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Summary

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Keywords: Carbon Tax, Seasonality and Volatility of Electricity Price

JEL Classification: C51, Q41, Q48

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May 30, 2020

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1 Introduction

Australia's National Electricity Market (NEM) is one of the largest geographically interconnected power system in the world. It has the role of enabling electricity to be generated, traded and delivered across east-coast and southern states, also allowing an efficient real-time matching of demand and supply. The NEM was established in 1998, following Hilmer Reforms, pursuing an improved efficiency to bring savings to customers (Parer, 2002), and currently serves the states of New South Wales, Queensland, South Australia, Tasmania and Victoria[1], which contribute roughly to the 80% of the overall country's consumption. The authority in charge of managing the NEM is the Australian Energy Market Operator (AEMO), that handles day-to-day operations of electricity and gas markets following the rules set by the Australian Energy Market Commissions (AEMC) on mandate of the Council of Australian Governments' (COAG) Energy Council.

As electrical energy storage (EES) technology is not mature yet for large-scale applications (Sing Lai and McCulloch, 2017), the NEM facilitates the exchange of electricity between generators and retailers, reselling it to final customers, on a wholesale market which is highly competitive, given the number of players participating. This exchange takes places around a regulated spot market, where the price is formed as a result of the matching of physical demand and supply, which also enables retailers to deal with the uncertainty due to price volatility.

Australia is a country which has historically relied on fossil fuels to satisfy its energy needs, in fact it is among those countries with the lowest share of power generation from renewable sources, which accounted for 15.1% in 2018 (Australian Energy Regulator, 2018; Xian L. et al., 2020). This, in part, derives from the fact that, even if policy makers struggled to integrate a comprehensive climate change policy within the energy market framework (Nelson et al., 2019), when the Australian market was liberalized the overriding priority was competitiveness (Pollitt and Haney, 2013), which is nowadays put besides energy security and decarbonization. From this situation arise the efforts of the Australian government to implement environmental policies aimed to respect the target of reducing emissions by $26\% - 28\%$ below 2005 levels by 2030 (Howard et al., 2018), whose main result was the enactment of the Clean Energy Act, in 2011, that introduced a carbon pricing scheme in Australia.

1.1 Carbon Pricing in Australia

Among other available policy options, the most environmentally effective and economically efficient is represented by tax and trading schemes. Carbon taxes belong to this category, that originates from the concept of Pigovian tax, aimed to recoup the damage arising as a by-product of a production process. The main tool introduced by the Clean Energy Act was the Carbon Pricing Mechanism (CPM). The CPM came into effect on July 1st, 2012, with the intent of easing the transition to an ultimate Emission Trading Scheme (ETS), but it ceased being effective backdated on July 1st, 2014, after its repealing on the 17th of the same month. Under the CPM, those businesses emitting more than 25

[1]Notice that Tasmania joined the NEM in 2005 and that Victoria includes the Australian Capital Territory (ACT).

thousand tonnes of carbon dioxide equivalent (tCO_2e) were required to buy the corresponding emission units from the government (Clean Energy Regulator, 2013). Since emission units were unlimited and available at a fixed price, this scheme was very similar to a tax and it was therefore commonly referred to as a carbon tax (Maryniak et al., 2019).

A widely used alternative to tax and trading schemes, is represented by subsidy schemes, which have been by far the most commonly used policy mechanism in Australia. Many approaches have been implemented as an inducement to undertake emission reduction measures (e.g. funds to pay for emissions reduction measures, market based approaches that create a price for cleaner generation, subsidized financing for certain technologies etc.), but their evaluation is complicated by the multiple objectives of these policies (Nelson et al., 2019). Another option is represented by the so-called command-and-control or direct regulations, such that the compliance failure generally involves fines or other penalties. Despite some advantages (inexpensiveness and relative familiarity of policy makers) they do not provide incentives for surpassing a goal and, more importantly, they fail to meet the criteria for allocative efficiency and and hence they are not the most cost-effective way to reach a desired goal (Daly and Farley, 2011). The ineffectiveness of this kind of policy is highlighted by the fact that Australian Government in 2011 failed to implement contracts for high emissions-intensive power plants due to the impossibility of agree closure price with generators (Combet, 2012).

Carbon tax is then supposed to contribute to the reduction of greenhouse gas (GHG) emissions and its efficiency depends on its impact on power generating companies' relative input costs, that then can be forced to maximize their profit through less polluting sources (Comincioli et al., 2019). The effectiveness and cost-efficiency of carbon tax is supported by wide empirical evidence (Hájek et al., 2019; Levin et al., 2019), especially in most developed countries, otherwise market and regulatory failures may reduce its power because of its price-instrument nature (Finon, 2019).

1.2 Our Contribution

The case of Australian CPM offers the unique opportunity of investigating the effects that both the introduction and the repealing of this kind of regulatory package had on a developed electricity market. Moreover, given the length of the period when the CPM was in force, it is also possible to investigate whether its introduction brought structural changes, that survived its repeal.

The key variable on which we focused, in order to investigate the effects of the CPM, is the volatility of electricity price (Sapio, 2012). This choice is motivated by the fact that its behavior, which is usually characterized by a periodic pattern and regular low-volatility periods interspersed by high-volatility clusters, showed a decrease in magnitude as well as a persistence of these clusters when the CPM was in force. Moreover, given the presence of a strong seasonality effect, we considered it appropriate to firstly analyze and remove periodic structure detectable within data and only later study the volatility structure.

For this purpose we studied electricity data from 2010 to 2018, with particular attention to electricity prices times series. However, in discontinuity with most of the literature, we studied also electricity traded volumes that, even if not directly affected by the introduction of the CPM, are valuable in order to double check overlapping results regarding price data. More in detail, our contribution to the literature is dual. The first goal of this study is to investigate the periodic structure affecting electricity data, by identifying separately its components by mean of a multiple linear regression model. For this purpose, most of econometric approaches (Smith and Shively, 2018), (Nazifi, 2016) focus either on the short term (Knittel and Roberts, 2005), (de Marcos et al., 2019) or on the long term (Marcjasz et al., 2019) while we conversely considered all the dynamics from the very short (one day) to the very long term (ten years) in order to obtain deseasonalized time series.

The second goal, which is subsequent but not less important than analysis of the periodic structure, is to investigate the stability of the process drawing deseasonalized residuals and study its volatility structure (Jaeck and Lautier, 2016; Qu et al., 2018). More in detail, we investigate the possibility that the process drawing deseasonalized residuals shows structural breaks in its coefficients in correspondence of the introduction and repeal of the CPM. After that, addressed by the presence of spikes (Manner et al., 2016) in the residuals which are seen as the outcome of a «stressed» regime, we model a gaussian Markov-switching model (Eichler and Türk, 2013) to describe the alternation between a «normal» low-volatility and a high-volatility sate of the world.

The structure of this paper is as follows. Section 2 introduces the models used first for remove the seasonal pattern form the time series of interest, and then to study their residual volatility structure. Section 3 provides a description of the dataset used to feed the models and the results of their fitting. Section 4 finally summarizes our findings and discusses their implications.

2 The Model

2.1 Time Series Decomposition

The construction of a deseasonalization process is based on the hypothesis that every time series y_t, over a sufficiently wide sample, can be expressed as a function of three components: long-term trend, cyclical fluctuations around this trend and short-term flicker, accounting for the so-called calendar effect. The relation between observed data and these components, henceforth denoted as μ_t, ν_t and ξ_t respectively, can be modeled both in multiplicative or additive forms. Since the trend and the amplitude of seasonal activity do not increase over time – in fact we observe that peaks and troughs are roughly of the same size across the sample – in this study we follow the second option, that allows to implement a building block approach to construct a linear regression equation, whose coefficient can be estimated through the OLS.

The first component analyzed is the long-term trend μ_t. Among the mathematical functions suitable to describe it, one of the most appropriate is a p-th degree polynomial, whose argument is the time index t. Even if some authors, for example (Pollock, 1999), suggest using more complex functions such as exponential or logistic, we consider a cubic function appropriate to well fit the long-term trend shown by observed data also allowing the presence of inflection points. This choice is motivated by the fact that the long-term moving average is highly correlated with economic cycle (Yu, 2015), whose variation changed the sign more than twice during the considered period. Then, we assumed that:

$$\mu_t = \alpha + \beta_1 t + \beta_2 t^2 + \beta_3 t^3. \tag{1}$$

The second component is assumed to represent the cyclical fluctuations around the trend defined above. Before providing the definition of the term ν_t, which aims to account for observed data's periodic component, it is necessary to provide an insight on the sinusoidal model.

When a time series y_t shows cyclical fluctuations, which is equivalent to have an autocorrelation structure with a regular pattern, its behavior can be modeled as the following composition of sinusoidal components (Hamilton, 1994; Bloomfield, 2000):

$$y_t = \alpha + \gamma \cos(2\pi f t) + \delta \sin(2\pi f t),$$

where α is the mean of y_t, a is the amplitude of the sin wave, f is it frequency, p is it phase[2], $\gamma = a\cos p$ and $\delta = -a \sin p$. More in general, if a time series y_t shows H cyclical components, it can now be modeled as it follows:

$$y_t = \alpha + \sum_{h=1}^{H} [\gamma_h \cos(2\pi f_h t) + \delta_h \sin(2\pi f_h t)]. \tag{2}$$

Since information about amplitude and phase is already included in the parameters to estimate, we just need to define which frequencies are observed in the sample, that is $f_1, \ldots, f_h$. To identify these frequencies, we exploited a tool borrowed from signal processing: the so-called spectral analysis (Penny, 2009). The idea behind this technique is that if a time series shows a periodic fluctuation, its autocovariance has approximately the same pattern over the different periods, and this happens also in case of more than one periodic fluctuations. Then, this regular autocovariance structure can be exploited to build a function able to detect the frequencies generating it. This function is the population spectrum, which is defined as:

$$s_y(\omega) = \frac{1}{2\pi}\left[\sigma_0 + 2\sum_{k=1}^{\infty}\sigma_k \cos(\omega k)\right],$$

where σ_k is the k-th autocovariance. We study this function for $\omega \in [0, \pi]$, because it is periodic with period π and it is symmetric around $\omega = 0$, in order to identify those ω_k corresponding to its peaks, which correspond to the frequency of detected fluctuation, in according to the relation $\hat{f}_k = \omega_k^{-1}$.

The last component is supposed to account for the presence of short-term flickers observed in electricity data, which are almost completely attributable to the day-of-the-week or holiday effects (Brubacher and Tunnicliffe Wilson, 1976; Hyndman and Fan, 2010; Bunn, 2000). There are two motivations to support the choice of considering these effects. On the one hand, during weekends pressure on demand is always lower than during weekdays and it reflects on the level and on the volatility of electricity price. On the other hand, the fact that a day is

[2]Recall that the amplitude of a wave is the difference between its extreme values, its frequency is the number of occurrences of a repeating event per unit of time and at last its phase is the relative value of that variable within the span of each full period.

public holiday[3] means by itself that electricity demand is lower than it would be if it was working day. To account for these effects, we build two sets of dummy variables: d_i^w, for $i = 1, \ldots, 7$ and d_j^h, for $j = 1, \ldots, 9$[4]. They take value 1 in correspondence of a specific day of the week or holiday and 0 elsewhere and they are used as additional regressors. Then, we assume that:

$$\xi_t = \sum_{i=1}^{7} \zeta_i d_{i,t}^w + \sum_{j=1}^{9} \eta_j d_{j,t}^h. \tag{3}$$

It is now possible to gather the components defined in equations (1), (2) and (3) in order to define the linear regression equation used to describe periodicity within observed data:

$$y_t = \alpha + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \sum_{h=1}^{H} \left[\gamma_h \cos(2\pi \hat{f}_h t) + \delta_h \sin(2\pi \hat{f}_h t) \right] + \sum_{i=1}^{7} \zeta_i d_{i,t}^w + \sum_{j=1}^{9} \eta_j d_{j,t}^h. \tag{4}$$

Residuals resulting from the estimation of the $20+2H$ parameters of equation above, henceforth denoted as r_t, are supposed to represent the behavior of electricity data that does not depend on seasonality. For this reason, the study of these series can focus on dynamics other than time, that is those conditioning the matching of demand and supply of electricity, that affect the volatility of both settlement price and traded volumes of electricity.

2.2 Regime-Switching Volatility

A simple idea to explain why a time series shows structural breaks, for instance in mean or in volatility, is to assume the existence of different possible states of the world, that affect the parameters of the process drawing observed data. Since the ultimate goal of this study is to describe electricity data as the result of a process with two changing volatility regimes, we introduced the following gaussian Markov-switching model.

The effectiveness of this model in describing the alternation between recurring states of the world is proved by its wide use in energy-related literature. Markov-switching models have been proven useful in a variety of fields, for example in driving investment decisions in oil and natural gas trading (De la Torre-Torres et al., 2019), disentangling the impact on electricity price of intermittent renewable generation (de Lagarde and Lantz, 2018), evaluating the effects of deregulation of electricity market on wholesale prices (Loi and Jindal, 2019) or – going closer to our studio – in modeling the volatility of energy sector's commodity price (Halkos and Tsirivis, 2019).

For our purpose, that is to model a two-states Markov-switching model to describe the alternation between a high- and a low-volatility regimes, given the strong autoregressive persistence in this data (Escribano and Sucarrat, 2018) we assumed that deseasonalized residuals of electricity data are drawn by the following $AR(1)$:

$$r_t = \alpha_{s_t} + \beta_{s_t} r_{t-1} + \sigma_{s_t} \epsilon_t, \tag{5}$$

[3]Australian public holidays are: New Year's Day, Australia Day (January 26th), Good Friday, Holy Saturday, Easter Sunday, Easter Monday, ANZAC Day (April 25th), Christmas and St. Stephen's Day.

[4]Notice that the first day of the week is Sunday and public holiday are in calendar order.

where $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ and s_t is the outcome of a 2-states Markov chain[5]. The unconditional density function of r_t is then defined as:

$$f(r_t|\underline{\theta}) = \sum_{j=1}^{n} \frac{\pi_j}{\sqrt{2\pi}\sigma_j} e^{-\frac{(r_t - \mathbb{E}[r_t|s_t=j])^2}{2\sigma_j^2}},$$

where $\underline{\theta}$ is the vector of the parameters of the distribution, containing mean and variance for both states of the world and the probability of being in each of them. The maximum likelihood estimators of distribution's mean and variance, in the i-th state of the world, are defined as:

$$\hat{\mu}_j = \frac{\sum_{t=1}^{T} r_t P(s_t = j|r_t, \hat{\theta})}{\sum_{t=1}^{T} P(s_t = j|r_t, \hat{\theta})} \quad \text{and} \quad \hat{\sigma}_j^2 = \frac{\sum_{t=1}^{T} (r_t - \hat{\mu}_j)^2 P(s_t = j|r_t, \hat{\theta})}{\sum_{t=1}^{T} P(s_t = j|r_t, \hat{\theta})},$$

while the probability of being in that state of the world is defined as:

$$\hat{\pi}_j = \frac{1}{T} \sum_{t=1}^{T} P(s_t = j|r_t, \hat{\theta}).$$

This probability represents the main result of the estimation of this model – performed by the EM algorithm because of estimators' non-linear functional form. For each date in analyzed time series it is possible to infer which state of the world it is most likely to be in, together with their specific means and variances. The analysis of this results for different subsamples allows to get an insight on possible discrepancies before, under and after the CPM was in force.

3 Empirical Results

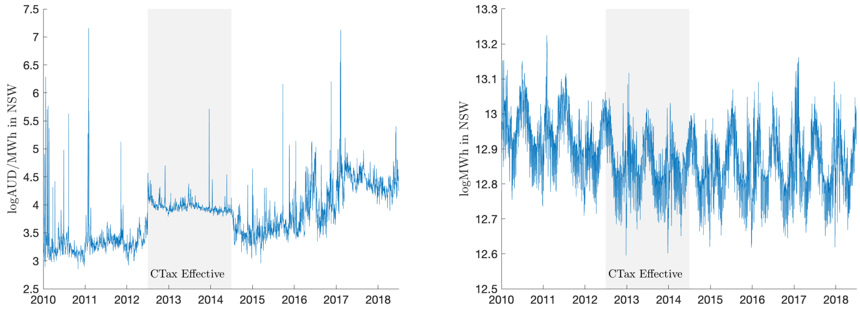
3.1 The Dataset and Preliminary Operations

The dataset exploited in this study originates from the historical tables provided by the AEMO[6], whose collection resulted in a panel of 10 time series, that is one for each region of the NEM, for both settlement prices and traded volumes. Observations are sampled at the half-hourly frequency and begin on December 7, 1998, at 2 AM, but the period on which this study is based ranges from January, 1, 2010 and June, 30, 2018.

Within this period of interest of about $150k$ observations, none was missing but negative prices were observed: 12 in New South Wales, 127 in Queensland, 1253 in South Australia, 966 in Tasmania and 261 in Victoria. Since most of periodic structure detectable concerns cycles longer than a day, we focus on price's daily averages and volume's daily total, also easing computational costs. Following this operation, the number of negative observations reduced to 0, 1, 14, 9 and 2 in the five states respectively and they were fixed by linear interpolation, to allow the logarithmic transformation for tractability purpose.

[5]A n-states Markov chain is a random variable s_t that can assume only the integer values $j = 1, \dots, n$ and such that $P(s_t = j|s_{t-1} = i, s_{t-2} = k, \dots) = P(s_t = j|s_{t-1} = i) \equiv p_{i,j}$ and where $\sum_{j=1}^{n} p_{ij} = 1$. All these probabilities are collected in the so-called transition matrix.

[6]All data used in our dataset are available at: `https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard`.



(a) Log-price.

(b) Log-volume.

Figure 1: Time series of log-price (left panel) and log-volume (right panel) in New South Wales between 2010 and 2018.

Finally, as the main goal of this study is to investigate the consequences that the introduction and repeal of carbon tax had on electricity data behavior, this sample has been divided in three subsamples: January, 1, 2010 to June, 30, 2012, July, 1, 2012 to June, 30, 2014 and July, 1, 2014 to June, 30, 2018. The model described in section 2 has then been fitted to time series regarding both prices and volumes for all the five regions composing the NEM. However, in this study, are presented mostly those results regarding the New South Wales region. Results from other regions of the NEM are fully comparable to those shown and are available upon request.

Figure 1 shows the time series of both log-price and log-volume recorded in New South Wales. From the graphical analysis of these plots it is clear that observed data are affected by the presence of a periodic structure – obviously more noticeable in the series of traded volumes. Moreover, it is evident that the introduction of carbon tax had a clear effect on the log-price series, that basically consisted in a volatility reduction. All the five regions composing the NEM have been considered in this study and we present all the numerical results, but we preferred to show only plots regarding New South Wales, for reasons of space. All other results – totally comparable with those presented – are available upon request to the authors.

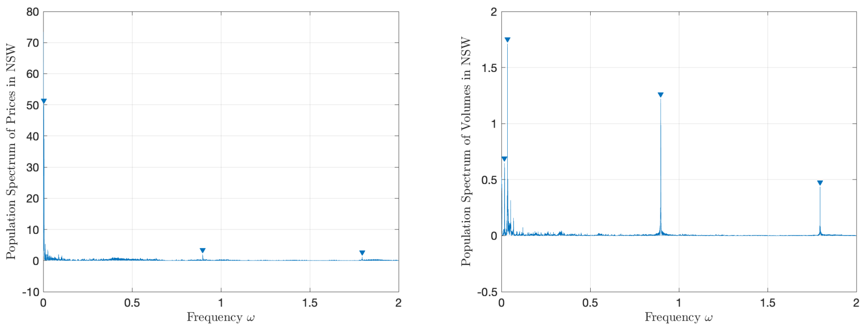
Table 1 provides a summary of preliminary statistic of time series analyzed, that is the logarithmic transformation of both settlement prices and traded volumes of electricity in the five regions composing the NEM, over the period of time of our interest. Already from these preliminary statistics it is clear that the smaller the average traded volume, the higher the volatility of settlement price, which explains why negative prices, both in half-hourly and daily sampling frequency, are more common in smaller regions, as mentioned above. Moreover, focusing on the key variable, that is price volatility, it is clear that under the CPM the value is – already at this stage – considerably lower.

Variable	Region	High	Mean	Low	Standard Deviation	Skewness	Kurtosis
Entire sample: 1 January 2010 - 30 June 2018, 3103 *observations*							
$\log P$	NSW	7.16	3.80	2.86	0.49	0.90	5.61
	QLD	7.54	3.80	−0.85	0.60	0.58	7.79
	SA	7.76	3.87	−1.14	0.65	0.45	6.65
	TAS	6.69	3.82	−1.00	0.60	0.30	5.49
	VIC	7.15	3.72	1.81	0.55	0.70	4.57
$\log Q$	NSW	13.22	12.88	12.60	0.10	0.06	2.84
	QLD	12.86	12.56	12.36	0.08	0.40	3.24
	SA	11.73	11.12	10.59	0.15	0.11	3.45
	TAS	11.14	10.89	10.52	0.09	0.09	2.82
	VIC	12.87	12.46	12.04	0.12	−0.31	2.90
Before carbon tax: 1 January 2010 - 30 June 2012, 912 *observations*							
$\log P$	NSW	7.16	3.35	2.86	0.37	5.58	44.58
	QLD	6.97	3.25	−0.85	0.39	1.93	42.97
	SA	7.76	3.33	0.10	0.47	2.89	31.45
	TAS	6.69	3.34	1.20	0.37	1.99	21.15
	VIC	7.15	3.27	1.86	0.37	4.47	40.35
$\log Q$	NSW	13.22	12.94	12.71	0.08	0.01	3.05
	QLD	12.78	12.55	12.36	0.07	0.28	3.13
	SA	11.73	11.19	10.83	0.13	0.21	3.71
	TAS	11.14	10.90	10.63	0.09	0.33	2.53
	VIC	12.80	12.53	12.25	0.09	−0.33	2.76
During carbon tax: 1 July 2012 - 30 June 2014, 730 *observations*							
$\log P$	NSW	5.71	3.97	3.79	0.12	5.37	62.33
	QLD	6.37	4.06	−0.18	0.35	0.06	42.74
	SA	6.69	4.09	3.46	0.36	2.57	13.26
	TAS	4.92	3.79	2.93	0.21	1.63	9.09
	VIC	6.58	3.95	3.61	0.24	4.89	40.02
$\log Q$	NSW	13.12	12.85	12.60	0.08	−0.11	2.95
	QLD	12.73	12.52	12.38	0.06	0.35	3.61
	SA	11.71	11.13	10.79	0.14	0.66	4.11
	TAS	11.11	10.89	10.65	0.08	0.07	2.73
	VIC	12.87	12.48	12.19	0.1	0.03	3.41
After carbon tax: 1 July 2014 - 30 June 2018, 1461 *observations*							
$\log P$	NSW	7.13	4.01	2.96	0.48	0.63	4.38
	QLD	7.54	4.02	1.03	0.58	0.89	7.35
	SA	7.31	4.10	−1.14	0.67	−0.10	7.10
	TAS	5.58	4.13	−1.00	0.65	−0.59	6.67
	VIC	6.81	3.89	1.81	0.59	0.18	2.82
$\log Q$	NSW	13.16	12.85	12.62	0.09	0.13	2.78
	QLD	12.86	12.59	12.37	0.08	0.28	3.09
	SA	11.59	11.07	10.59	0.15	0.10	3.21
	TAS	11.13	10.88	10.52	0.10	0.00	2.81
	VIC	12.71	12.40	12.04	0.11	−0.24	2.64

Table 1: Basic features of logarithm of settlement prices and traded volumes, expressed in logAU$/MWh and logMW respectively, for the five region composing the NEM, regarding the period 2010-2018 and its sub-periods before the introduction, the effectiveness and after the repealing of carbon tax.

3.2 Time Series Decomposition

As described in section 2.1, before fitting the model described by equation (4) it is necessary to perform the spectral analysis of the time series, in order to identify the frequencies corresponding to the cycles described by equation (2). Figure 2 shows the population spectrum of both log-price and log-quantity recorded in New South Wales. The periodic structure of the data analyzed is detected by this function, that returns a peak in correspondence of the frequency of a cycle recognized. The detection of a peak is performed by setting a proper set of parameters defining spikes' minimum height, prominence and distance. Despite the fact that a higher number of peaks is detected in the analysis of log-volume (because of its clearer periodicity) and despite their different values, a key point is that the frequency of pikes across the two time series are overlapped: this result proves that the two time series analyzed share (most of) their periodic structure.



(a) Log-price. **(b)** Log-volume.

Figure 2: Population spectrum of log-price (left panel) and log-volume (right panel) in New South Wales between 2010 and 2018.

This conclusion is reinforced by the results of the spectral analysis of other time series, whose results, together with those of New South Wales, are collected in table 2. For each frequency (and corresponding cycle's length) detected by spectral analysis of all time series, it is shown in which cases it has been observed. Notice that in no case a peak is detected in only a time series, while significant overlapping is common: this is a key point to enhance the confidence in results regarding log-price, whose volatility is object of interest in the second part of the paper.

After having collected the results of the spectral analysis, it is possible to exploit them to build a proper set of regressor accounting for time series' harmonic components, in order to estimate the model described in equation (4). Given the high number of estimated coefficients through the various regressions performed, the results of significancy test for all coefficients (~ 300) are not reported here. We only highlight the key statistics of the estimated model for the case of New South Wales: the R^2 is 47% and 43% for log-price and log-volume while the p-value of F-statistic of the estimated model against the constant one is zero in both cases.

Figure 3 collects the plots of the estimated four main components in which

Frequency	Length	NSW		QLD		SA		TAS		VIC	
		P	Q	P	Q	P	Q	P	Q	P	Q
$\omega = 0.002$	$\sim$ 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	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$\omega = 1.795$	$\sim$ 12 hours	✓	✓		✓		✓	✓	✓		✓

Table 2: 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.

time series of New South Wales have been decomposed, according to the model described in equation (4): the long-term trend, the harmonic component and short-term flickers, represented by the day-of-the-week and the holiday effects.

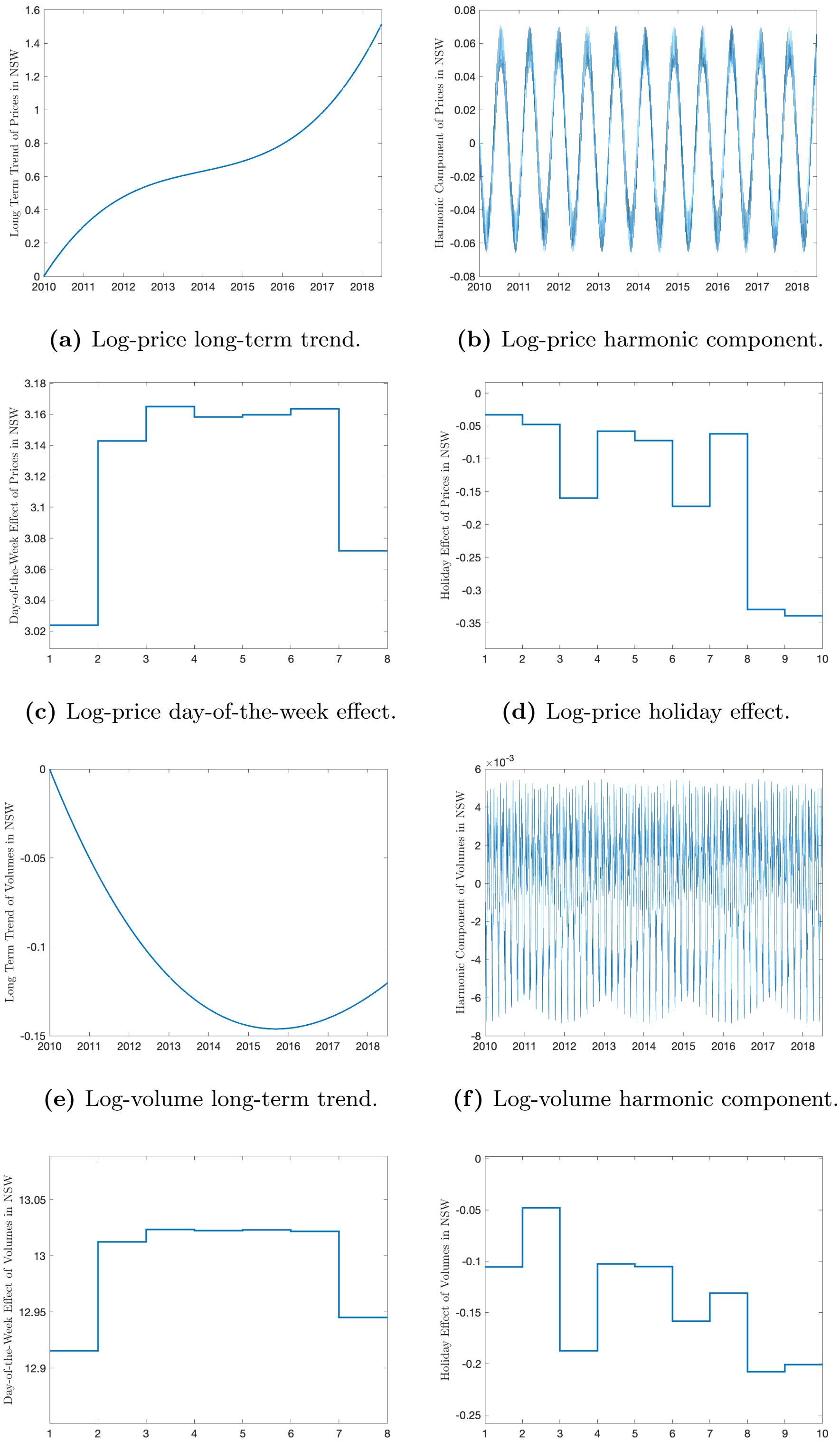
The long-term trend accounts for the behavior of analyzed variables in over the decade, thus can be also representative of the economic cycle, at least in the case of log-price it shows an inflection point. The harmonic component represents the composite effects of cycles detected by the spectral analysis: to each cycle correspond two sin waves. Thus, in the case of log-price (log-volume), as reported in table 2, three (four) cycles are detected, which correspond to six (eight) sin waves: for this reason the harmonic component of log-volumes is more complex. With regard to the short-term flickers, this analysis highlights that both log-prices and log-volumes are smaller during the weekends, while all the holidays have an overall negative effect, which is strongest in correspondence of Christmas and St. Stephen's Day.

3.3 Regime-Switching Volatility

The time series decomposition shown in the previous section, together with providing the described insight on periodic structures, produces the series of deseasonalized residuals, from which the periodic structure previously detected is removed. The upper panel of figure 4 shows deseasonalized residuals of New South Wales's log-prices, with a grey-shaded area representing the period in which the CPM was in force. These residuals are assumed to be drawn by equation (5), whose mean and variance depend on the unobserved state of the world s_i: s_1 and s_2 correspond to the low- and high-volatility, respectively.

The outcome of the model described in section 2.2 includes several information useful to understand log-price's volatility structure: the inference about the unobserved state of the world, the probability of switching or remaining for each state,[7] their average duration and recorded volatility. The inference on s_i is represented in the lower panel of figure 4. From this plot, it is clear that under the CPM, the probability of being in the low-volatility state was close to one most of time: compared to the other subsamples, there is a substantial

[7] These probabilities are collected in the so-called transition matrix, whose element in position i, j is the probability of being in the i-th state at present day and being in the j-th one the following day.



(a) Log-price long-term trend.

(b) Log-price harmonic component.

(c) Log-price day-of-the-week effect.

(d) Log-price holiday effect.

(e) Log-volume long-term trend.

(f) Log-volume harmonic component.

(g) Log-volume day-of-the-week effect.

(h) Log-volume holiday effect.

Figure 3: The four components in which in New South Wales's log-price and log-volume between 2010 and 2018 has been decomposed in according to equation (4).

decrease in magnitude and frequencies of high-volatility periods. This intuition is confirmed by the results collected in table 3.

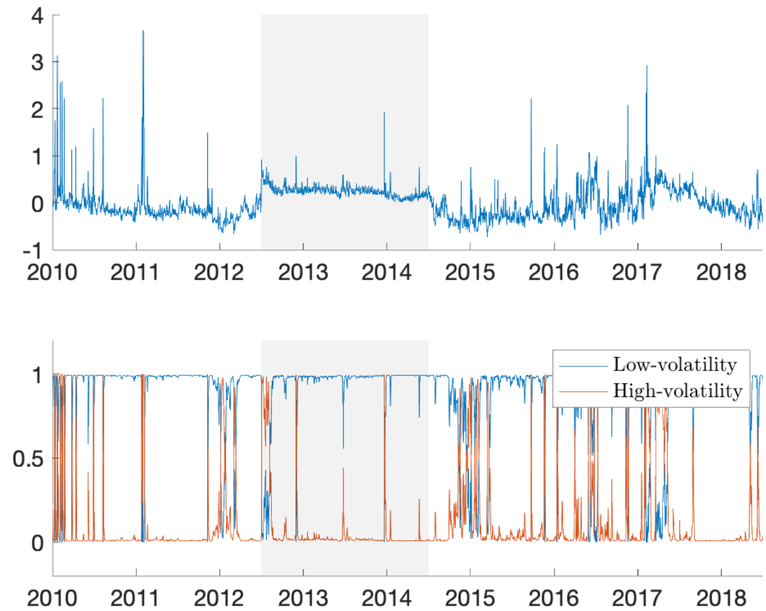


Figure 4: Deseasonalized residuals (upper panel) and inference about the unobserved state variable (lower panel) in New South Wales between 2010 and 2018.

Firstly, from the transition matrices it is clear that it is very likely to remain in the low-volatility state in all of the three subsamples. The probability of that is .98 in the first two cases and decreases to .97 in the last one. In reverse, the probability of remaining in the high-volatility state is maximum after the carbon tax, while it is significantly lower in the other cases. These results reflects into the average duration of the states: the one of the the low-volatility state is maximum (~ 64 days) under the CPM, while it is significantly shortened before and after that. In the same period we observe the second shortest average duration of the high-volatility state (~ 8 days). The probability of remaining in the high-volatility state and the average duration of this state are both slightly smaller before than during the CPM. This may contradict the hypothesis of the paper, however the difference is very small, thus it does not represent a contradiction.

Most importantly, it is finally pointed out that in all of the three subsamples the volatility of the first state is lower than the one of the second state. Moreover, among the three subsamples, the one with the lowest volatility is under the CPM in both the states. This result definitely proves that the introduction and the repealing of the CPM has a significant impact on electricity price's volatility, both in terms of the level itself and in term of persistence of the low-volatility state.

Parameter	Before	Under	After
		CPM	
Transition Matrix	$\begin{bmatrix} .98 & .15 \\ .02 & .85 \end{bmatrix}$	$\begin{bmatrix} .98 & .13 \\ .02 & .87 \end{bmatrix}$	$\begin{bmatrix} .97 & .05 \\ .03 & .95 \end{bmatrix}$
Duration s_1	44.57	64.28	36.27
Duration s_2	6.73	7.95	19.81
Volatility s_1	.0188	.0076	.0234
Volatility s_2	.0596	.0475	.1047

Table 3: Parameters resulting from the fitting of the two-states Markov-switching model to electricity prices' deseasonalized residuals in New South Wales. From top to bottom: transition matrix collecting transition probabilities between s_1 and s_2, average duration and volatility of the two states.

4 Conclusions

This study is intended to pursue the dual goal of understanding the periodic structure recognizable within electricity settlement price and the traded volumes as well as investigating the behavior of electricity price volatility. These goals are achieved through the models described in sections 2.1 and 2.2. On the one hand we obtained an estimate of the effect that a number of variables have on observable dynamics of electricity time series. On the other hand, we studied the volatility structure of deseasonalized residuals to highlight how it is affected by the presence of a carbon tax.

Even if the development of deseasonalization process applied in this study is functional to the analysis of volatility structure, it still contributes to the literature introducing the two following novelties. Firstly, the model proposed introduces a broad spectrum analysis of seasonal patterns: cycles of length spanning from to the short-term (daily) to the very long-term (more than annual) are considered within the same model, by using a wide set of tools able to catch the different dynamics affecting the observed data (long-term trend, calendar effects and, most importantly, the harmonic components). Secondly, all results obtained from the time series of electricity settlement price are double-checked with a parallel analysis of traded volumes – to strengthen their reliability – as these two variables are also influenced by the same drivers. Moreover, the estimation of deseasonalization model has always shown a strong statistical significance. Then, as the model is able to catch a relevant part of the variability of observed data, it could be a useful mean for investors – or other subjects involved in the wholesale market – to forecast future observations.

Understanding the volatility of the main source of revenue is a key point in the evaluation of an investment in any sector. The energy industry is not an exception, especially when liberalized as, in this case, utilities can no longer automatically transfer additional costs to consumers (Newbery et al., 2008). This means that is the investment risk burden is shifted from consumers to producers (Bazilian and Roques, 2009).

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. More in detail, whatever the method used for modeling risk aversion – classically classified into utility functions, risk-adjusted discount factors, mean-variance portfolio analysis or real options (Petitet, 2016) – within investment evaluation, the final decision is influenced by macroeconomic, competition and most importantly energy-specific factors. This last category, that refers to electricity system features including the economic conditions under which generators operate, is fundamental for investment decisions as energy-specific factors are likely to attract investors if profit prospects are high and uncertainty is low (European Commission, 2015). Moreover, among different sources of uncertainty identified in electricity generation projects – volume, price, cost and technical risk – price risk, that refers to unattended variations in price, is the most relevant one, also with regard to market with high shares of coal and gas exploitation (Newbery et al., 2006), that in Australia accounted for the 83% in 2017 (Australian Energy Regulator, 2018).

The volatility of electricity price – and then 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 – which is a consequence of the very 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 (European Commission, 2015). Moreover, if an electricity market is an energy-only market – as in the case of the AEMO – instead of complemented by a capacity mechanism, price are allowed to heavily rise (decrease) in case of over-demand (over-supply), increasing volatility and, in turn, the investment risk associated[8].

The worldwide introduction of a variety of policy aimed at reducing carbon dioxide emissions, increased the complexity of this framework for the corresponding new cost item for utility companies. A wide literature resulted from this innovation, mostly focused on the uncertainty of following carbon emissions (Hafstead and Williams, 2020) or on the uncertainty of carbon pricing itself (Burtraw et al., 2012; Murray et al., 2009). It has been proved that lower carbon price volatilities positively affects returns to investments which in turn can result in more, climate-friendly investment (Aldy, 2017). However, there is no evidence about this effect induced by electricity price volatility, especially in those environments – as the Australian case – where carbon price is fixed. Our study contributes in this direction, proving that the introduction of a CPM has a positive influence on electricity final market price. As it represents the main source of revenues for utility companies, this information could be useful to investors, especially under the real options approach (Dixit and Pindyck, 1994).

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

References

Aldy, J. E. (2017). Designing and updating a us carbon tax in an uncertain world. *Resources for the Future Discussion Paper*. 4

Australian Energy Regulator (2018). State of the energy market 2018. *Australian Competition and Consumer Commission*. 1, 4

Bazilian, M. and Roques, F. A. (2009). *Analytical Methods for Energy Diversity and Security*. Elsevier Science. 4

Bloomfield, P. (2000). *Fourier Analysis of Time Series*. Wiley Series in Probability and Statistics. 2.1

Brubacher, S. R. and Tunnicliffe Wilson, G. (1976). Interpolating time series with application to the estimation of holiday effects in electricity demand. *Journal of Royal Statistical Society*. 2.1

Bunn, D. W. (2000). Forecasting loads and prices in competitive power markets. *Proceedings of the IEEE*, 88(2):163–169. 2.1

Burtraw, D., Fell, H., and Morgenstern, R. D. (2012). Soft and hard price collars in a cap-and-trade system: A comparative analysis. *Journal of Environmental Economics and Management*. 4

Clean Energy Regulator (2013). Carbon pricing mechanism. *Australian Government Publication*. 1.1

Combet, G. (2012). Securing a clean energy future: implementing the australian government's climate change plan. *Budget 2012-13, Statement by the Honourable Greg Combet AM MP, Minister for Climate Change and Energy Efficiency, 8 2012*. 1.1

Comincioli, N., Moretto, M., and Vergalli, S. (2019). Optimal energy mix between photovoltaic and conventional energy sources in a LCOE framework. Presented at Elsevier 2nd International Conference on Energy Research and Social Science, Tempe, AZ. 1.1

Daly, H. and Farley, J. (2011). *Ecological Economics*. Island Press, Washington DC, second edition. 1.1

De la Torre-Torres, O. V., Galeana-Figueroa, E., and Álvarez-García, J. (2019). A test of using markov-switching garch models in oil and natural gas trading. *Energies*. 2.2

de Lagarde, C. M. and Lantz, F. (2018). How renewable production depresses electricity prices: Evidence from the german market. *Energy Policy*. 2.2

de Marcos, R. A., Bello, A., and Renses, J. (2019). Electricity price forecasting in the short term hybridising fundamental and econometric modelling. *Electric Power Systems Research*. 1.2

Dixit, A. and Pindyck, R. (1994). *Investment under Uncertainty*. Princeton University Press. 4

Eichler, M. and Türk, D. (2013). Fitting semiparametric markov regime-switching models to electricity spot prices. *Energy Economics*. 1.2

Escribano, A. and Sucarrat, G. (2018). Equation-by-equation estimation of multivariate periodic electricity price volatility. *Energy Economics*. 2.2

European Commission (2015). Investment perspectives in electricity markets. *Energy Economic Developments*, Institutional Paper 003 | July 2015. 4

Finon, D. (2019). Carbon policy in developing countries: Giving priority to non-price instruments. *Energy Policy*. 1.1

Hafstead, M. A. C. and Williams, R. C. (2020). Mechanisms to reduce emissions uncertainty under a carbon tax. *Resources for the Future Discussion Paper*. 4

Hájek, M., Zimmermannová, J., Helman, K., and Rozenský, L. (2019). Analysis of carbon tax efficiency in energy industries of selected eu countries. *Energy Policy*. 1.1

Halkos, G. E. and Tsirivis, A. S. (2019). Effective energy commodity risk management: Econometric modeling of price volatility. *Economic Analysis and Policy*. 2.2

Hamilton, J. D. (1994). *Time Series Analysis*. Princeton University Press. 2.1

Howard, B. S., Hamilton, N. E., Diesendorf, M., and Wiedmann, T. (2018). Modeling the carbon budget of the australian electricity sector's transition to renewable energy. *Renewable Energy*. 1

Hyndman, R. J. and Fan, S. (2010). Density forecasting for long-term peak electricity demand. *IEE Transactions on Power Systems*. 2.1

Jaeck, E. and Lautier, D. (2016). Volatility in electricity derivative markets: The samuelson effect revisited. *Energy Economics*. 1.2

Knittel, C. R. and Roberts, M. R. (2005). An empirical examination of restructured electricity prices. *Energy Economics*. 1.2

Levin, T., Kwon, J., and Botterud, A. (2019). The long-term impacts of carbon and variable renewable energy policies on electricity markets. *Energy Policy*. 1.1

Loi, T. S. A. and Jindal, G. (2019). Electricity market deregulation in singapore – initial assessment of wholesale prices. *Energy Policy*. 2.2

Manner, H., Türk, D., and Eichler, M. (2016). Modeling and forecasting multivariate electricity price spikes. *Energy Economics*. 1.2

Marcjasz, G., Uniejewski, B., and Weron, R. (2019). On the importance of the long-term seasonal component in day-ahead electricity price forecasting with narx neural networks. *International Journal of Forecasting*. 1.2

Maryniak, P., Trück, S., and Weron, R. (2019). Carbon pricing and electricity markets - the case of the australian clean energy bill. *Energy Economics*. 1.1

Murray, B. C., G., N. R., and Pizer, W. A. (2009). Balancing cost and emissions certainty: An allowance reserve for cap-and-trade. *Review of Environmental Economics and Policy.* 4

Nazifi, F. (2016). The pass-through rates of carbon costs on to electricity prices within the australian national electricity market. *Environmental Economics and Policy Studies.* 1.2

Nelson, T., Pascoe, O., Calais, P., Mitchell, L., and McNeill, J. (2019). Efficient integration of climate and energy policy in australia's national electricity market. *Economic Analysis and Policy.* 1, 1.1

Newbery, D. M., Nuttall, W. J., and Roques, F. A. (2006). Using probabilistic analysis to value power generation investments under uncertainty. 4

Newbery, D. M., Nuttall, W. J., and Roques, F. A. (2008). Fuel mix diversification incentives in liberalized electricity markets: A mean–variance portfolio theory approach. *Energy Economics.* 4

Parer, W. (2002). *Towards a truly national and efficient energy market.* The Council of Australian Governments, Energy Market Review. 1

Penny, W. D. (2009). *Signal Processing Course.* 2.1

Petitet, M. (2016). *Long-term dynamics of investment decisions in electricity markets with variable re- newables development and adequacy objectives.* PhD thesis, PSL Research University. 4

Pollitt, M. G. and Haney, A. B. (2013). Dismantling a competitive retail electricity market: Residential market reforms in great britain. *The Electricity Journal.* 1

Pollock, D. S. G. (1999). *Handbook of Time Series Analysis, Signal Processing, and Dynamics.* Academic Press. 2.1

Qu, H., Duan, Q., and Niu, M. (2018). Modeling the volatility of realized volatility to improve volatility forecasts in electricity markets. *Energy Economics.* 1.2

Sapio, S. (2012). Modeling the distribution of day-ahead electricity returns: a comparison. *Quantitative Finance.* 1.2

Sing Lai, C. and McCulloch, M. D. (2017). Levelized cost of electricity for solar photovoltaic and electrical energy storage. *Applied Energy.* 1

Smith, M. and Shively, T. S. (2018). Econometric modeling of regional electricity spot prices in the australian market. *Energy Economics.* 1.2

Xian L., H., Edwards, D. J., Reza Hosseini, M., and Costin, G. P. (2020). A review on renewable energy transition in australia: An updated depiction. *Journal of Cleaner Production.* 1

Yu, W. (2015). Analysis on the correlation between electricity consumption cycle and economic cycle. *Metallurgical and Mining Industry.* 2.1

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