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Structural breaks and electricity prices: Further evidence on the role of climate policy uncertainties in the Australian electricity market

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ABSTRACT

The primary objectives and the strategies of a national electricity market are the efficient delivery of network services and the electricity infrastructure to meet the long-term consumer's interests. Therefore, the objective of this study is to explore whether electricity prices across the six Australian States display instability. Such instability is closely associated with the presence of structural breaks in relevance to policy events on Australian carbon policies. The study makes use of weekly Australian wholesale electricity prices spanning the period from June 8th, 2008 to March 30th, 2014 along with linear and non-linear unit root testing methodologies. The results provide supportive evidence that the Australian electricity market can be described as a less stable electricity market, which implies that a high degree of market power is exercised by generators across regional markets. These findings are expected to have substantial consequences for the effectiveness of carbon dioxide mitigating policies, especially, when there is uncertainty as to whether the planned environmental policy is put in place for the lifespan of undertaken investments.

1. Introduction

Australian electricity markets experienced significant deregulation in the 1990s and policy questions have arisen since. The main domestic network is the *National Electricity Market* (NEM). It was established in 1998 and links regional markets in Queensland, New South Wales, Victoria and, more restrictively, Tasmania and South Australia. The primary objective of the NEM is to provide an efficient and nationally integrated electricity market, which in the long-run should provide similar prices for electricity across all six states and, thus, limit the market power of generators in the regional markets. Most consumers do not participate directly in the NEM; they purchase their electricity through retailers.

The wholesale market of the NEM is a real-time energy market where a centrally coordinated dispatch process is used to match demand and supply instantaneously in real time. Supply bids are stacked from the least price to the highest price and the dispatch price for each 5-min interval is set equal to the last bid needed to meet demand at a given period. The spot price is used as the basis for the settlement of financial transactions for all energy traded in the NEM (AEMO, 2013). Australia's highly emissions-intensive electricity sector is the main reason why Australia's emissions are the highest per capita among advanced economies. Around 75% of Australia's electricity supply is generated from coal, higher than in most other advanced countries, and very high in global comparison (World Bank, 2012). Electricity generation accounts for more than one-third of Australia's overall emissions, and emissions from this sector have grown faster than any other sector over the last years.

Over the period 2009–2010, the Australian government could not implement a key 2007 election commitment relating to the introduction of a greenhouse gas emissions trading scheme by the year 2010. The legislation underpinning the scheme was passed by the House of Representatives but rejected by the Senate. Eventually, this gas emissions trading scheme was adopted in July 2012 to become ineffective in July 2014. Nelson et al. (2010) argue that the lack of policy certainty in relation to climate change policy effectively prevented firms from investing in projects mitigating carbon emissions and in investing in non-fossil energy sources. The authors provide evidence that delaying the provision of policy certainty resulted in firms investing too heavily in open-cycle gas turbines, investments that minimize the risk associated with the investing capital. This led to a significant increase in wholesale electricity prices, thus, imposing a largely deadweight loss cost to society. Their results receive supplementary support by the study of Keating (2010). Garnaut (2011) suggests that without having enough interconnector capacity to cope with the potentially large shifts in interstate flows of electricity, much of the generation capacity must remain within a regional market, even if there are more economic sources

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elsewhere. Thus, interconnector constraints could be reflected in regionally differentiated, volatile und unnecessarily high electricity prices. In addition, Nelson et al. (2012) provide evidence on Australian carbon prices and their impact on the country's electricity markets. Their findings illustrate that there does not exist any unique way to estimate accurately carbon pass-through. This type of inconsistency of pass-through policies in carbon mitigate policies is expected to have important implications for policy makers in terms of households' compensation policies as well as for businesses under the scheme of Clean Energy Future. In that sense, Australian policy makers can easily rely upon other carbon mitigation schemes, such as the European Union Emissions Trading Scheme (ETS). In terms of carbon emissions policy, in 2001, Australia introduced legislation requiring investment in new renewable electricity generating capacity. This particular legislation was significantly expanded in 2009 to give effect to a 20% Renewable Energy Target (RET). The authors argue that the 'stop/start' nature of renewable policy development resulted in investors withholding new capital until greater certainty can be provided. More specifically, they investigate whether capital market efficiency losses could occur under certain policy scenarios. Their findings document that electricity costs definitely increase if the large-scale RET is abandoned, even after accounting for avoided renewable costs. Overall, they conclude that policymakers should be guided by a high level public policy principle in relation to large-scale renewable energy policy.

Given that the objective of establishing a national electricity market is the efficient delivery of network services and electricity infrastructure to meet the long-term interests of consumers, it is worth undertaking a study that explores whether electricity prices across the six Australian States display instability which is primarily associated with the presence of structural breaks arising from particular policy events, such as the uncertainty associated with Australian carbon policies. According to economic theory, the inability to implement carbon dioxide mitigation policies generates detrimental implications for energy and economic growth sustainability since the effect of uncertainty associated with future carbon emission regulations, magnifies the anxiety of risk-averse investors concerning profits (Fan et al., 2010). The elimination of such policy uncertainties is expected to lead to increasing investments in less carbon intensive technologies.

Worthington et al. (2005) examine the transmission of spot electricity prices and price volatility across the regional electricity markets in the Australian case. They make use of a multivariate generalized autoregressive conditional heteroskedasticity model to identify the source and magnitude of price and price volatility spillovers. Their results indicate the presence of positive own mean spillovers in only a small number of markets and no mean spillovers between any of the markets. These findings are directly related to the physical transfer limitations of the present system of regional interconnection. At the same time, their findings illustrate that shocks in some markets affect price volatility in others. Zhou (2009) attempts to explore how environmental policies, e.g. emission trading schemes, impact on the change of market power of generation companies. In particular, the author targets the Australian National Electricity Market and presents a Cournot market equilibrium model which incorporates an emission trading model that studies the potential changes of market power due to the introduction of the proposed Australian National Emission Trading Scheme (NETS). For an excellent review on the Australian electricity the interested reader should turn to the paper by Nelson et al. (2012) (along with the studies referenced there) where the role of climate change mitigation policies is emphasized. The authors argue that the way electricity prices are formed depends substantially on carbon prices and their impact on such electricity prices. Their empirical analysis developed an approach for testing the consistency of a number of methodological approaches in the literature, while their findings document that the literature related findings are inconsistent in terms of the carbon pass-through process. They also conclude that the variation of carbon pass-through estimates has important implications for policy makers, given much of the compensation to be paid to households and businesses under carbon mitigation policies. Overall, their conclusion is that Australian policy makers must be guided by relying upon the numerous a posteriori estimations of pass-through in the European Union Emissions Trading Scheme (ETS) rather than Australian a priori studies. Finally, Cotton and De Mello (2014) analyze the efficiency of the two largest schemes in Australia, the NSW Greenhouse Gas Abatement Scheme and the Mandatory Renewable Energy Trading Scheme, through their effect on the electricity prices. Their findings document that both schemes' emission prices have little effect on electricity prices, while when shocks are applied to electricity by the two schemes it returns to equilibrium very quickly, indicating that both schemes are not having the effect anticipated in their legislation.

Therefore, the goal of this paper is to explicitly investigate, for the first time, the stationarity properties of Australian electricity prices, making use of recent developments in panel unit root testing. In particular, the empirical analysis in this paper makes use of both linear and non-linear panel unit root tests. The novelties of our work are related to the advantages of the panel unit root tests this paper employs. In particular, there are certain key advantages in relevance to the issue of size distortions, where this testing procedure takes into account both serial correlation and cross-sectional dependency through the implementation of an autoregressive (AR)-based bootstrap. Moreover, the testing procedure allows for the presence of structural breaks that might arise with, say, changes in environmental policies, e.g. breaking the sample in the pre- and post-adoption of carbon dioxide eras. In this paper, however, we explicitly allow for different endogenously determined breaking dates across the individual electricity prices and across States in the panel.

To foreshadow the empirical findings of this study, the results indicate that Australian electricity prices in four out of six Australian States (i.e., New South Wales, Victoria, Tasmania and Western Australia) document a break type of behavior related to the failure of the Australian government to adopt an election commitment relating to the introduction of a greenhouse gas emissions trading scheme by the year 2010. In the case of South Australia, the break seems to occur in 2013, which coincides with the Senate's decision in March 2013, electricity supply has to heavily come from renewable sources, mainly, wind and solar. Interestingly, the South Australia government, as we are speaking today, has already exceeded its target of generating 33% of the state's electricity needs from renewables and has now set a 50% target by 2025. As a result, constantly since the summer of 2013 there have been several instances when wind energy has accounted for all, or nearly all, electricity demand in South Australia. We could also keep in mind that South Australia has nearly half the country's wind capacity with around 1.5GW of wind energy.

By contrast, the results seem not to be affected by the introduction of the Carbon Pricing Mechanism (CPM) that became effective on the first of July 2012, with a planned transition to an emissions trading scheme (ETS) in July 2015. The intention behind imposing a price on carbon was to encourage producers to switch away from coal-fired generation and move to gas and renewable sources of energy through increasing the costs of fossil fuel combustion. Despite that existing statistics illustrate that power prices within the Australian NEM increased significantly after July 2012, even by more than 100%, our results identified different events that could have significantly impacted electricity prices in Australia. These findings receive statistical support by Nazifi (2015) who provides empirical evidence that the CPM affected significantly electricity prices only in the cases of New South Wales and Victoria.

The findings are expecting to raise substantial interest for market participants in electricity markets since the presence of structural breaks can impact the stationarity properties of electricity prices and generate or delete profitable arbitrage opportunities in electricity prices, not only within the same State and across generators, but also across States. They will be of high interest to all electricity market participants (i.e., running from suppliers to final consumers) since this could increase the forecasting performance of modeling approaches in relevance to future movements in electricity prices based on past behavior.

Finally, to identify the event(s) giving rise to the presence of structural break(s), the findings are expected to provide strong evidence about the nature of policy uncertainties associated with the energy markets and in that perspective policy makers can take all the necessary precautionary measures to avoid the replication of such events in the future. Yang et al. (2008) argue that different technologies emit different amounts of greenhouse gases per unit of electricity generated. Therefore, investors in energy (electricity) judge that any risks associated with climate policies (such as carbon policy uncertainties) should be taken explicitly into consideration in the process investment decision. These uncertainties are mostly related to imposing (and when) carbon constraints as well as to heavy regulation, emissions controls and allocation of emission permits. Similar studies within the same framework include those by Laurikka (2006) who quantifies the value of technological investments under an emissions trading scheme and highlights that the European emission trading scheme generates substantial uncertainties for potential investors in energy and electricity markets, Lin et al. (2007) who document that the combined presence of ecological and economic uncertainties, then any climate related policy should be adopted only if the negative effects associated with emission go beyond a certain threshold level, Siddiqui et al. (2007) who reach the same conclusion in relevance to investors in renewable energy development, and Kuper and Soest (2006) who explore the influence of uncertainties in oil markets on energy use.

The remaining of the paper is organized as follows. Section 2 describes the data set used in the empirical analysis, while Section 3 provides the description of the methodologies used. Section 4 reports the empirical results, and finally, Section 5 concludes the paper.

2. Data

The data set consists of weekly wholesale electricity prices covering the period from June 8th, 2008 to March 30th, 2014. Data for Eastern Australian regions (New South Wales, Victoria, Queensland, South Australia and Tasmania) are sourced from the Australian Energy Regulator (AER, www.aer.gov.au), while data for Western Australia's SWIS market are sourced from the Independent Market Operator of Western Australia (IMOWA, www.imowa.com.au). Table 1 displays summary statistics of prices in the considered markets.

We can see that price averages are not too different across all regions, with probably an exception of prices in the State of South Australia. However, in NEM States there is a higher volatility, as expected given the energy-only nature of those markets. However, it is relevant to assess convergence of electricity prices, as argued in Section 2. An interesting result will be the formal identification of clustering group(s) of convergent supply characteristics across the regions under study.

3. Methodology

In this section, the hypothesis of long-term price convergence is examined by employing a new panel stationarity test developed by Hadri and Rao (2008, HR hereafter). This method maintains several advantages among the existing models of panel stationarity test with breaks.

Table 1
Summary statistics: average daily prices, NEM regions and Western Energy Market (Western Australia).

	NSW	QLD	SA	TAS*	VIC	WA
Mean	45.14	43.77	57.29	41.05	42.85	51.91
Std. Dev.	46.59	35.22	84.23	31.29	45.37	29.40
Max	627	400	693	405	619	231.64
Min	20	14	6	0	15	14.38

Average daily prices ($/MWh).
All data ranges from 01/01/1999 to 31/07/2014 except Tasmania (from 16/05/2006) and WA (from 21/09/2006). For SWIS data are calculated as daily averages of half-hourly Short-Term Energy Market Prices. WA includes the SWIS wholesale prices only.

In particular, it incorporates cross-sectional dependence across Australian states/territories, and this specification is important in convergence studies. Apart from the realistic consideration, the new method also corrects a number of econometrics issues, such as serial correlation in errors and unobserved heterogeneity in the trend function regarding the form and date of potential structural breaks.

3.1. Panel stationarity tests with structural breaks and cross-sectional correlation

The empirical analysis makes use of weekly electricity prices for six Australian States to construct the relative price series towards the average electricity prices across all six Australian States. Thus, the series of interest for state i, at time t is $y_{i,t}$, defined as follows:

$$y_{i,t} = ln\left(\frac{g_{i,t}}{\overline{g}_t}\right) \qquad t = 1\ldots..T \tag{1}$$

where $y_{i,t}$ is the relative price, $g_{i,t}$ is the electricity price for state i, and $\overline{g}_t$ is the average price for all six Australian States. Under the null hypothesis of stationarity, the model yields:

$$y_{i,t} = r_{i,t} + Z_{i,t}\beta + \varepsilon_{i,t} \tag{2}$$

$$r_{i,t} = r_{i,t-1} + \mu_{i,t} \tag{3}$$

where $Z_{i,t}$ is a deterministic component, $\varepsilon_{i,t}$ are stationary errors, while $\mu_{i,t}$ are independent identically distributed errors. $r_{i,t}$ is a random walk process with initial values $r_{i0} = 0\ \forall\ i$. $Z_{i,t}$ is the key variable that controls the dynamics of the above data generating process (DGP). When we set $Z_{i,t} = [1]$, it turns out to be a simple level stationary process without trend and any breaks. Following Hadri and Rao (2008) and the notation of Ranjbar et al. (2014), five models are under consideration, depending on the form the vector $Z_{i,t}$ takes:

$$\text{Model } 0: Z_{i,t} = [1, t]' \tag{4}$$

$$\text{Model } 1: Z_{i,t} = \left[1, D_{i,t}\right]' \tag{5}$$

$$\text{Model } 2: Z_{i,t} = \left[1, t,\ D_{i,t}\right]' \tag{6}$$

$$\text{Model } 3: Z_{i,t} = \left[1, t,\ DT_{i,t}\right]' \tag{7}$$

$$\text{Model } 4: Z_{i,t} = \left[1, t,\ D_{i,t}, DT_{i,t}\right]' \tag{8}$$

The dummy variables $D_{i,t}$ and $DT_{i,t}$ are, respectively, defined as:

$$D_{i,t} = \begin{cases} 1, & \text{if } t > T_{B,i}, \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$DT_{i,t} = \begin{cases} t - T_{B,i}, & \text{if } t > T_{B,i}, \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where $T_{B,i}$ is the break date in intercept and/or time trend function of relative price for state i. Model 0 is a trend-stationary process without breaks. Model 1 specifies a break in the level and no trend. Model 2 to model 4 are trend-stationary process. Model 2 allows for a break in the level only, while model 3 allows a break in the slope. Model 4 admits a break in both the level and the slope.

Based on the estimation strategy of Hadri and Rao (2008), models 0 to 3 can be estimated by a 3-steps procedure:

1) Estimation of break points: The appropriate break points are selected by minimizing the sum of squared residuals (SSR) of its form:

$$\left(\hat{T}_{B,i}\right) = \underset{\hat{T}_{B,i}}{\arg\min}\, SSR(T_{B,i}) \tag{11}$$

2) Selection of the appropriate model: The appropriate model is selected by minimizing the Schwarz Bayesian Information Criterion (BIC):

$$BIC_{ik} = \ln\left(\frac{SSR_{ik}}{T}\right) + q_{i,k}\frac{lnT}{T} \tag{12}$$

with SSR_{ik} being the sum of squared residuals of the i'th State and the k'th model, $q_{i,k}$ is the number of regressors, and T is the sample size.

3) Computation of test statistics with an unknown break: The univariate test statistic is calculated as follows:

$$LM(\lambda_i, k, T) = \hat{\omega}_i T^{-2}\sum_{t=1}^{T}\hat{S}_{i,t}^2 \tag{13}$$

where $\hat{S}_{i,t}^2$ is the partial sum of the estimated ordinary least squares, obtained from Eq. (2). The break is detected at the location λ_i, which is the fraction relative to the entire sample period T. Finally, the heteroskedasticity and autocorrelation consistent estimates of the long-run variance of $\varepsilon_{i,t}$ are represented by $\hat{\omega}_i$. The finite sample critical values for the individual univariate test statistic are calculated through Monte Carlo simulations, and the Monte Carlo simulations experiments are based on 20,000 replications.

3.2. Non-linear panel unit root test

It was well known that asset price contains non-linear components, and our relative price series are with no exception. As expected the data generating process (DGP) is non-linear and there is support for non-linearity in the series under the alternative hypothesis proposed by Teräsvirta (1994). Taylor et al. (2001) indicates that the power of the conventional ADF test is poor if the series under investigation follow a non-linear threshold process. Along with the same research strand, Lau et al. (2012) also found that linear panel unit root test may achieve lower power performance as compared to its alternative of non-linear panel unit test when the data generating process does not contain significant non-linear components. And the authors subsequently developed a series-specific non-linear panel unit root test.

The most widely used non-linear model in empirical works is the non-linear exponential smooth transition autoregressive (hereafter ESTAR) as proposed by Granger and Terasvirta (1993). ESTAR model was chosen by many researchers not only because of its econometrics advances that it can closely mimic real data generating process, but also because of its theoretical advantage in economic reasoning; ESTAR allows for the presence of market friction, for example transportation cost, delivery time delay, and imperfect market structure that rise implements to commodity price arbitrage, electricity price in our case (Dumas, 1992; Sercu et al., 1995). In face of such significant non-linear component the impact of transitory shock will be more persistent.

Linear panel unit tests are popular among researchers for empirical studies and to exploit its advantage of providing higher power by including cross-section information.[1] However, all these panel unit roots form the null hypothesis that all the individual series are stationary against the alternative of at least a single unit root in the panel. This restriction makes it impossible for researcher to identify individual series for a unit root while taking contemporaneous cross-sectional correlations into account (Lau, 2009). Subsequently, researchers develop several series-specific unit-root test that is able to distinguish I(1) and I(0) series in the panel while incorporating contemporaneous cross-section information into the model (see for example, Breuer et al., 2002; Lau, 2009).

Some non-linear panel unit root test that incorporates contemporaneous correlation among cross-section series was introduced (see for example, Kapetanios et al., 2003; Cerrato et al., 2013). Their non-linear tests are based on an ESTAR (1) model and it was demonstrated that the power of their test is higher than that of the ADF test. However their tests are still not able to identify individual series for a unit root. In face of practical needs researchers start to develop non-linear unit root tests that are series-specific (see Lau et al., 2012; Wu and Lee, 2009). This "series-specific non-linear panel unit-root test" model, NNSS hereafter, has several advantages over the conventional panel unit root tests. The existing NNSS detects unit root for each panel member while incorporating non-linearity and contemporaneous correlation. Cross-sectional dependence is a very distinctive feature for Australian electricity price, and they are subjected to some common factors. (i.e. international oil price fluctuation, international political risk, and national energy policies). It is worth mentioning here that Apergis and Salim (in press) have also employed non-linear unit root testing for exploring convergence of electricity prices across the Australian states.

Following Wu and Lee (2009), we apply Seemingly Unrelated Regression (SUR) technique with N states and T time periods; the following simultaneous equations form the non-linear SUR model as follows:

$$\begin{aligned}
\Delta y_{1,t} &= \delta_1 y_{1,\,t-1}^3 + \sum_{j=1}^{\rho_1}\eta_{1,j}\Delta y_{1,t-j} + \varepsilon_{1,t}\\
\Delta y_{2,t} &= \delta_2 y_{2,\,t-1}^3 + \sum_{j=1}^{\rho_2}\eta_{2,j}\Delta y_{2,t-j} + \varepsilon_{2,t}\\
\Delta y_{N-1,t} &= \delta_{N-1} y_{N-1,\,t-1}^3 + \sum_{j=1}^{\rho_{N-1}}\eta_{N-1,j}\Delta y_{N-1,t-j} + \varepsilon_{N-1,t}\\
&\vdots\\
\Delta y_{N,t} &= \delta_N y_{N,\,t-1}^3 + \sum_{j=1}^{\rho_N}\eta_{N,j}\Delta y_{N,t-j} + \varepsilon_{N,t}
\end{aligned} \tag{14}$$

The null and alternative hypotheses to be tested are as follows:

$$H_0^k:\ \delta_k = 0;\quad H_1^k\ :\ \delta_k < 0\quad \forall k = 1, 2, \ldots, N.$$

where H_0^k denotes the null hypothesis for the k'th state. The critical values are generated by bootstrapping method because of non-standard distribution of test statistics.[2] This research modifies the Gauss code provided by Wu and Lee (2009),[3] and we report t-statistic ($SURt_{NL}^k$ statistic) and the critical value at 5% and 10% for each series, $y_{k,t}$ in the empirical results section. If the t-statistics is less than the 5% $SURt_{NL}^k$ critical value, the null hypothesis of having a unit root is rejected.

4. Empirical results

4.1. Linear unit root test with a sharp break

In order to compare the results through the HR stationarity test, we first apply four univariate unit root tests, including the Augmented Dickey–Fuller test (Dickey and Fuller, 1979), the PP test (Phillips and Perron, 1988), the KPSS test (Kwiatkowski et al., 1992) and the structural breaks model test by Zivot and Andrews (1992), to the relative electricity prices in each Australian State.

The results for the model with a trend function indicate that the majority of States exhibit trend stationarity with respect to the relative electricity prices (panel A of Table 2). More specifically, the results from both the ADF and PP tests highlight that the relative electricity prices across all Australian States are stationary. However, the null hypothesis of stationary is rejected for the cases of New South Wales and

[1] For linear version see for example, Levin et al. (2002), Im et al. (2003), Smith et al. (2004), Choi and Chue (2007), Pesaran (2007) and Hadri (2000).

[2] A bootstrap-after-bootstrap method (Berkowitz and Kilian, 2000) is applied to obtain the effective empirical sizes of bootstrap tests given the nominal size of 5%.

[3] We thank Jyh-Lin Wu for making the Gauss code available online. A sample code can be downloaded from Jyh-Lin Wu's homepage: http://econ.nsysu.edu.tw/files/11-1124-1326-1.php.

Table 2
Linear univariate and panel unit root/stationarity test results.

Panel A: univariate unit root test/stationarity test. Zivot and Andrews (1992)					
Australian Sates/Territories	ADF	PP	KPSS	Model A	Model B
Queensland	−15.647***	−15.661***	0.045	−7.464***	−7.714***
New South Wales	−14.109***	−14.67***	0.218***	−15.317***	−15.277***
Victoria	−13.622***	−14.067***	0.054	−7.747***	−7.824***
South Australia	−12.786***	−12.779***	0.104	−13.071***	−13.345***
Tasmania	−10.866***	−11.348***	0.066	−11.175***	−11.829***
Western Australia	−8.893***	−9.41***	0.154**	−5.910***	−6.421***
Panel B: linear panel unit root tests			Test statistic	Probability	
Im et al. (2003)			−33.214***	0	
Levin et al. (2002)			−45.779***	0	
Hadri (2000)	Homogenous variance		3.176***	0.007	
	Heterogeneous variance		2.362***	0.0091	
Pesaran's CIPS (2007)			−4.138***	0	
Moon and Perron (2004)			−23.355***	0	

Notes: For PP and KPSS tests, the selected truncations for the Bartlett Kernel are based on the suggestion by Newey and West (1994).
The optimum lag order is selected based on the BIC criterion. Zivot and Andrews (1992) tests three models. Model A denotes break in the intercept of linear trend function and model B tests for breaks in the intercept and slope of linear trend function. We thank Christophe Hurlin for providing the Matlab codes for the test of Moon and Perron (2004).
The code is available at http://www.runmycode.org/companion/view/76.
* Denotes the significance level at 10%.
** Denotes the significance level at 5%.
*** Denotes the significance level at 1%.

Western Australia by the KPSS test at the 5% significance level. The null hypothesis of a unit root is also rejected across all States by the modeling approach of Zivot and Andrews (1992). Next, Panel B in Table 2 illustrates linear panel unit root/stationarity tests that reject the null of a unit root (Im et al., 2003; Levin et al., 2002). By contrast, the Hadri (2000) Lagrange multiplier (LM) test rejects the null hypothesis that all members in the panel are (trend) stationary, implying that some of the states are not converging to their national average electricity price. Furthermore, the empirical analysis makes use of a second-generation unit root test to provide robust support to the above results. In particular, the analysis makes use of the Pesaran (2007) test in where the augmented Dickey–Fuller (ADF) regressions are augmented with the cross-sectional average of the lagged levels and the first-differences of the individual time series. This way, the common factor is proxied by the cross-section mean of the variable under investigation, say $y_{i,}$, and its lagged values. The Pesaran test uses the cross-sectional ADF statistics (CADF). The test advances a modified IPS statistics based on the average of the individual CADF, which is denoted as a cross-sectional augmented IPS (CIPS). The results, also reported in Panel B in Table 2, highlight the rejection of the null hypothesis of a unit roots, thus, supporting the above findings. Another second generation panel unit test of Moon and Perron (2004) further supports the existing findings.[4]

The results of Hadri and Rao (2008) stationarity test on relative electricity prices are reported in Table 3. This test allows various types of breaks in a series to be different for the members in the panel. The univariate test statistic ($LM(\lambda_i, k, T)$) documents the results in the sixth column; these findings highlight that Model 0 (i.e., the trend-stationary process without breaks) is chosen in the case of Queensland, Model 1 (i.e., the model with the shift in the level and no trend) is chosen in the case of New South Wales, and Model 4 (i.e., the model with the trend function with a shift in the intercept and slope) is chosen in the cases of Tasmania and West Australia. The finite sample critical values for test statistics are calculated through Monte Carlo simulation, running 20,000 replications. The results at the 95% and 99% significant levels are presented in the third and the fourth columns, respectively, using the BIC criterion. The null hypothesis of stationarity is rejected in the case of Tasmania at the 5% significance level, while at the 1% significance level the null hypothesis is rejected in the case of Western Australia, suggesting that both Tasmania and Western Australia are not converging to their national average electricity prices in the long run. Finally, the estimated break dates of the selected models are presented in the last column of Table 3. These new results display that Australian wholesale electricity prices in four out of six Australian States (i.e., New South Wales, Victoria, Tasmania and Western Australia) are associated with a break type of behavior (2009 and 2010) based on the failure of the Australian government to adopt an election commitment about the introduction of a greenhouse gas emissions trading scheme by the year 2010. In the case of South Australia, the break occur in the spring of 2013, which coincides with the Senate's decision in March 2013 that electricity supply has to heavily come from renewable sources, mainly, wind and solar.

Table 3
Hadri and Rao (2008) stationarity test result.

Individual test statistics for model allows for serial correlation						
Australian Sates/Territories	Test statistic	95%	99%	Optimum lag(s) based on BIC	Selected model	Break dates
Queensland	0.045	0.149	0.218	1	0	No
New South Wales	0.189	0.322	0.502	1	1	21-Jun-09
Victoria	0.14	0.254	0.402	1	1	17-Jan-10
South Australia	0.072	0.106	0.155	1	4	14-Apr-13
Tasmania	0.131**	0.101	0.145	1	4	21-Jun-09
Western Australia	0.125***	0.081	0.117	1	4	07-Feb-10

Notes: Models 0, 1, and 4 examine the trend-stationary process without breaks process, shift in the level and no trend process, trend function with a shift in the intercept and slope process, respectively. We use the Schwarz Bayesian Information Criterion (BIC) to find the appropriate break-type model for the series. The optimum lag(s) are used in the Sul et al. (2005) procedure to estimate the consistent long-run variance. We computed the empirical distribution of panel test statistics using Bootstrap techniques that can be found in Maddala and Wu (1999) and using 20,000 replications.
** Denotes significance at 5%.
*** Denotes significance at 1%.

4.2. Non-linear series-specific non-linear panel unit root test

To provide robustness to the findings in the previous section we apply the series-specific non-linear panel unit-root test recommended

[4] We thank Christophe Hurlin for providing the Matlab codes for the test of Moon and Perron (2004).
The code is available at http://www.runmycode.org/companion/view/76. The second generation panel unit root test of Pesaran (2007) and Moon and Perron (2004) have been extensively discussed in Hurlin and Mignon (2004).

by Wu and Lee (2009) to investigate the unit root hypothesis of wholesale electricity prices in Australia. The new empirical results are reported in Table 4. The results provide strong empirical evidence for nonlinear stationarity in the cases of Tasmania and Western Australia, given that they reject the unit root hypothesis even when both nonlinearity and contemporaneous cross-section information are incorporated into the modeling process.

4.3. Seasonality across electricity markets

In order to provide robustness to the results reported in Table 4 we consider seasonality across electricity prices attributed to the presence of various weather patterns across the regional electricity markets in Australia.[5] The seasonal adjusted price data are obtained by using both the classical decomposition multiplicative model and the unobserved components model (UCM). The first method make use of moving average technique and hence the seasonal indexes to de-seasonalized the raw data, while the second method uses the state space estimation technique to decompose the raw data.[6] Apart from using the moving average method we also obtain the de-seasonalized electricity prices using an unobserved components model (UCM). Our results indicate that we have reached similar results regarding to the break dates for various Australian states.[7] The nonlinear panel unit root test still indicates that there are 2 Australian States diverging from the national average electricity price when using de-seasonalized data from UCM. However the diverting states increase to 3 Australian states. As a result this robustness check with seasonality taken into account further supports our view that the Australian electricity market is described as a less stable electricity market.

Becker et al. (2006) proposed a unit root with a nonlinear Fourier function, the main advantage of this test is that it allows for an unknown number of structural breaks with unknown functional forms. Using a Fourier function of the combination of sine and cosine functions the test can approximate unknown functional forms of nonlinearity, and hence incorporates gradual and smooth breaks, as some major breaks did not display their full impacts immediately.[8] Suppose a stochastic variable y_t has the following data generating process:

$$y_t = X_t'\beta + Z_t'\gamma + r_t + \epsilon_t \tag{15}$$

$$r_t = r_{t-1} + u_t$$

where ϵ_t are stationary errors and u_t are $iid(0, \sigma_u^2)$. We set $X_t = [1]$ for a level stationary process for y_t and $X_t = [1,t]'$ for a trend stationary process. Z_t is a time-varying deterministic component. The unknown number of smooth breaks of unknown or other type of unattended nonlinearity form Z_t is approximated by a Fourier series expansion as:

$$Z_t = \sigma_0 + \sum_{k=1}^{G} \delta_1^k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{G} \delta_2^k \cos\left(\frac{2\pi kt}{T}\right) \tag{16}$$

where t is a time trend, k is the number of frequencies of the Fourier function, T is the sample size, and $\pi = 3.1416$. For stationarity the process described by (15) is stationary under the null hypothesis $\sigma_u^2 = 0$. If the null hypothesis of no structural break, i.e., $\sigma_k \neq 0$ for $k = 1,2\ldots,G$ is rejected then then y_t contains at least one break and Eq. (15) should be modeled as a non-linear function. Becker et al. (2006) suggest using the following test statistic to test the null hypothesis of stationarity (i.e. $\sigma_u^2 = 0$):

$$\tau_\mu(k) = \frac{1}{T^2} \frac{\sum_{t=1}^{T} \tilde{S}_t(k)^2}{\tilde{\sigma}^2}. \tag{17}$$

Where $\tilde{S}_t(k) = \sum_{j=1}^{t} \tilde{e}_j$ and $\tilde{e}_j$ are the OLS residuals from the following equation for $\tau_\mu(k)$:

$$y_t = \alpha + \delta_1 \sin\left(\frac{2\pi kt}{T}\right) + \delta_2 \cos\left(\frac{2\pi kt}{T}\right) + e_t. \tag{18}$$

Table 5 indicates that the appropriate critical values are 0.171, 0.4076, 0.4238, and 0.4488 for the frequencies k = 1, 2, 4, and 3, respectively. We compare these values to the calculated sample values reported in Table 5 and the results indicate that the null hypothesis of stationary can be rejected for half of Australian state, providing supportive evidence that the Australian electricity market is described as a less stable electricity market.

5. Conclusions

Existing panel data unit root testing on energy and/or electricity prices provides limited insight into which panel members are characterized by stationary behaviors. Cross-sectional dependencies among panel members can lead to size distortion. By contrast, neglected structural breaks can also affect the outcome of the testing procedure. This empirical study explored whether electricity prices across the six Australian States displayed instability associated with the presence of structural breaks in relevance to policy events on Australian carbon policies. By making use of weekly Australian wholesale electricity prices spanning the period June 8th, 2008 to March 30th, 2014 along with recent linear and non-linear unit root testing, the empirical findings

Table 4
Wu and Lee (2009) Non-linear series-specific panel unit root test.

Estimation results (08-June-2008 to 30-March-2014)				
State	SURtKNL	CV 5%	CV 10%	Conclusion
Queensland	−3.233**	−3.158	−2.514	Stationary
New South Wales	−3.257**	−3.02	−2.745	Stationary
Victoria	−3.625**	−2.795	−2.53	Stationary
South Australia	−2.834*	−2.84	−2.649	Stationary
Tasmania	−0.306	−3.238	−2.786	Non-stationary
Western Australia	−0.683	−3.217	−2.716	Non-stationary

Notes: CV denotes the critical value of the corresponding statistics.
** Indicates significance at the 5% level.
* Indicates significance at the 10% level.

Table 5
Becker et al. (2006) Non-linear stationarity test.

Estimation results (08-June-2008 to 30-March-2014)					
State	k	$\tau_\mu(k)$	CV 5%	CV 10%	Conclusion
Queensland	1	0.462	0.171	0.1297	Non-stationary
New South Wales	2	0.251*	0.4076	0.3038	Stationary
Victoria	5	1.012	0.4488	0.3402	Non-stationary
South Australia	2	0.523	0.4076	0.3038	Non-stationary
Tasmania	4	0.303*	0.4238	0.3203	Stationary
Western Australia	2	0.121*	0.4076	0.3038	Stationary

Note: CV denotes the critical value of the corresponding statistics.
* Denotes that the convergence hypothesis is supported at the 5% significance level.

[5] The presence of seasonality maybe insignificant for relative price, even the seasonality of electricity price does occur at state i and its national average, but for relative price they may cancel each other.

[6] Some scholars are in favor of UCM because this model is far more effective than the simple counterpart of moving average model, especially when "messy" features are evident in the raw data, such as outliers, structural breaks, and nonlinear dynamics (Harvey et al., 1998). This modeling technique provides a flexible approach to smoothing and decomposition of a time series and Harvey and Trimbur (2003) discuss the properties of this model in more details.

[7] Results are not reported here, but are available upon request but it is interesting to highlight the finding that the common break date of June, 2009 has been shared by 4 Australian states, namely New South Wales, Victoria, Queensland, and Western Australia.

[8] Another reason we adopt this test as an alternative robustness check for convergence test is that this functional form has been extensively used in the literature seasonality model (see Busetti and Harvey, 2003).

provided supportive evidence that the Australian electricity market is described as a less stable electricity market, implying a high degree of market power exercised by generators across regional markets.

These empirical findings are expected to have substantial consequences for the effectiveness of carbon dioxide mitigating policies, especially, when there is uncertainty as to whether the planned environmental policy is put in place for the lifespan of undertaken investments. Moreover, the results could be also of high importance in relevance for the effectiveness of carbon dioxide mitigating schemes, especially, when investors are risk averse and cannot fully hedge risks in financial markets as well as when there is uncertainty as to whether the planned policy will be put in place for the lifespan of the investment. As a result, investors are discouraged to undertake further investments that will advance the future of electricity markets and maximize the sustainability outcome.

If this is the case, then to achieve adequate investments in the electricity sector, while hitting emission reduction goals and facilitating increased investments in energy efficient technologies and activities, an effective climate policy needs to include substantial public investments in areas where infrastructure is publicly owned (e.g., transit, electricity grids), where it is difficult to regulate (e.g., agricultural emissions), or when the climate policies may not initially be strong enough to produce needed results (e.g., renewable electricity), while revenues from carbon policies can provide an important source of funds for such public investments, particularly in a time of fiscal restraints. Climate policies are not supposed to create any negative impacts on private investments by increasing the cost of capital for private investors. After all, the elimination of such uncertainties and the promotion of investments in overall energy/electricity markets go beyond the direct environmental benefits.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.10.014.

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