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Abstract

In our analysis of electricity price series from Australia's National Electricity Market (NEM), we employ the indicator saturation (IS) approach to simultaneously model the stylised facts of electricity prices, including extreme spikes, seasonality, level-shifts, and autocorrelation. The standard modelling methods described in the literature tend to use regime-switching models to cope with these characteristics, but these models cannot fully reflect the stylised facts of interest. Using a range of model-evaluation tools, our analysis finds that the IS method outperforms the regime-switching models in various settings. In addition to the statistical superiority of this approach, we detail the relevance of our findings to policymaking in the NEM and provide recommendations for the development of the electricity markets in Australia.

Keywords: Australian National Electricity Market; Electricity Prices; Indicator Saturation; Price Spikes

JEL: C32; L97; Q48

1 Introduction

For electricity market stakeholders, understanding patterns in electricity prices is essential. If power generation firms better understand the features of electricity prices, they can make efficient investment decisions and develop network infrastructure. Financial organisations such as banks and hedge funds also participate in the electricity futures markets as a means of risk diversification. Given the importance of electricity, it is essential that policymakers, electricity-intensive companies, and electricity market participants are informed by a suitable modelling approach. Given that a primary characteristic of electricity as a commodity is its non-storable nature, electricity markets are usually considered to be substantially more volatile than other asset or commodity markets. In particular, they exhibit extreme price movements, typically referred to as price spikes, and periods of substantial price volatility, both of which represent major sources of risk for certain electricity market stakeholders (Potter, 2016). During such periods, the electricity markets in Australia display significant spillover effects of price volatility to the connected markets in the NEM (Australian Energy Market Operator, 2016).

Researchers have analysed electricity prices for several decades, and they have identified a number of stylised facts, most notably regarding seasonality, spikes, trends, and structural breaks (Ballester et al., 2015; Borovkova and Schmeck, 2017; Deschatre et al., 2021; Godin and Ibrahim, 2021).[1] Because of these features, modelling electricity prices is highly non-trivial. One popular technique for modelling electricity prices is the use of Markov regime-switching models, which allow different regimes to be used in the data generation process. Mount et al. (2006) adopted a two-regime switching model and showed that price spikes can be successfully identified if the reserve margin is measured accurately. Janczura and Weron

[1] Deschatre et al. (2021) reviewed the set of electricity price models and features of electricity price in the literature.

(2010) presented an empirical comparison of different regime-switching models and found that the best model was an independent spike three-regime time-varying model. Inspired by their study, Lindström and Regland (2012) applied a three-regime switching model to electricity prices in European markets. They used estimated regimes to analyse the probability of occurrence of extreme events and found they are associated with the amount of renewable energy sources in the power system. In a more recent study, Apergis et al. (2019) used a three-regime hidden semi-Markov model which allowed any sojourn time distribution to be specified to effectively model the very short sojourn time of the spikes[2], along with regimes related to the Carbon Tax scheme in Australian electricity markets.

Although numerous studies have developed different versions of Markov regime-switching models for electricity prices, this approach is still subject to some limitations. First, most Markov switching models assume that Markov chain determining regimes are independent of all other parts of the model, but this assumption seems unrealistic (Chang et al., 2017).[3] Second, traditional approaches based on the use of regime-switching models typically need two steps to model electricity prices: a first step for the deterministic part and a second step for the stochastic part (Huisman and Mahieu, 2003). However, there could potentially be an estimation error in the first step, which could disrupt the estimation in the modelling of the second step and thus impair the ability of the MS model to produce accurate estimates.[4]

To avoid such limitations, this study employs the indicator saturation (IS) approach to model electricity prices. The IS approach allows us to model outliers (spikes), structural breaks (level-shifts), and trends simultaneously through saturation with step-, impulse-, and trend-

[2] The sojourn time distribution of a traditional Markov model can only follow an exponential distribution implicitly.
[3] In practice, future transitions usually depend on the realisation of underlying time series and past states.
[4] We will discuss this issue later when we compare our results with those of Markov switching models.

indicators (Santos et al., 2008; Johansen and Nielsen, 2009; Castle et al., 2012; Castle et al., 2015).[5] The Australian NEM is one of the largest interconnected electricity systems in the world. Is also one of the most unique markets: it has experienced substantial power market reforms (Nepal and Foster, 2016), and its generators and retailers purchase, sell, and supply electricity across five regional states through non-physical floors at a particular spot price (Han et al., 2020). Because of these features, the Australian NEM has attracted considerable research interest.[6] Focusing on the Australian electricity market, we first demonstrate how the three types of indicators can suitably capture the spikes, level-shifts, and trends in electricity prices. Then, we show that the indicator saturation approach generally performs better than Markov switching models in terms of information criteria. As we discussed above, the findings have important implications for policymakers and market participants because electricity prices are sensitive to climate change policies and their associated uncertainty, power generation approaches, and geographical variation. Thus, we link the results from the indicator saturation to policy changes in the NEM and provide recommendations for the development of electricity markets in Australia.

This study contributes to the growing body of literature on pricing and forecasting in electricity markets (e.g. Becker et al., 2007; Janczura and Weron, 2010; Allcott, 2011; Maye and Trück, 2018; Apergis et al., 2019, 2020; Kanamura and Bunn, 2022; Schöniger and Morawetz, 2022; Jiang et al., 2023). In particular, Becker et al. (2007), Janczura and Weron (2010), and Apergis et al. (2019, 2020) have examined electricity pricing in Australia. In contrast to these studies, this study is the first, to the best of our knowledge, to apply an IS

[5] Another advantage of using the IS approach is that estimation is based on search algorithm autometrics, so it can automatically select the correct model when there are more variables than observations (Doornik, 2009; Pellini, 2021).
[6] https://www.power-technology.com/features/australia-energy-prices/ (assessed 14 January 2023)

approach to the modelling of wholesale electricity prices in Australia, and to justify the appropriateness of such an application. Moreover, this work is novel in that it documents the fact that the IS approach outperforms Markov-switching (MS) models. In particular, the IS approach is stronger in capturing spikes and issuing correct signals when such a spike occurs. Furthermore, we link the results from indicator saturation to policy changes and factors such as the future demand for electricity and the need to meet peak demand and restructure the market. Although the analysis focuses on the Australian market, price spikes are a generic feature of electricity markets worldwide (Escribano, et al., 2011), and our analysis is applicable to other countries as well. Another small contribution related to Australian electricity pricing is that we extend the analysis using updated Australian electricity data.

The rest of this paper proceeds as follows. In Section 2, we review the Australian electricity market and relevant studies. Section 3 describes the details of the indicator saturation approach, while Section 4 reports data sources, summary statistics, and stylised facts of electricity prices. Section 5 reports the main results. Section 6 provides a robustness check. Section 7 discusses the results and their policy implications. Finally, a conclusion is presented in Section 8.

2 Overview of Australian Electricity Market and Relevant Studies

The Australian National Electricity Market (NEM) is one of the largest interconnected power systems in the world.[7] It spans about 5,000 km from Port Douglas, Queensland to Port Lincoln, South Australia, and across the Bass Strait to Tasmania. This NEM grid covers five interconnected states, including Queensland, Victoria, New South Wales (including the

[7] Interested readers may refer to Rai and Nelson (2020) for a more comprehensive review of Australia's NEM.

Australian Capital Territory (ACT)), Tasmania, and South Australia.[8] Due to the distance between networks, the Northern Territory and Western Australia are not connected to the NEM.

The NEM is operated and managed by the Australian Energy Market Operator (AEMO). According to the Australian Energy Regulator (2017), the trading mechanism works as follows. The generators provide quantities of electricity at various prices for a specific period. To match supply and demand at every 5-minute interval, AEMO dispatches the demand quota to the lowest available bidders. The corresponding price is the 5-minute dispatch price, and the average 5-minute dispatch price over 30 minutes is regarded as the half-hourly spot price (settlement price). AEMO adjusts the maximum spot price based on CPI on an annual basis, where the maximum price is 267 per MWh (as of September 2020), and the minimum spot price is –1000 per MWh.

A number of studies have investigated the Australian NEM. Worthington et al. (2005) explored the transmission of spot prices and their volatility in the Australian regional electricity market.[9] By using a multivariate generalised autoregressive conditional heteroskedasticity model, they observed the presence of positive own mean spillovers in only a small number of markets, with no mean spillovers across any of the other markets. They further observed that Australian spot prices are stationary, in contrast to North American electricity markets. Higgs (2009) applied three different models to examine the inter-relationships of wholesale spot electricity prices across the four regional electricity markets (New South Wales, Queensland, South Australia, and Victoria). Although the findings from a constant conditional correlation show that two pairs of electricity markets (New South Wales–Queensland and New South

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[8] Note that the ACT does not have its own market but belongs to the NSW region.

[9] Ioannidis et al. (2021) also used a GARCH-type model for electricity pricing, but applied it to the German market.

Wales–Victoria) are significantly connected, Higgs (2009) concluded that the degree of connection between states in the Australian NEM is limited. From the perspective of long-term convergence, Nepal and Foster (2016) argue that the Australian NEM has not achieved full integration, while Apergis et al. (2017b) provide evidence in support of the view that price convergence of three regional markets is occurring. Ignatieva and Trück (2016) and Apergis et al. (2020) found some evidence of a positive dependence structure between the prices across markets, where the former found that markets that are connected via interconnector transmission lines exhibit the highest degree of dependence, and the latter found the strongest degree of dependence in the post-carbon period. Both Apergis et al. (2017a) and Do et al. (2020) examined interconnectedness within the Australian NEM by focusing on the risk transmission process. They both observed the presence of volatility (risk) spillovers across regions. Similarly, Naeem et al. (2022) showed that the Australian NEM has more connectedness within regions than across regions. Do et al. (2020) further suggested that increasing NEM generation capacity can help to reduce the transmission of risks.

In contrast to the above studies, a number of studies have modelled spike behaviour in electricity prices using regime-switching models.[10] Becker et al. (2007) built a two-regime time-varying probability model for Queensland and showed that it can help to predict spikes in this market. Janczura and Weron (2010) compared different regime-switching models used for modelling this spike behaviour in terms of goodness-of-fit. They argue that the best structure for modelling electricity prices is an independent spike three-regime model with time-varying transition probabilities, shifted spike regime distributions, and heteroskedastic diffusion-type base regime dynamics. Using a three-regime hidden semi-Markov model, Apergis et al. (2019)

[10] The regime-switching models have also been used for other electricity markets (e.g. Kapoor et al., 2021).

investigated the hidden regime for five states (Queensland, New South Wales, Victoria, South Australia, and Tasmania), and found evidence for low-price, high-price, and spike regimes. Clements et al. (2015) proposed a multivariate self-exciting point process model to explore the connectedness of price spikes across regions. They observe that spikes are transmitted across the regions, with the size of a spike depending on the available transmission capacity.

3 Methodology

In this section, we firstly review the traditional approaches based on the regime-switching models and then briefly describe the indicator saturation method.

3.1 Traditional approaches based on Markov switching model

Traditional approaches have modelled electricity prices using a two-step procedure. This method is based on the separation of the electricity price into two components (Huisman and Mahieu, 2003), as follows:

$$y_t = d_t + s_t,$$

where d_t denotes the deterministic part and s_t represents the stochastic part.

In the first step, the deterministic part is a deterministic function of time that captures predictable patterns, such as seasonality, level-shifts, and trend. There are a number of ways to estimate the deterministic part.[11] One straightforward method used by Huisman and Mahieu (2003) and Apergis et al. (2020) is to specify those deterministic components using different dummy variables,

$$d_t = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{D}_t^{(Year)} + \boldsymbol{\beta}_2 \boldsymbol{D}_t^{(Month)} + \boldsymbol{\beta}_3 \boldsymbol{D}_t^{(DoW)} + \boldsymbol{\beta}_4 \boldsymbol{D}_t^{(Shift)},$$

[11] Seasonality can be modelled using the Holt–Winters approach (Goodwin, 2010), seasonal ARIMA model, and Fourier series. Level-shifts can be detected via structural breaks and change-point tests (e.g. Horváth et al., 2017). There are numerous methods for detrending, such as the Hodrick–Prescott filter and the Hamilton filter.

where $\boldsymbol{D}_t^{(Year)}$ is a group of dummy variables representing the fiscal year[12] in the NEM, $\boldsymbol{D}_t^{(Month)}$ is a set of monthly dummy variables, $\boldsymbol{D}_t^{(DoW)}$ is a collection of day-of-week dummy variables, and $\boldsymbol{D}_t^{(Shift)}$ is a pool of dummy variables capturing the level-shifts.

Once the deterministic part is estimated, the stochastic part is the residual from the electricity price, that is, $s_t = y_t - \hat{d}_t$. The second step models the autocorrelation and spikes in the stochastic part. The regime-switching model is one of the most widely used in literature for this task. Huisman and Mahieu (2003) employed a two-regime MS model for deseasonalised log-prices, with the first regime of an AR(1) process and the second regime of a normal distribution in which mean and variance are much higher than in the first regime. De Jong (2006) modified such a two-regime MS model using a Poisson-driven spike regime. Mount et al. (2006) further improved the two-regime MS model by linking the transition probability with current market conditions. Janczura and Weron (2010) presented an empirical comparison of several regime-switching models for modelling spikes based on goodness-of-fit and suggested that the three-regime model has the best fit.

As a benchmark in this model, we will employ the two-regime and three-regime MS models, the latter of which can be expressed as follows:

$$s_t = \begin{cases} \alpha_1 + \phi_{1,1}s_{t-1} + \phi_{1,2}s_{t-2} + \cdots + \phi_{1,k}s_{t-k} + \varepsilon_{1,t}, \ \varepsilon_{1,t} \sim N(0, \sigma_1^2), & if\ R_t = 1, \\ \alpha_2 + \phi_{2,1}s_{t-1} + \phi_{2,2}s_{t-2} + \cdots + \phi_{2,k}s_{t-k} + \varepsilon_{2,t}, \ \varepsilon_{2,t} \sim N(0, \sigma_1^2), & if\ R_t = 2, \\ \alpha_3 + \phi_{3,1}s_{t-1} + \phi_{3,2}s_{t-2} + \cdots + \phi_{3,k}s_{t-k} + \varepsilon_{3,t}, \ \varepsilon_{3,t} \sim N(0, \sigma_1^2), & if\ R_t = 3, \end{cases}$$

where R_t denotes the regime at time t, and the transition probability matrix is

$$\boldsymbol{\Gamma} = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix}$$

where $p_{ij} = \Pr(R_{t+1} = j | R_t = i)$ represents the transition probability from regime i to j.

[12] The fiscal year in the NEM is from the previous July to June. This is because 1 July is the date that the market price cap adjustment comes into effect.

It is worth noting that the traditional approach based on the MS models has some limitations. Firstly, MS models assume that Markov chain determining regimes are independent of all other parts of the model, which is unlikely to be realistic (Change et al., 2007). Secondly, by decoupling the deterministic and stochastic parts, an estimation error in the first step can propagate into the second step, thus impairing the ability of the MS model to produce accurate estimates. As a result, the efficiency of such a two-step modelling technique suffers.

3.2 Indicator saturation

Because of the limitations inherent to MS models, we have used the indicator saturation approach, which allows us to model electricity prices that have spikes, level-shifts, and trends. The indicator saturation method is based on a general-to-specific (GETS) modelling approach that includes indicators of several specific types (Pretis et al., 2018). To start, GETS modelling for linear regression can be expressed as follows:

$$y_t = \beta_0 + \beta_1 X_{1t} + \cdots + \beta_k X_{kt} + u_t, \qquad t = 1,2,\dots,n \tag{1}$$

where y_t is the dependent variable, $X_{1t}, \dots, X_{kt}$ represents a set of regressors of indicator saturation that will be detailed later, $\beta_1, \dots, \beta_k$ are their slope coefficients, and u_t is the error term.

We consider three different types of indicator saturation: impulse (IIS), step (SIS), and trend (TIS). The respective general unrestricted models for a simple model of the mean of y_t using impulse-, step- and trend indicator saturation are given by

$$\text{IIS: } y_t = u + \sum_{j=1}^{N} \delta_j 1_{\{t=j\}} + u_t$$

$$\text{SIS: } y_t = u + \sum_{j=1}^{N} \delta_j 1_{\{t\geq j\}} + u_t$$

$$\text{TIS: } y_t = u + \sum_{j=1}^{N} \delta_j 1_{\{t>j\}} (t-j) + u_t$$

where n denotes the total number of observations in the sample.

IIS is the first saturation type that has been discussed widely in the indicator saturation literature (Santos et al., 2008). $I_t(\tau)$ is the impulse variable, which takes a value of 1 if $t = \tau$, and 0 otherwise. Hendry et al. (2008) analysed the properties of IIS when the observations are generated according to the model $y_t = u + \varepsilon_t$, $\mathrm{t} = 1, \dots, \mathrm{T}$. They employed a split-half approach to integrate IIS into the model for y_t. Formally,

$$y_t = u + \sum_{k=1}^{\lfloor T/2 \rfloor} \delta_{Ik} I_{(t)}(k) + \varepsilon_t, \qquad t = 1, \dots, T.$$

where $\lfloor T/2 \rfloor$ indicators for the first half of the sample are added to the model in the first step. The second $T - \lfloor T/2 \rfloor$ indicators replace the first ones when the indicators have been selected at the significance level α using the *t*-statistic. The selection procedure is then repeated.

SIS can be seen as the extension of IIS, where $I_t(\tau)$ is a step variable that takes a value of 1 if $t \geq \tau$, and a value of 0 if $t < \tau$ (Castle et al., 2015). Castle et al. (2015) evaluated the stability of SIS in the context of level shifts. They described the theoretical basis of SIS and conducted Monte Carlo simulations within a static framework. They observed that sequential selection improves the power of SIS in detecting location shifts through a reduction in the variance of the coefficients of the remaining indicators.

Lastly, TIS can be used to model trends that change by unknown magnitudes at unknown points in time (see Castle et al., 2019 and Walker et al., 2019 for applications). It is equivalent to applying multiplicative indicator saturation to a deterministic trend by interacting step indicators with the trend: $S_j \times t$, where *t* is a deterministic trend. Since it is deterministic (like the constant) and $\sum_{t=1}^{T} t^2 = \frac{1}{6} T(T+1)(2T+1)$, it grows at $O(T^3)$, rather than $O(T^2)$, which is the case for sums of squares of stationary variables. Hence, the gauge and potency properties of TIS are different to those of multiplicative indicator saturation.

For demonstration purposes, we have described IIS, SIS, and TIS separately above. When it comes to practical applications, it is worth devoting extra effort to the task of extending the specification to include different combinations of IIS, SIS, and TIS, such as IIS+SIS and IIS+SIS+TIS. To make this approach more general, we can also include the autoregressive lags of y_t and exogenous regressors on the right-hand side of Eq. (1),

$$y_t = \beta_0 + \sum_{s=1}^{k} \beta_s X_{st} + \sum_{p=1}^{P} \phi_p y_{t-p} + \sum_{q=1}^{Q} \gamma_q Z_{qt} \,,$$

where X_{st} represents indicator saturation, y_{t-p} denotes autoregressive lags, and Z_{qt} indicates exogenous regressors.

After choosing the relevant regressors, the procedure of GETS selection for the relevant indicator saturation consists of three important steps: First, a general unrestricted model that passes a set of chosen diagnostic tests is formulated. Second, backwards elimination is performed along multiple paths by removing, one-by-one, non-significant regressors determined by the chosen target significance level and conditioned not only *t*- and *F*-tests but also using the same set of diagnostic tests carried out at each step. Finally, the specification with the best fit among terminal models is selected according to a fit criterion.

For more technical details regarding GETS regression modelling and indicator saturation, we refer readers to Hendry et al. (2008), Doornik (2009), Castle et al. (2015, 2019), and Pretis et al. (2018).

4 Data and stylised facts

In this section, we firstly describe our empirical data and then review the stylised facts of electricity prices based on our data.

4.1 Data sources and summary statistics

Our variable of interest is the weekly average wholesale electricity spot price[13], which was obtained from the website of the Australian Energy Regulator[14]. Data were available for the period 1 July 2008 to 27 December 2020, resulting in a total of 656 weekly observations for each state. The sample consists of five states: Queensland (QLD), New South Wales (NSW), Victoria (VIC), South Australia (SA), and Tasmania (TAS). Table 1 summarises the descriptive statistics for electricity prices in each state. South Australia has the highest average wholesale electricity price at 70.62 $/MWh, while the remaining four states have an average of around 58 $/MWh. South Australia's electricity price is also the most volatile, with a standard deviation of 82.53. The lowest electricity price, nearly zero, was observed in Tasmania. The data were analysed using the Jarque–Bera test, and the results indicated that the electricity prices did not follow a normal distribution for any of the five states.

Regarding the correlation matrix, Victoria and South Australia show a high correlation, at over 70%. New South Wales and Queensland also have a high correlation, at around 55%. By contrast, Tasmania generally has a lower correlation with the other four states. This may be a result of its geographical location: it is isolated from the mainland, so its electricity market is weakly correlated with those in the other four states.

4.2 Stylized facts of electricity prices

Figure 1 shows the trajectories of electricity prices for each state from 8 June 2008 to 27

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[13] Following the literature (Narayan and Smyth, 2005; Apergis et al., 2017b; Apergis et al., 2019), we used the natural logarithm of electricity prices in our empirical analysis.

14 http://www.aer.gov.au/wholesale-markets/wholesale-statistics/weekly-volume-weighted-average-spot-prices (assessed on September 30, 2021).

December 2020. There are several noticeable features.

First, electricity spot prices are volatile and have large spikes, the latter of which are the result of a rigid demand curve (Higgs and Worthington, 2008). For example, obvious spikes are visible in the data for the beginning of 2017 in Queensland, resulting from high temperatures and two network outages (Australian Energy Regulator (AER), 2017).[15]

Second, a structural break can be seen in the data between July 2012 and July 2014. For example, the price for New South Wales remained at over 70 $/MWh for around two years from July 2012, before which it was higher. This period corresponds to the carbon tax scheme that was introduced by the Australian government in 2012 and repealed in 2014. Such a carbon pricing scheme could lead to higher prices (Nazifi, 2016; Apergis et al., 2019; Nazifi et al., 2021) and risk premiums (Maryniak et al., 2019).[16]

Third, spot prices show an upward trend across the five states after the carbon tax scheme was replaced by the Emission Reduction Fund scheme after July 2014. We observe, for instance, an upward trend in Queensland from July 2014 to the beginning of 2017. Moreover, a major outage occurred in the Basslink connecting Tasmania with Victoria, causing a huge spike in Tasmania over the period December 2015 to April 2016. Because of these features, the indicator saturation approach is suitable for modelling electricity prices as it allows us to capture structural breaks, spikes, and trends simultaneously.

It is worth noting that many factors are involved in the evolution of electricity prices in the five Australian states.[17] Cssereklyei et al. (2019) showed that solar capacity decreases the

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[15] AER have reported that high temperatures and outages in northern NSW significantly increased demand for electricity in QLD. https://www.aer.gov.au/communication/aer-releases-reports-on-wholesale-electricity-high-prices-in-queensland-on-13-and-14-january-2017 (assessed 30 September 2021).

[16] Han et al. (2020) also observed that carbon pricing schemes affect the volatility of electricity prices.

[17] Interested readers may refer to Simshauser and Gilmore (2020b) for discussions of factors driving recent electricity prices in Australia.

wholesale electricity price in Australia. Mwampashi et al (2021) observed that a 1 GWh increase in wind generation decreases daily electricity prices by up to 1.3 \$/MWh and typically increases price volatility by up to 2%. Mwampashi et al. (2022) reported similar findings. Aside from the increasing uptake of renewable energy technologies, other factors such as residential demand (Narayan and Smyth, 2005; Fan and Hyndman, 2011), entry cost (Simshauser and Gilmore, 2020a), gas prices (Simshauser and Gilmore, 2020b), state interconnector flow (Bell et al, 2017), and the closure of coal-fired power plants (Wiseman et al., 2017) have been shown to affect Australian electricity prices.

5 Empirical Results

In order to explore the potential performance benefits of model, we propose the use of the following four specifications of indicator saturation (IS) models, from simple to complex:

- IS-0: impulse- and step-indicators;
- IS-1: impulse- and step-indicators, with autoregressive lags;
- IS-2: impulse-, step-, and trend-indicators, with autoregressive lags;
- IS-3: impulse-, step-, trend-indicators, and monthly and yearly dummies, with autoregressive lags.

The benchmark models include a two-regime Markov switching model (MS-2R) and a three-regime Markov switching model (MS-3R). Figure 2 shows the autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) of electricity prices for each state. Clearly, the ACFs and PACFs of electricity prices are similar across states, but significant lags occur in different periods. For example, we observe a significant lag in the 12th term in South Australia, but a significant lag in the 9th term in Queensland. Following Taylor and Peel (2000) and Kayalar et al. (2017), we determined the order, p, of the models based on the significant lags in the partial autocorrelation function[18]. To ensure a low false detection rate, we followed the rule of thumb suggested by Pretis et al. (2018), to set $\alpha = min(0.05, [1/k])$, where $k = n - 1$ and n denotes the number of observations.

Table 2 compares the performance of the IS and Markov switching models. To evaluate the goodness-of-fit of fitted models, we used both the Akaike Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC). Overall, the results indicate that the IS models outperform the Markov Switching models. In Queensland and Tasmania, the results indicate that an IS-3 model (based on AIC) and an IS-2 model (based on BIC) are better fitted across all five models. South Australia prefers an IS-0 model based on AIC and an IS-3 model based on BIC. In Victoria, both AIC and BIC suggest that an IS-2 is the best fitted model as the values of AIC and BIC are the lowest across all models. One exception is that in the case of New South Wales, where the AIC suggest that Markov switching models achieve a better fit but the BIC still indicates that IS-2 is the best model.

Figure 3 shows the fitted values of IS models based on the BIC values for each state, where the BIC values generally suggest that an IS-2 model is the most suitable IS model and that MS-2R is the most suitable MS model. Thus, we compared the fitted results between the IS-2 and MS-2R models for each state. It is clear that the fitted model captures the electricity prices very well. In particular, it can capture the majority of the spikes in electricity prices across all five states. At the bottom of each panel, we can also see that there are structural breaks for each state.

To further show how well the IS model captures the spikes compared to MS, we followed

[18] Specifically, the lag lengths we chose were 9 for QLD, 11 for NSW, 10 for VIC, 12 for SA, and 11 for TAS.

the method of Apergis et al. (2020) and defined a nonparametric measure of the spikes. A spike is defined here as a price higher than the local mean plus three times the local standard deviation, where the local mean and local standard deviation at time t are calculated based on the range $[\min(0, t-25), \max(t+25, T)]$ (i.e., a centralised window minus or plus 25 calendar weeks (truncated at 0 and T)).

Following this definition, we calculated the spike frequency and compared whether the IS and MS models, based on both the BIC and AIC, were able to detect such spikes. Table 3 summarises the results. It can be observed empirically that spikes occur with a frequency of around 2%; the frequency of spikes is lowest in Tasmania (1.07%) and highest in South Australia (2.9%).

We then compared the detection rate (type I error) and the correct signal rate (type II error) across the IS and MS models. The detection rate is the percentage of spikes detected by each model as a proportion of the total number of spikes identified using nonparametric measures for each state, while the correct signal rate is the percentage of price spikes detected by each model that correspond to actual true positives/correct signals. As Table 3 illustrates, based on the BIC values, the IS model is markedly better at issuing a correct signal than the MS model. For example, the correct signal rate of the IS model for New South Wales is 90.0%, but that of the MS model is only 6.4%. However, the detection rate of the IS models is slightly lower than those of the MS models, except for Victoria. This is because we use a very small value of α to strictly control the false detection rate, which is recommended as a rule of thumb by Pretis et al. (2018). IS performs particularly poorly for Tasmania, which may be related to the fact that Tasmania is geographically isolated from the other states, and its electricity market is connected through Basslink. To check the sensitivity of the models, we also compared the spike detection performance based on the AIC values. We found that the results of the IS models vary slightly. However, the results of the MS model changed significantly: its detection rate decreased noticeably and its correct signal rate increased. We also found that the data for the number of spikes detected by each method for each state showed that the MS model over-identifies spikes. Overall, we found that the IS models usually have a higher correct signal rate than the MS models, and the MS models tend to over-identify spikes; thus, the IS models have better detection rates.

6 Robustness Check Using Daily Data

The increasing occurrence of negative prices in the NEM has been well documented in recent years; it is associated with periods of low demand combined with high supply, predominantly as a result of intermittent renewable energy generation (AEMO 2019). To deal with negative prices, these observations are typically removed or truncated. However, recent empirical studies (Kyritsis et al., 2017; Mwampashi et al., 2021) underscore the importance of accommodating negative prices in modelling approaches to better reflect electricity price dynamics.

In order to demonstrate that the indicator saturation approach can also accommodate negative prices, we repeated our analysis of the daily electricity spot price. The data were obtained from the AEMO website[19]. The sample period remains the same as that of our main analysis – that is, 1 July 2008 to 27 December 2020, for a total of 4563 daily observations for each state. Due to the presence of negative prices, we adjusted the model so that natural

[19] https://www.aemo.com.au/energy-systems/electricity/national-electricity-market-nem/data-nem/data-dashboard-nem#aggregated-data (assessed on 14 January 2023).

logarithms of the daily data were not included. An additional adjustment was the inclusion of day-of-week dummies in the IS-3 specification in order to reflect a weekly pattern. For the IS settings, we still used the partial autocorrelation function to determine the autoregressive order[20] and employed the rule of thumb to set the significance level at $\alpha = min(0.05, [1/k])$. Additionally, we found that the expectation-maximisation algorithm used to estimate the parameters of the Markov switching models cannot converge for daily electricity prices (without using a logarithm) in some states. Thus, we decided to focus on comparing different IS specifications in this robustness check.

Table 4 presents the AIC and BIC values for the daily electricity prices produced by the four IS specifications. The data show that IS-2 performs best for all five states. This can be explained by the fact that spikes are more prominent without the use of logarithms, and the multiple seasonality (encoded by the calendar dummies) becomes less crucial in the raw series of electricity price. Thus, without considering seasonality, IS-2 outperforms the IS-3 setting.

It is worth investigating the occurrence of spikes at the daily level, particularly for different subperiods. This enables us to focus our attention on the evolution of the occurrence of spikes in our sample period. It should be noted that spikes are selected at different significance levels for daily data and weekly data. This is because of the use of the rule of thumb that advises setting the significance level at $\alpha = min(0.05, [1/k])$, which depends on the number of observations. Since there are many more daily observations than weekly observations, we were much stricter in our selection of spikes for daily data. This enabled us to properly control the false detection rate, as suggested by Pretis et al. (2018).

[20] For daily data, the lag lengths we chose were 15 for QLD, 10 for NSW, 14 for VIC, 16 for SA, and 14 for TAS. To avoid unnecessarily large lag lengths, we arbitrarily restricted the maximum lag length to 16. Based on our experiments, such restrictions can help to produce a better model with lower AIC and BIC values.

Table 5 shows the number of spikes based on the daily data for different financial years (1 July to 30 June the following year) in our sample period. The data show that spikes occurred more frequently in the period prior to the carbon pricing scheme (July 2008–June 2012), particularly for South Australia and Tasmania during July 2009–June 2010. During the period of the carbon pricing scheme (July 2012–June 2014), the number of spikes remained at a relatively low level for all states except Queensland. After the introduction of the Emission Reduction Fund, the occurrence of spikes remained high for Queensland, most notably between July 2017 and June 2018, when 10 spikes occurred; the other four states show relatively low numbers of spikes for this period. Nevertheless, slight increases in the number of spikes have been observed in those four states in recent years (since July 2018), which could be partly attributed to the rapid integration of renewable energy generation in the NEM.

7 Discussions and Policy Implications

The indicator saturation method has provided a realistic picture of the NEM in Australia. It has detected location shifts and breaks, which should have a beneficial effect on the constancy of our modelling approach, as well as on forecast performance.

These findings are highly relevant for global environmental change, as future demand for electricity could be higher than is currently expected, leading to an increase in the associated environmental pressures. The results may also suggest that an electricity price saturation point is approaching as a result of the fact that traditional fossil energy sources are reaching the end of their lifetime. Thus, these sources should be replaced with renewable energy sources as a matter of urgency.

The methodology proposed here can be used to further improve the prediction performance of electricity price models. The recommended method has been shown to be an accurate and efficient modelling approach for price forecasting. The use of the proposed method in the prediction of electricity prices is both practical and feasible, and it could therefore be of great benefit to utility companies when formulating their long-term strategies.

Our results highlight the substantial impact that the treatment of extreme electricity events such as shifts and spikes may have on the estimation of electricity price patterns. Such results emphasise the importance of using a filtering procedure that detects and replaces extreme observations/events in electricity spot prices. Such modelling approaches can yield more consistent, unbiased estimates. In addition, the findings highlight for policymakers the extent to which electricity plants are an absolute necessity for meeting peak demand when the supply of electricity is not adequate, and in that sense regulatory instruments that ensure the viability of those plants (in the form of capacity markets) may, therefore, become increasingly relevant, especially in the case of price drops, which can trigger reductions in the stock of current capacities that are required to sustain system reliability. The shifts, spikes, and break events seen in the Australian electricity market underline the importance of the role of policymakers and regulators. In addition, accurate forecasting of extreme price events, such as price spikes and breaks, is an essential aspect of risk management in the electricity sector. Overall, given that the ability to predict electricity prices is a crucial component of security valuation in the electricity industry, it is imperative that this capacity is improved by explicitly incorporating the most salient features of electricity prices, including those mentioned above.

Furthermore, the accurate prediction of electricity prices under different characteristics and conditions is particularly important for certain segments of the population. More specifically, within a particular region or community, certain groups may be more significantly affected by climate change than others. For instance, low-income households are expected to bear a disproportionate burden, because those belonging to this demographic have fewer resources with which to adapt to the various climate impacts. For example, low-income households are less able to purchase and operate specific electricity-powered items, such as air conditioning units, during extreme heat events. In addition, some of the most significant climate impacts, such as heat and wildfire smoke, could disproportionately affect medically vulnerable populations, including children and the elderly, those with underlying medical conditions such as asthma and cardiovascular diseases, and those who spend a large amount of time outdoors, such as homeless populations and outdoor workers. Such extreme weather events could also disproportionately impact people who are institutionalised, such as hospital patients. These populations might not be able to go outside for days at a time because they are only allowed to spend time outside during specific hours of the day.

Existing market institutions should be restructured or improved so that regulators are better able to combat potential gaming and/or manipulation activities in electricity markets. The presence of structural weaknesses can lead directly to problems when rational economic players behave in such a way as to take advantage of market imperfections and institutional shortcomings. The message to policymakers is clear: such behaviour should not be tolerated, as the cost of the movement to stronger competition may be large. Policymakers should address and solve any such underlying institutional problems, and regulators must clearly demonstrate that they are willing to enforce rules that will establish an orderly electricity market. These aims can be achieved as follows: by adopting explicit and vigorous policies that prevent the manipulation of the NEM electricity market by ensuring that the basic conditions adequately support competition, including ensuring that the number of suppliers and their ability to bring the electricity product to market is sufficient to deliver workably competitive markets; ensuring that market institutions are well developed during the trading process so that conduct is transparent and disciplined by market forces; and monitoring electricity market performance such that participants are not engaged in actions that tend to tighten said markets with the aim of exploiting this dynamic through sales at inflated prices.

8 Conclusion

In this study, we have analysed stylised facts, including spikes, structural changes, and trends, in the modelling of electricity prices. The indicator saturation approach was used because it can directly model these stylised features and avoid the unrealistic assumptions of the Markov switching model, which assumes that Markov chain determining regimes are independent of all other parts of the model. Using various model evaluation tools, we have shown that this approach outperforms the regime-switching models with various settings. Using a nonparametric measure, we also showed that the IS approach had a better rate of signalling price spikes. We detected the dates of spikes, structural breaks, and trends for Australian states. Although our analysis focuses on the Australian NEM, those stylised facts are universal and are observed across all electricity markets, and our analysis is therefore applicable to other countries as well.

Our results emphasise the importance of detecting and mitigating extreme events in electricity spot prices and highlight for policymakers the extent to which electricity plants are an absolute necessity for ensuring that peak demand is met when the electricity supply is not adequate. In that sense, regulatory mechanisms that ensure the viability of those plants (in the form of capacity markets) may become increasingly relevant, especially in the case of price drops, which can trigger reductions in the stock of current capacities that are required to sustain system reliability. Future studies could consider the incorporation of external factors into the framework of indicator saturation. Moreover, researchers may use the indicator saturation method to forecast other economic variables, where this method may perform better as it can detect structural changes in a more timely manner (Marczak and Proietti, 2016). Overall, improved electricity price forecasting substantially enhances our knowledge of the clustering of different end-customer groups, and related strategies can therefore be used by energy providers to identify electricity usage patterns. These insights can be utilised to add to an improved customer view or to personalised marketing propositions such as new tariffs and incentives that might better engage end customers, helping them to save money and reducing churn rates at the same time. Hence, the timing is perfect for utilities and retail energy providers to update their load forecasting practices to reflect today's rapidly changing energy landscape.

One limitation of the use of indicator saturation is that the computational cost of this approach is much higher than that of other traditional methods if the sample size is large. It is worth noting that the shift-detecting ability of SIS is asymmetric because it is better able to detect shifts in the second half of the sample relative to the first half (Marcrak and Proietti, 2016).

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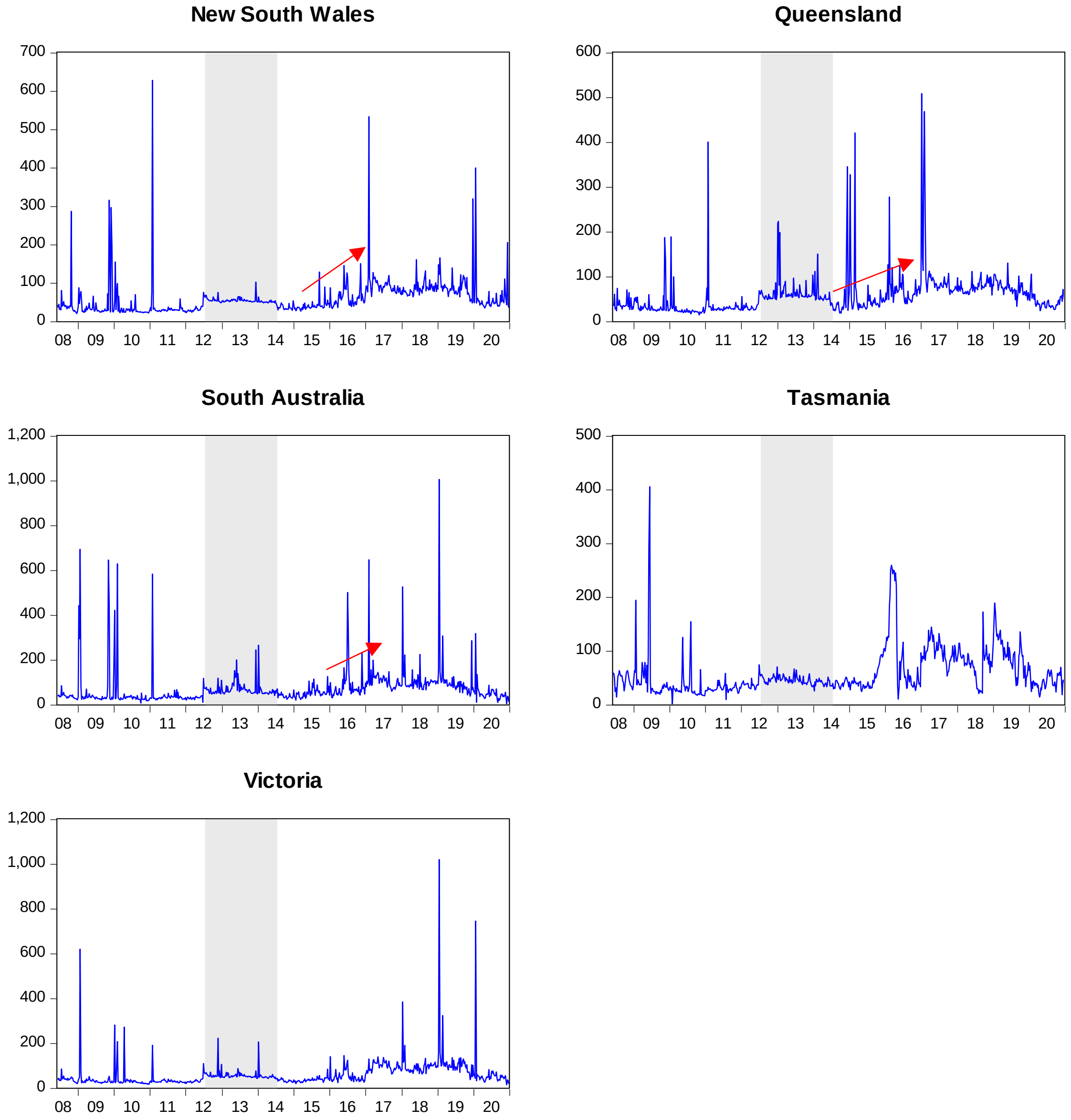
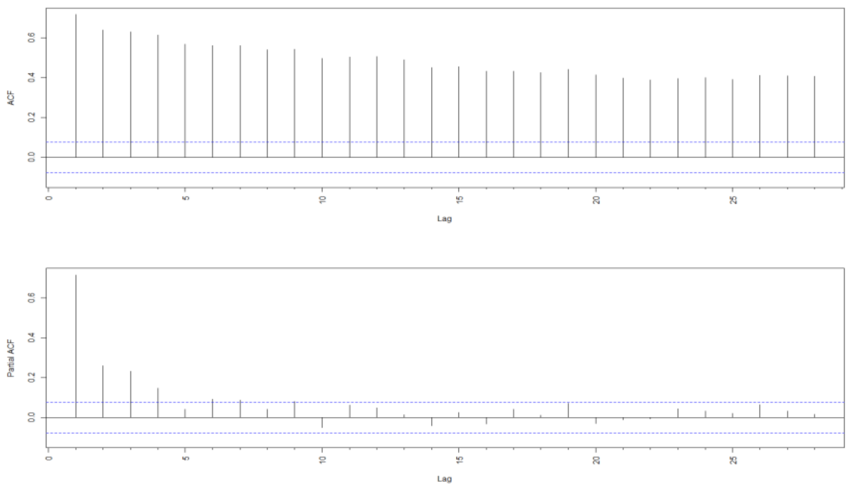
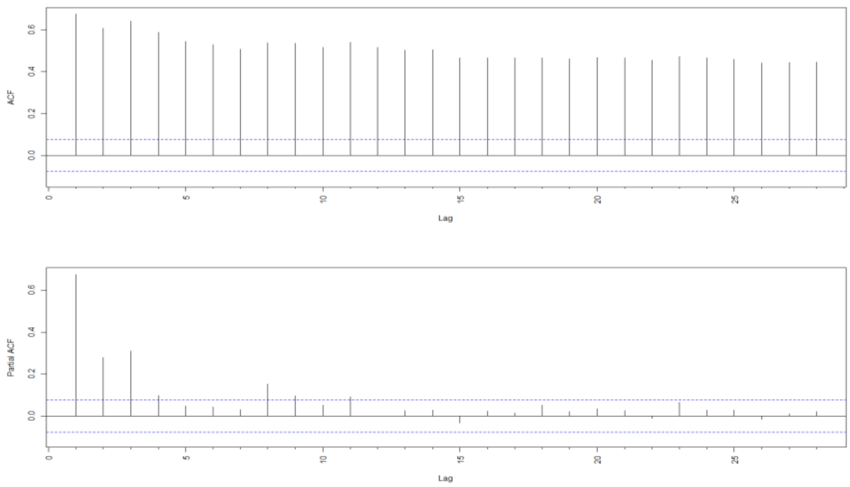


Figure 1. Weekly spot electricity prices for five Australian markets.

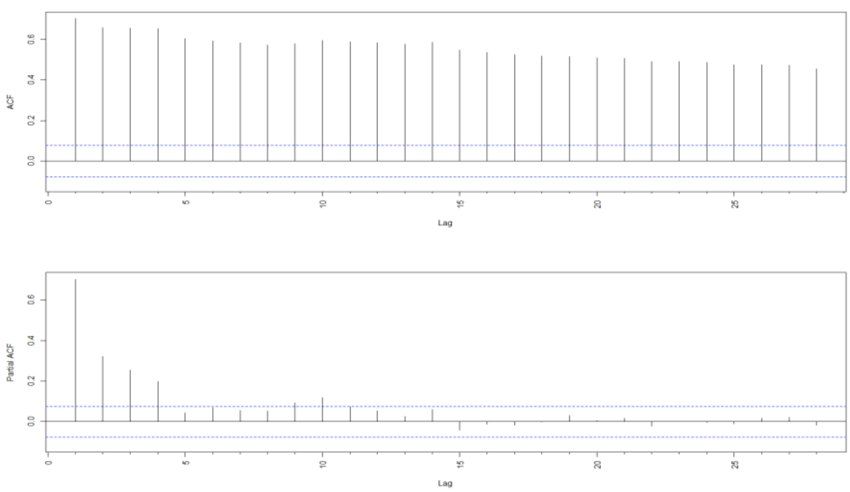
Note: Grey area indicates the period of carbon tax.



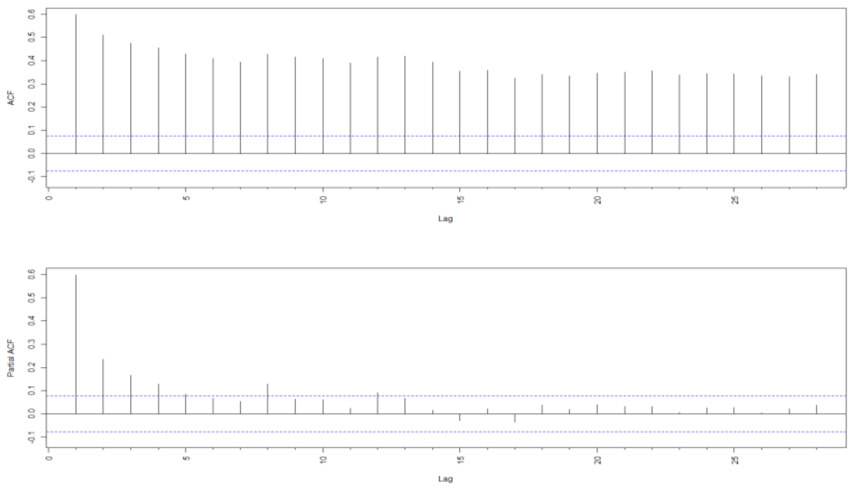
A: Queensland (QLD)



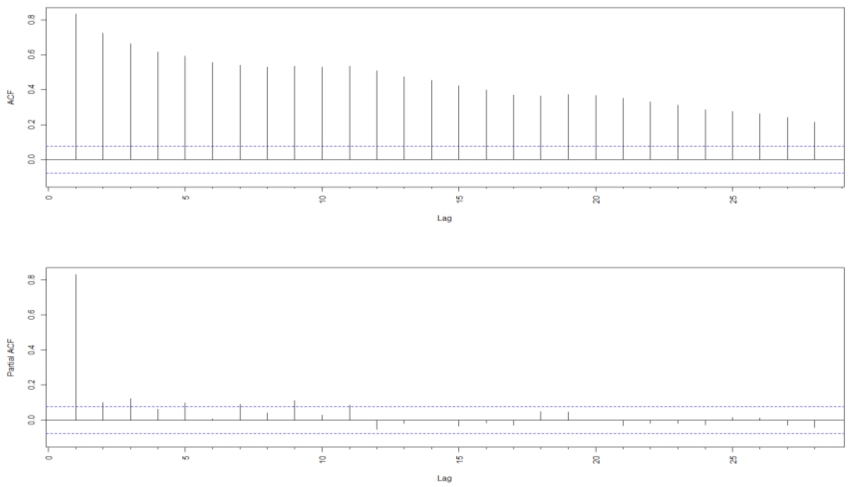
B: New South Wales (NSW)



C: Victoria (VIC)

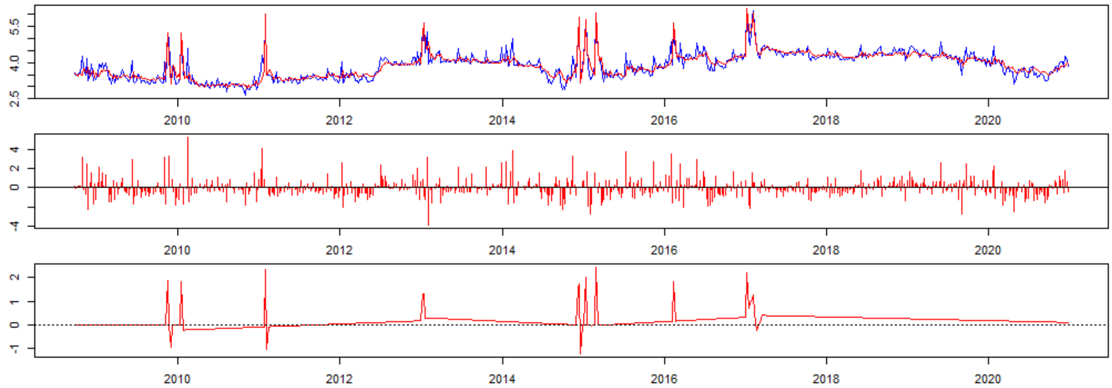


D: South Australia (SA)

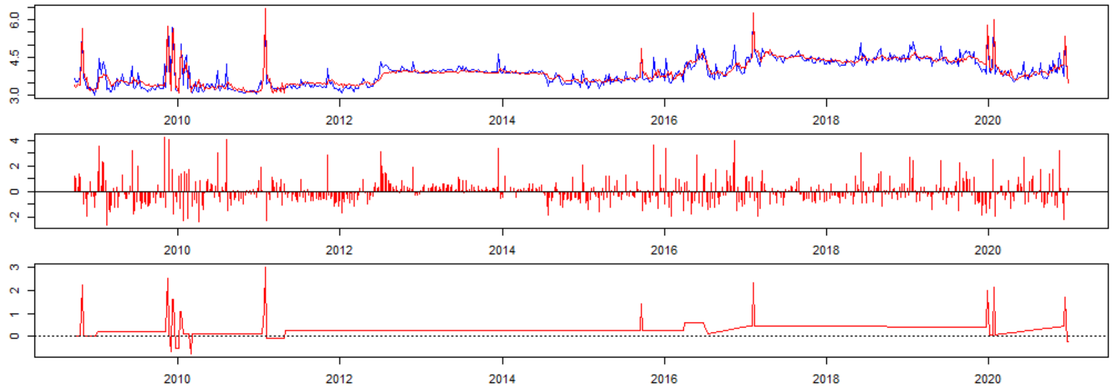


E: Tasmania (TAS)

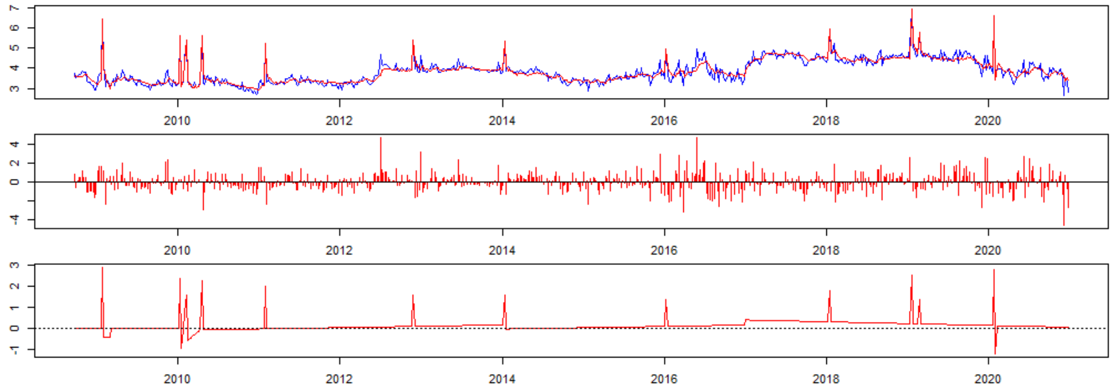
Figure 2. Autocorrelation functions (ACF) and partial autocorrelation functions (PACF)



A: Queensland (QLD)



B: New South Wales (NSW)

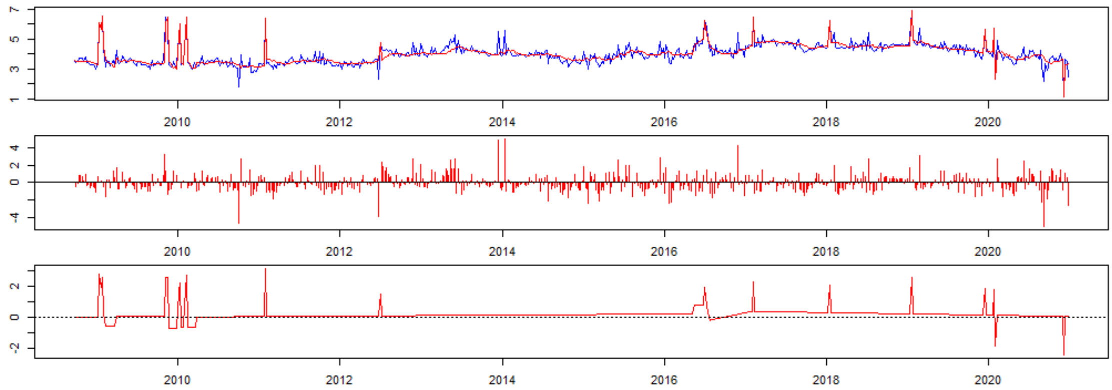


C: Victoria (VIC)

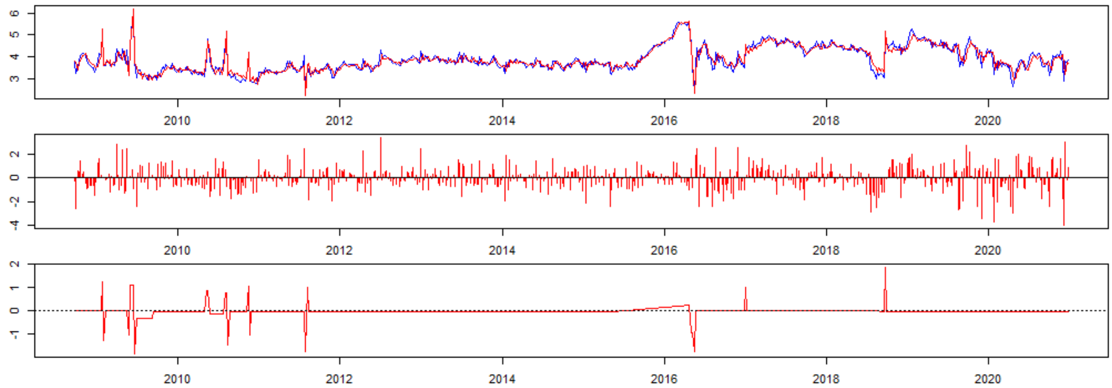
Figure 3. Model fitted results.

Upper panel: log of electricity price (actual – blue, fitted – red);

Middle panel: standardised residuals; Lower panel: coefficient path.

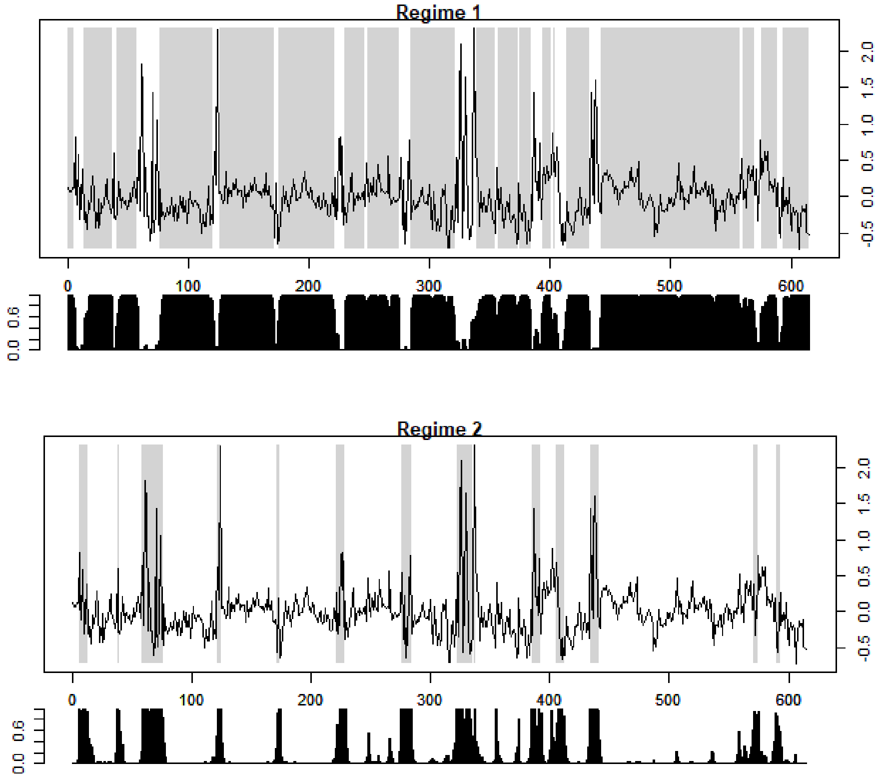


D: South Australia (SA)

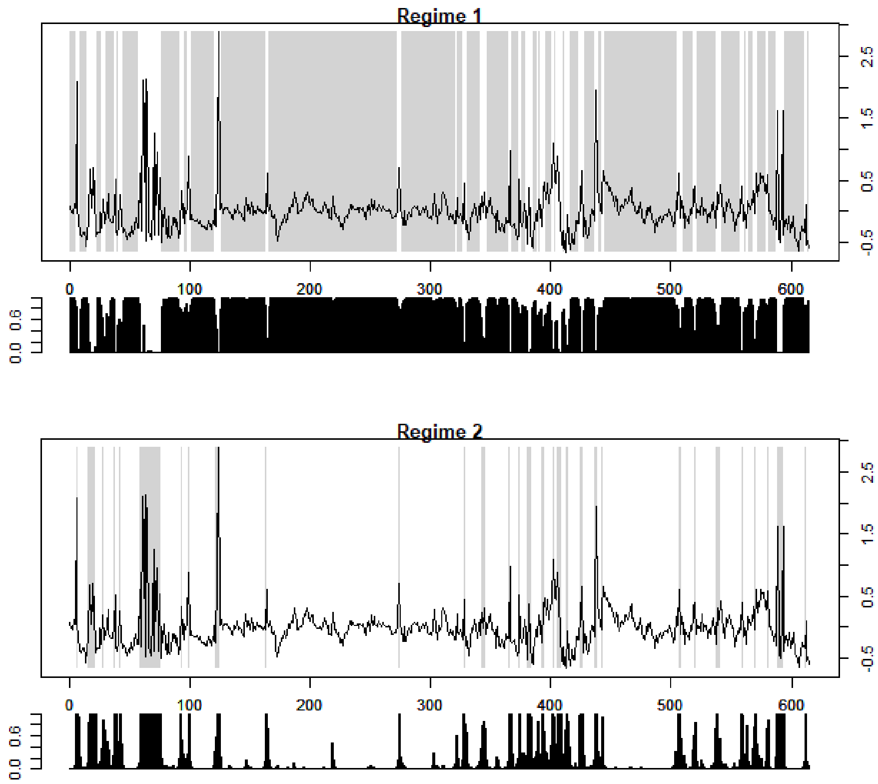


E: Tasmania (TAS)

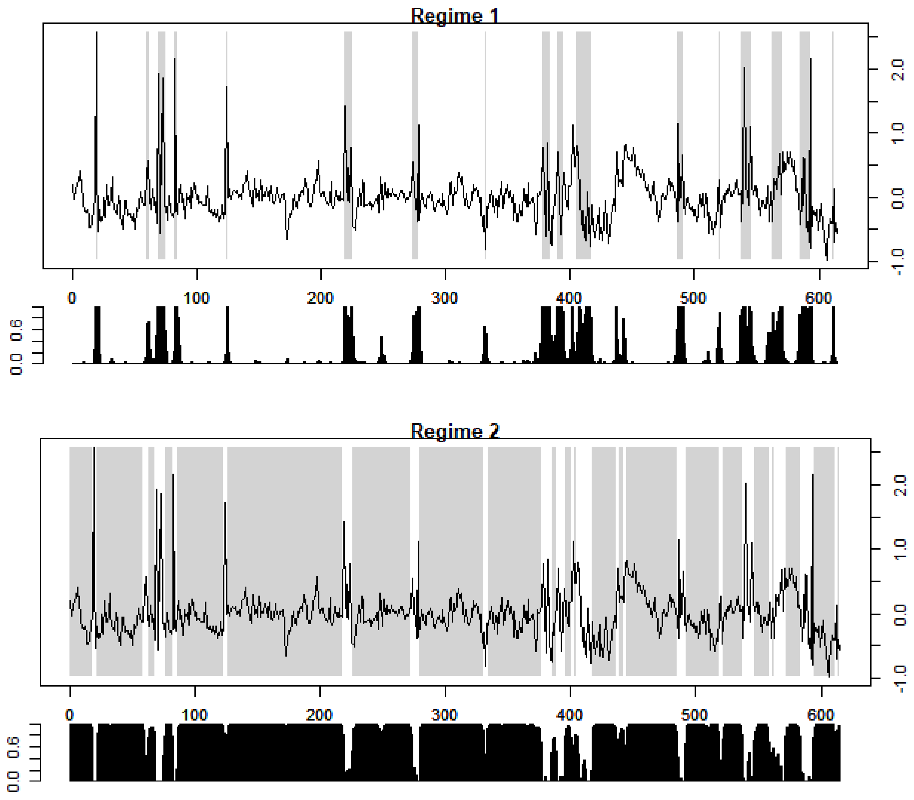
Figure 3. (Continued)



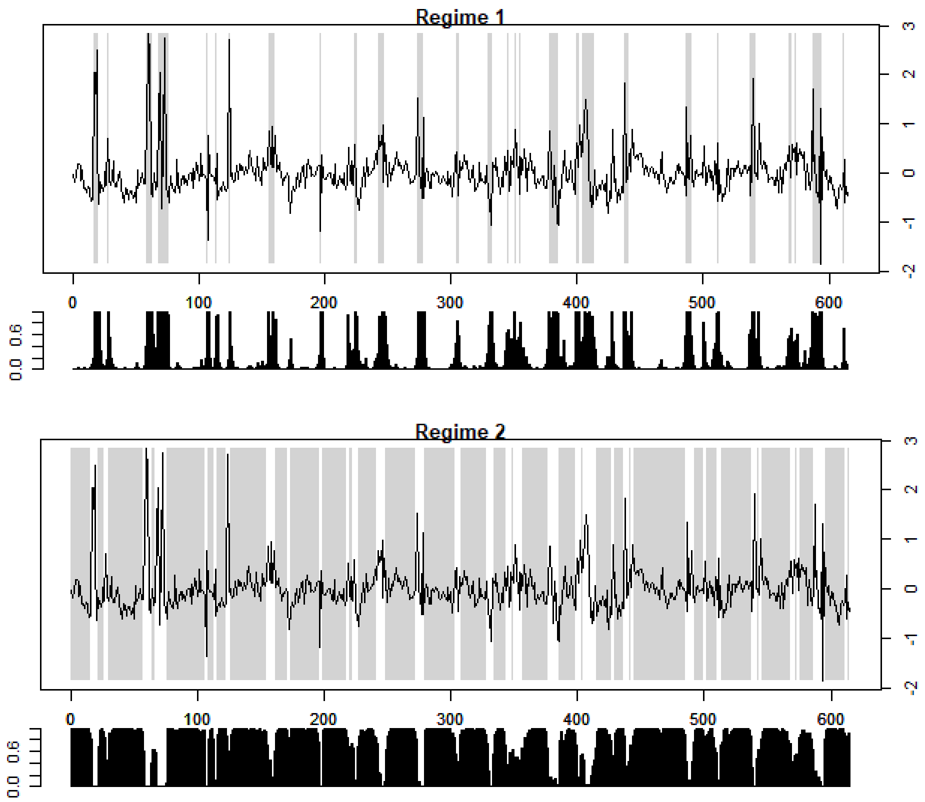
A: Queensland (QLD)



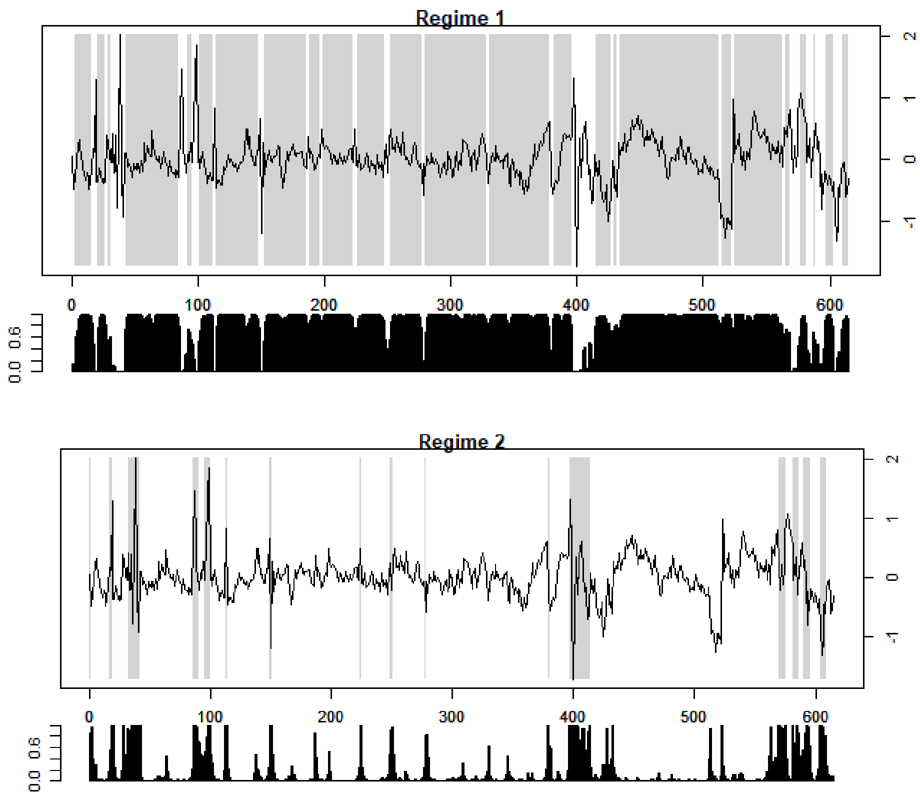
B: New South Wales (NSW)



C: Victoria (VIC)



D: South Australia (SA)



E: Tasmania (TAS)

Figure 4. Markov-switching regime.

Upper panel: demeaned and de-seasonal log of electricity price;
Lower panel: smoothed probability.

Table 1. Summary Statistics

	NSW	QLD	SA	TAS	VIC
Mean	58.39	57.32	70.62	57.62	58.57
Median	50.00	49.00	52.00	43.00	44.50
Maximum	627.00	508.00	1005.00	405.00	1019.00
Minimum	20.00	14.00	3.00	0.00	14.00
Std. Dev.	46.61	47.32	82.53	41.74	63.71
Skewness	6.10	5.10	5.85	2.88	8.74
Kurtosis	60.12	38.97	47.71	15.98	110.83
Jarque-Bera	93258.83	38201.49	58389.15	5508.73	326191.60
Probability	0.00	0.00	0.00	0.00	0.00

Pairwise Correlation coefficients

	NSW	QLD	SA	TAS	VIC
NSW	100%				
QLD	56%	100%			
SA	51%	33%	100%		
TAS	25%	27%	27%	100%	
VIC	44%	23%	73%	34%	100%

Table 2. Comparisons among Indicator Saturation and Markov switching models

	Indicator Saturation				Markov Switching	
A: Queensland (QLD)						
	IS-0	**IS-1**	**IS-2**	**IS-3**	**MS-2R**	**MS-3R**
AIC	315.25	15.66	-16.39	-51.01	91.83	52.83
BIC	395.89	150.06	135.93	177.47	318.24	354.70
B: New South Wales (NSW)						
	IS-0	**IS-1**	**IS-2**	**IS-3**	**MS-2R**	**MS-3R**
AIC	98.56	-65.25	-105.51	-158.44	-118.58	-200.76
BIC	174.72	78.11	60.25	79.01	125.59	127.75
C: Victoria (VIC)						
	IS-0	**IS-1**	**IS-2**	**IS-3**	**MS-2R**	**MS-3R**
AIC	324.67	-0.79	-55.52	-43.91	84.97	
BIC	391.87	138.09	92.32	189.05	320.26	
D: South Australia (SA)						
	IS-0	**IS-1**	**IS-2**	**IS-3**	**MS-2R**	**MS-3R**
AIC	440.72	406.80	387.83	374.16	458.92	431.43
BIC	552.72	568.08	558.07	625.04	711.97	773.26
E: Tasmania (TAS)						
	IS-0	**IS-1**	**IS-2**	**IS-3**	**MS-2R**	**MS-3R**
AIC	234.15	-183.20	-207.14	-259.09	-44.10	-57.73
BIC	319.27	-39.84	-50.34	0.75	204.50	275.23

Note: Yellow indicates the minimum value across groups of IS or Markov switching models.

Table 3. Results for spike detection

			QLD	NSW	VIC	SA	TAS
	Nonparametric Measure	No. of Spikes	15	15	11	19	7
		Frequency	2.3%	2.3%	1.7%	2.9%	1.1%
BIC	IS	No. of Spikes	10	10	12	13	12
		Detection Rate	40.0%	60.0%	91.7%	52.6%	28.6%
		Correct Signal	60.0%	90.0%	91.7%	76.9%	16.7%
	MS	No. of Spikes	109	109	90	138	90
		Detection Rate	100.0%	46.7%	91.7%	94.7%	100.0%
		Correct Signal	14.0%	6.4%	12.2%	13.0%	8.0%
AIC	IS	No. of Spikes	12	13	11	17	16
		Detection Rate	46.7%	60.0%	75.0%	52.6%	57.1%
		Correct Signal	58.3%	69.0%	81.8%	58.8%	25.0%
	MS	No. of Spikes	73	72	32	45	53
		Detection Rate	66.7%	46.7%	83.3%	73.7%	85.7%
		Correct Signal	14.0%	9.7%	31.3%	31.1%	11.0%

Table 4. Results of Indicator Saturation based on daily data

A: Queensland (QLD)				
	Indicator Saturation			
	IS-0	IS-1	IS-2	IS-3
AIC	40130.75	39559.25	38739.49	38928.45
BIC	40535.57	39996.20	39298.53	39577.45
B: New South Wales (NSW)				
	Indicator Saturation			
	IS-0	IS-1	IS-2	IS-3
AIC	39292.66	37852.39	37376.22	37775.42
BIC	39620.37	38250.79	37877.42	38308.75
C: Victoria (VIC)				
	Indicator Saturation			
	IS-0	IS-1	IS-2	IS-3
AIC	39887.78	39202.12	38842.80	38985.82
BIC	40144.81	39523.41	39234.77	39474.18
D: South Australia (SA)				
	Indicator Saturation			
	IS-0	IS-1	IS-2	IS-3
AIC	43837.73	43984.90	43534.62	43582.64
BIC	44210.42	44396.15	44022.98	44141.68
E: Tasmania (TAS)				
	Indicator Saturation			
	IS-0	IS-1	IS-2	IS-3
AIC	38680.81	37339.82	37263.34	37296.80
BIC	39098.48	37725.36	37681.01	37830.14

Table 5. Number of spikes based on daily data

Financial Year	QLD	NSW	VIC	SA	TAS
Jul 2008 - Jun 2009	1	3	0	0	0
Jul 2009 - Jun 2010	4	9	3	12	16
Jul 2010 - Jun 2011	3	4	6	5	9
Jul 2011 - Jun 2012	3	5	1	2	1
Jul 2012 - Jun 2013	0	0	1	0	0
Jul 2013 - Jun 2014	4	1	0	2	0
Jul 2014 - Jun 2015	4	0	1	1	0
Jul 2015 - Jun 2016	4	1	0	0	0
Jul 2016 - Jun 2017	2	1	1	4	0
Jul 2017 - Jun 2018	10	4	0	1	0
Jul 2018 - Jun 2019	0	0	2	4	3
Jul 2019 - Jun 2020	0	1	3	4	1
Jul 2020 - Dec 2020*	0	5	3	1	0
Total	35	34	21	36	30

Note: The last financial year ends in December 2020 because of data availability at the time of writing.