Risk Management in Electricity Markets: Premium Dynamics, Premium Forecasting and Industry Structure

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Declaration

This work has been carried out during the period of enrolment in the PhD program at Macquarie University and has not been submitted elsewhere for any other academic award. The contribution of authors has been acknowledged in the relevant chapters. Data sources and references used in the work have also been acknowledged.

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1. Abstract

The topic of this PhD thesis is the electricity market with emphasis on the liquidity of electricity futures contracts and the dynamics and forecasting of the futures premium. The futures market is an important tool for managing electricity price risk, particularly for stand-alone electricity retailers.

The first research paper titled 'Electricity Futures Markets in Australia – An Analysis of Risk Premiums during the Delivery Period' provides an empirical analysis of risk premiums of electricity futures contracts during the delivery period for the major eastern states of Australia. While current research on electricity futures markets typically focuses on risk premiums for the pre-delivery period, a specific feature of the Australian market is that as a contract enters delivery, it continues to be traded until expiry. We develop an approach that decomposes the observed futures price during the delivery period into three parts: the crystallised value of the portion already delivered, the expected average spot price for the remaining days of the contract, and the risk premium for the remaining days of the delivery period. We examine the dynamics of realised risk premiums during the delivery period for quarterly and peak load contracts, as well as drivers of the observed premiums such as liquidity-based measures, time to maturity, current and historical spot prices and the historical behaviour of premiums. We find that risk premiums are positive during the delivery period for the majority of the considered contracts. Further, our results suggest that a model using open interest, time to maturity, as well as recent characteristics of spot prices and risk premiums provides 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.

The second paper, 'Electricity Futures Markets in Australia: Generating Density Forecasts for Returns of Low Liquidity Instruments', examines density forecasts of price changes in electricity futures contracts. These instruments, used for risk management, typically exhibit low liquidity during periods of more than one year prior to delivery. We assess the performance of different density forecasting methods, using conventional approaches that are based on historical returns for the considered instruments. We find that such an approach performs

poorly and provides inaccurate predictions for day-ahead densities. The poor performance is due to a reliance on return data from a low liquidity period for making predictions relating to more liquid periods. To deal with this shortcoming, we introduce a new approach which enriches historical data for a contract with data from more liquid trading periods of identical contracts traded over the preceding three years. We find that our data enrichment approach significantly improves the correct specification of density forecasts of daily returns based on various evaluation metrics. Our results are of interest to risk managers and parties with exposure to electricity price risk. Our approach is also relevant for market participants who want to appropriately evaluate the risk of price changes for derivatives exhibiting different phases of return behaviour and liquidity, depending on their time to maturity.

The third paper, 'Vertical Integration of Generation and Retail: Foreclosure in the Electricity Futures Market', presents empirical evidence of foreclosure in the electricity futures market following vertical integration between the electricity retail and generation stages. This foreclosure limits risk mitigation options open to retailers and other participants and has the potential to reduce retail competition and harm consumers. We find a statistically significant fall in base load energy volume transacted on the Australian Securities Exchange (ASX) relating to a delivery period longer than 12 months. At the same time, we do not find a statistically significant change in the volume within the 12-month horizon, and total volume ignoring the horizon. The horizon beyond 12-months is particularly relevant for the commercial and industrial customer market segments as well as for the residential customer segment on contracts longer than 12 months. The reduction in the volume pertaining to horizons longer than 12 months shows that the structure of the futures market became more short-term; focused on the ≤ 12-month horizon. The sample that we use covers the period from 2007 to 2017 for New South Wales, the largest region in the Australian National Electricity Market in terms of energy volumes traded on the spot and futures markets. The impact of industry structure on stand-alone retailers and the potential to reduce competition is of interest to policy makers, regulators, consumers, and retailers with a net exposure to the spot electricity market.

2. Introduction

The topic of this PhD thesis is the electricity market with emphasis on the liquidity of electricity futures contracts and the dynamics and forecasting of the futures premium. The futures market is an important tool for managing electricity price risk, particularly for stand-alone electricity retailers. Each of the three main chapters is a research paper into an aspect of this topic. Following a section that describes the key features of the futures markets in Australia, the introduction presents the need for risk management by describing the main characteristics of the volatile electricity spot price and the main features of the futures market. The forward risk premium is then defined followed by a sketch of the relevant literature. Premium probability density forecasting is introduced next, followed by the area of vertical industry structure. The chapter concludes by describing the structure of the remainder of the thesis and the contributions made by each of the research papers.

The thesis provides empirical analysis of important aspects of the electricity futures market in Australia. It studies the dynamics and drivers of the forward premium between the futures price and the spot price during the delivery period of a contract. It then investigates the performance of one-day ahead probability density forecasts of the forward premium. The thesis ends by examining the impact that the vertical integration between the retail and generation stages of the industry has had on the volume of energy transacted on the futures market and its potential impact on competition in the market and consumer interests.

The first thread uses multiple regression analysis to analyse the dynamics and drivers of the premium during the delivery period of the contract. The analysis uses relevant explanatory variables that have been established in the literature. We study the realised forward premium in base load and peak load contracts for each of the four calendar quarters on which they are traded during the period from the 1st July 2007 to the 30th June 2014. The analysis covers the three states of Queensland, New South Wales and Victoria that account for nearly 95% of the traded volume. The state of South Australia is excluded from the analysis due to its very low volume.

In the second thread the thesis evaluates the performance of one-day ahead density forecasts of returns in a low liquidity environment using data from the Australian electricity futures market over the period 2005 to 2014. We investigate the highly volatile first calendar quarter pertaining to the states of New South Wales and Victoria. To assess whether different approaches to density forecasting are specified correctly, we use Probability Integral Transforms (PITs) originally suggested by Diebold et al. (1998) as well as the approach by Berkowitz (2001) and take an inverse normal transformation of the PIT.

The final aspect investigated in this thesis is the impact that the vertical integration of the retail and generation stages of the industry has had on the liquidity of electricity futures contracts in the Australian National Electricity Market. We regress electricity futures volume transacted on the Australian Securities Exchange against independent variables representing vertical integration, spot and futures price moments, demand, and other variables. The analysis covers the period from the first quarter of 2007 to the fourth quarter of 2017 for the state of New South Wales. The state of New South Wales is chosen for analysis because vertical integration occurred in one transaction, on or around March 2011, which makes the impact of the change in market structure more easily discernible. The analysis period covers the periods before and after vertical integration.

2.1 Key Features of the Futures Markets in Australia

The two main contract markets in Australia are the over-the-counter (OTC) market and the exchange traded futures market. The OTC market is a market for bilateral contracts between counterparties. Contracts can be negotiated directly between parties or, more standardised contracts transacted through brokers (Anderson et al., 2007). An advantage of this market is that the terms of a contract negotiated directly between the parties can be tailored to fit the requirements of the parties. Parties can negotiate duration, quantity, price and other terms that make agreements fit the particular needs of the counterparties. The following examples can help illustrate the range of variation in contract terms in the OTC market. A contract can specify a fixed quantity with take-or-pay obligations. On the other extreme, a load following contract does not incorporate obligations on the purchaser to use or pay for fixed quantities. Being bespoke contracts, the quantity can also be specified in any intermediate position between the two previously mentioned poles, which would result in varying degrees of sculpting of the contract quantity to the consumer's load shape. In relation to price, a contract price can be fixed in total or for a portion thereof. The variable portion can vary in several ways such as by being linked to the market (providing partial protection from price volatility) or to an index or a combination of indices. Examples of indices include, among others, the consumer price index, a fuel index, or an exchange rate pair. OTC contracts include swap contracts (the highest volume) and can refer to base load, peak load, off peak load, or to specially designed periods of the day, week and/or year. Contract type variations also include capped price contracts, options and swaptions. Other clauses in the contract can specify settlement and payment terms, conditions under which a contract can be reopened for negotiation, renewal terms, extension options, or any of many other terms that can be negotiated.

In contrast to OTC contracts, exchange traded contracts are standardised. Australian Electricity contracts that are traded on the ASX relate to the four states of Queensland, New South Wales, Victoria and South Australia. Futures contracts can be for base load calendar month, base load or peak load calendar quarter, $300/MWh calendar quarter caps, base load calendar year or financial year strip options, or base load calendar quarter average rate options. In contrast to OTC contracts exchange traded contracts are standardised and offer more limited choice. The main purpose of standardisation is to increase liquidity in the market. The duration of exchange traded futures contracts on the Australian Electricity ASX is fixed to a month, a quarter or a year (the latter consists of a strip of calendar quarters). The longest period for which a party can arrange cover is 16 to 17 quarters with some contracts trading over shorter horizons. Settlement periods and payment terms are set in the respective contracts. A base load or peak load contract is specified as 1 Megawatt (MW) of power per hour for every trading period of every day covered by the contract. The contract price applies to each trading interval in the contract. Settlement occurs on the basis of the difference between the futures contract price and the relevant average wholesale spot market price over the delivery period specified in the contract.

The average spot price for a base load (peak load) contract is calculated as the arithmetic average of prices for each (peak load) half-hour trading interval covered by the contract. Half-hourly prices are declared by the Australian Energy Market Operator (AEMO). While there are 48 half-hourly trading intervals in a base load day there are 30 half-hourly peak trading intervals in a working day. Peak intervals are defined as the trading intervals between 7 am and 10 pm on weekdays excluding public holidays as declared by the ASX. Although the energy is defined as 1 MW per hour, the quantity of energy varies among base load contracts as it does among peak load contracts. For example, a base load calendar quarter contract with 90 days equates to 2,160 Megawatt hours (MWh) while a 92-day contract equates to 2,208 MWh.

Similarly, for a peak load calendar quarter contract, the energy quantity varies according to the number of working days covered by the contract. A contract with 59 days equates to 885 MWh while a 66-day contract equates to 990 MWh (ASX, 2015).

Given the flexibility offered by the OTC market, including availability of longer-term contracts, what advantages can the exchange traded futures market offer? The advantages include price transparency, greater ease of adjusting position and lower counter party risk. Expounding on each of these advantages in turn, exchange traded contract prices are published on the ASX website and all participants have visibility of the market price. This contrasts with OTC contracts whose terms remain confidential. The Australian Financial Markets Association (AFMA) publishes annual turnover in MWh of energy transacted through OTC contracts. However, these do not contribute to making prices transparent. Positions can be more easily adjusted through exchange traded futures contracts by selling contracts to reduce a long position or buying contracts to reduce a short position. This contrasts with OTC contracts that require negotiations to effect a change in contracted (i.e. and adjustment of) position. In relation to position adjustment, OTC contracts involve potentially costly and possibly complex renegotiation that may or may not reach a satisfactory outcome. Adjusting position through futures market operations is almost guaranteed (primarily subject to liquidity constraints) but it is not cost free. In addition to exchange fees and the cost of money tied up in prudential margin, the bid-ask spread and the risk of change in the price level between transactions are relevant factors that need to be considered.

Figure 2.1 and Figure 2.2 provide a glimpse of the development of energy volumes traded in these markets. Figure 2.1 shows the amount of energy traded across the entire Australian National Electricity Market (NEM) in the OTC market by contract type and the underlying NEM system demand. The OTC data is reported by AFMA and available from financial year 2007/08. From 2015/16 onward, AFMA combined the data for the two categories “Collars and Asian Options” and “Other Options” into a new category “Collars/Asian and Other Options”. We reported the historical data under the new combined category.

Fig. 2.2 shows a comparison of the volume of energy traded in each financial year (July 1 – June 30 of the following calendar year) in the OTC and ASX contracts across the NEM. The OTC volume fell sharply in 2014/2015, to less than 50% of NEM demand, before increasing slightly to around the 60%–65% level. AFMA attributes this fall to the repeal of the carbon pricing mechanism on 1 July 2014 (in the 2014/2015 financial year) and to further vertical integration activity. As can be seen in Fig. 2.2, unlike OTC volumes, total ASX volumes did not fall.

While the ratio of traded energy volume on the futures market relative to the underlying NEM system demand (around 200 terawatt hours) has increased over time and reached a level above two, it remains lower than most liquid international markets. The German, Nordic and British markets have ratios of approximately eight, seven and three, respectively (Redl and Bunn, 2013). Open interest on the futures market is highest in the nearest two years. It gradually diminishes from the level in the nearest quarter and falls off materially beyond two years away. Time profiles of open interest are reported by the AER in their annual State of the Energy Market reports.

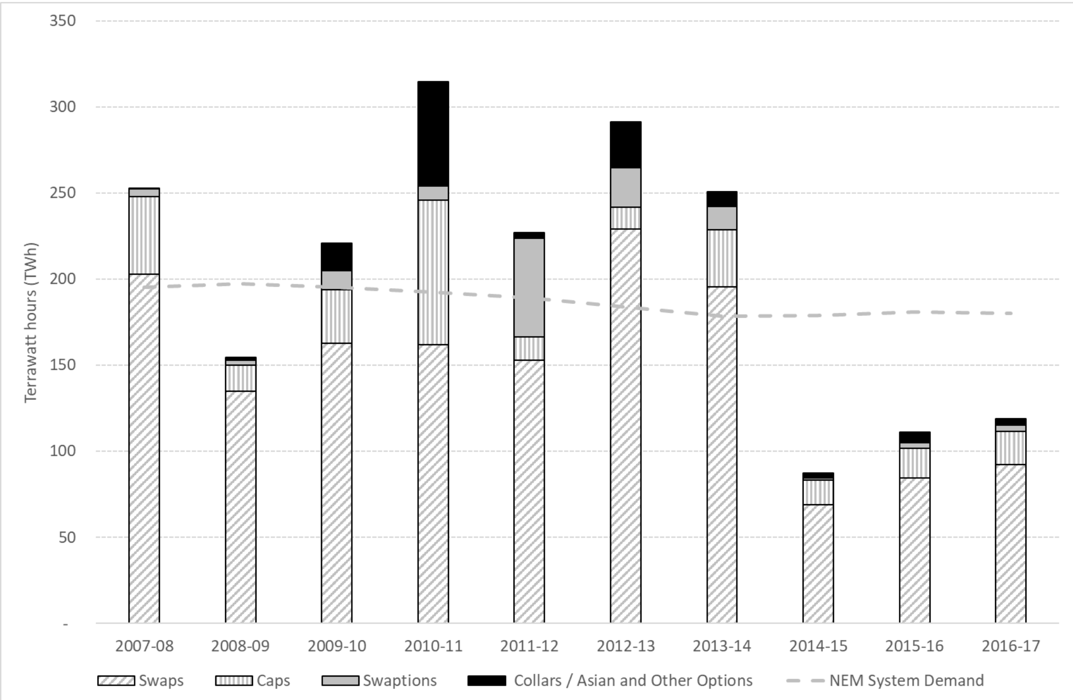

Fig. 2.1. OTC annual traded energy by instrument – NEM wide. The figure shows the amount of energy traded NEM wide on OTC markets by financial year. Compiled from AFMA data. The AFMA publishes data on a financial-year basis (1 July to 30 June of the following calendar year).

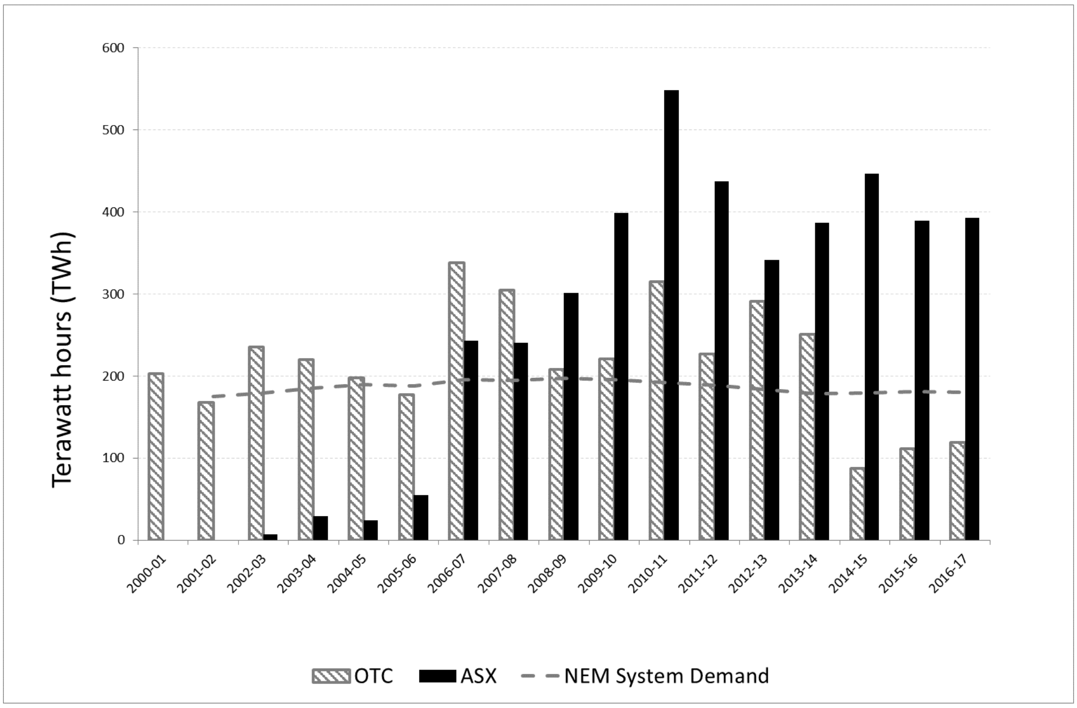

Fig. 2.2. OTC and ASX annual traded energy – NEM wide. The figure shows the amount of energy traded NEM wide on ASX and OTC markets by financial year. Compiled from AFMA, ASX and TRE data. Electricity futures started trading on 3 September 2002 (i.e. 2002/2003 financial year). The AFMA publishes data on a financial-year basis (1 July to 30 June of the following calendar year).

2.2 Premium Dynamics

Electricity prices in deregulated markets are characterised by high volatility (Coulon et al., 2013), large jumps (Cartea and Figueroa, 2005; Weron and Zator, 2014), and seasonality (Cartea and Villaplana, 2008; Lucia and Torró, 2011). Price volatility is due to electricity not yet being economically storable and to its limited transportability (Bierbrauer et al., 2007; Redl and Bunn, 2013; Wilkens and Wimschulte, 2007) This exposes participants in the market to significant price risk (Benth et al., 2008; Eydeland and Wolyniec, 2012). Financial markets have developed alongside spot markets and allow parties to manage their exposure to spot price risk. The two main types of markets are OTC markets and futures contracts markets (Anderson et al., 2008). OTC markets typically deal with bespoke contracts negotiated between the parties and provide the opportunity to tailor the contract to satisfy the individual requirements of the parties. Futures markets, on the other hand, trade standardised contracts through an exchange, typically, with no opportunity for tailoring contracts. The two markets have other significant differences. Participants in OTC markets are exposed to counter-party default risk, which can be significant. Another disadvantage of OTC markets is that prices are opaque and difficult to compare across contracts due to the differences between the terms contained in bespoke contracts.

By comparison, parties to exchange cleared futures contracts avoid the counter-party risk involved in OTC contracts.[1] Futures markets also allow parties to adjust their positions more easily compared to OTC contracts, which would involve potentially complex renegotiations of a contract. Prices in exchange traded markets are transparent to the public and the price discovery function is a significant benefit of such markets. Other benefits include that parties can execute anonymous trades, often using brokers to enhance anonymity.

Futures markets, however, are not unbiased predictors of spot prices. The difference between the futures price and the spot price during the specified delivery period of the contract is referred to as the futures premium. Understanding the behaviour of the premium is therefore important to parties wanting to manage risk through these markets. The premium has been defined in two ways.[2] The ex-ante electricity price risk premium is the difference between the futures price and expected spot price (e.g. see Haugom and Ullrich (2012).[3] A limitation of estimating the ex-ante premium is that the estimate depends on the model used to derive the (unobserved) expected value of the spot price. Karakatsani and Bunn (2008) discuss the limitations of fundamental models of electricity prices. In order to overcome the limitation related to model specification, researchers have studied the ex-post electricity futures premium, which is equal to the ex-ante premium plus a random shock.[4] The ex-post premium is defined as the difference between the future price and the realised spot. Its advantage is that both terms are observable and do not rely on model specification.

The literature investigating the forward premium can be broadly classified into two streams: Equilibrium models and statistical models. This thesis, Chapter 3, falls into the latter stream. Findings about the premium vary with respect to the existence of a risk premium and its sign (Bierbrauer et al., 2007; Daskalakis and Markellos, 2009; Diko et al., 2006; Hadsell and

[1] Parties have to maintain their margin accounts balance to the requirements of the exchange.
[2] While the above definitions are typically used in the literature, there is no unanimous agreement on the definition of the premium. Haugom and Ullrich (2012), for example, study the log of the premium, which they define as the difference between the logs of the futures and the spot prices (not the log of the difference).
[3] Where the futures price pertaining to a future date $t+x$ is observed at time t and the spot price, expected at the same future date $t+x$, is formed using the information available at the same time t, on which the future price was observed.
[4] The random shock is the difference between the expected value of the spot price and the realised spot price.

Shawky, 2006; Kolos and Ronn, 2008; Lucia and Torró, 2011; Redl and Bunn, 2013; Redl et al., 2009; Weron, 2008; Wilkens and Wimschulte, 2007).

The premium is not constant but dynamic, varying according to season (Bunn and Chen, 2013; Cartea and Villaplana, 2008; Handika and Trück, 2015; Haugom et al., 2014; Lucia and Torró, 2011), price level, price volatility and higher moments of price (Bessembinder and Lemmon, 2002; Botterud et al., 2010; Douglas and Popova, 2008; Furio and Meneu, 2010; Longstaff and Wang, 2004; Redl et al., 2009), time to maturity (Bierbrauer et al., 2007; Daskalakis and Markellos, 2009; Diko et al., 2006; Hadsell and Shawky, 2006; Kolos and Ronn, 2008; Redl et al., 2009), liquidity (Bevin-McCrimmon et al., 2018; Wilkens and Wimschulte, 2007), and other determinants.

To the best of our knowledge, so far there have been no studies on the dynamics of the premium during the delivery period of the contract. In Chapter 3, we study the example of the Australian electricity futures market in which contracts continue to trade during the delivery period until their expiry date.

2.3 Premium Probability Density Forecasting

The NEM is a wholesale spot market and is considered to be more volatile and prone to spikes than many other comparable spot electricity markets (Higgs and Worthington, 2008; Boland et al., 2016; Mayer and Trück, 2018). The NEM's design as an energy only market contributes to its volatility. Capacity markets that exist alongside energy markets provide generators with payment for making capacity available and are seen to encourage the entry of capacity into the market more readily than energy-only markets. There is no consensus on the most efficient design as compensation for capacity is derived from avoiding price peaks. (Keles et al., 2016; Batlle and Rodilla, 2010, among others discuss various aspects of this issue). Such high volatility motivates participants in the wholesale electricity market, such as generators, retailers or large consumers, to manage their price risk. Market participants have managed risk using financial instruments in the OTC market as well as using exchange traded electricity derivatives which developed alongside the NEM. The futures market offers many advantages over the OTC market. In addition to lower counterparty risk, exchange traded derivatives are transparent and available to all participants. It is also easier to adjust a position on the futures market through trading operations, compared to OTC contracts, which require bilateral negotiations. However, one of the main difficulties in using electricity futures contracts for hedging, is the low liquidity of these instruments (Anderson et al., 2007). This is true for both OTC and exchange traded futures contracts. The link between liquidity and return has been confirmed by many researchers who followed on from the seminal works on the topic by Amihud and Mendelson (1986a, b). Therefore, it is important to be cognisant of this link when, for example, considering return data from a lower liquidity period to estimate returns or measure risk in a higher liquidity period.

Value at Risk (VaR) has evolved as a popular risk measure used by managers, financial institutions and their regulators, among others (Jorion, 2006; Ziggel et al., 2014). VaR is simple to calculate and is able to combine several types of assets that may exist in a portfolio. As VaR is essentially a particular quantile of future returns, it relies on estimating the, often unknown, true generating process of returns, which can also be time varying. Models, such as the Conditional Autoregressive Value at Risk (CAViaR) (Engle and Manganelli, 2004), were developed to deal with such limitations of VaR. VaR has also been criticised for its narrow focus on a single quantile typically and not accounting for different processes in the tail (e.g. see Christoffersen and Pelletier, 2004; Huisman and Kilic, 2012; Engle and Manganelli, 2004). There is growing interest in the use of density forecasts, which provide a more comprehensive view of risk, instead of VaR, which typically reports only a single quantile of the return or loss distribution (Bunn et al., 2016; Clark, 2011; Fan et al., 2018; Gaglianone and Lima, 2014; González-Rivera and Sun, 2017; Kapetanios et al., 2015; Kenny et al., 2015; Nowotarskiet et al., 2014; Rossi and Sekhposyan, 2014; Wolters, 2015, among others).

In this paper, we evaluate the performance of one-day ahead density forecasts of returns in a low liquidity environment using data from the Australian electricity futures market from 2005 to 2014. Therefore, to assess whether different approaches to density forecasting are specified correctly, we use PITs originally suggested by Diebold et al. (1998). Following Berkowitz (2001) we apply an inverse normal transformation to the PIT to investigate the appropriate specification of the generated density forecast in a relatively small sample environment.

The literature on liquidity in financial markets is extensive and covers many aspects of liquidity and many different markets, including equity, bond, foreign exchange or derivatives markets. Interestingly, very few studies deal with liquidity in electricity markets. Our study is motivated by the difficulties that market participants typically face in measuring risk exposure, when the financial instrument relating to the underlying exposure has low liquidity. Bevin-McCrimmon et al. (2018) find a predominantly inverse relationship between the daily ex-post premium and liquidity. Some authors proposed dealing with illiquidity by hedging a similar instrument (Frestad, 2014), or making an illiquidity adjustment to VaR (Weiß and Supper, 2013).

Other related literature streams include risk management in electricity markets which deals predominantly with spot and day-ahead electricity markets. Numerous authors (Díaz et al., 2019; Fanone et al., 2013; Marcjasz et al., 2018; Pape et al., 2016; Steinert and Ziel, 2019; Ziel et al., 2015) research a variety of aspects related to forecasting the electricity spot prices. The literature on risk management in electricity futures markets is scant. Researchers of the comparative performance of hedging models includes Kayal and Lindgren (2014), who on balance come out in favour of the volatility updating model, and Zanotti et al. (2010), who similarly find that models that account for volatility updating perform better and, importantly for our topic of interest, that hedging is generally effective except in less liquid markets (French Powernext in their study).

There is strong interest in managing risk in the highly volatile NEM (Apergis et al., 2017; Clements et al., 2015; Ignatieva and Trück, 2016; Janczura et al., 2013, among others, discuss various topics on price volatility, price spikes and seasonality).. Using the futures market offers many advantages but is characterised by low liquidity, which has been shown to impact premiums in these markets. The paper on which Chapter four reports proposes a novel and versatile method of forecasting density functions of electricity premiums with promising applicability for other illiquid markets.

2.4 Vertical Industry Structure

Vertical integration means including, in the same firm, various stages of the supply chain of an industry that are typically performed by separate firms. The main stages of the electricity supply chain are generation, network and retail. A link between market structure and competitive behaviour motivated the design of liberalised electricity markets. When electricity markets were deregulated in the 90's, monopoly utilities were disaggregated into separate firms each dealing with a separate stage of the supply chain. The disaggregation was aimed at injecting competition and encouraging innovation and competition particularly in retail. This objective was achieved to various extents in various jurisdictions with the Australian National

Electricity Market considered among the most competitive retail markets in the world (Simshauser et al., 2015). Futures markets are an important tool in risk management, as they contribute to market completeness and enhance competitive behaviour in spot markets (Aïd et al., 2011; Allaz and Vila, 1993; Bushnell, 2008; Redl and Bunn, 2013). Liquidity in futures markets increased over time with trading volume at different multiples of the physical spot market, in different jurisdictions. The literature on vertical integration in general ranges from presenting views and findings that vertical integration is (almost) always anticompetitive (Bain, 1956; Mason, 1939; Ordover et al., 1990), to those that argue it is (almost) always procompetitive (Bork, 1978; Posner, 1976), to a range of intermediate findings that applied a higher level of theoretical rigour, more advanced techniques and/or considered vertical integration in specific contexts (Chipty, 2001; Hart and Tirole, 1990; Hortaçsu and Syverson, 2007; Joskow, 2010; Lafontaine and Slade, 2007; Mullin and Mullin, 1997; Rey and Tirole, 2007; Riordan, 1998; Salinger, 1988; Salop, 2018; Salop and Culley, 2014; Tirole, 1988; Williamson, 1975). In the latter stream, the main issue with vertical integration is due to foreclosure that raises the costs of rivals and leads to social harm. This negative effect may, under some circumstances, be outweighed by the positive effects of integration flowing from efficiencies, mainly the elimination of double marginalisation. Double marginalisation is obtained, in its pure form, when monopolies exist in successive stages of the supply chain and charge monopoly margins that are passed on to the consumer (Lafontaine and Slade, 2007). It can also occur at a reduced level when oligopolies exist (Joskow, 2010), but the benefits from integration eliminating this reduced margin are more tenuous and reliant on assumptions about the structure of the market following integration.

In the context of the electricity market, studies in favour of the vertical integration of retailers and generators to form what is referred to as gentailers argue that physical hedges outperform contractual arrangements as risk management tools (Boroumand and Zachmann, 2012). Gentailers who have a net deficit of generation output relative to their retail position tend to have an interest in keeping spot prices down, and vice versa (Hogan and Meade, 2007), a view supported by the findings of Bushnell et al. (2008) and Mansur (2007), that markets with integrated firms or contractual arrangements between retailers and generators resulted in lower prices than those where such arrangements did not exist. Perfect portfolio balance is not practically achievable in a competitive market. This leaves the opportunity for net long gentailers (and generators) to exert market power in the spot market and leverage that to raise prices in the futures market (Anderson and Hu, 2008; de Bragança and Daglish, 2016). A higher degree of vertical integration reduces the likelihood of a liquid futures market developing, and stand-alone retailers who cannot access the futures market to hedge their exposure are forced to integrate or exit (Aïd et al., 2011). Thus the absence of a liquid futures market, by virtue of forcing stand-alone retailers to exit or integrate, reduces competition. The positive case is stated in de Bragança and Daglish (2017), who show that the existence of a liquid futures market allows retailers to expand their market share. Other research shows that disaggregation of electricity utilities is not without cost (Meyer, 2012), but no conclusions are drawn about net benefit or cost. Others report on the impact of unbundling other stages of the supply chain, retail and low voltage network (distribution), on economies of scale and grid charges (Fetz and Filippini, 2010 and Heim et al., 2018).

The bundling of generation and retail entities into gentailer entities has been a growing trend in the NEM since 2006 (Anderson et al., 2007; Moran and Sood, 2013), reversing the unbundling of retail and generation into separate entities that characterised the electricity market liberalisation reforms of the nineties. Concerns have been voiced over the potential negative impact on reducing liquidity in the futures market from various quarters including academics (Anderson et al., 2007; Boroumand and Zachmann, 2012); futures market operator, d-cypha (ASX), as well as regulators, the Australian Energy Regulator (AER), who additionally voiced concerns over increasing barriers to entry in the annual State of the Energy Market report in 2007 (AER, 2007) and in every report since 2011 (refer for example to AER, 2011). But not all researchers hold the same view on the impact of VI in Australia. Simshauser et al. (2015), studying the effect of structure on the firm's ability to maintain an investment-grade credit rating, argues that theoretical and empirical evidence favours VI. The paper also presents NEM-wide data from the ASX and AFMA which visually indicates that no change has occurred in their combined futures volume following a number of identified VI events. Simshauser et al. (2015) further support this view by referring (correctly to the best of our knowledge) to the absence of empirical analysis relating to the NEM that supports concerns over the reduction of liquidity in futures markets. Our work therefore provides new evidence relating to this area.

In the context of the NSW electricity market, large gentailer entities were created overnight through a single transaction, executed on or around 1 March 2011. Private retailers Origin

Energy (Origin) and TRUenergy acquired out-right the three state-owned retailers and simultaneously, through a lease arrangement, obtained full commercial control of the output of around a third of the generating capacity in NSW. The generation capacity belonged to major state-owned generation businesses Eraring and (part of) Delta Electricity. The leased generation assets were subsequently sold to the lessees in 2013. The remaining state-owned electricity generation assets were later sold, in separate transactions, to other parties. Most notably the sale of Macquarie Generation (representing around 30% of NSW generation capacity) to AGL in September 2014, Delta Electricity's Colongra in December 2014 to Snowy Hydro and Delta Electricity's Vales Point power station in November 2015 to private investors. While a very low level of VI between retail and generation existed in NSW before 1 March 2011, the transaction represented a watershed moment in NSW which made the impact of VI more easily discernible.

Chapter 5 of this thesis analyses the impact of independent variables representing vertical integration, spot and futures price moments, demand and other variables on the volume of energy transacted on the futures market in NSW.

2.5 Structure and Contribution of the Thesis

The next three chapters contain the research papers comprising this thesis. The contribution made by each of the papers is described next.

Chapter 3 comprises the first research paper titled 'Electricity Futures Markets in Australia – An Analysis of Risk Premiums during the Delivery Period' provides an empirical analysis of the risk premiums of electricity futures contracts during the delivery period for the major eastern states of Australia. Our paper adds to this field of research, by providing a pioneering study that specifically focuses on the dynamics and driving factors of futures risk premiums during the delivery period of the contract. While existing literature has examined risk premiums in various contexts and markets around the world, to the best of our knowledge none of these studies has analysed the premiums during a period when electricity spot prices for a portion of the delivery period have been observed already by market participants. This paper aims to fill this important gap in the literature and shed new light on the analysis of risk premiums in power markets.

The paper makes several contributions to the literature. 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 crystallised value of the portion already delivered, the expected 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 examine whether factors that have been suggested to impact risk premiums in previous literature, are also relevant during the delivery period of an electricity futures contract. Thus, we consider variables such as spot price levels, volatility or higher moments of the price series, as well as variables related to the time to 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 characterised by diverging regimes of price levels and volatility (Handika and Trück, 2015). 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 further contribution of our paper is that we examine indicators of trading activity such as open interest and trading volume as 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 and hedging activity in the market, which should ultimately also impact the price that market participants are required to pay for a hedge.

Chapter 4 contains the second paper, ‘Electricity Futures Markets in Australia: Generating Density Forecasts for Returns of Low Liquidity Instruments’. The paper examines the performance of one-day ahead density forecasts in low liquidity markets using data from the Australian Electricity Futures market. The paper makes several contributions to the literature. First, we develop a method that generates density forecasts that are slightly improved over the conventional approach thus improving risk management outcomes. We enrich data for a particular financial instrument by incorporating data from similar instruments from periods of higher liquidity. This contrasts with the traditional approach of relying on historical data from periods with dissimilar liquidity levels. The literature has established a link between premium and liquidity (Amihud and Mendelson, 1986; Bevin-McCrimmon et al., 2018). Therefore, we contend, our method uses data from a more relevant period while still incorporating a rich variety of realised historical returns. A second contribution is that our method is versatile and can be applied to a number of models. This is because we do not propose a single model but rather an approach to enriching data that can then be used as part of various parametric and non-parametric modelling approaches, as we show in our analysis.

Our third contribution is applying this method to the Australian electricity market. The Australian electricity futures market is characterised by low liquidity in the period more than one year prior to the start of delivery. Most activity, and therefore interest in forecasting, lies in the year leading up to delivery. We enrich return data for the current contract (say Q1 2010) by incorporating data from contracts for the same quarter (Q1 in this example) delivered in previous years (we add to Q1 2010 data from Q1 2009 and Q1 2008). This approach offers a number of advantages over the traditional approach. It allows us to base our forecasts on historical data that exhibits liquidity characteristics that are more similar to those found in the period of most interest to market participants (the year leading up to delivery). Both the data enrichment and the approach proposed by Frestad (2014) recognise the existence of a similarity between instruments differing only in their delivery date. While Frestad (2014) considers the use of instruments still to be traded in the future in forming the hedge, we use price information of (similar) instruments that have been traded in the past to assess the risk of the instrument the hedger is interested in. An advantage of our approach compared to the one proposed by Frestad (2014), is that our method does not expose the portfolio to basis risk and costs associated with transacting different instruments. A fourth contribution is that we compare the traditional approach to the data enrichment approach using four forecasting models. Although it is not the purpose of this paper to compare different models, using our method in several models shows its versatility.

Chapter 5 is based on the third paper, ‘Vertical Integration of Generation and Retail: Foreclosure in the Electricity Futures Market’ and presents empirical evidence of foreclosure in the electricity futures market following vertical integration between the electricity retail and generation stages. Our study makes several contributions. First, it is one of the first studies to focus on the impact of VI in the electricity market on the volume traded on the electricity futures market. We regress the electricity futures volume transacted on the ASX against independent variables representing VI, spot and futures price moments, demand and other variables. Second, we present a novel method of analysing transacted futures contract volume by horizon. The method provides new insights into the impact of VI on the structure of the futures market and competition. We split the hedging horizon into a shorter term that is within 12 months of the transaction date (H1) and a longer-term hedging horizon of greater than 12 months (H2). H2 is particularly relevant for the commercial and industrial customer segments of the market as well as for the portion of the residential customer segment on contracts longer than 12 months. These horizons are used by The Australian Financial Markets Association (AFMA) in reporting data relating to the electricity OTC market, the other major futures (bespoke) market. Such impact appears to have been missed in studies that did not differentiate between shorter and longer-term horizons – Simshauser et al. (2015) in the Australian context. A third contribution is to show that, in the study period, base load and peak load futures contract volumes were impacted differently. The volume of base load futures electricity contracts on the ASX covering a horizon >12 months fell significantly following VI. On the other hand, peak load energy volume transacted over a horizon up to 12 months increased following VI. This is likely due to the continued need to hedge in the short term (H1) but not in the longer term (H2).

Overall, the thesis provides various new insights and results on the econometric behaviour and use of futures contracts for hedging in wholesale electricity markets. In particular, it contributes to the literature by examining the determinants of futures risk premiums during the delivery period of the contracts, developing a new data enrichment approach for generating density forecasts for illiquid instruments, and examining the impact of vertical integration on the liquidity of electricity futures contracts that have different maturity horizons.

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

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Abstract

We provide an empirical analysis of risk premiums of electricity futures contracts during the delivery period for the major eastern states of Australia. While current research on electricity futures markets typically focuses on risk premiums for the pre-delivery period, a specific feature of the Australian market is that as a contract enters delivery, it continues to be traded until expiry. We develop an approach that decomposes the observed futures price during the delivery period into three parts: the crystallised value of the portion already delivered, the expected average spot price for the remaining days of the contract, and the risk premium for the remaining days of the delivery period. We examine the dynamics of realised risk premiums during the delivery period for quarterly base load and peak load contracts, as well as drivers of the observed premiums such as liquidity-based measures, time to maturity, current and historical spot prices and the historical behaviour of premiums. We find that risk premiums are positive during the delivery period for the majority of the considered contracts. Further, our results suggest that a model, using open interest, time to maturity, as well as recent characteristics of spot prices and risk premiums provides 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 Market, Spot and Futures Price, Risk Premium, Hedging*

3.1 Introduction

Electricity markets in many jurisdictions around the world have undergone a transition since the 1990s from monopolistic, government-controlled systems to deregulated, competitive markets. One consequence of deregulated power markets is that market participants are exposed to substantial price risk as pointed out, for example, by Benth et al. (2008) and Eydeland and Wolyniec (2012). Seasonal variation in demand and price as well as significant price spikes are well known features of these markets (Pilipovic, 1998; Weron, 2006). 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 (Bierbrauer et al., 2007; Redl and Bunn, 2013; Wilkens and Wimschulte, 2007). Non-storability has two key implications. First, electricity markets must balance supply and demand at each point in time and cannot use inventories to smooth shocks (Weron, 2006). Shocks may necessitate dispatching generation that lies on a different position on the cost curve associated with a vastly different bid price level (Cartea and Villaplana, 2008). Consequently, a small change in either supply or demand can lead to significant jumps in spot prices. The other implication is more methodological, as non-storability means that the usual cost-of-carry approach for the relationship between commodity spot and futures prices cannot be applied (e.g. Redl and Bunn, 2013).

Typically, instruments such as electricity futures contracts that are traded over-the-counter or on organised stock exchanges have been used to manage the substantial risk of spot electricity prices. However, given the very volatile nature of electricity spot markets, prices of futures contracts are not necessarily unbiased predictors of expected levels of spot prices, but also contain substantial risk premiums that are driven by the demand for hedging (Bessembiner and Lemmon, 2002; Longstaff and Wang, 2004). As suggested by Benth et al. (2008), positive risk premiums are more likely to occur when retailers have a demand for going long in near term contracts (locking in prices in the short term) in order to hedge the risk of high volatility or price spikes in the market. Conversely, negative premiums can be expected when generators hedge their future production of electricity by taking short positions in the futures market. This will usually occur 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.

Interestingly, empirical results on risk premiums in electricity futures markets are rather ambiguous. Various studies in the literature have examined the nature of the premiums and often provide contradictory results on the existence and sign of observed premiums in electricity futures markets (Bevin-McCrimmon et al., 2018; Bierbrauer et al., 2007; Daskalakis and Markellos, 2009; Diko et al., 2006; Hadsell and Shawky, 2006; Kolos and Ronn, 2008; Lucia and Torró, 2011; Redl and Bunn, 2013; Redl et al., 2009; Weron, 2008; Wilkens and Wimschulte, 2007). As pointed out by Weron and Zator (2014), some of the ambiguity in the results can be explained by the confusion around the terminology in the published research, since the terms *risk premium*, *forward premium*, and *forward risk premium* are not uniquely defined and sometimes used interchangeably. Further, empirical studies typically consider datasets that differ significantly in many dimensions; for example, in relation to the considered electricity markets and their characteristics (generation mix, marginal costs of generation, supply stack, etc.), or the time scale (e.g., daily, weekly, monthly, quarterly), delivery period and time to maturity of the examined futures contracts. Overall, despite the large body of literature, the analysis of risk premiums in electricity futures markets remains a challenging and open area of research.

Our paper adds to this field of research, by providing a pioneering study that specifically focuses on the dynamics and driving factors of futures risk premiums during the delivery period of the contract. While existing literature has examined risk premiums in various contexts and markets around the world, to the best of our knowledge none of these studies has analysed premiums during a period when electricity spot prices for a portion of the delivery period have been observed already by market participants. This paper aims to fill this important gap in the literature and shed new light on the analysis of risk premiums in power markets.

Our paper makes several contributions to the literature. 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 crystallised value of the portion already delivered, the expected 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 examine whether factors that have been suggested to impact risk premiums in previous literature, are also relevant during the delivery period of an electricity futures contract. Thus, we consider variables such as spot price levels, volatility or higher moments of the price series, in addition to variables related to the time to the maturity of the futures contract. We further investigate whether the observed premiums exhibit 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 (Handika and Trück, 2015). 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 examine indicators of trading activity such as open interest and trading volume as 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 and hedging activity in the market, which should ultimately also impact the price that market participants are required to pay for a hedge. A recent paper by Bevin-McCrimmon et al. (2018) shows a link between liquidity and premium in the New Zealand electricity market.

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 organised as follows. Section 2 provides a brief overview of spot and futures trading in the Australian National Electricity Market (NEM). Section 3 discusses ex-post futures premium dynamics and their potential determinants and reviews some of the conflicting results in the literature. Section 4 describes the data and the applied models that are used to examine risk premiums during the delivery period. Section 5 investigates the determinants of the observed futures premiums using regression analysis. Finally, section 6 concludes and provides suggestions for future work.

3.2 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, the Australian government commenced significant structural reforms in the late 1990s which, among other objectives, included the separation of transmission from electricity generation and the merging of twenty-five electricity distributors into a smaller group. Additionally, 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 (Ignatieva and Trück, 2016).

The Australian National Electricity Market (NEM) began operating as a wholesale market in December 1998 and currently operates as an interconnected grid comprising several regional networks that supply electricity to retailers and end-users. The NEM includes the mainland states of New South Wales (NSW), Queensland (QLD), South Australia (SA) and Victoria (VIC), while Tasmania (TAS) is connected to the state of VIC via an undersea inter-connector. 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. The Australian Energy Market Operator (AEMO) determines the generators required to produce electricity in a cost-efficient way based on existing demand. A spot price is then determined, based on the dispatched energy, for every half-hour for each of the regional markets. Therefore, the spot price is an average of the six five-minute dispatch prices for each half-hourly trading interval. A daily average spot price for each regional market can also be calculated based on the average of the 48 half-hourly prices (AEMO, 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). Three types of contracts are used to hedge exposure to the NEM: bilateral OTC transactions between two entities directly, OTC transactions on standard products executed through brokers, and exchange traded standardised electricity derivatives traded on ASX Energy[5]. 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 1st July 2007 to 30th June 2014.[6]

Like most electricity exchanges, futures contracts traded on the ASX refer to the average electricity price during a delivery period. Therefore, for a base period, a futures contract refers to the delivery of one Megawatt (MW) of electricity per hour for each half-hour interval of every day 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, peak 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. 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 (ASX Energy, 2015). Given that electricity prices show strong intra-day variation and are heavily affected by demand at 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 can only be settled financially, physical delivery is not an option, 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 (ASX Energy, 2015).

[5]See, https://www.asxenergy.com.au/products/electricity_futures (accessed 09.01.2015) for contract specifications.

[6]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.

3.3 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 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 realised futures or forward premium in these markets:

$$RP_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \bar{S}_{[T_1,T_2]} \,. \qquad (3.1)$$

In equation (3.1), $RP_{t,[T_1,T_2]}$ denotes the realised risk premium measured as the difference between the quote for a futures base or peak load contract, $F_{t,[T_1,T_2]}$, refers 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.

The literature on the behaviour of the premium predominantly focuses on the pre-delivery period, while we were unable to find studies that focus on the premium during the delivery period. The literature on the pre-delivery period examines several facets of the forward premium such as the existence of significant premiums and their respective signs (positive or negative), as well as the significant impact of higher moments of spot electricity prices on the premium. Other factors such as seasonality, intraday variation, time to maturity, and to what degree these variables influence the premium over time are included in the academic literature. Despite a significant number of studies, due to the ambiguity of empirical results the analysis of risk premiums in electricity futures markets has to be considered an unresolved and challenging area of research (Weron and Zator, 2014). In the following we provide a brief review of some key studies, their applied methodology as well as empirical findings with regard to the sign and driving factors of risk premiums in electricity futures markets.

Sign of the Premium and Time to Maturity

The literature mostly finds positive premiums in various electricity markets. For example, Hadsell and Shawky (2006) find positive risk premiums in the day-ahead peak period of the New York State Independent System Operator between 2001 and 2004. The study defines the premium as the percentage difference between the day-ahead and real time prices and finds it to be between 2.3 and 15.3 percent on average. Using a GARCH model to estimate volatility, they find that real time volatility known prior to the submission of bids, significantly impacts day-ahead premiums. Using a factor model, Kolos and Ronn (2008) find negative premiums for long-term contracts but positive premiums for short-term and day-ahead contracts in the U.S. PJM Interconnection LLC. Interestingly, they report negative premiums (i.e. futures quotes being lower than average realised spot prices) for monthly, quarterly and yearly contracts in the European Energy Exchange (EEX) in Germany. They support this finding by establishing that energy markets are driven by a short-term mean reverting factor which has a reducing impact on long maturity contracts. Additionally, they find a long-term factor that has a permanent non-mean reverting impact on contracts with longer maturities. In contrast, Redl et al. (2009) find positive premiums for monthly contracts on the EEX and attribute this to the shorter period versus data over the longer period from November 2003 to May 2008. However, the study by Kolos and Ronn (2008) is by no means the only study that reports negative premiums. Daskalakis and Markellos (2009) incorporate spot returns of European Emissions Allowances into their model and report negative premiums for day-ahead and generally positive premiums for month-ahead contracts in the EEX, Nord Pool (Scandinavia) and Powernext (France) markets. These mixed results could be influenced by different methodological approaches, but the main take away from these studies is that the time to maturity seems to have a significant impact on premiums, encouraging us to also incorporate this variable into our model.

Diko et al. (2006) utilize principal component analysis and find a positive (negative in their scheme as they state the premium as spot minus futures) day-ahead risk premium in peak and negative (positive) in off peak periods on the EEX, Powernext and APX (The Netherlands). Their findings show that the impact of spot price skewness relative to that of the standard deviation reduces the premium as the time to maturity of the futures contract increases. Bierbrauer et al. (2007) use EEX data to compare the performance of different models in explaining the major characteristics of the spot price and their ability to predict expected spot prices. They find that the two-regime model results in a superior performance over others. The authors 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.

Liquidity of Contracts

Wilkens and Wimschulte (2007) look at the pricing of monthly based futures traded on the EEX between July 2002 and December 2003. They fit one and two factor models to spot prices and then compare the model forecast to the price of futures contracts (the difference between the futures contract price and the model forecast divided by the futures contract price). They report risk premiums are on average positive and increase with the level of spot price and decrease with time to maturity. Additionally, around fifty percent of the trading volume occurs in the front month and falls, along with trading frequency, as time to maturity increases. The paper recommends further investigation of the link between premiums and low liquidity of contracts with longer maturities. A recent paper by Bevin-McCrimmon et al. (2018) shows a link between liquidity and premium in the New Zealand electricity market. The authors analyse daily data over the period 2 October 2009 and 31 December 2015 for two reference nodes, Benmore and Otahuhu. They consider three base load quarterly contracts: The contract with the closest maturity, referred to as the Front-End contract, and the contracts with maturity of one and two years after that. They consider physical variables (reservoir storage, inflow and electricity demand), production cost variables (returns of oil and emissions certificates), spot price variables (price level, variance and skewness), a lagged risk premium term and a liquidity term. They estimate separate models each with a different liquidity measure as the liquidity term. One model uses daily volume and the other open interest, both expressed as the number of contracts. They find a predominantly inverse relationship between the daily ex-post premium and liquidity indicated by the negative coefficient of the liquidity measure. However, the volume coefficient is only significant for the two-year contract at Otahuhu, and the open interest coefficient significant only for one-year and two-year contracts at Otahuhu.[7] There are several material differences between our paper and that of Bevin-McCrimmon et al. (2018). We study both base load and peak load contracts, we do not limit them to certain maturities, we combine volume and open interest in the same model, and we express the liquidity measures in energy terms to better account for the different lengths of quarters.

Storage and Reservoir Levels

Botterud et al. (2010) investigate risk premiums in the Scandinavian Nord Pool market over the period from 1996 to 2006 for weekly contracts with delivery between one and six weeks ahead. They report a positive premium (negative based on their definition) of the short-term one-week ahead contract and typically negative premiums for other contracts with longer

[7] Bevin-McCrimmon et al. (2018) also estimates a third equation incorporating Amihud's measure of (il)liquidity. The findings are directionally similar to those of the volume and open interest models, but the significant coefficients are found to be for the one-year Belmore and Front-End Otahuhu contracts. We decided not to investigate this measure as the results were not qualitatively different from the more widely accepted measures in our models.

maturities. Overall, futures prices tend to be higher than spot prices with risk premiums ranging from 1.3 to 4.4 percent and decreasing with the holding period. Examining the factors driving the premiums, they suggest that factors related to storage such as reservoir levels, consumption, current expectations of deviation from historical inflow and deviation from historical consumption as well as recent spot price characteristics such as level, variance and skewness help to explain the premiums. Interestingly, a subsequent study by Weron and Zator (2014), examining the relationship between spot and future prices in the Nord Pool market between 1998 and 2010, suggests contradictory findings. Utilizing a GARCH model the authors find that the reservoir level has a negative effect on the premium (positive in their set up).

Annual Seasonality

Lucia and Torró (2011) examine the risk premiums of the four closest weekly contracts in the Nord Pool market over a period of nearly ten years from 1998 to 2007. They report a time-varying impact of the variance and skewness of spot prices on the observed premiums. Furthermore, they report the risk premium to be zero in summer and spring, positive in autumn and greatest in winter. This further provides evidence of the seasonal nature of the premium with greater demand in colder periods (via high usage of electrical heating equipment) resulting in large positive premiums. Haugom et al. (2014) incorporate seasonality and the time varying nature of the premium to model the behaviour of weekly futures contracts with one-week to six-week maturities on the Nord Pool over a sample period of 1996 to 2013. They find positive premiums in the autumn and winter periods but not in summer and spring. Handika and Trück (2015) study the base load and peak load futures of the four main markets of the NEM from 2000 to 2012. They find evidence of statistically significant positive premiums for the summer and winter quarters in NSW, QLD and SA, while for other quarters risk premiums are typically not significant. Overall, these studies encourage us to consider seasonality as a key factor for the determination of risk premiums.

Factors Related to Spot Price Behaviour

We now move to studies that further analysed the equilibrium model originally proposed by Bessembinder and Lemmon (2002) (referred to as BL2002 from here on in this chapter). Longstaff and Wang (2004) find evidence supporting the sign of coefficients of the variance (negative) and skewness (positive) of the spot price, as suggested by BL2002. The study estimates hourly forward premiums in day-ahead data from the PJM for the period 1st June 2000 to 30th November 2002. When looking at the individual hours, they find positive risk premiums in 14 of the 24 hours and negative for 10 of the 24 hours (1am low to 6am and 10am to 3pm) corresponding to low demand. The highest positive premiums are for the evening peak times of 6pm and 7pm at 12.8% and 13.8% respectively. These are extremely large premiums, given the one-day horizon of the forward contract and could be attributed to the lack of risk-sharing in electricity markets, as only a few companies bear large risks.

Douglas and Popova (2008) look at hourly spot and day ahead prices on the PJM from January 2001 to December 2004 and find signs for the coefficients in line with the BL2002 model; that is, statistically significant coefficients with a negative sign for the variance and a positive one for the skewness of the spot price. Their regression model extends BL2002 by including a term for gas storage and cooling and heating demand. Redl et al. (2009) augment the BL2002 model with the inclusion of a consumption index (actual consumption/long-term consumption) and a capacity index (generation capacity/long-term capacity) for the delivery month. They find significant positive premiums with skewness as a determinant of base load premiums in the EEX and variance as a determinant of peak load premiums. For month-ahead base load futures in the Nord Pool market, they find positive variance and negative skewness for the November 2003 to May 2008 period; that is, signs opposite to those suggested by BL2002. For base and peak contracts on the EEX, they find a statistically significant and positive variance but a non-statistically significant coefficient of the skewness term. The authors also find current spot prices to be a determinant of year-ahead premiums in the EEX and Nord Pool. This is in line with Lucia and Torró (2011), who report that findings from BL2002 have changed over time for Nord Pool. Botterud et al. (2010) find no support for BL2002, as the coefficients of the variance and skewness are not statistically significant. For the six-week contract, the signs are consistent with the BL2002 approach while for one-week contracts the skewness is consistent, but the variance term has the opposite sign and is significant at the 95% confidence level. Furio and Meneu (2010), examining the Spanish electricity market, find a significant and negative impact of spot price variance on risk premiums for a sample period from 2003 to 2008. However, in their study skewness does not have a significant impact on the observed risk premiums.

Fundamental Factors

Redl and Bunn (2013) find a positive coefficient for the skewness term in peak load (in agreement with BL2002) and a positive coefficient of the variance term in base load contracts (opposite to BL2002). Looking at month-ahead forward contracts in the German EEX market between 2003 and 2010, they find positive premiums. They report premiums of 9% for base load and 12% 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. Although the seasonal effects were found to be not significant, the premiums were highest in January and lowest in April and September. Redl and Bunn (2013) also propose a multifactor framework for the forward premium by making reference to fundamentals factors such as the gas premium and generation margin. This is an important observation given that gas comes into the fuel mix (the other being coal) during peak periods, and therefore results in a premium for the gas price. Additionally, they note behavioural aspects via the distribution of the spot price through variance, skewness and kurtosis, spikes in the spot market and volatility in the oil market as positive influencers on the forward premium. Further, market power in the spot market, dynamic effects via an increase in basis and margin shock are also deemed to influence the forward premium.[8]

Interestingly, despite the large body of literature analysing risk premiums in electricity forward and futures markets, to the best of our knowledge no study has so far focused on the behaviour of these premiums for contracts that have already been partially 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 new insights into the hedging behaviour and the pricing of risk in electricity derivatives markets for contracts with short maturities.

3.4 Modelling Approach

This section outlines how futures risk premiums can be extracted from observed spot prices and the price of quarterly futures contracts. As noted previously in the Australian market, as a futures contract enters delivery, it continues to be traded until expiry. Therefore, 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.

[8] Fundamental factors were also employed in the model by Fleten et al. (2015), who incorporated the natural log of returns of the natural gas and gas oil Intercontinental Exchange (ICE) indices, the API2 coal contract, and the Argus European Union Allowances Carbon Dioxide front year.

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,[9] therefore, the purchaser of a futures contract at time t (occurring before T_2) pays price $F_{t,[T_1,T_2]}$ 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, $S_{[T_1,T_2]}$. 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; that is, $T_1<t<T_2$, where the premium is expressed as the difference between the futures price per MWh quoted at time t and the realised average spot price $\bar{S}_{[T_1,T_2]}$ per MWh during the delivery period $[T_1, T_2]$:

$$\pi_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \bar{S}_{[T_1,T_2]} \tag{3.2}$$

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

$\bar{S}_{[T_1,t]}$ 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.

1) $E_t\left[\bar{S}_{[t+1,T_2]}\right]$ is the expected average spot price (\$/MWh) for the remaining k_2 MWh from time $t+1$ to expiry on day T_2.
2) $\pi_{[t+1,T2]}$ 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 or uncertainty embedded in the futures price relating to the first k_1 MWh that has passed and where the spot price is already known. Therefore, the uncertainty reflected in the futures price relates to the period remaining to expiry; that is, from $t+1$ to T_2. Therefore, we can extract the futures-implied average price per MWh for the remaining delivery period, $\bar{Q}_{[t+1,T_2]}$, using the following expression:

$$\bar{Q}_{[t+1,T_2]} = \frac{1}{k_2}\left[(k_1 + k_2)F_{t,[T_1,T_2]} - k_1\bar{S}_{[T_1,t]}\right] \tag{3.3}$$

The realised risk premium for the remaining k_2 MWh can then be calculated by subtracting the realised average spot price for the remaining k_2 MWh of the delivery period $\bar{S}_{[t+1,T_2]}$ from the futures-implied average price for the remaining k_2 MWh, $\bar{Q}_{[t+1,T_2]}$:

$$\pi_{[t+1,T_2]} = \bar{Q}_{[t+1,T_2]} - \bar{S}_{[t+1,T_2]} \tag{3.4}$$

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

Expressing the premium for the (ever shrinking) remaining period of the contract on a per MWh basis provides a uniform measure of risk that allows us to study the behaviour of the premium (per MWh) over the entire delivery period. It is important to recognise that the realised portion of the contract up to time t carries no risk and accounting for it in equation (3.3) is required to correctly calculate the remaining risk in the unrealised portion of the contract. Failure to account for the realised portion would result in underestimating the premium in the remaining risky part of the contract.

Given the typically low liquidity in the Australian electricity futures market, it is important to note that we only use data on actual trades; in other words, 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 realised 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 of BL2002 examines the relationship between the bias in the forward price (i.e. the risk premium) and variations in the demand for power. The specified equation for the ex-ante risk premium π_t then takes the form:[10]

$$\pi_t = \alpha_0 + \alpha_1 MEAN_t + \alpha_2 STD_t + \alpha_3 VAR_t, \tag{3.5}$$

where $MEAN_t$, STD_t and VAR_t 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, while most authors typically use the mean, standard deviation and variance of electricity spot prices instead of the load as explanatory variables. Furthermore, as mentioned earlier, the majority of empirical studies have rather analysed ex-post premiums than ex-ante premiums, since the latter are highly dependent on the chosen model for the expected spot price (Weron and Zator, 2014). As outlined in Section 3, several authors have further extended the original model by including additional explanatory variables related to higher moments of spot prices, seasonality, time-to-delivery of the contract, as well as characteristics of the electricity market examined (Cartea and Villaplana, 2008; Furio and Meneu, 2010; Handika and Trück, 2015; Redl et al., 2009).

[10] See, equation (18) in BL2002. Note that in the proposed model the ex-ante risk premium is measured as the difference between the one-month forward price for delivery in month t and the cost-based estimate of the expected spot price in month t.

Given that 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 expiry (i.e. the last day of the delivery period) of the futures contract (T_2-t) as a key variable in our model. Wilkens and Wimschulte (2007) suggest that the premium increases with the level of the spot price. We therefore test average spot price levels over the previous week, month and the same quarter in the previous three-year period; the average premium of the same quarter in the previous three-year period; volatility in the spot market; and additional risk measures – the number of price spikes (see, e.g., Redl et al., 2013) – as explanatory variables in measuring the magnitude and behaviour of risk premiums in the examined markets. Finally, we also include variables related to the liquidity of the contracts as well as learning by market participants. For liquidity, we use trading volume and open interest of a contract as proxy measures. The inclusion of terms relating to the liquidity of the contracts, the average premium and the average spot price of contracts referring to the same quarter in the previous three years and time to maturity is novel. In addition, our approach correctly calculates the ex-post premium per MWh by recognising that the crystallised portion of the spot price carries no price risk and assigning the risk to the period remaining to expiry.

In addition to 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 realised risk premiums for all quarters, we believe that the observed dynamics of the futures risk premiums would not justify such an approach. Our decision finds support in the literature that has established the effect of seasonality on the premium (see, e.g. Bunn and Chen, 2013; Cartea and Villaplana, 2008; Handika and Trück, 2015; Haugom et al., 2014; Lucia and Torró, 2011). Further details on the variables included in the models applied here are provided in the next section.

3.5 Empirical Analysis

3.5.1 The Data

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 and contracts, where the specific futures contract (e.g. the 2012 Q1 NSW futures) has actually been traded on the market; in other words, the traded volume is greater than zero.[11] 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 actual trades particularly for the peak futures contract. Recall that 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.

First, the term $\bar{Q}_{[t+1\,,\,T_2]}$ is calculated using equation (3.3), based on the already observed average spot price up to period *t*, $\bar{S}_{[T_1\,,t]}$, the closing daily futures price and the number of days remaining to expiry. The premiums for the base and peak load contracts are then extracted based on equation (3.4), where the term $\bar{S}_{[t+1\,,T_2]}$ is calculated as the average realised spot price for the remaining hours of the delivery period. Futures contracts 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, although the ASX has a clearly defined and transparent 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 has actually been traded. This ensures that the corresponding calculated premium reflects the actual value placed by market participants on the contract and avoids introducing possible biases that may be incorporated in a formula derived closing price.

[11] Traded volume here refers to the number of contracts for a specific quarterly futures traded on a given day on the ASX Electricity Futures market.

The spot data consists of half-hourly spot electricity prices for the period 1st July 2007 to 30th June 2014 published by the market operator AEMO.[12] The average daily price is the arithmetic mean of 48 half-hourly prices, which is then used to calculate most of the variables and statistics except the weekly standard deviation, skewness, kurtosis and the weekly and monthly spike counts, all of which are based on half-hourly price data.

3.5.2 Descriptive Statistics of the Risk Premiums

In the first step we investigate whether significant futures premiums are present during the delivery period. Consequently, the futures-implied risk premiums calculated from equation (3.4) 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 t-statistics and corresponding p-values to evaluate the significance. The findings in Table 3.1 show that statistically significant positive average premiums are present over the sample period in all states and quarters, except for Q2 in VIC 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. For example, Q3 peak load contracts in QLD have a p-value of less than 0.0035. Average significant premiums for base load contracts are typically between $3 and $6 per MWh for NSW, between $2.50 and $9.50 for QLD, and between $4.50 and $10 for VIC. For peak load contracts, the average premiums are significant and positive for all states and quarters and range from $2.83 to $5.51 per MWh in NSW, from $3.79 to $9.24 for QLD, and from $2.59 to $6.50 for VIC.

The positive premiums in all quarters and across the three states suggest that buyers of electricity futures contracts (e.g. retailers and large consumers) 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 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, for example, Bunn and Chen (2013), who also suggest 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,

[12] https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard#aggregated-data (accessed 31.07.2017).

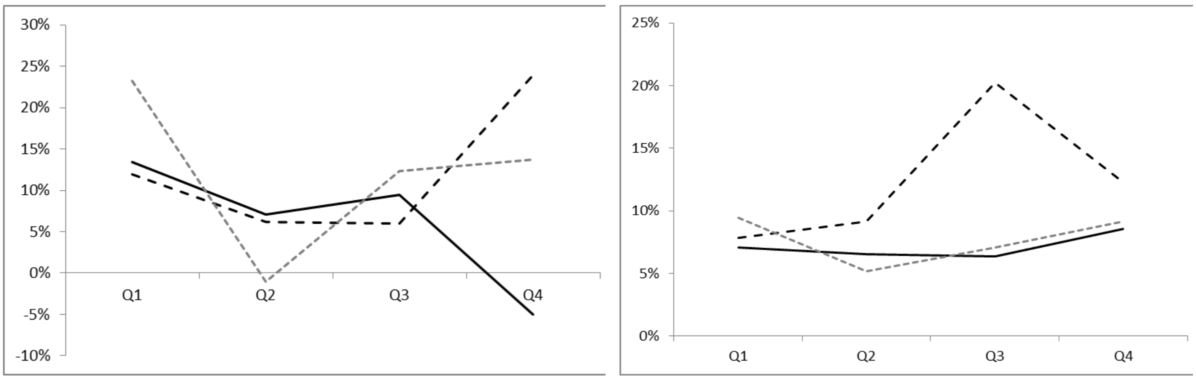
consider a quarterly base load contract with 92 days – referring to 2,208 MWh. If a large consumer in NSW decides to buy Q1 base load futures contracts halfway through the delivery period, on average the consumer would pay an approximate additional risk premium of $6,500 per contract to hedge the spot price risk.

Table 3.1

Observed ex-post futures premiums means.

		Base load			Peak load		
State	**Quarter**	**Mean**	**t-stat**	**# Obs**	**Mean**	**t-stat**	**# Obs**
NSW	**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

This table presents the observed ex-post futures premiums (in $/MWh) for quarterly base load and peak load futures contracts in NSW, QLD, and VIC for the period Q3 2007 – Q2 2014. ***significant at 0.01; **significant at 0.05; *significant at 0.10



Base Load

Peak Load

Fig. 3.1. Premiums for base load and peak load – NSW, QLD and VIC. Mean premium as a percentage of the corresponding mean spot price is shown for base load (left panel) and peak load (right panel). Each panel shows the three States of NSW (solid line), QLD (dashed line) and VIC (dotted line) in the sample period July 2007 to June 2014.

Fig. 3.1 shows the mean premiums expressed as a percentage of the corresponding mean spot price throughout the sample period for each quarter and state. The graph illustrates that for some of the quarters and states, the average premium is quite substantial and exceeds even 20% of the average spot price. We also find that for base load contracts, the average premium is higher for QLD and VIC during periods of high demand – in Q1 and Q4 in comparison to Q2 and Q3. For NSW, during Q1 the average premium is also higher than for Q2 and Q3, while it is negative (although insignificant) for Q4. For peak load contracts, we find that in NSW and VIC average premiums are typically between 5% and 10% of the spot price level for each of the quarters, while they are significantly higher for QLD in Q3 and Q4.

Having established that the average premiums are highly significant and positive, we report the descriptive statistics of the premiums in Tables 3.2 and 3.3. 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 Q1 and Q4. This is consistent with the fact that these quarters typically exhibit higher spot price volatility which drives interest in covering positions and therefore liquidity and trading frequency are higher. For peak load contracts, Q1 contracts are also traded most frequently, with the exception of NSW where Q4 contracts are traded at a higher frequency than Q1.

Other characteristics to note are that the standard deviation of the premium is lower for peak load than for base load contracts. The coefficient of variation, although not reported here, is 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 for 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 minimum premiums for base contracts have large negative magnitudes but are rather small for peak load contracts. Overall, our findings suggest widely consistent positive premiums for peak load contracts during the delivery period, compared to a wider range of the observed premiums for base load contracts. This may suggest that buyers of these contracts (large consumers and retailers) are even more risk averse, and therefore consistently willing to pay a premium to hedge their exposure to spot price risk for peak hours.

Table 3.2

Descriptive statistics for premiums – base load contracts

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

Descriptive statistics for ex-post futures premiums during the delivery period for base load contracts, sample period Q3 2007 to Q2 2014 ($/MWh). ***significant at 0.01; **significant at 0.05; *significant at 0.10

Table 3.3

Descriptive statistics for premiums – peak load contracts

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

Descriptive statistics for ex-post futures premiums during the delivery period for peak load contracts, sample period Q3 2007 to Q2 2014 ($/MWh). ***significant at 0.01; **significant at 0.05; *significant at 0.10

3.5.3 Model Development

We estimate a multiple regression model by pooling the premiums for each quarter, base and peak load separately, across the different regional state markets, as we expect similar premium drivers across the NEM regions. We believe that this assumption is justified, since the physically interconnected transmission network allows the flow of electricity (although subject to capacity constraints) between the regional markets of NSW, QLD and VIC. Further, it is reasonable to assume that common seasonal drivers of demand in the three states such as temperature and weather, contribute to the common dynamics of the price levels and, potentially, premiums across the regional markets.

We specify our multiple regression model by using a two-step procedure to select the explanatory variables that are included in the model. First, we systematically test (using univariate regression) individual explanatory variables deemed as possible driving factors of the premium, as this allows us to assess the significance, sign and strength of the relationship of each variable. We evaluate factors related to liquidity, time to expiry, level of spot price, higher moments of the spot, price spikes, premiums from previous years, and dummies for carbon emissions, year and state. The variables that pass this first test are then shortlisted and we perform a correlation analysis between pairs of variables, before deciding on which explanatory variables enter the multiple regression 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 the following, we provide additional information on the rationale for including the considered variables into a model as well as on the expected sign of the estimated coefficients.

Proposition on liquidity: We test the indication in the literature that higher liquidity is a measure of increased competition and leads to lower premiums. Starting with liquidity, Wilkens and Wimschulte (2007) recommend investigating the link between premiums and low liquidity contracts. We test volume (number of contracts traded on a given day) and open interest (the number of contracts on a given day that have not been closed by a trade or exercised thereby offsetting the original position) as measures of liquidity and the level of participation in the market. Huisman and Kilic (2012) emphasize the role liquidity, as a higher traded volume indicates a higher degree of competition. BL2002 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. Given the large magnitude of open interest relative to the other variables we scaled it by dividing the data by 1,000 so a magnitude of 1 signifies 1,000 contracts.

Proposition on time to expiry: We test the proposition that as the contract nears expiry, a shorter period remains unrealised, hence premiums are expected to fall. 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 to expiry, the shorter the period of uncertainty and potentially the lower the premium. Time to maturity is well established in the literature as a factor affecting pricing and premium in futures contracts. Benth et al. (2013), Diko et al. (2006), Kolos and Ronn (2008) and Wilkens and Wimschulte (2007) point to a relationship between premium and time to maturity in futures contracts.

Proposition on the level of the spot price: We test the indication in the literature that a higher level of spot prices leads to higher premiums. The next set of explanatory variables relate to the level of the historical spot price. Wilkens and Wimschulte (2007) find that premiums increase with the level of historical spot price; Botterud et al. (2010) use the level of weekly spot price as a regressor for premiums; and Handika and Trück (2015) find that the premium depends on the mean level of spot electricity prices in the month prior to delivery. We explore the impact of the long, medium and short-term average spot price, using the three 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 the historical behaviour of the spot price. In a similar way, dependence of the premium on short-term spot price behaviour could indicate the influence of more recent information on the premiums. We define the three-year average price as the average spot price of the same quarter over the previous three 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 period.

Proposition on higher moments of the spot price: We test the proposition in the literature that the premium increases with higher moments of the spot price. We estimate the dependence of the premium on risk, employing the standard deviation, skewness and kurtosis of the distribution of spot prices over the long, medium and short horizons as a proxy. The three-year, one-month (28 days) and weekly periods are used as defined for the average spot price. Our decision to test these variables is motivated by the fact that Handika and Trück (2015), Redl et al. (2009), and Redl and Bunn (2013) all include higher moments of spot electricity prices (kurtosis) to cater for the impact of fat tails in the price distribution. There is a nuance to this proposition related to the BL2002 model. If both the variance and skewness terms enter the multiple regression equation and both relate to the same period (i.e. both weekly or both monthly) then we would expect the variance term to have a negative sign and the skewness to be positive. However, in the univariate regression, as well as if only one of these variables enters the multiple regression model, we would expect the sign of the variable to be positive.

Proposition on spikes: We test the indication in the literature that the premium increases with the number of spikes in the spot price. 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, and the premium increases with the presence of spikes (Redl et al., 2013). Redl et al. find that the number of spikes exceeding two standard deviations influences the premium of peak contracts, while price spikes are not significant for base load premiums. However, there is no universally agreed definition of a price spike in the literature. Two approaches have been used to define a spike – Lapuerta and Moselle (2001) defined it by reference to an arbitrary price level, and Cartea and Figueroa (2005) defined a spike as occurring when returns exceed a threshold, such as three standard deviations. 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.[13] Therefore, 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

[13] 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.

captured using a weekly spike count based on half-hourly spot prices exceeding $300/MWh during the seven days (one week) prior to *t*.

Proposition on the premium level in previous years: We test the proposition that premium levels are mean reverting. We test whether the market learns from the behaviour of premiums in previous years and adjusts premiums up if they have been historically low and down if they have been historically high. We include the level of the premium of similar contracts in previous years, since it is also likely to influence the pricing of futures contracts as the variable indicates the risk embodied in the premium. We capture this by including the average of the daily premium of the same quarter over the previous three years. For clarity, this is not the lagged premium paid for the contract in question, nor can it be, because the delivery period is only one quarter not three years.

Proposition on carbon pricing: We test whether the premiums were higher during the two years when the fixed price carbon mechanism was in place. We use yearly dummy variables to investigate the premium relative to a base year – the Australian financial year (FY) from 1st July 2011 to 30th June 2012 (FY2012). FY2012 is selected, as the carbon tax commenced the following financial year 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.[14] 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) find an impact from European Emissions Allowance returns on premiums, while Redl et al. (2013) suggest there is no significant relationship between a price on carbon and risk premiums in electricity markets.

Having stated our propositions and defined the variables to test, we start the first step of our procedure by regressing the premium on each explanatory variable individually. An explanatory variable passes this filter if it is found to be significant in three or more quarters in the univariate regression. For base load contracts we find that open interest, time to expiry of the futures contract (T_2-t), the three-year-average spot price, the three-year-average premium,

[14] 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.

the monthly standard deviation, the average weekly spot price, the weekly standard deviation, the monthly and weekly spike counts, as well as a dummy for the carbon tax period, pass the filter. Therefore, along with the year and state dummies these variables are candidates for further assessment and inclusion in the multiple regression model. For the peak load premium, the following variables pass the first step filter: the average monthly spot price, the monthly standard deviation, the time remaining to expiry of the futures contract (T_2-t), the average weekly spot price, the weekly standard deviation, the weekly skewness, the monthly and weekly spike counts as well as the year and state dummy variables.

We note that the base load group represents a broader range of short, medium and long-term variables, while the peak load group represents shorter and medium-term variables. From tables A.1 (base load) and A.2 (peak load) presented in the Appendix, we can see that the coefficient of the three-year-average spot price and three-year-average premium is significantly different from zero for the base load model, but not for peak load contracts. In addition, 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 contracts). Further, the coefficient of open interest is significant only for base load contracts, while time to expiry is significant for both base load and 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. The signs of the variables that pass this filter are generally as expected, and we discuss this in more detail in the context of the multiple regression model.

Table 3.4

Correlation matrix between explanatory variables

	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

This table presents the correlation matrix between explanatory variables that passed the univariate regression first step of observed ex-post futures premiums during the delivery period – base load Quarter 2 for the study period.

In the next step we calculate and examine linear correlations between pairs of the explanatory variables that passed the variable selection filter. The pairwise correlations for Q2 are presented in Table 3.4 as an example. The other correlations across the remaining quarters are not reported but some key findings are discussed below.

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 the weekly standard deviation in three quarters but is not correlated with the monthly standard deviation. Hence, we retain the monthly standard deviation and average weekly spot. Perhaps not surprisingly, the monthly spike count is correlated with the monthly standard deviation in three quarters and 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. We can find support for our decision to exclude a specifically carbon-related variable in Redl et al. (2013), who suggest that the price of carbon is already included in the electricity spot price volatility. The average three-year premium and the average three-year spot price are negatively correlated for Q2 and to a lesser extent for Q1 (ρ=-0.63). In addition, in regressions that are not reported, when we included the three-year spot variable, whether on its own or with the three-year premium variable, it resulted in an extremely high intercept term; therefore, we retain the average three-year premium and drop the average three-year spot.

For 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 exhibits a highly positive correlation with the average monthly spot price in Q1 and Q4. The latter variable is significant in three quarters, and therefore the 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 (in Q1, Q2 and Q4) with the monthly standard deviation. As a result, the monthly spike count is also excluded from the model. Furthermore, for the peak load model, the time remaining to contract expiry (T_2-t) is significant in all quarters and is not correlated with any of the other variables. Therefore, (T_2-t) as well as the monthly standard deviation are included in the model. As in the case for variables being based on observations for the last month, the weekly spike count, weekly standard deviation and weekly average spot price are also 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 in the model. As in the model for base load contracts, we also include dummy variables for the financial year and state.

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

$$\pi_{[t+1\,,T2]} = \beta_0 + \beta_1(OI) + \beta_2(T2 - t) + \beta_3(m.SD) + \beta_4(w.Spot) + \beta_5(3yr.P) + \delta_1(FY08) + \delta_2(FY09) + \delta_3(FY10) + \delta_4(FY11) + \delta_5(FY13) + \delta_6(FY14) + \theta_1(Qld) + \theta_2(Vic) \quad (3.6)$$

For realised risk premiums of quarterly peak load futures contracts in NSW, QLD and VIC, the following model (7) is applied:

$$\pi_{[t+1\,,T2]} = \beta_0 + \beta_1(T2 - t) + \beta_2(m.SD) + \beta_3(w.Skew) + \delta_1(FY08) + \delta_2(FY09) + \delta_3(FY10) + \delta_4(FY11) + \delta_5(FY13) + \delta_6(FY14) + \theta_1(Qld) + \theta_2(Vic) \quad (3.7)$$

Recall that $\pi_{[t+1\,,T_2]}$ denotes the premium in \$/MWh remaining from day *t+1* in the delivery period till the expiry of the quarterly futures contract, *OI* is 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 realised premium for futures contracts in the 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, while NSW is used as a reference state, such that dummies for QLD and VIC are included.

3.5.4 Estimation Results

Results for the estimation of model (6) for base load contracts are presented in Table 3.5. The models yield a relatively high explanatory power for the observed risk premiums during the delivery period. The coefficient of determination ranges from 0.347 for Q1 base load contracts up to 0.718 for Q3 contracts. The explanatory power of the model is the lowest for Q1 contracts, where the regional markets are typically most volatile and realised risk premiums for the futures contracts also 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.

In our discussion we relate the results to the propositions developed in Section 5.3. We find that premiums are related to open interest in the market – the variable *OI* is significant in Q2 and Q4. In particular, *OI* is significant and negative in Q2, with Q4 returning a large positive and significant coefficient. The results for Q4 could indicate that premiums are driven by high degrees of risk aversion with consumers willing to pay a high premium. The negative coefficients in Q1 to Q3 are consistent with the relationship found in Bevin-McCrimmon et al. (2018) and the argument in BL2002 that the presence of speculators is expected to reduce premiums. As the contracts approach expiry, the premiums adjust slowly as indicated by the significant and small coefficients for the time to expiry variable T_2-t (measured in days) in Q1 and Q2. In line with expectations, base load premiums are reduced as the contracts approach expiry, indicated by the positive coefficients for Q1 and Q3. Interestingly, however, the opposite occurs for Q2 and Q4 contracts, which are found to have negative coefficients. Initially, the negative coefficients for Q2 and Q4 are counter-intuitive, as a longer period to maturity carries more risk. However, we explain the negative coefficients of Q2 and Q4 with reference to the behaviour of the standard deviation of spot prices across the different months in Fig. 3.2. 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 in the spot price for June is 17.74 – significantly higher in comparison 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. Results are 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).

Table 3.5

Based load regression

	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)
T_2-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

This table presents the base load multiple regression for the observed ex-post futures premiums (in $/MWh) during the delivery period from Q3 2007 to Q2 2014. ***significant at 0.01; **significant at 0.05; *significant at 0.10

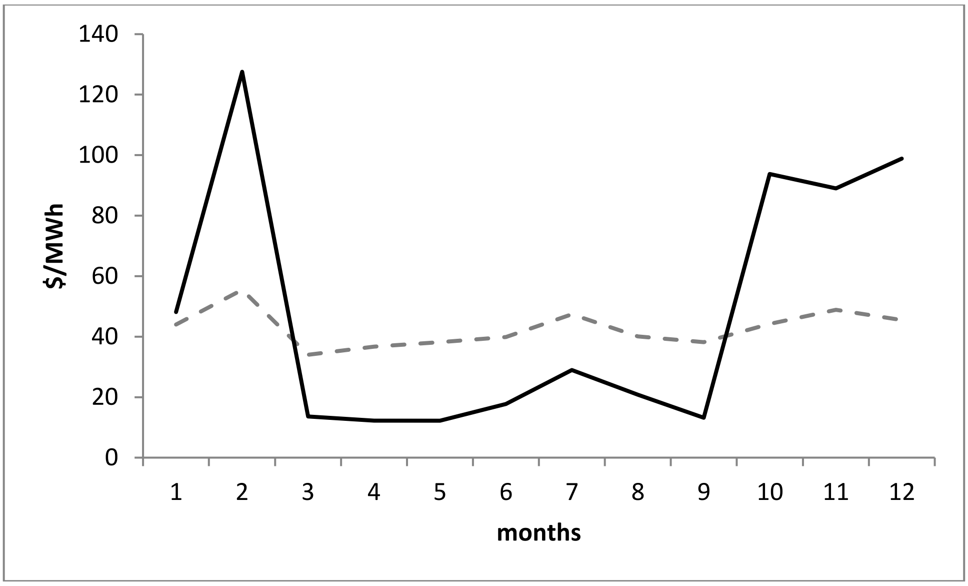


Fig. 3.2. Mean and standard deviation of daily spot electricity prices. The figure shows the mean (dotted line) and standard deviation (solid line) of daily spot electricity prices by month during the sample period July 2007 to June 2014 in NSW

The base load premium increases with higher volatility in the spot price in the previous month, as indicated by a positive coefficient for the monthly standard deviation (*m.SD*). The base load premium also increases with a higher level of the average spot prices in the previous week (*w.Spot*). Both have positive coefficients consistent with the expectation that higher volatility and higher price levels of the recent past lead to higher risk aversion, translating into higher premiums. It seems that the market adjusts the premiums in a mean reverting fashion based on the past behaviour of the premium. 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 Fig. 3.2. The coefficient is negative in all quarters except Q3 (which is not significant), which can be interpreted as participants learning from previous experience and correcting the premium they pay for the current quarter; that is, paying a lower premium if they paid a higher one 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 were typically lower in comparison to 2012. The sign is mixed for the years prior to 2012. Looking at the state dummy variables we find that, compared to NSW, the premium is significantly lower in QLD in Q2, while it is significantly higher in VIC for Q2 and in both QLD and VIC for Q4.

Next, we report the results for peak load contracts in Table 3.6, based on estimation results for 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.

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

We now turn to examining the impact of the applied explanatory variables on realised risk premiums during the delivery period. We find that premiums increase with volatility in the spot market. The coefficient for the standard deviation in spot prices in the previous month (*m.SD*) is positive in all four quarters, but it is significant only for Q1 and Q4. The sign of the coefficient 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. We also find that the premium generally increases with the skewness of the spot price. The coefficient for *w.Skew* (i.e. skewness of the spot price in the most recent week) is positive and significant for Q1 and Q4. A likely explanation for the negative coefficient of *w.Skew* in Q2 relates to its low spot price volatility. The lower price risk means that consumers are not as motivated to cover their exposure using peak contracts, and the producers are more motivated to cover their exposure. This then limits the premium obtained on the market; for Q3 any unexpected increase in the spot price (positive skewness) therefore reduces the premium that the sellers of the futures contracts enjoy.

Table 3.6

Peak load regression

	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)
T_2-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

This table presents the peak load multiple regression for the observed ex-post futures premiums (in $/MWh) during the delivery period from Q3 2007 to Q2 2014. ***significant at 0.01; **significant at 0.05; *significant at 0.10

We also find that risk premiums for peak load contracts are lower as the contract nears expiry. The coefficient for the time remaining till the expiry of the futures contract (T_2-t) is negative and significant for all four quarters. 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 extreme risk aversion that motivates them to cover their exposure during the peak periods even at the cost of paying a higher premium. We find that the financial year dummies indicate that relative to the base financial year *FY12* most of the years show a higher premium and most of these estimates are significant. The years *FY10* and *FY11* show predominantly lower premiums than *FY12*, but most of these estimates are not significantly different from zero and quite small. We also find that premiums in QLD are not significantly different from NSW with the exception of Q4, while for VIC we find significantly higher premiums for Q1, and significantly lower premiums for Q2 and Q4.

Finally, we also conduct some robustness checks with regard to the applied shift in the Box-Cox transformation. Recall that, originally, we performed a transformation using a shift just large 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 (T_2-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 unduly influenced by the Box-Cox transformation of the dependent variable.

3.6 Conclusion

We provide a pioneering study examining risk premiums of electricity futures contracts during the delivery period for quarterly base load 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 period when partial information about electricity spot prices for the reference period of the contract 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 as the contract approaches maturity.

In the first step, we develop a framework 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 crystallised 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 from July 2007 to June 2014.

We also develop multiple regression models for base and peak load contracts that help to explain the dynamics of the premiums during the delivery period of the respective futures contracts. The developed models yield 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, such that risk premiums also exhibit 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 observed premiums. We further find that premiums have a negative relationship with realised historical risk premiums of contracts referring to the same quarter in previous years. We interpret this as a form of learning by market participants. In 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, premiums are 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 those 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 find a positive relationship between observed risk premiums and the standard deviation of electricity spot prices, as reported for example by BL2002, Longstaff and Wang (2004), Redl et al. (2009) and Redl and Bunn (2013). However, many of our results also indicate the specific behaviour of risk premiums 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 the 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 in an appropriate model. Suggestions for future work include extending this work to futures contracts of longer and shorter delivery periods (e.g. annual or monthly contracts) as well as to options and caps. Another line of enquiry could be to compare premiums during delivery of futures contracts against premiums during delivery of OTC contracts. Such work would require access to information on OTC contracts that is typically not publicly available. Standardised OTC contracts, traded through brokers, would be more easily comparable, while more careful consideration would need to be given to OTC contracts that incorporate peculiar features.

Risk Managers may benefit from the findings in this paper that show declining premiums for both base and peak load contracts as the contract approaches maturity. At the same time, premiums for both base and peak load contracts increase with higher spot price volatility in the previous month. For base load contracts they also increase with average spot prices in the previous week, pointing towards the risk averse behaviour of market participants that may not be in the best economic interest of the hedging party.

Despite considering 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 when using electricity futures contracts.

Appendix A

Table A.1

Base load regression

	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)
T_2-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

This table represents the base load univariate regression of the observed ex-post futures premiums (in $/MWh) during the delivery period Q3 2007 to Q2 2014. ***significant at 0.01; **significant at 0.05; *significant at 0.10

Table A.2

Peak load regression

	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)
T_2-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

This table represents the peak load univariate regression of the observed ex-post futures premiums (in $/MWh) during the delivery period Q3 2007 to Q2 2014. ***significant at 0.01; **significant at 0.05; *significant at 0.10

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4. Electricity Futures Markets in Australia: Generating Density Forecasts for Returns of Low Liquidity Instruments

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Abstract

We examine density forecasts for price changes in electricity futures contracts. These instruments, used for risk management, typically exhibit low liquidity during periods of more than one year prior to delivery. We assess the performance of different density forecasting methods using conventional approaches based on historical returns for the considered instruments. We find that such an approach performs poorly and provides inaccurate predictions for day-ahead densities. The poor performance is due to reliance on return data from a low liquidity period to make predictions relating to more liquid periods. To deal with this shortcoming, we introduce a new approach which enriches historical data for a contract with data from more liquid trading periods of identical contracts traded over the previous three years. We find that our data enrichment approach significantly improves the correct specification of density forecasts of daily returns based on various evaluation metrics. Our results are of interest to risk managers and parties with exposure to electricity price risk. Our approach is also relevant for market participants who want to appropriately evaluate the risk of price changes for derivatives exhibiting different phases of return behaviour and liquidity, depending on their time to maturity.

JEL Classification: Q40, G32, G17, C53

Keywords: *Electricity Market, Futures Contracts, Value-at-Risk, Density Forecast, Risk Management*

4.1 Introduction

The Australian electricity market embarked on its deregulation journey in late 1998. The National Electricity Market (NEM) is a wholesale spot market and is considered to be more volatile and prone to spikes than many other comparable spot electricity markets (Higgs and Worthington, 2008; Boland et al., 2016; Mayer and Trück, 2018). Such high volatility requires participants in the wholesale electricity market, such as generators, retailers or large consumers, to manage their price risk. Market participants have managed risk using financial instruments in the over-the-counter (OTC) market as well as using exchange traded electricity derivatives which developed alongside the NEM.[15] The futures market offers many advantages over the OTC market. In addition to lower counterparty risk, exchange traded derivatives are transparent and available to all participants. It is also easier to unwind a position on the futures market through trading operations, compared to OTC contracts, which require bilateral negotiations. However, one of the main difficulties in using electricity futures contracts for hedging, is the low liquidity of these instruments (Anderson et al., 2007).[16] Low liquidity can detract from market efficiency as liquid markets are seen to incorporate information into prices and fulfil price discovery more readily than illiquid markets (Growitsch and Nepal, 2009). This is true for both OTC and exchange traded futures contracts. The link between liquidity and return has been confirmed by many researchers who followed on from the seminal works on the topic by Amihud and Mendelson (1986a, b). Therefore, it is important to be cognisant of this link when, for example, considering return data from a lower liquidity period to estimate returns or measure risk in a higher liquidity period.

Value at Risk (VaR) has evolved as a popular risk measure used by managers, financial institutions and their regulators among others (Jorion, 2006; Ziggel et al., 2014). VaR is simple to calculate and is able to combine several types of assets that may exist in a portfolio. As VaR is essentially a particular quantile of future returns, it relies on estimating the, often unknown, true generating process of returns, which can also be time varying. Engle and Manganelli (2004) propose a new approach – Conditional Autoregressive Value at Risk (CAViaR) – to

[15] Quarterly Futures base load and peak load contracts started trading on the Sydney Futures Exchange on 3 Sep 2003. At present they trade 16 to 17 quarters out of delivery according to the information on the ASX.

[16] More recent data for trade in electricity futures on the ASX for the period in our data set "The trading volume in 2012−13 was equivalent to 186 per cent of underlying energy demand, down from 231 per cent in 2011–12 and 285 per cent in 2010−11". According to the State of the Energy Market report 2013 published by the Australian Energy Regulator. This compares to multiples of eight and seven times for international markets such as EEX and Nord Pool (Redl and Bunn, 2013).

overcome this limitation. CAViaR includes an autoregressive process to deal with volatility clustering, typically found in returns. To test their model, they used a sample of 3,392 daily stock returns for GM, IBM and S&P500; they optimized their model on part of the data and used observations from the last 500 days as an out-of-sample test. They show that CAViaR can adapt to changes in volatility and observe that the process in the tail of the distribution appears to be different to that of the rest of the distribution. VaR has been criticised for its narrow focus and for not providing information about the entire risk distribution, particularly in the tail area beyond the VaR estimate (see, e.g., Christoffersen and Pelletier, 2004; Engle and Manganelli, 2004). There is growing interest in the use of density forecasts, which provide a more comprehensive view of risk, instead of VaR, which typically reports only a single quantile of the return or loss distribution (Clark, 2011; Fan et al., 2018; Gaglianone and Lima, 2014; González-Rivera and Sun, 2017; Kapetanios et al., 2015; Kenny et al., 2015; Rossi and Sekhposyan, 2014; Wolters, 2015, among others).[17]

In this paper, we evaluate the performance of one-day ahead density forecasts of returns in a low liquidity environment, using data from the Australian electricity futures market from 2005 to 2014. To assess whether different approaches to density forecasting are specified correctly, we use Probability Integral Transforms (PITs) originally suggested by Diebold et al. (1998) as well as the approach by Berkowitz (2001) and take an inverse normal transformation of the PIT.

The literature on liquidity in financial markets is extensive and covers many aspects of liquidity and many different markets, including equity, bond, foreign exchange or derivatives markets. Interestingly, very few studies deal with liquidity in electricity markets. Our study is motivated by the difficulties market participants typically face in measuring risk exposure, when the financial instrument relating to the underlying exposure has low liquidity. The influence of liquidity on premiums of electricity futures has been shown in a recent paper by Bevin-McCrimmon et al. (2018). The authors analyse daily data over the period from 2 October 2009 to 31 December 2015 for two reference nodes – Benmore and Otahuhu in New Zealand. They consider three base load quarterly contracts: The contract with the closest maturity, referred to as the Front-End contract, and the contracts with maturity of one and two years after that. They consider physical variables (reservoir storage, inflow and electricity demand), production cost

[17] Abad et al. (2014) provide an extensive review of VaR methodologies.

variables (returns of oil and emissions certificates), spot price variables (price level, variance and skewness), a lagged risk premium term and a liquidity term. They estimate separate models each with a different liquidity measure as the liquidity term. The first model uses daily volume; the second open interest, both expressed as the number of contracts; and the third the (il)liquidity measure proposed by Amihud (2002). They find a predominantly inverse relationship between the daily ex-post premium and the liquidity measure. However, the coefficient of the liquidity term is significant only for some combinations of contract and node. Frestad (2014), who studied the Scandinavian electricity market Nord Pool, proposes a hedging approach for assets with low liquidity by replacing the low liquidity instrument – say the Nord Pool system price in year *y+3* – with a more liquid contract identical in all respects but with a mismatched delivery date – say years *y+2* or *y+1*. The hedge effectiveness of, what the author calls, the *dirty hedge* is traded off against the lower cost of implementing more liquid instruments. The lower cost is due to the lower bid-ask spreads of the higher liquidity instrument in comparison to those with significantly lower liquidity. To improve the effectiveness of the hedging strategy, the position can be updated closer to the delivery time. It is noted that Frestad's (2014) approach exposes the hedger to basis risk, a source of reduction in hedging effectiveness, since it uses a different instrument.

Another approach to dealing with low liquidity instruments is to estimate a so-called (il)liquidity adjusted VaR. Weiß and Supper (2013) estimate a liquidity adjusted intraday VaR for portfolios of NASDAQ stocks from high frequency data by modelling the joint distribution of price and liquidity using vine copulas. Consequently, while there is a well-established link between returns and liquidity, there is no single method for dealing satisfactorily with illiquid instruments.

There are three further literature streams that are relevant to this paper: risk management in electricity markets, risk management in electricity futures markets and studies of the Australian electricity market. The literature on risk management in electricity markets deals predominantly with spot and day-ahead electricity markets (among others, Díaz et al., 2019; Fanone et al., 2013; Marcjasz et al., 2018; Pape et al., 2016; Steinert and Ziel, 2019; Ziel et al., 2015).[18] Bunn et al. (2016) forecast electricity prices by extending a multifactor dynamic

[18] Note that in most of these studies the day-ahead market is considered as the spot market, notwithstanding the presence of a real-time balancing market with much lower trading volume in those jurisdictions.

quantile regression model using GARCH. The model includes the fundamental drivers of fuel prices, emissions, and demand and reserve capacity forecasts. As such models are difficult to estimate using conventional approaches, the authors adopted a two-stage approach by first estimating the GARCH process with a factor model in price levels, and then using the latter to augment a multifactor quantile regression model. They test this model against the highly volatile half-hourly evening peak 18:30–19:00 in the British day-ahead market and report more accurate forecasts than provided by traditional alternatives. They find that a linear quantile regression model outperforms the skewed GARCH-t and the CAViaR approach (Engle and Manganelli, 2004). Nowotarski et al. (2014) evaluate forecast averaging schemes as a means of improving day-ahead forecasts of electricity prices. They use data from electricity markets in the US (PJM) and Europe (Nord Pool and EEX) and find that an equally weighted average of forecasts performs best unless there is a clear forecasting model that consistently outperforms other models.[19]

The literature on risk management in electricity futures markets is scant. Zanotti et al. (2010) compare the performance of six hedging models in reducing base load portfolio volatility based on daily prices in the Nord Pool, EEX and Powernext electricity markets.[20] Analysing a naïve, ordinary least squares (static and dynamic hedge ratios) approach, a GARCH model with constant conditional correlations, a GARCH model with dynamic conditional correlations (DCC) and a GARCH DCC model with exponential smoothing, they draw two conclusions. The first is that hedging is generally effective, except in the case of the less liquid Powernext market. Second, models that take into account the change in volatility over time perform better in reducing portfolio volatility. Kayal and Lindgren (2014) compare the performance of three models – RiskMetrics EWMA, DCC, and a GARCH-BEKK model – through a backtesting analysis. Their backtesting results on portfolios of monthly forward[21] electricity contracts for the Swedish market do not indicate a clear difference among the models in predicting VaR. The authors make a recommendation in favour of the RiskMetrics EWMA model due to its simplicity. Huisman and Kilic (2012) indicate the occurrence of extreme returns in forward

[19] Weron (2014) provides an extensive review of electricity price forecasting techniques with comments on strengths and weaknesses.

[20] Zanotti et al.'s data for Nord Pool covered 2.1.2004 to 14.2.2006, for EEX 2.7.2002 to 14.2.2006 and for Powernext 18.6.2004 to 14.2.2006.

[21] The main difference between futures and forwards is that the latter have higher counter party risk compared to futures instruments which are cleared tough the intermediation of an exchange.

and futures power instruments. They advocate applying extreme value theory to better assess risk from these return distributions characterised by fatter tails than in the normal distribution. Our approach differs from the above in that we use data from similar contracts to improve risk estimation. Besides its suitability for electricity futures markets that often suffer from low liquidity, our proposed data enrichment approach has the potential to be applied to various other financial markets for risk assessment.

There have been many studies of various aspects of the NEM, which covers the states of Australia, excluding Western Australia and the Northern Territory. Anderson et al. (2007) explore the contracting process in Australia's forward electricity market based on interviews with participants. The authors report a significant gap between practice and assumptions in the literature such as on arbitrage-free pricing theory. As mentioned earlier they also identify low liquidity in both the forward and, more particularly, in the exchange traded futures electricity market in Australia. Higgs (2009) studies the interrelationship among interconnected regional markets in the NEM, using three conditional correlation MGARCH type models. Her findings suggest that geographic proximity and interconnection capacity between the regions is the main determinant of volatility spillover. Wild et al. (2015) investigate the effect of a carbon price on wholesale prices and pass-through rates using an agent-based model. Their analysis showed a less than full pass-through of carbon prices to wholesale electricity prices. They also reported differences in optimal wholesale prices between the individual states.

Ignatieva and Trück (2016) examine the dependence structure of the four major markets in the NEM, using GARCH models in combination with copulas to capture the dependence structure of daily prices through 2006–2010. They find a positive dependence between regional prices, being strongest in physically interconnected regions, confirming earlier findings by Higgs (2009). The dependence decreases from 2008 onward. Backtesting of VaR forecast characteristics for stylized portfolios over two and four markets shows that none of the models tested yields a satisfactory out of sample forecast due to the high level of volatility and spikiness in prices. It can be added that the reduction in dependence observed in this study is possibly linked to reduced demand (mainly from industry) and a change in the peak patterns (particularly the morning peak) associated with increased permeation of roof-top photovoltaic capacity.[22] This period is also associated with an increase in wind power capacity. Renewable power capacity continued to increase steeply after 2010 in the Australian electricity market. Janczura et al. (2013) show that estimating short and long-term seasonal components of spot prices can be improved by first filtering outliers (price spikes) from the data before applying de-seasonalisation routines. They use daily data over five years from the European Energy Exchange in Germany, and the Australian NEM region of NSW. While the study does not come out in favour of a specific method for identifying outliers, it does conclude that applying a recursive filter or a recursive seasonal model to filter out spikes helps to improve estimations of seasonal components in comparison to using raw price data that includes price spikes. Clements et al. (2015) study the transmission of spikes and their size across three major NEM regions – Queensland, NSW and Victoria. They find that the transmission of spikes and their size across the states depends on the available interconnection capacity and is also related to unexpected changes in load. Their results show that taking interregional effects into account improves forecasts of the probability and size of spikes compared to when each region is considered separately. Apergis et al. (2017) investigate the presence of asymmetries in volatility spillovers between NEM regions and quantifies them.[23] They use intraday 5-min Australian dispatch electricity prices over the period from 8 December 1998 to 5 May 2016. They find that although NEM connectedness has strengthened since 2001, it remains weak. The paper identifies two periods of volatility spillovers. The first, associated with positive shocks, exhibits larger volatility spillovers, while the second, associated with negative shocks, exhibits smaller spillovers. The first period (2006–2011) is characterized by prolonged positive returns probably due to high demand and weather events, drought and high summer temperatures. The resulting high prices affected both spot and contracted electricity prices. The second period, from 2011 to the present, is characterised by negative prices and is associated with a higher uptake of wind [and other renewables] and possibly by policy reforms including the introduction of the carbon pricing mechanism from 2012 to 2014. Maryniak et al. (2019) analyse the impact of carbon trading on the price of electricity futures contracts in the NEM. Their analysis accounts for the futures premium in futures markets excluding carbon. Their results show that prices of futures contracts written on Q2 2012 to Q2 2014 were impacted by

[22] Rooftop PV installations capacity increased from 6,645 kW in January 2006 to 15,316 kW in January 2008 to 120,997 kW in December 2009, according to data from The Australian Photovoltaic Institute website http://apvi.org.au/.

[23] The paper defines good and bad spillovers as being associated, respectively, with positive and negative shocks to demand and returns, following Segal et al. (2015).

carbon pricing (carbon pass through) from Q4 2011, when market participants had a high level of certainty that the law would be passed, and until its repeal at the end of Q2 2014.

We make several contributions to the literature. First, we develop a data enrichment method that allows us to generate improved density forecasts in comparison to conventional approaches, thereby improving risk management outcomes. In particular, we enrich data for a financial instrument by incorporating data from similar instruments from periods of higher liquidity. This contrasts with the traditional approach of relying on historical data from periods with dissimilar liquidity levels. The literature has established a link between premium and liquidity (Amihud and Mendelson, 1986a; Bevin-McCrimmon et al., 2018). Therefore, we contend that our method uses data from a more relevant period, while still incorporating a rich variety of realised historical returns. A second contribution is that our method is versatile and can be applied to a number of models. This is because we do not propose a single model but rather an approach to enriching data that can then be used as part of various parametric and non-parametric modelling approaches, as we show in our analysis. Our third contribution is applying this method to the Australian electricity derivatives market. The Australian electricity futures market is characterised by low liquidity in the period more than one year prior to commencing delivery. Most activity, and therefore interest in forecasting, lies in the year leading up to delivery. We enrich return data for the current contract (say Q1 2010) by incorporating data from contracts for the same quarter (Q1 in this example) delivered in previous years (we add to Q1 2010 data from Q1 2009 and Q1 2008). This approach offers a number of advantages over the traditional approach. It allows us to base our forecasts on historical data that exhibits liquidity characteristics that are more similar to those found in the period of most interest to market participants (the year leading up to delivery). Both the data enrichment and the approach proposed by Frestad (2014) recognise the existence of a similarity between instruments differing only in their delivery date. While Frestad (2014) considers the use of instruments still to be traded in the future in forming the hedge, we use the price information of (similar) instruments that have been traded in the past to assess the risk of the instrument the hedger is interested in. An advantage of our approach compared to the one proposed by Frestad (2014), is that our method does not expose the portfolio to basis risk and the costs associated with transacting different instruments. A fourth contribution is that we compare the traditional approach to the data enrichment approach using four forecasting models. Although it is not the purpose of this paper to compare different models, using our data enrichment method in several models shows its versatility.

The remainder of the paper is organised as follows. Section 2 describes conventional methods for the creation of risk or density forecasts as well as our proposed data enrichment approach. Section 3 describes the data, reports empirical results and provides a discussion of our findings. Finally, Section 4 concludes and makes suggestions for possible future work.

4.2. Methodology

In this section, we briefly review conventional approaches to risk management such as historical simulation or volatility updated historical simulation. We also provide the framework for our proposed data enrichment approach as well as a review of standard tests that can be used to evaluate the generated forecasts.

Our analysis focuses on the prediction of one-day ahead daily returns for futures contracts – a return on day *t* that is calculated from the daily closing prices of electricity futures contracts, F_{t-1} and F_t, on day *t* and *t-1*:

$$r_t = \frac{F_t - F_{t-1}}{F_{t-1}} \quad (4.1)$$

In what follows we consider a market participant at the end of day *t* prior to delivery of a contract, who aims to forecast the next day's return r_{t+1}. We start at the end of day *t = 0*, *m* days prior to delivery and generate a density forecast for the return on day *t = 1*. In recognition of the time changing parameters of the process, we use a rolling forecast to update our forecast for day *t+1* (at the end of day *t*, *m-1* days away from delivery) up to and including the forecast for day *m*, immediately preceding delivery.

The conventional approach to density forecasting, and VaR modelling for that matter, utilizes data for the contract of interest, as it trades over its 16 or 17 quarters on the futures exchange. For example, to analyse the Q1 2010 base load electricity futures contract, the data used would be the closing prices of the Q1 2010 futures contract as it is traded from the beginning of 2006 onward over 16–17 quarters on the ASX. The conventional approach therefore uses data from periods with low liquidity to forecast returns, or VaR, in more liquid periods as illustrated in Fig. 4.1. The figure shows an overall picture of reducing volatility of daily returns associated with increasing liquidity as the contract approaches delivery. The upper left panel shows high magnitude jumps in daily returns becoming smaller and less volatile as the contract approaches delivery. The middle left panel shows a simple moving average of returns volatility calculated over a rolling window of 126 observations. The first such period covers the 126 returns starting with the day immediately before the start of delivery date and moving backward in time. To calculate subsequent periods of 126 observations in length, we move backward one day at a time, dropping the observation closest to delivery and adding the point adjacent to the observation furthest from delivery in the previous period. The plot confirms the reducing volatility in returns exhibited in the top left panel. The period furthest from delivery is characterised by a high magnitude of jumps in volatility and a generally higher volatility level. The lower left panel shows closing prices in Australian $/MWh. Fewer jumps in prices are consistent with the picture of lower volatility closer to delivery. The top right panel shows the bid-ask spread reducing as the contract approaches delivery. The middle and bottom right panel show the two liquidity measures, open interest and volume, respectively, increasing as the contract approaches delivery.

Fig. 4.2 displays the same data for the 2010 VIC base load contract. The price for both NSW and VIC starts to rise during the last 100 trading days prior to the delivery period. However, while prices for the NSW contract gradually fell, before rising again over the last 100 days before delivery, the price for the VIC contract fluctuated around a higher level, then fell suddenly before finally rising again over the last 100 days before the delivery period. This drives the break in volatility to occur much later, closer to delivery, for VIC than for NSW in 2010. This is probably the main reason for VIC forecasts not performing well until we start our density forecasts much closer to delivery (the six months case). These graphs provide evidence backing the primary criticism of the conventional approach that the forecasts generated for the higher liquidity periods rely on historical information from a period with a different return process. To use the same example, to forecast Q1 2010 we use recent data from Q1 2010 but enrich it with data from Q1 2009 and Q1 2008. The conventional approach uses data from Q1 2010 sourced from the second year prior to delivery. We will illustrate the conventional and data enrichment approach in detail with reference to the historical model as it is the base model for nonparametric models and the simplest to use for illustrating the two methods.

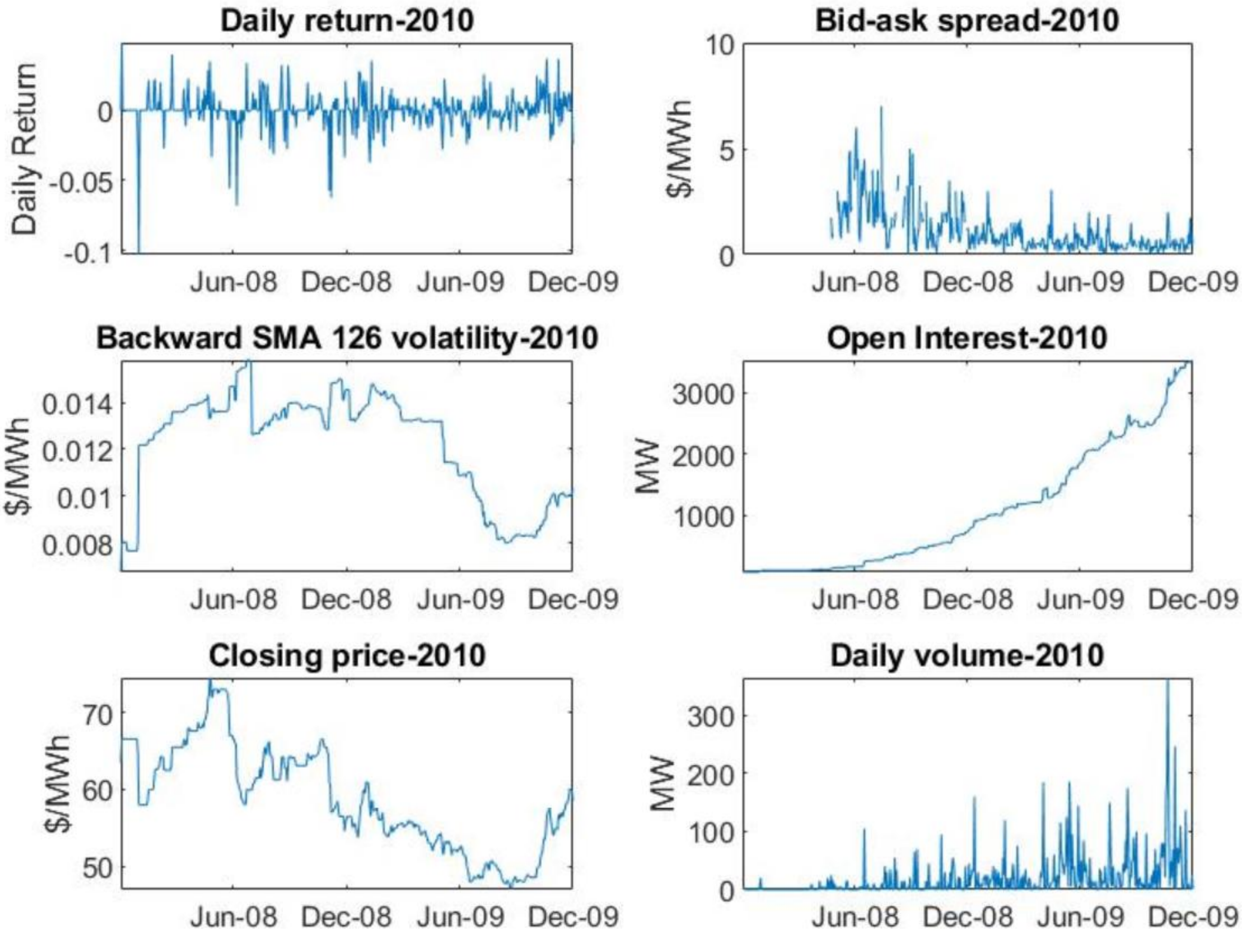

Fig. 4.1. Daily data for an NSW base load contract. Shows daily data for the NSW base load Q1 2010 futures contract over a period of 504 trading days prior to delivery. The upper left panel shows daily returns becoming less volatile with smaller magnitude jumps closer to delivery. The middle left panel shows a simple moving average of return volatility calculated over a rolling window of 126 observations. The first period for calculating volatility relates to the period from the day immediately before the start of delivery date and the 125 points backward in time from that day. Subsequent periods, of fixed length of 126 days, move backward one day at a time. The plot confirms the reducing volatility in returns exhibited in the top left panel. The lower left panel shows closing prices in Australian $/MWh. Fewer jumps in prices are consistent with the picture of lower volatility closer to delivery. The top right panel shows the bid-ask spread reducing as the contract approaches delivery. The middle and bottom right panel show, respectively, increasing open interest and volume as the contract approaches delivery. The overall picture is that higher volatility of returns is associated with lower liquidity periods.

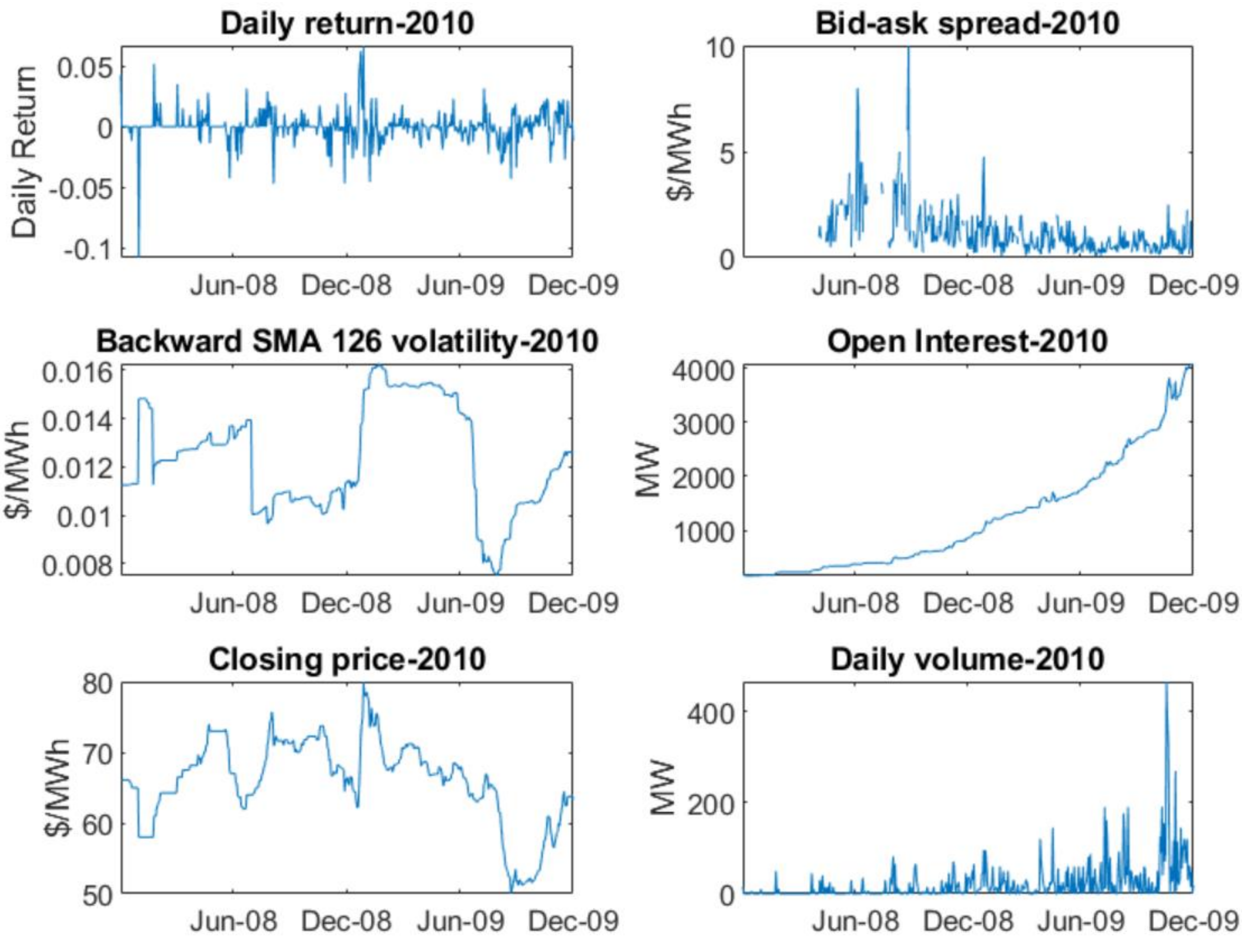

Fig. 4.2. Daily data for a VIC base load contract. Shows daily data for the VIC base load Q1 2010 futures contract over a period of 504 trading days prior to delivery. The upper left panel shows daily returns becoming less volatile with smaller magnitude jumps closer to delivery. The middle left panel shows a simple moving average of return volatility calculated over a rolling window of 126 observations. The first period for calculating volatility relates to the period from the day immediately before the start of delivery date and the 125 points backward in time from that day. Subsequent periods, of fixed length of 126 days, move backward one day at a time. The plot confirms the reducing volatility in returns exhibited in the top left panel. The lower left panel shows closing prices in Australian $/MWh. Fewer jumps in prices are consistent with the picture of lower volatility closer to delivery. The top right panel shows the bid-ask spread reducing as the contract approaches delivery. The middle and bottom right panel show, respectively, increasing open interest and volume as the contract approaches delivery. The overall picture is that higher volatility of returns is associated with lower liquidity periods.

Fig. A.1 and A.2 in the Appendix provide returns, price and traded volume data for NSW and VIC by year. The price patterns are broadly similar in NSW and VIC, particularly toward delivery, which is in line with the findings of studies on the *spot* market that geographically adjacent markets with physically joined transmission interconnectors exhibit similar *spot* price patterns (Ignatieva and Trück, 2016; Higgs, 2009). A feature of the data is that trading volume and frequency is higher in NSW across all years. High volume trading generally starts earlier in NSW than in VIC, indicating higher liquidity in that market.[24]

[24] 2010 is the only year where volume traded and open interest in Victoria exceeded those in NSW.

4.2.1 Historical method

We illustrate the historical method by reference to Figure 4.3.

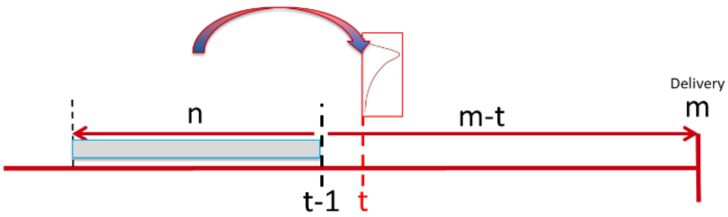

Fig. 4.3. Illustration of the historical forecasting method. The figure depicts *n* historical observations prior to day *t-1* used to forecast the distribution of one-day ahead returns for day *t*.

The historical model offers the advantages of simplicity and being free of assumptions about the distribution of returns (Down, 2002). The historical method uses historical returns to forecast future returns. Standing at $t = 0$ and forecasting the daily return for $t = 1$, we select a historical window of prior returns of length = n. Typical windows are one year and six months corresponding to $n = 252$ and $n = 126$ trading days respectively. We assume that the return on $t = 1$ could be any of the observed returns in the previous n days in the selected historical window. In other words, the forecast distribution of returns for day $t = 1$, made on day $t = 0$, is made up of the n historical returns in the window of n days prior to $t = 0$. To forecast the returns for $t = 2$, standing at $t = 1$, we update our historical data window to comprise *n* returns prior to $t = 1$. This is done by removing the oldest return observation at $t = -n$ from the historical window and adding the now known realised return at $t = 1$, r_1. This keeps the window length equal to n. The forecast distribution of returns for day $t = 2$, consists of the 'n' historical realised return observations in our selected window ($t = 1$ to $t = 1 - n$). We continue to forecast the distribution of day ahead returns by updating our window in this manner until we reach the end of our forecasting period at $t = m$, being the day immediately preceding the start of contract delivery.

While the historical method is simple, its clear disadvantage is that the forecast is limited by the distribution of returns realised historically. There is therefore an assumption that the return generating process does not change over time. However, we saw how in the case of electricity futures in NSW and VIC the return process volatility changes, generally, being more volatile in periods more than one year away from the start of the delivery date.

$$r_{t,i} = \{r_{t,(t-n+i-1)}\ ;\ for\ t = 1\ to\ m, \qquad i = 1\ to\ n\} \quad (4.2)$$

Equation (4.2) shows that for each day we forecast a distribution of returns for day *t* based on the realised historical returns available up to the previous day *t-1*. Applying the data enrichment approach to the historical model follows a similar approach but with one straightforward and important difference. Instead of using a window of historical returns to form the forecast, we use the set of returns compiled by the application of the data enrichment method described in subsection 4.2.2.

4.2.2 Data enrichment approach

We explain the data enrichment approach by reference to Figure 4.4.

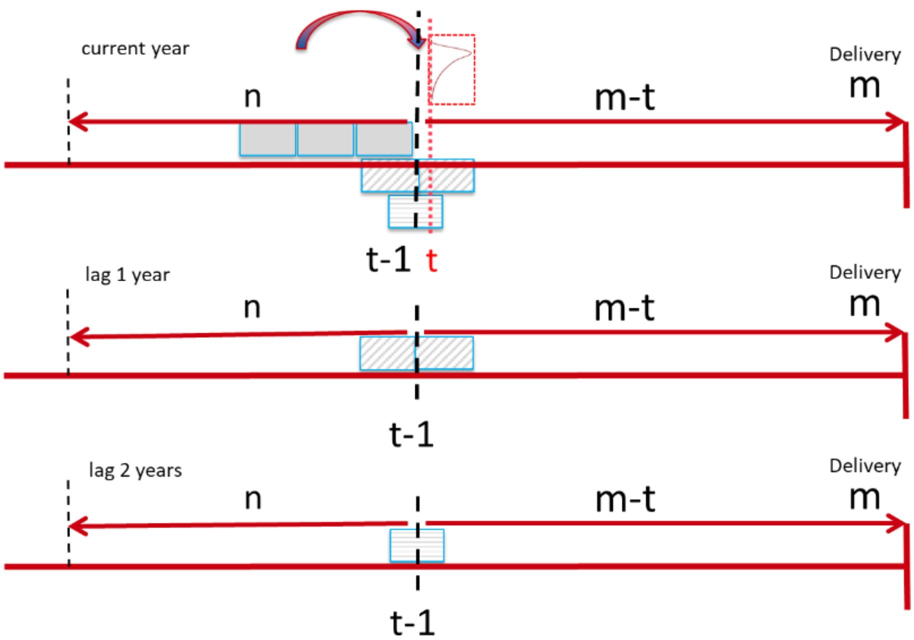

Fig. 4.4. Illustration of the data enrichment approach. The figure shows the construction of the enriched data set using data from the current year and the two previous years, the case of centred offset. The observer is standing at day *t-1* forecasting the return for day *t*, one-day ahead. The bottom panel depicts the return data historical observations from two years ago (y_2); that is, return data for the same contract delivered two years ago. Being the centred offset case, the data set is centred around time *t-1*. The middle panel is similar to the bottom panel but for the contract delivered one year ago (y_1). The top panel depicts the return observations for the same contract delivered one (y_1) and two years (y_2) ago added to the historical returns of the contract from the current year (y_0). There is one important difference in that the current year is not centred because information is available only up to day *t-1*. The sum of the three return sets make up a total of *n* observations.

The data enrichment approach aims to overcome the shortcoming of the conventional method by basing the forecast on data from higher liquidity periods. An observer standing at day *t-1* forecasting the return for day *t* one-day ahead will use data for the same contract being forecast but sourced from the contract of the current year (y_0), the contract with the same delivery period of the previous year (y_1), and the contract with the same delivery period two years ago (y_2). For example, for the contract with a delivery period from 1 January 2011 until 31 March 2011 – a contract referring to a delivery period in the first quarter (Q1) of 2011 – these would be the contracts for Q1 2011 (y_0), Q1 2010 (y_1), and Q1 2009 (y_2). The three years y_0, y_1 and y_2 are illustrated in the top, middle and bottom panels of Fig. 4.4. respectively. For the centred offset case, the data sets for years y_1 and y_2 are centred around time *t-1* for the current year, which is legitimate, as this information is available to us at *t-1* in the current year. There is one important difference in that the current year is not offset because information is available only up to day *t-1* of the current year. For example, in the case of electricity futures in NSW and VIC, the return process further from delivery is generally more volatile than in the period closer to delivery.

We first select the number of observations to be used from each of the three years y_0, y_1 and y_2 such that their total is *n*. The number of observations from each of these years is s_0, s_1 and s_2 respectively such that $s_0 + s_1 + s_2 = n$. Next we determine the degree of offset. The three cases are: *not offset*, *centred* and *fully offset*. As the name implies, there is no offset for the *not offset* case. We use the observations s_0, s_1 and s_2 prior to *t* for years y_0, y_1 and y_2 respectively. For the two offset cases, *centred* and *fully offset* case, we *forward* offset the observations from the previous years, y_1 and y_2, but not from the current year y_0. This is because the observations from the current year, y_0, are available only up to day *t-1* whereas all the observations from y_1 and y_2 are already available to us on day *t-1* of the *current* year. The extent of offset of the data for the years y_1 and y_2 is different in each of the two offset cases. In the *fully offset* case, we *forward* offset the observations from years y_1 and y_2 by s_1 and s_2 observations respectively. Thus, we use data from *t* to $t + s_1 - 1$ from year y_1 and from *t* to $t + s_2 - 1$ from year y_2. The observations from these two years in the *centred* case are offset by half the number of observations used from that year, by centring them on day *t-1*. Thus, in the *centred* case we use observations from $t - \frac{s_1}{2}$ to $t - \frac{s_1}{2} + (s_1 - 1)$ from year y_1 and from $t - \frac{s_2}{2}$ to $t - \frac{s_2}{2} + (s_2 - 1)$ from year y_2. We summarise the above in Table 4.1 which additionally differentiates between odd and even numbered observations for the *centred* case. In the *fully offset* case, when we get close to delivery such that the period remaining to the start of delivery is shorter than s_1 for year y_1 or s_2 for year y_2, we do not update the observation set, from that year, so as not to use data from the delivery period. For the same reason, we apply an analogous restriction to the *centred* case. The effect of this novel data enrichment approach is to use recent information from the current contract and relevant data from similar contracts from the two previous years sourced from a period with similar liquidity.

Table 4.1

Data enrichment method range of observations

year	Not offset	Centred	Fully offset
Current year y_0	From $t - s_0$ to $t - 1$	$t - s_0$ to $t - 1$	From $t - s_0$ to $t - 1$
One year ago, y_1	From $t - s_1$ to $t - 1$	$from\ t - \frac{s_1}{2}\ to\ t - \frac{s_1}{2} + (s_1 - 1)$ when s_1 is even and $from\ t - \frac{s_1-1}{2}\ to\ t - \frac{s_1-1}{2} + (s_1 - 1)$ when s_1 is odd	From $t = 0$ to $t + (s_1 - 1)$
Two years ago, y_2	From $t - s_2$ to $t - 1$	$from\ t - \frac{s_2}{2}\ to\ t - \frac{s_2}{2} + (s_2 - 1)$ when s_2 is even and $from\ t - \frac{s_2-1}{2}\ to\ t - \frac{s_2-1}{2} + (s_2 - 1)$ when s_2 is odd	From $t = 0$ to $t + (s_2 - 1)$

The table presents the range of observations used in each of the years for each of the three methods.

The data enrichment approach and the approach proposed by Frestad (2014) both recognise the existence of a similarity between instruments that differ only in their delivery date. Quarterly base load futures contracts Q1 2011 and Q1 2010, for example, differ only in the year in which they are delivered. Frestad (2014) considers the use of instruments still to be traded in the future in forming the hedge, we use price information of (similar) instruments that have been traded in the past to assess risk of the instrument the hedger is interested in.

4.2.3 Volatility Updated Simulation

The volatility updated returns scheme addresses the disadvantage of the standard historical simulation model by updating the returns to reflect more recent volatility information, while maintaining the advantages of remaining free of assumptions about the distribution of returns

(Hull and White, 1998). The volatility updating scheme as proposed by Hull and White (1998) basically suggests rescaling historical returns based on the ratio of the most recent volatility σ_t for today divided by the historical volatility estimate σ_i for day *i*. The updating scheme can then be defined as in equation (4.3), where $r^*_{t,i}$ denotes the rescaled returns and $r_{t,i}$ the historical return observed on day *i*. The updating formula can be applied to both the conventional and new approach.

$$r^*_{t,i} = r_{t,i}\ x\ \frac{\sigma_t}{\sigma_i} \qquad (4.3)$$

We follow Hull and White (1998) and estimate σ_i and σ_t based on an exponentially weighted moving average (EWMA) scheme that is also applied in *RiskMetrics* to update volatility equation (4.4):

$$\sigma_i^2 = \lambda\sigma_{i-1}^2 + (1-\lambda)r_{i-1}^2 \quad (4.4)$$

We use λ=0.94 for the daily return data, following Hull and White (1998) and *RiskMetrics* (J.P. Morgan, 1996). To seed the scheme, σ_1 is estimated as the standard deviation of the initial set of returns.

4.2.4 Density forecasting models

While it is not the purpose of this paper to conduct an extensive survey of all models and determine which works best with our new approach, we want to explore and report how the new and conventional approaches perform across a selection of models. In addition, applying the method to a range of models demonstrates its versatility. In total, we select four different models: two based on a parametric approach that involves estimating the normal distribution for each rolling window of returns, and two based on the empirical return distribution.

The first normal model is the normally distributed historical model (NDH), where the mean and standard deviation are estimated based on historical return observations. The second model is normally distributed but with adjusted volatility (NDU). It has the same mean as for the NDH, while the current level of market volatility is estimated using the *RiskMetrics* approach – equation (4.4).

The first empirical distribution model (EDM) uses an empirical fit to historical returns – we fit a non-parametric kernel density estimator to the data to create a density forecast. The final model (EUV) is an empirical fit to volatility updated returns – the non-parametric kernel density estimator is fitted to volatility updated returns that are created using equation (4.3) and (4.4).

To test the performance of the proposed data enrichment approach, we apply all four models to both the conventional and enriched data approaches to evaluate the correct specification of the models with regard to generating density forecasts for returns and discuss the performance of the two approaches.

4.2.5 Density forecast evaluation

We evaluate the absolute performance of density forecast models by testing them for correct specification. In this paper, we use techniques based on the PIT from Diebold et al. (1998) to evaluate the correct specification of density forecasts of returns. The first transformation is the PIT (Diebold et al., 1998), which employs the transformation by Rosenblatt (1952), whereby if the forecast model is properly specified for the actual data generating process then the PIT will be i.i.d. uniformly distributed on [0,1]. This relationship holds regardless of the underlying distribution process of returns. The PIT, u_t in equation (4.5), is the cumulative density function (CDF) of the forecast returns evaluated at the ex-post actual realisations of returns r_t.

$$u_t = \int_{-\infty}^{a_t} f(u)\, du = F(r_t) \qquad (4.5)$$

We test the PIT for uniformity using the Kuiper test and report that as a robustness check on the performance of our approach. We also perform a visual inspection of the histograms of PITs for uniformity.

The second transformation follows Berkowitz (2001), who suggested taking advantage of a well-known fact that the inverse normal transformation of a U(0,1) variable will be distributed N(0,1). So if the PIT is correctly specified, and is U(0,1), then its inverse normal transformation is N(0,1) and can be tested for normality. We use the Kolmogorov-Smirnov test (KS), which is widely used in the literature such as in Rossi and Sekhposyan (2014).

$$z_t = \Phi^{-1}(u_t) \qquad (4.6)$$

We reserve evaluating forecast combinations for future work, which could prove interesting in future research into the data enrichment approach.

4.2.6 Evaluating the performance of the data enrichment approach and the conventional approach

We test the density forecast of returns generated by each of the four models described in Section 2.4 across both the conventional and data enrichment approaches. We use three significance levels – 1%, 5% and 10% as critical values. A p-value lower than the selected critical value rejects the null hypothesis that z_t is distributed N(0,1) whereas a p-value higher than the selected significance threshold indicates failure to reject the null.

In addition to presenting the main result, we perform robustness checks of the performance of our approach at different points in time away from delivery, at different levels of offset (defined in Table 4.1), using an alternative number of observations from the different contracts and finally using the Kuiper test on the PIT instead of the KS test.

4.3 Results and discussion

In this section we describe the data set used, briefly discuss relevant properties and report and discuss our main results relating to the evaluation of density forecasts.

4.3.1 Data description

Our dataset consists of the daily closing price, in AUD/MWh, and the traded volume of base load Q1 futures contracts for NSW and VIC from 2005 to 2014. Each year has 504 observations giving us a total of 5,040 observations. A trading year on the ASX comprises 252 trading days. A base load contract for Q1 is written on the first calendar quarter and has a size of 1 MW per hour. The price paid for the contract applies to every hour from 1 January to 31 March of the relevant year. Settlement is calculated as the difference between the arithmetic average of the NEM half-hourly spot price and the futures price over the calendar quarter. Tables 4.2 and 4.3 below provide descriptive statistics for NSW and VIC for three periods: the six months closest to delivery, the year closest to delivery and the second year out of delivery. The purpose is to see how the return data may differ over these horizons. For NSW the mean is very close to zero and the median is zero in all years except 2011 in the six months closest to delivery. The sign of the mean in the first year matches that in the first six months in all but one year but it only matches the sign of the mean in the second year in only four out of ten years. Skewness is mainly positive in the six months and year closest to delivery and mostly negative in the second year. Kurtosis is higher in the second year compared to the first year and six months. Overall, the second year is different from the first year across the higher moments of the return distribution. The higher kurtosis indicates fat tails and a likely violation of normality in the second year out of delivery. Years 2005 and 2006 have particularly low liquidity which may be the reason for the higher kurtosis across the three horizons.

Table 4.2
Descriptive statistics – NSW Q1 base load futures contract simple daily returns

Closest six months to delivery										
	Q1-05	**Q1-06**	**Q1-07**	**Q1-08**	**Q1-09**	**Q1-10**	**Q1-11**	**Q1-12**	**Q1-13**	**Q1-14**
mean $x10^{-3}$	0.980	-0.304	0.037	-2.411	-1.014	0.949	-1.836	0.517	-0.022	-0.492
median $x10^{-3}$	0.000	0.000	0.000	0.000	0.000	0.000	-0.994	0.000	0.000	0.000
std dev	0.007	0.006	0.009	0.030	0.012	0.010	0.005	0.011	0.009	0.005
skewness	1.583	-4.256	-0.364	0.806	0.546	0.556	-0.237	0.223	0.541	0.367
kurtosis	11.914	36.303	5.050	6.132	8.816	4.774	3.065	5.071	5.575	6.490
minimum	-0.015	-0.048	-0.028	-0.066	-0.045	-0.024	-0.015	-0.031	-0.028	-0.020
maximum	0.039	0.014	0.026	0.133	0.055	0.037	0.011	0.036	0.032	0.021
Closest year to delivery										
	Q1-05	**Q1-06**	**Q1-07**	**Q1-08**	**Q1-09**	**Q1-10**	**Q1-11**	**Q1-12**	**Q1-13**	**Q1-14**
mean $x10^{-3}$	0.559	-0.271	0.228	0.148	-1.146	0.229	-1.187	0.556	-0.256	-0.274
median $x\ 10^{-3}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
std dev	0.008	0.006	0.007	0.026	0.015	0.011	0.008	0.013	0.008	0.005
skewness	1.230	-2.376	-0.397	1.079	-0.353	0.215	-1.931	2.450	0.711	0.215
kurtosis	11.076	25.088	7.117	8.992	6.504	4.903	13.787	21.477	7.253	6.271
minimum	-0.034	-0.048	-0.028	-0.066	-0.069	-0.038	-0.054	-0.046	-0.028	-0.020
maximum	0.041	0.021	0.026	0.145	0.055	0.037	0.019	0.105	0.040	0.021
Second year out of delivery										
	Q1-05	**Q1-06**	**Q1-07**	**Q1-08**	**Q1-09**	**Q1-10**	**Q1-11**	**Q1-12**	**Q1-13**	**Q1-14**
mean $x10^{-3}$	-0.369	0.216	0.012	0.351	1.159	-0.390	-1.425	-1.297	0.861	-1.292
median $x10^{-3}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
std dev	0.014	0.007	0.005	0.006	0.020	0.015	0.014	0.007	0.008	0.009
skewness	-6.777	-0.732	1.480	-0.787	0.439	-2.214	-0.619	-1.643	8.741	-5.352
kurtosis	101.315	12.725	19.926	8.018	9.608	16.679	21.969	14.134	106.924	56.799
minimum	-0.180	-0.044	-0.021	-0.032	-0.095	-0.103	-0.096	-0.049	-0.014	-0.100
maximum	0.086	0.034	0.032	0.021	0.096	0.048	0.101	0.024	0.103	0.023

For VIC the magnitude of the mean is close to zero and the median is zero except for 2011 in the closest six months which mirrors NSW. The sign of the mean in the closest year matches that in the closest six months in seven out of the ten years and only in five for the second year out. The distribution of returns is mainly positively skewed. All three horizons have a similar number of positively skewed years. Perhaps the biggest difference from NSW is that kurtosis is higher in both the first and second year compared to the closest six months and is generally higher than NSW in those horizons. With more extreme observations in the tails this could signal that modelling the VIC market is a more difficult task.

Table 4.3

Descriptive statistics – VIC Q1 base load futures contract simple daily returns

Closest six months to delivery										
	Q1-05	**Q1-06**	**Q1-07**	**Q1-08**	**Q1-09**	**Q1-10**	**Q1-11**	**Q1-12**	**Q1-13**	**Q1-14**
mean $x10^{-3}$	0.501	-0.414	0.616	-1.751	-0.824	-0.448	-1.870	0.111	0.664	-0.637
median $x10^{-3}$	0.000	0.000	0.000	0.000	0.000	0.000	-1.141	0.000	0.000	0.000
std dev	0.007	0.010	0.011	0.031	0.013	0.013	0.007	0.008	0.009	0.006
skewness	-0.136	3.256	0.192	1.955	-0.569	-0.460	0.412	0.385	0.885	-0.560
kurtosis	7.824	27.797	4.093	17.889	5.690	3.876	5.503	6.287	6.400	8.919
minimum	-0.030	-0.028	-0.034	-0.097	-0.043	-0.043	-0.019	-0.028	-0.024	-0.030
maximum	0.024	0.072	0.032	0.205	0.045	0.031	0.029	0.035	0.043	0.026
Closest year to delivery										
	Q1-05	**Q1-06**	**Q1-07**	**Q1-08**	**Q1-09**	**Q1-10**	**Q1-11**	**Q1-12**	**Q1-13**	**Q1-14**
mean $x10^{-3}$	-0.102	-0.549	0.666	1.936	-0.581	-0.073	-1.692	0.088	-0.029	-0.469
median $x10^{-3}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
std dev	0.011	0.009	0.010	0.029	0.015	0.013	0.010	0.009	0.009	0.006
skewness	0.008	2.468	0.957	1.432	-0.618	0.796	-0.618	0.436	2.106	-0.408
kurtosis	9.676	25.332	9.824	14.881	6.464	8.035	6.592	6.064	18.339	8.128
minimum	-0.049	-0.030	-0.038	-0.111	-0.067	-0.045	-0.048	-0.028	-0.029	-0.030
maximum	0.049	0.072	0.061	0.205	0.046	0.067	0.037	0.042	0.069	0.026
Second year out of delivery										
	Q1-05	**Q1-06**	**Q1-07**	**Q1-08**	**Q1-09**	**Q1-10**	**Q1-11**	**Q1-12**	**Q1-13**	**Q1-14**
mean $x10^{-3}$	-0.633	-0.153	-0.146	0.640	0.931	0.234	-1.228	-1.569	0.917	-0.703
median $x10^{-3}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
std dev	0.020	0.010	0.008	0 .008	0.021	0.013	0.011	0.009	0.005	0.008
skewness	-6.864	1.074	0.267	0.607	0.696	-2.506	-1.578	-4.081	5.101	2.259
kurtosis	87.288	19.157	8.108	10.239	12.855	27.105	17.987	40.124	30.602	24.650
minimum	-0.248	-0.047	-0.029	-0.038	-0.110	-0.108	-0.087	-0.088	-0.007	-0.025
maximum	0.063	0.072	0.040	0.037	0.119	0.052	0.036	0.029	0.034	0.070

4.3.2 Empirical results

In this section, we evaluate and compare the performance of the conventional and data enrichment approaches in generating well specified one-day-ahead density forecasts of returns of low liquidity instruments. For each approach, we generate density forecasts from each of the four models for every contract in our data set and assess the quality of the created forecasts by applying a KS goodness-of-fit test to the PIT. The conducted tests then allow us to examine whether an approach generates density forecasts that are mis-specified and thus rejected. As we are interested in whether the two approaches yield a consistently different performance, we explore their performance at different points in time prior to the delivery date. We conduct further robustness checks on the data enrichment approach by varying parameters that are unique to the new approach. We vary the data offset of the lagged contract and the number of observations from the current and lagged contract (while keeping the total number of observations unchanged). As a final robustness check we evaluate the correct specification of the forecasting models by testing the uniformity of the PIT by applying the Kuiper test instead of a KS test (see, e.g. Crnkovic and Drachman, 1996).

Our results indicate that the data enrichment method performs well and is superior to the conventional method when forecasting one year out from delivery. The difference in performance between the two methods narrows when the starting point is reduced to nine months before the beginning of the delivery period. Interestingly, when considering the last six months prior to delivery only, the conventional approach outperforms the proposed data enrichment method. Furthermore, both the conventional and data enrichment approach perform better in NSW than VIC instruments.

4.3.2.1. Forecasting one year out of delivery

In the first step, we consider results for the created one-day ahead density forecasts during the twelve months prior to delivery. Tables 4.4 and 4.5, for NSW and VIC respectively, provide p-values for the conducted KS tests for each contract. The left-hand side of the table reports results for the conventional approach, while the right-hand side reports results for the applied data enrichment method that uses data from the current contract and contracts referring to the same quarter of the previous two years. Note that we use 126 observations to generate the density forecast in both the conventional and data enrichment approaches. In the conventional approach all 126 observations come from the current contract, while for the data enrichment model we use the highest number of observations from the current contract, as that contract should reflect the most recent information, and the least from the contract two years ago. We apply a ratio of 3:2:1 to the total of 126 observations, which gives us 63 observations from the current contract, 42 from the lag one-year contract and 21 from the lag two year contract (indicated in the tables as 63/42/21). Given that we have data for contracts from 2005 onward, we create density forecasts for contracts from Q1 2007 up to Q1 2014. For the Q1 2007 contract, we utilize data from Q1 2005, Q1 2006 and Q1 2007. Hence, for the sake of comparison, we show results starting at 2007 for both methods.

Starting one year out from delivery, the evidence indicates that the data enrichment method is able to generate better density forecasts. For a relatively large number of contracts, the conducted tests suggest that the model should not be rejected at the 5% significance level. At the same time, we find that for the conventional approach a far greater number of rejections can be observed. However, the performance of the data enrichment approach and its performance differential relative to the conventional method vary from model to model. The EUV model has the best performance and greatest differential with five non-rejections out of eight years. This is followed by the EDM with four non-rejections. This is likely due to both models being empirically fitted, and therefore free of distributional assumptions about the returns process. The better performance of the EUV approach is probably due to its ability to consider time-varying volatility. The EUV model is empirically fitted to returns that are updated based on the latest volatility information for equations (4.3) and (4.4). The relatively good performance of EUV confirms similar findings in the literature relating to the performance, in commodity and electricity futures markets, of models that incorporate time-varying volatility (see, e.g. Füss et al., 2010; Kayal and Lindgren, 2014).

By comparison, the conventional method indicates a weaker performance. EDM records three non-rejections, EUV two, while the correct specification of the density forecasts is rejected for all contracts but one for the parametric model using the normal distribution. This is likely due to the data, upon which the estimates are based in this approach, coming from a low liquidity period and having different characteristics to the forecast period. Furthermore, the two normal models NDU and NDH do not perform as well as the empirically fitted models, indicating that the normality assumption does not hold for the returns of these instruments. This does not come as a surprise given the non-normality of returns for most contracts illustrated in Table 4.2 and

4.3. This is also in line with many prior studies in the literature that refer to non-normal returns for financial assets. For VIC contracts we report results in Table 4.5, overall illustrating a higher rejection rate for the created density forecasts for all approaches: the performance drops for both approaches, while we observe a marginally better performance for the data enrichment method, with typically higher p-values and a lower number of rejections for the EUV and EDM approach.

Table 4.4
NSW Q1 One day ahead density forecast evaluation, KS test p-values one year out from delivery – centred

	Conventional approach				**Data Enrichment, centred, 63/42/21[1]**			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**	**Normal Distribution (NDH)**	**Normal with adjusted volatility (NDU)**	Empirical Distribution (EDM)	**Empirical Updated Volatility (EUV)**
Q1 2007	0.022*	0.018*	0.147	0.117	0.0485*	0.177	0.143	0.172
Q1 2008	0.675	0.158	0.214	0.451	0.030*	0.051	0.000**	0.470
Q1 2009	0.000**	0.001**	0.006**	0.006**	0.000**	0.000**	0.005**	0.001**
Q1 2010	0.000**	0.003**	0.029*	0.020*	0.000**	0.064	0.068	0.108
Q1 2011	0.000**	0.001**	0.001**	0.001**	0.000**	0.005**	0.002**	0.011*
Q1 2012	0.000**	0.011*	0.004**	0.002**	0.003**	0.003**	0.121	0.072
Q1 2013	0.015*	0.036*	0.057	0.011*	0.009**	0.037*	0.134	0.210
Q1 2014	0.000**	0.000**	0.003**	0.004**	0.000**	0.000**	0.000**	0.003**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Table 4.5
VIC Q1 One day ahead density forecast evaluation, KS test p-values one year out from delivery – centred

	Conventional approach				**Data Enrichment, centred, 63/42/21[1]**			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**	**Normal Distribution (NDH)**	**Normal with adjusted volatility (NDU)**	Empirical Distribution (EDM)	**Empirical Updated Volatility (EUV)**
Q1 2007	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Q1 2008	0.000**	0.000**	0.018*	0.012*	0.003**	0.000**	0.026*	0.015*
Q1 2009	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.002**	0.002**
Q1 2010	0.009**	0.018*	0.036*	0.025*	0.000**	0.016*	0.128	0.289
Q1 2011	0.001**	0.001**	0.004**	0.013*	0.000**	0.001**	0.007**	0.013*
Q1 2012	0.007**	0.022*	0.009**	0.011*	0.005**	0.013*	0.019*	0.026*
Q1 2013	0.000**	0.000**	0.001**	0.000**	0.000**	0.000**	0.006**	0.035*
Q1 2014	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.006**	0.014*

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

4.3.2.2 Forecasting starting at nine and six months out of delivery

In order to assess whether the new method is robust to different starting points, we explore the forecasting performance when starting at nine months (189 observations) and six months (126 observations) out from delivery. Tables 4.6 and 4.7 have the same layout as Tables 4.4 and 4.5

and show the KS test results for NSW and VIC. For NSW, the performance of the data enrichment model surprisingly records a higher number of rejections relative to the one-year case. Despite typically recording higher p-values for EUV, EDM and NDU, a correct specification of the density forecasts is rejected for all but three contracts for both EUV and EDM. Interestingly, for the conventional approach, the forecasting performance improves for EUV and EDM, recording an additional non-rejection each and generally higher p-values compared to the one-year case. The best performance for the data enrichment approach is achieved in combination with the EUV. In this approach, we obtain high p-values for several years, suggesting reasonably good density forecasts, while for one contract the correct specification is rejected with a p-value of 0.0468. For the conventional approach, EDM yields the best results, while the correct specification of density forecasts is rejected for most contracts for both normal models as well as NDH.

An overall assessment at nine months is that there is no evidence to support the conclusion of a significant performance differential between the two approaches in the NSW market. Similar to the results for 12 months, both approaches yield results that are worse for VIC than for NSW.

Table 4.6
NSW Q1 One day ahead density forecast evaluation, KS test p-values nine months out from delivery – centred

	Conventional approach				**Data Enrichment, centred, 63/42/21**[1]			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**	**Normal Distribution (NDH)**	**Normal with adjusted volatility (NDU)**	Empirical Distribution (EDM)	**Empirical Updated Volatility (EUV)**
Q1 2007	0.023*	0.019*	0.362	0.269	0.0930	0.257	0.305	0.174
Q1 2008	0.010**	0.0070**	0.052	0.013*	0.031*	0.025*	0.000**	0.047*
Q1 2009	0.000**	0.001**	0.016*	0.014*	0.000**	0.002**	0.014*	0.007**
Q1 2010	0.001**	0.011*	0.395	0.320	0.000**	0.258	0.276	0.738
Q1 2011	0.000**	0.018*	0.003**	0.003**	0.000**	0.030*	0.004**	0.029*
Q1 2012	0.000**	0.042*	0.008**	0.006**	0.002**	0.005**	0.016*	0.009**
Q1 2013	0.187	0.320	0.415	0.388	0.163	0.224	0.770	0.756
Q1 2014	0.000**	0.000**	0.001**	0.003**	0.000**	0.000**	0.001**	0.002**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Table 4.7
VIC Q1 One day ahead density forecast evaluation, KS test p-values nine months out from delivery – centred

	Conventional approach				Data Enrichment, centred, 63/42/21[1]			
	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)
Q1 2007	0.000**	0.001**	0.000**	0.001**	0.007**	0.008**	0.004**	0.001**
Q1 2008	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.028*	0.030*
Q1 2009	0.000**	0.000**	0.000**	0.000**	0.000**	0.005**	0.000**	0.000**
Q1 2010	0.007**	0.039*	0.014*	0.013*	0.000**	0.072	0.265	0.438
Q1 2011	0.001**	0.011*	0.002**	0.034*	0.002**	0.022*	0.017*	0.026*
Q1 2012	0.006**	0.028*	0.019*	0.023*	0.005**	0.010**	0.016*	0.028*
Q1 2013	0.011*	0.010**	0.038*	0.053	0.008**	0.015*	0.253	0.113
Q1 2014	0.000**	0.002**	0.009**	0.022*	0.000**	0.002**	0.019*	0.022*

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Table 4.8
NSW Q1 One day ahead density forecast evaluation, KS test p-values six months out from delivery – centred

	Conventional approach				Data Enrichment, centred, 63/42/21[1]			
	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)
Q1 2007	0.061	0.063	0.142	0.533	0.389	0.675	0.035*	0.127
Q1 2008	0.071	0.053	0.080	0.049*	0.005**	0.141	0.000**	0.334
Q1 2009	0.000**	0.000**	0.000**	0.000**	0.000**	0.002**	0.001**	0.000**
Q1 2010	0.016*	0.026*	0.135	0.120	0.000**	0.071	0.106	0.177
Q1 2011	0.005**	0.007**	0.002**	0.002**	0.000**	0.005**	0.001**	0.003**
Q1 2012	0.117	0.254	0.136	0.173	0.105	0.100	0.036*	0.051
Q1 2013	0.373	0.284	0.854	0.638	0.259	0.396	0.956	0.431
Q1 2014	0.001**	0.003**	0.027*	0.043*	0.000**	0.023*	0.011*	0.029*

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Starting even closer to the delivery date, only six months away, we observe that for NSW (Table 4.8) the evidence is in favour of the two models based on updated volatilities, the EUV and NDU, with five non-rejections each for data enrichment. This reinforces the view that taking the time-varying nature of volatility into account helps to improve the forecasting performance. For the conventional approach the models all improve and perform similarly. The EDM provides the best results with five non-rejections, while for all other approaches the correct specification of the forecasts cannot be rejected for four of the contracts. What drives this improvement in the conventional approach is probably the fact that starting closer to delivery, the data is now sourced from a period with similar liquidity and characteristics to the period of interest.

Table 4.9
VIC Q1 One day ahead density forecast evaluation, KS test p-values six months out from delivery – centred

	Conventional approach				**Data Enrichment, centred, 63/42/21[1]**			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**	**Normal Distribution (NDH)**	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**
Q1 2007	0.017*	0.021*	0.048*	0.067	0.393	0.207	0.188	0.102
Q1 2008	0.000**	0.000**	0.001**	0.001**	0.000**	0.000**	0.028*	0.045*
Q1 2009	0.001**	0.002**	0.003**	0.002**	0.000**	0.002**	0.002**	0.003**
Q1 2010	0.241	0.215	0.115	0.204	0.011*	0.109	0.730	0.245
Q1 2011	0.000**	0.000**	0.000**	0.002**	0.000**	0.001**	0.000**	0.000**
Q1 2012	0.117	0.166	0.135	0.114	0.008**	0.007**	0.012*	0.018*
Q1 2013	0.046*	0.071	0.132	0.110	0.048*	0.094	0.363	0.196
Q1 2014	0.004**	0.008**	0.062	0.069	0.000**	0.002**	0.163	0.288

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Surprisingly for futures contracts from the VIC market, we also observe a much better performance for both the conventional and data enrichment approaches. For data enrichment the empirically fitted models EUV and EDM score four non-rejections each and one rejection for the EUV at the 0.0454 level of significance. What is more interesting though is that the EDM has higher p-values than the EUV suggesting that updating in the EUV model based on information from current and lagged years has disadvantaged the EUV model. The two normal models NDU and NDH score three and two non-rejections respectively, still a weak performance despite showing a huge improvement. The performance of the conventional method is no less surprising. As in the data enrichment approach, the EUV and EDM show the best performance with five and four non-rejections each. The EUV model using the conventional method scores more non-rejections than its enriched counterpart, which is likely due to the fact that it is being updated with more recent information (purely from current contract data) compared to the new method, which has a combination of current and lagged contract data. The EUV here also performs better than the EDM, which underscores the advantage of updating seen in the literature. Like their data enrichment counterparts, the NDU and NDH, with three and two non-rejections, still exhibit weak performance despite the step improvement. This further underscores the inadequacy of normality assumptions for returns of this market. What the six-month case brings into relief is first, a significant improvement in density forecasts when using data with similar characteristics to the period of interest. This is seen by the good results in both NSW and VIC for both approaches, and especially, the improvement in the conventional approach. Second, the benefits of updating the models based on current information as seen by the EUV model using the conventional approach yielding the best performance.

4.3.2.3 Varying the degree of data offset

A further robustness test of the new method involves observing the effect on its performance of varying the degree of offset of the lagged contracts. The change in offset does not apply to the conventional method, so we show the results for the two changes side-by-side in Table 4.10 for NSW and Table 4.11 for VIC. The tables present the cases of not offsetting the lagged contracts, left half, and of doubling the degree of offset from being centred (half offset) to fully offset; being offset is defined in Table 4.1. Our analysis shows that for the NSW market, the data enrichment approach outperforms the conventional method at both full and no offset, although the 'centred' approach still has the best performance among the three. Of the two non-centred offsets, the EUV model of the fully offset method provides the strongest performance with four non-rejections and reasonably high p-values, higher than the other models in both non-centred methods. For the fully offset case the other models do not perform strongly. The EDM, NDU and NDH record three, two and one non-rejections respectively. For the not offset case, EDM is the better performer followed by NDU. Both score four non-rejections each but the higher p-values for the EDM support it as a better calibrated forecast model. The EUV has higher p-values than either of the two former models but scores only three non-rejections, although one rejection is very close to the non-rejection threshold at 0.0488. The better performance of data enrichment at full and no offset provides further confidence in the method. The EUV is the best performer, followed by EDM and NDU supporting the previous indication of better performance among the empirically fitted models (EUV and EDM) or volatility updated models (EUV and NDU) or models with both (EUV). Victoria's performance continues to be weak with only one non-rejection for each of the NDU, EDM and EUV models of data enrichment and none for the conventional method.

Table 4.10
NSW Q1 One day ahead density forecast evaluation, KS test p-values one year out from delivery – fully offset

	Data Enrichment, not offset, 63/42/21[1]				Data Enrichment, fully offset, 63/42/21[1]			
	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)
Q1 2007	0.084	0.167	0.054	0.049*	0.091	0.368	0.288	0.318
Q1 2008	0.039*	0.068	0.000**	0.726	0.044*	0.039*	0.000**	0.635
Q1 2009	0.000**	0.000**	0.015*	0.016*	0.000**	0.000**	0.002**	0.000**
Q1 2010	0.000**	0.074	0.067	0.118	0.000**	0.105	0.098	0.149
Q1 2011	0.000**	0.016*	0.013*	0.028*	0.000**	0.002**	0.001**	0.006**
Q1 2012	0.001**	0.003**	0.149	0.042*	0.005**	0.007**	0.011*	0.015*
Q1 2013	0.004**	0.056	0.247	0.237	0.016*	0.047*	0.1117	0.165
Q1 2014	0.000**	0.000**	0.002**	0.010**	0.000**	0.000**	0.000**	0.000**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Table 4.11
VIC Q1 One day ahead density forecast evaluation, KS test p-values one year out from delivery – fully offset

	Data Enrichment, not offset, 63/42/21[1]				Data Enrichment, fully offset, 63/42/21[1]			
	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)	Normal Distribution (NDH)	Normal with adjusted volatility (NDU)	Empirical Distribution (EDM)	Empirical Updated Volatility (EUV)
Q1 2007	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Q1 2008	0.002**	0.000**	0.032*	0.014*	0.003**	0.000**	0.035*	0.037*
Q1 2009	0.000**	0.000**	0.001**	0.001**	0.000**	0.000**	0.000**	0.000**
Q1 2010	0.000**	0.015*	0.240	0.385	0.000**	0.069	0.169	0.230
Q1 2011	0.000**	0.000**	0.023*	0.042*	0.000**	0.001**	0.001**	0.003**
Q1 2012	0.001**	0.005**	0.0378*	0.035*	0.005**	0.009**	0.008**	0.004**
Q1 2013	0.000**	0.003**	0.002**	0.004**	0.000**	0.000**	0.023*	0.022*
Q1 2014	0.000**	0.001**	0.018*	0.041*	0.000**	0.000**	0.002**	0.002**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

4.3.2.4 Effect of using an alternate mix of observations

We explore how the performance of the data enrichment method is affected by changing the relative number of observations taken from each contract. To test this, we keep the total number of observations at 126 and take an equal number of observations from each contract – 42 observations of past returns from the current contract as well as 42 observations from the previous year contract and the contract two years ago. This is indicated as 42/42/42 in Tables 4.12 and 4.13 for NSW and VIC. As this change does not have any impact on the results of the conventional method, we do not report these results.

For the data enrichment method, we do not observe a material change in performance. Overall, the data enrichment approach still outperforms the conventional approach with the best performing models being those based on an empirical distributional fit and the volatility updating scheme (i.e. EUV, NDU and EDM). The EUV still provides the best performance with five non-rejections but the p-values are slightly lower than for the base case. The lower p-values could be due to the base case using a higher number of observations from the current contract which should embody more recent information. The EUV model is followed by NDU and EDM with four and three non-rejections respectively (the reverse of the base case). Similar to the EUV, the EDM's p-values are also lower than in the base case but the NDU's are higher. The fact that we get a similar performance profile (including which years are significant) as for the base case weights provides us with confidence about the performance of the data enrichment approach. VIC (Table 4.13) shows one non-rejection for the EUV with data enrichment compared to one non-rejection each for the EUV and EDM in the base case, and no non-rejections for the conventional approach.

Table 4.12
NSW Q1 One day ahead density forecast evaluation, KS test p-values one year out from delivery – centred with equal observations

	Data Enrichment, centred, 42/42/42[1]			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**
Q1 2007	0.045*	0.322	0.051	0.055
Q1 2008	0.002**	0.052	0.000**	0.258
Q1 2009	0.000**	0.000**	0.001**	0.001**
Q1 2010	0.000**	0.211	0.044*	0.104
Q1 2011	0.000**	0.005**	0.003**	0.006**
Q1 2012	0.004**	0.002**	0.119	0.146
Q1 2013	0.011*	0.134	0.177	0.190
Q1 2014	0.000**	0.000**	0.000**	0.000**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

Table 4.13
VIC Q1 One day ahead density forecast evaluation, KS test p-values one year out from delivery – centred with equal observations

	Data Enrichment, centred, 42/42/42[1]			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**
Q1 2007	0.001**	0.002**	0.000**	0.000**
Q1 2008	0.008**	0.000**	0.003**	0.005**
Q1 2009	0.000**	0.000**	0.005**	0.003**
Q1 2010	0.000**	0.009**	0.040*	0.162
Q1 2011	0.000**	0.000**	0.003**	0.003**
Q1 2012	0.001**	0.001**	0.009**	0.008**
Q1 2013	0.000**	0.005**	0.012*	0.022*
Q1 2014	0.000**	0.000**	0.001**	0.002**

*significant at 0.05, **significant at 0.01 . [1]num of obs from current/lag1yr/lag2yr contracts

4.3.2.5 Kuiper test versus KS test

Table 4.14
NSW Q1 One day ahead density forecast evaluation, Kuiper test p-values one year out from delivery

	Conventional approach				Data Enrichment, centred, 63/42/21[1]			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**	**Normal Distribution (NDH)**	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**
Q1 2007	0.001**	0.002**	0.002**	0.001**	0.000**	0.048*	0.060	0.050*
Q1 2008	0.332	0.021*	0.007**	0.235	0.000**	0.017*	0.000**	0.449
Q1 2009	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Q1 2010	0.000**	0.000**	0.001**	0.001**	0.000**	0.001**	0.002**	0.018*
Q1 2011	0.000**	0.000**	0.002**	0.008**	0.000**	0.001**	0.000**	0.0120*
Q1 2012	0.000**	0.000**	0.004**	0.014*	0.000**	0.000**	0.177	0.133
Q1 2013	0.002**	0.005**	0.009**	0.000**	0.000**	0.010*	0.071	0.265
Q1 2014	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

We report a final robustness check by evaluating the performance using the Kuiper test to see if our conclusions are sensitive to the test method used. The Kuiper test evaluates the correct specification of the underlying forecast model by testing the PIT for uniformity. For NSW (Table 4.14), our tests indicate that the data enrichment method outperforms the conventional method. Within the group of models tested with data enrichment, the empirically fitted models (EUV and EDM) perform best with three non-rejections each compared to five and four respectively under the KS test. All models score a lower number of non-rejections under the Kuiper test compared to the KS test. With data enrichment, the EUV still leads the pack with three non-rejections and higher p-values than other models (one of the misses is at 0.0499 so the EUV is close to four non-rejections). None of the models perform well in the conventional approach and yield fewer non-rejections than for the KS test. Specifically, the EUV and NDH score one non-rejection each.

Table 4.15
VIC Q1 One day ahead density forecast evaluation, Kuiper test p-values one year out from delivery

	Conventional approach				**Data Enrichment, centred, 63/42/21[1]**			
	Normal Distribution (NDH)	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**	**Normal Distribution (NDH)**	**Normal with adjusted volatility (NDU)**	**Empirical Distribution (EDM)**	**Empirical Updated Volatility (EUV)**
Q1 2007	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Q1 2008	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.002**
Q1 2009	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Q1 2010	0.000**	0.000**	0.005**	0.002**	0.000**	0.000**	0.039*	0.107
Q1 2011	0.000**	0.000**	0.004**	0.065	0.000**	0.000**	0.008**	0.031*
Q1 2012	0.000**	0.001**	0.007**	0.002**	0.000**	0.010*	0.016*	0.010*
Q1 2013	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.001**
Q1 2014	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**

*significant at 0.05, **significant at 0.01 [1]num of obs from current/lag1yr/lag2yr contracts

4.4 Conclusion

This paper examines the performance of one-day ahead density forecasts in low liquidity markets using data from the Australian Electricity Futures market. We find that the forecasts generated by the conventional approach based on historical data do not perform well essentially because this uses data from less liquid periods to form density forecasts for more liquid periods closer to delivery of the contract. We propose a new method that enriches the data of the instrument of interest with data from similar contracts traded in previous years closer to the period of interest. We apply the same four models in both the conventional and data enrichment approach and assess their performance using the KS test, applied to the inverse normal transformation of the PIT.

We find that the density forecasts of the proposed data enrichment approach are typically better, which is evidenced by a lower number of rejections of the created forecasts for the futures contracts. Both the conventional and data enrichment approaches perform better in the New South Wales (NSW) than the Victorian (VIC) market. We also perform a number of robustness checks for both methods and find that typically the superior performance of the data enrichment approach is confirmed. The data enrichment holds up to the robustness checks of using different offsets, a different number of observations and using the Kuiper test to assess performance instead of the KS test. Interestingly, when we start our forecast closer to the delivery period, we find that the gap between the performance of the two approaches narrows due to the better performance of the conventional approach. This is true in particular when we create daily density forecasts only for the last six months prior to the delivery period of the contract. We suggest that these results are due to the data used in the conventional approach being drawn from a more liquid period with similar characteristics to the forecasting period.

Furthermore, while it is not the purpose of the paper to conduct an extensive evaluation of the performance of different VaR models, we can observe that of the four models tested the empirical fitting of data updated according to the volatility updated simulation, referred to as the EUV model in this paper, performed best. This was followed by either the model fitted empirically to historical data or the normal model with updated volatility depending on the case being considered.

Future work could assess the performance of combining forecasts from different models probably preceded by a more extensive evaluation of different models to determine the best candidates for inclusion in such a combination (e.g. Hall and Mitchell, 2007; Kascha and Ravazzolo, 2010). Such an evaluation could also be conducted by testing the relative performance of the forecasting models as suggested, for example, by Manzan and Zerom (2013). Other future work could involve testing the approach on different financial markets with low liquidity, including electricity markets other than in Australia or other energy and commodity markets. The natural gas market is likely to be a good candidate due to its low liquidity. Investigating policy responses to improve liquidity such as by imposing mandatory market making obligations or encouraging participants to provide such services voluntarily is yet another possible research topic. Voluntary market making started in the Australian electricity futures in July 2019 but it is too early to determine its impact.[25] Finally, future work

[25] ASX website https://asxonline.com/content/asxonline/public/notices/2019/june/0653.19.06.html accessed on 15 September 2019. The market making arrangements are outlined in a brief document https://www.asx.com.au/communications/notices/2019/ASX-AU-Electricity-Market-Making-Summary-2019.pdf accessed on 15 September 2019.

could also drill down into the characteristics of the data to help in the selection of model parameters, such as the number of contracts from previous years being used to enrich the data or the amount of data being used to generate the forecasts.

Overall, we believe that the proposed data enrichment method and the conducted empirical analysis should be of interest to risk managers and other participants exposed to the electricity market and other markets characterised by periods of low liquidity.

Appendix B

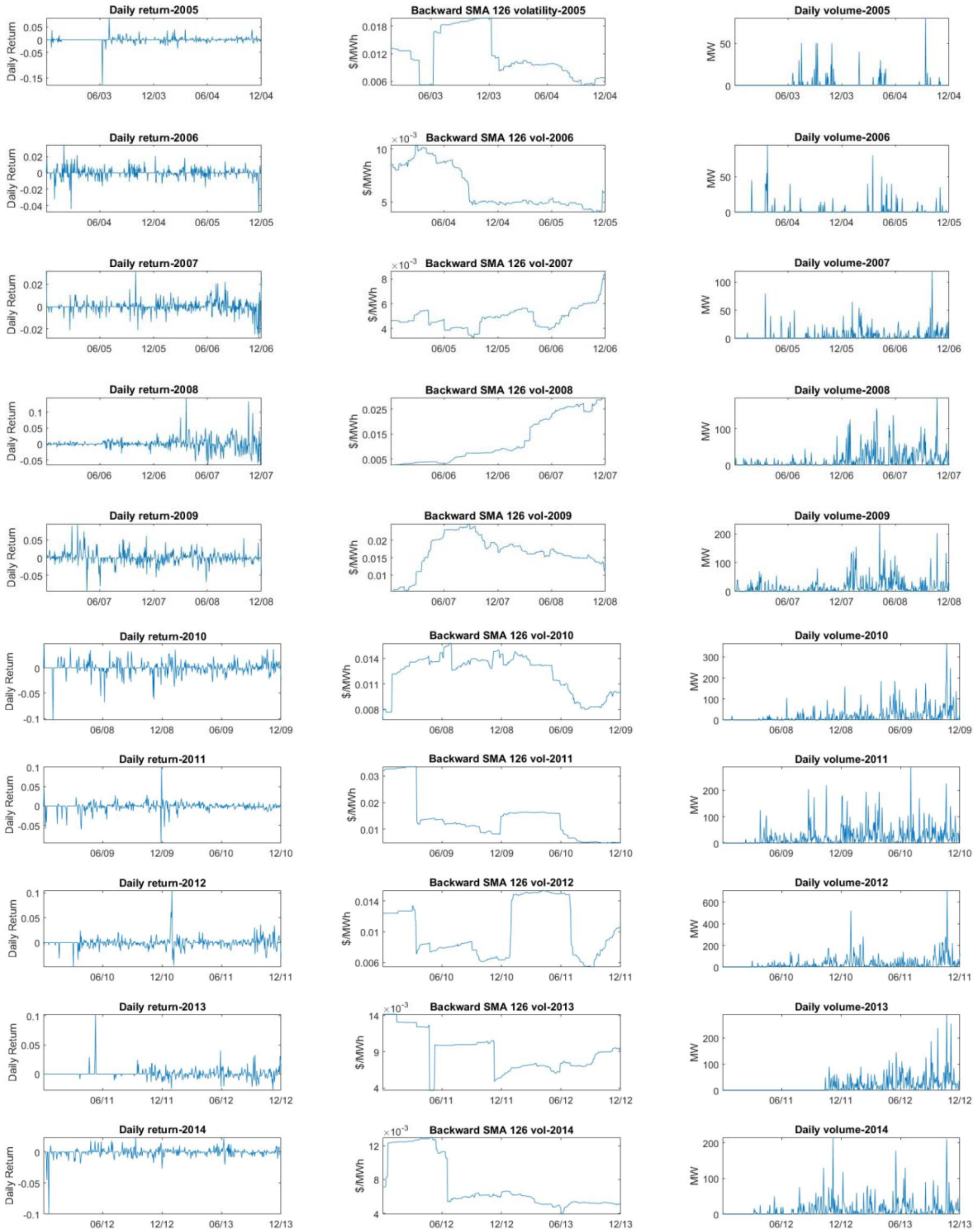

Fig. B.1. Daily return, backward moving average volatility and trading volume for NSW base load Q1 2005-14 futures contracts. Shows daily data for NSW base load Q1 futures contract over a period of 504 days (two years) prior to delivery. Each set of three panels in a row correspond to one year. The left panel shows daily returns, generally becoming less volatile with smaller magnitude jumps closer to delivery. The middle panel shows backward volatility, moving average of 126 observations (six months) of futures prices in Australian $/MWh. Lower volatility closer to delivery. The right panel shows daily traded volume, indicating higher liquidity as the contract approaches delivery. The overall picture is that higher volatility of returns is associated with lower liquidity periods.

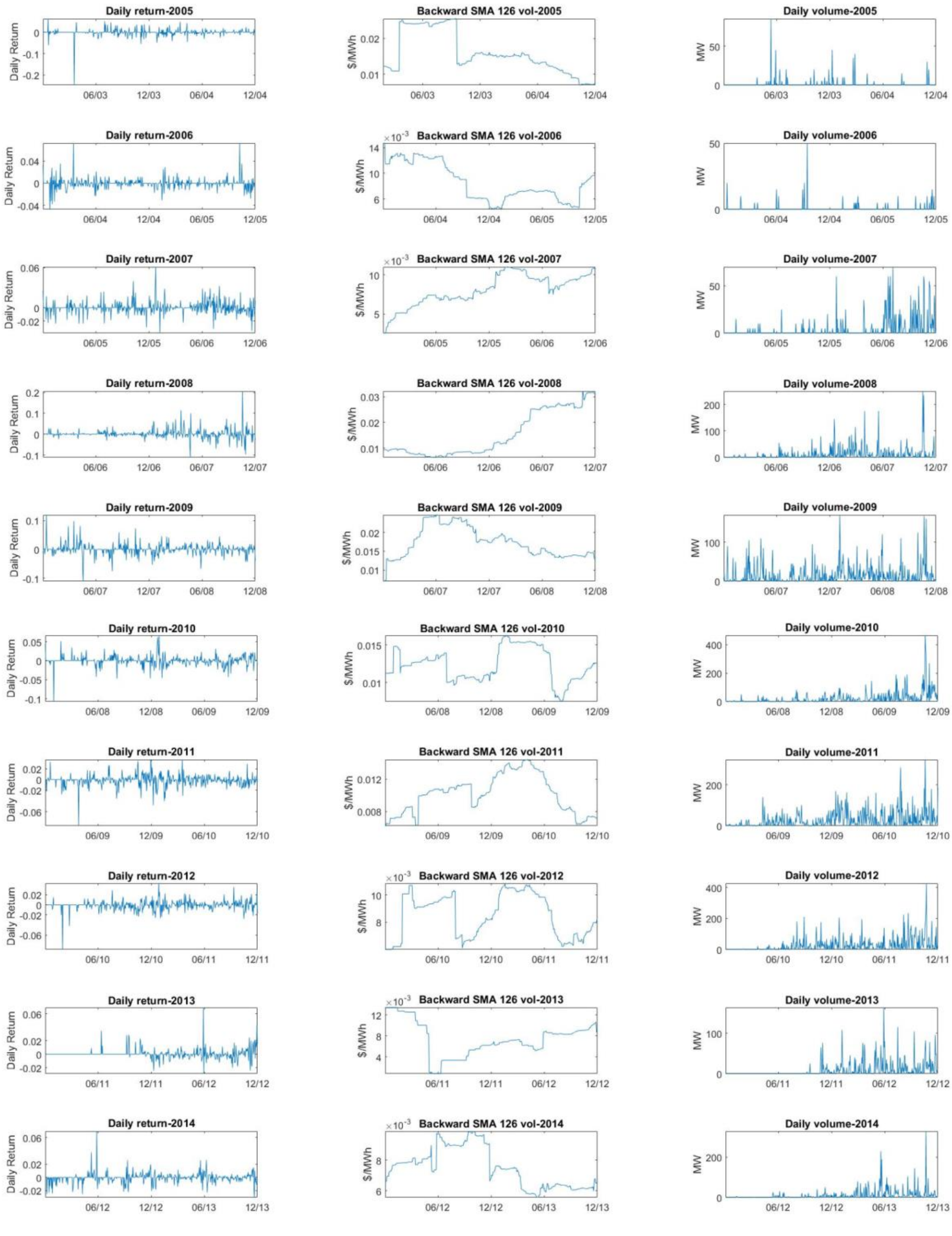

Fig. B.2. Daily return, backward moving average volatility and trading volume for VIC base load Q1 2005-14 futures contracts. Shows daily data for VIC base load Q1 futures contract over a period of 504 days (two years) prior to delivery. Each set of three panels in a row correspond to one year. The left panel shows daily returns, generally becoming less volatile with smaller magnitude jumps closer to delivery. The middle panel shows backward volatility, moving average of 126 observations (six months) of futures prices in Australian $/MWh. Lower volatility closer to delivery. The right panel shows daily traded volume, indicating higher liquidity as the contract approaches delivery. The overall picture is that higher volatility of returns is associated with lower liquidity periods.

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5. Vertical Integration of Generation and Retail: Foreclosure in the Electricity Futures Market

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Abstract

We present empirical evidence of foreclosure in the electricity futures market following vertical integration between the electricity retail and generation stages. This foreclosure limits the risk-mitigation options open to retailers and other participants, and can reduce retail competition and harm consumers. We investigate the volume of transacted electricity futures against independent variables representing vertical integration, spot and futures price moments, demand, and other variables. A multiple regression analysis shows a statistically significant decline in the base load energy volume transacted on the Australian Securities Exchange for delivery periods longer than 12 months. This horizon is particularly relevant for the commercial and industrial customer market segments as well as for the residential customer segment on contracts longer than 12 months. However, we find no statistically significant change in the volume within the 12-month horizon or in total volume when ignoring the horizon. The differences in the volume changes by horizon following vertical integration show that the structure of the futures market became more short-term, focused on horizons shorter than 12 months. Our sample covers 2007 to 2017 data for New South Wales, the largest region in the Australian National Electricity Market. The impact of industry structure on standalone retailers and the potential to reduce competition are of interest to policymakers, regulators, consumers, and retailers exposed to the spot electricity market.

Keywords: *Electricity market, Futures market, Foreclosure, Vertical integration, Risk management*

JEL Classification: *Q40, G12, G18, L42, L94, G32, G13, L94*

5.1 Introduction

Vertical integration (VI) is a controversial issue both in the academic literature and among regulators and policy makers. VI is the process of carrying out in one firm activities, relating to more than one stage of a supply chain that are typically carried out by other firms. This can occur through either mergers and acquisitions or internal capability development.

In this study, we examine the impact of VI on the liquidity of electricity futures contracts in the Australian National Electricity Market (NEM). We regress electricity futures volume transacted on the Australian Securities Exchange (ASX) against independent variables representing VI, spot and futures price moments, demand, and other variables. The results show a statistically significant reduction in the volume of electricity futures transacted following VI between the generation and retail stages of the electricity industry. The VI variable explains the largest portion of the drop. The decline in volume can reduce electricity retail competition and harm consumers. A liquid futures market is an important tool for managing risk (Allaz and Vila, 1993) and electricity futures markets (Aïd et al., 2011). Liquid electricity futures markets reduce the disadvantage of standalone retailers relative to retailers that are vertically integrated with generators (often referred to as 'gentailers'; Aïd et al., 2011). Regulators have recognised that a reduction in traded volume in futures markets affects the ability of stand-alone retailers to manage risk and compete effectively (AEMC, 2018)[26]. Thus, our finding of a significant reduction in the volume of electricity futures provides an important contribution to both the academic and regulatory spheres. Our analysis is based on data drawn from the New South Wales (NSW) market, the largest region of the NEM, covering January 2007 to December 2017.

This study is one of the first to focus on how VI in the electricity market affects the volume traded on the electricity futures market. It makes another important contribution by splitting the hedging horizon into one within 12 months of the contract transaction date (H1) and a second that is greater than 12 months from the transaction date (H2). H2 is particularly relevant for the commercial and industrial customer segments of the market as well as for the residential customer segment on contracts longer than 12 months. These horizons are used by the Australian Financial Markets Association (AFMA) to report data relating to the electricity

[26] AEMC stands for 'Australian Energy Market Commission'.

Over-the counter (OTC) market, the other major futures (bespoke) market. Our novel method of analysing transacted futures contract volume by horizon provides new insights into the impact of VI on the structure of the futures market and competition. The impact appears to have been missed in studies that did not differentiate between short- and long-term horizons [e.g. Simshauser et al. (2015) in the Australian context]. Further contribution is made by analysing base load and peak load electricity futures contract volumes over the study period. The volume of base load contracts exceeding 12 months fell significantly following VI. However, peak load volumes transacted up to 12 months increased following VI. These results are likely due to the continued need to hedge in the short term (H1) but not in the longer term (H2).

Views on the effects of VI on competition and social welfare are not unanimous. While early studies were either entirely for or against VI,[27] more rigorous and advanced techniques showed that its impact is situation dependent. Tirole (1988) applied game theory techniques and developed rich models that incorporated real-world choices faced by business actors and analytical rigour. Further contribution by Hart and Tirole (1990) explored the circumstances under which VI can be beneficial and those under which regulation is justified to prevent harmful consequences. Another approach, which motivated a large number of subsequent studies, was transaction cost economics (TCE). TCE addresses the limitation of contracts being incomplete instruments that can lead to moral hazard issues (Joskow, 2005; Joskow, 2010).[28] One way of overcoming the limitations of contracts is for businesses to incorporate physical assets into their supply chain. Hence, VI can be a more efficient option for reducing risk than financial contracts (Joskow, 2010; Williamson, 1971). Futher, Boroumand and Zachmann (2012) find that including physical generation in a retailer's portfolio reduces its risk more effectively than contracts do.

VI can also result in vertical foreclosure, as pointed out by (among others) Hart and Tirole (1990), Loertscher and Reisinger (2014), Ordover et al. (1990), Rey and Tirole (2007), Salinger (1988), and Salop and Culley (2014). Vertical foreclosure occurs when the quantity of goods

[27] The Structuralist School, developed mainly at Harvard University, opposed VI on the grounds that it was anti-competitive (Mason, 1939; Bain, 1956). The opposite view was advanced by the Chicago School, which saw VI as enhancing social welfare (e.g. Posner, 1976; Bork, 1978).
[28] TCE gained prominence following Williamson (1974) and Williamson (1975). Property rights and moral hazard (aka 'principal–agent') are other theories in the field of industrial organisation.

and/or services transacted between vertically integrated and non-vertically integrated firms is lower than would be the case if the integrated firms had no bargaining power (Grimm et al., 1992). Foreclosure can constitute competitors' full or partial denial of proper access to a bottleneck good as noted by Rey and Tirole (2007). Even when VI results in foreclosure, its net effect may still turn out to be positive if the negative effects of foreclosure are outweighed by efficiency benefits (Chipty, 2001; Hortaçsu and Syverson, 2007; Mullin and Mullin, 1997) or the elimination of double marginalisation (DM; Bork, 1978; Joskow, 2010; Lafontaine and Slade, 2007). In its pure form, DM occurs when two monopolies exist in successive stages of a supply chain and each charges a margin that is passed on to the consumer.

The impact of VI on futures markets is important for competition as futures markets are important for risk-management and enhancing competition (Aïd et al., 2011; Allaz and Vila, 1993), particularly for non-integrated retailers. De Bragança and Daglish (2016) showed that individual net generators can exert market power in the spot market. De Bragança and Daglish (2016) and Anderson and Hu (2008) show that spot market power can increase prices in forward and futures markets. Non-integrated retailers who cannot access futures markets are forced to integrate or exit (Boroumand and Zachmann, 2012).

The literature discusses several other benefits of VI, including facilitating the entry of base load generation capacity into the market (Caplan, 2012; Simshauser et al., 2015), reducing generators' incentive to overstate their bids (Hogan and Mead, 2007), and mitigating market power (Bushnell et al., 2008; Mansur, 2007).

The blueprint for market liberalisation involved disaggregating electricity utility monopolies. Disaggregating electricity supply chain stages is not costless. Meyer (2012) estimates that the costs of disaggregating U.S. electricity monopolies were considerable due to the loss of coordination and to market risk. The study qualifies its findings by indicating that only the costs, and not the benefits, of unbundling are addressed; thus, no conclusion is made about the net cost or benefit of the disaggregation.[29] The findings on the effect of disaggregating distribution from other stages are mixed. Fetz and Filippini (2010) study the Swiss electricity

[29] Depending on which stages are disaggregated in the scenario, the costs of unbundling for an average-sized firm are estimated to be 4%, 8% to 10%, and 19% to 26% based on data covering 2001 to 2008. The largest losses are associated with the unbundling of generation from combined retail and distribution.

market and conclude that, in their sample comprised mainly of companies with fewer than 100,000 customers, significant economies occurred due to VI between generation and distribution. Heim et al. (2018) find that unbundling retail and distribution reduced grid charges between 5% and 9% in Germany.

Overall, the regulation pendulum has swung in favour of VI, but calls to strengthen the regulation of VI continue, as in Salop (2018). Similarly, support for VI is strong where for example Joskow, (2010) and Lafontaine and Slade, (2007) find overwhelming support for VI. Importantly, however, these reviews also emphasise that the net impact of VI is situation dependent.

In the NSW electricity market, large gentailer entities were created overnight through a single transaction executed on or about 1 March 2011. Private retailers Origin Energy (Origin) and TRUenergy acquired the three state-owned retailers outright while obtaining simultaneously full commercial control of the output of around a third of NSW generating capacity through a lease arrangement.[30] The generation capacity belonged to major state-owned generation businesses Eraring and (part of) Delta Electricity. The leased generation assets were subsequently sold to the lessees in 2013. The remaining state-owned electricity generation assets were later sold to other parties in separate transactions. Most notable were the sale of Macquarie Generation (representing around 30% of NSW generation capacity) to AGL Energy Limited (AGL) in September 2014,[31] the sale of Delta Electricity's Colongra to Snowy Hydro in December 2014, and the sale of Delta Electricity's Vales Point power station to private investors in November 2015. While NSW had seen very little VI between retail and generation before 1 March 2011, the transaction represented a watershed moment in NSW that made the impact of VI more easily discernible.

The bundling of generation and retail entities into gentailer entities has been a growing trend in the NEM since 2006 (Anderson et al., 2007; Moran and Sood, 2013).[32] It reversed the unbundling of retail and generation into separate entities that had characterised the electricity

[30] The AER State of the Energy Market report 2011 (AER, 2011) shows that the combined generation capacity in NSW represented by Origin Energy and TRUenergy is 36% (18% for each), up from 4% (4% and 0% respectively) in the previous year's report AER (2010).
[31] AGL 2015 annual report.
[32] AER (2011) is one of many references that provide information about VI in the NEM.

market liberalisation reforms of the 1990s. Concerns have been voiced about a potential reduction in futures market liquidity in various quarters, including academia (Anderson et al., 2007; Boroumand and Zachmann, 2012), futures market operator d-cypha (ASX),[33] and the Australian Energy Regulator (AER), who also voiced concerns over the increasing barriers to entry in the 2007 State of the Energy Market report (AER, 2007) and in every report since 2011 (e.g. AER, 2011).[34] However, scholars have differing views on VI's impact in Australia. Simshauser et al. (2015),[35] studying the effect of structure on the firm's ability to maintain an investment-grade credit rating, argues that the theoretical and empirical evidence favours VI. They also present NEM-wide data from the ASX and AFMA indicating that no change occurred in their combined futures volume following a number of identified VI events. Simshauser et al. (2015) support this view by pointing out (accurately, to our knowledge) that no empirical analysis on the NEM supports concerns about the potential for reduced futures market liquidity. Our work provides new evidence relating to this area.

The remainder of the paper is organised as follows. Section 2 provides important background information and reviews the literature. Section 3 outlines the study's methodology, and section 4 describes the study's sample data. The results are presented and discussed in section 5. Finally, section 6 concludes the paper.

5.2 Background and Literature Review

5.2.1 Vertical integration and foreclosure

Within the broad literature on VI, foreclosure is the issue most relevant to our topic. The literature contains many models with varying assumptions and model constraints on market structure, firm characteristics, and allowable strategies. These differences can, and often do, lead to materially different, sometimes contradictory, conclusions. Therefore, care needs to be exercised when interpreting the conclusions resulting from theoretical models. Ordover et al. (1990) developed a game theoretic model with two identical upstream and two identical downstream firms. One downstream firm is allowed to integrate with one upstream firm, and

[33] d-cyphaTrade, Strategic priorities for energy market development, Submission to AEMC, 2011. https://www.aemc.gov.au/sites/default/files/content/fef7952b-272e-4137-9b30-107a1738c431/d-cyphaTrade-13-May-201.PDF; accessed on 17 November 2018. The AEMC is the Australian Energy Market Commission.

[34] AER (2011) and AER (2012) also voiced concerns about the potential of VI to increase electricity prices.

[35] Simshauser et al. (2015) explored the impact of VI on a firm's ability to sustain an investment-grade credit rating by modelling a firm's after-tax net profit under three scenarios: integrated gentailer, non-integrated retailer, and non-integrated generator.

the model predicts that the other (non-integrated) downstream firm cannot make a bid that is acceptable to the other (non-integrated) upstream firm. The model goes on to explore the impact on the non-integrated downstream firm. The study concludes that foreclosure obtains as an anticompetitive equilibrium outcome that affects the non-integrated downstream firm by increasing its costs. Increasing rivals' costs is achieved through agreement made between the integrated firm divisions to charge the non-integrated downstream firm a price above the marginal cost. Hart and Tirole (1990) disagree with the conclusion drawn by Ordover et al. (1990). They develop a richer game theoretic model with two upstream and two downstream firms, but they allow the non-integrated firms to have differing marginal costs, investment costs, and capacity and to choose from a broader array of options in response to the integrated firm. The allowable strategies include the option to integrate, stay non-integrated, or exit. Their model also allows two-part tariffs[36] and shows that the non-integrated downstream firm could prevent the integrated firm from influencing its cost by entering into a two-part tariff arrangement[37] with the non-integrated upstream firm, setting the unit price equal to the marginal cost and negotiating the fixed part. They further argue that the integrated firm stands to gain more by supplying the downstream non-integrated firm than by foreclosing on it. Thus, on these two counts, they argue that the conclusion in Ordover et al. (1990) that VI leads to foreclosure is doubtful. One goal of the Hart and Tirole (1990) model is to provide guidance on when regulating VI is warranted. Far from denying the possibility of foreclosure as a consequence and/or driver of VI, the authors conclude that authorities should scrutinise VI between firms that have had many dealings with other firms more closely than they scrutinize VI between firms that have dealt exclusively with each other, as the former circumstance (which is similar to that of the NSW electricity market) can be more damaging to competition than the latter. The conclusion of Loertscher and Reisinger (2014) that regulators should scrutinise VI when there is a large number of competitors supports the conclusion in Hart and Tirole (1990). Loertscher and Reisinger (2014) developed a theoretical model to explore the dependence between VI's impact and a market's competitive structure.[38]

[36] A two-part tariff involves an upfront fixed amount and a per-unit amount. The upfront part is equivalent to the purchase price of a firm and setting the per-unit amount equal to the marginal cost avoids distortions. However, there are various ways of structuring these two amounts depending on the risk appetite, information, and goals of the parties, as discussed in Tirole (1988).

[37] Hart and Tirole (1990) base their two-part tariff argument on Tirole (1988). Joskow (2005) disagrees with the conclusion in Hart and Tirole (1990) that VI and two-part tariffs are equivalent mechanisms, arguing that the transaction costs associated with each option, as well as the characteristics of the firms and the transaction, are important considerations in choosing between alternatives.

[38] In the limit, their model arrives at the conclusion that VI by a dominant firm is anticompetitive in a market in which it is competing with smaller fringe firms. Riordan (1998) finds the same result.

Given the complexities of and differences between the conclusions of the theoretical models, it is not surprising to see Lafontaine and Slade (2007) conclude that ‘there are few unambiguous results. Ambiguity in the theories makes an analysis of the data even more important’. Lafontaine and Slade (2007) conducted an extensive review of VI models and of empirical studies of transactions that are best integrated into the firm and the economic consequences of VI. The study drew a wide range of conclusions, finding that, in most (but not all) cases, VI promotes social welfare. The study also found that, although foreclosure can increase rivals’ costs and consumer prices, the net result may not be harmful if foreclosure is counterbalanced by the benefits of eliminating DM. A separate review of the theoretical and empirical literature (Joskow, 2010) also came out in favour of VI in most cases. The study puts forward similar arguments on foreclosure, and also extends them, more explicitly than do Lafontaine and Slade (2007), from the pure monopoly case to circumstances in which imperfect competition prevails, conditions more commonly found in the real world and which more closely resemble the pre-VI NSW electricity market.[39] Joskow (2010) points out that DM occurs at a lower level in the case of imperfect competition than in the case of pure monopolies in the upstream and downstream stages. Joskow (2010) argues that, due to the reduced DM, the social welfare effects of VI ‘are now more likely to be ambiguous’ and dependent upon assumptions made about the nature of the competition prior to VI and how it will be affected by it. Salop and Culley (2014) present several arguments for why the elimination of DM is not a foregone conclusion. One of the arguments is that DM is not eliminated if the merging entities follow a policy of arm’s-length dealings. Some gentailers have a policy of arm’s-length dealings between their divisions in setting transfer prices. This could mean that the elimination of DM did not follow from VI in NSW.

5.2.2 Forward markets and competition

The notion that contracts[40] are incomplete instruments for managing risk is a commonly cited motivation for VI (Joskow, 2010; Lafontaine and Slade, 2007; Williamson, 1971) because

[39] Retail electricity prices in NSW for clients consuming under 160 MWh per year were regulated pre-VI by the Independent Pricing and Regulatory Tribunal (IPART), which limited retailers’ opportunity to exercise market power and inflate margins in the retail market. The retail margin component of a typical residential electricity bill in NSW in 2010 and 2011 was 5% according to data compiled from sources such as IPART, published by the AER in Table 4.2 of its State of the Energy Markets annual reports (AER, 2010; AER, 2011).

[40] The studies we reference in this paper examine forward and futures markets depending on their setting. Although they are not the same, strictly speaking, we do not differentiate between these contract types. Counterparty default

contractual arrangements do not cover all eventualities, particularly as circumstances and the interests of the involved parties change over time.[41] Research has shown that introducing a physical hedge into a portfolio reduces the retailer's risk.[42] Boroumand and Zachmann (2012) run simulations using 2006 and 2007 data from the French market and show that, in the presence of stochastic demand, a retailer minimises its portfolio's 5% daily VaR if it includes physical plant along with financial contracts and spot operations. Note that financial contracts continue to play a role in risk management, even for gentailers.

Forward markets can help standalone retailers compete in the retail market. Aïd et al. (2011) develop an equilibrium model (which does not assume any market power), add retail to the models of Allaz (1992) and Bessembinder and Lemon (2002), and include four types of agents: non-integrated generators and retailers, gentailers, and traders. They analyse settings with and without a forward market and conclude that a gentailer with the same risk-aversion level as a standalone retailer obtains a larger market share, but the advantage to the integrated retailer is significantly reduced in the presence of a forward market. The authors then confirm their model by analysing five years of French market data starting from 1 January 2005.

Aïd et al. (2011) find that non-integrated retailers who cannot trade forward exit the market regardless of their risk-aversion characteristics. The study specifically notes the exit of non-integrated retailers from the New Zealand market. The degree of VI between retailers and generators in a market negatively affects the likelihood that a liquid contract market will develop. This in turn increases pressure on non-integrated retailers to integrate or exit (Boroumand and Zachmann, 2012). De Bragança and Daglish (2017) affirm that retailers are more likely to grow their market share when markets are concentrated or heavily vertically integrated or have well-developed derivatives markets. The study uses the framework developed in de Bragança and Daglish (2016), which is explained in subsection 2.3 below.

risk is an important difference between the two. Contracts can be exchange cleared or not, financial or physical, standardised or bespoke, and futures or forward.

[41] Additionally, writing, negotiating, and entering into a contract, as well as renegotiating and enforcement (due to performance or other default), are difficult and/or expensive.

[42] Examples of introducing a physical hedge include building a generating asset, acquiring a generation asset, and acquiring a generating business. All amount to VI.

Given the importance of futures markets for expanding retailer participation, our finding of a reduction in futures market liquidity following VI supports the conclusion that VI reduces retail competition and can disadvantage consumers.

5.2.3 Gentailers' behaviour in the spot and futures markets

Vertically integrated generators have an incentive to bid lower in the wholesale spot market if they are net short-generation and have a reduced incentive to bid higher if they are net long-generation. Bushnell et al. (2008) study three electricity markets in the US with different market structures[43] during the summer period from 1 June to 30 September 1999, the first high-demand period after all three markets were restructured. The authors utilise the supply function equilibrium concept of Klemperer and Meyer (1989) and calculate three prices for each market: the hourly competitive price, Cournot prices ignoring vertical arrangements, and Cournot prices taking these arrangements into account. They also estimate the cost functions of each producer and the residual demand by market. They find that Cournot prices are a better estimate than competitive prices in all three markets. However, VI (in Pennsylvania/New Jersey/Maryland) and long-term vertical arrangements (in New England) between generators and retailers mitigated market power, and prices would have been higher without them. Hogan and Meade (2007) also agree that the firm's net position is what determines bidding behaviour. Applying a two-stage game model in a static situation, they conclude that a firm with a net requirement to sell (buy) power in the spot market will over- (under-) report its inverse supply function when bidding into the wholesale market. The authors advocate pursuing a balanced VI (i.e. zero net exposure) to keep prices down.

Other research shows that individual net generators can exert power in the spot market. De Bragança and Daglish (2016) develop a market model that allows for VI and derive an equilibrium relationship between spot prices and state variables affecting cost and demand. They then apply the two-factor arbitrage model of Lucia and Schwartz (2002) and derive a forward price. They conclude that individual gentailers who are net long energy can exert market power in the spot market. However, in the case of a fully integrated market, the net price mark-up is zero. They point out that individual net gentailers can leverage their spot

[43] Pennsylvania/New Jersey/Maryland (PJM), where retail was not unbundled from generation, New England, where unbundling occurred and the retailers entered into long-term contractual arrangements with generators, and California, where the unbundled retailers chose to be heavily exposed to the spot market.

market power to acquire power and drive up prices in the hedge market. Their conclusion about hedge market power is in line with Anderson and Hu (2008), who use a two-stage game static model to show that spot market power increases prices in the forward market, which forces retailers to seek partnerships or integrate with generators; they argue that the latter option reduces competition.

Thus, while VI's effect on spot market prices may be positive (depending on the net generation positions), the research indicates the presence of negative outcomes for competition due to the exercise of power and increased prices in hedge markets.

5.2.4 VI and entry of base load generation capacity

VI is seen to facilitate the entry of new generation capacity. Simshauser et al. (2015) model a firm's net profit after tax in three scenarios: integrated gentailer, non-integrated retailer, and non-integrated generator. Their modelling shows that VI enhances a firm's ability to sustain the investment-grade credit rating required by lenders to finance projects, thus facilitating the entry of new generation capacity. Caplan (2012) analyses new generation projects in the US that were constructed in 2011 and a further set of new generation capacity projects that cleared Pennsylvania/New Jersey/Maryland's Base Residual Auction in May 2012 (to procure capacity from June 2015 to May 2016). The author concludes that long-term power purchase agreements and integrated utilities' ownership of generation are the primary drivers of investment in generation. A related argument by Cooper et al. (2005) is that, even if VI increases rivals' costs, the overall effect could be positive because the expansion of output by the dominant firm could outweigh the reduction of output among the non-integrated firms. In NSW, we have seen the retirement, and announcements of the further retirement, of base load capacity along with warnings of a supply shortfall in 2022 following the announced closure of Liddell base load station. Thus, VI has not resulted in an expansion of base load capacity in the NSW electricity market.

5.3 Methodology

We conduct an empirical analysis of how the VI[44] of electricity retail and generation in NSW has impacted the electricity futures market, using data covering Q1 2007 to Q4 2017. Australia has two electricity futures (hedge) markets: standardised futures contracts transacted through the ASX exchange and bilateral contracts, containing bespoke terms, transacted on the OTC[45] market (Anderson et al., 2007).[46] The OTC market data published by AFMA are available annually, which does not provide a sufficient number of observations for reliable statistical estimation. Additionally, AFMA changed its survey methodology beginning with the data for 2015/2016, which created a discontinuity with previously published data.[47] We do not include OTC data in our regression analysis but focus on the higher frequency ASX futures market data. Using daily volume data, we construct the amount of energy transacted over each quarter. The Australian electricity futures market started on 3 September 2002 with thin trading. The volume slowly built up before jumping to, and holding above, 100% of the NEM physical demand in 2007 (see Fig. 5.2).[48] Consequently, we start our analysis in Q1 2007, when the ASX market reached a sufficient level of maturity, as signified by a trading volume above 100% of the underlying NEM physical demand. We analyse quarterly base load swap contracts, the most liquid contract, accounting for over 50% of the energy traded, as well as quarterly peak load swap contracts.

We distinguish between two horizons, for two reasons. First, the proportion of the volume retailers and other participants typically hedge over a period of 12 months[49] is greater than what is hedged beyond 12 months. Second, the over-12 month horizon (i.e. H2) is particularly relevant for the corporate and industrial sector of the market, where contracts are typically

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[44] Although the long-term lease of generation assets transaction of 1 March 2011, is, strictly speaking, an instance of vertical restraint, we include it in the VI period since the gentailer entities had full commercial control over the output of the generation assets. These generation assets are listed in the SOEM reports under 'Origin' and 'TRUenergy', the latter rebranded as 'EnergyAustralia'.

[45] The OTC market can be further subdivided into bilateral trades and trades through brokers.

[46] This is also described in, for example, AER (2008).

[47] In its Australian Financial Markets Report 2016, the AFMA expresses the hope that the change will improve future data reliability.

[48] The State of the Energy Market 2007 annual report (p. 109) provides the reasons behind this increase.

[49] Frontier Economics' experience indicates that retailers tend to have the next 12 months more or less fully hedged (Frontier Economics, May 2007, Analysis of recent changes in NEM wholesale electricity prices. Report. Advice provided to IPART; accessed on 19 February 2019; https://www.ipart.nsw.gov.au/files/sharedassets/website/trimholdingbay/supplementary_energy_costs_advice_from_frontier_economics_-_final_final_version_-_stc_-_webdoc.pdf.

longer than one year,[50] but it also applies to the portion of the residential sector with contracts longer than one year. Additionally, these two horizons are common in the industry and are used by the AFMA to report data on electricity OTC forward contracts.

We illustrate our horizons and relationships to contracts in Fig. 5.1. If a contract transacted at time *t* has a delivery period lying entirely in the period up to 365 days (366 in a leap year) ahead of *t*, such as contract 'j' in Fig. 5.1, the entire energy of that contract is counted in H1. A contract in delivery,[51] such as 'i', has an expired portion, and the remaining portion is counted in H1. If a contract transacted at time *t* relates, in its entirety, to the delivery period beyond H1, such as contract 'v' in Fig. 5.1, the transaction is counted in H2. Contracts whose delivery period straddles both horizons (i.e. falls in part in H1 and the remainder in H2, such as contract 'k' in Fig. 1) are divided such that the portion of energy that relates to a delivery period within 12 months of the transaction is counted in H1 and the remainder is counted in H2. The sum of energy from all such transactions taking place in quarter q,yy make up the energy transacted in quarter q,yy in horizons H1 and H2, as is appropriate. For base load (BL), this is denoted as $BLH1_{q,yy}$ and $BLH2_{q,yy}$ respectively. For example, for Q1 2007 (1 January 2007 to 31 March 2007), these would be designated $BLH1_{1,07}$ and $BLH2_{1,07}$. Peak load (*PK*) contracts are denoted similarly by substituting *PK* for *BL*.

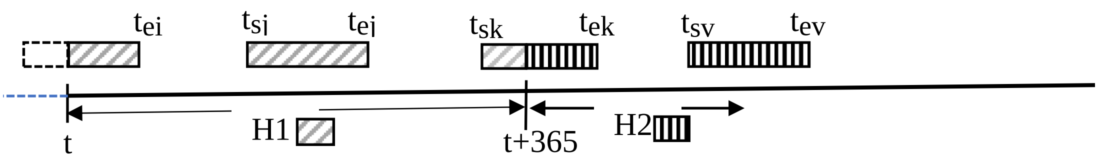

Fig. 5.1. Illustration of horizons H1 and H2. The figure depicts the relationship between the position of electricity futures contracts and horizons H1 and H2. t_{sx} and t_{se} indicate the start and end dates of contract x where x can be 'i', 'j', 'k' or 'v'. There would be multiple contracts 'j' trading in H1 and multiple contracts 'v' trading in H2, but only one contract is represented in the figure for the purpose of illustration.

Base load and peak load quarterly swap contracts are offered relating to a delivery period of up to 16 to 17 quarters ahead of the transaction date.[52] To illustrate, let us take base load contracts

[50] Affidavit by Angus Carl Torquil Macleod, Managing Director – Energy Markets Consulting Firm. In the Australian Competition Tribunal, ACT file No. 1 of 2014, May 16, 2014.
[51] For example, a quarterly contract starting in January 1, 2007, and ending on March 31, 2007, is said to be in delivery at time 't' if time 't' falls between the start and end dates of this contract (January 1 to March 31, 2007, in this example).
[52] https://www.asx.com.au/documents/products/ASX_AU_Electricity_Contract_Reference_Guide_Sept2015.pdf; accessed on 11 November 2018.

trading at time t during Q1 2007. The contracts could relate to any delivery quarter from Q1 2007 up to Q4 2010 (16 quarters). The energy in each contract x traded at time *t* is counted in H1 or H2, as is appropriate.

Equations (1) and (2) express the scheme mathematically, where

- t is the time at which a contract is traded. It ranges from time $t = 1$ to $t = w$ (1 January 2007 to 31 March 2007 for contracts traded in Q1 2007, for example).
- C_x is the number of contracts of position x. A position refers to whether the contract lies entirely or partially within the H1 or H2 horizon. Referring to Fig. 5.1, there could be 'n' such contracts of position 'j', 'a' of 'v', and one quarterly[53] contract of position 'i' or 'k' trading at time *t*. Contract position x can be i, j, k, or v.
- t_{sx} is the start date of the delivery of a contract of position x
- t_{ex} is the end date of the delivery of a contract of position x

Equations (5.1) and (5.2) specify how the energy transacted over H1 and H2 base load, respectively, is calculated:

$$BLH1q,yy = 24\,\{\sum_{t=1}^{t=w}\ [\sum_{i=1}^{i=m} c_i(t_{ei} - t + 1) + \sum_{j=1}^{j=n} c_j\left(t_{ej} - t_{sj} + 1\right) + \sum_{k=1}^{k=u} c_k \frac{(t+365-\ t_{sk}+1)}{(t_{ek}-t_{sk}+1)}\,]\,\}x10^{-6} \qquad (5.1)$$

$$BLH2q,yy = 24\,\{\sum_{t=1}^{t=w}\ [\sum_{k=1}^{k=u} c_k \frac{(t_{ek}-(t+365))}{(t_{ek}-t_{sk}+1)}\ + \sum_{l=1}^{l=a} c_v(t_{ev} - t_{sv} + 1)\,]\,\}\,x10^{-6} \qquad (5.2)$$

Each ASX contract is one MW over each hour of the specified contract period. The number of hours covered by the contract (for base load, 24 hours times the number of days in the contract period) is equivalent to the energy quantity in MWh in that contract. Multiplying by 10^{-6} in equations (5.1) and (5.2) converts the energy to units of TWh.[54]

Peak load energy is denoted as $PKH1_{q,yy}$ and $PKH2_{q,yy}$. The energy embodied in peak contracts is calculated by multiplying by 15 hours (7 AM to 10 PM) each working day in the delivery

[53] If monthly contracts are included, there would also be one such contract. In general, there would be one such contract for each contract duration (e.g. quarterly, monthly).

[54] Megawatt hour (MWh) is a unit of energy representing 1 Megawatt (1 million watts) supplied constantly over one hour. One Terawatt hour (TWh) is 1,000,000 MWh.

period of the contract. There are zero peak hours on weekends and public holidays in NSW declared on ASX.

In addition to differentiating our data between horizons H1 and H2 for each of *BL* and *PK*, we also divide our study period, Q1 2007 to Q4 2017, into three subperiods: pre-VI, VI1, and VI2. Pre-VI corresponds to the period from Q1 2007 to Q4 2010. VI1, the first VI subperiod, commences with the gentailer lease transaction (involving about a third of the generation capacity in NSW) in Q2 2011 and runs to Q3 2014. VI2 covers the remainder of the study period commencing in Q4 2014, corresponding to the sale of Macquarie Generation (representing a further third of the generation capacity in NSW) to AGL and includes the sale of Vales Point generating station in 2015, as well as the sale of other Delta Electricity assets to other parties. Dividing the VI period into two subperiods provides insight into how the degree of VI impacts the futures market. Loertscher and Reisinger (2014) show that VI is more likely to be competitive at lower degrees of integration and harmful at higher degrees of integration. Boroumand and Zachmann (2012) also note that the degree of VI between generators and retailers is likely to negatively affect liquidity in futures markets. There was a higher degree of integration in the VI2 subperiod.

The study's independent variables relate to the presence of VI, the presence of a price effect of the carbon scheme, moments of the spot and futures prices, and the mean system demand. Most related studies deal with the relationship between such variables and returns or the risk premium between spot and futures price. As it is reasonable to postulate a linkage between price or return and volume, we consider the same types of independent variables in our regression analysis to explain the variation in the amount of energy transacted on the ASX electricity futures market:

VI1 – A dummy variable taking the value 1 in the subperiod Q2 2011 to Q3 2014 and 0 otherwise.

VI2 – A dummy variable taking the value 1 in the subperiod Q4 2014 to Q4 2017 and 0 otherwise.

Bessembinder and Lemmon (2002), Wilkens and Wimschulte (2007), Redl et al. (2009), and Redl and Bunn (2013) suggest that also the level, volatility and skewness of spot electricity prices influence hedging decisions and risk premiums. We therefore include the following variables:

MSP4Q – Mean base load price of daily prices in the NSW node of the electricity wholesale (spot) market over the four quarters prior to that in which futures transactions occurred. It is expressed in Australian dollars per MWh.

SDSP4Q – Average sample standard deviation of the daily spot prices in the four quarters prior to that in which the transaction occurred. The average is weighted by the number of days of each of the four quarters concerned.

SKSP4Q – Analogous to *SDSP4Q* but relating to the bias-corrected skew of the daily base load spot price. Included as a proxy for the potential influence of spot price spikes on hedging decisions. include skewness in their models.

MFP4QH1, MFP4QH2, and *MFP4Q* – Simple average (not volume-weighted) daily closing futures contract prices of the contracts transacted in the four quarters prior to that in which the transaction occurred. The variables refer to H1, H2, and ignoring horizon, respectively. They are calculated for base load and peak load contracts separately. Including these variables allows us to test the impact (if any) of the prior four quarters mean futures' price on the volume of contracts transacted.

SDFP1QH1, SDFP1QH2, and *SDFP1Q* – Average of sample standard deviations of the daily close futures contract prices of the four quarters prior to that in which the transaction occurred. The variables refer to H1, H2, and ignoring horizon, respectively. They are calculated for base load and peak load contracts separately. Including these variables allows us to test the impact (if any) of the volatility of the prior four quarters futures' price on the volume of contracts transacted.
DSP4Q – Average demand in units of MW in the NSW reference node of the wholesale spot market (NEM) as published by the Australian Energy Market Operator (AEMO). Redl and Bunn (2013) and Cartea and Villaplana (2008) include demand in their model.

Carb – Dummy variable reflecting the effect of climate change policy and schemes on electricity prices. Carb takes the value of 1 in the period when price is influenced by climate policies. The *Clean Energy Bill* created a carbon pricing mechanism for two years, from Q2 2012 until the end of Q2 2014.[55] In its 2014 Australian Financial Markets Reports, the AFMA refers to uncertainty about the repeal of climate policies and, in its 2015 report, mentions the repeal of the carbon pricing mechanism as factors impacting the liquidity of electricity contracts.

We ran OLS multiple regression models for the base load and peak load and selected the best subset (i.e. with the highest adjusted R^2). When choosing between subsets with the same number of independent variables, we also considered the Akaike Information Criterion (AIC), which, in our case, confirmed the choice based on the adjusted R^2. We also conducted residual diagnostics to avoid multicollinearity and ensure that the model residuals did not violate OLS assumptions.

5.4 Data

The number of quarterly base load and peak load contracts traded each day is converted into base load and peak load energy and aggregated over each quarter and horizon (H1 and H2). The highest traded volume was that of quarterly swap base load contracts, which exceeded 50% of the total energy traded. Data on volume and closing prices up to December 2014 were sourced from ASX Energy and, for the remaining period, from Thompson Reuters Eikon.[56] Spot price and half-hourly demand data published by AEMO were aggregated into daily data.[57]

[55]The Clean Energy Bill was repealed in July 2014 with effect from 1 July 2014. Q2 2014 was the last quarter to which it applied (http://www.environment.gov.au/climate-change/government/repealing-carbon-tax; Department of the Environment and Energy, Australian Government website; accessed 19 February 2019).
[56] Thompson Reuters Eikon (TRE) has rebranded to 'Refinitiv' in October 2018
[57] Refer to https://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data.

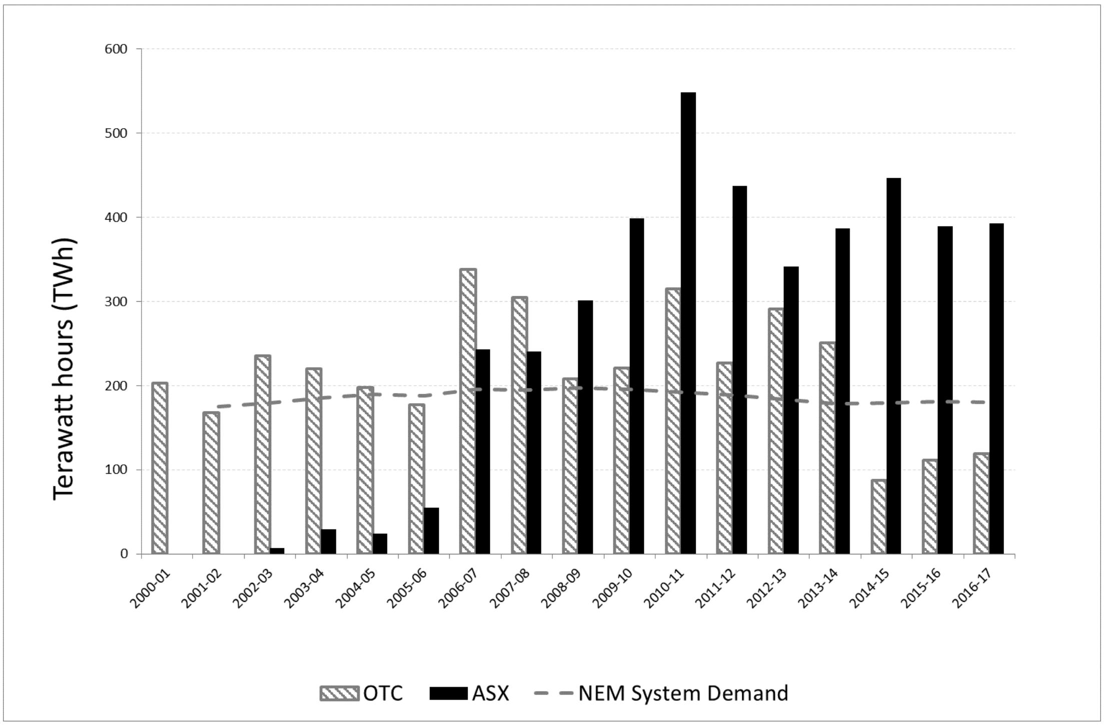

Fig. 5.2. OTC and ASX annual traded energy – NEM wide. The figure shows the amount of energy traded NEM wide on ASX and OTC markets by financial year. Compiled from AFMA, ASX and TRE data. Electricity futures started trading on 3 September 2002 (i.e. 2002/2003 financial year). The AFMA publishes data on a financial-year basis (1 July to 30 June of the following calendar year).

Fig. 5.2 shows the energy traded in each financial year (July 1 – June 30 of the following calendar year) in OTC and ASX contracts across the NEM. The OTC volume fell sharply in 2014/2015, to less than 50% of NEM demand, before increasing slightly to around the 60%–65% level. The AFMA attributes this fall to the repeal of the carbon pricing mechanism on 1 July 2014 (in the 2014/2015 financial year) and to further VI activity.[58] Fig. 5.2 also shows that, unlike OTC volumes, total ASX volumes did not fall.

Fig. 5.3 shows energy traded for base load quarterly swap contracts transacted over horizons H1 and H2 and aggregated over the two for the NSW market. Base load swaps typically represent over 50% of the total energy traded on the ASX. The amount of energy transacted on the ASX in NSW, as with the total NEM, did not fall after the repeal of the carbon legislation in Q3 2014. Note that there does not appear to be a substantial decline in total traded (i.e. combined, ignoring horizon) base load energy following VI.

[58] AFMA's Australian Financial Markets Report 2015

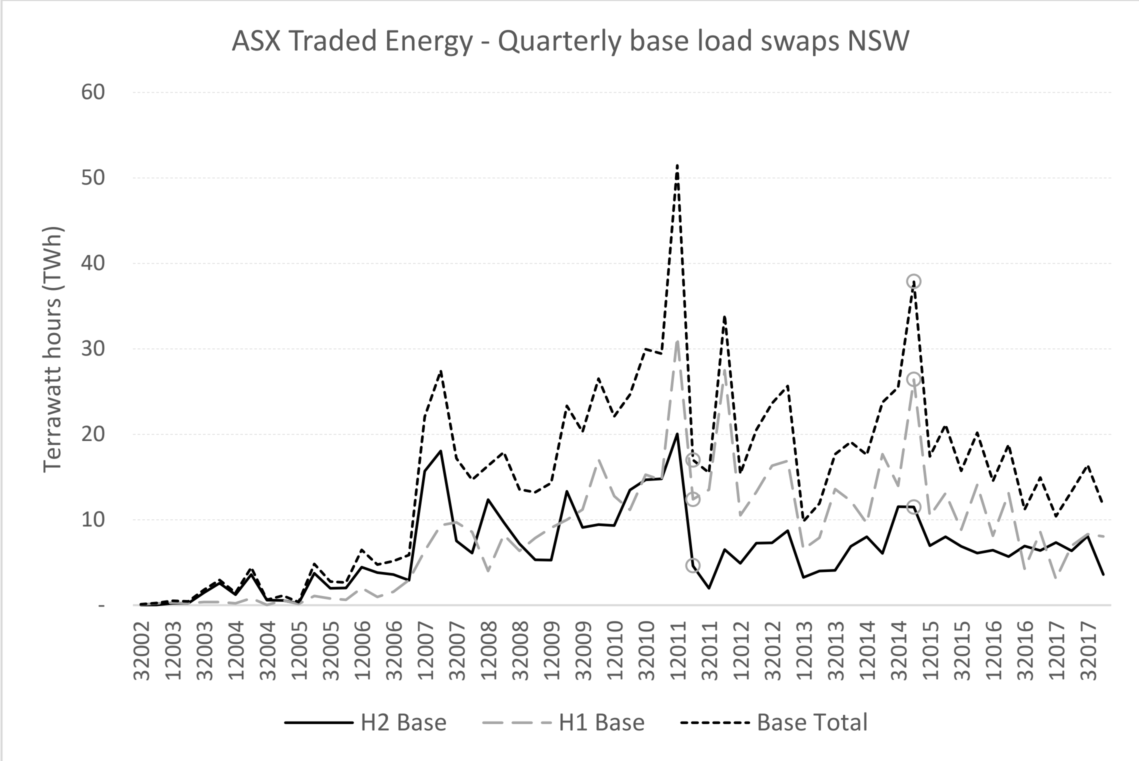

Fig. 5.3. ASX traded energy – Quarterly base load swaps NSW. The figure shows the amount of base load energy of the specified contract traded each quarter on ASX. Three amounts are shown relating to horizon H1 (H1 Base), H2 (H2 Base) and in aggregate (Base Total). Adapted from ASX and TRE data. Circles indicate the beginning of the VI1 and VI2 subperiods. VI1 refers to the first VI subperiod, from Q2 2011 to Q3 2014. VI2 refers to the second VI subperiod, from Q4 2014 to Q4 2017.

However, as Fig. 5.3 shows, the picture is different when we take hedging horizons into account. There is a visually obvious lower level of transaction after Q1 2011 (i.e. after VI) over horizon H2, shown as a solid line, but not over H1. The only notable exception is the spike in Q1 2011 (more pronounced for H1), which occurred due to position adjustments related to the gentailer transaction. Following the gentailer transaction (i.e. VI), one-off hedge book transfers occurred through trades on the ASX futures market to adjust positions, which contributed to an increase in the volume traded in Q1 2011.[59] The volume increase was due to adjustments, and not to the impact of VI on the market. We lack the information necessary to make a reliable volume adjustment for the effect of these one-off transactions. Since the Q1 2011 observation was influential, we excluded this observation (quarter) from the regression analysis.

[59] Affidavit by Dean Charles Price, Senior Manager, Energy at ASX Operations. In the Australian Competition Tribunal, ACT file No. 1 of 2014, 13 May 2014. Refer also to the affidavit by Angus Carl Torquil Macleod, Managing Director – Energy Markets Consulting Firm. In the Australian Competition Tribunal, ACT file No. 1 of 2014, 16 May 2014. In addition, the Electricity Tariff Equalisation Fund (ETEF) scheme was falling at 20% per quarter from Q3 2010 and coming to an end of Q2 2011. ETEF provided a hedge between government-owned generators and retailers against fluctuations in the wholesale price relating to non-contestable retail customers (those consuming less than 160 MWh per year).

The continuation of VI activity represented by the sale of Macquarie Generation to AGL in September 2014 and Delta's Colongra sale to Snowy Hydro in December 2014, could explain the larger base load volume relating to (H2 Base) traded in Q3 and Q4 2014 and in H1 Base in Q4 2014. However, we took a conservative approach and retained these observations, as removing them would have contributed to a stronger (larger) VI2 effect. Similar to what is shown in Fig. 5.3, the amount of energy transacted over H1 and H2 on the ASX in NSW did not experience a sudden fall after the repeal of the carbon legislation in Q3 2014. However, H1 base volumes seem to be clearly lower from Q3 2016 onward.

Fig. 5.4 shows an increase in H1 peak load energy volumes that started just shortly before VI. Peak load energy volumes are much smaller than the base load volumes, as would be expected. Similar to what is seen in Fig. 5.3, we notice high volumes in Q3 2014 and Q4 2015, coinciding with the sale of the Macquarie Generation and Delta assets, but they were not the only high points. Analogously to the base load case, we adopt a conservative approach and retain these observations. Again, we find that H1 peak load volumes are lower as of Q1 2016.

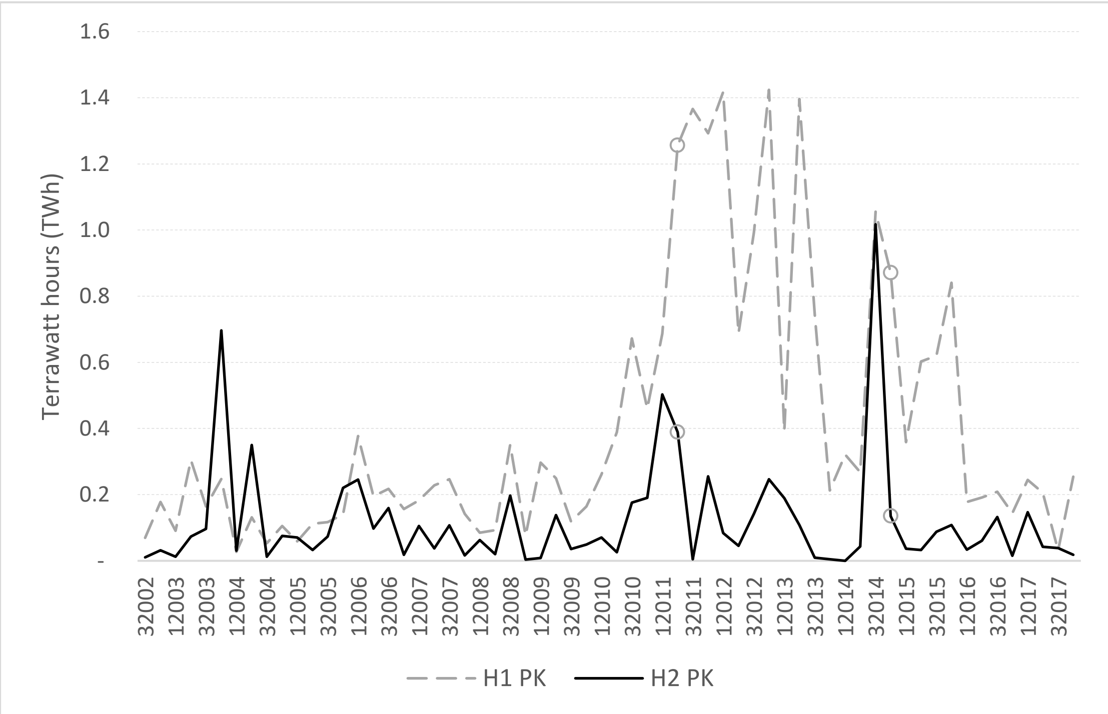

Fig. 5.4. ASX traded energy – Quarterly peak load swaps NSW. The figure shows the amount of peak load energy of the specified contract traded each quarter on ASX. The amount relating to horizon H1 is indicated as (H1 PK) and to H2 as (H2 PK). Adapted from ASX and TRE data. Circles indicate the beginning of the VI1 and VI2 subperiods. VI1 refers to the first VI subperiod, from Q2 2011 to Q3 2014. VI2 refers to the second VI subperiod, from Q4 2014 to Q4 2017.

Tables 5.1 and 5.2 provide descriptive statistics of the amount of base load and peak load energy, transacted on the ASX based on the periods noted in the footnote of Table 5.1 and 5.2. Table 5.1 shows that the mean of the total base load (shown in the first panel) has not fallen significantly (17%), the change in mean differs across the two horizons, H1 and H2. The mean increased (at least initially in VI1) over the H1 horizon but decreased over the H2 horizon. In H1, the mean increased by 36% in VI1 before returning in VI2 to just around 2% above the pre-VI level. In H2, the mean volume dropped by 43% in VI1 and remained 35% lower than its pre-VI levels, in VI2. The standard deviation and skewness both increased, the latter from a modest value of 0.19 to 2.28. In the pre-VI subperiod, the mean volume of H2 was slightly higher than that of H1 whereas, in VI2, the H2 mean fell to about two-thirds that of the H1 mean.

Table 5.1

Descriptive statistics for energy (TWh) traded on ASX for the NSW market–Base load quarterly swap contracts, Q1 2007 to Q4 2017.

	Mean	*Median*	*Standard deviation*	*Skewness*	*Min*	*Max*	*Count*
Base load Total							
Pre VI	20.81	21.17	5.72	0.19	13.20	29.95	16
VI1	19.78	18.40	6.30	0.60	9.82	33.97	14
VI2	17.20	15.72	7.06	2.28	10.39	37.89	13
Base load H1							
Pre VI	10.11	9.57	3.49	0.42	4.00	17.08	16
VI1	13.71	13.39	5.11	1.39	6.55	27.52	14
VI2	10.26	8.55	5.84	1.81	3.06	26.40	13
Base load H2							
Pre VI	10.70	9.56	3.98	0.23	5.26	18.02	16
VI1	6.07	6.26	2.50	0.45	1.96	11.53	14
VI2	6.93	6.88	1.77	1.00	3.59	11.49	13

The mean peak load volumes of H1 and H2 (see Table 5.2) increased by 265% and 133% in VI1 over the pre-VI mean, and were 43% above and 12% below, respectively, in VI2. The H1 mean volume went from being three times that of H2 in the pre-VI subperiod to being more than five times that figure following VI. One would thus expect the much larger H1 peak volumes to have a strong influence on total (i.e. ignoring or combining horizons) peak volumes. Peak load mean volumes are much smaller than the mean base load volumes.

Table 5.2

Descriptive statistics for energy (TWh) traded on ASX for the NSW market–Peak load quarterly swap contracts, Q1 2007 to Q4 2017.

	Mean	*Median*	*Standard deviation*	*Skewness*	*Min*	*Max*	*Count*
Peak load Total							
Pre VI	0.33	0.30	0.21	1.18	0.079	0.849	16
VI1	1.10	1.25	0.60	-0.14	0.217	2.073	14
VI2	0.43	0.34	0.30	0.94	0.070	1.006	13
Peak load H1							
Pre VI	0.25	0.24	0.16	1.32	0.08	0.67	16
VI1	0.92	1.02	0.47	-0.38	0.21	1.42	14
VI2	0.37	0.24	0.27	0.93	0.03	0.87	13
Peak load H2							
Pre VI	0.08	0.06	0.07	0.74	0.00	0.20	16
VI1	0.18	0.10	0.27	2.66	0	1.017	14
VI2	0.07	0.04	0.05	0.63	0.015	0.147	13

Notes Table 5.1&5.2:
Note1: H1 refers to the period ≤ 12 months from the date of the transaction covered by the futures contracts and H2 to the period > 12 months. These horizons are used by AFMA to report OTC contract data.
Note 2: Pre-VI refers to the subperiod prior to VI, from Q1 2007 to Q4 2010. VI1 refers to the first VI subperiod, from Q2 2011 to Q3 2014. VI2 refers to the second VI subperiod, from Q4 2014 to Q4 2017.

The Jarque–Bera test indicated that some series were not normally distributed. Non normality can affect means comparison tests if analysis of variance (ANOVA) is applied. To be conservative, we conducted the Kruskal–Wallis test, a non-parametric alternative to ANOVA, and applied the Dunn–Sidak correction to the multiple comparison tests in order to control the familywise error rate. The tests showed a significant difference at the 1% level between the mean volumes of base load energy transacted over the H2 horizon. Pairwise comparisons showed that the pre-VI volume was significantly higher than that of VI1 (at the 1% level) and VI2 (at the 5% level). In other words, the mean volume of base load energy dropped in VI1 and VI2 relative to the pre-VI subperiod. No significant difference between VI1 and VI2 was observed.

For peak load transacted over the H1 horizon, significant differences were observed between the subperiod means at the 1% level. Pairwise comparisons showed that the mean volume in the VI1 subperiod was significantly higher (at the 1% level) than both means in the pre-VI and VI2 subperiods. However, the means of the pre-VI and VI2 subperiods were not significantly different. The mean comparison results for total peak load are the same as for H1, because the H1 peak load volume is much larger than the H2 volume.

These results provide an initial indication that the differences in means depend on the horizon and motivate further analysis of the differences that occurred in Base H2 and Peak H1. We explore and explain the differences between the horizons and between the base load and peak load in more detail in the following section.

The dataset covers 11 years, including the global financial crisis and periods of low and high electricity price levels and volatility. The dataset has some limitations, however. The ASX data do not classify trade volumes by type of business entity (e.g. retailer, speculator, generator, gentailer), so we cannot draw conclusions concerning the distribution of changes in activity according to business type following VI. The dataset does not include caps and options volume, which are less liquid than quarterly base load swaps. While 1 March 2011 was a defining point for VI, gentailer operations were limited in NSW prior to that date, and the sale of state-owned generation assets continued after that date until the end of 2015, as discussed above. The last point could indicate that our estimates of the impact of VI are somewhat understated.

5.5 Results and Discussion

Our regression models indicate that changes in futures contract volumes transacted following VI depends on the horizon and differ between base and peak loads. We present below a general form of the model for base load and peak load volumes transacted covering a specified horizon:

$$tLHh_{q,yy} = \beta_0 + \beta_1 \, VI1_{q,yy} + \beta_2 \, VI2_{q,yy} + \sum_{b=3}^{B} \beta_b V_{q,yy} \quad (5.3)$$

where

$tLHh_{q,yy}$ depends on the type of load and horizon being analysed

- tL can be either BL or PL for Base Load or Peak Load, respectively

- *Hh* can be either horizon H1 or H2
- *q,yy* in the subscripts refers to the calendar quarter (1 to 4) and year (07 to 17, for 2007 to 2017)
- For example, $BLH2_{1,07}$ is the volume of energy transacted covering the H2 horizon

VI1 and *VI2* are dummy variables indicating the first and second VI subperiod.
Vq,yy in the summation operator indicates one of the moments of the spot and futures markets, defined individually in the methodology section.

Table 5.3 presents the regression results for nine base load models, three triplets for each of the Base Total (i.e. ignoring horizon), Base H1, and Base H2 horizons. For each triplet, the regression results of a simple model (involving only the VI variables) are followed by those of the full model and the selected model. The selected model is in each case the subset of the full model with the highest adjusted r^2. Starting with Base H2 (see the last 3 columns of Table 5.3), the F-tests' low p-values (Sig-F row) indicate the significance of the overall regression for all three models. The selected model has the highest adjusted r^2 (0.331), indicating the benefit of adding *MFP4Q* to the VI model (adjusted r^2 0.306) and removing the *SDFP1Q* and *SKSP4Q* variables from the full model (adjusted r^2 0.296). Both VI1 and VI2 are negative and significant at the 1% level (except VI2 in the full model, significant at the 5% level, with a p-value of 0.02), indicating that VI is useful in explaining the reduced volume following VI in both subperiods over H2. *MFP4Q*, in both the full and selected models, is negative but not significant. The negative coefficient indicates an inverse relationship between volume transacted and *MFP4Q*, the mean future price, which is consistent with a standard demand function. It may also indicate that participants time their purchases: In other words, less energy is purchased in the futures market when the mean future price is trending high and more is purchased when it is trending low. Finally, the coefficient estimates in the triplet of the Base H2 models are very close, indicating the robustness of the estimates.

Table 5.3

Multiple regression output. Base load models.

	Base Total			Base H1			Base H2		
	VI	Full	Selected	VI	Full	Selected	VI	Full	Selected
Constant	20.81*** (13.14)	31.96*** (4.63)	32.91*** (5.78)	10.11*** (8.38)	17.44*** (3.33)	18.08*** (4.11)	10.7*** (14.33)	14.52*** (4.27)	14.99*** (5.34)
VI1	-1.02 (-0.44)	1.41 (0.5)	-	3.6** (2.04)	5.66** (2.64)	5.41*** (2.95)	-4.62*** (-4.23)	-4.25*** (-3.05)	-4.36*** (-4.01)
VI2	-3.61 (-1.53)	-0.53 (-0.18)	-	0.15 (0.08)	3.15 (1.39)	3.05 (1.39)	-3.76*** (-3.37)	-3.68** (-2.51)	-3.62*** (-3.30)
MFP4Q	-	-0.34** (-2.36)	-0.35*** (-2.82)	-	-0.26** (-2.39)	-0.26** (-2.5)	-	-0.08 (-1.12)	-0.09 (-1.58)
SDFP1Q	-	0.34 (1.07)	0.43* (2.01)	-	0.38 (1.57)	0.41* (1.95)	-	-0.04 (-0.24)	-
SKSP4Q	-	0.43 (0.29)	-	-	0.26 (0.23)	-	-	0.17 (0.24)	-
Sig-F	0.31	0.15	0.020	0.092	0.055	0.028	$2.5\text{x}10^{-4}$	$2.5\text{x}10^{-3}$	$3.0\text{x}10^{-4}$
r2	0.057	0.191	0.178	0.112	0.246	0.244	0.339	0.380	0.379
Adj r2	0.0097	0.081	0.137	0.068	0.144	0.165	0.306	0.296	0.331
AIC	283.65	283.07	277.74	260.29	259.30	257.37	218.96	222.20	218.28

t-statistic (shown in parentheses). ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

The models for base load H1 (see columns 4 to 6 of Table 5.3) have lower r^2 than those for H2 (0.246 vs. 0.380). The F-tests' p-values indicate model significance at the 10% level for the VI and full models and at 5% for the selected model, a weaker result than that for H2. In this model triplet, the sign of *VI1* and *VI2* is positive, as opposite to that in H2. However, only *VI1* is significant; *VI2* is not. The positive sign of these coefficients indicates that energy volumes increased following VI, albeit not significantly different from zero in the VI2 subperiod. This increase indicates that participants tend to adjust short-term positions within the one-year horizon. *MFP4Q* is significant and, as in H2, has a negative coefficient. The coefficient of *SDFP1Q* is positive, which indicates that more energy is purchased when there is more volatility in the futures market price of the previous quarter.

When horizon is ignored (Base Total), the F-test p-values (0.31 and 0.15) indicate that the VI and full regression models are not significant, even at the 10% level, while the selected model is significant overall at the 5% level. This set of models has low r^2 values. Notably, neither *VI1* nor *VI2* is significant, and both drop out of the selected model, which has two variables relating to the level and volatility of the futures market price (see the first three columns of Table 5.3). *MFP4Q* has a negative coefficient, while that of *SDFP1Q* is positive; both are consistent with the signs in the base load H1 model and can be interpreted similarly. We offer this negative finding to underscore the importance of the horizon and to show that our model arrives at results consistent with other findings produced when the horizon is overlooked (e.g. Simshauser, 2015).[60]

The regression results for peak load models are provided in Table 5.4 following the same scheme used for base load models shown in Table 5.3. The results underscore that the horizon covered by futures swaps is an important determinant of the change from pre-VI levels in the amount of energy transacted on the ASX. The H1 peak load models (see columns 4 to 6 of Table 5.4) are all highly significant, as shown by the low p-value of the F statistic, and have a higher r^2 than the base load models. For the peak load, the amount of energy transacted in swap contracts in H1 increased following VI.[61] This is shown by the positive coefficient estimates of *VI1* and *VI2*, both of which are significant at the 1% level. Similar to the base load case, the coefficient of *MFP4QH1* is negative, indicating an inverse relationship between volume and *MFP4QH1*, the mean future price in H1. The adjusted r^2 of the VI model is lower than that for the other two models, indicating that introducing the additional variables was beneficial. The adjusted r^2 of the selected model is marginally higher than that of the full model, but the former has a Q–Q plot that more closely follows a normal distribution. The H2 models (see last three columns of Table 5.3) are not significant, as seen from the high p-values of the F-statistic. It is no surprise, therefore, that their r^2 values are low. As the H1 peak volumes are much larger than the H2 peak volumes, the combined-horizons peak models (columns 1 to 3 of Table 5.4) are heavily influenced by the H1 subperiod. Moreover, *SDSP4Q* is included in the Peak Total selected model and has a positive estimated coefficient, which indicates that the volume of peak energy volume transacted on the ASX increases as the volatility of the spot market price increases.

[60] Simshauser et al. (2015) used data covering 10 years to 2013/2014 in their analysis of net profit after tax. However, the data presented on vertical foreclosure (see Fig. C.1 in their appendix) cover 1999/2000 to 2012/2013.

[61] The increase in peak load energy lends support to the statement made in the Australian Competition and Consumer Commission (ACCC) report, , that Origin and EnergyAustralia are likely to be net purchasers of peak load energy after the acquisition of Macquarie Generation by AGL. ACCC's Report in the Australian Competition Tribunal, ACT file No. 1 of 2014, 13 May 2014. Paragraph 7.84.

Table 5.4

Multiple regression output. Peak load models.

	Peak Total			Peak H1			Peak H2		
	VI	**Full**	**Selected**	**VI**	**Full**	**Selected**	**VI**	**Full**	**Selected**
Constant	0.33*** (3.28)	0.73** (2.69)	0.76*** (2.83)	0.25*** (3.12)	0.58*** (2.79)	0.61*** (2.95)	0.08* (1.94)	0.15 (1.2)	0.078* (1.94)
VI1	0.77*** (5.24)	0.97*** (5.86)	0.96*** (5.86)	0.67*** (5.65)	0.86*** (6.69)	0.84*** (6.62)	0.1* (1.76)	0.12 (1.54)	0.1* (1.76)
VI2	0.11 (0.7)	0.29* (1.82)	0.3* (1.89)	0.11 (0.95)	0.28** (2.3)	0.29** (2.37)	-0.01 (-0.16)	0.0083 (0.12)	-0.01 (-0.16)
MFP4Q H1	-	-0.014** (-2.63)	-0.015*** (-3.11)	-	-0.012*** (-2.92)	-0.013*** (-3.51)	-	-0.002 (-0.85)	-
SDFP1Q H1	-	-0.011 (-0.68)	-	-	-0.012 (-0.98)	-	-	0.0013 (0.17)	-
SDSP4Q	-	0.0067* (1.96)	0.0056* (1.88)	-	0.0064** (2.43)	-	-	0.0003 (0.2)	-
Sig-F	$1.0\text{x}10^{-5}$	$4.7\text{x}10^{-6}$	$1.5\text{x}10^{-6}$	$3.2\text{x}10^{-6}$	$4.1\text{x}10^{-7}$	$1.5\text{x}10^{-7}$	0.13	0.45	0.13
r2	0.4374	0.5714	0.5661	0.469	0.6269	0.6172	0.0968	0.1152	0.0968
Adj r2	0.4092	0.5135	0.5205	0.442	0.5765	0.5769	0.0517	0.0044	0.0517
AIC	46.30	40.60	39.13	27.39	18.20	17.31	-32.70	27.58	32.70

t-statistics shown in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

To summarise, following VI, the base load volume is lower for horizons beyond one year (H2) and higher for horizons within one year (H1), although the coefficient of *VI2* is not significant; we observe no significant change in volume when the horizon is ignored (i.e. combined). The statistical significance of the negative estimated regression coefficients *VI1* and *VI2* in the H2 base load models indicates that VI is useful in explaining the reduction in volume. By contrast, the VI variables do not explain any of the change when the horizon is ignored. For the peak load, volumes increase over H1 but not over H2. The estimated coefficients *VI1* and *VI2* are useful in explaining the change. The changes following VI likely indicate that, while the reduction in volume over H2 is consistent with foreclosure in that horizon, participants still need to adjust their market positions in the short term (note that none of the gentailers is perfectly balanced).[62] The results described above may also suggest that the structure of the ASX futures market has shifted toward the short term following VI.

We ran robustness checks on our models. As mentioned, we did not include highly correlated variables (with correlation coefficient magnitude above 0.7) in the same model to avoid introducing multicollinearity into our models. *VI1* is highly positively correlated with Carb (+0.90), and *VI2* is highly negatively correlated with *DSP4Q* (-0.71). Thus, we did not include Carb (the carbon dummy variable) or *DSP4Q* (the demand variable) in the same models as VI1 and VI2. Carbon is reported to influence futures prices (Maryniak et al., 2019). As it is reasonable to postulate that price and volume are linked, we ran models with carbon and demand variables (*Carb* and *DSP4Q*) and excluded the (highly correlated) *VI1* and *VI2* explanatory variables. Table 5.5 presents the results for the base load H2 and peak load H1 models, which performed the best. The table shows three sets of models for base load H2 and peak load H1: one for *Carb* and *DSP4Q*, one for the full model, and one for the selected model. The models performed worse than their counterpart models containing the VI variables. The R^2 and adjusted r^2 were lower, by about a quarter for the base load and by more than a third for the peak load, and the AIC was higher; all these measures indicate worse performance. For base load H2, the demand variable was significant at the 5% level (but not in the full model) and had a similar magnitude and a positive sign in all models. The positive sign indicates that the volume hedged is directly proportional to demand. The *Carb* coefficient was negative and had a similar magnitude in all three models, suggesting that less volume was transacted during the period when the carbon scheme was in place. While this is surprising, it could indicate that market participants had already hedged their exposure prior to the period when the carbon passthrough took effect. Another explanation could be that market participants reduced the energy purchased on the futures market when prices increased due to the carbon passthrough. For peak H1, the demand variable was not significant in any of the models. The estimated coefficient of the carbon variable was significant at the 1% level and had a positive sign and a similar magnitude in all models. The base load and peak load models both had negative estimated coefficients for the mean future price variable (*MFP4Q* and *MFP4QH1*). This check indicates that the VI variables explain variability in the transacted futures volumes better than carbon or demand do.

[62] Delta Electricity continues to operate as a non-integrated generator. Macquarie Generation was acquired by AGL in September 2014, but remained net long in energy in NSW. Origin and EnergyAustralia (previously TRUenergy) remained net short in physical energy in NSW.

Table 5.5

Multiple regression output–Robustness check: Base load H2 and Peak load H1 models.

Base H2				**Peak H1**			
	Carb & Demand	**Full**	**Selected**		**Carb & Demand**	**Full**	**Selected**
Constant	-12.04 (-1.26)	-3.91 (-0.24)	-7.17 (-0.72)	Constant	0.16 (0.14)	2.31 (1.55)	2.34 (1.63)
Carb	-2.87** (-2.64)	-2.47* (-1.9)	-2.58** (-2.37)	Carb	0.52*** (4.11)	0.59*** (4.4)	0.59*** (4.48)
DSP4Q	2.47** (2.2)	2.02 (1.07)	2.42** (2.18)	DSP4Q	0.024 (0.18)	-0.17 (-0.97)	-0.17 (-1.02)
MFP4Q		-0.099 (-1.26)	-0.089 (-1.52)	MFP4QH1		-0.014** (-2.64)	-0.014*** (-2.94)
SDFP1Q		0.0265 (0.14)		SDFP1QH1		-0.0016 (-0.1)	
SKSP4Q		0.1527 (0.19)		SDSP4Q		0.0041 (1.15)	0.004 (1.2)
Sig-F	2.82×10^{-3}	1.86×10^{-2}	3.12×10^{-3}	Sig-F	8.12×10^{-4}	6.25×10^{-4}	2.11×10^{-4}
r2	0.2544	0.2974	0.2959	r2	0.2994	0.4301	0.4299
Adj r2	0.2171	0.2024	0.2417	Adj r2	0.2643	0.3531	0.3699
AIC	224.14	227.59	223.68	AIC	39.30	36.42	34.43

t-statistics shown in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

5.6 Conclusion

We present empirical evidence that base load energy traded on the ASX electricity futures market in NSW following VI is lower over the longer horizon (more than 12 months) and is unchanged over the shorter horizon (under 12 months). For peak load energy, volumes within the shorter horizon increased but remained unchanged over the longer horizon. This could indicate that the market became more short-term over the course of our sample period following VI.

The finding of lower energy transacted over the H2 horizon supports a conclusion of foreclosure[63] over the longer horizon. This horizon is particularly relevant for the commercial and industrial market segment but is also relevant for consumer segments with contracts longer than one year. The foreclosure in the futures market is particularly important given the material reduction in OTC contracts shown in Fig. 5.3. Non-integrated retailers are disadvantaged compared to gentailers when hedge markets are weaker (Aïd et al., 2011). Therefore, the reduction in H2 volume may reduce competition and disadvantage consumers.

This insight is made possible through our novel method of analysing the amount of energy transacted over two commercially meaningful horizons, which are also used by the AFMA to report industry statistics. We also confirm that ignoring horizons leads to the unwarranted conclusion that the energy transacted on the ASX did not change following VI. The overnight change to a gentailer-dominant model in NSW made it easier to discern the impact of VI.

These findings are supported by the literature. The NSW electricity market pre-VI did not contain pure monopolies in successive stages of the supply chain; hence, the benefits flowing from the elimination of DM are less likely to be welfare-enhancing (Joskow, 2010). The futures market encourages retail competition and reduces the disadvantages faced by non-integrated retailers (Aïd et al., 2011). Our finding of a statistically significant reduction in volume transacted in the futures market following VI indicates that foreclosure in this market can harm consumers. Our findings are particularly important given that benefits in the spot market are ambiguous and, up to the time of writing, no new base load generation capacity has been added to the market, which is what VI is supposed to facilitate.

Future studies could reassess the impact of VI on H1 peak load and H1 base load, given the lower energy volumes of both the base and peak loads as of 2016. The number of observations currently available is too small to determine whether this indicates a drop in transacted energy, but the issue could be revisited when more data are made available. Future research could also investigate the impact on consumer electricity prices, ideally separating them into their major components: retail, energy, and network costs. Another possibility, if the required data are available, would be to investigate whether the impact of VI varies by business type (i.e. non-integrated versus integrated retail and generation). It is also important to conduct interview-based research on the market that incorporates representative stakeholder views. A final suggestion is to include OTC data, if they are available on a quarterly (or more frequent) basis.

The finding of a material reduction in energy traded following VI between the generation and retail stages and its potential impact on consumer interests suggests possible policy responses that could enhance consumer welfare.

One possible response is to implement policies aimed at increasing the volume of energy transacted in the futures market. This could be achieved through voluntary participation, including through tendering to provide market making services, potentially supplemented by a mandatory obligation in the event a target liquidity level is not achieved.

Transparency is an important feature of markets that enhances market efficiency by facilitating the dissemination of prices and other information to all market participants. The paper alludes to lack of transparency in the OTC market. Improving transparency of the OTC market is therefore another, additional, possible policy response.

The above policies are candidates for future research topics. Similar arrangements have been implemented in other jurisdictions, New Zealand for example.

In Australia, initiatives related to the above recommendations are in motion. The ASX announced on 28 June 2019 a voluntary market making scheme for calendar quarter base load in Australian electricity futures starting on 1 July 2019.[64] It is too early to conclude what impact this modest step will have on liquidity. A related initiative by the AER is the announcement of the Market Liquidity Obligation (MLO) mechanism. The MLO requires generators with market share exceeding a certain threshold to provide market making through the ASX, final guidelines to be published in 2020. The MLO is an acknowledgement of liquidity concerns in the contracts' markets, including in the futures market. However, the obligation is part of the Retailer Reliability Obligation (RRO) legislation and is only triggered if a material future gap in power system reliability is forecast.[65]

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[64] ASX website https://asxonline.com/content/asxonline/public/notices/2019/june/0653.19.06.html accessed on 15 September 2019. The market making arrangements are outlined in a brief document https://www.asx.com.au/communications/notices/2019/ASX-AU-Electricity-Market-Making-Summary-2019.pdf accessed on 15 September 2019.

[65] The RRO aims to support power system reliability by encouraging retailers to contract firm, or dispatchable, resources. The RRO is in response to the growing concern about power system security as the share of intermittent resources grows and base load generation assets retire. AEMO can apply to the AER to trigger the RRO if the former forecasts a material gap in reliability (three years and three months out or one year out). The MLO responds to concerns by retailers of insufficient liquidity in contracts markets. MLO instruments include calendar quarter

The New Zealand Government imposed market making obligations on the five largest generators as of 1 June 2011 with a target of 3,000 GWh. The Electricity Authority of New Zealand encouraged generators to enter into agreements with the ASX. Four generators did so in 2011.

To improve transparency the Australian Competition and Consumer Commission (ACCC) recommended the creation of an OTC public repository administered by the AER that discloses deidentified trade information with the aim of disseminating market information. The ACCC recommends that the AER, AEMC and AEMO have access to the underlying contract information including the identity of the trading partners.[66]

contracts for base load, peak load and caps. Refer to the AER website for more details https://www.aer.gov.au/retail-markets/retailer-reliability-obligation.

[66] For more details on these and other ACCC's recommendations refer to the report published on the ACCC's website https://www.accc.gov.au/publications/restoring-electricity-affordability-australias-competitive-advantage accessed on 15 September 2019.

Appendix C

Table C.1

Pairwise comparison of means of energy each quarter transacted among the three subperiods.

	Subperiods compared		**Kruskal-Wallis Dunn-Sidak**	**ANOVA Difference in means**
Base Total			$\chi^2(2) = 3.98$	F (2,40) = 1.21
	Pre-VI (n=16) Pre-VI (n=16) VI1 (n=14)	VI1 (n=14) VI2 (n=13) VI2 (n=13)	1.81 9.00 7.19	1.02 3.61 2.59
Base H1			$\chi^2(2) = 5.92$*	F (2,40) = 2.53*
	Pre-VI (n=16) Pre-VI (n=16) VI1 (n=14)	VI1 (n=14) VI2 (n=13) VI2 (n=13)	-9.14 1.58 10.72*	-3.60* -0.15 3.45
Base H2			$\chi^2(2) = 12.20$***	F (2,40) = 10.26***
	Pre-VI (n=16) Pre-VI (n=16) VI1 (n=14)	VI1 (n=14) VI2 (n=13) VI2 (n=13)	15.21*** 11.73** -3.48	4.62*** 3.76*** -0.86
Peak Total			$\chi^2(2) = 14.29$***	F (2,40) = 15.55***
	Pre-VI (n=16) Pre-VI (n=16) VI1 (n=14)	VI1 (n=14) VI2 (n=13) VI2 (n=13)	-16.71*** -3.50 13.21**	-0.77*** -0.11 0.66***
Peak H1			$\chi^2(2) = 17.36$***	F (2,40) = 17.66***
	Pre-VI (n=16) Pre-VI (n=16) VI1 (n=14)	VI1 (n=14) VI2 (n=13) VI2 (n=13)	-18.35*** -3.60 14.75***	-0.67*** -0.11 0.55***
Peak H2			$\chi^2(2) = 0.94$	F (2,40) = 2.14
	Pre-VI (n=16) Pre-VI (n=16) VI1 (n=14)	VI1 (n=14) VI2 (n=13) VI2 (n=13)	-3.64 0.62 4.26	-0.10 0.01 0.11

Notes
Note 1: H1 refers to the period ≤ 12 months from the date of the transaction covered by the futures contracts and H2 for the period > 12 months. These horizons are used by AFMA to report OTC contract data.
Note 2: Pre-VI refers to the subperiod prior to VI, from Q1 2007 to Q4 2010. VI1 refers to the first VI subperiod, from Q2 2011 to Q3 2014. VI2 refers to the second VI subperiod, from Q4 2014 to Q4 2017. The number in brackets next to the subperiod name in columns 2 and 3 indicates the number of observations in that subperiod.
Note 3: ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively
Note 4: The difference in means (last column of Table C.1) is the difference between the means of the subperiods being compared. A positive difference indicates that, for the pair being compared, the mean of the first subperiod is higher than that of the second subperiod and vice versa.
Note 5: The Kruskal–Wallis test with Dunn–Sidak adjustment was carried out using MATLAB procedures. The test statistic is approximately distributed as $\chi^2(2)$. The degrees of freedom = number of subperiods (groups) being compared minus one.

Table C.1 shows the pairwise comparison of means among the three subperiods in our study period. The study period from Q1 2007 to Q4 2017 is divided into three subperiods: pre-VI, VI1, and VI2. We ran the Jarque-Bera test and found that some of the volume series were not normally distributed. Departure from normality can affect ANOVA means comparison test results. Therefore, we utilised the Kruskal-Wallis non parametric test alternative to ANOVA and applied the Dunn–Sidak correction to the multiple comparison tests in order to control the familywise error rate. In Table C.1 we also present the ANOVA results. The benefit of presenting the ANOVA results in Table C.1 is that relating the discussion to subperiod means is more intuitive than relating it to a statistic based on rank. The non-parametric Kruskal–Wallis test is based on rank and does not represent group means.

The test showed a significant difference between the mean volumes of base load energy transacted over the H2 horizon. The $\chi^2(2)$ statistic is 12.20 and the F(2,40) statistic is 10.26, both of which are significant at the 1% level. Pairwise comparisons show that Pre-VI is significantly higher at the 1% level than VI1 and is significantly higher at the 5% level than VI2 (1% in ANOVA). In other words, the mean volume of base load energy dropped in VI1 and VI2 relative to the Pre-VI subperiod. There is no significant difference between VI1 and VI2.

For peak load transacted over the H1 horizon, there are significant differences between the subperiod means as indicated by the $\chi^2(2)$ statistic of 17.36 and F(2,40) statistic of 17.66, both of which are significant at the 1% level. Pairwise comparisons show that the mean volume in the VI1 subperiod is significantly higher at the 1% level than both means in the Pre-VI and VI2 subperiods. However, the means of the Pre-VI and VI2 subperiods are not significantly different.

As seen in Table C.1, for Base H1, the two tests predict an overall difference between the groups at the 10% level but differ as to which pair is different, again at the 10% level. There is only a weak case for any difference in Base H1.

The Kruskal–Wallis test and Dunn–Sidak correction were conducted using MATLAB procedures. As a robustness check, the Bonferroni correction was applied, and it led to the same conclusions as the Dunn-Sidak correction.

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6. Thesis Summary and Conclusions

This thesis has explored the behaviour of wholesale electricity markets with emphasis on the liquidity of electricity futures contracts and the dynamics and forecasting of the futures premium. First, it investigated the premium dynamics and addressed the gap in the literature relating to the premium during the delivery period. It then developed a new approach to forecasting the probability density function of daily changes in futures prices. Finally, it presented evidence of the impact of vertical industry structure on the futures market using data from the largest regional electricity market in Australia.

6.1 Main Results

The first research paper titled 'Electricity Futures Markets in Australia – An Analysis of Risk Premiums during the Delivery Period' provides an empirical analysis of risk premiums of electricity futures contracts during the delivery period for the major eastern states of Australia. We develop multiple regression models for base and peak load contracts that help to explain the dynamics of the premiums during the delivery period of the respective futures contracts. The developed models yield relatively high explanatory power, with coefficients of determination ranging from 0.35 to 0.7 for base load contracts and from 0.55 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, such that risk premiums also exhibit high variation.

We find that the 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 realised historical risk premiums of contracts referring to the same quarter in previous years. We interpret this as a form of learning by market participants. With regard 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, premiums are negatively related to the time remaining until contract expiry, while 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 premiums relative to New South Wales, while premiums in Queensland typically behave quite similar to those 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 find a positive relationship between observed risk premiums and the standard deviation of electricity spot prices, as reported, for example, 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 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 the 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 to formulate an appropriate model.

Risk Managers may benefit from the findings in this paper that show declining premiums for both base and peak load contracts as the contract approaches maturity. At the same time, premiums for both base and peak load contracts increase with higher volatility of the spot price in the previous month. For base load contracts, they also increase with average spot prices in the previous week, indicating the risk averse behaviour of market participants that may not be in the best economic interest of the hedging party.

Chapter 4 contains the second paper, 'Electricity Futures Markets in Australia: Generating Density Forecasts for Returns of Low Liquidity Instruments'. The paper examines the performance of one-day ahead density forecasts in low liquidity markets, using data from the Australian Electricity Futures market. We find that the forecasts generated by the conventional approach based on historical data do not perform well, essentially because they use data from less liquid periods to form density forecasts for more liquid periods closer to delivery of the contract. We propose a new method that enriches the data of the instrument of interest with data from similar contracts traded in previous years closer to the period of interest. We apply the same four models in both the conventional and data enrichment approach and assess their performance using the KS test, applied to the inverse normal transformation of the PIT.

We find that the density forecasts of the proposed data enrichment approach are typically better, which is evidenced by the lower number of rejections of the created forecasts for the futures contracts. Both the conventional and data enrichment approach perform better in the New South Wales (NSW) than in the Victorian (VIC) market. This is likely due to the higher liquidity of NSW relative to VIC. We also perform a number of robustness checks for both methods and find that typically the superior performance of the data enrichment approach is confirmed. The data enrichment holds up to robustness checks using different offsets, a different number of observations and the Kuiper test to assess performance instead of the KS test. Interestingly, when we start our forecast closer to the delivery period, we find that the gap between the performance of the two approaches narrows due to the better performance of the conventional approach. This is true in particular, when we create daily density forecasts for only the last six months prior to the delivery period of the contract. We suggest that these results are due to the data used in the conventional approach being drawn from a more liquid period with similar characteristics to the forecasting period. The link between liquidity and returns has been established in general markets
(see, e.g. Amihud and Mendelson, 1986a, 1986b; Liang and Wei, 2012). The data enrichment method has been shown to improve the forecast performance of one-day ahead returns in illiquid markets. This is achieved without exposing the hedger to basis risk and higher hedging costs associated with the method proposed by Frestad (2014). The applications of data enrichment need not be restricted to the electricity market but should have potential application in other illiquid markets such as the natural gas markets.

Furthermore, while it is not the purpose of the paper to conduct an extensive evaluation of the performance of different VaR models, we can observe that of the four models tested, a so-called volatility updated scheme, see, e.g. Hull and White (1998), referred to as the EUV model in this paper, performed best. This was followed by either the model fitted empirically to historical data or the normal model with updated volatility depending on the case being considered. This accords with other findings in the literature where models that incorporate a time-varying specification of volatility are found to perform better in commodity and electricity futures markets (see, e.g. Füss et al., 2010, Kayal and Lindgren, 2014, Zanotti et al.,2010).

Chapter 5 presents the third study, 'Vertical Integration of Generation and Retail: Foreclosure in the Electricity Futures Market', and provides empirical evidence of foreclosure in the electricity futures market following vertical integration between the electricity retail and generation stages. We regress electricity futures volumes transacted on the ASX against independent variables representing VI, spot and futures price moments, demand and other variables. The results show a statistically significant reduction in the volume of electricity futures transacted following VI between the generation and retail stages of the electricity industry. The VI variable explains the largest portion of the drop. The fall in volume can reduce electricity retail competition and harm consumers. We find that base load energy traded on the ASX electricity futures market in NSW following VI is lower over the longer horizon (> 12 months) and unchanged over the shorter horizon (≤ 12 months). For peak load energy, volumes within the shorter horizon (≤ 12 months) increased but remained unchanged over the longer horizon (> 12 months). This could indicate that the market has become more short term following VI over our sample period. The evidence of lower energy transacted over the H2 horizon supports a conclusion of foreclosure[67] over the > 12 months horizon. This horizon is particularly relevant for the commercial and industrial market segment, but also relevant for consumer segments with contracts longer than one year. The foreclosure in the futures market is particularly important given the material reduction in OTC contracts shown in Fig. 5.3. Non-integrated retailers are disadvantaged compared to gentailers when hedge markets are weaker (Aïd et al., 2011). Therefore, the reduction in the H2 volume has potential to lessen competition and disadvantage consumers.

[67] Foreclosure occurs when the quantity of goods and/or services transacted between vertically integrated and non-vertically integrated firms are lower than would be the case under no bargaining power of the integrated firms, Grimm et al. 1992.

This insight is made possible through our novel method of analysing the amount of energy transacted over two commercially meaningful horizons that are also used by AFMA in reporting industry statistics. We also confirm that ignoring horizons leads to the unwarranted conclusion that the energy transacted on the ASX has not changed following VI. The overnight change to a gentailer-dominant model in NSW made it easier to discern the impact of VI.

These findings are supported by the literature. The NSW electricity market pre-VI did not contain pure monopolies in successive stages of the supply chain, hence, benefits from the elimination of DM are less likely to be welfare enhancing (Joskow, 2010). The futures market encourages retail competition and lessens the disadvantage of non-integrated retailers (Aïd et al., 2011). Our findings of a statistically significant reduction in volume transacted on the futures market following VI indicate that foreclosure on this market potentially harms consumers. Our findings gain added importance given that benefits in the spot market are ambiguous and, up to the time of writing, there has been no new base load generation capacity added to the market, which VI is supposed to facilitate.

6.2 Contributions

The thesis contributes to a number of streams of the literature.

Electricity futures premium literature

The thesis developed a method to extract the futures premium for contracts trading during the delivery period. The method decomposes observed futures prices into three parts: the crystallised value of the portion already delivered, the expected average spot price for the remaining days of the delivery period, and the risk premium for the remaining days of the delivery period. The premium is expressed in $/MWh and this measure is useful for comparison across contracts and durations.

The thesis differentiated between the behaviour of the premium of base load and peak load contracts. It demonstrated that the premium is dynamic and depends on season, variables related to the level and higher moments of price as well as time remaining to expiry.

An important contribution is that the thesis demonstrates that the dynamics of base load premiums are linked to a measure of liquidity being open interest.

Density forecasting literature

The thesis developed an approach that generates density forecasts that are slightly improved over the conventional approach, thus improving risk management outcomes. The approach enriches data for a particular financial instrument by incorporating data from contracts of the same type delivered in an earlier year. Therefore, it employs data from periods of higher liquidity, and of similar liquidity and volatility characteristics to the period of interest to the forecaster. This contrasts with the traditional approach of relying on historical data from periods with dissimilar liquidity levels. Therefore, it is contended that the data enrichment approach uses data from a more relevant period while still incorporating a rich variety of realised historical returns.

An important contribution is the versatility of the data enrichment approach which can be used as part of various parametric and non-parametric modelling approaches, as shown in the analysis presented in the thesis. The data enrichment approach does not expose the portfolio to basis risk and costs associated with transacting different instruments.

A further contribution is the comparison of the traditional approach to the data enrichment approach using four forecasting models. Although it is not the purpose of this paper to compare different models, using data enrichment in several models shows its versatility.
Finally, the data enrichment approach has potential application to other illiquid markets, such as the natural gas markets.

Vertical integration literature

The thesis presents research that is among the first to focus on the impact of vertical integration in the electricity sector on liquidity in the electricity futures market. The regression analysis presented shows that the electricity futures volume transacted on the ASX has reduced, following the consolidation of the industry into large gentailer entities. The volume is also related to the level of the futures price.

Second, the thesis presents a novel method of analysing the transacted futures contract volume by horizon. The method provides new insights into the impact of VI on the structure of the futures market and competition. Key to the method presented is splitting the hedging horizon into a shorter term; that is, within 12 months of the transaction date (H1) and a longer-term hedging horizon of greater than 12 months (H2). H2 is particularly relevant for the commercial and industrial customer segments of the market as well as for the portion of the residential customer segment on contracts longer than 12 months. These horizons are used by The Australian Financial Markets Association (AFMA) in reporting data relating to the electricity OTC market – the other major futures (bespoke) market. Such an impact appears to have been missed in studies that did not differentiate between shorter and longer-term horizons.

Australian electricity futures market literature

The thesis contributes to the Australian electricity futures market by analysing the premium during the delivery period in the three major electricity markets of Queensland, New South Wales and Victoria. Further, the behaviour of the premium in different seasons is explained with reference to characteristics of the Australian market and seasonal patterns.

The thesis also applies the data enrichment approach to Australian electricity futures instruments. The Australian electricity futures market is characterised by low liquidity in the period more than one year prior to the start of delivery. Most activity, and therefore interest in forecasting, lies in the year leading up to delivery. The thesis demonstrates how to enrich return data for the current contract (say Q1 2010) by incorporating data from contracts for the same quarter (Q1 in this example) delivered in previous years (add to Q1 2010 data from Q1 2009 and Q1 2008). This approach offers a number of advantages over the traditional approach. It allows us to base our forecasts on historical data that exhibits liquidity characteristics that are more similar to those found in the period of most interest to market participants (the year leading up to delivery).

The thesis shows that base load and peak load futures contract volumes were impacted differently in New South Wales following integration. The volume of base load futures electricity contracts on the Australian Stock Exchange (ASX) covering a horizon >12 months fell significantly following VI. On the other hand, peak load energy volumes transacted over a horizon up to 12 months increased following VI. This is likely due to the continued need to hedge in the short term, H1, but not in the longer term, H2.

6.3 Suggestions for Future Research

While the thesis makes novel and important contributions to the field there are some limitations to our analysis. The thesis analyses data from the Australian electricity futures contracts traded on the ASX market using the most liquid calendar quarter swap contracts. This decision was made to ensure that our results are not unduly influenced by price movements in much lower liquidity instruments. A limitation related to low liquidity is that the analyses do not extend to all contracts and states of the NEM. As discussed in the relevant chapters restricting the choice of instruments to those with high liquidity is an established approach in the literature. Another limitation is due to the unavailability of public OTC contract data. Had this data been available, it would have enriched the analysis, particularly in Chapter five on vertical integration. A recognised challenge to contend with when analysing OTC data is how to compare contracts with differing features in a valid manner.

Suggestions for future work include extending the examination of premium dynamics to futures contracts of longer and shorter delivery periods (e.g. annual or monthly contracts) as well as to options and caps. Another line of enquiry could be to compare premiums during the delivery of futures contracts to premiums during the delivery of OTC contracts. Such work would require access to information on OTC contracts that is typically not publicly available. Standardised OTC contracts, traded through brokers, would be more easily comparable, while more careful consideration would need to be given to OTC contracts that incorporate peculiar features.

Future work could also assess the performance of combining forecasts from different models, probably preceded by a more extensive evaluation of different models to determine the best candidates for inclusion in such a combination (Hall and Mitchell, 2007; Kascha and Ravazzolo, 2010). Such evaluation could be conducted by testing the relative performance of forecast models (see Manzan and Zerom, 2013). Other future work could involve testing the approach to different markets including electricity markets other than in Australia or other energy and commodity markets. The natural gas market is likely to be a good candidate due to its low liquidity. Other future work could drill down into data characteristics to help in the selection of model parameters such as the number of lagged years, the amount of data to use in generating the forecast and the number of lagged years to use in enrichment.

With regard to the last study, for future work we suggest reassessing the impact of VI on H1 peak load and H1 base load contracts. This is based on the observed lower energy volumes of both base load and peak load as of 2016. The number of observations available at present is too small to establish whether this indicates a drop in transacted energy but could be revisited when more data is made available over time. Another suggestion is to investigate the impact on consumer electricity prices, ideally separating the price into its major components – retail, energy and network costs. A further suggestion, if data is available in sufficient detail, would be to investigate whether the impact of VI varies by business type (i.e. non-integrated versus integrated retail and generation). It would also be important to conduct interview-based research of the market, incorporating representative views of stakeholders. A final suggestion is to include OTC data if the data is available at quarterly or higher frequency.

Given our finding on the changes to the liquidity of the futures market following vertical integration and the conclusions in the literature on its impact on futures prices, we suggest that future work could aim to examine more thoroughly the relationship of the dynamics of risk premiums and market structure. This might be of particular relevance for the Australian electricity market, as in recent years, vertical integration has become more widespread in the NEM.

The finding of a material reduction in energy traded following VI between the generation and retail stages and its potential impact on consumer interests suggests possible policy responses that could enhance consumer welfare.

One possible response is to implement policies aimed at increasing the volume of energy transacted in the futures market. This could be achieved through voluntary participation, including through tendering to provide market making services, potentially supplemented by a mandatory obligation in the event a target liquidity level is not achieved.

Transparency is an important feature of markets that enhances market efficiency by facilitating the dissemination of prices and other information to all market participants. The paper alludes to lack of transparency in the OTC market. Improving transparency of the OTC market is therefore another, additional, possible policy response.

The above policies are candidates for future research topics. Similar arrangements have been implemented in other jurisdictions, New Zealand for example.

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