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Carbon Taxation and Electricity Price Dynamics: Empirical Evidence from the Australian Market

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Abstract

In this paper, we study the change of Australian electricity price dynamics that was observed before, during and after the two-year period in which a Carbon Pricing Mechanism was in force. We fit a two-states Markov Switching Model, representing a high- and a low-volatility state of the world. To avoid the interference due to periodic patterns, a deseasonalization process accounting for short- and long-term seasonality is carried out prior to the study of volatility. Estimation results highlight that, during the period when the carbon tax applies, the volatility level is lower for both the states of the world. Furthermore, the persistence in the low-volatility state is increased in the presence of the carbon tax. This conclusion is particularly relevant for macroeconomic and investment considerations because the increased uncertainty in electricity prices can significantly influence firms' investment decisions and shape inflation expectations.

Keywords Carbon pricing · Electricity price volatility · Markov switching models

JEL Classification C51 · Q41 · Q48

1 Introduction

Australia's National Electricity Market (NEM) allows electricity to be generated, traded and delivered across the east-coast and southern states. As of 2022, it serves about 10.6 million customers, accounting for approximately 90% of the national electricity consumption of 204TWh (see Australian Energy Regulator 2022), located in New South Wales (NSW), Queensland (QLD), Victoria (VIC), South Australia (SA) and Tasmania (TAS). These regions are interconnected via three alternating current and three direct current interconnectors, covering a distance of roughly 5000 km, making it the widest interconnected power system in the world (see Gu et al. 2019). The NEM was established in 1998 and has since facilitated the exchange of electricity between generators and retailers on a

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highly competitive regulated wholesale market.[1] The authority responsible for managing the NEM is the Australian Energy Market Operator (AEMO), which oversees the day-to-day operations of electricity and gas markets. The NEM operates according to the rules set by the Australian Energy Market Commission (AEMC) under the mandate of the Council of Australian Governments' (COAG) Energy Council.

As reported by Xian et al. (2020), Australia has historically largely relied upon fossil fuels to satisfy its primary energy and electricity needs, and it is one of the OECD countries with the lowest renewable primary energy use.[2] Besides having 14% of the world's proved recoverable reserves of coal, according to Pollitt and Haney (2013), the reason for its historical dependence on fossil fuels is to be found in Hilmer and related reforms,[3] liberalizing the electricity market, and establishing the NEM. This legislative package pursued efficiency and competitiveness as overriding priorities, leading to a massive use of the cheapest energy source available (see Parer 2002). During the past decades, however, growing concerns related to energy security, decarbonization, and climate change reshuffled the priorities of many governments worldwide. As a consequence, the Australian government implemented several environmental policies aimed at reducing the 2005 level of emissions by $26\% - 28\%$ before 2030 (see Howard et al. 2018). The main result of these efforts was the enactment of the Clean Energy Act in 2011.

The most relevant innovation of the Clean Energy Act was the Carbon Pricing Mechanism (CPM), which has *de facto* imposed a carbon tax in Australia. The Australian CPM, intended to ease the transition to an ultimate Emission Trading Scheme (ETS), was in force only between July 1st, 2012, and June 30th, 2014, when it was repealed despite its effectiveness in reducing greenhouse gas emissions.[4] More in detail, businesses emitting more than 25 thousand tonnes of carbon dioxide equivalent (tCO_2e) were required to buy the corresponding emission units from the government (see Clean Energy Regulator 2013). Since permits were unlimited and available at a fixed price (23.00AUD/tCO_2 in the first

[1] According to Australian Energy Regulator (2017), the Herfindahl–Hirschman Index (HHI) of all NEM's regions ranged between 0.17 and 0.25 from 2010 to 2017. hese values are consistent with other competitive markets, such as England and Wales, Singapore, and Sweden, whose HHI values are respectively 0.16, 0.27 and 0.32 (see Chang 2007).

[2] As reported by the Australian Government Department of Climate Change, Energy, the Environment and Water (2022), in the period between 2020 and 2021, fossil fuels (renewable sources) accounted at the national level for 73.3% (26.7%) of overall electricity generation, showing a 10-year change of −1.5% (10.3%). At the level of individual NEM regions, however, important differences are observed. New South Wales, Queensland, and Victoria are the most reliant upon coal, with a share of 51.35%, 52.75%, and 33.30%, respectively, in terms of installed capacity excluding rooftop solar. South Australia and Tasmania indeed satisfy most of their electricity needs by means of gas-powered generation and hydropower respectively, with a share of 46.66% and 74.61%. See Australian Energy Regulator (2022) for further details. Moreover, in 2021 only 8.3% of primary energy supply was satisfied by renewable sources (see OECD 2023).

[3] The National Competition Policy, implemented in Australia in the 1990s, is a framework of regulations designed to promote economic efficiency in several industries. These policies, often referred to as the Hilmer reforms in recognition of the committee chair responsible for their recommendations (King 1997), seek to achieve greater productivity and allocative efficiency. With regard to the energy sector, Hilmer reforms aimed to achieve greater productivity and allocative efficiency by shifting the risks of investment away from consumers and taxpayers, surpassing the previous government-owned monopoly. While the adoption of these reforms has been uneven across Australia, a trend towards restructuring the energy sector into competitive segments encompassing generation, transmission, and distribution has been observed nationwide (Rai and Nelson 2020).

[4] O'Gorman and Jotzo (2014) observe that overall emissions decreased by 8.2% under the CPM, compared to the previous two-year period.

year and 24.15AUD/tCO_2 later), this scheme was comparable to a carbon tax, and in fact, it is commonly referred to as such (see Maryniak et al. 2019). Among the market-based policy options to tame climate change, the carbon tax is one of the most environmentally effective and economically efficient (see Acemoglu et al. 2012; Hagmann et al. 2019).[5] The carbon tax originates from the concept of Pigouvian taxation. It is aimed at recouping the damage generated from CO_2 emissions, a negative externality deriving from the production process, and it can contribute to the reduction of greenhouse gas (GHG) emissions. By impacting on the relative input costs of the power generating companies, and therefore on the electricity spot price as measured by pass-through rates (see Maryniak et al. 2019; Nazifi et al. 2021), it can provide an incentive to employ less polluting energy inputs. There is wide consensus about the effectiveness and cost-efficiency of the carbon tax, especially for developed countries (see, among others, Hájek et al. 2019; Levin et al. 2019).[6] The specific case of the Australian CPM hence offers the unique opportunity to investigate the effects that both the introduction and repeal of this kind of regulatory package had on a well-developed electricity market. Furthermore, it is also possible to investigate whether its introduction brought structural changes that survived its repeal (see Geroe 2022).

In this paper, we therefore study the dynamics of Australian electricity price, with a particular focus on price volatility, and how its behavior changed when the CPM was in force. Our interest is motivated by the fact that, in this period, there was a well-documented increase in the average price (Wong and Zhang 2022), along with a reduction in volatility.

According to the scientific literature, changes in electricity price volatility can be traced to the following events. First, electricity prices tend to experience increased volatility in case of extreme weather conditions or technical issues on the grid, as these events induce volatility on the supply side (see Michelfelder and Pilotte 2022). Second, transmission network congestion might also be an important source of price volatility (see Sapio 2012; Yang and Ozdaglar 2016), and the magnitude of this effect can be empirically estimated (see Hadsell and Shawky 2006). Third, a lack of competitiveness, due to a significant change in market concentration, and the possible consequent tacit collusion among operators, may also impact electricity price volatility (see Fabra and Reguant 2014; Ganapati et al. 2020). Finally, price volatility might also be increased by a higher market share of renewable sources, solar and wind in particular, due to their intermittency and difficulty in adjusting to demand (Abban and Hasan 2021; Martinez-Anido et al. 2016).

However, for the Australian case, none of these four factors seems compelling. The Australian Energy Regulator (2022) reports that, in the period 2012–2014, an average of 20.7 loss of supply events was reported each year, in line with (even higher than) the previous (following) period 2006–2011 (2015–2020) when the average was 22.8 (10.8). The reduction of these events after the period when the CPM was in force was observed despite tightening in the balance between demand and supply, mainly due to the coincident closure or mothballing of coal plants and a peak in demand observed in particular in Queensland, South Australia, and Tasmania. In addition, wide network investments in the period 2006–2014 eliminated most of congestion-related issues (see Australian Energy Regulator 2022). Moreover, market concentration showed no significant changes, as evidenced by the HHI index that remained stable in all the period analyzed in this study. Finally, notwithstanding an increase in the market share

[5] At a higher level of distinction, the literature has also focused on the comparison of market-based and command-and-control policies (see, for example, Lamperti et al. 2020).

[6] However, there are some concerns because market failures or regulatory distortions may reduce the power of a carbon tax because of its price-instrument nature (see, among others, Finon 2019).

of renewables observed during the period under study (Australian Energy Regulator 2022), volatility did not increase. Therefore, none of the factors that typically explain variations in electricity price volatility can explain the phenomenon observed in the Australian market at CPM, leaving open the possibility that the variation is linked to the introduction of the carbon tax.

Our analysis is based on a six-year period, from mid-2010 to mid-2016. This allowed to study three timeframes (before, during, and after the CPM) with the same length. We examine the series of electricity prices and traded volumes, the latter to double-check the periodic component, for all five regions of the NEM. However, for the sake of brevity, we present only the results of the main regions. The contribution of the work is twofold. On the one hand, we propose a comprehensive approach to account for seasonal patterns within electricity data. Unlike most literature, where short- and long-term components are treated separately (see, among others, Knittel and Roberts 2005; de Marcos et al. 2019; Marcjasz et al. 2019), in this paper, we introduce and estimate an all-embracing model. On the other hand, using deseasonalized time series, we investigate the stability of the price dynamics with respect to the introduction and repeal of the CPM. More in detail, as the electricity price is characterized by regime-switching behavior (see, among others, Eichler and Türk 2013; Manner et al. 2016; Scarcioffolo and Etienne 2021) and by the presence of spikes, we employ a Gaussian Markov Switching Model (MSM) to study the occurrences of a low- and a high-volatility state of the world. The pertinence of this choice is also well-supported by the literature (see, among others, Weron 2007; Bunn 2004) as well as by theoretical considerations. As a matter of fact, the contribution by Ellen and Zwinkels (2010) suggests that energy demand can be decomposed into a speculative component and a real component. Since speculators' expectations can be heterogeneous and evolving over time, large fluctuations in price can emerge with periods of large volatility followed by periods of volatility stabilization. Thus, our study relates to this literature without deriving a theoretical model. Instead, it primarily entails an empirical analysis. Consequently, our capacity to establish a causal relationship between the implementation of a carbon tax and the altered behavior of electricity prices is limited. However, given the inability of the four factors identified by the scientific literature to jointly explain the rise in average price and the reduction in volatility observed in the NEM between 2012 and 2014, one might conjecture that the carbon tax might be a likely explanation.

Besides providing a significant time series decomposition into its seasonal components, our results suggest that during the period in which the carbon tax has been active, the uncertainty about electricity price shocks was undoubtedly smaller in all the analyzed regions. To the best of our knowledge, we are the first to provide this result. Indeed, second-order effects of environmental policies are currently underinvestigated. However, they potentially have important implications for the conduct of monetary policy, as the electricity price is one important component of CPI inflation. Therefore, future studies shall aim at further investigating the relevance and the magnitude of these effects as well as the pass-through on more aggregate variables, such as inflation and inflation expectations.

This paper is structured as follows. Section 2 describes the methodology adopted to study periodic patterns and the behavior of deseasonalized data volatility and describes the dataset used. Section 3 discusses the empirical results obtained, while Sect. 4 finally concludes and provides final remarks.

2 Methods and Data

2.1 Time Series Decomposition

A time series y_t, observed over a sufficiently long sample, can be decomposed by generalized additive models to identify its periodic pattern (see Dozie and Ijomah 2020).[7] It is customary to separate the time series into four different components characterizing the long-term trend μ_t, the cyclical fluctuations ν_t, the effects due to specific days (e.g. holidays) ξ_t and, ultimately, the idiosyncratic shocks u_t. The decomposition formally reads as follows:

$$y_t = \alpha + \mu_t + \nu_t + \xi_t + u_t \,. \tag{1}$$

The most appropriate mathematical function to describe the long-term trend μ_t is a p-th degree polynomial of the time index t (see Feng et al. 2020). For our case, we opt for a cubic function of t which appears an appropriate choice allowing to capture inflection points. Thus, the long term component is given by:

$$\mu_t = \sum_{\tau=1}^{3} \beta_\tau t^\tau \,. \tag{2}$$

The second component ν_t represents instead the cyclical fluctuations around the trend component, and aims at capturing the autocorrelation structure of the series. This component can be equivalently represented using either the time or the frequency domain. Following Hamilton (1994) and Bloomfield (2004), we employ the second approach and model the autocorrelation structure by means of a trigonometric function with regular patterns defined as:

$$\nu_t = \vartheta \cos(2\pi f t) + \delta \sin(2\pi f t) \,,$$

where $\vartheta = a \cos p$ and $\delta = -a \sin p$, with a and p respectively measuring the amplitude and the phase of the sin wave, while the term f measures the frequency.[8] More in general, a time series y_t can display more than a single cyclical component. For a series with H components we have:

$$\nu_t = \sum_{h=1}^{H} \Big[\vartheta_h \cos(2\pi f_h t) + \delta_h \sin(2\pi f_h t) \Big]. \tag{3}$$

To estimate the parameters ϑ_h and δ_h one needs to define a set of frequencies $f_1, \ldots, f_H$ which are *a priori* unknown. To identify these frequencies, we exploit spectral analysis (see Alessio 2015). If a time series displays a periodic fluctuation, its autocovariance has approximately the same pattern over the different periods. This happens also in the case of

[7] The decomposition can also be made throughout multiplicative models. However, since in our case the trend and amplitude of seasonal activity do not change over time (see Fig. 1) we choose an additive model which has a simpler interpretation and can be estimated via OLS. To increase the reliability of our findings, we executed a robustness check employing the standard Christiano-Fitzgerald (CF) filter for time series decomposition (Christiano and Fitzgerald 2003). Even using this method, as shown in Appendix 1, the main results of the study remain unaffected, which further demonstrates the reliability of our findings.

[8] Let us recall that the amplitude of a wave is the difference between its max and min values; the frequency is the number of occurrences of a repeating event per unit of time; the phase is the relative value of that variable within the span of each full period.

more than one periodic fluctuation. A regular autocovariance structure can be detected by the population spectrum s_y:

$$s_y(\omega) = \frac{1}{2\pi}\left[\gamma_0 + 2\sum_{h=1}^{\infty}\gamma_h \cos(\omega h)\right], \tag{4}$$

where γ_0 is the variance of the series under scrutiny, γ_k is the k-th order autocovariance and ω is a real scalar. Because the spectrum is a periodic function with period π and symmetric around $\omega = 0$, we can study this function for the domain $\omega \in [0, \pi]$. Finally, in order to identify the frequencies of interest, associated to the peaks of the population spectrum at a specific value ω, we can use the relationship $f_h = \omega_h^{-1}$ where the index h denotes a specific peak of the spectrum.

The third component ξ_t accounts for the presence of short-term flickers observed in electricity data. They are almost completely attributable to specific weekdays or to holiday effects, which strongly impact upon electricity demand and, ultimately, electricity prices (see Brubacher and Tunnicliffe Wilson 1976; Hyndman and Fan 2010; Bunn 2000). More specifically, both during weekends and holidays pressure on demand is always lower than during working days and this reflects on the level and on the volatility of electricity prices.[9] To account for these effects, we build two sets of dummy variables: d_i^w, with $i = 1, \dots, 6$ and d_j^h, with $j = 1, \dots, 9$ to account for weekdays (w) and holidays (h).[10] It follows that:

$$\xi_t = \sum_{i=1}^{6}\zeta_i d_{i,t}^w + \sum_{j=1}^{9}\eta_j d_{j,t}^h . \tag{5}$$

In order to obtain time series that are cleaned from the effects of the three components as defined in Eqs. (2), (3) and (5), we plug them into Eq. (1) and we estimate the following linear regression model:

$$y_t = \alpha + \sum_{\tau=1}^{3}\beta_\tau t^\tau + \sum_{h=1}^{H}\left[\vartheta_h \cos(2\pi f_h t) + \delta_h \sin(2\pi f_h t)\right] + \sum_{i=1}^{6}\zeta_i d_{i,t}^w + \sum_{j=1}^{9}\eta_j d_{j,t}^h + u_t . \tag{6}$$

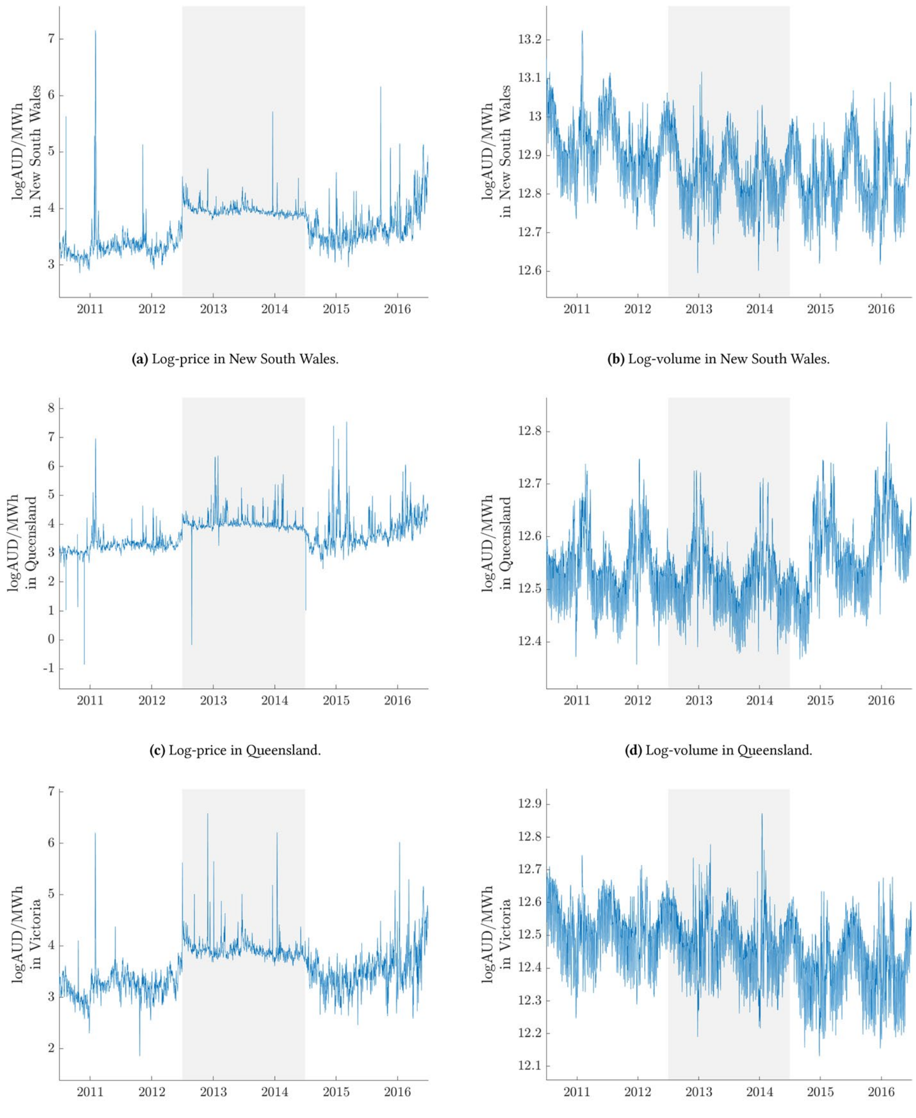
The residuals $\hat{u}_t$ of the estimation of the $19 + 2H$ parameters of the above equation, represent the deseasonalized electricity data (be it measured in prices or volumes). For this reason, the study of this series can focus on dynamics other than temporal ones, that is those conditioning the matching of electricity supply and demand, which, in turn, affects the volatility of both settlement prices and traded volumes of electricity.

2.2 Regime-Switching Volatility

Linear time series models typically assume that one set of model parameters can be used to describe the behavior of the data over all time periods. This assumption, however, isn't always satisfied in reality. For energy related time series, in particular, the linearity assumption does not seem to fit particularly well. In fact, some characteristics of the energy price

[9] The nine Australian public holidays here considered are New Year's Day, Australia Day (January 26th), Good Friday, Holy Saturday, Easter Sunday, Easter Monday, ANZAC Day (April 25th), Christmas Day and Boxing Day.

[10] The dummy variable for one day of the week is not used to avoid multicollinearity.



(a) Log-price in New South Wales.

(b) Log-volume in New South Wales.

(c) Log-price in Queensland.

(d) Log-volume in Queensland.

(e) Log-price in Victoria.

(f) Log-volume in Victoria.

Fig. 1 Time series of log-price (left panels) and log-volume (right panels) observed in the three main regions of the NEM, over the whole period of interest. The grey-shaded area represents the period in which the CPM was in operation

and volume time series (e.g., mean and autocovariance) might vary across time periods (see Fig. 1 for a graphical intuition). For this reason, it seems more appropriate to model electricity price and volumes data by means of nonlinear regime-switching models.

This class of models allows to characterize observed data as belonging to different regimes and allows the characteristics of time series data, including means, variances, as well as model parameters, to change across the regimes. In particular, a regime-switching model assumes that at any given time period there is a probability that the series belongs to a specific regime and another probability that the variable will shift to a different regime in the next period. All these features allow regime-switching models to better capture the behavior of electricity price and volume data than standard models do. The effectiveness of these models in describing the alternation between recurring states of the world is proved by their wide use in energy-related literature. MSMs have proved useful in a variety of fields, for example in driving investment decisions in oil and natural gas trading (see De la Torre-Torres et al. 2019), disentangling the impact on electricity prices of intermittent renewable generation (see de Lagarde and Lantz 2018), evaluating the effects of deregulation of the electricity market on wholesale prices (see Loi and Jindal 2019) or, similarly to our study, in modeling the volatility of the energy sector commodity prices (see Halkos and Tsirivis 2019).

We estimate a Gaussian MSM to understand how the carbon pricing mechanism impacted upon the likelihood of electricity price and volume time series to display a high/low volatility. For our purpose, a two-states MSM is employed to describe the alternation between a high- and a low-volatility regime.[11] Given the autoregressive persistence in the data (see Escribano and Sucarrat 2018) we assume that the deseasonalized electricity price and volume data are drawn by the following MSM process with one lag[12]:

$$x_t = \begin{cases} \phi_{0,L} + \phi_1 x_{t-1} + \sigma_L \varepsilon_t & \text{if } S_t = L \\ \phi_{0,H} + \phi_1 x_{t-1} + \sigma_H \varepsilon_t & \text{if } S_t = H \end{cases}, \tag{7}$$

which can be compactly rewritten as:

$$x_t = \phi_{0,S_t} + \phi_1 x_{t-1} + \sigma_{S_t} \varepsilon_t \ , \tag{8}$$

where $\varepsilon_t \sim \mathcal{N}(0, 1)$ is an i.i.d. shock and S_t represents the outcome of a 2-states Markov chain.

In this model, we allow the constant ϕ_{0,S_t} and the standard deviation of the error term σ_{S_t} to be regime-specific, while we keep the autoregressive parameter ϕ_1 fixed across regimes. We opted for this specification of the model because we expect the carbon pricing mechanisms to have two important effects on the dynamics of electricity price. The first-order effect is that of increasing/decreasing the price/volume levels, thus impacting on the value of the constant term ϕ_{0,S_t}. The second-order effect instead, if there is one, should be on the price and volume volatility, which is here captured by the standard deviation of the error term σ_{S_t}, rather than on the price series persistence.[13] The state transition of the model in Eq. (7) is governed by the transition probabilities $P(S_t = H|S_{t-1} = L) = \rho_L$ and $P(S_t = L|S_{t-1} = H) = \rho_H$ with $\rho_j \in (0, 1)$. Thus the transition matrix reads:

$$P = \begin{bmatrix} 1 - \rho_L & \rho_H \\ \rho_L & 1 - \rho_H \end{bmatrix}, \tag{9}$$

[11] For details about MSMs we redirect the reader to Tsay and Chen (2019).

[12] Note that the dependent variable is the vector of residual $\hat{u}_t$ stemming from Eq. (6). It is here labelled x_t for simplicity.

[13] We have carried out a robustness check allowing also the first-order autoregressive parameter ϕ_1 to be state dependent (hence ϕ_{1,S_t}). Results are qualitatively unchanged. It is only worth noticing that in that case, the autoregressive parameter for the low volatility state $\phi_{1,L}$, is always estimated to be larger than its high volatility counterpart $\phi_{1,H}$.

where a row represents the state in period $t-1$ and a column the state in period t. Here, however, a note of caution is due as it is well known that the MSM has an inherent labeling issue, as the labels of the states are arbitrary. Nevertheless, in our application the label is quite natural. Among the two regimes, the *H state*/*L state* (H and L respectively for high and low volatility) is the one for which the volatility parameter σ_{S_t} is larger/smaller.[14]

The parameters of the model as well as the transition probabilities can be estimated via maximum likelihood using the Expectation Maximization (EM) algorithm, because the estimators have a non-linear functional form. In addition, it is possible to infer which regime is most likely for each available observation. In other words, the analysis of these results for different sub-samples will give us insights into possible changes in the conditional mean and variance of electricity price and volumes before, during and after the introduction of the CPM.

2.3 Data and Preliminary Stylized Facts

The dataset used in this study originates from the historical tables of settlement price and traded volume provided by the AEMO. These data are available for each geographical region composing the Australia's NEM, starting December 7th, 1998, and are sampled at 30 min frequency.[15] Electricity price and volume data are then complemented by two additional series, employed as control variables: the S &P/ASX200 Volatility Index (A-VIX) and the Baltic Dry Index (BDI).[16] The choice of controlling for these two variables is twofold. From a technical viewpoint, these variable are sampled at daily frequency and they match the frequency used for our core analysis. From an economic theory viewpoint, they are good predictors of the volatility in financial markets and in the real economy (see Wang 2019; Lin et al. 2019).

Since the main goal of this study is to investigate the changes observed in correspondence of the introduction and repeal of the CPM, we focus on the period between July 1st, 2010, and June 30th, 2016, to investigate the dynamics of electricity market over three sub-periods of the same length: before, during and after the CPM. Within this period of interest we have 105, 216 observations. No data is missing but few observations with negative prices were recorded.[17] For this reason, and given the fact that most of the detectable

[14] This type of labeling is also customary in business cycle analysis where the two states represent expansion and recession. In that case, the variable defining the labels is the conditional mean, rather than the conditional variance.

[15] See: https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard

[16] The A-VIX is a volatility index that reflects the expected future volatility of the main Australian stock index, thereby representing a "fear gauge". Extensively documented in empirical literature, is the inverse relationship between this index and stock and bond returns (Smales 2016). Consequently, the A-VIX can be used as a proxy for assessing the health of the financial economy (Smales 2017). On the other hand, the BDI is a composite index representing the average sea freight cost of raw materials across the globe (Katris and Kavussanos 2021). Since this index plays a critical role in the production chain of a wide variety of goods, it serves as an informative indicator of world real economic activity (Bakshi et al. 2010).

[17] A peculiar, though well-known, phenomenon observed in electricity markets is the possibility of recording negative prices. A good with a negative price is such that its destruction is worth more than its creation, thus this is a waste product (see Sewalt and De Jong 2003). Negative electricity prices are usually observed when a high supply meets a very low demand. According to Fanone et al. (2013) this might happen in case of exceptional slumps in demand, limited flexibility of power plant operations and limited transmission capacities. For further details about the occurrence of negative prices in specific national markets, we refer the reader to Bosco et al. (2007) for Italy and to De Vos (2015) for a focus on Germany, France and

periodic structure in the data concerns cycles which are longer than a day, we focus on daily averages. Following this operation, the length of time series drops to 2, 192 observations and negative prices occurrence reduce to just 1 in Queensland and 11 in Victoria, while none remain in New South Wales. We then correct these few observations by means of a linear interpolation. Positive prices are needed in order to allow for a logarithmic transformation of the data. The resulting log-price and log-volume time series, as well as the A-VIX and the BDI time series used as controls, are depicted in Fig. 1 and 2; these are then employed to fit the regime-switching model as described in Sect. 2.2.

From a first visual inspection of the price data and a preliminary analysis of their summary statistics reported in Table 1, we notice four interesting features. First, the presence of a periodic structure, which is obviously more marked in the traded volumes series, is evident. Second, the price distribution is characterized by positive skewness and leptokurtosis, almost resembling the shape of a logNormal density (a set of Kolmogorov-Smirnov tests, however reject the null hypothesis of equality with a logNormal density with equivalent mean and variance). Third, the CPM evidently impacted upon the final price, as the time series shifted upward during the period between July 2012 and June 2014. For example, if the average log-price before the CPM was about 3.34 in New South Wales, during the carbon pricing period this has increased to 3.97. In monetary terms, this implies an price difference of about 25 AU$/MWh between the two periods.[18] Fourth, the log-price volatility has fallen after the introduction of the CPM phase while it has increased after its repeal for all regions.

The last two insights are also confirmed by data collected in Table 1, that provides a summary statistics of the log-price time series analyzed with a focus both on the entire period of interest and on the three timeframes into which it was divided. In fact, we can observe that when the CPM was in force, the mean (standard deviation) of log-prices was always higher (lower) than in other subsamples. These differences proved to be statistical significant by means of a set of *t*-test on means and a *F*-test on variances whose results are reported in Table 2.

3 Empirical Results

In this Section we present results for observed prices in New South Wales, Queensland and Victoria while excluding those of the South Australia and Tasmania. These three regions account for more than 88% of total traded volumes on the NEM during the period of interest. Additionally, being the largest and more populated regions, their markets are more stable and less prone to anomalies and outliers. The results for the two smaller regions, which have been omitted from the manuscript for sake of brevity, are largely coherent with the ones presented here.[19]

Footnote 17 (Continued)

Belgium. In particular, we have 7 negative occurrences in New South Wales, 100 in Queensland and 135 in Victoria.

[18] This figures is therefore coherent with the fact that the CPM has de-facto imposed a tariff of 23 to 24 AU$/MWh.

[19] The complete set of results is available from the authors upon request.

3.1 Time Series Decomposition

As described in Sect. 2.1, before attempting any estimation of the regime switching model of Eq. (6) it is necessary to identify the trend, harmonic and daily components displayed in Eqs. (2)–(5) to clean the original price series from these predictable components.

For all time series hereby analyzed, the harmonic component is built upon the results of spectral analysis, which identifies the frequencies of the cycles recognized within the data. These frequencies correspond to the peaks of the population spectrum, as defined in Eq. (4), that are identified starting from a spike's minimum height, prominence and relative distance (see Fleming et al. 2002, among the others). Figure 3 displays the population spectrum of both log-price (left panels) and log-volume (right panels) recorded in New South Wales, Queensland and Victoria with the identified peaks graphically denoted by the triangle-shaped markers.

It is easy to immediately recognize regular features in the peak detection of all series. More specifically, the frequency of spikes across the time series of the three regions and for both variables are partially overlapping, suggesting that the analyzed time series share most of their periodic structure. More quantitatively detailed results of the spectral analysis are collected in Table 3 where we also convert the scaling parameter ω into time intervals, to better evaluate the periodic recurrence of the series. We find that for all series, be they prices or volumes, the daily component is present. Furthermore, for all price series we detect a 9-months harmonic component and for all volume series a 2-months component.

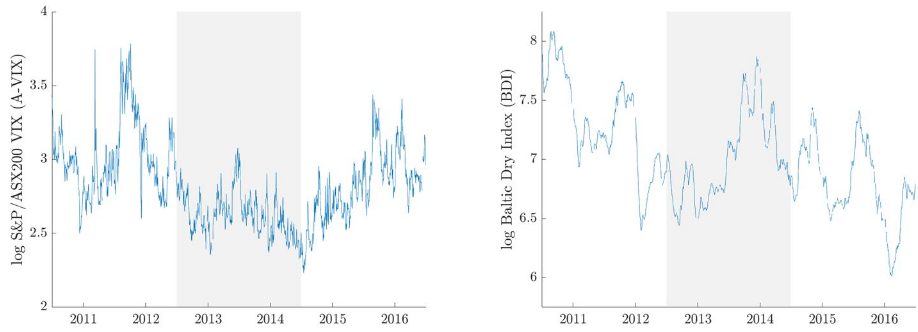
After collecting the results of the spectral analysis, we exploit them to build the set of H regressors accounting for time series' harmonic components as described by Eq. (3), which allows us to estimate Eq. (6). Given the high number of parameters – whose number is also region-specific, depending upon the number of identified peaks H – in Table 4 we report only the estimates of the constant, and the coefficients related to the third-order polynomial. These results are region-specific and obtained through separate regressions. We only highlight that the fitness, as measured by the adjusted R^2 is always between 28% and 31% and that the F-statistic suggest the joint significance of the model's regressors at the 1% confidence level. Analyzing the results of the estimate for the electricity prices of the three regions, we observe that all the long-term trend polynomial terms are significant, pointing toward the presence of an inflection point in the series. The harmonic components and the daily flickers are also significant, highlighting that the log-prices are smaller during weekends and holidays.

3.2 Regime-Switching Volatility

After removing the long-term, harmonic and flickers components, we can proceed with the core exercise of our analysis which is the estimation of the MSM as described by Eq. (7).

The time series decomposition described in the previous Section, besides allowing to investigate the different periodic phenomena recognizable within data, provides a series of filtered data where volatility structure can be studied without the interference produced by seasonality. We assume that these filtered series are drawn by the MSM presented in Eq. (8). In this Section, we present the estimation results of such model.

The outcomes of the MSM include several pieces of information, all useful to better understand the log-price's volatility structure. First, the inference about the unobserved state of the world (labelled high or low volatility states). Second, the transition matrix which collects the probabilities (ρ_H, ρ_L and their complement to one) of switching or



(a) Logarithm of Australian VIX.

(b) Logarithm of BDI.

Fig. 2 Time series of the control variables used in this study, namely the A-VIX (left panel) and the BDI (right panel). The grey-shaded area represents the period in which the CPM was in operation

Table 1 Summary statistics (count, average, standard deviation, coefficient of variation, quartile variation coefficient, skewness and kurtosis) of log-prices, expressed in logAU$/MWh, for the three main regions of the NEM, over the whole period of interest and the three subsamples

Region	Period	Count	Mean	Std. Dev.	C.V.	Q.C.V.	Skewness	Kurtosis
NSW	Whole sample	2192	3.67	0.39	0.11	0.08	1.40	10.75
	Before CPM	731	3.34	0.33	0.10	0.03	6.67	64.17
	During CPM	730	3.97	0.12	0.03	0.01	5.37	62.33
	After CPM	731	3.69	0.35	0.10	0.05	1.88	8.64
QLD	Whole sample	2192	3.69	0.56	0.15	0.10	0.71	10.57
	Before CPM	731	3.27	0.38	0.12	0.04	0.83	45.23
	During CPM	730	4.06	0.35	0.09	0.02	0.06	42.74
	After CPM	731	3.74	0.59	0.16	0.08	1.63	9.49
VIC	Whole sample	2192	3.58	0.43	0.12	0.09	0.73	6.32
	Before CPM	731	3.24	0.29	0.09	0.05	2.26	27.01
	During CPM	730	3.95	0.24	0.06	0.02	4.89	40.02
	After CPM	731	3.54	0.41	0.12	0.06	1.03	6.21
A-VIX	Whole sample	1589	2.81	0.27	0.09	2.74	0.74	3.62
	Before CPM	506	3.02	0.26	0.08	2.94	0.77	3.26
	During CPM	532	2.63	0.14	0.05	2.59	0.470	2.98
	After CPM	551	2.81	0.23	0.08	2.76	0.10	2.98
BDI	Whole sample	1589	2.81	0.27	0.09	2.74	0.740	3.62
	Before CPM	506	3.02	0.26	0.08	2.94	0.77	3.26
	During CPM	532	2.63	0.14	0.05	2.59	0.470	2.98
	After CPM	551	2.81	0.23	0.08	2.76	0.10	2.98

In the bottom part of the Table, the same summary statistics are also reported for the log of the control variables

remaining in each state. Third, the average duration of each state of the world. Fourth, the estimate of the volatility in the two states.

Table 2 Results of the t-test for "equality of means" and F-test for "equality of variances" of the log-prices time series for the three largest regions of the NEM

Region	Period	t-stat	p-value	F-stat	p-value
NSW	Before CPM vs. During CPM	−48.25	0.00	146.15	0.00
	Before CPM vs. After CPM	−19.37	0.00	80.94	0.00
	During CPM vs. After CPM	20.53	0.00	348.77	0.00
QLD	Before CPM vs. During CPM	−41.17	0.00	33.72	0.00
	Before CPM vs. After CPM	−18.07	0.00	166.80	0.00
	During CPM vs. After CPM	12.43	0.00	241.51	0.00
VIC	Before CPM vs. During CPM	−50.57	0.00	95.97	0.00
	Before CPM vs. After CPM	−16.19	0.00	65.02	0.00
	During CPM vs. After CPM	22.71	0.00	232.78	0.00

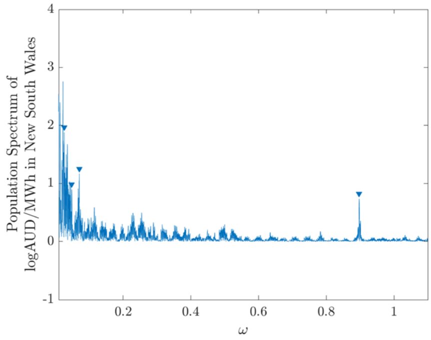
We divide the discussion in two separate parts, the first concerns the estimation of one model using the full sample, covering the period from July 2010 to June 2016. In the second part instead, we discuss the results stemming from the same model, but estimated over three sub-timeframes: before the introduction of the CPM (July 2010 – June 2012), during the CPM (July 2012 – June 2014), and after the repeal of the CPM (July 2014 – June 2016).[20]

3.2.1 Estimation on the whole sample

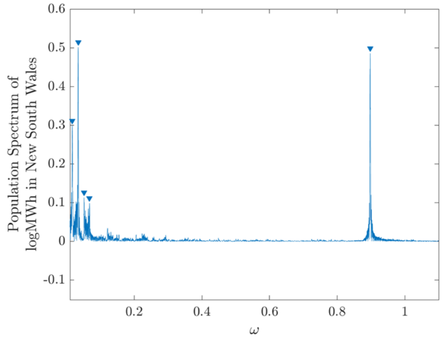
The inference on the volatility state $S_t = H$ is represented in Table 5. From a first inspection of the rows related to the *Whole Sample*, it is evident that periods of low volatility have been the rule for all regions. The high volatility state has occurred only 7%, 13% and 11% of the times for New South Wales, Queensland and Victoria, respectively. This result is coherent with the estimates of the transition probabilities, which are provided in Table 6. These estimates suggest that when using the full sample in all the Australian regions, if the economy is in a state of low electricity price volatility at time t, there is about 95% to 98% probability that it will remain there also in period $t + 1$. It is therefore natural that also the average duration of a given state (not reported here for sake of brevity) is longer for the low volatility state (about 64 days) rather than for the high volatility state (about 8 days). These estimates remain robust to the inclusion of the two control variables which take into account the possible influences that financial and real markets have on the Australian electricity price.

At last, by looking at the estimates of the MSM estimated on the whole sample (see Tables 7, 8 and 9) we draw four main insights. First, the price volatility in the H state is about 6 to 7 times larger than in the L state. This implies that notwithstanding the probability of incurring in the H state being relatively small (as reported above) the uncertainty associated to this state is higher by almost one order of magnitude. This difference has potentially severe impacts on firms' investment decisions. When firms face higher uncertainty about future costs (see also the discussion in the conclusive Section of the paper)

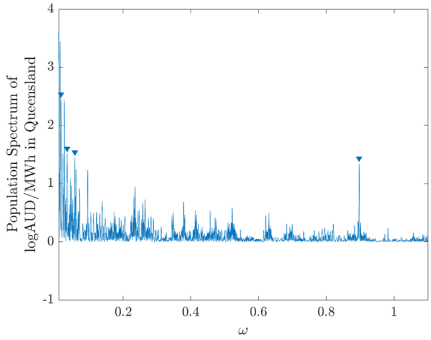
[20] The CPM has been in force for a two-year period. For the sake of uniformity, the two subsamples before and after this period were selected on the basis of its duration.



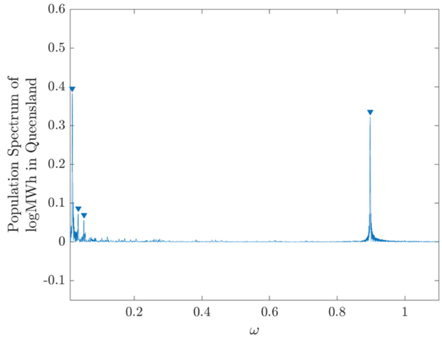
(a) Population spectrum of log-price in New South Wales.



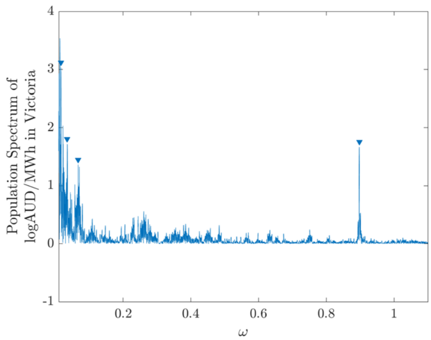
(b) Population spectrum of log-volume in New South Wales.



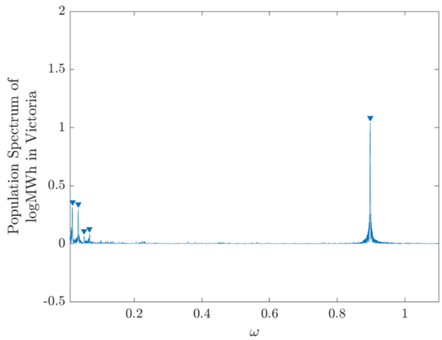
(c) Population spectrum of log-price in Queensland.



(d) Population spectrum of log-volume in Queensland.



(e) Population spectrum of log-price in Victoria.



(f) Population spectrum of log-volume in Victoria.

Fig. 3 Population spectrum of log-price (left panels) and log-volume (right panels) observed in the three main regions of the NEM, over the whole period of interest

they might react by cutting investment.[21] Second, by keeping constant the autoregressive

[21] The effects of uncertainty on investment level is a topic widely investigated in the scientific literature. Since the seminal paper by Hartman (1972), variety of models highlighted the depressing effect of pricing uncertainty on investment has been proposed (e.g., Zeira 1990; Bloom 2014). Mohn and Misund (2009) suggesting that macroeconomic uncertainty creates a bottleneck for oil and gas investment and stress the negative relevant effect of uncertainty within the theory of irreversible investments and real options. Gross et al. (2010) showed that investment in electricity sector is driven by expected returns and that investors have an inherent "hedge" against fuel and electricity price fluctuations.

Table 3 Frequencies of occurrence of population spectrum spikes and corresponding length of cycles recognizable within log-price and log-volume for each region of the NEM

Frequency	Length	NSW		QLD		VIC	
		log-price	Log-volume	Log-price	Log-volume	Log-price	Log-volume
$\omega = 0.002$	$\sim$ 1.5 years				✓	✓	
$\omega = 0.004$	$\sim$ 9 months	✓		✓		✓	
$\omega = 0.017$	$\sim$ 2 months		✓		✓	✓	✓
$\omega = 0.034$	$\sim$ 1 month		✓	✓	✓	✓	✓
$\omega = 0.898$	$\sim$ 1 day	✓	✓	✓	✓	✓	✓

Table 4 Result of estimation of Eq. (6) to log-price observed in the three main regions of the NEM, over the whole period of interest

	NSW	QLD	SA	TAS	VIC
(constant)	2.9001***	2.5979***	2.7039	2.7895	2.6775***
	(0.0327)	(0.04770)	(0.0480)	(0.0440)	(0.0365)
β_1	$2.10E-03$***	$2.87E-03$***	$2.56E-03$	$2.69E-03$	$2.50E-03$***
	$(1.10E-04)$	$(1.61E-04)$	$(1.62E-04)$	$(1.48E-04)$	$(1.23E-04)$
β_2	$-1.67E-06$***	$-2.30E-06$***	$-1.93E-06$	$-2.69E-06$	$-1.99E-06$***
	$(1.16E-07)$	$(1.70E-07)$	$(1.72E-07)$	$(1.57E-07)$	$(1.30E-07)$
β_3	$4.18E-10$***	$5.82E-10$***	$4.57E-10$	$8.49E-10$	$4.80E-10$***
	$(3.49E-11)$	$(5.11E-11)$	$(5.14E-11)$	$(4.69E-11)$	$(3.91E-11)$
Harmonic component	✓	✓	✓	✓	✓
Dummy variables	✓	✓	✓	✓	✓
R^2	0.3008	0.2974	0.2678	0.3899	0.3159
Adjusted R^2	0.2917	0.2883	0.2590	0.3820	0.3070
F-statistic	33.23	32.69	30.46	49.37	35.67
p-value	$7.13E-146$	$1.25E-143$	$2.27E-126$	$1.94E-208$	$7.42E-156$

The standard error is shown in brackets below each estimate, while *** denotes statistical significance at the 1% level

parameter, we can interpret the estimate of the difference in the constants between the two states (i.e. $\phi_{0,H} - \phi_{0,L}$) as the difference in the (unconditional) average price between the two states. We observe that for all Australian regions this difference is positive, meaning that in the high volatility state, also the average price is larger than in the low volatility one. Therefore, our estimates suggest in this respect that there are no trade-offs for Australian firms between price level and price dispersion. Third, and related to the first one, our nonlinear model performs better in the low volatility state, indicating that it is easier for firms to forecast future electricity prices when the volatility is lower. Fourth, we notice that whether we include the controls for the A-VIX or for the BDI, all the main insights remain valid.

Table 5 Fitted probability and frequency of high-volatility state, in the three main regions of the NEM, over the whole period of interest and, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns)

Region	Period	Without controls			Control for A-VIX			Control for BDI		
		Count	High count	High %	Count	High count	High %	Count	High count	High %
NSW	Whole Sample	2192	155	0.07	1482	105	0.07	1482	102	0.07
	Before CPM	731	35	0.05	492	23	0.05	492	21	0.04
	During CPM	730	15	0.02	493	12	0.02	493	13	0.03
	After CPM	731	105	0.14	497	70	0.14	497	68	0.14
QLD	Whole Sample	2192	280	0.13	1482	272	0.18	1482	254	0.17
	Before CPM	731	45	0.06	492	42	0.09	492	38	0.08
	During CPM	730	87	0.12	493	75	0.15	493	72	0.15
	After CPM	731	148	0.20	497	155	0.31	497	144	0.29
VIC	Whole Sample	2192	245	0.11	1482	152	0.10	1482	144	0.10
	Before CPM	731	24	0.03	492	13	0.03	492	10	0.02
	During CPM	730	44	0.06	493	34	0.07	493	33	0.07
	After CPM	731	177	0.24	497	105	0.21	497	101	0.20

Table 6 Transition matrices $\hat{P}$ estimated on the three states using the full sample or the three sub-samples, as indicated from the first row

Region	State	Whole Sample		Before CPM		During CPM		After CPM	
		Low	High	Low	High	Low	High	Low	High
Without controls									
NSW	Low	0.98	0.23	0.99	0.20	0.98	0.12	0.96	0.15
	High	0.02	0.77	0.01	0.80	0.02	0.88	0.04	0.85
QLD	Low	0.96	0.23	0.98	0.47	0.96	0.27	0.98	0.07
	High	0.04	0.77	0.02	0.53	0.04	0.73	0.02	0.93
VIC	Low	0.95	0.27	0.97	0.34	0.94	0.27	0.93	0.19
	High	0.05	0.73	0.03	0.66	0.06	0.73	0.07	0.81
Control for A-VIX									
NSW	Low	0.97	0.29	0.98	0.20	0.95	0.22	0.94	0.12
	High	0.03	0.71	0.02	0.80	0.05	0.78	0.06	0.88
QLD	Low	0.94	0.24	0.97	0.33	0.92	0.26	0.91	0.18
	High	0.06	0.76	0.03	0.67	0.08	0.74	0.09	0.82
VIC	Low	0.96	0.28	0.99	0.34	0.96	0.32	0.99	0.06
	High	0.04	0.72	0.01	0.66	0.04	0.68	0.01	0.94
Control for BDI									
NSW	Low	0.98	0.30	0.99	0.21	0.95	0.17	0.95	0.13
	High	0.02	0.70	0.01	0.79	0.05	0.83	0.05	0.87
QLD	Low	0.94	0.24	0.97	0.33	0.92	0.29	0.91	0.21
	High	0.06	0.76	0.03	0.67	0.08	0.71	0.09	0.79
VIC	Low	0.96	0.28	0.99	0.35	0.96	0.30	0.99	0.04
	High	0.04	0.72	0.01	0.65	0.04	0.70	0.01	0.96

The Table also distinguishes the estimates according to whether no-control, the A-VIX, or the BDI were used as control variable

3.2.2 Estimation on the three sub-samples

By looking at the inference about the probability of being in the high volatility state (see Table 5), we observe some regional heterogeneity. While for NSW, the introduction of the CPM corresponded to a decrease in the occurrences of high price volatility periods, in QLD and VIC the likelihood of the high state has steadily increased over time. However, unambiguously for all regions, the likelihood of having high electricity price volatility has been maximal after the repeal of the CPM. In fact, the probability of occurrence of the H state after the CPM repeal, has increased respectively by a factor of 7 in NSW, a factor of 2 in QLD and a factor of 4 in VIC. These results are robust to the inclusions of the A-VIX or the BDI as control variables in the MSM.

Coherently, also in the transition matrices we observe similar patterns (Table 6). The probability of switching from the low price volatility state to the high volatility one, has changed over the three sub-periods. In particular, we observe that the likelihood of remaining in the low state $(1 - \rho_L)$ has slightly diminished over time (from 99% to 95%, on average), while the probability of remaining in the high state $(1 - \rho_H)$ has increased over time (from 70% to 85%, on average). This result seems to be detached from the introduction and repeal of the CPM, possibly signifying a more long-term

Table 7 Result of estimation of Eq. (8) to filtered log-price observed in New South Wales, over the whole period of interest, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns)

State	Variable	Without controls				Control for A-VIX				Control for BDI			
		Whole	Before	During	After	Whole	Before	During	After	Whole	Before	During	After
		Sample	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM
Low	ϕ_0	−0.01	−0.04	0.12	−0.09	0.05	−0.05	−0.00	−0.24	−0.10	−0.90	0.23	−0.25
	ϕ_1	0.78	0.74	0.25	0.55	0.68	0.62	0.15	0.37	0.69	0.56	0.18	0.41
	β_{AVIX}					−0.00	−0.00	0.01	0.01				
	β_{BDI}									0.01	0.11	−0.02	0.02
	σ	0.09	0.08	0.05	0.11	0.10	0.10	0.05	0.10	0.10	0.10	0.05	0.11
	R^2	0.82	0.78	0.11	0.45	0.74	0.63	0.20	0.30	0.72	0.69	0.31	0.29
High	ϕ_0	0.10	0.20	0.29	0.16	0.11	1.08	0.41	−0.22	−0.11	6.29	−3.22	−0.11
	ϕ_1	0.78	0.74	0.25	0.55	0.68	0.62	0.15	0.37	0.69	0.56	0.18	0.41
	β_{AVIX}					0.00	−0.04	−0.01	0.02				
	β_{BDI}									0.04	−0.80	0.51	0.04
	σ	0.57	0.81	0.21	0.37	0.68	0.89	0.22	0.34	0.69	0.90	0.18	0.37
	R^2	0.45	0.47	0.06	0.28	0.36	0.42	0.03	0.23	0.36	0.42	0.13	0.18

Gray shadowed cells contain parameters which are statistically significant at the 5% level

Table 8 Result of estimation of Eq. (8) to filtered log-price observed in Queensland, over the whole period of interest, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns)

State	Variable	Without controls				Control for A-VIX				Control for BDI			
		Whole Sample	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM
Low	ϕ_0	−0.03	−0.06	0.09	−0.16	0.20	−0.03	−0.22	−0.36	−0.26	−1.06	0.43	0.77
	ϕ_1	0.63	0.64	0.38	0.50	0.63	0.67	0.24	0.46	0.61	0.62	0.28	0.44
	ϕ_{AVIX}					−0.00	−0.00	0.02	0.01				
	ϕ_{BDI}									0.03	0.13	−0.05	−0.14
	σ	0.15	0.14	0.09	0.15	0.69	0.13	0.08	0.15	0.14	0.13	0.08	0.16
	R^2	0.65	0.65	0.14	0.23	0.69	0.68	0.41	0.53	0.66	0.72	0.28	0.51
High	ϕ_0	0.18	0.15	0.39	0.21	0.04	0.36	0.78	0.02	1.20	2.34	1.04	2.07
	ϕ_1	0.63	0.64	0.38	0.50	0.63	0.67	0.24	0.46	0.61	0.62	0.28	0.44
	ϕ_{AVIX}					−0.00	−0.01	−0.02	0.01				
	ϕ_{BDI}									−0.15	−0.30	−0.09	−0.27
	σ	0.80	1.04	0.62	0.66	0.13	0.84	0.43	0.66	0.70	0.83	0.44	0.67
	R^2	0.31	0.32	0.30	0.47	0.33	0.40	0.08	0.22	0.33	0.38	0.09	0.23

Gray shadowed cells contain parameters which are statistically significant at the 5% level

Table 9 Result of estimation of Eq. (8) to filtered log-price observed in Victoria, over the whole period of interest, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns)

State	Variable	Without controls				Control for A-VIX				Control for BDI			
		Whole	Before	During	After	Whole	Before	During	After	Whole	Before	During	After
		Sample	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM	CPM
Low	ϕ_0	−0.00	−0.02	0.12	−0.07	0.06	−0.01	−0.02	−0.21	−0.13	−0.57	0.24	−0.63
	ϕ_1	0.78	0.84	0.32	0.66	0.69	0.76	0.19	0.50	0.69	0.72	0.21	0.50
	ϕ_{AVIX}					−0.00	−0.00	0.01	0.01				
	ϕ_{BDI}									0.02	0.07	−0.02	0.08
	σ	0.12	0.11	0.09	0.17	0.13	0.12	0.09	0.17	0.13	0.12	0.09	0.17
	R^2	0.78	0.84	0.25	0.52	0.71	0.76	0.07	0.23	0.69	0.76	0.11	0.37
High	ϕ_0	0.02	0.01	0.41	0.08	−0.06	0.17	0.98	−0.18	−0.10	2.89	−1.15	−0.30
	ϕ_1	0.78	0.84	0.32	0.66	0.69	0.76	0.19	0.50	0.69	0.72	0.21	0.50
	ϕ_{AVIX}					0.01	0.01	−0.03	0.02				
	ϕ_{BDI}									0.03	−0.33	0.24	0.06
	σ	0.53	0.71	0.50	0.44	0.62	1.18	0.53	0.48	0.64	1.16	0.53	0.45
	R^2	0.46	0.51	0.07	0.39	0.34	0.34	0.15	0.39	0.34	0.39	0.07	0.23

Gray shadowed cells contain parameters which are statistically significant at the 5% level

trend. This has a clear implication in terms of duration of the periods of high volatility, which have become unambiguously longer during the analyzed sample. However, a note of caution in the interpretation of these results is necessary. In fact, we will see that the unconditional volatility during the CPM period is substantially smaller than the one registered before its introduction and after its repeal. In fact, the electricity price volatility in the H state during the CPM, is quantitatively comparable to the volatility recorded in the L state of the other two sub-samples.

Moving to the analysis of the MSMs, as estimated on each region and for each sub-sample, we draw four main conclusions (Tables 7, 8 and 9). First, the state-specific constant term ϕ_{0,S_t} is significantly larger during the CPM phase for all regions. This should come as no surprise because this term measures the unconditional electricity price, which is larger when the carbon pricing mechanism is at work. Second, notice that by the definition of the H and L states, the electricity price shocks (i.e. σ) are notably larger during the H period than the L one. However, the difference in the volatility between the H and L states, is much smaller during the CPM period, compared to before and after it. For example, let's focus on the estimates for NSW without any additional control. The shocks' volatility in the L state, is 0.08 before the CPM introduction, 0.05 during the CPM period, and 0.11 after its repeal. In the H state, the volatilities are instead 0.81, 0.21, and 0.37, respectively in the same three timeframes. In addition, as a third observation, we notice that the autocorrelation term ϕ_1, which is constant across the H and L states for each region and sub-period, is smaller during the CPM phase with respect to the pre- and post-CPM phases. This indicates lower persistence in the dynamics of electricity price. Finally, we observe that the model fitness is always larger in the L phase, which is also due to the definition of the H and L states (the L state has a smaller SSR). However, the fitness is also smaller during the CPM phase, possibly denoting some features specific to the carbon pricing system that our model is not able to capture.

From our exercise it is difficult to draw causal statements, as we do not evaluate the causal effect of the policy and because the electricity prices can be affected by other variables not taken into account here (Aggarwal et al. 2009). However, the aim of this work is to investigate and quantify the alterations in electricity price dynamics observed, within main National Electricity Market (NEM) regions, in relation to the introduction and subsequent repeal of the carbon tax. These alterations, both in mean and variance, are proved to be statistically significant, as detailed in Table 2. Our findings highlight two relevant features. Firstly, under the carbon tax, a notable decrease in price volatility occurred, particularly during periods of electricity market stress. Conversely, upon the revocation of such measure, alongside volatility increase, a heightened persistence of high-volatility state also emerged. Consequently, it is deducible that, as discussed in the following section, the period of the carbon tax showed favorable features for stakeholders within this market domain.

4 Conclusion and Policy Implications

In this paper, we investigated the behavior of electricity price in Australia, with a focus on how it has changed when the Carbon Pricing Mechanism (CPM) was in force. This task was carried out by means of (i) a dynamic multivariate model to deseasonalize electricity data and (ii) a regime switching model to estimate volatility parameters, conditional upon the state of the economy.

The contribution of our study is twofold. On the one hand, the deseasonalization process proposed allows a broad spectrum analysis of seasonal patterns. More in detail, we take into consideration, in a unique model, cycles of length spanning from the very short-term (daily) to the long-term (annual). For this purpose we use a wide set of tools able to catch the different dynamics affecting observed data (long-term trend, calendar effects and, most importantly, the harmonic components). In addition, all results regarding electricity settlement prices are double-checked with a parallel analysis of traded volumes, to strengthen their reliability, as these two variables are influenced by a common set of drivers. Estimation results are always characterized by high statistical significance, reinforcing the reliability of the model proposed. For this reason, we believe that this deseasonalization model, able to detect a relevant part of observed data variability, can play an important role among those market operators or investors for whom electricity price forecasting is critical (see Deng 2005; Fanelli et al. 2016, among the others). On the other hand, we investigate the volatility structure of electricity data by means of a Gaussian Markov Switching Model (MSM). As changes in volatility structure in correspondence of the introduction and repeal of the CPM were abrupt and significant, without smooth and gradual changes, this approach was the most suitable.

The emphasis on electricity price in this paper is driven by several factors. Firstly, it represents a pivotal macroeconomic parameter whose bidirectional causal relationship with economic growth is worldwide extensively supported by empirical evidence (Shahbaz et al. 2017). Consequently, the price of electricity is widely taken into account within macroeconomic modeling, such as agent-based and computational general equilibrium models (see Ciola et al. 2023; He et al. 2011, among the others). Moreover, this variable exerts significant influences on inflation formation mechanism (Schnabel 2022), thereby garnering substantial attention within the financial sector (Batten et al. 2020) and playing a consequential role within shaping monetary policy (De Gregorio 2012). Last but not least, from a microeconomic standpoint, the electricity price is both a common source of uncertainty and a critical determinant of firms' profitability. Consequently, this variable assumes a pivotal role in the decision-making process for investments in several industries (Dixit and Pindyck 1994). Energy sector is not an exception, especially in the case of competitive liberalized electricity markets like the Australian one, where utilities can no longer entirely transfer additional costs to consumers (see Newbery et al. 2008) and therefore, as highlighted by Bazilian and Roques (2009), part of the investment risk burden is shifted from consumers to producers.

The importance of electricity price volatility within the investment evaluation process arises from its predominant role both among exogenous factors affecting the decision and among sources of uncertainty. Whatever the method used for modeling risk aversion,[22] the final investment decision is influenced by macroeconomic, market and most importantly energy-specific factors. The latter, which refers to electricity system features, including the economic conditions under which generators operate, is fundamental for investment decisions because energy-specific factors are likely to attract investors if profit prospects are high and uncertainty is low (see European Commission 2015). Moreover, among different sources of uncertainty identified in electricity generation projects, e.g. volume, price, cost and technical risk, the most relevant one is related to unexpected price variations, namely price risk, especially in markets with high shares of coal and gas exploitation (see Newbery et al. 2006). The volatility of electricity price, and thus the riskiness of an investment in this sector, can be further increased by the peculiarity of this commodity and by market design. Firstly, the combined effect of instantaneous consumption, consequence of the very

[22] Classically classified into utility functions, risk-adjusted discount factors, mean-variance portfolio analysis or real options (see Petitet 2016).

limited storage capacity, and inelastic demand allow prices to reach very high levels if the demand is not met, even for a short period, or very low levels, when a relevant part of the capacity remains idle (see European Commission 2015). Moreover, if an electricity market is an energy-only market, as in the case of the NEM, instead of complemented by a capacity mechanism, price are allowed to heavily increase (decrease) in case of excess-demand (excess-supply), increasing volatility and, in turn, the associated investment risk.[23]

The worldwide introduction of a variety of policies aimed at reducing carbon dioxide emissions to curb global warming (see the seminal contribution by Stern 2022) increased the complexity of this framework for the corresponding new cost items for utility companies. A wide literature resulted from this innovation, mostly focused on the uncertainty of following carbon emissions (see Hafstead and Williams 2020) or on the uncertainty of carbon pricing itself (see Burtraw et al. 2012; Murray et al. 2009). Aldy (2017) showed that lower carbon price volatility positively affect returns to investments which, in turn, can result in more, climate-friendly investments. However, there is yet no evidence about a causal effect of carbon pricing on electricity price volatility, not even in those markets, like the Australian case, where carbon price was fixed.

Despite not providing explanations by which carbon pricing affects electricity price volatility, our study proves the significant effect of the CPM on final electricity price and its volatility, also ruling out the possibility that this phenomenon is attributable to other causes. Nevertheless, knowing how electricity price behavior changes when carbon pricing is in effect is a crucial information to a wide range of economic agents, as electricity price is one of the main sources of uncertainty across sectors and a key factor in investment decision Dixit and Pindyck (1994). A *caveat* is however necessary: results obtained relate to (i) a peculiar market, since it is not interconnected with foreign countries, and to (ii) a period when the market share of renewable energy was not yet sizable, and, finally, to (iii) a regulatory intervention in the form of a Pigouvian tax. We can expect that considering a market in which one or more of the above characteristics are different can lead to different results. Deepening these aspects and extending the model to new markets is left to future research.

Appendix 1

Robustness checks

In this section we present results similar to the ones presented in Tables 5, 7, 8, 9 and 6. The main difference is that here the original time series of electricity prices have not been deseasonalized using the procedure described in Sect. 2.1 but using the standard Christiano-Fitzgeral (CF) filter (Christiano and Fitzgerald 2003). We find that all results, presented below, are qualitatively consistent with the evidence described in the main text. For this reason, we decided to report the following tables without additional comments and descriptions.

A.1 Estimates of the Fitted probabilities

See Table 10.

[23] For this reason energy-only markets usually set a cap and a floor for electricity prices.

Table 10 Fitted probability and frequency of high-volatility state, in the three main regions of the NEM, over the whole period of interest and, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns)

Region	Period	Without controls			Control for A-VIX			Control for BDI		
		Count	High count	High %	Count	High count	High %	Count	High count	High %
NSW	Whole Sample	2192	236	0.11	1482	183	0.12	1482	183	0.12
	Before CPM	731	57	0.08	492	51	0.10	492	52	0.11
	During CPM	730	17	0.02	493	13	0.03	493	13	0.03
	After CPM	731	162	0.22	497	119	0.24	497	118	0.24
QLD	Whole Sample	2192	559	0.26	1482	420	0.28	1482	416	0.28
	Before CPM	731	103	0.14	492	77	0.16	492	74	0.15
	During CPM	730	139	0.19	493	100	0.20	493	100	0.20
	After CPM	731	317	0.43	497	243	0.49	497	242	0.49
VIC	Whole Sample	2192	299	0.14	1482	194	0.13	1482	191	0.13
	Before CPM	731	31	0.04	492	24	0.05	492	24	0.05
	During CPM	730	40	0.05	493	33	0.07	493	33	0.07
	After CPM	731	228	0.31	497	137	0.28	497	134	0.27

A.2 Estimates of the Markov-Switching Models

See Tables 11, 12 and 13.

Table 11 Result of estimation of Eq. (8) to filtered log-price observed in New South Wales, over the whole period of interest, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns). Gray shadowed cells contain parameters which are statistically significant at the 5% level

State	Variable	Without controls				Control for A-VIX				Control for BDI			
		Whole Sample	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM
Low	ϕ_0	−0.01	−0.00	−0.01	−0.01	0.01	0.02	0.03	0.04	0.01	0.07	0.09	0.03
	ϕ_1	0.60	0.62	0.11	0.61	0.47	0.49	0.03	0.40	0.47	0.50	0.07	0.46
	β_{AVIX}					0.00	−0.00	−0.00	−0.00				
	β_{BDI}									−0.00	−0.01	−0.01	−0.00
	σ	0.07	0.08	0.05	0.11	0.07	0.08	0.05	0.11	0.07	0.08	0.05	0.12
	R^2 0.4601	0.5045	0.0212	0.4369	0.3292	0.4104	0.0108	0.2372	0.3388	0.4224	0.0275	0.2763	
High	ϕ_0	0.06	0.04	0.18	0.10	−0.08	−0.24	0.67	−0.67	0.07	−0.66	−5.71	−0.57
	ϕ_1	0.60	0.62	0.11	0.61	0.47	0.49	0.03	0.40	0.47	0.50	0.07	0.46
	β_{AVIX}					0.01	0.02	−0.03	0.05				
	β_{BDI}									0.01	0.10	0.85	0.12
	σ	0.49	0.69	0.29	0.48	0.54	0.75	0.28	0.58	0.54	0.76	0.23	0.61
	R^2	0.3206	0.3760	0.0109	0.2973	0.2062	0.2573	0.0923	0.2368	0.2001	0.2489	0.3801	0.1628

Table 12 Result of estimation of Eq. (8) to filtered log-price observed in Queensland, over the whole period of interest, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns). Gray shadowed cells contain parameters which are statistically significant at the 5% level

State	Variable	Without controls				Control for A-VIX				Control for BDI			
		Whole Sample	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM
Low	ϕ_0	−0.01	−0.01	−0.02	−0.03	−0.01	−0.00	0.05	0.01	−0.02	−0.13	−0.02	0.29
	ϕ_1	0.42	0.39	0.29	0.47	0.42	0.43	0.30	0.43	0.42	0.43	0.30	0.43
	β_{AVIX}					0.00	0.00	−0.00	−0.00				
	β_{BDI}									0.00	0.02	0.00	−0.04
	σ	0.09	0.09	0.07	0.16	0.09	0.09	0.07	0.15	0.09	0.09	0.07	0.15
	R^2	0.3036	0.2532	0.1635	0.3273	0.3114	0.3319	0.1668	0.3038	0.3077	0.3369	0.1591	0.3093
High	ϕ_0	0.05	0.06	0.07	0.10	0.10	−0.01	0.00	0.10	0.12	0.79	−0.03	−0.42
	ϕ_1	0.42	0.39	0.29	0.47	0.42	0.43	0.30	0.43	0.42	0.43	0.30	0.43
	β_{AVIX}					0.00	0.01	0.01	0.00				
	β_{BDI}									−0.00	−0.10	0.02	0.09
	σ	0.60	0.72	0.52	0.73	0.57	0.67	0.42	0.72	0.57	0.68	0.42	0.73
	R^2	0.1663	0.1499	0.0807	0.1967	0.1662	0.1796	0.0871	0.1677	0.1658	0.1806	0.0855	0.1696

Table 13 Result of estimation of Eq. (8) to filtered log-price observed in Victoria, over the whole period of interest, without controls (left columns), controlling for A-VIX (middle columns) and for the BDI (right columns). Gray shadowed cells contain parameters which are statistically significant at the 5% level

State	Variable	Without controls				Control for A-VIX				Control for BDI			
		Whole Sample	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM	Whole CPM	Before CPM	During CPM	After CPM
Low	ϕ_0	−0.00	−0.00	−0.02	−0.00	0.00	0.00	0.10	0.07	0.00	−0.01	−0.06	0.08
	ϕ_1	0.52	0.57	0.31	0.56	0.40	0.47	0.24	0.42	0.39	0.48	0.23	0.44
	β_{AVIX}					0.00	0.00	−0.01	−0.00				
	β_{BDI}									0.00	0.00	0.01	−0.01
	σ	0.11	0.13	0.08	0.17	0.11	0.11	0.07	0.16	0.11	0.11	0.08	0.16
	R^2	0.3592	0.3803	0.1737	0.3487	0.2272	0.3003	0.2071	0.2219	0.2218	0.3088	0.1455	0.2334
High	ϕ_0	0.04	0.14	0.15	0.04	0.06	−0.46	0.05	−0.73	−0.16	−1.21	0.66	−0.36
	ϕ_1	0.52	0.57	0.31	0.56	0.40	0.47	0.24	0.42	0.39	0.48	0.23	0.44
	β_{AVIX}					0.00	0.04	0.01	0.05				
	β_{BDI}									0.04	0.21	−0.06	0.07
	σ	0.49	0.78	0.54	0.50	0.56	0.88	0.52	0.58	0.56	0.89	0.56	0.58
	R^2	0.2358	0.2923	0.0851	0.2663	0.1358	0.2416	0.0537	0.1946	0.1363	0.2153	0.0492	0.1582

A.3 Estimates of the Transition Matrices

See Table 14.

Table 14 Transition matrices $\hat{P}$ estimated on the three states using the full sample or the three sub-samples, as indicated from the first row

Region	State	Whole Sample		Before CPM		During CPM		After CPM	
		Low	High	Low	High	Low	High	Low	High
Without controls									
NSW	Low	0.97	0.21	0.99	0.13	0.97	0.41	0.96	0.23
	High	0.03	0.79	0.01	0.87	0.03	0.59	0.04	0.77
QLD	Low	0.95	0.14	0.96	0.22	0.95	0.15	0.95	0.14
	High	0.05	0.86	0.04	0.78	0.05	0.85	0.05	0.86
VIC	Low	0.96	0.20	0.99	0.34	0.96	0.28	0.97	0.14
	High	0.04	0.80	0.01	0.66	0.04	0.72	0.03	0.86
Control for A-VIX									
NSW	Low	0.97	0.23	0.98	0.18	0.96	0.39	0.96	0.34
	High	0.03	0.77	0.02	0.82	0.04	0.61	0.04	0.66
QLD	Low	0.94	0.15	0.95	0.31	0.94	0.14	0.94	0.16
	High	0.06	0.85	0.05	0.69	0.06	0.86	0.06	0.84
VIC	Low	0.96	0.22	0.99	0.26	0.95	0.29	0.97	0.18
	High	0.04	0.78	0.01	0.74	0.05	0.71	0.03	0.82
Control for BDI									
NSW	Low	0.97	0.23	0.98	0.18	0.97	0.37	0.96	0.34
	High	0.03	0.77	0.02	0.82	0.03	0.63	0.04	0.66
QLD	Low	0.94	0.15	0.95	0.32	0.94	0.14	0.94	0.16
	High	0.06	0.85	0.05	0.68	0.06	0.86	0.06	0.84
VIC	Low	0.96	0.22	0.99	0.26	0.96	0.30	0.97	0.16
	High	0.04	0.78	0.01	0.74	0.04	0.70	0.03	0.84

The Table also distinguishes the estimates according to whether no-control, the A-VIX, or the BDI were used as control variable

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References

Abban AR, Hasan MZ (2021) Solar energy penetration and volatility transmission to electricity markets-an Australian perspective. Econ Anal Policy 69:434–449

Acemoglu D, Aghion P, Bursztyn L, Hemous D (2012) The environment and directed technical change. Am Econ Rev 102(1):131–66

Aggarwal SK, Saini LM, Kumar A (2009) Electricity price forecasting in deregulated markets: a review and evaluation. Int J Electr Power Energy Syst 31(1):13–22

Aldy JE (2017) Designing and updating a US carbon tax in an uncertain world. Harv Envtl L Rev F 41:28–40

Alessio SM (2015) Digital signal processing and spectral analysis for scientists: Concepts and applications. Springer, Heidelberg

Australian Energy Regulator (2017), 'State of the energy market 2017', Australian Competition and Consumer Commission

Australian Energy Regulator (2022), 'State of the energy market 2022', Australian Competition and Consumer Commission

Australian Government Department of Climate Change, Energy, the Environment and Water (2022), 'Australian energy update 2022'

Bakshi G, Panayotov G, Skoulakis, G (2010) 'The Baltic Dry Index as a predictor of global stock returns, commodity returns, and global economic activity', Commodity Returns, and Global Economic Activity

Batten S, Sowerbutts R, Tanaka M (2020) Climate change: Macroeconomic impact and implications for monetary policy. Ecological, societal, and technological risks and the financial sector. Palgrave Macmillan, Cham, pp 13–38

Bazilian M, Roques FA (eds) (2009) Analytical Methods for Energy Diversity and Security: A Tribute to Shimon Awerbuch. Elsevier

Bloom N (2014) Fluctuations in uncertainty. J Econ Perspect 28(2):153–76

Bloomfield P (2004) Fourier analysis of time series: An introduction, John Wiley & Sons

Bosco BP, Parisio LP, Pelagatti MM (2007) Deregulated wholesale electricity prices in Italy: An empirical analysis. Int Adv Econ Res 13(4):415–432

Brubacher SR, Tunnicliffe Wilson G (1976) Interpolating time series with application to the estimation of holiday effects in electricity demand. J Royal Stat Soc 25(2):107–116

Bunn DW (2000) Forecasting loads and prices in competitive power markets. Proc IEEE 88(2):163–169

Bunn DW (2004) Modelling prices in competitive electricity markets, United Kingdom

Burtraw D, Fell H, Morgenstern RD (2012) Soft and hard price collars in a cap-and-trade system: A comparative analysis. J Environ Econ Manag 64(2):183–198

Chang Y (2007) The new electricity market of Singapore: Regulatory framework, market power and competition. Energy Policy 35(1):403–412

Christiano LJ, Fitzgerald TJ (2003) The band pass filter. Int Econ Rev 44(2):435–465

Ciola E, Turco E, Gurgone A, Bazzana D, Vergalli S, Menoncin F (2023) Enter the MATRIX model: A multi-agent model for transition risks with application to energy shocks. J Econ Dyn Control 146:104589

Clean Energy Regulator (2013), 'Carbon pricing mechanism', Australian Government Publication

De Gregorio J (2012) Commodity prices, monetary policy, and inflation. IMF Econ Rev 60(4):600–633

De la Torre-Torres OV, Galeana-Figueroa E, Álvarez-García J (2019) A test of using markov-switching GARCH models in oil and natural gas trading. Energies 13(1):129

de Lagarde CM, Lantz F (2018) How renewable production depresses electricity prices: Evidence from the German market. Energy Policy 117:263–277

de Marcos RA, Bello A, Renses J (2019) Electricity price forecasting in the short term hybridising fundamental and econometric modelling. Electr Power Syst Res 167:240–251

De Vos K (2015) Negative wholesale electricity prices in the German, French and Belgian day-ahead, intraday and real-time markets. Electr J 28(4):36–50

Deng SJ (2005) Valuation of investment and opportunity-to-invest in power generation assets with spikes in electricity price. Manag Financ 31(6):95–115

Dixit A, Pindyck R (1994) Investment under Uncertainty, Princeton University Press

Dozie KCN, Ijomah MA (2020) A comparative study on additive and mixed models in descriptive time series. Am J Math Comput Modell 5(1):12–17

Eichler M, Türk D (2013) Fitting semiparametric Markov regime-switching models to electricity spot prices. Energy Econ 36:614–624

St Ellen, Zwinkels RCJ (2010) Oil price dynamics: A behavioral finance approach with heterogeneous agents. Energy Econ 32(6):1427–1434
Escribano A, Sucarrat G (2018) Equation-by-equation estimation of multivariate periodic electricity price volatility. Energy Econ 74:287–298
European Commission (2015), 'Energy economic developments – investment perspectives in electricity markets. Institutional Paper **3**
Fabra N, Reguant M (2014) Pass-through of emissions costs in electricity markets. Am Econ Rev 104(9):2872–2899
Fanelli V, Maddalena L, Musti S (2016) Modelling electricity futures prices using seasonal path-dependent volatility. Appl Energy 173:92–102
Fanone E, Gamba A, Prokopczuk M (2013) The case of negative day-ahead electricity prices. Energy Econ 35:22–34
Feng Y, Gries T, Fritz M (2020) Data-driven local polynomial for the trend and its derivatives in economic time series. J Nonparametric Stat 32(2):510–533
Finon D (2019) Carbon policy in developing countries: Giving priority to non-price instruments. Energy Policy 132:38–43
Fleming SW, Marsh Lavenue A, Aly AH, Adams A (2002) Practical applications of spectral analysis to hydrologic time series. Hydrol Process 16(2):565–574
Ganapati S, Shapiro JS, Walker R (2020) Energy cost pass-through in us manufacturing: Estimates and implications for carbon taxes. Am Econ J Appl Econ 12(2):303–342
Geroe S (2022) Technology not taxes: A viable Australian path to net zero emissions? Energy Policy 165:112945
Gross R, Blyth W, Heptonstall P (2010) Risks, revenues and investment in electricity generation: Why policy needs to look beyond costs. Energy Econ 32(4):796–804
Gu H, Yan R, Saha T (2019) Review of system strength and inertia requirements for the national electricity market of Australia. CSEE J Power Energy Syst 5(3):295–305
Hadsell L, Shawky HA (2006) Electricity price volatility and the marginal cost of congestion: An empirical study of peak hours on the NYISO market, 2001–2004. The Energy J 27(2):157–180
Hafstead MAC, Williams RC (2020) Mechanisms to reduce emissions uncertainty under a carbon tax. Resources for the Future Discussion Paper **4**
Hagmann D, Ho EH, Loewenstein G (2019) Nudging out support for a carbon tax. Nat Clim Chang 9(6):484–489
Hájek M, Zimmermannová J, Helman K, Rozenský L (2019) Analysis of cxarbon tax efficiency in energy industries of selected EU countries. Energy Policy 134:110955
Halkos GE, Tsirivis AS (2019) Effective energy commodity risk management: Econometric modeling of price volatility. Econ Anal Policy 63:234–250
Hamilton JD (1994) Time Series Analysis. Princeton University Press, Princeton
Hartman R (1972) The effects of price and cost uncertainty on investment. J Econ Theory 5(2):258–266
He YX, Yang LF, He HY, Luo T, Wang YJ (2011) Electricity demand price elasticity in China based on computable general equilibrium model analysis. Energy 36(2):1115–1123
Howard BS, Hamilton NE, Diesendorf M, Wiedmann T (2018) Modeling the carbon budget of the Australian electricity sector's transition to renewable energy. Renew Energy 125:712–728
Hyndman RJ, Fan S (2010) Density forecasting for long-term peak electricity demand. IEE Trans Power Syst 25(2):1142–1153
Katris C, Kavussanos MG (2021) Time series forecasting methods for the Baltic dry index. J Forecast 40(8):1540–1565
King SP (1997) National competition policy. Econ Record 73(222):270–284
Knittel CR, Roberts MR (2005) An empirical examination of restructured electricity prices. Energy Econ 27(5):791–817
Lamperti F, Napoletano M, Roventini A (2020) Green transitions and the prevention of environmental disasters: Market-based vs. command-and-control policies. Macroecon Dyn 24(7):1861–1880
Levin T, Kwon J, Botterud A (2019) The long-term impacts of carbon and variable renewable energy policies on electricity markets. Energy Policy 131:53–71
Lin AJ, Chang HY, Hsiao JL (2019) Does the Baltic dry index drive volatility spillovers in the commodities, currency, or stock markets? Transp Res Part E: Logist Transp Rev 127:265–283
Loi TSA, Jindal G (2019) Electricity market deregulation in Singapore-Initial assessment of wholesale prices. Energy Policy 127:1–10
Manner H, Türk D, Eichler M (2016) Modeling and forecasting multivariate electricity price spikes. Energy Econ 60:255–265

Marcjasz G, Uniejewski B, Weron R (2019) On the importance of the long-term seasonal component in day-ahead electricity price forecasting with NARX neural networks. Int J Forecast 35(4):1520–1532
Martinez-Anido CB, Brinkman G, Hodge B-M (2016) The impact of wind power on electricity prices. Renew Energy 94:474–487
Maryniak P, Trück S, Weron R (2019) Carbon pricing and electricity markets-the case of the Australian clean energy bill. Energy Econ 79:45–58
Michelfelder RA, Pilotte EA (2022) Climate change, extreme winter weather and electricity production costs. Electr J 3(3):107093
Mohn K, Misund B (2009) Investment and uncertainty in the international oil and gas industry. Energy Econ 31(2):240–248
Murray BC, G NR, Pizer WA (2009) 'Balancing cost and emissions certainty: An allowance reserve for cap-and-trade', Review of Environmental Economics and Policy
Nazifi F, Trück S, Zhu L (2021) Carbon pass-through rates on spot electricity prices in Australia. Energy Econ 96:105178
Newbery DM, Nuttall WJ, Roques FA (2006) Using probabilistic analysis to value power generation investments under uncertainty. University of Cambridge, Electricity Policy Research Group, England
Newbery DM, Nuttall WJ, Roques FA (2008) Fuel mix diversification incentives in liberalized electricity markets: A mean-variance Portfolio theory approach. Energy Econ 30(4):1831–1849
OECD (2023), 'Oecd (2023), renewable energy (indicator)', https://doi.org/10.1787/aac7c3f1-en(Accessed on 15 February 2023)
O'Gorman M, Jotzo F (2014) 'Impact of the carbon price on australia's electricity demand, supply and emissions', Crawford School of Public Policy, The Australian National University CCEP Working Paper **1411**
Parer W (2002) Towards a truly national and efficient energy market. The Council of Australian Governments, Energy Market Review
Petitet M (2016) Long-term dynamics of investment decisions in electricity markets with variable renewables development and adequacy objectives, PhD thesis, PSL Research University
Pollitt MG, Haney AB (2013) Dismantling a competitive retail electricity market: Residential market reforms in Great Britain. Electr J 27(1):66–73
Rai A, Nelson T (2020) Australia's national electricity market after twenty years. Aust Econ Rev 53(2):165–182
Sapio S (2012) Modeling the distribution of day-ahead electricity returns: A comparison. Quant Finance 12(12):1935–1949
Scarcioffolo AR, Etienne XL (2021) Regime-switching energy price volatility: The role of economic policy uncertainty. Int Rev Econ Finance 76:336–356
Schnabel I (2022) Looking through higher energy prices? Monetary policy and the green transition. Int Monet Rev 9:2
Sewalt M, De Jong C (2003) Negative prices in electricity markets. Commod Now 7(74):74–77
Shahbaz M, Sarwar S, Chen W, Malik M (2017) Dynamics of electricity consumption, oil price and economic growth: Global perspective. Energy Policy 108:256–270
Smales LA (2016) Risk-on/risk-off: Financial market response to investor fear. Financ Res Lett 17:125–134
Smales LA (2017) Effect of investor fear on Australian financial markets. Appl Econ Lett 24(16):1148–1153
Stern N (2022) A time for action on climate change and a time for change in economics. Econ J 132:1259–1289
Tsay RS, Chen R (2019) Nonlinear time series analysis, Wiley series in probability and statistics. Wiley, Hoboken
Wang H (2019) Vix and volatility forecasting: A new insight. Physica A 533:121951
Weron R (2007) Modeling and forecasting electricity loads and prices: A statistical approach. Wiley, New York
Wong JB, Zhang Q (2022) Impact of carbon tax on electricity prices and behaviour. Financ Res Lett 44:102098
Xian LH, Edwards DJ, Reza Hosseini M, Costin GP (2020) A review on renewable energy transition in Australia: An updated depiction. J Clean Prod 242:118475
Yang I, Ozdaglar AE (2016) 'Reducing electricity price volatility via stochastic storage control', *American Control Conference (ACC), IEEE* pp. 4138–4144
Zeira J (1990) Cost uncertainty and the rate of investment. J Econ Dyn Control 14(1):53–63