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Integration of regional electricity markets in Australia: A price convergence assessment☆

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ABSTRACT

From an electricity market design perspective, it is relevant and practical to know which market structures allow for price convergence, and how long this takes to achieve. This study employs the Phillips and Sul (2007, 2009) methodology to test for the convergence of wholesale electricity prices across the Australian States. We identify a long-run, common price growth pattern that applies to a cluster formed by three Eastern States that share common market characteristics and limited physical interconnection. We also find another cluster with less competitive market structures that, although not interconnected, strongly converge towards their own trend. These findings confirm theoretical expectations while quantifying the rate of convergence. Finally, we also investigate the role that the carbon tax regime has played in the convergence process, with new empirical showing that the previous results are not affected, with the notable exception being the case of South Australia.

1. Introduction

The Australian electricity market experienced significant deregulation in the 1990s, and policy questions have arisen since. The main domestic network is the National Electricity Market (NEM), which was established in 1998 and links regional markets in Queensland, New South Wales, Victoria and, more recently, Tasmania and South Australia. Both producers and retailers trade through a spot market operated by the Australian Energy Market Operator. Despite the policy efforts to integrate these markets, their price convergence has yet to be formally examined, which is the primary objective of this study.

To the best of our knowledge, the study by Nepal and Foster (2013) is the only empirical study testing the long-run convergence of electricity prices across Australian markets. The authors argue that the lack of pair-wise cointegration, i.e. long-term fixed relationships, may be indicative of the convergence or divergence of electricity prices across markets. The authors propose an examination of time-varying estimates obtained through a Kalman-filter procedure applied to paired states. The use of cointegration methodologies for assessing electricity market integration is not uncommon. For instance, Dempster et al. (2008) use cointegration and Granger causality tests to examine the 'extent of integration' of re-structured electricity markets supplying to California. However, this paper will argue that more recent econometric developments are better suited for this particular test.

Despite the lack of any relevant literature on long-run trends of spot electricity prices in Australia, a few studies have analyzed short-term phenomena, such as spikes and volatility, based on daily or intra-daily data. Using copula analysis, Ignatieva and Trück (2016) find evidence of spot price dependence across various regional markets in Australia, which is especially strong for extreme price co-movements (spikes). These results are consistent with Aderounmu and Wolff (2014a, 2014b), who also find evidence of dependence of price spikes in Australia. Some other studies examining high-frequency data for Australia have focused on the emergence of volatility clusters. For instance, Higgs (2009) finds evidence of inter-relationships between spot price levels and volatility, while Worthington et al. (2005) have identified transmission channels for price and price volatility with a multivariate GARCH model.

This study will employ weekly data to assess the convergence of long-run trends, but it will not focus on intra-week issues such as those described above. We argue that a disadvantage of Nepal and Foster's (2013) long-run integration test is the use of half-hourly prices, which leads to short-run dynamics that are very difficult to model (or

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filter) due to the presence of intra-day and weekly seasonality and the spikes that characterize the Australian markets (Aderounmu and Wolff, 2014a; Ignatieva and Trück, 2016).

The main novelty of this study is the use of Phillips and Sul's (2007, 2009) methodological approach, which has three clear advantages over the cointegration analysis used in Nepal and Foster (2013): First, it allows for rigorous econometric testing of 'convergence clubs' and estimation of convergence paths relative to some identified common trends. Second, the latter is implemented on a single data set comprising all States. Third, our methodology does not need to rely on strong assumptions on trend or stochastic stationarity in the data. Phillips and Sul's methodology is relatively new and has been applied in the context of the integration of energy markets (Li et al., 2014; Ma and Oxley, 2012).

We hypothesize about two types of price convergence, which we refer to as short and long run. In the short-run, price convergence is driven by arbitrage, i.e. the process of making profits at no risk by buying and selling a good across different markets. As it is well known, in efficient markets, short-run profit maximization eliminates arbitrage possibilities. In the long-run, price convergence is led by the exploitation of economic profits under free entry and exit conditions. Competitive markets are dynamically efficient. This distinction is particularly relevant for the case of electricity markets. Electricity is a perfectly homogeneous, non-storable[2] good, delivered through a physically connected network. The physics of electricity implies that in the short run, the only possibility to exert arbitrage exists in buying and selling in markets that are physically interconnected. The amount of transmission capacity determines the extent of short-run price convergence: When it is large enough, it eliminates the likelihood of price differentials between net electricity demanded and supplied. When it is limited, there can be a price differential between the net-exporting zones or countries and the net importing ones, depending on the respective energy demand and supply. Price differentials give rise to congestion rents (i.e., measured by the difference in prices × the energy transmitted through the congested transmission line) and a possible inefficiency (unless the transmission capacity has been planned optimally, i.e. up to the point in which the marginal cost of expanding it equals the price differential).

In the long run, price convergence depends on the structure and evolution of power markets. Over time, zones or States with high prices would attract power producers, which lowers their net demand (and this potentially reduces net supply in power exporting zones if power plants, which are taken off-line, are not replaced by a sufficient flow of new investments). The overall effect may lead to price convergence, even with limited interconnection capacity. However, several factors can be an obstacle to this convergence process, such as differences in power supply structures, the degree of competitiveness, load levels and profiles, the costs and availability of primary energy sources, financial costs and risk attitudes, and market design and market intervention. Moreover, technological changes might impact long-run convergence; for instance, by reducing the opportunity cost and therefore fostering adoption of renewable-based technologies (such as PV) that rely on primary energy sources unevenly distributed across Australia. The more electricity markets are homogeneous with regard to these elements, the more we can expect price convergence to occur, even with limited or absent interconnection capacity, and vice versa. Long-run price convergence is affected, inter alia, by energy policies targeted at reducing externalities, and in particular, power production from carbon-intensive fuels.

[2] We refer here to traditional electricity networks, where electricity is delivered through transmission networks in which demand and supply are balanced in real time (dispatching). For these networks, storage is either technically unfeasible or economically unsustainable. Of course, storage in batteries exists for limited charges or unconnected applications.

In Australia, a carbon tax was implemented from July 2012 to July 2014 to foster this target. It affected power production from fossil fuels, regardless of the specific physical location of the power plant. The impact of the introduction of a carbon tax on price convergence is twofold. On the one hand, by altering the marginal cost of electricity in a homogeneous way across markets, the carbon tax could foster price convergence. By contrast, by affecting the electricity costs of those power supply systems that are more carbon intensive, it can enhance the different costs of power supply and, therefore, reduce price convergence. In the case of Australia, we have a sufficient number of observations to analyze both short- and long-term convergence and investigate whether the carbon tax has influenced the convergence process.

In addition to NEM member States, our study covers Western Australia (WA). WA's main wholesale market is the South West Interconnected System (SWIS), which covers the area of Perth and surroundings and is operated by WA's Independent Market Operator (IMO). In WA, there is no existing interconnection with any other power system outside the state. Including WA in the sample provides interesting insights into integration issues within Australian electricity markets. The lack of interconnection capacity between the SWIS and the rest of Australia does not allow for arbitrage of electricity prices in the short run. In the long run, nevertheless, convergence cannot be ruled out. As long as cost drivers (i.e., primary energy costs, financial costs, technological costs and availability) are homogeneous across Australia, there is enough justification for long-run price convergence. It is, therefore, of interest to test whether there exists any convergence between electricity prices in WA and other regions in the long run, despite the absence of physical interconnection.

The remainder of this study is organized as follows. Section 2 reviews the role of the carbon tax in price convergence and discusses the main differences between NEM and SWIS. Section 3 discusses the methodology used, and Section 4 describes the data set used in this study. Empirical findings are presented in Section 5 and are discussed in Section 6. The impact of the carbon tax regime on price convergence is analyzed in Section 7. The study concludes in Section 8.

2. Long-run electricity price convergence in Australia: the role of carbon tax and the WA capacity remuneration mechanism (CRM)

2.1. Long-run price convergence and the role of carbon tax

Between July 1, 2012 and July 17, 2014, the Australian authorities had a carbon pricing scheme in place, which was a central piece of the 2011 Clean Energy Act passed under Julia Gillard's Labour Party administration. It envisaged a plan to transition from a three-year carbon-tax policy to an emissions trading mechanism, although the law was abolished in 2014 under the Tony Abbott administration, prior the trading mechanism being implemented. Carbon emissions were taxed at $23/ton during the 2012–13 financial year (ending in June 30) and $24.15/ton during the 2013–2014 financial year. Emitters responsible for over 60% of Australia's emissions were covered by a liability to acquit permits for emissions arising from the combustion of fossil fuels and other sources. 348 of Australia's highest emitting entities, including power stations, mines and emissions-intensive manufacturers, benefited from this concession. The effects of the carbon tax policy on the electricity sector seem to be substantially significant as emissions from electricity generations are the largest contributor to Australia's overall emissions. Retail and residential electricity prices rose substantially across Australia over the two years following the introduction of the carbon price, while electricity demand stagnated. The carbon tax affected electricity prices unevenly across Australia because electricity is produced from various technologies of varying carbon intensities. It has been estimated that the isolated cost of carbon reflected on spot electricity prices has been consistently in the range of 15–18 Australian dollars per MWh in Queensland, NSW, Victoria and South

Australia, while the impact on Tasmania is about half of that figure (AER, 2013, p. 9).

A tax on carbon affects the economics of generation, increasing the cost of producing electricity for any form of generation that intensely produces carbon dioxide emissions, namely, brown coal and inefficient black coal power plants (Daley and Edis, 2011). Since the introduction of the carbon price, there have been significant changes in the composition of electricity supplied. Electricity generated from renewables and gas increased, whilst the share of electricity generated from black and brown coal reached a record low; according to the Australian Energy Regulator, in the period in which the carbon tax was in place, almost 2000 M-watts of coal fired plants were shut down and coal fired generation declined by 11% (AER, 2014, p.6). In addition, considering that the price elasticity of demand for electricity is especially high in Australia (Hill and Cao, 2013), the carbon tax had a strong effect on household electricity savings. Households reacted by changing practices and adopting more energy-efficient equipment. The amount of solar power produced by households and businesses increased, driven largely by subsidies for the installation of solar panels and feed-in tariff schemes. However, such changes did not occur symmetrically across the Australian States, given that domestic governments adopted different subsidies schemes and feed-in tariff policies (Saddler, 2013). It is then of interest to examine whether the introduction of a carbon tax in Australia increased market homogeneity (due to its across-markets features and the aforementioned impacts on end consumers) and accelerated convergence rates, or whether it enlarged the differences in power systems structures and therefore impeded or reduced long-run price convergence.

2.2. CRMs and long-term price convergence

There exists an important distinction in electricity market design between so-called 'energy-only' markets and markets with CRMs. The former are markets where energy is the only good traded, while in the latter, there is an explicit remuneration for power on top of energy prices. NEM is an energy-only market, and SWIS is a market with a CRM (called a reserve capacity mechanism; the capacity remuneration is termed capacity credit). This is not the only relevant market design difference between NEM and SWIS. In particular, NEM is a pool (where all energy is traded), while SWIS is a power exchange in which roughly 20% of the load is traded. The difference in capacity remuneration could be relevant for long-run price convergence since it refers to the way investments in power production are remunerated. In energy-only markets, investments are remunerated implicitly, depending on the frequency and amount of price spikes (price that goes to the marginal social value of the non-served load, i.e. the VOLL). By contrast, in markets with CRMs, investments are remunerated explicitly. This difference is sometimes claimed to be a major obstacle to market integration (see, for instance, ACER, 2013, for the case of the European electricity market integration).

From a theoretical point of view, for competitive markets, this should not be the case. In perfectly competitive energy-only markets, the expected discounted value of the super marginal profits gained by a power plant under those occurrences (i.e., the price–cost margin when the price is set to the VOLL × the quantity of energy × the capacity factor of a given plant) equals the investment (fixed) costs of the plant (Stoft, 2002). Thus, investments are induced up to the point where power producers can cover both their fixed and marginal costs. In markets with CRMs, investments are directly remunerated by the capacity remuneration scheme itself. When the value of the capacity is competitively set—for instance, through an auction mechanism (or properly administratively set)-it equals the (yearly) discounted value of the super marginal profits that producers would gain *ex post*, had the CRM not been in place. The main difference is thus in the timing of the remuneration itself: with CRMs, capacity is remunerated *ex ante* rather than *ex post*, i.e. once energy is produced. Under (perfect) competition, both energy-only and CRM markets attract sufficient investments to serve the load. In other words, the long-run price trend towards convergence should not be affected by how the different market designs remunerate investments. This is an important point and an interesting element to be tested, motivating our inclusion of SWIS in the analysis.

3. Methodology

We employ Phillips and Sul's (2007, 2009) methodological approach for testing the convergence hypotheses. By taking into account the heterogeneity of the time series in our panel, we identify clubs (i.e., groups of States), each possibly converging towards a common club trend. Our full-panel dataset is formed by $N = 6$ time series noted as $(y_{it})_{t\,=\,1,\ldots,T\,=\,304}$, where y_{it} is the filtered value of the natural log of the electricity price in state i at time t. The time series are filtered individually (see Section 4).

Our approach has a number of clear advantages. First, it measures the relative convergence of cross-sectional averages, which contrasts the concept of absolute level convergence analyzed in Bernard and Durlauf (1996). Second, it outperforms standard panel unit root tests that could apply to the series $(y_{it}–y_{jt})_{t\,=\,1,\ldots,T}$ in our panel, as the latter may retain non-stationary characteristics even when the convergence condition holds, i.e. panel unit root tests may classify the difference between gradually converging series as non-stationary. Third, our approach may detect convergence that would not be detected in a panel cointegration test. Only when the series (y_{it}, y_{jt}) stabilize around steady-state values they would share a common trend. However, if the series are slowly approaching a long-run trend in a non-linear fashion, a standard cointegration test might reject a long-term stable relationship between the variables. Finally, a mixture of stationary and non-stationary series in the panel may bias the results if the correct specification is not identified, leading to results that are not particularly robust. In contrast to these traditional approaches, the specification of the Phillips and Sul's (2007, 2009) test does not rely on unit root or cointegration testing of the variables in the panel.

It should be noted that for some applications, the highly modified unit root test that incorporates relevant characteristics of the data could be used to test for convergence. A good example of this is Meng et al. (2013), which implements a RALS-LM unit root tests, allowing for two endogenously-determined structural break dates, and finding significant support for per capita energy use convergence across 25 OECD countries, spanning the period 1960–2010. In our study, endogenously-determined breaks are not needed. Still, there could be some potential dynamic issues associated with the introduction of the carbon task; we address this issue in Section 7.

The methodology employed in this study makes use of the following time-varying common factor representation for our set of observable series y_{it}:

$$y_{it} = \delta_{it}\mu_t \tag{1}$$

where μ_t is a single common component and δ_{it} is a time-varying idiosyncratic element which captures the deviation of state i from the common path defined by μ_t. Within this framework, all N 'groups' (either in terms of the entire sample or within a cluster) will converge at some point in the future to the steady state if $\lim_{k\to\infty} \delta_{it+k} = \delta$ for all $i = 1, 2, \ldots, N$, irrespective of whether states are near the steady state(s) or in transition. Since δ_{it} cannot be directly estimated from Eq. (1), Phillips and Sul (2007) eliminate the common component μ_t by rescaling to the cross-sectional average:

$$h_{it} = y_{it} \Big/ \left[1/N\sum_{j=1}^{N} y_{jt}\right] = \delta_{it} \Big/ \left[1/N\sum_{j=1}^{N} \delta_{it}\right] \tag{2}$$

The relative measure, h_{it}, captures the transition path with respect to the panel average. In order to define a formal econometric test of

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convergence as well as an empirical algorithm for identifying clubs, the following semi-parametric form for the time varying coefficients δ_{it} is assumed:

$$\delta_{it} = \delta_i + \sigma_{it}\ \xi_{it} \tag{3}$$

where $\sigma_{it} = \sigma_i / [L(t)\ t^{\alpha}]$, $\sigma_i > 0$, $t \geq 0$, and ξ_{it} may be weakly dependent over time, but *i.i.d.*(0,1) over *i*. The function L(*t*) is increasing in *t* and divergent when *t* tends to infinity.[3] Under this specific form for δ_{it}, the null hypothesis of convergence for all *i* takes the form:

H_0. $\delta_{it} = \delta, \alpha \geq 0$,

while the alternative hypothesis of non-convergence for some *i* is expressed as:

H_1. $\delta_{it} \neq \delta$, or $\alpha < 0$.

Essentially, the test reduces to examining the sign of α. When the null hypothesis of convergence is rejected for a particular group of individuals from the panel, this does not preclude the possibility that these individuals may converge to some other cluster in the panel. Thus, a potential issue in this test is the possible presence of multiple equilibria. In such a case, rejection of the null hypothesis that all states in the sample are under convergence does not imply absence of different convergence clubs in the panel.

To test the null hypothesis above can be tested, according to Phillips and Sul (2007, 2009) through the following regression[4]:

$$\log(H_1/H_t)\text{-}2\log L(t) = \hat{c} + b\log t + \hat{u}_t, \tag{4}$$

where:

$$H_t = (1/N)\sum_{i=1}^{N} (h_{it}-1)^2$$

is the square cross-sectional distance relative transition coefficients. Regression (4) is estimated for t = [rT], [rT} + 1, …, T, where r > 0 is set on the [0.2, 0.3] interval, following Phillips and Sul's (2007) recommendation. Noting that $b = 2\breve{\alpha}$, the null hypothesis above can be conducted as the one-sided test of $b \geq 0$ against $b < 0$. Because the OLS standard errors in regression (4) may be weakly time-dependent, Phillips and Sul (2007, 2009) recommend estimating heteroskedasticity and autocorrelation consistent standard errors for b. In this one-sided test, the null hypothesis of convergence is rejected is $t_b < -1.65$ (the limiting critical *t*-value, using the 5% significance level, is approximately −1.65).

The test could be applied to different club formations in the panel. A robust clustering algorithm for identifying clubs in a panel is proposed by Phillips and Sul (2007). We implement this algorithm following these steps: (i) we order the *N* states according to the final values of their times series; (ii) starting from the highest-order state, we add adjacent states from our ordered list. For each formation, we run regression (4). Then, we select a core group using the following cut-off point criterion: $k^* = \text{ArgMax}_k\{t_{bk}\}$ subject to $\text{Min}_k\{t_{bk}\} > -1{,}65$, for k = 2, 3, …, N; (iii) we sieve the data adding one of the remaining members at a time to the core group, and we re-estimate Eq. (4) for each formation. We use a sign criterion to decide whether a member should join the core group; (iv) for the remaining states, we repeat the steps (ii)–(iii) iteratively. We stop when we can no longer form clubs. Each club will be associated with its own convergence path. If the last group arising from the algorithm does not have a convergence pattern, we conclude that their members form a divergent club. Some clubs may be weakly divergent, i.e. associated with $-1.65 < t_b < 0$. As noted by Phillips and Sul (2007, 2009), using a sign criterion in step (ii) may lead to over-estimation of the number of clubs. To remedy this potential problem, the authors recommend performing club merging tests after running the algorithm, again through regression (4).

Table 1
Average weekly wholesale electricity prices ($/MWh) for NEM regions and Western Energy Market (Western Australia).

	NSW	QLD	SA	TAS	VIC	WA
Whole sample statistics						
Mean	45.14	43.77	57.28	41.14	42.85	47.60
Std. Dev.	46.60	35.22	84.23	31.20	45.37	19.75
Max	627	400	693	405	619	166
Observations	304	304	304	304	304	304
Pre-carbon-tax statistics						
Mean	40.90	33.93	50.92	38.97	36.28	44.38
Std. Dev.	55.09	32.23	97.25	36.81	50.27	21.99
Max	627	400	693	405	619	166
Observations	212	212	212	212	212	212
Carbon tax regime statistics						
Mean	54.91	66.43	71.96	46.16	57.99	55.03
Std. Dev.	7.32	31.24	37.13	8.01	25.76	9.84
Max	102	223	264	74	221	79
Observations	92	92	92	92	92	92

Notes: SWIS data are calculated from half-hourly short-term energy market prices. WA includes the SWIS wholesale prices only.

4. Data

The data set consists of weekly wholesale electricity prices, spanning the period January 1, 1999 to July 31, 2014. Data for Eastern Australian States (New South Wales, Victoria, Queensland, South Australia and Tasmania) are obtained from the Australian Energy Regulator (AER, www.aer.gov.au). Data for Western Australia's SWIS market are obtained from the Independent Market Operator of Western Australia (IMOWA, www.imowa.com.au). For SWIS, we calculate weekly averages from the half-hourly clearing prices of the short-term energy market. The Northern Territory is not included in the sample. Table 1 displays the summary statistics of the prices in the considered markets.

Table 1 reveals higher average prices after the introduction of the carbon tax (part of it is attributed to inflation). The carbon tax pass-through affected regional markets unequally, presumably due to differences in demand and supply elasticities. However, the statistical differences are to be taken with care as other regional factors have also shifted demand and supply (the exact quantification of the pass-through is beyond the scope of this paper). Overall, the introduction of the carbon tax raises interesting questions with regard to electricity price convergence. In the methodology described in Section 3, this break does not affect the cross-sectional estimates. However, it affects the definition of the steady state. To assess the practical implications of this issue, in Section 7 we assess convergence excluding the carbon tax period.

Table 1 reveals that there is higher volatility across NEM states, which was expected given the energy-only nature of those markets. Moreover, the price floor and ceiling in the NEM regions is higher than the counterparts in WA. It is worth noting that the latter does not allow negative prices, whereas NEM does.

The power supply structure differs across NEM[5] markets, as well as between them and SWIS. Coal is the predominant source of electricity generation in the NEM; coal generators accounted for 53% of the registered capacity and supplied 74% of power in 2014 (AER, 2014, p. 25). Other installed capacity includes natural gas (21%), hydroelectric (16%) and wind (6.3%) generators. In Queensland, NSW and Victoria,

[3] Following Phillips and Sul (2007, 2009), we adopt L(t) = log(t). The purpose of this function is to guarantee convergence when α = 0, in order to write the null hypothesis of convergence as α ≥ 0.

[4] The analytic proof under the convergence hypothesis for this regression equation is reported in Appendix B of Phillips and Sul (2007).

[5] Unless stated otherwise, all data are derived from the AER State of the Energy Market reports from the several years.

coal accounts for approximately 66%, 65% and 55% of generation capacity, respectively.[6] In South Australia and Tasmania, there is no coal generation capacity. In the former, the largest share of fuel source is gas (60% of capacity), while nearly all generation in Tasmania is hydroelectric (86%). South Australia has the largest share of non-hydro renewable energy sources installed, with wind power accounting for 29% of capacity (supplying 35% of energy in 2014). In Western Australia, SWIS has also a power supply structure dominated by fossil fuels. Coal amounts to about 40% of the capacity, and combined with natural gas, they account for 80% of the total capacity. Renewables reach 9% of WA's power production.[7]

The ownership of power generators varies across states as well. In Tasmania, virtually all generation capacity is controlled by a state-owned monopolist, i.e. Hydro Tasmania. Similarly, the SWIS market comprises 4200 M-watts of installed generation capacity, of which 74% is owned by the state utility Verve (AER, 2014, p. 205), which receives 50% of the capacity credits (IMO, 2014, p. 39). In the remaining States, markets are more contestable, as reflected in the following generation capacity Herfindhal–Hirschman Index (HHI) concentration estimates: 0.2122 for New South Wales, 0.241 for Queensland, 0.2276 for South Australia and 0.2138 for Victoria.[8]

Dynamically, the NEM annual growth rates for the generation of electricity from both black and brown coal have been negative between 2012 and 2014. Nevertheless, gas, hydro and wind usage have been growing at an increasing rate since 2000 (AER, 2014, p. 6). Due to stagnation of electricity demand since 2010, there has been limited investment in new generation capacity; NEM investment in new generation capacity from 2010 to 2014 consisted mostly of new wind and natural gas plants (AER, 2014, p. 33). Electricity trade patterns in the NEM remained relatively stable, except for Tasmania. More specifically, Tasmania was a net electricity importer from 2007 to 2009; it became the major exporter in 2013–14 (AER, p. 42). However, it must be taken into account that in the NEM region, and in addition to electricity flows, there are also substantial natural gas flows. Flows of natural gas across Eastern States are generally highly seasonal, indicating that the installed capacity does not work at full capacity during the year. The major producer on the East Coast is Queensland, which is connected to a major distribution point for South Australia and New South Wales through the South West Queensland pipeline; Victoria is connected to this network only indirectly through South Australia and New South Wales. The major natural gas producer in Australia is WA; however, there is no physical network for transporting natural gas from WA to the Eastern States.

It is also worth considering that the interconnection capacity is limited across NEM markets. There exist six interconnectors in the NEM: Heywood (South Australia–Victoria), Basslink (Tasmania–Victoria), Murraylink (Victoria–South Australia), NSW–Victoria, QNI (Queensland–New South Wales) and Directlink (Queensland–New South Wales). Their overall capacity[9] does not exceed 8% of the overall peak demand. A map presenting main power stations and connection networks in NEM markets is provided in Fig. A2 in the Appendix.

All the factors described above play a significant role in defining long-term price convergence across the various electricity markets. Due to data limitations, it is not possible to include all factors in a single convergence model as the exclusion of any relevant variable driving convergence would lead to misleading, biased results. However, it is relevant to assess the convergence of various electricity prices, as argued in Section 2 and as found in other energy economics studies based on the Phillips and Sul's (2007, 2009) methodology. An interesting result will be the formal identification of clustering group(s) of convergent supply characteristics across the regions under study.

Finally, the issue of seasonality is rather critical for the case of electricity prices across states, given that the regional markets across the Australian States have different weather patterns, and therefore, they also experience different seasonal patterns. To avoid any biasness in the relevance of our findings in the presence of large short term spikes, we employ filtered (trended) data in our estimations; following the methodological approach in Hodrick and Prescott (1997) filter, we estimate the trend that minimizes the squared changes in trend and deviations:

$$\min_{y_{t*}}\left\{\sum_{t=1}^{T}\left(y_t-y_t^{*}\right)^2+\lambda\sum_{t=2}^{T\text{-}1}\left[\left(y_{t+1}{}^{*}-y_t{}^{*}\right)-\left(y_t{}^{*}-y_{t\text{-}1}{}^{*}\right)\right]^2\right\} \tag{5}$$

This filtering technique is especially well-suited for extracting long-run trends of interest from the data while eliminating short-run 'spiky behaviour'. Following a reviewer's recommendation, the Appendix illustrates the picture of the original and the trended data across the six States (Fig. A1). The overall picture clearly displays the smoothing character of the electricity prices across all six States which permits the analysis to obtain more valid findings with respect to the convergence hypothesis.

5. Empirical results

Table 2 reports the panel convergence results for the Australian electricity prices. To implement the algorithm described in Section 3, the states are ordered according to the final values of each series. The resulting order is as follows: 1. South Australia, 2. Victoria, 3. Queensland, 4. NSW, 5. WA and 6. Tasmania. The first row displays the results testing for full convergence (i.e., convergence among all six states), while rows 2 to 4 display the results arising from the club-clustering procedure. As the first row of Table 2 indicates, the null hypothesis of full-panel convergence cannot be rejected as: $t_b = -0.231 > -1.65$; however, the speed of adjustment, i.e. $\tilde{\alpha} = b/2 = -3.619/2$, is negative, suggesting (weak) divergence. According to Phillips and Sul (2007, 2009), the sign of the point estimate is also a valid way of evaluating convergence patterns. Based on this sign observation, we proceed to the implementation of the algorithm to see if with identification of convergent clubs we can improve this basic result. It is not surprising that the heterogeneity in the panel has led to a weakly divergent pattern. Consider the fact that the production mix is substantially different for some of the States (i.e. South Australia: high share of renewables; Tasmania: hydro energy), which implies that States are coping with quite different costs of production. The results that follow from the club clustering algorithm in rows 2

Table 2
Test statistics for convergence of Australian electricity prices and regional clustering.

	Cluster	b	t_b
Full sample	South Australia, Victoria, Queensland, New South Wales, WA, Tasmania	−3.619	−0.231
1st club	Victoria, Queensland, New South Wales	−1.154	−0.169
2nd club	WA, Tasmania	0.971	1.348
3rd club	(non-converging) South Australia	–	–

Note: for testing the one-sided null hypothesis: $b \geq 0$ against $b < 0$, we use the critical value: $t_{0.05;rT-2-1=228} = -1.65156$ in all cases.

[6] Own calculations based on data from AER (2014, p. 27).

[7] Own elaboration on data provided by IMO. Capacity is calculated as the share of capacity credits by technology. Dual (coal/gas) are attributed to coal. Demand side management is not included.

[8] Own calculations using 2014 data from AER (2014, p. 37). The HHI is calculated as the sum of squared market shares of firms. The HHI is defined in the interval [0, 1], with 1 indicating full concentration (i.e. one supplier). One squared market share in the HHI includes firms categorized as "others"; the value of this component is 0.02 (2%) for New South Wales, 0.02 (2%) for Queensland, 0.03 (3%) for South Australia and 0.6 (6%) for Victoria.

[9] Source: Our elaboration based on data from AEMO. In particular, we calculate the average interconnection capacity as the yearly average from AEMO's Interconnector Quarterly Performance Reports, and for simplicity, we report the figure of the overall average interconnection capacity compared to the overall peak. For each interconnector, the specific figure does not differ much from the overall average (see also Nepal and Foster, 2013, Table 1).

through 4 show that over the period under investigation, three distinctive clubs were identified. Starting with South Australia (the first State in our ordered list), the algorithm added contiguous States to try to identify a core group; for each of these formations, we found that: $t_b < -1.65$. Following Phillips and Sul (2007, 2009) recommendation, the analysis isolated South Australia and proceeded to the next iteration of the algorithm. Starting with Victoria, the analysis found that the maximum $t_{\hat{b}}$ in the core grouping step was -0.169, which is associated with the inclusion of Queensland and NSW. Although the null hypothesis of convergence cannot be rejected at the 5% level, the negative sign of the point estimate is -1.154 implies a negative speed of adjustment, i.e. $\breve{\alpha} = -1.154/2$, which suggests divergence. However, the Phillips and Sul (2007, 2009) test is set so that $\alpha = 0$ implies convergence (because of the presence of L(t)), and the null hypothesis that $b = 2\breve{\alpha}$ is statistically different from zero cannot be rejected either. In line with Phillips and Sul (2007, 2009) interpretation of cases in which $-1.65 < t_b < 0$, we conclude that Victoria, Queensland and New South Wales should be classified as a club with its own convergence pattern (as $t_b > -1.65$), exhibiting weak transitional divergence (as b is negative). The two remaining States from our list, WA and Tasmania, form a third club which strongly converges to its own path; the null hypothesis of convergence cannot be rejected: $t_b = 1.348 > -1.65$) and the speed of adjustment is positive.

In sum, we have identified three underlying convergence groups in our panel. The first one is South Australia's own path, which bears no relationship with the other two trends identified in the algorithm and which can be characterized as a non-converging case. Interestingly, the club formed by the best interconnected states (club 2) is only weakly convergent. Finally, we could confirm that WA and Tasmania, two markets that are not physically interconnected, appear to convergence towards the same trend.

To complement the analysis conducted so far, relative transition curves are presented in Fig. 1. The right axis measures relative transition with respect to full ($N = 6$) cross-sectional averages, as defined in Eq. (2). Under the assumption of overall convergence in the sample, the relative transition parameters should all converge to one. Visual inspection of these curves enables us to gain some insight into the outcomes of the testing methodology, and it allows us to monitor the convergence of electricity prices for each State relative to the sample average. In particular, the transition curves report the tendency of the cluster participants to converge or diverge from above or below one. All six transition curves show no clear convergence towards one. In the case of WA, rather than approaching and stabilizing around the cross-sectional average, its transition curve seems to cut the one horizontal line from above. Visually, the dynamic path of WA's transition curve share similarities with that of Tasmania, which we confirmed with our findings. The case of Victoria and NSW is interesting: their transition curves approach and reach the cross-sectional average in the first quarter of 2013, but from this point onwards they appear to

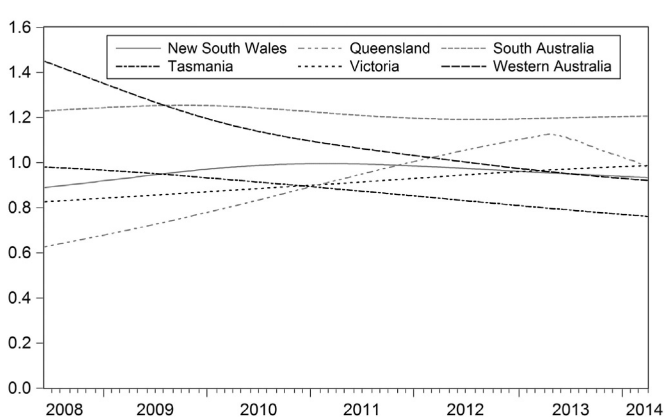

Fig. 1. Electricity prices: relative transition curves of convergence clubs.

show some transitional divergence. Queensland's transition path is rather erratic: it is convergent (with respect to the cross-sectional average) up to mid-2011, divergent between mid-2011 and mid-2013, and convergent from mid-2013 and onwards. The transition pattern of South Australia appears not to bear any convergence pattern with respect to the panel average or possible clusters. The formal identification of convergence patterns has helped us reach conclusions on the number of statistically significant clubs. As noted by Phillips and Sul (2009), the procedure is consistent with periods of transitional divergence.

To ensure that the cluster classification is correct, one more test is needed. Phillips and Sul (2009) argue that step (iii) of their convergence club methodology tends to over-estimate the true number of clubs. To address this issue, they run regression (4) on merged clubs to assess whether any evidence exists to support the merging of adjacently numbered clubs into larger clubs. The regression (4) results for mergers 1–2 and 2–3 are reported in Table 3. In both cases, we strongly reject the null hypothesis of convergence. These empirical findings show that there is no evidence to support mergers of the original clubs.

6. Analysis and implications of the results

The empirical results presented above show that in Australia there has been no fast, short-run convergence of wholesale electricity prices. Given the limitations of the physical interconnections of these markets, short-run full price convergence based on the exploitation of arbitrage opportunities was not expected. We find evidence of three price convergence patterns for Australia that can identify long-run price tendencies.

First, we have been able to formally identify a common pattern between New South Wales, Queensland and Victoria. This finding suggests that the characteristics of these markets are homogenous enough as to facilitate long-term convergence. These characteristics include (i) a common regulatory framework under the NEM, (ii) similar generation technological structures, (iii) relatively competitive generation market structures and (iv) a diversified number of retailers (AER, 2014, p. 126), as well as full retail contestability which allows electricity customers to enter contracts with their retailer of choice. The case of Queensland is interesting as we observe 'overshooting' of its relative convergence curve around 2013 (Fig. 1). A possible explanation for this pattern is the high degree of uncertainty associated with the carbon tax and the development of Queensland's natural gas resources.

In the events leading up to the current state of Queensland's electricity market, there has been speculation and uncertainty about the possibility of natural gas prices in Asia affecting energy prices in Queensland and, subsequently, electricity prices. The empirical study of the determinants of the natural gas price in Queensland and its spill-over effects is, however, beyond the scope of this study. The overall important finding here is that the above characteristic has allowed for electricity price convergence. This empirical finding sets an important reference for electricity market designers and policy makers. What is interesting is that this result was robust to the introduction of a national carbon tax policy (see Section 7 below).

Second, we have been able to identify a second group of States with a different price convergence pattern. This group includes Tasmania and Western Australia. To some extent, these findings are rather surprising: these two markets are distant and not physically connected, and their

Table 3
Club merging analysis.

		New club	Club-merging test statistic
I	Club	1 + 2	−0.083* (−6.71)
II	Club	2 + 3	−0.071* (−5.88)

* Denotes statistical significant at the 5% level while it rejects the null hypothesis of convergence. The figures in parenthesis denote t-statistics. The critical value: $t_{0.05;\ rT-2-1=228} = -1.65156$ in all cases.

market design differs, as does their power supply structure. A common trait of these markets is the presence in both States of a high degree of government ownership of generation capacity and limited competition (in electricity as well as in the markets of the energy inputs/fuels). In Tasmania, the state-owned Hydro Tasmania does not directly compete with Eastern coal and gas producers for production inputs. In Western Australia's SWIS market, the market share of capacity credits suggests the presence of a price leadership oligopolistic structure, which does not favor price convergence, while, as argued above, we can expect price convergence only when markets with CRMs are perfectly competitive. This does not seem to be the case in WA. Therefore, the second group adheres to (what we can call) a 'non-competitive' electricity price convergence pattern. Clearly, the methodology does not allow us to directly test whether the competitiveness of WA's SWIS and Tasmania markets or the ownership structure are statistically significant factors that both can affect price convergence. We can only point out the differences in relevance to these aspects across Australian electricity markets and highlight that the results in this paper confirm that WA and Tasmania are not moving in the same direction as the first group we have identified.

Third, there is the case of South Australia, in which electricity prices follow a long-run trend of their own. The average wholesale electricity price in South Australia is higher than in other States (Table 1); however, the dynamic evolution does not match any of the two patterns identified above. Fig. 1 suggests that the pattern has been rather divergent from mid-2013 to mid-2014. The power generation structure of South Australia is different than in the other NEM regions since no coal is used in the production of electricity. Compared to first convergence club (i.e., NSW, Queensland and Victoria), where coal generation is predominant, the findings document a fundamental difference driving production decisions. In addition, the connection to the NEM electricity network is very limited. As a result, the supply of electricity in South Australia is inadequate to satisfy demand at the price set by the first convergence group. Moreover, South Australia has the highest investment in new generation capacity in Australia, the majority of which goes to wind generation, which for technical reasons is not a popular technology in the remaining Eastern States. As long as the rate of return for wind generators and other types of generation remain high, South Australia will continue to attract high levels of investments relative to other States. In the future, we expect to see the convergence of South Australia with electricity prices from the first club; however, the effects of new investments have yet to produce an impact on electricity prices.

7. Convergence robustness test: the carbon tax period

Based on the discussion in Section 2, we re-ran similar convergence tests excluding the years under the carbon tax policy. The new results are reported in Table 4. The findings in the first row indicate that, as before, there is evidence of weak divergence when the panel is tested as a whole. The results of the club clustering algorithm, reported in rows 2 and 3, show that over the period without the carbon tax, two convergence clubs are formed, with test statistics: $t_b = -0.346$ and $t_b = 1.235$, respectively, which are not too different from what we found earlier. However, the interesting finding is that without considering the impact of the carbon tax on electricity prices, the State of South Australia joins now the club of Victoria, Queensland and NSW. This occurs after eliminating a potential factor that contributes significantly to electricity price divergence, and it confirms our hypothesis that South Australia had been slowly converging to the first group through investments in renewables. The introduction of the carbon tax has lowered this convergence process by affecting those markets that were most sensitive to it due to their predominance of coal-fired power production (i.e., Queensland, NSW and Victoria). Once again, the second club continues to include, as separate cases, Tasmania and Western Australia, indicating that the remaining factors that drive convergence (mentioned above) persistently remained.

Table 4
Australian electricity prices (excluding the carbon tax years).

	Cluster	b	t_b
Full sample	South Australia, Victoria, Queensland, New South Wales, WA, Tasmania	−2.953	−0.428
1st club	South Australia, Victoria, Queensland, New South Wales	−1.016	−0.346
2nd club	Tasmania, WA	1.117	1.235

Note: for testing the one-sided null hypothesis: $b \geq 0$ against $b < 0$, we use the critical value: $t_{0.05;rT-2-1=154} = -1.65481$ in all cases.

8. Conclusion

From a market design perspective, it is interesting to identify the common traits of the markets whose prices may converge over time. This study has covered the case of Australia and contributed to it in different ways. First, it contributed by formally identifying three distinctive underlying growth patterns for wholesale electricity prices across the six Australian States. Second, it confirmed that markets that have limited physical interconnection can achieve price convergence over the long run under certain degrees of homogeneity in their market structures. Third, the empirical findings documented that Tasmania and Western Australia, which are characterized by less competitive markets in which a major role is played by state-owned companies, share a separate, non-competitive convergence pattern. This is despite any major differences between WA and Tasmanian market designs regarding capacity remuneration, namely, the latter being an energy-only market and the former being a market with a CRM. Fourth, we illustrated that the introduction of a carbon tax has not altered the price convergence process of the identified clubs of Australian States, with the notable exception of South Australia, which would have converged to the club formed by the other NEM States (except Tasmania) had the carbon tax not been in place.

Policy makers and electricity market design experts should take note of these findings. In practice, it is important to know which market structures have led to electricity price convergence in Australia and which have not. The results have confirmed some theoretical expectations while quantifying the convergence rates. In future research venues, it would be very interesting to compare the results of this paper with those derived from electricity markets in other parts of the globe, as well as assessing the impact of possible technological changes on the convergence trend. For instance, it could be interesting to assess the impact on the long-run convergence of the introduction of storage capacity, which would allow to balance uncontrollable RES on the one hand, but that might also impact profits of flexible thermal power plants on the other.

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Appendix A. Supplementary data

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