Price Adjustment and Market Transition in the Carbon Price Era: 
A Study of Australia's Electricity Spot and Derivative Markets

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Abstract

This paper studies the effect of the Carbon Pricing Mechanism (CPM) on Australia’s electricity spot and derivative markets. We measure the changes in price and volatility level to find out whether the CPM affects both markets differently. In order to explore the response in the electricity derivative market, we study the price dynamics in the exchange-traded derivative (ETD) and the over-the-counter (OTC) markets. Furthermore, the analysis regarding the turnover, liquidity and speculation reviews the transition of electricity derivative market. Given the different mechanisms to incorporate the CPM in the ETD and OTC market, we derive an implied carbon price to reveal the market expectation on the fate of CPM throughout its implementation. The results indicate an increasing electricity price level as the consequence of the CPM. Comparing to the abrupt adjustment of electricity spot price, the price transition in the electricity derivative market is smoother. Before the CPM effectiveness, the financial intermediaries become active in the electricity derivative market. Their speculation activities drive up the liquidity, which stimulates the market growth and motivates the product innovation. Overall, the electricity derivative market demonstrates its advantage in managing the carbon price risk. Despite the effect in emission reduction, the environmental policy is associated with considerable challenges and uncertainties. The experience from Australia shows the importance of policy design and persistence.

JEL Classification: C22; C58; G14; L98; Q58

Keywords: Carbon Price, Environmental Policy, Liquidity and Speculation, Price and Volatility, Implied Carbon Price, Nonlinear Price Dynamics, STAR Model

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1. Introduction

Concerns over the threats from the climate change have prompted mitigation policy in many jurisdictions around the world. After ratifying the Kyoto Protocol in 2007, the Australian government outlines a target to reduce the greenhouse gas (GHG) emission by 80% compared with 2000 levels by 2050 (Department of Climate Change and Energy Efficiency, 2011). Since the proposal for the Carbon Pricing Mechanism (CPM) in 2010, Australia is in an era of carbon price. On 1 July 2012, the CPM comes into effect as Australia's domestic GHG mitigation framework. The imposed carbon price starts with a fixed rate of $23 (Australian Dollar) per ton of carbon dioxide equivalent (tCO2-e), which is set to increase at a rate of 4% annually until July 2015. A transition to an Emission Trading Scheme (ETS) is scheduled to start in July 2015 (Clean Energy Act, 2013). Further plans to link Australia’s CPM with European Union's ETS in July 2018 is also announced later (Australian Government, 2013). However, the newly elected Government repeals the CPM on 17 July 2014 (Clean Energy Legislation (Carbon Tax Repeal) Bill, 2014).

According to the International Energy Agency (2012), coal and natural gas make up 75% and 15% of fuel sources for electricity generation in Australia. The combustion of fossil fuels for electricity production generates a large amount of GHG emission. In 2013, the electricity sector contributes 35% of Australia's national GHG emission (Australian Energy Regulator (AER), 2013a). Meanwhile, the generation capacity of Australia’s electricity industry is still growing, which reaches 199 TWh (Terawatt hours) in 2013 valued at $12.2 billion. According to the Clean Energy Act (2013), the carbon price is applicable to the liable entities, which is either direct emitter of

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3 In 2010, the former Prime Minister Julia Gillard proposed the introduction of carbon price as promised to the political partners in the parliament. However, Tony Abbot, the opposition leader at the time, strongly criticized the concept. As the CPM became effective on 1 July 2012, it was used as a political weapon against the Labor Party during the 2013 election campaign. The proposal to accelerate towards an ETS did not save the Labor Party from a vote swing in September 2013. The new Liberal Party government led by Tony Abbot abolished the CPM in July 2014 Rootes (2014).

4 1 TWh (terawatt hour) = $10^{12}$ Wh (watt hour)
GHG or owns facilities with at least 25,000 ton GHG emission every year. Therefore, Australia's electricity sector is exposed to the CPM due to its heavy reliance on the fossil fuels (Clean Energy Regulator, 2013).

Given the significance of the electricity industry to the GHG emission, the carbon pricing and its effect on the electricity sector has been under research focus in recent years. Kara et al. (2008) measure the elasticity of electricity price to the EU ETS allowance price in the Nordic region from 2008 to 2012. They find that a 1 Euro/ton carbon price change would bring a rise of 0.74 Euro/MWh in spot electricity price on average. Bunn and Fezzi (2007) discover a lagged pass-through of carbon price to UK's electricity price. Zachmann and Von Hirschhausen (2008) also find correlation between carbon price and electricity spot price in Germany. The study by Alberola et al. (2008) shows that there are structural breaks in the European carbon permit market due to the carbon policy announcements. Benz and Trück (2009) use Markov switching and AR-GARCH models to model the price dynamics of EU emission allowance price. Daskalakis, Psychoyios, and Markellos (2009) apply the stochastic differential equation method to model the emission allowance and derivative price movement on three major European emission trading markets.

Besides the studies conducted on the European market, there are some works done regarding the impact of the CPM on Australia's electricity sector. Wild (2012) applies an agent based model to explore the effect of carbon pricing on supply and demand in Australia's wholesale electricity market. Their findings show that the growth in average wholesale prices and the carbon price pass-through rate differ across Australian states. O'Gorman and Jotzo (2014) also examine the impact of carbon pricing on Australia's electricity demand, supply and emission. They assert that it is hard to attribute the observed changes in demand and supply completely to the CPM implementation, although there is short-term effect from the carbon price. Garnaut (2014) concludes that, rather than the carbon constraint, the effect from the deepening integration with the global energy markets and the electricity market privatization are the major drivers for Australian electricity price increase since early 21st century.
Meng (2014) conducts economic forecasts based on the Computable General Equilibrium (CGE) model. His result suggests that the carbon tax would not only increase wholesale electricity prices, but also transform Australian electricity generation to a low emission industry in the long term. Having evaluated CPM by taking into account its effect on electricity price, GDP growth and fiscal effect, Robson (2014) points out that the poor policy implementation fails to gather sufficient public support, which finally leads to the CPM abolishment.

While most of the previous studies focuses on the effects of the CPM on Australia's electricity spot market, the current paper extends the research scope to the electricity derivative market, as it plays substantial role in the price discovery. The study covers the whole period of Australia's carbon price era from 2010 to 2014. We measure the changes of price and volatility level to find out whether the CPM has affected electricity spot and derivative markets differently. In order to investigate the different reactions to the CPM within the electricity derivative market, we apply the Smooth Transition Autoregressive (STAR) Model to study the price transition characteristics in the exchange-traded derivative (ETD) and the over-the-counter (OTC) markets. Furthermore, we look into the turnover, liquidity and speculation to analyze the effect of the CPM on the transition of the electricity derivative market. Since the OTC electricity derivative contracts do not include the carbon price as the ETD contracts, we derive an implied carbon price to reveal the market expectation on the fate of CPM throughout its implementation. As far as we are aware, this is a first study to explicitly look into the effects of the CPM on both OTC and ETD electricity derivative markets.

The paper is organized as follows: the first section describes the data and methods applied in the study. This is followed by the overview of results, which summarizes the price and volatility level adjustment, the transition of electricity derivative market and the results of the STAR model estimation. After interpreting the observed phenomenon and discussing the effect of the CPM on the electricity market, the fifth section concludes.
2. Data and Method

2.1 Market and Data

The analysis of spot electricity price is based on the daily average Regional Reference Price (RRP) for Australia’s key states (New South Wales, Queensland and Victoria) from 2011 to 2014 (Figure 1). The RRP is the official price for the National Electricity Market (NEM), which covers Queensland (QLD), New South Wales (NSW), the Australian Capital Territory (ACT), Victoria (VIC) and South Australia (SA) (AEMO, 2014). It is a pooling spot market, where the electricity generators trade with the retailers. In 2012-2013, the annual electricity generation amount traded on NEM is 195.5 TWh, valued at $11.4 billion (AEMO, 2014).

Figure 1: Daily Average RRP 2011-2014 ($/MWh)

Figure 2: Price Profile of Electricity Derivatives 2009-2014 ($/MWh)
The electricity derivative market is a crucial component of the electricity sector. As the varying demand and limited generation capacity usually cause serious network congestion, the electricity market is characterized with high volatility. Therefore, generators and retailers use electricity derivatives to manage future price exposure and demand variation. Australia's electricity derivative market is comprised of two distinct submarkets, namely the ETD and the OTC market. In contrast to the OTC market, where participants negotiate bilaterally tailored derivative contracts, registered participants trade standardized derivative contracts in the ETD market. The turnover of the total electricity derivative contracts amounts to $633 billion in 2012-13 (Australian Financial Markets Association (AFMA), 2014).

The study of the electricity derivative market covers the ETD and OTC market for NSW, QLD and VIC from 2009 to 2013 (Figure 2). The analysis of ETD market is based on the ASX Energy daily market data for Base Load (the period from 00:00 hours Monday to 24:00 Sunday) Quarterly Futures and Base Load Strip Futures Option. The Base Load Strip Futures Option is an option on consecutively traded quarterly futures bought or sold simultaneously. The analysis of OTC market is based on the daily forward curves provided by the Australian Financial Markets Association (AFMA). The OTC Base Load Strip Forward Curve is an average price built up by the forward curves with maturities up to one year. All data include only derivative price with non-zero trading volume.

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5 ASX Energy, the energy submarket of Australian Stock Exchanges, is Australia's major real-time electricity derivatives trading platform. In 2013, there were 156,674 financial contracts traded on ASX Energy, which equals to the value of $16 billion or 333 TWh (ASX Energy, 2013).

6 The Australian Financial Markets Association (AFMA) is a financial industry association with more than 130 members ranging from leading banks to financial companies such as broker and energy trading institutions. It collects OTC financial product data independently from contributors on daily basis. The forward curves are daily average OTC electricity forward prices.
2.2 Measurement of Price and Volatility Changes

2.2.1 Measurement of Price Change

The CPM comes into effect on 1st July 2012 with an initial tax rate of $23 per tCO2-e in 2012-13. As in Equation (1),

\[
\text{Carbon Price} = \text{Generation (MWh)} \times \text{CDEII (tCO}_2\text{-e/MWH)} \times \text{Tax Rate ($/tCO}_2\text{-e)}
\]

the carbon price for the liable entities in the electricity sector is dependent on the Carbon Dioxide Equivalent Intensity Index (CDEII) (AEMO, 2013). The CDEII is the daily emission intensity published by the Australian Energy Market Operator (AEMO), which is dependent on generator's thermal efficiency (AEMO, 2013).

Also, we derive the carbon-exclusive electricity price to investigate the effect of the CPM on the electricity price. As described in Equation (2), the electricity price excluding the carbon component, which is the product of the CDEII and carbon tax rate, becomes carbon-exclusive.

\[
\text{Carbon-Exclusive Price} = \text{Price($/MWh)} - \text{CDEII (tCO}_2\text{-e/MWH)} \times \text{Tax Rate ($/tCO}_2\text{-e)}
\]

2.2.2 Measurement of Volatility Change

The volatility is a measure of the dispersion of electricity price under the effect of the CPM. We calculate the intraday volatility for RRP and electricity derivative price as described in Equation (3), where \( P_t \) and \( P_{t-1} \) denote the observed prices in consecutive days.

\[
\text{Intraday volatility} = \sqrt{(P_t - \bar{P})^2} = \sqrt{[P_t - (P_t + P_{t-1})/2]^2}
\]

The implied volatility is an indirect way to look into the expectation about the underlying price variation embedded in the derivative price. In contrast to the historical volatility, which is the standard deviation of the past prices, the implied

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7 This refers to the financial year in Australia covering the period from 1 July to the 30 June of next year.
volatility is derived from the current derivative price. This extracted volatility implicitly reveals the anticipated future electricity price fluctuation until the maturity of the associated electricity derivatives (Chevallier, 2011; Hull, 2006; Mayhew, 1995). In this paper, we study the implied volatility for Base Load Strip Futures Option from 2010 to 2013. Equation (4) describes the derivation of implied volatility for European call option based on the Black-Scholes Model (Merton, 1976),

\[ C(S,t) = N(d_1)S - N(d_2)Ke^{-(T-t)} \]  \hspace{1cm} (4)

where \( C(S,t) \) is the option price with the underlying asset currently priced at \( S \). The \( t \) denotes the remaining time to the maturity, when the option could be exercised at the strike price \( K \). The implied volatility is calculated by numerically inverting the Black-Scholes Model (Chriss, 1996). For simplicity, the underlying price \( S \) is set equal to the strike price \( K \), so that it is the "at-the-money" implied volatility.\(^8\)

### 2.3 Liquidity and Speculation Ratio

The change of liquidity during the carbon price era reflects the effect of the CPM on the electricity derivative market. The liquidity ratio in Equation (5) measures the relation between the turnover in the electricity derivative market and the total underlying demand in the spot electricity market (AFMA, 2014).

Liquidity Ratio = Turnover in Electricity Derivative Market / Demand in NEM  \hspace{1cm} (5)

A high liquidity ratio implies more frequent trading activities in the electricity derivative market based on the same energy demand.

We further investigate the speculation in the electricity derivative market under the effect of the CPM. The purpose of derivative trading could be distinguished into hedging and speculation. Besides the generator and retailer, who use derivatives to manage their exposures to the future variation in electricity price and supply, other participants attempt to make speculative profit in the derivative market. Lucia et al.

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\(^8\) An option is called at-the-money, when the underlying’s market price equals to its strike price.
(2014) develop the SPEC ratio as in Equation (7) to explore the speculation in the daily trading activities on the European Carbon market,

\[ SPEC_t = \frac{V_t}{OI_t} \]  

where \( V_t \) is the trading volume of each trading period \( t \) and \( OI_t \) denotes the open interest at the end of correspondent trading period. The open interest is the cumulated number of trades, which are not closed out by the end of period \( t \). It is unchanged until both counterparties close their positions. As speculators take advantage of the short-term market trend, they enter and exit the market quickly, which in turn generates a high trading volume but an unchanged open interest. Therefore, the SPEC ratio is positively correlated with the speculative activity on the market (Robles, Torero, & Von Braun, 2009).

2.4 Modelling Price Transition in the Electricity Derivative Market

The electricity markets are characterized with high degree of volatility. The Smooth Transition Autoregressive (STAR) model is widely applied in the nonlinear economic time series analysis (Baum, Barkoulas, & Caglayan, 2001; Robinson, 2000; Taylor, Peel, & Sarno, 2001). According to the apparent nonlinear price profile observed in Figure 2, we apply the STAR model to study the price transition and dynamic in the electricity derivative market under the effect of the CPM.

2.4.1 Smooth Transition Autoregressive Model

The STAR model, developed by Terasvirta and Anderson (1992), is a derivation from the Threshold Autoregressive (TAR) model introduced by Tong (1983). It is an extension of the autoregressive (AR) model, which allows dynamic switch of regimes. The change of regimes is determined by an exogenous threshold value. The threshold value and the delay parameter enable the division of one dimensional space into \( k \) regimes with a linear autoregressive model (Chan & Tong, 1986; Dijk, Teräsvirta, & Franses, 2002).
Let $y_i$ be a $(n \times 1)$ vector of variables. A STAR model for univariate time series of order $p$ is defined as follows:

$$y_i = a_{i0} + a'_i y_i + (a_{20} + a'_2 y_i)F(y_{i-d}) + u_i$$

$$u_i \sim \text{nid}(0, \sigma^2)$$

$$a_j = (a_{j1}, \ldots, a_{jp})', j = 1, 2,$$

$$y_i = (y_{i-1}, \ldots, y_{i-p})',$$

where the monotonic function $F(y_{i-d})$ represents a continuous transition function in Equation (8).

$$F(y_{i-d}; \gamma, c) = (1+\exp[-\gamma(y_{i-d}-c)])^{-1} \quad \gamma > 0$$

In comparison to the discontinuous abrupt transition in the TAR model, the STAR model is characterized by a smooth transition function. It allows a dynamic switch of regime according to the relation between the lagged times series variable $y_{i-d}$ and the threshold value $c$. A regime-switching process is triggered, once the lagged variable $y_{i-d}$ is beyond the threshold value $c$ (Dueker, Owyang, & Sola, 2010). The speed of transition is dependent on the parameter $\gamma$, which is normally non-negative. Furthermore, it determines with the threshold value $c$ together the local regime dynamics. For instance, when $\gamma \to \infty$ and $y_{i-d} > c$, the $F(y_{i-d})$ then approaches to 1, which makes the model become a TAR($p$) model. When $\gamma \to 0$, the Logistic-STAR (LSTAR) model turns to a linear AR($p$) model (Potter, 1999). The transition function is bounded between 0 and 1.

### 2.4.2 STAR Model Estimation

The parameter estimation for the STAR model follows the procedure introduced by Teräsvirta (1994). After detecting the nonlinearity with the BDS test (Appendix A), the order of the AR model ($p$) is specified according to the autocorrelation function (ACF) and the Akaike Information Criterion (AIC). The appropriate value for the
delay parameter $d$ could be determined by F-version LM-type test following the auxiliary regression given by Teräsvirta (1994).

$$y_t = \beta_0 + \beta_1 x_{t-1} + \ldots + \sum_{j=1}^{p} \beta_{2j} R_{t-j} R_{t-d} + \sum_{j=1}^{p} \beta_{3j} R_{t-j} R_{t-d}^2 + \sum_{j=1}^{p} \beta_{4j} R_{t-j} R_{t-d}^3 + \varepsilon_t \quad (9)$$

Under the null hypothesis, the F-version LM-type test assumes the linearity among the data with $H_0 : \beta_{2j} = \beta_{3j} = \beta_{4j} = 0$. The delay parameter $d$ is determined by iterative regression process until the $H_0$ is rejected. In the case of multiple rejections against the null hypothesis, $d$ with the minimum $p$-value is selected.

The parameter estimation of the STAR model is carried out in MATLAB by the nonlinear least squares procedure with no grid search. The estimators include the threshold value $c$, the transition speed $\gamma$, and other nonlinear regression parameters. Under the iterative reweighted least squares algorithm of nonlinear regression, the robust weights are recalculated based on each observation’s residual from the previous iteration. The estimation achieves robust results when the weights converge (Giovanis, 2008). According to the STAR model assumption, the initial values of $\gamma$ is set at 0, while the starting value for threshold parameter $c$ is set at the mean price of the electricity derivatives.

### 2.5 Implied Carbon Price

In order to explore the market valuation and expectation on the CPM, we derive an implied carbon price based on the different mechanisms to incorporate the carbon price in the ETD and the OTC market. In contrast to the ETD market, where the carbon price is inclusive in the electricity derivative price, the carbon component is excluded from the OTC derivative price. According to the AFMA Carbon Benchmark Addendum, the carbon price will be added separately to the OTC derivative contracts at maturity (Australian Financial Markets Association (AFMA), 2012a). Therefore,

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9 As the interval of estimator is unknown, a no grid search is applied for the nonlinear least square regression. Thus, the estimation starts from the initial value and stops once the results converge.
there is price difference between the ETD and the OTC derivative, which could be recognized as an implied carbon price (EUAA, 2011). In this paper, the implied carbon price is the spread between two derivative groups in the ETD and OTC market, namely the Base Load Quarterly Futures and the OTC Base Load Quarterly Forward Curve from 2010 to 2014,

\[
\text{Implied Carbon Price} = \text{Price}^{\text{ETD}}(t, T) - \text{Price}^{\text{OTC}}(t, T)
\]

, where \( t \) in Equation (10) indicates the trading date, while \( T \) denotes the maturity date. Thus, the implied carbon price is derived from the electricity derivative products of same maturity traded on the same day.

3. Results

3.1 Price and Volatility Adjustment in the Spot Electricity Market

There is a structural break in the spot electricity price on the day of the CPM enforcement. On 1st July 2012, the daily RRP increases from $33.45 to $58.09 in NSW, from $31.36 to $52.49 in QLD, and from $37.86 to $60.47 in VIC (Figure 1). During the lifetime of the CPM, the average RRP increases by $24.09 in NSW, $30.74 in QLD, and $25.14 in VIC. The carbon-exclusive spot electricity price shows the impact from the CPM. After removing the carbon component as described in Equation (2), the average RRP decreases by $21.36 in NSW, $19.58 in QLD, and $27.72 in VIC.

However, the magnitudes of intraday price volatility adjustment vary across states. After the introduction of the CPM, the average level of intraday volatility increases from 2.65 to 5.84 in QLD, and from 2.24 to 4.02 in VIC. In contrast, it decreases from 1.9 to 1.8 in NSW. Furthermore, there is no significant change in volatility level after excluding the carbon component. In the same time, there are obviously more extreme volatilities during the lifetime of the CPM between July 2014 and June 2014 (Figure 3).
3.2 Price and Volatility Adjustment in the Electricity Derivative Market

The price adjustment processes within the electricity derivative market are different under the effect of the CPM. While the ETD price increases gradually to a higher level, the price level in the OTC market is hardly changed (Figure 2). In comparison to the electricity derivative price level in 2010 and 2011, the average price of Base Load Quarterly Futures rises by $12 in NSW, $21 in QLD and $13 in VIC since 2012. Meanwhile, the Base Load Strip Futures Option increase by $11 in NSW, $18 in QLD and $9 in VIC. Furthermore, the price development in the OTC market shows a different trend. While the OTC Base Load Quarterly Forward Curve demonstrates a cyclical and volatile price movement, the price trend of OTC Base Load Strip Forward Curve is stable within the interval between $30 and $40.

The CPM does not affect the volatility level in the electricity derivative market. From 2010 to 2014, there is no change in intraday volatility for the entire electricity derivative market. Moreover, the implied volatility of ETD product stays stable during the CPM effectiveness. Comparing to other states, NSW has the lowest implied volatility, which is always below 15 (Figure 4). It starts to decrease in early 2012, and stabilizes after that. Despite a jump of implied volatility in QLD and VIC at the end of 2012, it remains relative constant below 20 until the end of 2014.
3.3 Turnover and Development of Electricity Derivative Market

There are turnover changes in Australia's electricity derivative market in the carbon price era. The turnover of the total electricity derivative market reaches 863 TWh in 2010-11. This can be mainly attribute to the rapid growth of the ETD market since 2007-08, which reaches the highest level of 548 TWh in 2010-11 (Table 1). The turnover of the OTC market also attains a higher level of 314 TWh. However, the trading volume in both ETD and OTC markets declines in 2011-12. In comparison to the rapid growth in the ETD market, the turnover of the OTC market is relative stable, which results in a loss of market share across time. The market share of the OTC drops from 76.42% in 2005-06 to 46.1% in 2012-13.

<table>
<thead>
<tr>
<th>Year</th>
<th>OTC</th>
<th>ETD</th>
<th>Total</th>
<th>NEM Demand</th>
<th>Liquidity Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004-05</td>
<td>198.88</td>
<td>23.82</td>
<td>222.70</td>
<td>187.87</td>
<td>1.2</td>
</tr>
<tr>
<td>2005-06</td>
<td>177.13</td>
<td>54.65</td>
<td>231.77</td>
<td>192.51</td>
<td>1.2</td>
</tr>
<tr>
<td>2006-07</td>
<td>337.17</td>
<td>243.00</td>
<td>580.17</td>
<td>193.91</td>
<td>3.0</td>
</tr>
<tr>
<td>2007-08</td>
<td>304.08</td>
<td>240.79</td>
<td>544.88</td>
<td>195.14</td>
<td>2.8</td>
</tr>
<tr>
<td>2008-09</td>
<td>208.07</td>
<td>300.83</td>
<td>508.90</td>
<td>197.36</td>
<td>2.6</td>
</tr>
<tr>
<td>2009-10</td>
<td>221.01</td>
<td>398.90</td>
<td>619.91</td>
<td>195.34</td>
<td>3.2</td>
</tr>
<tr>
<td>2010-11</td>
<td>314.60</td>
<td>548.64</td>
<td>863.24</td>
<td>192.30</td>
<td>4.5</td>
</tr>
<tr>
<td>2011-12</td>
<td>293.03</td>
<td>436.90</td>
<td>663.94</td>
<td>188.95</td>
<td>3.5</td>
</tr>
<tr>
<td>2012-13</td>
<td>291.18</td>
<td>341.68</td>
<td>632.87</td>
<td>183.73</td>
<td>3.4</td>
</tr>
<tr>
<td>2013-14</td>
<td>250.76</td>
<td>386.70</td>
<td>587.18</td>
<td>178.61</td>
<td>3.3</td>
</tr>
</tbody>
</table>

The fourth column indicates the total annual turnover (TWh) of Australia’s electricity derivative market comprised of the OTC and ETD markets in the second and third column. The fifth column is the annual electricity demand in the NEM (TWh).

Data source: AFMA 2008-2014

Table 1: Liquidity Ratio and Turnover of Australia’s Electricity Derivative Market 2004-2014

Data source: ASX
In the meantime, the product structure in the electricity derivative market becomes more diversified. Despite the dominance of quarterly futures in the ETD market, there is significant growth of new products such as calendar options and caps (Figure 5). In the OTC market, the market share of swaptions falls from 25% in 2011-12 to less than 8% in 2012-13, while other products such as swaps gain more weight in the market.\footnote{A Swaption is an option to enter into an electricity swap contract with the predetermined conditions.}

The left bar in each year indicates the total turnover of ETD market. The right bar in each year indicates the total turnover of OTC market.

Data Source: AFMA, 2014

Figure 5: Turnover of Australia’s Total Electricity Derivative Market 2007-2014 (TWh)

3.4 Liquidity and Speculation in the Electricity Derivative Market

The liquidity in the electricity derivative market reaches the highest level prior to the introduction of the CPM in July 2012. After a dramatic rise from 1.2 to 3 in 2006-07, the liquidity ratio grows significantly in 2010-11, and reaches the historical peak of 4.5. Despite the decline in the subsequent years, it remains at a higher level around 3.5 from 2011 to 2014. (Table 1)

There is accumulated speculation in the ETD electricity derivative market before the introduction of the CPM. The SPEC ratio of Base Load Quarterly Futures shows increasing events of speculation since the third quarter of 2011 until the end of 2012 (Figure 6). There is a concentration of higher SPEC ratios during this time, which are
usually above 40%. The average SPEC ratios in NSW, QLD and VIC jump up by 65%, 91% and 30% respectively. However, the high speculation fades away since the end of 2012.

![SPEC Ratio of Base Load Quarterly Futures 2010-2014](image)

**Figure 6: SPEC Ratio of Base Load Quarterly Futures 2010-2014**

### 3.5 Results of Price Transition in the Electricity Derivative Market

After confirming the existence of significant nonlinearity in all electricity derivative prices with the BDS test (Appendix A), we detect the existence of joint autocorrelation in derivative prices using the ACF. The lag order of the AR model is selected according to the AIC, which serves as the starting point for the STAR modeling procedure. The results of STAR model parameter estimation are summarized in Table 2.

The STAR modeling results indicate that the price transition characteristics in the electricity derivative market under the CPM. Firstly, the lower transition speed $\gamma$ indicates a smooth price transition process in the electricity derivative market. For all ETD and OTC derivatives under observation, the estimated transition speed $\gamma$ are no greater than 1 except for the Base Load Quarterly Futures of NSW, whose transition speed is 2.2114. The transition speeds for the ETD derivatives are lower than those for the OTC derivatives, the implication will be discussed in the next section. Secondly, the price transition speeds are different among the states. In comparison, derivatives in QLD usually have faster transition speed except for the Base Load Quarterly
Futures. Furthermore, the transition speeds within the electricity derivative market are different. A comparison between the same class derivatives in the ETD and OTC markets indicates that the transition speed $\gamma$ of Base Load Quarterly Futures is higher than that of OTC Base Load Quarterly Forward Curve, while it is lower for Base Load Strip Futures Option than OTC Base Load Strip Forward Curve.

<table>
<thead>
<tr>
<th>Quarterly Base Futures</th>
<th>c</th>
<th>$\gamma$</th>
<th>d</th>
<th>p(F type)</th>
<th>AR (p)</th>
<th>Modulus(Low)</th>
<th>Modulus(High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSW</td>
<td>47.18</td>
<td>2.21</td>
<td>5</td>
<td>1.09E-14</td>
<td>9</td>
<td>0.3892</td>
<td>0.5632</td>
</tr>
<tr>
<td>QLD</td>
<td>45.62</td>
<td>1</td>
<td>2</td>
<td>-1.46E-13</td>
<td>12</td>
<td>0.7799</td>
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<th>Modulus(High)</th>
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This table is a summary of the STAR modeling results. The second column indicates the estimated threshold value. The third column indicates the estimated transition speed $\gamma$. The fourth column indicates the estimated delay parameter. The fifth column indicates the $P$-value of the F-Version LM test. The sixth column indicates the estimated order for AR model. The seventh and the eighth columns indicate the characteristics root for modulus in upper (F=1) and lower (F=0) regimes.

Table 2: STAR Model Estimation Results
The other feature detected by the STAR model is the location of the price regime switch. The threshold estimator \( c \), displayed in the second column of Table 2, shows the gauged location, where the CPM starts to change the characteristics of current price regime. The results indicate that the switch takes place between $35.97 and $49.92 for all derivative groups. In comparison to the OTC products, the switch of the price regime for ETD products starts from a higher price level. Among all products, the OTC Base Load Strip Forward Curve has the lowest threshold value. The threshold value of NSW is generally higher than those of other states.

The results of the STAR model estimation are evaluated by the residual analysis and characteristic roots test. The remaining residuals are dramatically reduced after the STAR model fitting. While the extra kurtosis and standard deviation still signals a wide variation of unexplained variability, the skewness of residual suggests that the distribution of residuals is close to the white noise. Moreover, the ACF of residuals indicates a significant reduction of autocorrelation among the residuals. Furthermore, the characteristic roots calculated by solving the polynomials in Equation (11) explicitly indicate a converging estimation result.

\[
Z^p - \sum_{j=1}^{p} (w_{1j} + w_{2j} F) Z^{p-j} = 0 \quad F=0, 1
\] (11)

As could be seen in Table 2, most of the roots modulus in upper (\( F=1 \)) and lower (\( F=0 \)) regime are within the unit circle. However, OTC Quarterly Forward Curve for NSW and OTC Strip Forward Curve for VIC still have explosive unit roots, which implies large price fluctuation.

### 3.6 Implied Carbon Price

The implied carbon price reveals the expectation on the fate of the CPM. Despite the slight variation in price level, the implied carbon prices of three states follow the same trajectory (Figure 7). Before April 2011, there is rarely price discrepancy between the ETD and OTC derivatives. The spread starts to increase quickly since then and
fluctuates in the interval between $15 and $20 until February 2013. In July 2012, the implied carbon price touches the historical level of $23. However, it quickly returns to $20 and remains stable ever since. After a cliff drop in February 2013, the implied carbon price starts to decrease and drops to the level below $15. Despite a rebound in the mid-2013, it keeps decreasing until the end of year, where the spread becomes less than $5. Among the three states, NSW has a higher level of implied carbon price.

Figure 7: Implied Carbon Price 2010-2014 ($/MWh)
4. Discussion

4.1 Reasons for Inconsistent Price and Volatility Adjustment

The difference in energy consumption structure across states leads to difference in electricity price adjustment under the effect of the CPM. Despite the diversified energy source, Australia’s electricity generation still relies on fossil fuels. In 2013-14, black and brown coal generators contribute 74% of electricity supply in the NEM, while the gas powered generators deliver 12% of supply. In NSW and QLD, the weight of coal fired generation is more than 65%, while it is around 50% in VIC (Australian Energy Regulator (AER), 2013b). In general, the coal-fired generators have higher emission intensity than gas-powered generators. As the carbon price is determined by the emission intensity (Equation (1)), which is dependent on the combustion efficiency, the different energy consumption structure for electricity generation leads to discrepancy in price increase across states.

Furthermore, other factors also contribute to the price and intraday volatility increase over the lifetime of the CPM. According to the estimation by AER, the average carbon pass-through to the spot price is 17.70 $/MWh. However, the average price increase in 2012-13 across NEM is around 31 $/MWh (Australian Energy Regulator (AER), 2014a). The statistics by AER (2014) indicate that the network upgrade and other expenditures cause an increase of wholesale electricity price. This echoes the results from previous work done by O'Gorman and Jotzo (2014). Moreover, the removal of the carbon component does not eliminate the volatility increase observed in the electricity markets. The visual observation suggests that the more frequent occurrence of peak volatility drives up the average volatility level (Figure 3). In addition, the stable implied volatility in the electricity derivative market indicates that the market does not anticipate fundamental changes in electricity price (Figure 4). This suggests that factors such as congestion and unexpected peak demand due to extreme weather also influence the price volatility. Therefore, it can be concluded that the CPM is not
the major cause for the volatility adjustment.

4.2 Smooth Price Transition in the Electricity Derivative Market

The STAR modelling results extends the knowledge regarding the price transition characteristics in the electricity derivative market under the effect of the CPM. The transition coefficient $\gamma$ indicates a convincing smooth transition process in the derivative market, as it is no more than the unit transition speed for most of the electricity derivatives (Table 2). Since the carbon price is not inclusive in the OTC derivative contracts, the transition is only obvious in the ETD market, where the abundant liquidity and speculation gradually push up the price level. Furthermore, because of its function for price discovery and ad hoc risk management, the price transition in the ETD market starts prior to the CPM introduction from a lower level (Figure 2). In addition, the transition speed $\gamma$ also finds its application in risk management practice. For instance, under the circumstance of policy intervention such like the CPM implementation, a high transition speed $\gamma$ is a clear signal for rapid price increase, which could imply a rising nervousness in the market.

The different price path implies difference in market liquidity and flexibility between the ETD and OTC market. Although the Financial Services Reform Act 2001 sets disclosure provisions for the OTC market, its characteristics still lead to less transparency in volume, price and counterparties comparing to the ETD market (AER, 2012). As the tailored contracts, the OTC derivatives are usually bound between counterparties, which are inflexible for further price renegotiation and trading among others. Consequently, the reassignment of counterparty usually requires assistance from the intermediaries, which increases the transaction time and costs. Moreover, the concerns over the risk of the credit worthiness depresses the trading desire mutually. The increasing ETD market turnover in the carbon price era reflects its advantage in lower market barrier and swift price reaction. In comparison, the price transition in the OTC market is lagged and less sensitive.
4.3 Speculation Induced Liquidity Growth in the Electricity Derivative Market

The increasing liquidity shows that the CPM affects the trading activities in the electricity derivative market. Because of its function for ad hoc price risk management, the market transition takes place prior to the CPM introduction. While the total demand of NEM fluctuates between 187.87 TWh and 197.36 TWh, the total turnover of electricity derivative market reaches the highest level of 863.24 TWh in 2010-11. As the result, the liquidity ratio of the total electricity derivative market mounts up to 4.5 in the same time (Table 1). The liquidity of the electricity derivative market remains at a higher level in the subsequent periods. It implies an increasing ad hoc hedging need for the future electricity price uncertainty under the influence of the CPM.

The SPEC ratio and the market participant structure explain the reason for the increasing liquidity in the electricity derivative market. As in Figure 6, there is accumulated speculation in the ETD market since the third quarter of 2011. And it fades away quickly after the end of 2012. In the meantime, the financial intermediaries become increasingly active in the electricity derivative market in 2011-12 (Figure 8). As the evidence, the volume traded by them is almost doubled comparing to the previous period. However, the turnover by financial intermediaries shrinks radically in 2012-13, while the generators and retailers regain the market share. This dramatic change demonstrates that the financial intermediaries enter and exit the electricity derivative market in pursuit of speculative opportunities. They close the opening positions and leave the market once they extract the speculative profit, which is limited by the fixed rate carbon tax in the initial period of the CPM. This explains the decreasing turnover and SPEC ratio in the subsequent periods.
From another perspective, the participation of financial institutions also stimulates the development of electricity derivative market. Their expertise in sophisticated derivative contracts provides professional financial service to the customers from electricity sector. Moreover, the engagement of financial intermediaries also promotes the risk management innovation, which leads to the turnover growth for derivatives such as swaps, swaptions, collars and Asian options (Figure 5). The wider client coverage of financial intermediaries assists to enhance the market liquidity as well.

### 4.4 Implied Carbon Price and the Fate of the CPM

The implied carbon price reveals the market valuation on the CPM, and the expectation on its fate throughout the implementation (Figure 7). After announcement of the plan for carbon tax in February 2011, the speculation about the likelihood of establishing a carbon price amplifies the spread between the ETD and OTC derivative price (ABC, 2014). Since November 2011, the spread increases to above $20 after the pass of the Clean Energy Bill. On 1st July 2012, the enforcement of the CPM pushes the implied carbon price to the level beyond $23, which then stabilizes around $20.

---

11 A Collar is a compounded derivative contract comprised of simultaneous buying and selling options at different strike prices, which aims at limiting gain or loss within certain range. An Asian option is an exotic derivative, whose payoff is dependent to the average price of reference underlying within certain period. (Australian Financial Markets Association (AFMA), 2012b)
until early 2013. However, due to the controversy regarding the CPM during Australia's Federal Election Campaign, concerns over the policy uncertainty soars since early 2013. Meanwhile, the price collapse in EU ETS market also hits the confidence in the carbon price policy. As a result, the implied carbon price starts to decline. Although there is turbulence caused by the rivalry during the 2013 election campaign, the implied carbon price drops to lower than $5 at the end of 2013 after Tony Abott, who is always an opponent against the CPM policy, becomes the new Prime Minister (ABC, 2010).

4.5 Lessons from Australia's Carbon Pricing Mechanism

Australia's electricity sector achieved lower GHG emission during the lifetime of the CPM. Higher electricity prices, which are partially caused by the CPM, constraints the electricity demand and indirectly reduces the GHG emission. According to the statistics of Australian Energy Regulator (AER), the total electricity generation decrease from 204 TWh in 2010-11 to 194 TWh in 2013-14 (Australian Energy Regulator (AER), 2011, 2013a). Meanwhile, the emission intensity in the NEM decreases by 5.4% since the introduction of the CPM.

The enforcement of the CPM also motivates the switch to the cleaner energy in the electricity sector. The proportion of coal fired generation in NEM decreases by 7% in 2012-13, which is followed by a further decline of 5% in 2013-14 (Australian Energy Regulator (AER), 2014a). Meanwhile, the CPM and other climate change policy such as Renewable Energy Target (RET) boost together the generation capacity of renewable energy. The wind generators account for 6.3% of NEM capacity by the end of 2014. Around 1.3 million households across Australia install the rooftop Solar panel system. Most of the instalments take place since 2010-11 (Australian Energy Regulator (AER), 2014b).

Furthermore, the electricity derivative market demonstrate its advantage in limiting the price risk associated with the CPM. An efficient derivative market would
substantially reduce the risk associated with the carbon price policy. For instance, financial contracts such as cap, swaps and swaption are eligible to mitigate the price uncertainty, while leaving the potential for profit during the price adjustment in the carbon price era. More sophisticated trading strategy such as collar strategy could also lock in the speculative profit during price fluctuation period. Besides, by settling the carbon component separately at the maturity, the OTC market substantially lowers the risk from carbon price uncertainty for the participants.

The experience from Australia’s CPM is valuable to the countries that are proposing carbon price scheme. Robson (2014) points out that the CPM abolishment is due to the lack of good management, which causes additional fiscal burden and GDP impact. Furthermore, the fluctuating implied carbon price reflects the influence from the political side. Therefore, we urge that the carbon price should be used as policy instrument against the climate change rather than a political tool.

4.6 Remarks

As other time series models, the STAR model cannot capture the complete information in the electricity derivative price because of the high nonlinearity (De Jong & Huisman, 2002; Janczura & Weron, 2010; Janczura & Weron, 2012; Weron, Bierbrauer, & Trück, 2004). Meanwhile, there are still topics open for further research in terms of the CPM. These include questions such as the impact of policy uncertainty on electricity industry's abatement investment, the features of electricity derivative price volatility, the role of carbon price in electricity price variation and so on. Seeing the awareness of global cooperation in GHG reduction, the carbon market linkage should also gain attention.
5. Conclusions

In July 2012, Australia introduces the Carbon Pricing Mechanism (CPM) as the climate change mitigation policy. This paper studies its effect on the electricity spot and derivative markets. In contrast to the abrupt price adjustment in the electricity spot market, the price transition in the electricity derivative market is smoother. Furthermore, the exchange-traded derivative (ETD) and the over-the-counter (OTC) markets exhibit different price transition characteristics. We find that the CPM implementation is not the major cause for the volatility adjustment. The derived implied carbon price reveals the market expectation on the fate of the CPM throughout its life. The speculative opportunities due to the CPM implementation attracts the financial intermediaries into the electricity derivative market, whose activities significantly promote the market growth and liquidity.

The electricity derivative market demonstrates its advantage in absorbing the risk associated with the CPM. The engagement of financial institutions promotes the liquidity and market development. While Australia's electricity sector achieves lower emission during the lifetime of the CPM, it motivates with other policies together the transition to the clean energy in the electricity industry. The lesson from Australia’s CPM demonstrates the effect of environmental policy in constraining the greenhouse gas (GHG) emission in the energy-intensive sector. However, there are still considerable uncertainties influence the CPM. For the sustainable development of the human society, we encourage active and persistent engagement in the climate change policy.
Appendix A: BDS Test for Nonlinearity

As a nonlinear time series model, the nonlinearity of data is a prerequisite for the STAR model application. Besides the conventional linearity tests such as Tar-F Test, LR Test and Keenan Test (Gibson & Nur, 2011; Tsay, 1989), Brock, Dechert and Scheinkman (BDS) test is also favored by economists for purpose of testing nonlinearity (Brock, Hsieh, & LeBaron, 1991; Chu, 2001; Hsieh, 1991). This parametric asymmetry test is designed based on the spatial correlation concept from the chaos theory (Broock, Scheinkman, Dechert, & LeBaron, 1996), which was initially designed for testing independence and identical distribution (Brock et al., 1991). Its null hypothesis assumes that the data follow an independent identically distribution (I.I.D.). The favor of the alternative hypothesis indicates no linear dependency but the existence of nonlinearity (Belaire - Franch & Contreras, 2002; Lin, 1997).

The BDS test is completed in five steps with MATLAB according to the procedure developed by Kanzler (1999). After converting the time series data into first difference of natural logarithms (Equation (A1)), an embedding dimension value \( m \) will be selected, so that the time series could be transformed into \( m \)-dimensional overlapping successive vectors (Equation (A2)).

\[
[X_i]= [X_1, X_2, X_3, ..., X_N] \quad \text{(A1)}
\]

\[
X^m_{N-m} = (X_{N-m}, X_{N-m+1}, ..., X_N) \quad \text{(A2)}
\]

By adding the pairs of points \((i,j)\) among the \( m \)-dimensional space within a radius or tolerance \( \varepsilon \), spatial correlation among points could be measured as the correlation integral in Equation (A3).\(^{12}\)

\[
C_{\varepsilon,m} = \frac{1}{N_m (N_m - 1)} \sum_{i < j} I_{i,j,\varepsilon}, \quad \text{where} \quad I_{i,j,\varepsilon} = \begin{cases} 1 & \|x^m_i - x^m_j\| \leq \varepsilon \\ 0 & \text{else} \end{cases} \quad \text{(A3)}
\]

\(^{12}\) In the context of time series, spatial correlation measures the correlation between pairs of points within a range of \( \varepsilon \) along the time horizon.
The time series is I.I.D if \( C_{t,m} \approx [C_{t,1}]^m \) (Brock & Sayers, 1988; Kuok KunChu, 2001). In this study, the embedding dimension \( m \) is set to 2, and spatial distance \((\epsilon/\sigma)\) is set to 1.5. The results of BDS test are summarized in the table below.

### BDS Test Results

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### Critical Value

- OTC Base Load Quarterly Forward Curve
- OTC Base Load Strip Forward Curve

### Table A1: Results of BDS Test Statistics (\( \epsilon/\sigma = 1.5 \), \( m=2 \), \( n=\text{sample size} \))

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Source of critical value: (Kanzler, 1999)
Reference


AEMO Carbon Dioxide Equivalent Intensity Index Procedure, (2013).


Clean Energy Act, § 3-4 (2013).


