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Electricity Futures Markets in Australia – An Analysis of Risk Premiums during the Delivery Period

WORKING PAPER 16-03

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Abstract

We provide an empirical analysis of the changing risk premium of electricity futures contracts during the delivery period. As a futures contract enters delivery, it continues to be traded until expiry and the observed futures price can be decomposed into three parts: the crystalised value of the portion already delivered, the average spot price for the remaining days of the delivery period, and the risk premium for the remaining days of the delivery period. We examine ex-post or realized futures premiums during the delivery period for quarterly base and peak load contracts for the three main regional Australian electricity markets of New South Wales, Queensland and Victoria. We also examine drivers of the observed risk premiums such as open interest, time to maturity of the contract, current and historical spot electricity prices as well as the average historical behaviour of premiums. We find that risk premiums are positive during the delivery period for the majority of the considered contracts. Our results suggest that a model, using open interest, the remaining number of days until maturity, spot volatility in the previous month, price level in the previous week as well as the average premium of the same quarter in the previous three years, provides a relatively high explanatory power for the observed premiums. Our findings are of interest to market participants such as traders, retailers, producers, consumers and hedgers and are relevant in particular for risk management and hedging strategies during the delivery period of futures contracts.

JEL Classification: Q40, G32, G13, L94

Keywords: *Electricity Markets, Spot and Futures Prices, Risk Premiums, Hedging*

1. Introduction

Over the last two decades electricity markets all over the world have undergone a transition from monopolistic, government controlled systems into deregulated, competitive markets. One consequence of deregulated power markets is that market participants are exposed to substantial risk as pointed out by e.g. Weron (2006), Benth et al. (2008). Seasonal variation in demand and price as well as significant price spikes are well known features of these markets. In addition to the challenges posed by analysing a complex set of data, managing electricity price risk is limited by the fact that electricity is typically not yet economically storable and has limited transportability.

Typically, instruments such as electricity futures contracts that are traded over-the-counter or on organised stock exchanges can be used to manage the substantial risk of spot electricity prices. However, given the very volatile nature of electricity spot markets, prices for these contracts do not necessarily reflect expected levels of spot prices, but also contain substantial risk premiums that are driven by the demand for hedging. Various studies in the literature have studied the nature of these premiums and provide sometimes contradicting results on the magnitude and sign of observed premiums in electricity futures markets (Hadsell and Shawky, 2006; Diko et al., 2006; Bierbrauer et al. (2007); Wilkens and Wimschulte, 2007; Weron, 2008; Kolos and Ronn, 2008; Daskalakis and Markellos, 2009; Lucia and Torro, 2011; Redl et al., 2009; Redl and Bunn, 2013). Our paper adds to this literature, by providing a pioneer study that specifically focuses on the dynamics and explanatory variables of futures risk premiums during the delivery period.

The existing contradictory conclusions on the nature could be a result of different time periods until the delivery of the contract as well as characteristics of the considered delivery period itself. Handika and Trück (2015) argue that for the Australian electricity market, different quarters typically exhibit very different risk premiums due to seasonal characteristics of electricity consumption and spot prices. It can also be expected that high spot price levels, changes in volatility or the occurrence of price spikes will have an influence on observed risk premiums, see, e.g., Redl and Bunn (2013). A positive premium will typically exist when retailers have a demand for going long in near term contracts (lock in prices in the short term) in order to hedge the risk of high volatility or price spikes in the market. A negative premium is more likely to occur when the producers or generators of electricity hedge their future production by taking a short position in the futures markets (Benth et al., 2008). This usually occurs for contracts with longer maturities, as generators tend to hedge their risk far more in advance, often more than 12 months before the actual delivery period.

While existing literature on electricity futures markets has examined risk premiums in various contexts and markets in the U.S., Europe and Australia, to the best of our knowledge none of these studies has particularly focused on the dynamics and driving factors of risk premiums during the delivery period of the contract. Therefore, this paper fills an important gap in the literature: it is the first to examine premiums of futures contracts during a time period when observations of electricity spot prices for the delivery period have been observed already by market participants.

We make several contributions to the literature on risk premiums in electricity spot and futures markets. First, we develop an approach that allows us to extract futures risk premiums during the delivery period, by decomposing observed futures prices into three parts: the crystalised value of the portion already delivered, the average spot price for the remaining days of the delivery period, and the risk premium for the remaining days of the delivery period.

Second, we also examine whether factors that have been suggested to impact risk premiums in previous literature, are also relevant during the actual delivery period of an electricity futures contract, when the contract approaches maturity. Thus, we consider variables such as spot price levels, volatility or higher moments of the price series, as well variables related to the maturity of the futures contract. We further investigate whether the observed premiums exhibit a specific behaviour for different regional markets in Australia as well as for different delivery quarters throughout the year that are typically characterized by diverging regimes of price levels and volatility. Hereby, we argue that futures premiums are dynamic rather than static, that is the premiums vary from quarter to quarter and within each quarter depending on several factors. As pointed out by Huisman and Kilic (2012), these dynamics are challenging to analyse as we cannot single out a particular model for explaining risk premiums in different electricity markets.

A third additional contribution of our paper is that we also examine indicators of trading activity such as open interest and trading volume are possible determinants of the dynamics of futures risk premiums during the delivery period. We believe that incorporating these factors into our analysis is relevant, since these variables represent the level of participation in the market what should ultimately also impact on hedging activity as well as the price, market participants are required to pay for a hedge.

Overall, our study provides new and important insights for market participants such as generators and retailers, as well as regulators and policy makers who are interested in the magnitude and behaviour of risk in volatile electricity markets.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of spot and futures trading in the Australian National Electricity Market (NEM). Section 3discusses ex-post futures premium dynamics and their potential determinants. Section 4 describes the data and the applied model that is used to examine risk premiums during the delivery period. Section 5 investigates determinants of the observed futures premiums using regression analysis and finally, Section 6 concludes and provides suggestions for future work.

2. The Australian Electricity Market

The Australian electricity market has experienced significant changes during the last two decades. Prior to 1997 the market consisted of vertically integrated businesses operating independently in each State, without any connection between them. The businesses were owned by State governments and operated as natural monopolies. To promote energy efficiency and reduce the costs of electricity production, in the late 1990s the Australian government commenced significant structural reforms which, among others objectives, included the separation of transmission from electricity generation and the merging of twenty-five electricity distributors into a smaller group. Additionally, the electricity distribution was separated from the retail distribution arm. Competition was introduced so the State's electricity purchases could be made through a competitive process and customers were now free to choose their supplier.

The NEM began operating as a wholesale market in December 1998 and presently operates as an interconnected grid comprising several regional networks which supply electricity to retailers and end-users[1].The link between electricity producers and consumers is established through a pool which aggregates the output from all generators in order to meet the anticipated demand. Unlike many other markets, the Australian spot electricity market is not a day-ahead market, instead electricity is traded in a constrained real time spot market. Prices are set every five minutes by the market operator with generators submitting offers for every five minute interval. This helps determine the number of generators required to produce electricity in a more cost-efficient way based on existing demand. A final price is then determined for every half-hour for each of the regions as an average over the 5-minute spot prices for each trading interval. Based on the half-hourly spot prices, also a daily average spot price for each regional market can also be calculated (Australian Energy Market Operator, 2010).

There is also a number of over-the-counter (OTC) and exchange traded electricity derivatives for the NEM, including forwards, futures and options contracts, see, e.g., Anderson et al. (2007), Handika and Trück (2015). Next to bilateral OTC transactions between two entities directly, bilateral OTC transactions on standard products executed through brokers, electricity derivatives are also traded on an exchange through ASX Energy[2]. For the NEM, exchange traded contracts include quarterly, yearly and more recently also monthly base load and peak load futures. In our study we will concentrate on the typically most liquid quarterly futures contracts traded at ASX Energy from 1 July 2007 to 30 June 2014[3].

Like for most electricity exchanges, futures contracts traded on the ASX refer to the average electricity price during a delivery period. Thus, for a base period, a futures contract refers to the delivery of one Megawatt (MW) of electricity per hour for each hour from 00:00 hours to 24:00 hours over the duration of the contract. For a quarterly base load contract, the size will vary depending on the number of days within the calendar quarter. For example, for a quarter with 90 days, the contract size is 2,160 MWh during the delivery period while for a quarter with 92 days, it is 2,208 MWh. In addition to base load futures contracts, also peak

[1]The NEM includes the States of QLD, NSW, VIC and SA, while TAS is connected to the state of VIC via an undersea inter-connector

[2] See www.asxenergy.com.au.

[3]Note that ASX Energy also offers a number of alternative derivatives contracts including options and $300 cap products that are not considered in this study.

period contracts are traded referring to average electricity spot prices during the hours of 7.00-22.00 Monday to Friday (excluding public holidays) over the duration of the contract. This implies that the off peak period includes the hours from 22:00 to 07:00 on weekdays and all hours on Saturday, Sunday and public holidays. Therefore, the size of a quarterly peak period futures contract will vary depending on the number of days and peak-load hours within the quarter: for example a contract with 62 weekdays during a quarter (a so-called 62 day contract quarter) will equate to 930 MWh. Given that electricity prices show strong intra-day variation and are heavily affected by demand in every precise moment (Lucia and Schwartz, 2002), the distinction between the whole day and the peak delivery period is important for market participants.

Note that contracts in the Australian futures electricity market do not require physical delivery of electricity, but are settled financially which increases market liquidity, as participants who do not own physical generation assets can still trade the futures. The cash settlement price of a base (peak) period contract is calculated by taking the arithmetic average of the NEM final base (peak) load spot prices on a half hourly basis, rounded to two decimal places over the contract quarter. A provisional cash settlement price is declared on the first business day after expiry of the contract, while the final cash settlement takes place on the fourth business day after expiry of the contract.

3. **Ex-Post Risk Premiums in Electricity Markets**

The literature suggests that the difference between the futures price and the expected spot price can be interpreted as a compensation for bearing the spot price risk (Bessembinder and Lemmon, 2002; Longstaff and Wang, 2004). It is often referred to as the ex-ante risk premium. However, as the ex-ante premium is basically unobservable, empirical studies often concentrate on the ex-post or realized futures or forward premium in these markets:

$$RP_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \bar{S}_{[T_1,T_2]} . \quad (1)$$

Hereby, $RP_{t,[T_1,T_2]}$ denotes the realized risk premium measured as the difference between the quote for a futures base or peak load contract, $F_{t,[T_1,T_2]}$, referring to delivery period $[T_1,T_2]$ at time t and the actual average base or peak load spot price, $\bar{S}_{[T_1,T_2]}$ that is observed during the delivery period.

Empirical studies have generally found significant positive premiums in electricity forward or futures markets. Longstaff and Wang (2004) find positive risk premiums of up to 14 percent for the PJM day ahead market for the period Oct 2003 to May 2008, while Redl et al. (2013) find positive premiums for month-ahead forward contracts in the German EEX market for the period Oct 2003 to Jan 2010. They report premiums of 9 percent for base load and 12 percent for peak load contracts in the EEX market based on average monthly futures prices that fall to 5% and 7% when based on the futures price on the last day of trading. Botterud et al. (2010) report that futures prices tend to be higher than spot prices with risk premiums ranging from 1.3 to 4.4 percent for the Nord Pool market, when considering forward contracts with a delivery period from one week up to six weeks ahead. A number of other studies also confirm the significance of forward premiums in various electricity markets. Significant premiums are reported, for example, by Hadsell and Shawky (2006) for the New York Independent System Operator (NYISO), by Diko et al. (2006) for the EEX, the Dutch APX and French Powernext. Also, Bierbrauer et al. (2007), Wilkens and Wimschulte (2007), Weron (2008), Kolos and Ronn (2008), Daskalakis and Markellos (2009) report significant risk premiums for various electricity markets, including the EEX, PJM, Powernext, the Scandinavian Nord Pool market and the and England and Wales (E&W) market.

Interestingly, the studies provide quite different results on the actual sign of the risk premium even for the same markets: while Redl et al. (2013) find significant positive premiums for monthly base load and peak load futures contracts in the EEX, Kolos and Ronn (2008) find a positive forward premium for monthly, quarterly and yearly contracts in the EEX during the 2002-2003 trading period. Botterud et al. (2010) and Weron (2008) find positive (on average) risk premiums in the Nord Pool Asian options and futures prices, but in a more recent study, Weron and Zator (2014) report that futures premiums vary significantly over time and with time to maturity. Their finding suggest that for shorter maturities (i.e. 1 week) the futures premium is on average negative, while for longer maturities (i.e. 6 weeks) the premiums are on average positive. Bierbrauer et al. (2007) find positive ex-ante risk premiums for short-term futures contracts, while for contracts with maturities more than six months ahead the observed premiums are negative. Haugom et al. (2014) obtain similar results for medium-term futures contracts examining the Nordic power market. Overall, while the majority of authors seem to find rather positive risk premiums in electricity futures markets, the sign and magnitude of the premium seems to highly depend on the maturity of the contract. This will be of particular relevance for our study, since we examine risk premiums during the delivery period of the contract, i.e. premiums for contracts with typically very short maturities.

Another area of research has investigated the relationship between the risk premium and higher moments of price and demand. Starting with the work of Bessembinder and Lemmon (2002), and followed by other researchers such as Douglas and Popova (2008), Lucia and Schwartz (2002), Redl et al. (2009), Botterud et al. (2010), Furio and Meneu (2010). The research findings are mixed as to significance and sign. Longstaff and Wang (2004) find evidence supporting Bessembinder and Lemmon (2002) equilibrium model of a negative coefficient for the variance and a positive coefficient for the skewness of the spot price in the PJM market. Douglas and Popova (2008) find a negative coefficient for the variance and a positive coefficient for the skewness of the recent spot price in the PJM market. Most of their results are statistically significant. Lucia and Torro (2011) observe a positive coefficient for the variance and a negative coefficient for the skewness of spot prices during the delivery period in the Nord Pool power market for the time period mid 2003 till end of 2007. However, they find a negative coefficient for the variance and a positive coefficient for the skewness when considering futures prices from early 1998 until mid-2002. Their results are statistically significant for the skewness while for the variance, significant results are obtained only for the so-called pre-shock periods from 1998-2002. Redl et al. (2009) and Redl and Bunn (2013) add to the price moment terms other terms relating to oil price, spot market power and supply margin in the electricity market. They find positive coefficients for both variance and skewness of spot prices in the month prior to the delivery period when examining the EEX market. However, Redl et al. (2009) also obtain a positive coefficient for the variance and a negative coefficient for the skewness parameter for the Nord Pool market. Their results are statistically significant only for the estimated variance coefficient (EEX peak period) and the skewness coefficient (EEX base period). Botterud et al. (2010) find mainly negative coefficients for both variance and skewness of the spot price in the week prior to the delivery period in the Nord Pool market. However, only the coefficient for the variance one week prior to the delivery period is statistically significant. Finally, Furio and Meneu (2010) find negative coefficients for both variance and skewness in the Spanish electricity market. Also in their study, only the coefficient for the variance is found to be statistically significant.

In addition to the impact of variance and skewness, studies have also attempted to model the role of seasonality on the premiums. Interestingly, observed risk premiums in electricity futures markets seem to be subject to strong seasonal effects. Cartea and Villaplana (2008) conclude that the premium of monthly forward contracts is higher during months of high demand volatility. Lucia and Torro (2011), investigating risk premiums in the Scandinavian Nord Pool market, find that the statistical significance of premiums strongly varies throughout the year, being largest in winter, positive in autumn and insignificant in summer and spring. Handika and Trück (2015) also find strong differences between observed risk premiums for different quarters and markets for the Australian NEM and form the basis of our analysis where we analyse each quarter separately.

Interestingly, despite the large body of literature on analysing risk premiums in electricity forward and futures markets, to the best of our knowledge so far no study has focused on the behaviour of these premiums for contracts that have already partially been delivered. Our paper aims to fills this gap by undertaking a thorough analysis of ex-post futures premiums during the delivery period for quarterly electricity futures contracts in Australia. We believe that such an analysis will provide important and new insights on the hedging behaviour and the pricing of risk in electricity derivatives markets for contracts with short maturities.

4. **Modeling Approach**

In the following we will describe how futures risk premiums can be extracted from observed futures prices and the final settlement price of quarterly futures contracts. As mentioned earlier, for the Australian market, as a futures contract enters delivery, it continues to be traded until expiry. Thus, the quoted futures price can be decomposed into the value of the portion of electricity that has already been delivered, the expected average spot price for the remaining days of the delivery period as well as the risk premium for the remaining days of the delivery period.

We denote the first day of the delivery period of a futures contract as T_1, while the last day of the period – referring also to the expiry of the contract - is denoted by, T_2. A futures contract is written for 1 MWh[4], thus, the purchaser of a futures contract at time t (occurring before T_2) pays a price $F_{t,[T1\,,T2]}$ for 1 MWh over the entire period of the contract (i.e. from the start of delivery, T_1, until expiry of the contract at time T_2). The purchaser also receives an amount equal to the sum of the spot price over the same period, $S_{[T1\,,T2]}$. The contracts are cash settled for the difference between these two amounts and do not involve physical delivery of electricity. We investigate futures premiums at time t during the delivery period, i.e., $T_1<t<T_2$, where the premium is expressed as the difference between the futures price per MWh quoted at time t and the realized average spot price $\bar{S}_{[T1\,,T2]}$ per MWh during the delivery period $[T_1, T_2]$:

$$\pi_{t,[T1\,,T2]} = F_{t,[T1\,,T2]} - \bar{S}_{[T1\,,T2]} \tag{2}$$

Because we are operating in the delivery period of a futures contract, the observed futures price can be decomposed into three parts:

1) $\bar{S}_{[T1,t]}$ is the average spot price (in \$/MWh) already observed over the period between the start of delivery T_1 to the current day t. This period refers to the delivery of k_1 MWh.
2) $E\left[\,\bar{S}_{[t+1\,,T2]}\,\right]$ is the expected average spot price (\$/MWh) for the remaining k_2 MWh from time $t+1$ to expiry on day T_2.
3) $\pi_{[t+1\,,T2]}$ is the risk premium (\$/MWh) for the remaining k_2 MWh of the delivery period from time $t+1$ to expiry on day T_2.

There is no price risk embedded in the futures price relating to the first k_1 MWh that have passed and where the spot price is already known. Therefore the price risk reflected in the futures price relates to the period remaining to expiry (i.e. from $t+1$ to T_2). Therefore, we can extract the futures-implied average price per MWh for the remaining delivery period, $\bar{Q}_{[t+1\,,T2]}$, by using the following expression:

$$\bar{Q}_{[t+1\,,T2]} = \frac{1}{k_2}\left[(k_1 + k_2)F_{t,[T1\,,T2]} - k_1\bar{S}_{[T1\,,t]}\right] \tag{3}$$

The realized risk premium for the remaining k_2 MWh can then be calculated by subtracting the realized average spot price for the remaining k_2 MWh of the delivery period $\bar{S}_{[t+1\,,T2]}$ from the futures-implied average price for the remaining k_2 MWh, $\bar{Q}_{[t+1\,,T2]}$:

$$\pi_{[t+1\,,T2]} = \bar{Q}_{[t+1\,,T2]} - \bar{S}_{[t+1\,,T2]} \tag{4}$$

[4]MWh (Megawatt hour) is a unit of energy equivalent to one Megawatt (a unit of power) used continuously over one hour.

This expression of the premium for the remaining period of the contract allows us to study the behaviour of the premium per MWh over the entire delivery period.

Given the typically low liquidity in the Australian electricity futures market, it is important to note that we only use data on actual trades, i.e. observed prices on electricity futures. This is particularly important during the earlier years of our sample when trading was less frequent than in the latter part of the sample period.

As previously noted, empirical research on realized risk premiums in electricity futures exchanges has covered a number of markets and investigated premiums for different periods ranging from day-ahead to month-ahead and covered base load and peak load contracts. The equilibrium model proposed by Bessembinder and Lemmon (2002) has been investigated and extended by various researchers. They propose the following equation for the forward premium π_t

$$\pi_t = \alpha_0 + \alpha_1 MEAN_t + \alpha_2 STD_t + \alpha_3 VAR_t, \qquad (5)$$

Where MEAN, STD and VAR denote the mean of the electricity load for month *t*, and the standard deviation and variance of the daily electricity load for month *t*. The model has been adjusted and extended in many subsequent studies, and typically instead of using electricity loads, many authors use the electricity spot price as well as its standard deviation and variance of the spot price instead of the load. Several authors have further extended this model to include additional explanatory variables for the premium. For example, Redl et al. (2009) augment the model by adding a consumption index and a generation index from hydro and nuclear sources, while, among others, Handika and Trück (2015) augment the model by incorporating also higher moments of spot price behaviour such as skewness and kurtosis and the number of recently observed price spikes in the market.

Given our objective is to model the behaviour of futures risk premiums also with respect to the maturity of the contracts, we include the number of days left until the expiry (last day of delivery period) of the futures contract as a key variable in our model. Based on the literature we also test average spot price levels over the previous week, month and the same quarter in the previous 3-year period; the average premium of the same quarter in the previous 3-year period; volatility in the spot market; and additional risk measures, i.e. the number of price spikes, as explanatory variables in measuring the magnitude and behaviour of risk premiums in the examined markets. Finally, we also include variables related to demand (open interest) and liquidity (trading volume) of the considered futures contracts.

Further note that recognising the substantial differences in the observed risk premiums in the different delivery quarters, we estimate the models for each quarter separately. While it would be beneficial to have one model that is able to capture the dynamics of the realized risk premiums for all quarters simultaneously, we believe that the observed dynamics of the futures risk premiums would not justify such an approach. Further details on the included variables in the applied models will be provided in the next section

5. Empirical Analysis

5.1 Dataset description

Data on Australian electricity base load and peak load futures contracts is obtained from ASX Energy. As mentioned before in our analysis we only include futures closing prices for days where the contract has actually been traded in the market, i.e. the traded volume is greater than zero[5]. In our analysis we cover three major regional markets in the NEM, namely New South Wales (NSW), Queensland (Qld) and Victoria (Vic). Note that we decided to exclude the South Australian (SA) market due to the small number of observations particularly for the peak futures contract. The peak periods are defined as the working day hours between 07:00 and 22:00. Given that public holidays in Australia vary from State to State, peak contract hours are not uniform across the considered markets. The public holidays applicable to the peak load contracts are published by the ASX and are different from those nominated by the market operator uniformly across all States in the NEM.

The premiums for the base and peak load contracts are calculated based on equation (4), where the term $\bar{S}_{[t+1,T2]}$ is calculated as the average realized spot price for the remaining hours of the delivery period. The term $\bar{Q}_{[t+1,T2]}$ is calculated using equation (3), based on the already observed average spot price up to period t, $\bar{S}_{[T1,t]}$, the closing daily futures price and the number of days remaining to expiry. Futures contacts typically trade with varying frequencies and liquidity on the ASX, with the quarterly contract being the most liquid. This gives sufficient observations and an opportunity to compare seasonality across the different quarters. Furthermore, while the ASX has a clearly defined procedure for arriving at the daily closing price on days when no trade has occurred, we only use data from the days where the contract is traded. This ensures that the corresponding calculated premium reflects the actual value placed by markets participants on the contract.

The spot data consists of half hourly spot electricity prices for the period 1 July 2007 to 30 June 2014 published by the market operator AEMO.[6] The average daily price is the arithmetic mean of forty eight half hourly prices which is then used to calculate most of the variables and statistics except weekly standard deviation, skewness, kurtosis and the weekly and monthly spike counts, all of which are based on the half hourly prices.

5.2 Average risk premiums during the delivery periods

In a first step we investigate the significance of futures premiums during the delivery period. Hereby, the futures-implied risk premiums calculated from equation (4) are initially regressed on a constant only, and then the significance of the estimate of the intercept being different from zero is examined. We use White's heteroskedasticity robust standard errors to calculate the t-statistic and the corresponding p-values to evaluate significance. The findings in Table 1 show that the average premium over the sample period is positive and significantly different

[5]Traded volume is the number of contracts traded on a given day on the ASX Electricity Futures market.

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

from zero except for Q2 in Victoria and Q4 in NSW where base load contracts are found to have statistically insignificant negative premiums of -0.44 (p-value 0.44) and -2.30 (p-value 0.21) \$/MWh, respectively. All remaining premiums for base and peak load contracts are positive and statistically significant with, for example, the Q3 peak load contract in Queensland having a p-value of less than 0.0035. Average significant premiums for base load contracts typically are between \$3-\$6 per MWh for NSW, between \$2.50-\$9.50 for Qld, and between \$4.50-\$10 for Vic. For peak load contracts, average premiums are significant and positive for all States and quarters and range from \$2.83-\$5.51 in NSW, from \$3.79-\$9.24 for Qld, and from \$2.59-\$6.50 for Vic.

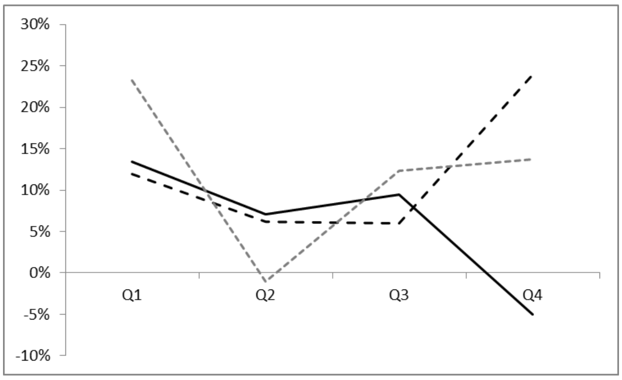
The positive premiums in all quarters and across the three States most likely indicate that, buyers of electricity futures contracts (retailers, large consumers and possibly speculators) are willing to pay an additional risk premium above the expected average price to cover their exposure to electricity spot price risk. The sellers on the other hand, comprising of producers and speculators, seem not to be under pressure to hedge their positions during the delivery period and can ask for an additional premium to take a short position in a futures contract. The evidence of significant and positive premiums is in line with findings by, e.g., Bunn and Chen (2013) who also find positive premiums in peak load contracts. Note that these premiums imply quite a substantial additional cost for someone taking a long position in the futures contracts. For example, consider a quarterly base load contract with 92 days, i.e. referring to 2,208 MWh. Thus, if a large consumer in NSW decides to buy Q1 base load futures contracts halfway through the delivery period, on average the consumer would pay an approximate additional risk premium of \$6,500 per contract to hedge spot price risk.

Table 1
Observed ex-post futures premiums (in \$/MWh) for quarterly base load and peak load futures contracts in NSW, Qld Vic for the time period Q3 2007 – Q2 2014.

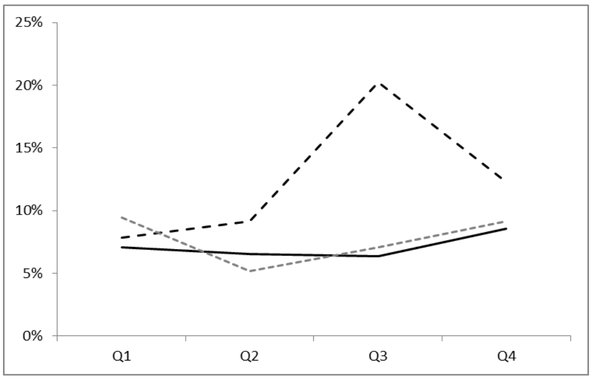
		Base load			Peak load		
State	**Quarter**	**Mean**	**t-stat**	**# Obs**	**Mean**	**t-stat**	**# Obs**
	Q1	5.97***	6.16	206	4.15***	10.45	52
	Q2	3.08***	9.48	161	2.83***	14.45	39
	Q3	3.56***	8.23	147	3.08***	9.85	42
	Q4	-2.30	-1.25	188	5.51***	12.07	65
Qld	**Q1**	6.11***	5.35	242	6.00***	12.72	44
	Q2	2.46***	8.07	133	3.79***	3.59	15
	Q3	2.66***	6.07	105	9.24***	3.79	12
	Q4	9.51***	6.58	195	6.73***	8.13	22
Vic	**Q1**	10.04***	14.03	195	6.50***	7.84	38
	Q2	-0.44	-0.78	139	2.59***	8.50	33
	Q3	4.95***	8.41	123	3.48***	9.19	28
	Q4	4.77***	6.98	123	4.05***	3.44	23

(***significant at 0.01; **significant at 0.05; *significant at 0.10)

In order to get a sense of the magnitude of the premium relative to the spot market for base load, in the following, the premium is expressed as a percentage of the corresponding spot market average price for each quarter in each State. In Panel A of Figure1 for Qld and Vic, we observe that the premium is higher during periods of high demand, i.e., in Q1 and Q4 compared to Q2 and Q3. For NSW, during Q1 the premium is also higher than for Q2 and Q3. Recall that the negative values for the premiums are not significantly different from zero.



Panel A: Base Load



Panel B: Peak Load

Figure 1: Premiums for base and peak load as a percentage of the corresponding average spot price for the three States of NSW (solid line), Qld (dashed line) and Vic (dotted line) in the sample period July 2007 to June 2014

Having established that the average premiums are highly significant and positive, we report the descriptive statistics of the premiums in Table 2 and 3. The number of observations reported is the number of days on which a contract referring to the specific quarter (Q1, Q2, Q3, Q4) and State (NSW, Qld, VIC) has actually been traded. We observe that in general base load contracts exhibit a higher trading frequency than peak load contracts. We further find that for the base load, the most frequently traded contracts are in Q1 and Q4. This is consistent with the fact that these quarters exhibit higher spot price volatility which drives interest in covering positions and therefore liquidity and trading frequency. The peak load follows a similar pattern with the exception of NSW where Q4 contracts are traded at a high frequency than Q1.

Other observations to note are that the standard deviation of the premium is lower for peak load than for base load contracts. The coefficients of variation, although not reported here, are below 100% for all peak contracts except for Q4 in Victoria and Q2 in Qld sitting at 143% and 112%, respectively. By contrast, the magnitude of the coefficient of variation for base load contracts is above 100% for all quarters. Less than half of the 12 base load quarters (four quarters by three States) are positively skewed whereas all peak quarters are positively skewed. This is consistent with the finding that the minimum premium is negative for all base contracts but negative for only 3 peak contracts. Moreover the minima for base contracts have large negative magnitudes but are only small when they occur for the peak. This finding of a consistent positive peak premium compared to base premiums suggests that buyers of these contracts (large consumers and retailers) are more risk averse and, thus, more willing to pay a premium to hedge their exposure to spot price risk.

Table 2
Base Load descriptive statistics of observed ex-post futures premiums ($/MWh)

State	Quarter	# Obs	Mean	StdDev	Skewness	Kurtosis	min	max
NSW	**Q1**	206	5.97^{***}	13.92	-1.53	6.15	-42.11	30.62
	Q2	161	3.08^{***}	4.14	0.77	4.57	-5.90	20.39
	Q3	147	3.56^{***}	5.27	1.83	12.52	-8.86	36.09
	Q4	188	-2.30	25.33	-1.63	4.47	-75.61	28.83
Qld	**Q1**	242	6.11^{***}	17.81	-0.33	3.45	-52.24	47.28
	Q2	133	2.46^{***}	3.53	-0.25	4.03	-8.27	13.55
	Q3	105	2.66^{***}	4.49	0.90	4.38	-8.04	18.72
	Q4	195	9.51^{***}	15.79	1.32	5.72	-22.39	66.32
Vic	**Q1**	195	10.04^{***}	10.02	-0.05	2.91	-17.74	37.99
	Q2	139	-0.44	6.71	0.34	8.03	-19.40	33.66
	Q3	123	4.95^{***}	8.33	2.39	10.88	-9.24	40.92
	Q4	123	4.77^{***}	7.59	-0.00	6.99	-19.13	34.61

(***significant at 0.01; **significant at 0.05; *significant at 0.10)

Table 3
Peak Load descriptive statistics of observed ex-post futures premiums ($/MWh)

State	Quarter	# Obs	Mean	StdDev	Skewness	Kurtosis	min	max
NSW	**Q1**	52	4.15^{***}	2.89	0.08	4.25	-2.70	11.56
	Q2	39	2.83^{***}	1.24	1.36	3.78	1.63	6.26
	Q3	42	3.08^{***}	2.05	1.64	5.28	0.82	9.69
	Q4	65	5.51^{***}	3.71	2.78	12.76	1.80	23.62
Qld	**Q1**	44	6.00^{***}	3.17	0.49	2.73	-1.10	13.49
	Q2	15	3.79^{***}	4.24	2.09	5.58	1.33	14.86
	Q3	12	9.24^{***}	8.81	1.23	3.04	2.31	28.41
	Q4	22	6.73^{***}	3.98	0.63	1.91	1.78	14.18
Vic	**Q1**	38	6.50^{***}	5.18	2.56	9.89	1.68	28.05
	Q2	33	2.59^{***}	1.78	1.08	5.01	-1.31	8.18
	Q3	28	3.48^{***}	2.04	1.26	4.94	0.83	10.09
	Q4	23	4.05^{***}	5.77	2.26	8.00	0.39	24.52

(***significant at 0.01; **significant at 0.05; *significant at 0.10)

5.3 Model development

We estimate a multiple regression model by pooling the premiums of each quarter across the different States markets as we expect the premium drivers to be similar across different NEM regions on a quarterly basis. This expectation is reasonable, since (i) the physically interconnected transmission networks that allow the flow of electricity, subject to capacity constraints, between the NEM regions and (ii) the common seasonal drivers of demand in these States (including climate) contribute to common dynamics of the price levels and, potentially, premiums across the States.

We employ a 2-step procedure to select the explanatory variables to be included in the model. First, we systematically introduce suitable explanatory variables deemed as driving factors of the premium, as this allows us to assess the significance, sign and strength of the relationship of each variable. The suitable variables are then shortlisted as we perform a correlation analysis between the pairs and ultimately decide on a suitable model. The second step minimises the chance of multicollinearity which can occur if we select explanatory variables that are highly correlated with each other. The outcome of these two steps is a multiple regression model which we analyse to provide insights into the dynamics of the premium during the delivery period. In step 1, we first test the role of liquidity by incorporating volume (number contracts traded on a given day) and open interest in driving the premium as these variables represent the level of participation in the market. Huisman and Kilic (2012) emphasise the role liquidity as a higher traded volume indicates a higher degree of competition. Open interest (OI) is the number of contracts on a given day that have not been closed by a trade or exercised thereby offsetting the original position. Given the magnitude of the OI relative to the other variables we scaled it by dividing the data by 1,000 so a magnitude of 1 signifies 1,000 contracts. Bessembinder and Lemmon (2002) argue that the presence of speculators is likely to reduce premiums as speculators are initially drawn to markets experiencing high premiums, but their ensuing competition drives premiums down. Speculators are more likely to maintain open positions in the commodity hence our inclusion of this variable.

Next the time to expiry (expressed here as days to expiry) on the futures contract is selected to examine its potential influence on the premium. The closer the contract is to expiry, the shorter is the period of uncertainty and potentially the lower is the premium. However, as we discuss later in the paper, there are other influences on the premium of quarterly contracts at least in the context of the Australian market. Time to maturity is well established in the literature as a factor affecting pricing and premium of futures contracts. Diko et al (2006) find that the premium depends on time to maturity due to the risk of price spikes in peak hours. This finding is in line with the model developed by Bessembinder and Lemmon (2002). Wilkens and Wimschulte (2007) also find that time to maturity is one of the factors affecting the premium. Benth et al (2013) investigated the pricing of future contracts depending on time to maturity. While Kolos and Ronn (2008) find a positive premium for short time horizons in electricity markets.

We next test the dependence of the premium on average historical spot prices of prior periods in line with Bessembinder and Lemmon (2002), Wilkens and Wimschulte (2007) and Handika and Trück (2015) who find that the premium depends on the price level of spot electricity prices. We explore the impact of the long, medium and short term average spot price using the 3 year, monthly and weekly average spot price. If the premium is found to be dependent on the long term variable, this could indicate learning by market participants from the information on historical behaviour of the spot price contained in this variable. Similarly, dependence of the premium on short term spot price behaviour could indicate the influence of more recent information on the premiums. We define the 3 year average price as the average spot price of the same quarter over the previous 3 years while the average monthly spot price is the average over the 28 days (four week period) prior to *t* and finally the average weekly spot price is the average of the week prior to *t*. It is worth clarifying that a four-week period rather than a calendar month was selected to ensure the same number of weekdays and weekends in each such period.

We estimate the dependence of premium on risk employing the standard deviation, skewness and kurtosis of the distribution of spot prices over the long, medium and short horizons as proxy. The 3 year, month (28 days) and weekly periods are used as defined for the average spot price. Our decision to estimate the impact of these variables is motivated by the fact that Redl et al. (2009), Redl and Bunn (2013) and Handika and Trück (2015) include higher moments of spot electricity prices (kurtosis) to cater for the impact of fat tails in the price distribution which motivates exploring these terms. Note that there are no clear-cut results on the sign of these terms: Benth et al. (2013), for example, find a positive coefficient for variance and a negative coefficient for skewness contrary to the findings of Bessembinder and Lemmon (2002).

We also capture the potential dependence of premiums on the number of monthly and weekly price spikes, an alternative indicator of risk proposed in the literature. The presence of price spikes (i.e. prices higher than normal) indicates volatility, with a higher count indicating potentially higher volatility. However, there is no universally agreed definition of a price spike in the literature. A spike has been defined by reference to an arbitrary price level, Lapuerta and Moselle (2001), or when returns exceed a threshold, such as three standard deviations, Cartea and Figueroa (2005), to name but two approaches. In this paper we adopt a market based approach and define a spike as a half-hourly price exceeding $300/MWh corresponding to the Cap Futures Contracts traded on the ASX that participants can use to hedge their exposure.[7] Thus we define the number of monthly spikes as the number of half hourly spot prices exceeding $300/MWh during the 28 days (four weeks) prior to *t*. The short term impact is captured using a weekly spike count based on half hourly spot prices exceeding $300/MWh during the seven days (one week) prior to *t*.

The historical behaviour of the premium is also likely to influence the pricing of future contracts as this indicates the risk embodied in the premium. We capture this by including the 3-year-average premium which is the average of the daily premium of the same quarter over the previous 3 years. We also use yearly dummy variables to investigate the premium relative to a base year which is chosen as the Australian financial year from 1st July 2011 to 30th June

[7]Quarterly Base Load $300 Cap Futures Contracts are for 1 Megawatt per hour for the base load profile. The cash settlement value is the cash settlement price multiplied by the size of the contract in MWh. The cash settlement price is the weighted average price of half hourly prices exceeding $300/MWh in the quarter. It is calculated for each Region (corresponds to a State) according to the following formula published by the ASX.

The Cash Settlement Price = (C - (300 x D)) / E, where:
C = the sum of all base load half hourly spot prices for the Region in the Calendar Quarter greater than $300.
D = the total number of base load half hourly spot prices for the Region in the Calendar Quarter > $300
E = the total number of base load half hour spot prices for the Region in the Calendar Quarter.

2012 (FY2012). This particular year is selected as the carbon tax commenced on the 1st of July 2012. In order to capture the role of the carbon tax an additional dummy variable is included for this period[8]. While it is rational to expect that the price of carbon will be reflected in the price of power it is not immediately obvious how it may impact the premium. Daskalakis and Markellos (2009) report a positive relationship between the emissions allowance spot returns on the European Emissions Trading Scheme and premium in the electricity markets of EEX, Nord Pool and Powernext.

We include variables if they are found to be significant in three or more quarters and are estimated individually in a bivariate setting. The explanatory variables are included if they are found to be significant in three or more quarters. Based on this for base load contracts, Open Interest, time remaining to expiry of the futures contract (T_2-t), the 3-year-average spot price, the 3-year-average premium, the monthly standard deviation, the average weekly spot price, weekly standard deviation, monthly and weekly spike counts, a carbon tax dummy and the year and State dummies are included in the model. For the peak load, the following variables are selected: the average monthly spot price, the monthly standard deviation, the time remaining to expiry of the futures contract (T2-t), the average weekly spot price, the weekly standard deviation, weekly skewness, the monthly and weekly spike counts as well as the year and State dummy variables.

Overall, we find a wider spread of short, medium and longer term variables driving premiums during for base load contracts, while it seems that shorter and medium term factors play a dominant role for peak load contract premiums. From table A.1 (base load) and A.2 (peak load) presented in the Appendix, we can see that the coefficient of the 3-year-average spot price and 3-year-average premium is significantly different from zero for the base load model but not for the peak. Additionally, all monthly and weekly variables are found to be significant for base load contract premiums, including the average monthly spot and weekly skewness (absent from base load). Further, the coefficient of open interest is significant only in the case of base load, while time to expiry is significant for both base load and the peak load contracts. We also find that the remaining variables are not consistently significant across the quarters, do not exhibit a pattern and are therefore excluded from the model.

In a next step, based on the results for the univariate regression models, we continue our analysis by examining linear correlations between pairs of the selected explanatory variables with particular focus on a subset of uncorrelated variables so as to avoid multicollinearity in the multiple regression model. The pairwise correlations for Q2 are presented in Table 4 as an

[8] The scheme required around 500 entities with more than 25,000 tonnes of carbon dioxide direct emissions per year, carbon for simplicity, to surrender certificates (one certificate equivalent to one tonne of carbon) on an annual basis to acquit their emissions or pay a fine. The scheme was originally divided into two phases with the first phase being a fixed price phase while the second had planned the price of emissions to be determined by an emissions trading market under a cap and trade scheme. In the fixed price period the price of emission certificates was set at $23 rising by 2.5% per year in real terms. Note that the scheme was abolished by July 2014 such that only the fixed price carbon tax between July 2012 – June 2014 is relevant for our analysis.

example. All other correlations across the remaining quarters are available upon request but some key findings are discussed below.

Table 4
Correlation matrix of significant explanatory variables from observed ex-post futures premiums during the delivery period –Base load Quarter 2.

	Open Int	T2-t	3yr. Spot	3yr. Prem	m.SD	w. Spot	w.SD	m. Spike	w. Spike	Carbon Tax
OpenInt	1.00									
T2-t	-0.06	1.00								
3yr.Spot	0.29	-0.03	1.00							
3yr.Prem	-0.19	0.02	-0.93	1.00						
m.SD	0.12	0.03	0.21	-0.09	1.00					
w.Spot	0.08	-0.02	-0.07	0.13	0.51	1.00				
w.SD	0.10	0.00	0.14	-0.05	0.64	0.85	1.00			
m.Spike	0.12	0.06	0.27	-0.15	0.94	0.45	0.63	1.00		
w.Spike	0.10	0.04	0.14	-0.05	0.65	0.81	0.97	0.63	1.00	
Carbon Tax	-0.04	0.04	-0.38	0.34	-0.10	0.41	-0.06	-0.15	-0.08	1.00

For base load premiums, the monthly standard deviation variable is significant in all four quarters and is positively correlated with its weekly counterpart in Q2 and Q4. To avoid multicollinearity only one of the two standard deviation variables should be included in the multiple regression model. Further, the average weekly spot price variable is highly positively correlated with weekly standard deviation in three quarters but it is not correlated with monthly standard deviation and hence we only retain the monthly standard deviation and average weekly spot. The monthly spike count is correlated with the monthly standard deviation in three quarters while the weekly spike count is highly correlated with average weekly spot prices in Q2 (ρ=0.81) and Q4 (ρ=0.78). Therefore both spike count variables are excluded from the multiple regression model. Since, the carbon tax dummy is positively correlated with the yearly dummy variables for 2013 and 2014, we decided to drop it in favour of retaining yearly dummies. The average 3-year premium and the average 3-year spot price are negatively correlated for Q2 and to a lesser extent for Q1 (ρ=-0.63). Including the spot variable, whether on its own or with the premium variable, results in an extremely high intercept term and therefore we retain the average 3-year premium and drop the average 3-year spot.

For the peak load contracts we investigate the three monthly variables that produced significant results in the univariate regressions. The monthly standard deviation is significant in all four quarters and is highly positively correlated with the average monthly spot price in Q1 and Q4. The latter variable is significant in three quarters and therefore monthly standard deviation is retained, while the average monthly spot price is excluded from the model. Given that price variability increases with spikes, it is not surprising that the monthly spike count is highly positively correlated (Q1, Q2 and Q4) with the monthly standard deviation. As a result, the monthly spike count is also excluded from the model. Further, for the peak load model, the time remaining to expiry (T_2-t) of the contract is significant in all quarters and is not correlated with any of the other variables and therefore (T_2-t) as well as the monthly standard deviation are included in the model. The dummy financial year (FY 2012) and State (NSW) dummy are the base dummies similar in line with the base load model.

Similar to the case for variables being based on observations for the last month, also the weekly spike count, weekly standard deviation and weekly average spot price are highly correlated. Among these variables, based on the univariate regression, the average spot price over the last week yields the best results and is included into the model.

Overall, the following multiple regression model (6), using both short-term, medium-term and long-term explanatory variables is estimated for the realized risk premiums for base load futures contracts in the three market:

$$\pi_{[t+1,T2]} = \beta_0 + \beta_1(OI) + \beta_2(T2 - t) + \beta_3(m.SD) + \beta_4(w.Spot) + \beta_5(3yr.P) + \delta_1(FY08) + \delta_2(FY09) + \delta_3(FY10) + \delta_4(FY11) + \delta_5(FY13) + \delta_6(FY14) + \theta_1(Qld) + \theta_2(Vic) \quad (6)$$

For realized risk premiums for quarterly peak load futures contracts in NSW, Qld and Vic, the following model (7) is estimated:

$$\pi_{[t+1,T2]} = \beta_0 + \beta_1(T2 - t) + \beta_2(m.SD) + \beta_3(w.Skew) + \delta_1(FY08) + \delta_2(FY09) + \delta_3(FY10) + \delta_4(FY11) + \delta_5(FY13) + \delta_6(FY14) + \theta_1(Qld) + \theta_2(Vic) \quad (7)$$

Recall that, hereby, $\pi_{[t+1,T2]}$ denotes the premium in \$/MWh remaining from day t+1 in the delivery period till the expiry of the quarterly futures contract, OI is the open interest expressed in thousands of contracts, T_2-t is the number of days remaining till the expiry of the contract, m.SD is the monthly standard deviation of electricity spot prices over the previous month (four weeks), w.Spot denotes the average daily spot price of the previous week, 3yr.P denotes the average realized premium for futures contracts in same quarter over the previous three years, while FY08 to FY14 are yearly dummies corresponding to the financial year in Australia. As previously mentioned FY12 is taken as the reference year with NSW used as a reference State, such that dummies for Qld and Vic are included.

Results for the estimation of model (6) are presented in Table 5. The models yield a relatively high explanatory power for the observed risk premiums during the delivery period. The coefficients of determination range from 0.347 for Q1 base load contracts up to 0.718 for Q3 contracts. Note that the explanatory power of the model is the lowest for Q1 contracts, where the regional markets are typically most volatile and also realized risk premiums for the futures contracts show the highest variation. On the other hand, for Q3, where the market is typically less volatile and also risk premiums in futures contracts are of lower magnitude, the model yields the highest explanatory power.

Table 5

Based Load multiple regression for the observed ex-post futures premiums (in $/MWh)

	Base load Q1	Base load Q2	Base load Q3	Base load Q4
Variable	**Coeff**	**Coeff**	**Coeff**	**Coeff**
Intercept	17.23*** (2.83)	5.91*** (3.63)	-5.09*** (-3.48)	-18.21*** (-3.13)
OI	-1.17 (-0.56)	-1.90** (-2.57)	-0.35 (-0.74)	8.24*** (3.39)
T2-t	0.07*** (3.42)	-0.04*** (-4.06)	0.01 (1.62)	-0.01 (-0.25)
m.SD	0.05*** (6.52)	0.01 (0.92)	0.10*** (3.46)	0.05** (2.28)
w.Spot	0.03*** (4.21)	0.03** (2.35)	0.15*** (3.34)	-0.02 (-0.35)
3yr.P	-0.88*** (-4.36)	-0.16 (-1.30)	0.08 (0.37)	-0.75*** (-6.99)
Dummy variables for years and States				
FY08	-5.09 (-1.50)	-1.27 (-0.35)	12.79*** (3.74)	21.70*** (6.16)
FY09	2.29 (0.85)	4.29 (1.07)	-6.45*** (-3.97)	7.38*** (3.30)
FY10	-3.51 (-1.03)	-1.43 (-0.33)	6.93*** (6.50)	-28.47*** (-6.36)
FY11	-18.05*** (-9.95)	5.66*** (11.27)	1.63 (1.42)	6.21*** (4.21)
FY13	-14.69*** (-9.85	-1.35 (-1.30)	-1.02 (-0.67)	-6.36*** (-3.38)
FY14	-15.95*** (-11.13)	3.90*** (4.53)	-0.69 (-0.56)	-5.68*** (-3.42)
Qld	-0.49 (-0.25)	-2.49*** (-3.31)	-0.67 (-1.28)	24.47*** (9.06)
Vic	0.98 (0.91)	4.71*** (4.42)	0.30 (0.55)	19.37*** (8.10)
Adj R^2	0.347	0.395	0.718	0.545
Obs	645	433	383	510

(***significant at 0.01; **significant at 0.05; *significant at 0.10)

For the individual variables, we find that OI is significant and negative in Q2, with Q4 returning a large positive and significant coefficient. The result of Q4 indicates that premiums are driven by high degrees of risk aversion with consumers willing to pay a high premium. The significant and negative coefficients in Q1 and Q2 are consistent with the findings in Bessembinder and Lemmon (2002) which state that the presence of speculators is expected to reduce premiums. The significant and small coefficients for the variable T_2-t in Q1 and Q2 indicate that as the contracts approach maturity premiums adjust very slowly, while interestingly Q1 and Q3 are positive whereas Q2 and Q4 are found to be negative. Initially, the negative coefficients for Q2 and Q4 are counter intuitive as a longer period to maturity carries more risk and the coefficient of this variable is therefore expected to be positive. However, we explain the negative coefficients of Q2 and Q4 with reference to the behaviour of the standard deviation of the spot price across the different months in Figure 3. The last month of Q2 (June) is the beginning of winter in Australia and given the change in temperature compared to the previous two months the standard deviation of the spot price for the June month is 17.74, compared to 12.28 and 12.21 for April and May. These results give a strong indication that risk averse consumers will be willing to pay a premium to hedge their risk exposure. As we draw closer to expiry, the effect on the premium as a result of higher volatility in the last month of the contract becomes more prominent. This outcome is similar for Q4 where the first month of summer (December) in Australia exhibits a higher volatility (98.91) compared to November (93.80) and October (89.05).

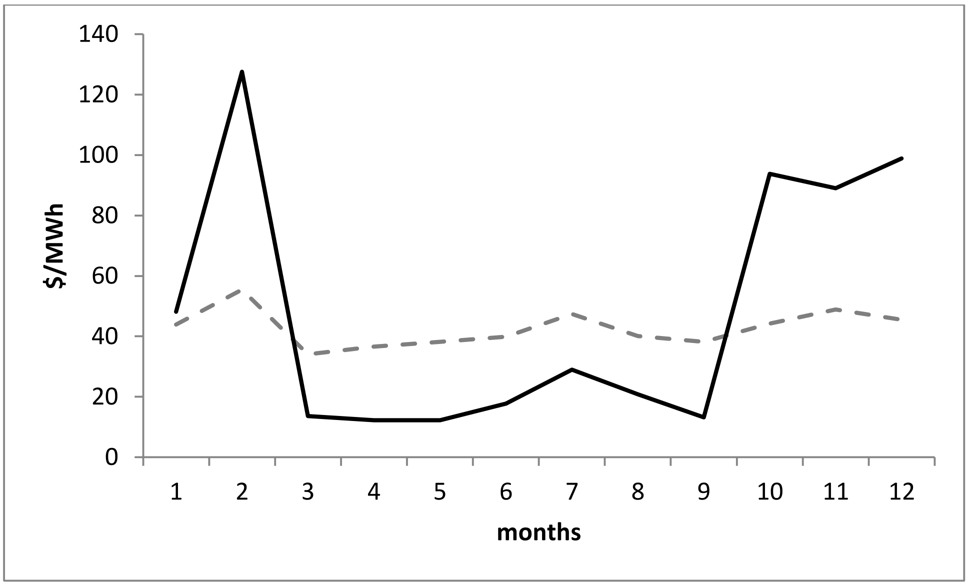


Figure3: Average (dotted line) and standard deviation (solid line) of daily spot price for base load by month in the sample period July 2007 to June 2014 in NSW

The monthly standard deviation of spot electricity prices (m.SD) and the average weekly spot price level (w.Spot) have positive coefficients consistent with the expectation that higher volatility and higher price levels of the recent past lead to higher risk aversion translated in higher premiums. The average premium of the same quarter in the previous three years (3yr.P) is significant in Q1 and Q4, which typically exhibit higher volatility as illustrated in Figure 3. The coefficient is negative in all quarters except Q3, what can be interpreted as participants learning from previous experience and correcting the premium they pay for the current quarter – paying a lower premium if they paid higher previously and vice versa.

The predominantly negative coefficients of the financial year dummy variables FY13 and FY14 show that during the period of the carbon tax risk premiums during the delivery period were typically lower in comparison to 2012. The sign is mixed for the years prior to 2012. Looking at the State dummy variables we see that, compared to NSW, the premium is significantly lower in Qld in Q2, while it is significantly higher in Vic for Q2 and for both markets (Qld and Vic) in Q4.

Next we report the results for peak load contracts in Table 6 based on estimating model (7). Note that when initially estimating model (7), using the raw observations for the risk premiums, a clear pattern in the plot of residuals versus fitted values was observed. Following Box and Cox (1964), we therefore employed a shifted Box-Cox transformation of the premium (dependent variable) to overcome this deficiency. The shifted transformation formulation is based on $y^{(\lambda)} = \frac{(y+\lambda_2)^{\lambda_1} - 1}{\lambda_1}$ $(\lambda_1 \neq 0)$. As noted in Box and Cox (1964) the analysis of variance is not altered by a linear transformation. The shift λ_2 for Q1 and Q2, which had negative premiums, is equal to the minimum of the observed premium for each quarter +\$0.1/MWh. Q3 and Q4 did not have negative values for the premiums and there was no need to shift the values (i.e. $\lambda_2 = 0$). We first shift the premium data then use Minitab version 16 to arrive at the optimum value of λ_1 for the transformation.

Note that peak contracts are typically traded less frequently than base load contracts during the delivery period. As can be seen in tables 6a and 6b the number of observations for peak load contracts is only about one fifth of the number of observations for base load contracts. The profile from quarter to quarter is about the same for base load and peak load. Q1 is the most frequently traded and Q3 is the least. Q4 is traded at about 80% of the frequency of Q1 while Q2 and Q3 are traded at about 60% to 67% of the frequency of Q1. The frequency of trading is one reflection of the fact that consumers are more motivated (and are more active) to cover their exposure in the more volatile quarters (Q1 and Q4) than the less volatile quarters (Q2 and Q3).

The estimated models yield an explanatory power ranging from a coefficient of determination of 0.548 for Q1 up to 0.784 for Q4. Thus, overall, the models are able to explain over 50% up to almost 80% of the variation in the realized risk premiums for peak load futures contracts. Similar to the results for base load contract, for Q1, where spot prices are most volatile and the model yields the lowest explanatory power.

The coefficient of the standard deviation of spot prices of the previous month is positive in all four quarters but it is significant only for Q1 and Q4. The sign of the coefficient of m.SD is consistent with the expectation that higher price variability in peak load prices drives higher risk aversion among consumers and translates into a willingness to pay a higher premium. The coefficient of the skewness of the previous week variable w.Skew is significant in three quarters, not significant in Q3, and positive in three quarters, being negative in Q2. A likely explanation for the negative coefficient of m.SD in Q2 relates to its low spot price volatility characteristic. The lower price risk means that consumers are not as motivated to cover their exposure using peak contracts which then puts a ceiling on the premium obtained in the market; higher volatility of the spot price therefore reduces the premium that the sellers of the futures contracts enjoy.

Table 6
Peak Load multiple regression for the observed ex-post futures premiums (MWh)

	Peak load Q1	**Peak load Q2**	**Peak load Q3**	**Peak load Q4**
Variable	**Coeff**	**Coeff**	**Coeff**	**Coeff**
Intercept	2.92*** (20.94)	3.06*** (33.08)	(-0.69*** (-29.00)	1.98*** (32.04)
T2-t	-0.008*** (-3.79)	-0.019*** (-14.87)	-0.003*** (-10.18)	-0.008*** (-9.21)
m.SD	0.003*** (7.28)	0.004 (0.82)	0.001 (1.60)	0.003*** (4.88)
w.Skew	0.025* (1.70)	- 0.025* (-1.87)	0.002 (0.55)	0.012* (1.90)
Dummy variables for years and States				
FY08	-0.10 (-0.50)	0.29** (2.04)	0.14** (2.22)	0.67*** (6.88)
FY09	0.50*** (3.02)	-0.07 (-0.29)	-0.09 (-1.21)	0.34** (3.36)
FY10	-0.15 (-0.58)	-0.23 (-1.65)	0.11*** (3.08)	-0.79** (-2.39)
FY11	-0.83*** (-5.19)	0.12 (1.59)	-0.04 (-1.66)	-0.07 (-1.06)
FY13	0.14 (1.26)	0.18** (2.23)	0.09*** (4.11)	0.01 (0.24)
FY14	-0.34** (-2.05)	0.50*** (6.77)	0.10*** (5.82)	0.24*** (2.99)
Qld	0.10 (0.93)	0.07 (0.96)	0.03 (1.47)	-0.20*** (-3.01)
Vic	0.21** (2.03)	-0.12** (-2.20)	-0.01 (-0.89)	-0.46*** (-8.41)
Adj R^2	0.548	0.773	0.769	0.784
Obs	134	87	82	110

(***significant at 0.01; **significant at 0.05; *significant at 0.10)

The coefficient for the time remaining till expiry of the futures contract (T_2-t) is negative in all four quarters for peak load contracts, whereas for base load the coefficient for this variable has positive coefficients in Q1 and Q3 but negative in Q2 and Q4. Here again it is important to note that the negative sign of these coefficients matches the sign in the univariate regressions thus emphasizing that it is not an artefact of the multiple regression model. Consumers are driven by an extreme risk aversion that motivates them to cover their exposure during the peak periods even at the cost of paying a higher premium. The rationale for negative coefficients in Q2 and Q4 is the same for peak load contracts as it is for base load contracts and is illustrated in Figure 4. The last month of Q3 is characterized by a higher standard deviation of the spot price than the first two (28.8 vs 15.1 and 14.5) and the same rationale holds for Q4 (194.8 for the last month vs 179.4 and 169.5 for the first two). Our analysis suggests that lower volatility reduces risk aversion among consumers thus reducing their willingness to pay higher premiums to cover their exposure to the electricity spot market. The magnitude of the coefficient of T_2-t in the model is higher for Q2 (-0.019) than for Q4 (-0.008) which is consistent with the larger relative difference in standard deviation between the last month and the first two that we find in Q2 compared to Q4. The increasing trend in standard deviation of the spot price for Q1 is not quite as pronounced as in Q2 and Q4. The standard deviation increases as we go from the first to the second month but then plummets in the third month which typically has milder temperature. The negative coefficient of T_2-t in Q1 is most likely driven by the higher willingness to cover exposure in the second month of the quarter, the month with the highest standard deviation in the entire year. Q3 has a much lower standard deviation of the spot price reflecting the fact that it does not typically exhibit price spikes. Consumers are not as motivated to use peak load contracts to cover their exposure to price spikes and the negative coefficient of T_2-t is likely a reflection of the willingness on the part of the producers to cover their exposure even at a lower (but still positive) premium. We note that the magnitude of the coefficient is the smallest in this quarter -0.003 of any of the four quarters. We find that the financial year dummies indicate that relative to the base financial year 2011/2012 (FY12) most of the year's show a higher premium relative to FY12 and most of these estimates are significant. The years FY10 and FY11 show predominantly lower premiums (negative coefficients) than FY12 but most of these estimates are not significantly different from zero even at the 0.10 level. The State of Victoria shows predominantly lower premiums than the base State of NSW except in Q1. Queensland on the other hand has only one significant quarter at the 0.01 level, Q4, with a negative coefficient, while the other quarters show positive coefficients but are not significant.

Recall that we perform a Box-Cox transformation using a shift big enough to eliminate non-positive values (minimum + 0.1) for Q1 and Q2. As a robustness check we repeat the Box-Cox transformation using different magnitudes of the shift (minimum + 5 and minimum + 10). We find that the coefficients of the resulting models have the same sign for all the variables and that the adjusted values for R^2 are quite similar. Considering the non-dummy variables (T2-t, m.SD and w.Skew) we find that varying the magnitude of the shift parameter also generally preserves the significance level of the coefficient estimates for the included variables. Overall, these findings suggest that our results are not driven by the conducted Box-Cox transformation of the dependent variable.

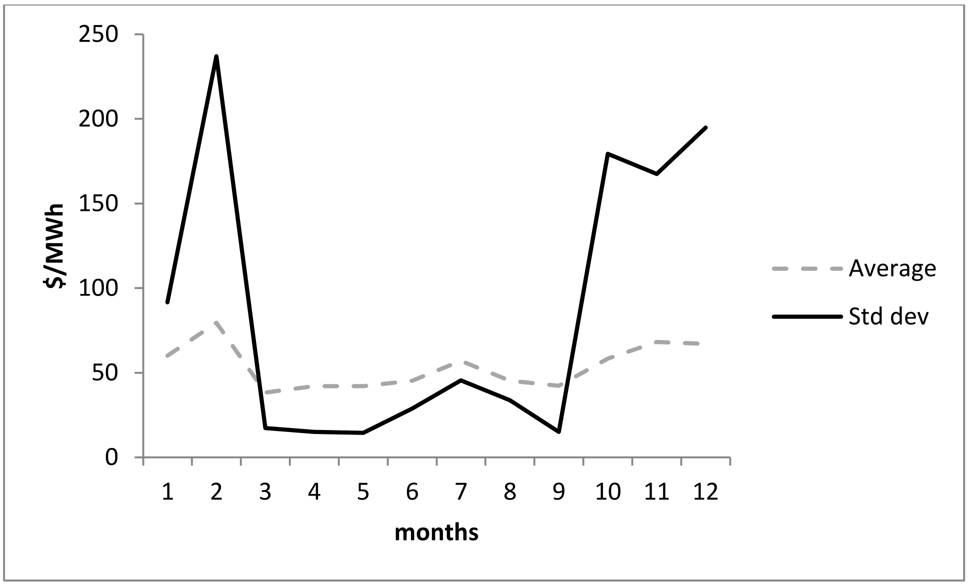


Figure 4: Average (dotted line) and standard deviation (solid line) of daily spot price for the peak load on a monthly basis from July 2007 to June 2014 in NSW

5. Conclusion

We provide a pioneering study on examining risk premiums of electricity futures contracts during the delivery period for quarterly base and peak load contracts in three major Australian electricity markets. Our analysis fills an important gap in the literature, since it is the first to examine the dynamics of futures premiums during a time period when some information about actual electricity spot prices during the delivery period is available already to market participants. Our study also examines whether factors that have been suggested for the analysis of risk premiums in previous studies are still relevant during the actual delivery period, when the contract approaches maturity.

In a first step, we develop an approach that allows us to extract futures risk premiums during the delivery period. To extract the premiums, we decompose observed futures prices into three parts: the crystalised value of the portion already delivered, the average spot price for the remaining days of the delivery period, and the risk premium for the remaining days of the delivery period. We then analyse the extracted premiums and find evidence of significant positive premiums for base load and peak load electricity futures contracts during the sample period considered, ranging from 1 July 2007 to 30 June 2014.

We also develop a multiple regression models for base and peak load contracts that explains the dynamics of the premiums during the trading period of the respective futures contracts. The developed models yield a relatively high explanatory power, with coefficients of determination ranging from 0.35 up to 0.7 for base load contracts and from 0.55 up to almost 0.80 for peak load contracts. The explanatory power is typically the lowest for the first annual quarter, where spot electricity prices exhibit the highest price and volatility levels and risk premiums also exhibit a high variation.

We find that observed risk premiums for base load contracts during delivery are often negatively related to open interest. Our results also suggest that risk premiums typically decline as the contract approaches its maturity date, while most recent observations on the standard deviation and the level of electricity spot prices are positively related to the observed premiums. We further find that premiums have a negative relationship with the average premium of the same quarter over the previous three years, indicating a form of learning by market participants. With regards to the considered markets, we find that the premiums in Queensland and Victoria are typically higher than in New South Wales for quarters with high demand, while they are smaller during quarters with lower demand. These findings emphasize the strong dependence of the premium on seasonal factors and specific characteristics of regional Australian markets.

For peak load contracts, the premium is negatively related to the time left until expiry of the contract, while it is positively correlated with the standard deviation of spot electricity prices over the last four weeks. Premiums are typically also positively related to spot price skewness during the most recent week. We also find that for peak load contracts, Victoria generally exhibits lower risk premium relative to New South Wales, while premiums in Queensland typically behave quite similar to the ones in New South Wales. There was no indication of dependence on longer term variables in our estimated model for peak load contracts, which emphasises the greater influence of short term factors for peak load futures in comparison to base load contracts.

Some of our findings for futures premiums during the delivery period confirm earlier results in the literature. We also find a positive relationship between observed risk premiums and the standard deviation of electricity spot prices, as it has been reported, e.g., by Bessembinder and Lemmon (2002), Longstaff and Wang (2004), Redl et al (2009) and Redl and Bunn (2013). However, many of our results also point towards the specific behaviour of risk premiums in futures electricity contracts during the delivery period, as the contracts approach maturity. In particular, we find significant differences between individual quarters and regional markets, as well as between base and peak load contracts. Our results make it clear that to appropriately model risk premiums, there is no one-size-fits-all model available. Instead, specific characteristics of the reference delivery period (seasonal factors, price levels, price volatility), contract specification (base or peak load), region (in our case the interconnected markets of New South Wales, Queensland and Victoria), trading behaviour (open interest and liquidity of the contracts) as well as recent characteristics of spot price behaviour (level, volatility and higher moments of spot prices) need to be included into an appropriate model. This also suggests that additional work on determining the dynamics of futures premium related to market characteristics will be required. This might be of particular relevance for the Australian electricity market, as in recent years vertical integration has become more wide spread in the NEM.

Despite taking into account a great variety of factors, the models we propose comprise variables that are based on accessible data typically pertaining to prior periods and recent observations. Therefore, the proposed models have the potential to be easily used as part of a strategy to hedge exposure to electricity spot price dynamics, using electricity futures contracts.

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APPENDIX

Table A.1
Base Load univariate regression of the observed ex-post futures premiums ($/MWh)

	Base load Q1	**Base load Q2**	**Base load Q3**	**Base load Q4**
Variable	**Coeff**	**Coeff**	**Coeff**	**Coeff**
Vol	-0.00 (-0.37)	-0.00 (-0.43)	0.02 (1.50)	-0.03 (-0.77)
OpenInt	4.18*** (7.01)	1.36*** (4.28)	0.44 (0.70)	-17.78*** (-9.12)
T2-t	0.03 (1.26)	-0.05*** (-3.99)	0.02** (2.13)	0.00 (0.10)
3yr.Spot	0.47*** (5.50)	0.09*** (4.53)	0.04 (0.74)	0.29*** (5.94)
3yr.SD	-0.06 (-0.39)	0.12*** (4.77)	-0.08 (-0.73)	0.75*** (8.41)
3yr.Skew	-0.71 (-0.72)	0.06 (0.15)	2.77*** (6.62)	-1.90*** (-2.91)
3yr.Kurt	0.17 (0.70)	0.34*** (4.33)	0.15 (1.59)	0.77*** (5.53)
3yr.Prem	-0.52*** (-3.99)	-0.08*** (-5.32)	-0.03 (-0.19)	-0.60*** (-8.00)
m.Spot	0.07*** (5.27)	-0.01 (-0.39)	0.18*** (7.46)	-0.04 (-0.93)
m.SD	0.04*** (9.04)	-0.01* (-1.90)	0.26*** (6.14)	-0.05** (-2.07)
m.Skew	-0.09 (-0.29)	0.34* (1.95)	1.11*** (6.77)	-0.28 (-0.65)
m.Kurt	-0.02 (-0.33)	0.04 (1.25)	0.23*** (6.35)	-0.07 (-0.66)
w.Spot	0.03*** (4.74)	-0.00 (-0.05)	0.16*** (5.95)	-0.09** (-2.14)
w.SD	0.01*** (4.79)	0.00 (0.22)	0.04*** (3.31)	-0.02** (-2.31)
w.Skew	0.02 (0.14)	0.26*** (4.01)	0.35*** (3.88)	0.02 (0.11)
w.Kurt	-0.01 (-0.67)	0.02*** (4.41)	0.02*** (3.44)	0.01 (1.24)
m.Spike	0.46*** (7.35)	-0.14** (-2.55)	0.43*** (2.78)	-0.19 (-1.12)
w.Spike	0.69*** (5.01)	-0.11 (-0.88)	3.69*** (5.98)	-0.95* (-1.78)
Carbon Tax	-4.84*** (-5.00)	-1.00** (-1.97)	1.31** (2.35)	-0.92 (-0.66)
Obs	643	433	375	506

(***significant at 0.01; **significant at 0.05; *significant at 0.10)

Table A.2
Univariate regression of the observed ex-post futures premiums (in \$/MWh) -Peak load

	Peak load Q1	**Peak load Q2**	**Peak load Q3**	**Peak load Q4**
Variable	**Coeff**	**Coeff**	**Coeff**	**Coeff**
Vol	0.02* (1.89)	0.01 (1.05)	-0.04** (-2.28)	-0.00 (-0.24)
OpenInt	-0.00*** (-2.86)	-0.2 (-0.24)	-2.40 (-1.09)	1.15 (0.37)
T2-t	-0.08*** (-3.53)	-0.07*** (-5.57)	-0.10*** (-4.67)	-0.12*** (-6.31)
3yr.Spot	-0.05 (-1.26)	-0.01 (-0.75)	-0.10** (-2.03)	-0.00 (-0.04)
3yr.SD	-0.03 (-0.23)	-0.04 (-1.10)	-0.23 (-1.17)	-0.01 (-0.18)
3yr.Skew	-2.28 (-0.84)	1.34 (1.29)	-12.52*** (-3.60)	2.22 (0.97)
3yr.Kurt	-0.21 (-0.82)	0.12 (1.21)	-1.27*** (-3.53)	0.20 (0.90)
3yr.Prem	0.15 (0.67)	-0.23 (-1.42)	-0.36 (-1.42)	-0.01 (-0.05)
m.Spot	0.04*** (8.54)	0.02 (1.33)	0.08*** (3.02)	0.10*** (7.64)
m.SD	0.01*** (8.46)	-0.04* (-1.67)	-0.03*** (-2.93)	0.05*** (5.49)
m.Skew	0.57** (2.08)	-0.13 (-0.64)	0.53 (1.30)	0.80*** (4.31)
m.Kurt	0.08* (1.71)	0.02 (1.28)	0.09 (1.26)	0.11** (2.40)
w.Spot	0.01*** (3.31)	0.05** (2.28)	0.07*** (2.93)	0.10*** (3.21)
w.SD	0.00*** (4.47)	0.02* (1.90)	-0.00 (-0.62)	0.02** (2.34)
w.Skew	0.20* (1.73)	0.24** (2.60)	-0.37 (-1.25)	0.62*** (4.10)
w.Kurt	0.01 (0.78)	0.01* (1.97)	-0.01 (-0.37)	0.05*** (2.85)
m.Spike	0.13*** (7.14)	-0.55** (-2.43)	1.27* (1.94)	0.59*** (4.02)
w.Spike	0.17*** (3.93)	1.43*** (5.99)	0.53 (0.40)	2.36*** (6.46)
Carbon Tax	0.28 (0.39)	0.46 (0.83)	3.02*** (3.78)	-0.59 (-0.72)
Obs	134	87	82	110

(***significant at 0.01; **significant at 0.05; *significant at 0.10)