-0.01506	0.12151	-0.00215	0.14770
38	18:30	-0.15975	0.16910	-0.10106	0.00143	-0.03606	0.00245	-0.00169	0.33216
39	19:00	0.00538	0.29102	-0.11402	0.00000	-0.02668	0.03695	-0.00196	0.14183
40	19:30	0.00000	0.00000	-0.10510	0.00000	0.00000	0.00000	-0.00221	0.01012
41	20:00	0.00000	0.00000	-0.08930	0.00000	0.00000	0.00000	-0.00082	0.02286
42	20:30	0.00000	0.00000	-0.09255	0.00000	0.00000	0.00000	-0.00551	0.00606
43	21:00	0.00000	0.00000	-0.07386	0.00000	0.00000	0.00000	0.00028	0.84457
44	21:30	0.00000	0.00000	-0.09281	0.00000	0.00000	0.00000	-0.00283	0.05255
45	22:00	0.00000	0.00000	-0.06447	0.01271	0.00000	0.00000	-0.00029	0.80494
46	22:30	0.00000	0.00000	-0.06530	0.00000	0.00000	0.00000	-0.00004	0.97574
47	23:00	0.00000	0.00000	-0.05067	0.00001	0.00000	0.00000	0.00172	0.20000
48	23:30	0.00000	0.00000	-0.05632	0.00001	0.00000	0.00000	-0.00035	0.68067

Table C.12: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in VRE generation and VRE generation plus curtailed generation for New South Wales. The subscript *vre* denotes variable renewable energy generation, and *vcurt* denotes variable renewable energy generation plus curtailed generation.

	Time	MOEvre	pMOEvre	VOLvre	pVOLvre	MOEvcurt	pMOEvcurt	VOLvcurt	pVOLvcurt
1	00:00	-0.00276	0.00000	-0.00009	0.23949	-0.00274	0.00001	-0.00009	0.25297
2	00:30	-0.00261	0.40865	-0.00017	0.03293	-0.00260	0.00000	-0.00016	0.01761
3	01:00	-0.00308	0.00000	-0.00013	0.03785	-0.00307	0.00000	-0.00013	0.03762
4	01:30	-0.00273	0.00000	-0.00006	0.38665	-0.00272	0.00000	-0.00006	0.39367
5	02:00	-0.00333	0.13387	-0.00005	0.58175	-0.00332	0.00001	-0.00004	0.56912
6	02:30	-0.00320	0.00000	0.00001	0.72413	-0.00321	0.00000	0.00001	0.69178
7	03:00	-0.00327	0.00115	-0.00000	0.98914	-0.00324	0.00000	0.00000	0.95208
8	03:30	-0.00312	0.00000	-0.00012	0.12577	-0.00313	0.00000	-0.00011	0.14015
9	04:00	-0.00375	0.00010	-0.00004	0.54293	-0.00374	0.00000	-0.00004	0.52231
10	04:30	-0.00273	0.00000	-0.00006	0.46181	-0.00274	0.00002	-0.00006	0.56083
11	05:00	-0.00244	0.00000	-0.00008	0.27171	-0.00244	0.00000	-0.00007	0.31220
12	05:30	-0.00234	0.01002	-0.00018	0.11402	-0.00234	0.00000	-0.00017	0.10866
13	06:00	-0.00287	0.00000	-0.00009	0.18515	-0.00287	0.00000	-0.00009	0.17983
14	06:30	-0.00298	0.00000	-0.00006	0.49796	-0.00304	0.00000	-0.00006	0.46555
15	07:00	-0.00491	0.00700	-0.00013	0.07012	-0.00488	0.00127	-0.00013	0.07837
16	07:30	-0.00397	0.00000	-0.00021	0.00175	-0.00395	0.00009	-0.00020	0.00148
17	08:00	-0.00416	0.00000	-0.00016	0.06380	-0.00423	0.00000	-0.00016	0.05536
18	08:30	-0.00513	0.00004	-0.00003	0.63506	-0.00533	0.00000	-0.00004	0.51701
19	09:00	-0.00491	0.00000	0.00002	0.75225	-0.00500	0.00000	-0.00002	0.78576
20	09:30	-0.00430	0.00000	-0.00001	0.84958	-0.00446	0.00000	-0.00002	0.75066
21	10:00	-0.00497	0.00000	-0.00004	0.44832	-0.00515	0.02481	-0.00005	0.36427
22	10:30	-0.00515	0.00000	-0.00001	0.88174	-0.00529	0.00000	-0.00002	0.73110
23	11:00	-0.00485	0.00000	-0.00008	0.19770	-0.00500	0.00000	-0.00009	0.13561
24	11:30	-0.00516	0.95042	-0.00006	0.76878	-0.00530	0.00000	-0.00006	0.30523
25	12:00	-0.00560	0.00000	-0.00008	0.16070	-0.00574	0.00000	-0.00008	0.18374
26	12:30	-0.00514	0.00000	-0.00008	0.11448	-0.00539	0.00000	-0.00007	0.13864
27	13:00	-0.00470	0.00000	-0.00001	0.88658	-0.00492	0.00195	-0.00001	0.89515
28	13:30	-0.00462	0.00000	-0.00006	0.49190	-0.00482	0.00000	-0.00004	0.58742
29	14:00	-0.00544	0.00000	-0.00008	0.26680	-0.00557	0.21253	-0.00007	0.31463
30	14:30	-0.00467	0.00000	-0.00003	0.62232	-0.00473	0.04087	-0.00003	0.82579
31	15:00	-0.00448	0.00236	-0.00015	0.00697	-0.00443	0.00000	-0.00015	0.00890
32	15:30	-0.00370	0.00000	-0.00015	0.00974	-0.00325	0.00000	-0.00007	0.19642
33	16:00	-0.00419	0.00000	-0.00011	0.22980	-0.00418	0.00000	-0.00011	0.20920
34	16:30	-0.00446	0.00000	-0.00022	0.01349	-0.00391	0.00000	-0.00022	0.00465
35	17:00	-0.00358	0.00000	-0.00027	0.00088	-0.00362	0.00000	-0.00026	0.00170
36	17:30	-0.00421	0.00000	-0.00034	0.00010	-0.00537	0.00000	-0.00033	0.00052
37	18:00	-0.00579	0.00000	-0.00019	0.04919	-0.00560	0.00002	-0.00018	0.06713
38	18:30	-0.00537	0.00000	-0.00016	0.08304	-0.00523	0.00054	-0.00015	0.09474
39	19:00	-0.00638	0.00001	-0.00012	0.15182	-0.00633	0.00000	-0.00010	0.20814
40	19:30	-0.00529	0.73923	-0.00013	0.64268	-0.00528	0.00000	-0.00013	0.05975
41	20:00	-0.00465	0.00000	-0.00013	0.03113	-0.00461	0.00000	-0.00013	0.03332
42	20:30	-0.00483	0.00000	-0.00006	0.34083	-0.00476	0.00000	-0.00006	0.33456
43	21:00	-0.00445	0.00000	-0.00025	0.00137	-0.00442	0.00000	-0.00025	0.00135
44	21:30	-0.00450	0.00000	-0.00020	0.04788	-0.00449	0.00000	-0.00020	0.04610
45	22:00	-0.00417	0.00000	-0.00006	0.14348	-0.00415	0.00000	-0.00006	0.14444
46	22:30	-0.00363	0.00000	-0.00008	0.12843	-0.00362	0.00000	-0.00007	0.13928
47	23:00	-0.00354	0.00000	-0.00013	0.46530	-0.00353	0.00000	-0.00012	0.46407
48	23:30	-0.00340	0.00000	-0.00010	0.20858	-0.00337	0.00001	-0.00010	0.23525

Table C.13: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in VRE generation and VRE generation plus curtailed generation for Victoria. The subscript *vre* denotes variable renewable energy generation, and *vcurt* denotes variable renewable energy generation plus curtailed generation.

	Time	MOEvre	pMOEvre	VOLvre	pVOLvre	MOEvcurt	pMOEvcurt	VOLvcurt	pVOLvcurt
1	00:00	-0.00185	0.27112	-0.00004	0.11873	-0.00187	0.22292	-0.00003	0.12524
2	00:30	-0.00287	0.09318	-0.00018	0.00485	-0.00300	0.00000	-0.00004	0.12775
3	01:00	-0.00248	0.03618	-0.00018	0.01113	-0.00275	0.00722	-0.00016	0.01279
4	01:30	-0.00223	0.00000	-0.00007	0.18277	-0.00282	0.50699	-0.00006	0.23343
5	02:00	-0.00220	0.00371	0.00003	0.65782	-0.00282	0.97457	0.00005	0.98621
6	02:30	-0.00254	0.07225	0.00002	0.79217	-0.00350	0.00002	0.00006	0.35046
7	03:00	-0.00292	0.03206	0.00003	0.70905	-0.00376	0.00000	0.00007	0.26638
8	03:30	-0.00276	0.00028	-0.00004	0.59670	-0.00401	0.00003	0.00002	0.77541
9	04:00	-0.00287	0.04108	0.00001	0.91059	-0.00412	0.00000	0.00006	0.44313
10	04:30	-0.00344	0.01146	0.00001	0.88524	-0.00434	0.00000	0.00003	0.60759
11	05:00	-0.00389	0.00000	-0.00001	0.82983	-0.00462	0.00000	0.00000	0.98153
12	05:30	-0.00431	0.00104	-0.00003	0.63011	-0.00473	0.00107	-0.00001	0.78586
13	06:00	-0.00419	0.00000	0.00007	0.23459	-0.00453	0.00000	0.00009	0.11673
14	06:30	-0.00422	0.18848	-0.00008	0.12839	-0.00450	0.00000	-0.00007	0.15399
15	07:00	-0.00487	0.52707	-0.00006	0.22268	-0.00528	0.00000	-0.00004	0.35960
16	07:30	-0.00664	0.00000	-0.00015	0.00611	-0.00683	0.00000	-0.00014	0.00555
17	08:00	-0.00824	0.57743	-0.00011	0.53618	-0.00782	0.00000	-0.00008	0.04767
18	08:30	-0.00833	0.00000	-0.00005	0.23566	-0.00784	0.00000	-0.00005	0.27644
19	09:00	-0.00797	0.00000	-0.00004	0.13094	-0.00793	0.00000	-0.00003	0.19569
20	09:30	-0.00689	0.00000	-0.00007	0.01007	-0.00668	0.00000	-0.00004	0.09850
21	10:00	-0.00717	0.00000	-0.00006	0.03894	-0.00696	0.00265	-0.00004	0.62929
22	10:30	-0.00592		0.00000		-0.00825	0.00000	0.00001	0.80300
23	11:00	-0.00875	0.00000	0.00004	0.47492	-0.00852	0.00543	0.00003	0.57372
24	11:30	-0.00842	0.00000	0.00013	0.02473	-0.00831	0.00000	0.00011	0.04029
25	12:00	-0.00867	0.00783	0.00007	0.44392	-0.00844	0.00000	0.00006	0.27967
26	12:30	-0.00820	0.00000	0.00005	0.51100	-0.00797	0.00000	0.00006	0.51623
27	13:00	-0.00784	0.00000	0.00013	0.03350	-0.00089		-0.00000	
28	13:30	-0.00790	0.00001	0.00005	0.26875	-0.00785	0.00000	0.00019	0.00777
29	14:00	-0.01038	0.00000	0.00013	0.07559	-0.00979	0.00000	0.00015	0.05805
30	14:30	-0.00965	0.00000	0.00007	0.29590	-0.00928	0.00000	0.00009	0.17617
31	15:00	-0.00888	0.00000	0.00005	0.51555	-0.00848	0.00000	0.00010	0.27747
32	15:30	-0.00826	0.76517	0.00008	0.50921	-0.00810	0.02835	0.00012	0.15743
33	16:00	-0.00838	0.19990	0.00000	0.99933	-0.00729	0.00000	0.00010	0.14829
34	16:30	-0.00699	0.00617	-0.00002	0.80032	-0.00681	0.00000	0.00000	0.95655
35	17:00	-0.00864	0.00000	-0.00001	0.89215	-0.00817	0.00000	0.00001	0.90160
36	17:30	-0.01009	0.00000	-0.00010	0.22009	-0.00971	0.00107	-0.00009	0.29795
37	18:00	-0.01251	0.00000	-0.00001	0.81768	-0.01247	0.22281	-0.00013	0.19544
38	18:30	0.00129	0.99948	0.00004	0.99667	-0.00950	0.00000	-0.00000	0.00000
39	19:00	-0.00887	0.86884	-0.00017	0.87577	-0.00863	0.78705	-0.00016	0.86221
40	19:30	-0.00481	0.00000	-0.00023	0.00051	-0.00567	0.00000	-0.00017	0.02240
41	20:00	-0.00493	0.00038	-0.00024	0.00096	-0.00547	0.03760	-0.00019	0.04535
42	20:30	-0.00600	0.00030	-0.00012	0.14486	-0.00591	0.00000	-0.00011	0.17969
43	21:00	-0.00494	0.00000	-0.00013	0.04188	-0.00564	0.00000	-0.00021	0.00999
44	21:30	-0.00560	0.00000	-0.00003	0.34511	-0.00566	0.00000	-0.00003	0.35276
45	22:00	-0.00453	0.31242	-0.00001	0.56615	-0.00502	0.00000	-0.00019	0.03063
46	22:30	-0.00547	0.00000	-0.00025	0.00011	-0.00547	0.00000	-0.00023	0.00024
47	23:00	-0.00415	0.00150	-0.00015	0.00303	-0.00412	0.00000	-0.00014	0.00508
48	23:30	-0.00344	0.00000	-0.00003	0.22905	-0.00347	0.00608	-0.00003	0.30360

Empty cells indicate models that failed to return the p-values. But since most of the estimated coefficients are close to ones estimated before or after the time in concern, we find it reasonable to include them in the analysis.

Table C.14: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in VRE generation and VRE generation plus curtailed generation for South Australia. The subscript *vre* denotes variable renewable energy generation, and *vcurt* denotes variable renewable energy generation plus curtailed generation.

	Time	MOEvre	pMOEvre	VOLvre	pVOLvre	MOEvcurt	pMOEvcurt	VOLvcurt	pVOLvcurt
1	00:00	-0.01368	0.00000	-0.00016	0.75847	-0.01184	0.00000	-0.00007	0.24478
2	00:30	-0.01354	0.00000	-0.00015	0.13552	-0.01117	0.00000	-0.00001	0.86515
3	01:00	-0.01409	0.00000	-0.00015	0.05242	-0.01149	0.00000	-0.00003	0.67352
4	01:30	-0.01500	0.00000	-0.00011	0.24716	-0.01331	0.00000	0.00006	0.47338
5	02:00	-0.01389	0.99712	-0.00015	0.99648	-0.01182	0.61852	0.00005	0.69797
6	02:30	-0.01478	0.00000	-0.00006	0.59945	-0.01221	0.00000	0.00009	0.45655
7	03:00	-0.01707	0.00000	-0.00014	0.20592	-0.01474	0.00000	-0.00001	0.94464
8	03:30	-0.01822	0.00000	-0.00020	0.06204	-0.01534	0.00000	-0.00000	0.96433
9	04:00	-0.01667	0.00002	-0.00025	0.05925	-0.01483	0.00000	-0.00006	0.62877
10	04:30	-0.01592	0.00000	-0.00006	0.46171	-0.01418	0.00000	0.00003	0.64686
11	05:00	-0.01693	0.00000	-0.00011	0.17498	-0.01552	0.00000	0.00005	0.66199
12	05:30	-0.01742	0.00000	-0.00006	0.59197	-0.01538	0.00000	0.00016	0.17671
13	06:00	-0.01560	0.00000	-0.00011	0.27040	-0.01426	0.00000	0.00013	0.30069
14	06:30	-0.01272	0.00000	-0.00004	0.64659	-0.01180	0.00000	0.00011	0.33698
15	07:00	-0.01861	0.37648	-0.00029	0.84402	-0.01661	0.00000	-0.00008	0.13207
16	07:30	-0.01533	0.00000	-0.00035	0.00060	-0.01349	0.00000	-0.00015	0.05881
17	08:00	-0.01649	0.00000	-0.00019	0.00134	-0.01501	0.00000	-0.00008	0.05616
18	08:30	-0.01348	0.00000	-0.00016	0.01610	-0.01283	0.00000	-0.00004	0.41601
19	09:00	-0.01328	0.00000	-0.00011	0.36388	-0.01340	0.00000	0.00005	0.42171
20	09:30	-0.01438	0.00000	-0.00009	0.42614	-0.01556	0.00000	0.00018	0.03433
21	10:00	-0.01619	0.00000	-0.00003	0.67032	-0.01750	0.00000	0.00022	0.05115
22	10:30	-0.01695	0.00048	0.00002	0.91870	-0.01894	0.00000	0.00038	0.00007
23	11:00	-0.01918	0.00000	0.00002	0.84423	-0.02099	0.00000	0.00038	0.00052
24	11:30	-0.01797	0.15380	-0.00007	0.86587	-0.02145	0.00000	0.00036	0.00061
25	12:00	-0.02029	0.00000	0.00000	0.97321	-0.02360	0.00078	0.00042	0.00125
26	12:30	-0.02007	0.00000	-0.00008	0.34251	-0.02519	0.00000	0.00044	0.00735
27	13:00	-0.01873	0.00000	-0.00002	0.78417	-0.02308	0.00000	0.00039	0.00185
28	13:30	-0.02088	0.00271	0.00017	0.34444	-0.02426	0.00000	0.00054	0.00000
29	14:00	-0.01881	0.00000	0.00005	0.68490	-0.02256	0.00000	0.00049	0.00000
30	14:30	-0.01967	0.00000	-0.00001	0.91611	-0.02363	0.00000	0.00046	0.00001
31	15:00	-0.01950	0.00000	-0.00007	0.46986	-0.02233	0.00000	0.00032	0.00280
32	15:30	-0.01692	0.00001	-0.00018	0.10677	-0.01807	0.00039	0.00013	0.12318
33	16:00	-0.01618	0.00000	-0.00007	0.40433	-0.01591	0.00000	0.00018	0.00638
34	16:30	-0.01675	0.00000	-0.00001	0.85609	-0.01673	0.00000	0.00019	0.15997
35	17:00	-0.01481	0.00000	-0.00004	0.61692	-0.01387	0.00000	0.00007	0.31402
36	17:30	-0.01524	0.00000	-0.00011	0.20351	-0.01373	0.00000	-0.00004	0.58659
37	18:00	-0.02222	0.00000	-0.00033	0.00004	-0.01963	0.00000	-0.00021	0.00254
38	18:30	-0.02332	0.00000	-0.00045	0.00000	-0.01978	0.00000	-0.00030	0.00007
39	19:00	-0.01948	0.00000	-0.00043	0.00000	-0.01551	0.00025	-0.00019	0.02232
40	19:30	-0.01316	0.00000	-0.00035	0.00001	-0.01081	0.00000	-0.00023	0.00046
41	20:00	-0.01127	0.00012	-0.00045	0.00053	-0.00884	0.00000	-0.00024	0.00231
42	20:30	-0.01230	0.00000	-0.00042	0.00000	-0.01041	0.24073	-0.00032	0.49038
43	21:00	-0.01227	0.00000	-0.00035	0.00005	-0.01067	0.00000	-0.00025	0.00260
44	21:30	-0.01217	0.00000	-0.00028	0.00468	-0.01070	0.00000	-0.00020	0.03185
45	22:00	-0.01145	0.00000	-0.00009	0.42479	-0.01041	0.00000	-0.00003	0.73041
46	22:30	-0.01465	0.00000	-0.00021	0.01313	-0.01295	0.00000	-0.00011	0.22343
47	23:00	-0.01316	0.00000	-0.00013	0.19395	-0.01177	0.00000	-0.00003	0.73531
48	23:30	-0.01254	0.00002	-0.00016	0.14836	-0.01106	0.00000	-0.00006	0.49571

Table C.15: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in VRE generation and VRE generation plus curtailed generation for Queensland. The subscript *vre* denotes variable renewable energy generation, and *vcurt* denotes variable renewable energy generation plus curtailed generation generation.

	Time	MOEvre	pMOEvre	VOLvre	pVOLvre	MOEvcurt	pMOEvcurt	VOLvcurt	pVOLvcurt
1	00:00	-0.00741	0.00000	-0.00026	0.25771	-0.00650	0.00020	-0.00029	0.16854
2	00:30	-0.00574	0.00379	0.00002	0.92129	-0.00528	0.00847	-0.00001	0.98600
3	01:00	-0.00724	0.06260	-0.00010	0.55779	-0.00657	0.00005	-0.00009	0.55153
4	01:30	-0.00744	0.00000	-0.00018	0.40519	-0.00702	0.00000	-0.00017	0.37674
5	02:00	-0.00868	0.00000	-0.00010	0.56858	-0.00818	0.00000	-0.00009	0.58658
6	02:30	-0.00798	0.00000	-0.00014	0.25860	-0.00742	0.11579	-0.00013	0.35134
7	03:00	-0.00795	0.00000	-0.00029	0.01638	-0.00735	0.00000	-0.00025	0.04348
8	03:30	-0.00852	0.25943	-0.00016	0.35783	-0.00799	0.00000	-0.00014	0.21562
9	04:00	-0.00933	0.00000	-0.00013	0.26250	-0.00859	0.00025	-0.00010	0.38620
10	04:30	-0.00734	0.00067	-0.00008	0.58429	-0.00679	0.00000	-0.00007	0.60997
11	05:00	-0.00802	0.00017	-0.00013	0.38126	-0.00802		-0.00000	
12	05:30	-0.00914	0.00000	-0.00004	0.79678	-0.00886	0.00000	-0.00002	0.91256
13	06:00	-0.00838	0.00000	0.00007	0.66451	-0.00850	0.00002	0.00007	0.64050
14	06:30	-0.00592	0.00042	-0.00001	0.92553	-0.00647	0.00000	-0.00001	0.92675
15	07:00	-0.00539	0.00001	-0.00024	0.13952	-0.00640	0.00000	0.00001	0.83751
16	07:30	-0.00619	0.00000	0.00007	0.14007	-0.00550		0.00009	
17	08:00	-0.00779	0.00000	0.00004	0.52448	-0.00810	0.00000	0.00010	0.13246
18	08:30	-0.00815	0.00000	0.00001	0.86261	-0.00921	0.00000	0.00010	0.18136
19	09:00	-0.00773	0.00000	-0.00000	0.93292	-0.00867	0.00107	0.00008	0.25865
20	09:30	-0.00637	0.00000	-0.00012	0.05817	-0.00860	0.00000	0.00004	0.59924
21	10:00	-0.00441	0.17658	-0.00009	0.17552	-0.00735	0.00000	0.00007	0.28473
22	10:30	-0.00331	0.05264	-0.00015	0.04169	-0.00714	0.00000	0.00003	0.70702
23	11:00	-0.00237	0.17874	-0.00018	0.03404	-0.00795	0.00000	0.00002	0.71933
24	11:30	-0.00164	0.18518	-0.00014	0.02301	-0.00694	0.00000	0.00009	0.22044
25	12:00	-0.00221	0.12201	-0.00009	0.14535	-0.00761	0.01938	0.00009	0.13626
26	12:30	-0.00337	0.27905	-0.00003	0.49182	-0.00844	0.00000	0.00011	0.19897
27	13:00	-0.00453	0.00334	0.00002	0.54316	-0.00745	0.00000	0.00018	0.02680
28	13:30	-0.00461	0.72816	0.00005	0.90600	-0.00651	0.00000	0.00022	0.00162
29	14:00	-0.00423	0.01054	-0.00014	0.04749	-0.00562	0.00000	-0.00002	0.76012
30	14:30	-0.00587	0.71368	-0.00021	0.31089	-0.00615	0.00000	-0.00001	0.91793
31	15:00	-0.00721	0.00000	0.00002	0.81061	-0.00690	0.00000	0.00010	0.16954
32	15:30	-0.00683	0.00013	0.00003	0.63752	-0.00632	0.00003	0.00007	0.11451
33	16:00	-0.00830	0.00000	-0.00013	0.16003	-0.00739	0.00000	-0.00001	0.93726
34	16:30	-0.00596	0.00043	-0.00023	0.02991	-0.00532	0.00025	-0.00011	0.34443
35	17:00	-0.00860	0.00000	-0.00004	0.05283	-0.00886	0.00000	-0.00004	0.02270
36	17:30	-0.01203	0.00000	-0.00005	0.05032	-0.01187	0.47407	-0.00004	0.04974
37	18:00	-0.01950	0.00000	-0.00002	0.45748	-0.02121	0.00000	-0.00003	0.41813
38	18:30	-0.01658	0.00722	0.00004	0.27737	-0.02024	0.00524	0.00001	0.90063
39	19:00	-0.01361	0.00061	0.00005	0.17609	-0.01589	0.00000	0.00004	0.41234
40	19:30	-0.01589	0.24514	0.00012	0.51277	-0.01596	0.00000	0.00008	0.58152
41	20:00	-0.01165	0.44963	0.00021	0.17444	-0.01164	0.19179	0.00017	0.20788
42	20:30	-0.01459	0.00899	0.00008	0.16827	-0.01471	0.01272	0.00007	0.15706
43	21:00	-0.01336	0.00000	0.00002	0.60551	-0.01384	0.00000	0.00001	0.84742
44	21:30	-0.00989	0.00000	0.00003	0.26397	-0.00851	0.00000	0.00016	0.33519
45	22:00	-0.00765	0.00000	-0.00001	0.72559	-0.00780	0.00000	-0.00003	0.53838
46	22:30	0.01826		0.00000		-0.00868	0.00585	0.00012	0.25982
47	23:00	-0.00741	0.03695	0.00001	0.59032	-0.00756	0.00000	0.00001	0.60904
48	23:30	-0.00814	0.00000	0.00000	0.98294	-0.00824	0.00000	-0.00003	0.82933

Empty cells indicate models that failed to return the p-values. But since most of the estimated coefficients are close to ones estimated before or after the time in concern, we find it reasonable to include them in the analysis.

Table C.16: Changes in spot electricity prices (MOE), volatility (VOL), and corresponding p-values (pMOE and pVOL) per 1 MWh increase in VRE generation and VRE generation plus curtailed generation for Tasmania. The subscript *vre* denotes variable renewable energy generation, and *vcurt* denotes variable renewable energy generation plus curtailed generation generation.

	Time	MOEvre	pMOEvre	VOLvre	pVOLvre	MOEvcurt	pMOEvcurt	VOLvcurt	pVOLvcurt
1	00:00	-0.00929	0.00004	0.00002	0.91781	-0.00898	0.02523	0.00003	0.88710
2	00:30	-0.00694	0.00000	-0.00006	0.78277	-0.00740	0.75875	-0.00021	0.39427
3	01:00	-0.00659	0.00019	-0.00006	0.80623	-0.00659	0.00481	-0.00002	0.93521
4	01:30	-0.00332	0.07028	0.00016	0.58880	-0.00311	0.18000	0.00024	0.42305
5	02:00	-0.00661	0.00686	0.00011	0.73205	-0.00653	0.01739	0.00010	0.75499
6	02:30	-0.00859	0.00076	0.00012	0.63753	-0.00893	0.00339	0.00011	0.65158
7	03:00	-0.00954	0.00073	0.00026	0.22143	-0.00921	0.00000	0.00029	0.15753
8	03:30	-0.01047	0.00187	0.00022	0.30967	-0.01039	0.01458	0.00020	0.36600
9	04:00	-0.00708	0.00431	0.00030	0.28179	-0.00692	0.00554	0.00028	0.28999
10	04:30	-0.00819	0.00002	0.00019	0.43805	-0.00824	0.00009	0.00018	0.45027
11	05:00	-0.00817	0.00239	0.00017	0.49243	-0.00811	0.00139	0.00021	0.40832
12	05:30	-0.00945	0.00002	0.00003	0.91639	-0.00912	0.00010	0.00009	0.71355
13	06:00	-0.00711	0.00005	0.00038	0.18962	-0.00967	0.02992	0.00025	0.61065
14	06:30	-0.00998	0.00009	0.00013	0.63964	-0.00965	0.00018	0.00018	0.53465
15	07:00	-0.01023	0.00160	0.00001	0.97717	-0.01019	0.00065	0.00004	0.82129
16	07:30	-0.01325	0.00006	-0.00010	0.78421	-0.01329	0.43411	-0.00009	0.82303
17	08:00	-0.01742	0.00000	-0.00020	0.56413	-0.01748	0.00000	-0.00014	0.59902
18	08:30	-0.01424	0.00002	-0.00026	0.13175	-0.01404	0.00000	-0.00021	0.24029
19	09:00	-0.01173	0.00110	-0.00018	0.53741	-0.01071	0.02083	-0.00008	0.80181
20	09:30	-0.01113	0.00000	0.00001	0.98055	-0.01299	0.00000	0.00002	0.81795
21	10:00	-0.01227	0.00003	-0.00028	0.38540	-0.01186	0.00000	-0.00021	0.47190
22	10:30	-0.01218	0.00040	-0.00003	0.88270	-0.01165	0.00000	0.00003	0.89512
23	11:00	-0.00834	0.00000	0.00036	0.11700	-0.00855	0.00000	0.00040	0.07605
24	11:30	-0.01243	0.00004	0.00017	0.61251	-0.00893	0.00000	0.00036	0.15194
25	12:00	-0.01138	0.00004	0.00046	0.15222	-0.01096	0.00004	0.00035	0.34315
26	12:30	-0.01184	0.00103	0.00070	0.00583	-0.01117	0.11418	0.00072	0.01308
27	13:00	-0.00875	0.00337	0.00088	0.00255	-0.00849	0.00463	0.00090	0.00134
28	13:30	-0.00833	0.00087	0.00104	0.00338	-0.00801	0.04583	0.00106	0.00469
29	14:00	-0.01224	0.00003	0.00074	0.01663	-0.01206	0.00258	0.00072	0.01585
30	14:30	-0.01165	0.00000	0.00019	0.44048	-0.01143	0.00000	0.00023	0.35814
31	15:00	-0.01260	0.00000	-0.00004	0.65732	-0.01234	0.09287	-0.00001	0.92247
32	15:30	-0.01304	0.00000	-0.00010	0.59021	-0.01302	0.00000	-0.00008	0.69919
33	16:00	-0.01378	0.00000	0.00013	0.57554	-0.01336	0.00000	0.00014	0.53321
34	16:30	-0.01701	0.00000	-0.00024	0.08222	-0.01678	0.00000	-0.00020	0.16109
35	17:00	-0.01850	0.00000	-0.00018	0.11400	-0.01843	0.00000	-0.00018	0.10965
36	17:30	-0.01993	0.00000	-0.00014	0.58672	-0.01950	0.00000	-0.00012	0.65485
37	18:00	-0.01490	0.08225	-0.00034	0.20351	-0.01447	0.00033	-0.00029	0.24155
38	18:30	-0.01661	0.00000	-0.00032	0.21784	-0.01628	0.00000	-0.00026	0.27244
39	19:00	-0.01939	0.00000	-0.00037	0.08540	-0.01915	0.00000	-0.00033	0.10756
40	19:30	-0.01639	0.00000	-0.00033	0.01423	-0.01621	0.00000	-0.00031	0.02328
41	20:00	-0.01462	0.00125	-0.00014	0.02375	-0.01452	0.00817	-0.00013	0.03233
42	20:30	-0.01596	0.00001	-0.00087	0.01322	-0.01554	0.00000	-0.00083	0.01650
43	21:00	-0.01340	0.00000	0.00009	0.69832	-0.01295	0.00002	0.00009	0.69704
44	21:30	-0.01522	0.00000	-0.00053	0.03374	-0.01504	0.00000	-0.00053	0.03673
45	22:00	-0.00996	0.00000	0.00000	0.99373	-0.00974	0.00000	-0.00001	0.93868
46	22:30	-0.01049	0.00000	0.00006	0.80417	-0.01024	0.00001	0.00008	0.74233
47	23:00	-0.00958	0.00000	0.00031	0.16536	-0.00949	0.00000	0.00030	0.16475
48	23:30	-0.00932	0.00000	-0.00010	0.45715	-0.00928	0.00000	-0.00011	0.39355

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