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Abstract

We investigate the impacts of the carbon tax (effective July 2012 to July 2014) on wholesale electricity prices in the Australian National Electricity Market (NEM). Analyzing spot and futures contracts in four major regional markets, we first compute ex-ante forward risk premiums in the pre-tax period, then use them to derive market-implied *carbon premiums* and pass-through rates in the carbon tax and post-tax periods. We find that carbon premiums and pass-through rates became increasingly higher, once the *Clean Energy Bill* had been introduced and subsequently passed in 2011. We also find strong evidence for a quick reaction of the extracted carbon premiums to changes in opinion polls for the Australian federal election in 2013 and the decision to repeal the tax. On the other hand, during periods where market participants could be relatively certain that the tax would be effective, we find expected carbon pass-through rates between 65% and 140%, which seem to be inversely related to emission intensities.

Keywords: Carbon Tax, Carbon Pass-Through Rate, Forward Risk Premium, Electricity Market, Spot and Futures Prices.
JEL: C51, C53, G13, Q41, Q58

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1. Introduction

Australia's CO_2 emissions levels are among the highest of all OECD countries (International Energy Agency, 2010). Hereby, stationary energy (including emissions from fuel consumption for electricity generation, fuels consumed for manufacturing, construction, commercial sectors and domestic heating) is the largest source of CO_2 emissions in Australia. Electricity generation contributes by far the most to emissions in this sector with a share of close to 50% of all energy emissions, and approximately 35% of all CO_2 emissions in Australia (Australian Treasury, 2011). As a result of Australia's high CO_2 emissions, in 2011 the Clean Energy Act as a package of legislation was introduced in order to reduce greenhouse gas emissions to 5% below 2000 levels by 2020, and to 80% below 2000 levels by 2050. The *Carbon Pricing Mechanism* (CPM) was a central component of this Act with the aim to encourage Australia's largest emitters to enhance energy efficiency and invest in more sustainable and renewable energy. Under the CPM, all businesses emitting over 25,000 tonnes of carbon dioxide equivalent (tCO_2e) emissions annually were required to purchase emissions units from the government (Clean Energy Regulator, 2013). The CPM became effective on 1 July 2012, with an introductory phase during which the price of uncapped permits was fixed: the initial price was determined to be 23 Australian dollars per tonne of carbon dioxide equivalent emissions (AUD/tCO_2e), increasing to 24.15 dollars from 1 July 2013 and to 25.40 dollars from 1 July 2014 to 30 June 2015. The original plan was then to have a transition to an Australian *Emissions Trading Scheme* (ETS) in July 2015 after the 3-year period of a fixed carbon price. However, after the election of a new government in September 2013, the Clean Energy Act, including the CPM and the carbon tax, was repealed by the Australian Senate on 17 July 2014.

Using futures data for four major regional markets within the Australian National Electricity Market (NEM), in this paper we investigate pass-through rates and the impact of the carbon tax on wholesale electricity prices. Following Nazifi (2016), we define the *carbon pass-through rate* as the ratio of change in the price of electricity to the change in marginal costs due to the carbon tax. Similarly, Nelson et al. (2012) and Huisman and Kilic (2015) define the carbon pass-through as the proportion of carbon prices passed through into electricity prices, which is effectively the proportion of higher costs incurred by consumers in the form of higher electricity prices attributable to the carbon tax.

We develop a framework that takes into account dynamic forward risk premiums in the futures markets, i.e., the relationship between quoted futures and expected spot prices during the delivery period, in order to extract the expected additional cost of the carbon tax for Australian wholesale electricity prices. Using futures prices instead of spot prices does not only allow us to take a forward-looking approach, but is also less sensitive to short-term events in electricity spot markets, such as extreme price spikes (Weron, 2006). This is of particular importance for the Australian NEM, where regional markets have been characterized as being among the most volatile and spike-prone in the world (Higgs and Worthington, 2008; Christensen et al., 2012; Janczura et al., 2013; Clements et al., 2015; Mayer and Trück, 2015; Ignatieva and Trück, 2016). Using futures instead of spot electricity prices, we also do not require detailed information on the actual fuel mix for the generation of electricity at each point in time to determine carbon pass-through rates. Instead we can derive directly market expectations on the impact of the introduction and abolishment of the tax on wholesale prices in the NEM. Finally, examining market reactions to key policy events such as the passing of the Clean Energy Act or the abolishment of the tax allows us to investigate how quickly market participants adapt to a changing regulatory environment.

So far, the relationship between carbon and energy prices as well as pass-through rates of carbon on electricity prices have mainly been studied for the European Union Emissions Trading Scheme (EU-ETS), see, e.g., Sijm et al. (2006), Hirschhausen and Zachmann (2008), Bunn and Fezzi (2009), Daskalakis and Markellos (2009), Fell (2010), Nazifi and Milunovich (2010), Chevallier (2011), Gronwald et al. (2011), Sijm et al. (2012), Jouvet and Solier (2013), Huisman and Kilic (2015) and Kanamura (2016). Most of these studies find a significant impact of carbon prices on electricity markets in the European Union, and typically suggest pass-through rates ranging from 30% up to even more than 100%, for a review see, e.g., Gulli and Chernyavska (2013). Some of the cost pass-through to wholesale prices has often been characterized as windfall profits to the electricity industry, since originally there was a free allocation of the permits to the sector in the EU-ETS (Sijm et al., 2006). Findings also suggest that emissions trading induced changes in the merit order of power generation technologies, while the impact of strategies such as maximising market shares or sales revenues of power companies are key factors that will impact on the pass-through of carbon costs to electricity prices (Sijm et al., 2012). Further, there is some evidence that pass-through rates vary over time and were significantly lower in 2009, after the global financial crisis (Jouvet and Solier, 2013; Huisman and Kilic, 2015).

While there have been a number of studies investigating the impact of the price of emission allowances on electricity prices in the European Union, the effects of the carbon tax on electricity prices in Australia have not been investigated by many authors. As pointed out by Nelson et al. (2012), a number of modeling and simulation studies on the potential impacts of introducing a carbon tax on electricity prices and broader economic impacts related to the introduction of an emission trading scheme have been conducted a few years before the actual tax was implemented. The analysis was undertaken mainly by leading Australian economic modeling firms using techniques such as linear programming, general equilibrium models or dynamic partial equilibrium analysis. These studies were rather inconsistent in their estimation of carbon pass-through rates and provide very different results, with rates ranging from 17% McLennan Magasanik Associates (2008)), 100% ROAM (2008), 128% in the Garnaut (2008) report, up to more than 393% (Simshauser and Doan, 2009), the latter reflecting a potential strategic and disruptive generator exit scenario.

Recently, there have also been a few empirical studies on the pass-through rate of the CPM on wholesale electricity prices in the Australian NEM. Nazifi (2016) investigates the interaction between a carbon price signal and wholesale electricity spot prices within the NEM. The author suggests that for the initial period of the carbon tax in Australia until October 2013, carbon costs were indeed fully passed on to wholesale electricity spot prices resulting in higher electricity prices for consumers and potential windfall profits for some generators. Apergis and Lau (2015) examine the role of climate policy uncertainties in the Australian electricity market and suggest that the NEM can be described as a less stable electricity market in comparison to other electricity markets around the world. They suggest that in the NEM also a relatively high degree of market power is exercised by generators across regional markets. This might have significant consequences for the effectiveness of carbon dioxide mitigating policies, especially, when there is uncertainty as to whether the planned environmental policy is put in place for the lifespan of undertaken investments. O'Gorman and Jotzo (2014) investigate the impact of the carbon tax on electricity demand, supply and emissions during the period 1 July 2012 to 30 June 2014, namely the period when the tax was in place. Their findings suggest that during the considered period electricity demand in the NEM declined by 3.8%, while at the same time the emissions intensity of electricity supply was also reduced by almost 5%. Overall this has led to a reduction in emissions by roughly 8% compared to the two-year period before the carbon price. The authors also suggest that the carbon price markedly changed relative costs between different types of power plants, leading to emissions-intensive generators such as brown coal and black coal reducing their output. They conclude that the carbon tax has worked as expected in terms of its short-term impacts, while its effect on investment in power generation assets has probably been limited, due to political uncertainty about the continuation of the carbon pricing mechanism.

Our study contributes to the literature in several dimensions. First, we extend the relatively sparse literature on the impact of the Australian CPM on wholesale electricity prices. To the best of our knowledge, we also provide a pioneering analysis of pass-through rates of the tax on electricity futures prices in the NEM. While few studies have focused on carbon pass-through rates on spot electricity prices in Australia, so far there is no work that measures and quantifies the impact of the carbon tax on expectations and risk premiums in electricity derivative markets.

Another contribution of our analysis is that we develop a framework that allows us to take into account existing forward risk premiums in electricity futures markets in order to appropriately estimate carbon pass-through rates. Further, using futures prices instead of spot prices allows us to take a forward-looking approach, and to thoroughly examine the impact of key policy events on observed carbon premiums in the electricity markets. Hereby, we analyse the impact of announcements about the introduction of the tax, opinion polls on upcoming federal election, as well as the actual change of the federal government that was accompanied by the promise to repeal the tax.

Finally, we examine carbon pass-through rates over a long sample that includes the period before the carbon tax became effective, the period of its lifetime from July 2012 to June 2014 as well as the period after the tax had been repealed. While previous studies in the Australian context were either entirely based on simulation results (McLennan Magasanik Associates, 2008; ROAM, 2008; Simshauser and Doan, 2009) or restricted to spot prices from shorter periods (O'Gorman and Jotzo, 2014; Nazifi, 2016), we examine a significantly longer time period of spot and futures prices that will allow us to gain additional insights on the impact of the introduction and abolishment of the tax on wholesale electricity prices in Australia.

Overall, our results on futures-implied carbon pass-through rates clearly indicate the impact of political news on the premiums. We find that the market reacted relatively quickly to the passing of the *Clean Energy Bill* by the Labor government in July 2011. Even more striking is the inclusion of news about opinion polls for the 2013 Australian federal election with regards to the existing Labor government vs. the Liberal/National opposition. On the other hand, during the period where market participants could be relatively certain that the tax would be effective, we find expected carbon pass-through rates between 65% and 140%. Interestingly, the carbon pass-through rates seem to be inversely related to emission intensities and were relatively low for the market with the highest emission intensity (Victoria, VIC), while they were the highest for the market with the lowest emission intensities (South Australia, SA).

The remainder of the paper is organized as follows. In Section 2 we provide an overview of the Australian National Electricity Market. Next, in Section 3 we introduce our framework, including the suggested model for spot electricity prices, the relationship between spot and futures markets and the applied methodology to derive implied carbon pass-through rates in observed electricity futures prices. In Section 4 we discuss the empirical results. In particular we focus on the carbon pass-through rates at different time instances and consider the effect of political announcements as well as the introduction and repeal of the tax on the these rates. In Section 5 we wrap up the results and conclude.

2. The Australian National Electricity Market

As a wholesale market the National Electricity Market (NEM) in Australia began operating in December 1998. It is an interconnected grid comprising several regional networks which provide supply of electricity to retailers and end-users. The NEM includes the states of New South Wales (NSW), Queensland (QLD), South Australia (SA) and Victoria (VIC), while the state of Tasmania (TAS) is connected to VIC via an undersea inter-connector. The link between electricity producers and electricity consumers is established through a pool which is used to aggregate the output from all generators in order to meet the forecasted demand. The pool is managed by the Australian Energy Market Operator (AEMO) which follows the National Electricity Law and is in conjunction with market participants and regulatory agencies (Australian Energy Regulator, 2015; Nepal et al., 2016).

Electricity generation in Australia is predominantly based on coal and natural gas such that until 2010, over 90% of electricity was generated using fossil fuels (Clean Energy Australia, 2010). In particular, coal fired power plants had a share of more than 80% of electricity generation, while generation from natural gas was also greater than 10%. At the same time, similar to many other countries, recently also the development of renewable energy in Australia has been encouraged by government policy, implemented in response to concerns about climate change and energy independence (Higgs et al., 2015; Ignatieva and Trück, 2016). As a result, the share of renewable energy has undergone significant growth in Australia over the last decade: from less than 4% of nationally generated electricity in 2006, to almost 9% in 2010 and over 12% in 2015 (Clean Energy Council, 2015).

Unlike many other markets, the Australian spot electricity market is not a day-ahead market but electricity is traded in a constrained real time spot market where prices are set each 5 minutes by AEMO (Australian Energy Regulator, 2015). Therefore, generators submit offers every five minutes. This information is used to determine generators required to produce electricity in a more cost-efficient way based on the existing demand. The final price is determined every half-hour for each of the regions as an average over the 5-minute spot prices for each trading interval. Based on the half-hourly spot prices, also a daily average spot price for each regional market can be calculated. AEMO determines the half-hourly spot prices for each of the regional markets separately (Australian Energy Market Operator, 2010; Christensen et al., 2012).

Over the last decade, also the market for electricity derivatives has developed rapidly including forward, futures and option contracts. Anderson et al. (2007) note that there are three types of Australian electricity derivatives: (i) bilateral over-the-counter (OTC) transactions between two entities directly, (ii) bilateral OTC transactions on standard products executed through brokers, and (iii) futures and options traded on the Australian Securities Exchange (ASX) operated through ASX Energy.[1] In our study we will concentrate on quarterly futures contracts traded on the ASX, respectively SFE before 2013, during the time period 2003-2014. Note that the ASX also offers a number of alternative derivatives including option contracts or 300 AUD/MWh cap products that will not be considered in this study.

Like in almost every electricity exchange, futures contracts traded on the ASX refer to the average electricity price during a delivery period. Thus, for a base period futures contract the unit is one Megawatt of electricity per hour (MWh) for each hour from 00:00 hours to 24:00 hours over the duration of the contract.[2] For a quarterly base load contract, the size (in MWh) will vary depending on the number of days within the quarter. For example, for a quarter with 90 days, a contract refers to 2,160 MWh during the delivery period while for a quarter with 92 days, a contract refers to 2,208 MWh. The quarterly contracts they will be denoted in the text by **Q*x* 20*yy***, where x stands for the quarter $(1, 2, 3, 4)$ and yy for the last two digits of the year of delivery.

The contracts do not require physical delivery of electricity but are settled financially. Therefore, market participants can participate in the electricity futures market and increase market liquidity without owning physical generation assets. The cash settlement price of a base load contract is calculated by taking the arithmetic average of the NEM final base 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.

3. The Econometric Framework

Using futures data on the Australian National Electricity Market (NEM) for the four major regional markets (NSW, QLD, SA and VIC), we aim to investigate carbon pass-through costs on wholesale electricity prices in a forward looking manner. Recall that the carbon tax became effective on 1 July 2012, with an intended introductory phase until 30 June 2015) during which the price of uncapped permits was fixed: first at 23 AUD/tCO_2e, then from 1 July 2013 at 24.15 AUD/tCO_2e and from 1 July 2014 at 25.40 AUD/tCO_2e. After the election of a new government, the carbon tax was repealed by the Australian Senate on 17 July 2014. Based on the introduction and later abolishment of the tax, we therefore have three periods of particular interest for this study:

1. the sample period when the tax was not around yet, but futures prices for periods referring to the carbon tax period were already available (before July 2012),
2. the sample period referring to the years when the tax was effective, while due to the political climate (upcoming elections with abolishment of the CPM as a key promise of the opposi-

[1] Note that formerly these products were traded at the Sydney Futures Exchange (SFE) operated through d-cyphaTrade, however the SFE and ASX merged in 2006 and d-cyphaTrade was acquired by the ASX in 2013.

[2] Next to base load futures contracts, also peak load contracts are being traded. In Australia, the peak period refers to the hours from 07:00 to 22:00 on weekdays (excluding public holidays) over the duration of the contract quarter. Note, however, that in this study only base load contracts are considered.

tion) there was uncertainty among market participants about how long the tax would be in place (July 2012 – September 2013),

3. and the period when the tax was still effective, but when it became clear that the tax would be abolished in the near future (after September 2013, before July 2014).

Note that for the latter case, we will investigate the pass-through costs for periods referring to the remaining tax period (Q4 2013, Q1 and Q2 2014) as well as for the post-tax period (from Q3 2014 onward).

3.1. Risk Premiums in Electricity Futures Markets

Due to the non-storability of electricity as a commodity, the literature usually suggests a theory that considers equilibrium in expectations, and risk aversion amongst agents with heterogeneous requirements for hedging the uncertainty of future spot prices (Bessembinder and Lemmon, 2002). Using this approach, electricity forward and derivative prices can be determined as the expected spot price plus an ex-ante *forward risk premium* (Longstaff and Wang, 2004; Weron, 2008; Redl et al., 2009; Botterud et al., 2010; Bunn and Chen, 2013; Handika and Trück, 2014b); the latter typically interpreted as compensation for bearing the spot price risk. Hence, in electricity markets, the relationship between the observed price for a futures contract at time t referring to the delivery of electricity over the period $[T_1, T_2]$, i.e., $F_{t,[T_1,T_2]}$, and the expected at time t average spot price over the period $[T_1, T_2]$, i.e., $\mathbb{E}_t(\bar{S}_{[T_1,T_2]})$, can be formally written as:

$$F_{t,[T_1,T_2]} = \mathbb{E}_t(\bar{S}_{[T_1,T_2]}) + \pi^F_{t,[T_1,T_2]}, \tag{1}$$

where $\pi^F_{t,[T_1,T_2]}$ is the *forward risk premium* or simply *forward premium*.[3]

Empirical studies on the existence of forward risk premiums in electricity futures markets do not provide clear-cut results and have been mainly conducted for realized (or ex-post) premiums. Comparing day-ahead ('forward') and real-time ('spot') prices, Longstaff and Wang (2004) and more recently Haugom and Ullrich (2012) examine whether the realized premiums paid in the PJM electricity market are significant. They conclude that these very short-term forward premiums are generally positive, but their significance decreases over the years. Redl et al. (2009) find positive ex-post premiums for month-ahead futures contracts in the Nord Pool and EEX markets. They report premiums ranging from 8% for considered base load contracts in the Nord Pool market and 9% for base load and 13% for peak load contracts in the EEX market.

Botterud et al. (2010) find positive on average ex-post risk premiums (hence negative forward premiums) in the Nord Pool Asian options and futures prices, but in more recent studies Haugom et al. (2014) and Weron and Zator (2014) report that ex-post premiums vary significantly over time. In particular, studying Nord Pool data from the years 1998-2010, Weron and Zator (2014) find that for 1 week maturities the realized forward premiums are on average negative, while for 6 week maturities the premiums tend to be positive. On the other hand, analyzing a longer and

[3] Note that some authors (see e.g. Benth et al., 2008; Haugom and Ullrich, 2012; Haugom et al., 2014) use the term *risk premium* to denote $\pi^F_{t,[T_1,T_2]}$. This is confusing since the risk premium is typically defined as the negative of the forward premium, i.e., the difference between the expected spot price and the forward price (for a discussion see Weron and Zator, 2014).

more recent data set (for the years 1996-2013), Haugom et al. (2014) find negative on average ex-post forward premiums for 1 to 6 week Nord Pool futures contracts, which decrease in the Winter and increase (to become slightly positive) in the Summer. For Australia, so far only two studies have investigated the existence of premiums in electricity futures contracts (Handika and Trück, 2014a,b), suggesting typically positive and also relatively high ex-post forward premiums in most of the regional markets.

The few existing studies on ex-ante premiums in electricity markets are also not conclusive. Considering only one time point (30 September 2003) and three stochastic models for the spot price (a jump-diffusion and two regime-switching models), Bierbrauer et al. (2007) conclude that futures prices in the German EEX market are generally greater than the expected future spot (i.e., the forward premium is positive in the short term) for the first six months and less than the expected spot (i.e., the forward premium is negative) for the second, third and fourth quarter in 2004. In a related study on forward premiums in the EEX market, Benth et al. (2008) propose a framework that explains how the premium depends on the risk preferences of market players. They argue that long-term contracts will be mainly used by producers to hedge their future electricity production, who may be willing to accept prices lower than the actual expected spot prices in order to guarantee sales (→ a negative long-term forward premium). On the other hand, in the short-term, retailers or consumers, aiming to hedge the risk of extreme price outcomes in the spot market, may be willing to pay an additional premium for their hedge (→ a positive short-term forward premium). The authors support their conjectures with a limited empirical study involving three time points (1 January 2002, 3 March 2003, 4 October 2005), monthly, quarterly and yearly EEX futures contracts and a jump-diffusion model for the spot price.

On the other hand, quite contradictory results are reported by Weron (2008) for the Nord Pool market. Studying a selection of so-called block contracts (i.e., futures with four week delivery periods) in the 3-year period from Spring 1998 to Spring 2001 and using a jump-diffusion model, the author finds that for most of the time the forward premium is positive and increasing with time to maturity.[4] Weron (2008) further argues that the positive forward premium can be explained by a higher incentive for hedging on the demand side relative to the supply side, because of the non-storability of electricity as compared to the (limited and costly but still existent) storage capabilities of water and fossil fuels. Apparently, as emphasized by Huisman and Kilic (2012), the forward premium may behave differently depending on the characteristics of the market. Hence our study contributes to the literature by conducting an extensive empirical analysis of forward premiums in the extremely volatile and so far unexplored (from this point of view) Australian electricity market.

Note that in our analysis, we are not only interested in analyzing forward premiums, but we would expect an additional effect of news about the introduction or abolishment of the carbon tax in future periods. Therefore, we consider the following modification of Eqn. (1):

$$F_{t,[T_1,T_2]} = \mathbb{E}_t(\bar{S}_{[T_1,T_2]}) + \pi^F_{t,[T_1,T_2]} + \pi^C_{t,[T_1,T_2]}. \tag{2}$$

[4] Note that Weron (2008) presents the results in terms of the risk premium, i.e., the negative of the forward premium defined by (1), hence the ‘opposite’ conclusions.

Based on this relationship, the *carbon premium* can then be calculated as:

$$\pi^C_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \left\{\mathbb{E}_t(\bar{S}_{[T_1,T_2]}) + \pi^F_{t,[T_1,T_2]}\right\}. \tag{3}$$

Ultimately, we are interested in comparing the extracted carbon premium, $\pi^C_{t,[T_1,T_2]}$, to the emission intensity adjusted additional cost of electricity prices. The latter is simply the (expected) average emission intensity of electricity generation multiplied by the price of the tax per ton of CO_2, i.e., $\mathbb{E}_t(\overline{EI}_{[T_1,T_2]}) \times CT_{[T_1,T_2]}$.

Note that two of the components on the right hand side of Eqn. (3) are not directly observable. Therefore, to extract the carbon premium implied in futures prices, we require an appropriate estimate for the expected spot price under a business-as-usual scenario as well as an estimate for the forward premium. In the following we will lay out in more detail, how these estimates can be obtained.

3.2. Models for the Electricity Spot Price

3.2.1. Dealing with Seasonality

As Janczura et al. (2013) argue, the first crucial step in defining a model for electricity spot price dynamics consists of finding an appropriate description of the seasonal pattern. The standard approach to seasonal decomposition splits the series under investigation into the trend-cycle or *long-term seasonal component* (LTSC; L_t), the periodic short-term seasonal component (STSC; s_t) and remaining variability (i.e. the stochastic component; X_t), either in an additive or a multiplicative fashion (Hyndman and Athanasopoulos, 2013). Since our goal here is to analyze the prices of quarterly futures contracts, we ignore the short-term periodicities and consider only the LTSC.

In an extensive study on the estimation and forecasting of the LTSC, Nowotarski et al. (2013) considered a battery of over 300 models from three classes: (i) piecewise constant functions or dummies, possibly combined with a linear trend or with weather variables, (ii) sinusoidal functions or sums of sinusoidal functions of different frequencies and (iii) wavelets. They found that the wavelet-based models were not only better in extracting the LTSC from a series of spot electricity prices but also significantly better in terms of forecasting these prices up to a year ahead than the other two classes of LTSC models. In a follow up study, Weron and Zator (2015) raised the issue of numerical complexity of the wavelet-based technique and advocated the Hodrick and Prescott (1997) filter as a simpler, yet equally flexible alternative to wavelet smoothing. In an independent study, Lisi and Nan (2014) found it to be a very well performing smoother as well.

Following the latter advice, we have focused on two classes of well-performing LTSC models: wavelet-based and Hodrick-Prescott (HP) filter-based. We have found that the latter turned out be a more robust and a better-behaving model for the considered Australian electricity spot prices, both in- and out-of-sample, and selected it as the only specification of the trend-seasonal component in this paper. Recall, that for a noisy (or volatile) input series y_t, the HP filter returns a smoothed series L_t which minimizes:

$$\min_{L_t}\left\{\sum_{t=1}^{T}(y_t - L_t)^2 + \lambda\sum_{t=2}^{T-1}\left[(L_{t+1} - L_t) - (L_t - L_{t-1})\right]^2\right\}, \tag{4}$$

where T is the number of observations (in this study: $1095 \times 24 = 26280$ hours of the 3-year calibration window) and λ is a smoothing parameter.

Since the Australian electricity spot prices are extremely volatile, we use a spike dampening transformation to preprocess the spot prices beforehand. For a series of spot prices P_t, the transform yields series:

$$y_t = \begin{cases} \log(P_t + 1 - \eta), & \text{for } P_t \geq \eta, \\ -\log(\eta + 1 - P_t), & \text{for } P_t < \eta, \end{cases} \tag{5}$$

where η is the median of P_t. This transformation is an alternative to the commonly used logarithmic transformation, which dampens spikes (a wanted feature) but unnecessarily pronounces price drops for prices below the 'normal' level (thus distorting the scale). The transform defined by (5), on the other hand, has a symmetric impact on prices below and above η. Such a transformation makes the observations in the 'normal' price regime the most significant for estimation of the LTSC.

3.2.2. Modeling the Stochastic Behavior of Spot Electricity Prices

For modeling the stochastic nature of spot electricity prices, we utilize the class of *Markov regime-switching* (MRS) processes. The latter are more versatile than the so-called *hidden Markov models* (HMM; in the strict sense), since they allow for temporary dependence within the regimes, and in particular, for mean reversion. They are also a better tool than the more popular jump-diffusion models, as they admit spike clustering, a feature observed on the hourly as well as the daily time scale (for a discussion see Weron, 2014).

The idea underlying MRS models is to represent the (deseasonalized and detrended) spot price process X_t by a collection of J states or regimes with different underlying stochastic processes $X_{t,j}$, $j = 1, 2, \ldots, J$. The switching mechanism between the states is assumed to be an unobserved (latent) Markov chain R_t governed by a transition matrix containing the probabilities $p_{ij} = P(R_{t+1} = j \mid R_t = i)$ of switching from regime i at time t to regime j at time $t+1$. Because of the Markov property the current state R_t at time t depends on the past only through the most recent value R_{t-1}. In general, multi-regime models can be considered, but two or three regimes are typically enough to adequately model the dynamics of electricity spot prices (Janczura and Weron, 2010; Karakatsani and Bunn, 2010). Indeed, two-regime MRS models provide a reasonable fit to log-prices in the regional NSW, QLD, SA and VIC markets and we use them in the empirical part of the paper. Moreover, we apply a specification popular in the energy economics literature where the individual regimes are driven by independent processes (Bierbrauer et al., 2007; Eichler and Türk, 2013; Huisman and Mahieu, 2003; Janczura et al., 2013; Janczura, 2014; Liebl, 2013; Weron et al., 2004).

In this approach, the first or base regime ($R_t = 1$) describes the 'normal' price behavior and is given by a mean-reverting process. In discrete time, the process can be written as

$$X_{t,1} = \alpha_1 + (1 - \beta_1) X_{t-1,1} + \sigma_1 \epsilon_t, \tag{6}$$

where ϵ_t is standard i.i.d. Gaussian noise. The second regime ($R_t = 2$) then represents the sudden price spikes caused by unexpected supply shortages and is given by i.i.d. random variables from the shifted log-normal distribution:

$$\log(X_{t,2} - q_2) \sim \mathrm{N}(\mu_2, \sigma_2^2), \quad X_{t,2} > q_2. \tag{7}$$

In general, q_2 can be numerically optimized (see e.g. Weron, 2014), but here it is set to the median of the dataset. Such a specification of the spike regime distribution ensures that the observations below the median will not be classified as spikes.

Calibration of MRS models is not straightforward, since the state process is latent and not directly observable. We have to infer the parameters and state process values at the same time. In this paper we use a variant of the Expectation-Maximization (EM) algorithm, optimized for MRS structures with independent regimes by Janczura and Weron (2012).[5]

3.2.3. Forecasting the Seasonal Components and Spot Electricity Prices

As discussed in Section 3.2.1, in this paper we use the Hodrick and Prescott (1997) filter for modeling the LTSC. Like a wavelet-based filter or other non- or semiparametric smoothers, the HP filter is able to provide a good in-sample fit, but its use for forecasting is limited. To extrapolate the output of the HP filter-based LTSC we use the well performing 'exponential decay to the median' method of Nowotarski et al. (2013). Within this approach the 1095-day calibration window is first extended one year forward by connecting the last day of the calibration period (on the time axis) and the current spot price (on the price axis) with a time point 365 days into the future (on the time axis; observation no. 1460) and the median of the spot prices in the calibration window (on the price axis), using an exponentially decaying deterministic function with a 180-day mean lifetime of the decay (i.e., a decay factor of $\frac{1}{180}$). Since in this study we require spot price forecasts for up to four years ahead, we further extend the exponentially decaying function for the following three years (at the level of the median of the spot prices in the 3-year calibration window).

Next, we apply a HP filter with smoothing parameter $\lambda = 10^5$ to all 2555 (= 1095 + 4 · 365) observations. The values of the HP smoother for observations no. $1096, 1097, \ldots, 2555$ are taken as the 4-year forecast of the LTSC (for an illustration see Figs. 3 and 4 in Nowotarski et al., 2013).[6] Finally, we simulate 10,000 trajectories of the MRS model fitted to the 3-year calibration window ('forecasts' of the stochastic component) and add them to the forecasts of the LTSC to yield 10,000 simulated trajectories of the spot price. The latter are used to obtain the expected at time t average spot price over the delivery period $[T_1, T_2]$, i.e., $\mathbb{E}_t(\bar{S}_{[T_1,T_2]})$.

4. Empirical Results

4.1. The Data

Half-hourly data on spot electricity prices and emission intensities is available from the Australian Energy Market Operator (AEMO). We consider average daily values for our analysis and

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[5] The Matlab codes for estimating (`mrs2ir_est.m`) and simulating (`mrs2ir_sim.m`) independent regime MRS models is available from the HSC RePEc repository at `https://ideas.repec.org/s/wuu/hscode.html`.

[6] The Matlab code for estimating and forecasting the LTSC using wavelets combined with the 'exponential decay to the median' method (`ltscwave.m`) is available from the same HSC RePEc repository.

Table 1: Descriptive statistics for electricity spot prices in NSW, QLD, SA, and VIC, for the entire sample period (*upper panel*), the considered period before the carbon tax (*second panel*), the carbon tax period (*third panel*), and the considered sample period after the carbon tax (*bottom panel*).

Market	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Entire Sample Period (1 January 2010 – 31 December 2015; N = 2191 days)							
NSW	41.45	35.01	1282.01	17.36	44.36	20.07	512.67
QLD	45.78	33.44	1885.87	-13.98	73.79	15.84	323.66
SA	48.55	37.03	2347.72	-103.16	81.21	18.61	445.46
VIC	39.43	33.20	1276.90	-4.89	46.64	17.88	409.92
Pre Carbon Tax Period (1 January 2010 – 30 June 2012; N = 912 days)							
NSW	33.77	27.02	1282.01	17.36	64.50	15.61	280.33
QLD	30.14	24.99	1062.37	-13.98	53.28	15.43	260.01
SA	36.51	27.35	2347.72	-103.16	113.24	16.09	286.19
VIC	31.15	25.70	1276.90	-4.89	62.43	16.23	295.76
Carbon Tax Period (1 July 2012 – 30 June 2014; N = 730 days)							
NSW	53.68	51.84	303.12	44.32	11.26	15.52	332.44
QLD	62.72	53.76	585.63	0.81	42.28	8.18	87.32
SA	65.73	54.57	806.26	31.93	50.63	8.45	98.92
VIC	54.46	49.37	722.65	36.95	34.95	13.42	224.06
Post Tax Period (1 July 2014 – 31 December 2015; N = 549 days)							
NSW	37.94	35.01	472.77	19.24	21.65	15.40	299.35
QLD	49.25	33.67	1885.87	2.75	117.72	12.65	178.72
SA	45.69	36.92	259.59	-5.82	31.37	3.14	16.74
VIC	33.18	31.97	160.94	11.63	11.62	3.20	30.63

the calibration of the models. Daily quotations of futures prices for quarterly base load contracts for NSW, QLD, SA and VIC are obtained from ASX Energy.[7].

In Table 1 we provide descriptive statistics for spot electricity prices for all four regional markets and the time period from 1 January 2010 to 31 December 2015. The substantial price increase during the carbon tax period from (1 July 2012 – 30 June 2014) is clearly visible. Overall, the regional markets in VIC and QLD yield the lowest prices during the sample period, while prices were the highest in SA. The data also shows typical features for electricity spot prices, like high standard deviation, extreme skewness and excess kurtosis, with prices being right-skewed such that he median is always significantly lower than the mean.

The average daily spot price in NSW over the entire sample period was 41.45 AUD/MWh. Hereby, the average price before the carbon tax period (1 January 2010 – 30 June 2012) was 33.77 AUD/MWh, the average price during the carbon tax period (1 July 2012 – 30 June 2014) was 53.68 AUD/MWh, while for the post tax period, the average price level was 37.94 AUD/MWh. We get similar results for the other three major markets in the NEM: for the considered sample period in all markets prices were the lowest before the introduction of the carbon tax, increased significantly for the carbon tax period and did not return to their pre-tax levels after abolishment of

[7] See https://asxenergy.com.au/.

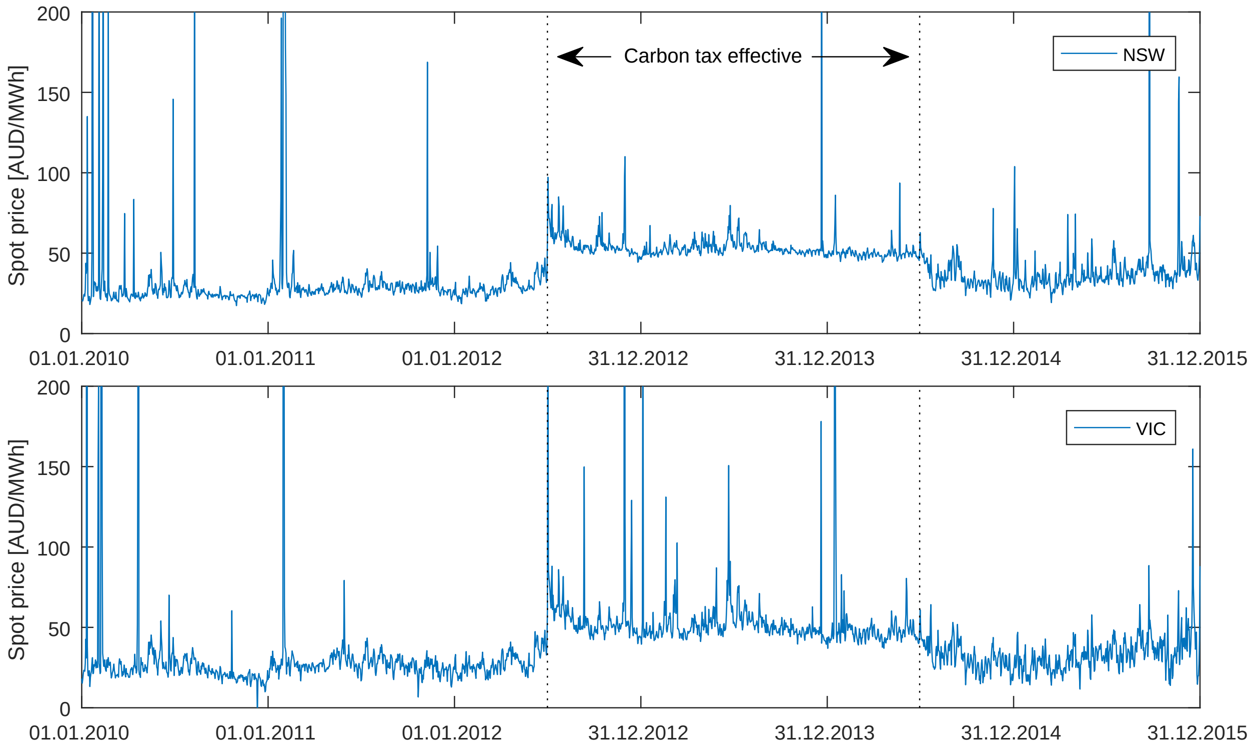

Figure 1: Daily spot electricity prices from 1 January 2010 to 31 December 2014 for NSW (*upper panel*) and VIC (*lower panel*). Note that for the purpose of illustrating the price shift due to the introduction of the carbon tax, prices were capped at 200 AUD/MWh. The dotted vertical lines indicate the period when the carbon tax was effective, i.e., from 1 July 2012 to 30 June 2014.

the tax. During the carbon tax prices increased by roughly 20 AUD/MWh for NSW, 32 AUD/MWh for QLD, 19 AUD/MWh for SA and 23 AUD/MWh for VIC.

This can be also seen in Figure 1 where we plot daily spot electricity prices for NSW and VIC for the entire sample period. The figure illustrates the typical extreme variation in spot electricity prices as well as a number of substantial price spikes. Note that for the purpose of illustration, in Figure 1 prices were capped at $200, while actually for both markets there were a number of occasions where average daily prices exceeded $1000.[8][9] The figure also illustrates the impact of the carbon tax on electricity prices: there is a clear shift in price levels for the period of the tax, while as indicated in Table 1, after the tax prices did not revert back to their average before-tax levels.

In Figure 2 we plot the emission intensities for the sample period for NSW and VIC. In particular for VIC, we observe a reduced level of emission intensities that has also been pointed out by O'Gorman and Jotzo (2014). For NSW the reduction is not that obvious, although overall emission levels during the carbon tax period also seem to be slightly lower. Table 2 provides additional information on emission intensities for the four markets for the entire sample period as well as

[8] Note that half-hourly prices exhibited even a higher degree of volatility and also more extreme observations up to ca. $12,500 in several of the regional markets.

[9] bluePrice Cap.

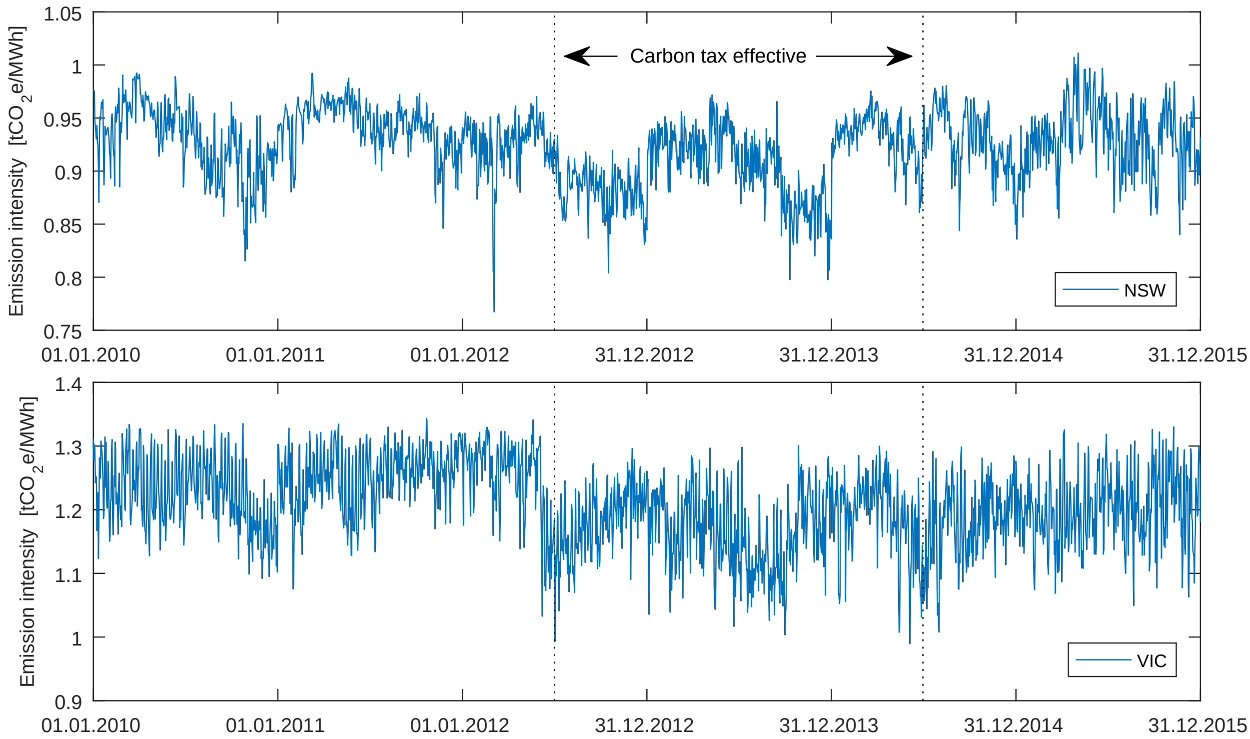

Figure 2: Daily emission intensities from 1 January 2010 to 31 December 2015 for NSW (*upper panel*) and VIC (*lower panel*). The dotted vertical lines indicate the period when the carbon tax was effective, i.e., from 1 July 2012 to 30 June 2014.

for the pre-tax, the carbon tax and the post-tax periods. We find that for all markets, apart from QLD, emission intensities were reduced during the carbon tax period in comparison to the pre-tax period. The most significant decrease can be observed for the markets in SA and VIC, where emission intensities were respectively reduced from 1.24 to 1.17 tCO_2e/MWh and from 0.61 to 0.50 tCO_2e/MWh. Interestingly, for QLD emission intensities were even slightly higher during the carbon tax period than before, while NSW also indicated a slight reduction from 0.93 to 0.91 tCO_2e/MWh. Overall, we observe a reduction in emission intensities of approximately 3.0% for NSW, 17.7% for SA and 5.4% for VIC. For the period after the abolishment of the tax, we observe that emission intensities reverted back almost to their pre-tax levels in NSW and to an even higher level in QLD. For VIC we observe a slight post-tax increase in emission intensities, while with 1.20 tCO_2e/MWh emission intensities are still lower than during the pre-tax period. Due to the substantial increase of renewable energy generation in SA, emission intensities remain at a relatively low level of 0.51 tCO_2e/MWh also for the post-tax period.

4.2. Ex-ante Forward Premiums

In a next step, we use quarterly futures contracts for the period 1 April 2008 – 31 March 2011 to determine ex-ante forward premiums in the considered markets. Hereby, we solve Eqn. (1) for $\pi^F_{t,[T_1,T_2]}$ in order to extract appropriate estimates of the ex-ante premiums. Thus, we compare simulated spot prices based on the calibrated models with actually observed futures quotes in the

Table 2: Descriptive statistics for emission intensities (in tCO_2e/MWh) in NSW, QLD, SA and VIC. Like in Table 1, the results are presented separately for the entire sample period (1 January 2010 – 31 December 2015), the considered period before the carbon tax (1 January 2010 – 30 June 2012), the carbon tax period (1 July 2012 – 30 June 2014), and the considered sample period after the carbon tax (1 July 2014 – 31 December 2015).

	Entire Period		Pre-Tax Period		Carbon Tax Period		Post-Tax Period	
	Mean	Std. Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
NSW	0.9238	0.0339	0.9342	0.0296	0.9058	0.0336	0.9305	0.0310
QLD	0.8336	0.0244	0.8272	0.0154	0.8300	0.0192	0.8492	0.0341
SA	0.5497	0.1313	0.6106	0.1062	0.5028	0.1183	0.5110	0.1448
VIC	1.2078	0.0654	1.2420	0.0553	1.1746	0.0614	1.1950	0.0583

Table 3: Mean (μ), standard deviation (σ) and skewness (skew) for daily spot electricity prices for Q1, Q2, Q3 and Q4 in NSW, QLD, SA and VIC for the whole sample period from 1 January 2010 to 31 December 2015.

	Q1			Q2			Q3			Q4		
	μ	σ	skew	μ	σ	skew	μ	σ	skew	μ	σ	skew
NSW	45.55	82.24	12.25	38.32	13.15	1.56	42.68	24.84	11.00	39.29	19.29	6.07
QLD	63.54	124.32	9.00	36.40	16.39	2.62	40.01	18.46	1.19	43.42	73.83	18.87
SA	53.45	148.25	11.88	47.63	43.50	6.02	50.75	30.21	2.80	42.44	42.64	11.19
VIC	40.95	65.14	11.57	39.79	55.05	20.89	40.60	18.10	4.83	36.40	33.92	15.33

markets for the time period before the introduction of the carbon tax. As described in Section 3.2, the expected average spot price at time t for delivery in period $[T_1, T_2]$, i.e., $\mathbb{E}_t(\bar{S}_{[T_1,T_2]})$, is determined based on the estimated seasonal pattern and 10,000 simulated trajectories of the stochastic component. Note that we use historical spot price data with a window length of 3-years (or 1095 days) prior to the first day of each month to calibrate the seasonal pattern and the stochastic models for the spot prices; we re-estimate the models on a monthly basis. Using these trajectories we then calculate the expected average spot price for each of the delivery quarters (defined by $[T_1, T_2]$) and estimate the ex-ante forward premium based on Eqn. (1).

Forward premiums for Australian electricity futures contracts show significant variations, depending on the considered quarters and regional markets (Handika and Trück, 2014a,b). For example, for all markets typically Q1 is the period that is characterized by the highest spot price levels and is also the most volatile. This is often a result of extreme temperature during the summer months in Australia. As illustrated in Table 3, we find that for all markets average spot prices during the sample period are typically higher and in particular far more volatile for Q1 in comparison to the other quarters. Given that in particular retailers and large customers use futures contracts to hedge against the risk of extreme price fluctuations in the spot market, the behaviour of electricity spot prices throughout the quarters also results in significant ex-ante forward risk premiums for the markets and quarters.

We estimate the premiums for each of the quarters and regional markets separately. Note that we calculate ex-ante forward premiums π^F at different times to delivery based on monthly median estimates of these premiums for futures contracts quoted between 1 April 2008 and 31 March 2011. The choice of the latter time interval is not arbitrary. On one hand, it is driven by the desire

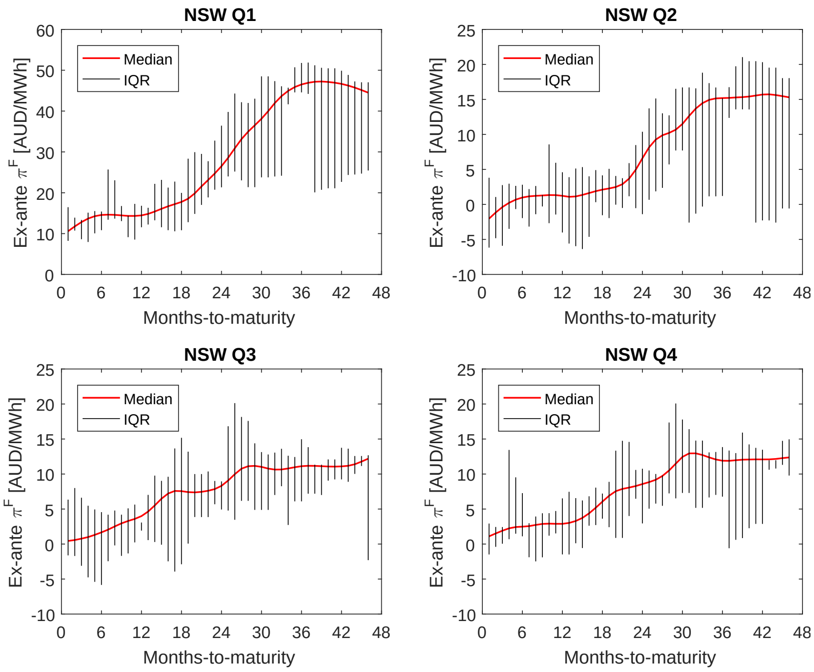

Figure 3: Smoothed ex-ante median forward risk premiums, π^F, for Q1 (*upper left panel*), Q2 (*upper right panel*), Q3 (*lower left panel*) and Q4 (*lower right panel*) contracts for the NSW market in the period 1 April 2008 – 31 March 2011. The vertical bars indicate the interquartile (IQR) range for each month-to-maturity.

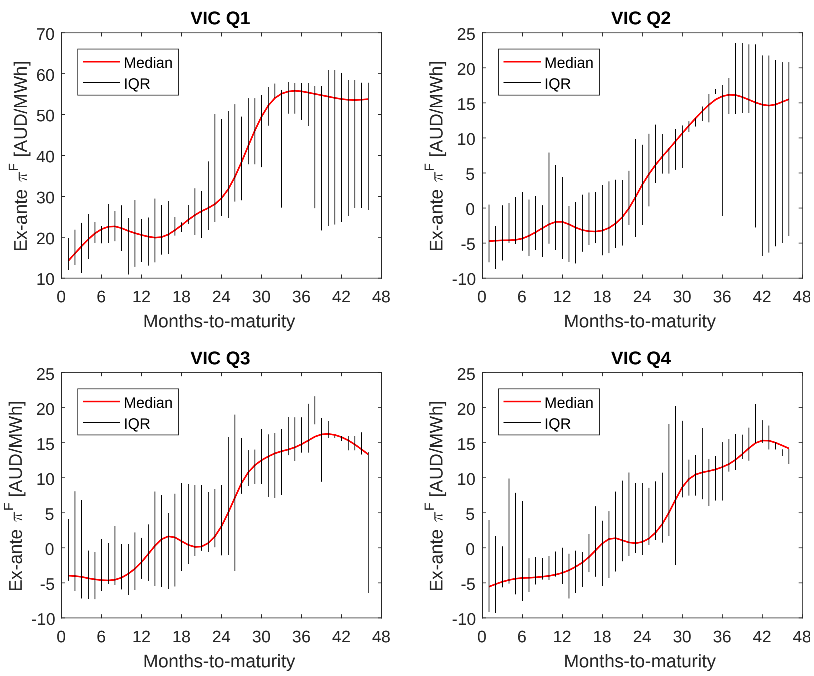

Figure 4: Smoothed ex-ante median forward risk premiums, π^F, for Q1 (*upper left panel*), Q2 (*upper right panel*), Q3 (*lower left panel*) and Q4 (*lower right panel*) contracts for the VIC market in the period 1 April 2008 – 31 March 2011. The vertical bars indicate the interquartile (IQR) range for each month-to-maturity.

Table 4: Emission intensities per MWh during the two financial years from June 2010 to July 2012 for each regional market and expected additional cost of electricity generation based on the introduced carbon tax.

Market	Emission Intensity per MWh	Cost 2012-2013 in AUD/MWh	Cost 2013-2014 in AUD/MWh	Cost 2014-2015 in AUD/MWh
NSW	0.944	21.71	22.80	23.98
QLD	0.836	19.23	20.19	21.23
SA	0.630	14.49	15.21	16.00
VIC	1.246	28.66	30.09	31.65

to use as recent data as possible (hence the lower limit of April 2008), on the other, the restriction not to use data from the period when the carbon tax was effective or very likely to become effective in the near future (hence the upper limit of March 2011; the final version of the *Clean Energy Bill* was released by the Labor government on 10 July 2011). For example, the ex-ante premium for the NSW Q1 contract 12 months prior to delivery is determined as the median of the estimated ex-ante premiums for three 12 months to delivery Q1 contracts: the Q1 2010 contract quoted for all business days in January 2009, the Q1 2011 contract quoted for all business days in January 2010, and the Q1 2012 contract quoted for all business days in January 2011. Note that we are using a monthly time grid, whereby all days in January are 12 months 'prior to delivery' in Q1 of the next year and all days in December are 1 month 'prior to delivery'. To eliminate noise in the term structure of the forward premiums we smooth the estimated premiums with a Hodrick and Prescott (1997) filter.

In Figure 3 we plot the estimated ex-ante forward premiums for the different quarterly contracts (Q1, Q2, Q3 and Q4) for NSW, while in Figure 4 the premiums for VIC. The vertical bars indicate the interquartile (IQR) range for each month-to-maturity, i.e., the interval spanned by the 25th and 75th percentiles of the premium distribution for a given month. Clearly, the obtained term structures of the forward premiums are increasing with time to maturity. More specifically, for the first 12-18 months-to-maturity the premiums are close to zero for all quarters but Q1, then they increase to 10-15 AUD/MWh for distant maturities (third and fourth year). For the first quarter, the shape is similar but the premiums are much higher – ca. 10-20 AUD/MWh for the first 12-18 months-to-maturity and ca. 45-55 AUD/MWh for 30-46 months-to-maturity. These results resemble the findings of Weron (2008) for the Nord Pool market, but contradict the results of Bierbrauer et al. (2007) and Benth et al. (2008) for the German EEX market where the term structure was rather downward sloping with time to maturity. Apparently, the forward premium may exhibit different dynamics depending on the characteristics of the market (as noted by Huisman and Kilic, 2012) and the behavior of market participants.

4.3. Carbon Premiums and Pass-Through Rates

We now compare the futures implied carbon pass-through costs to an expected price increase based on emission intensities for the four markets. In Table 4 we provide information on emission intensities per MWh of electricity generation for the two financial years from June 2010 to July 2012 (the two years preceding the carbon tax) for each of the regional markets as well as the expected additional costs of electricity generation based on the tax. Recall, that the price of carbon was determined to be 23 AUD/MWh for the period 1 July 2012 – 30 June 2013, 24.15 AUD/MWh for the period 1 July 2013 – 30 June 2014 and 25.40 AUD/MWh for the period 1 July 2014 – 30 June 2015. We find that in particular for VIC quite dramatic increases by more than 30 AUD/MWh in the costs of electricity generation could be expected due to the tax. Also for NSW and QLD the additional costs are above 20 AUD/MWh.

In a next step we then calculate the futures-implied carbon premiums. After estimating historical ex-ante forward premiums in futures contracts, we now apply Eqn. (3) to extract the carbon premiums for the considered markets. Hereby, we follow an approach that is quite similar to the one used for extracting ex-ante forward premiums. Thus, we simulate average 'expected' spot prices, i.e., $\mathbb{E}_t(\bar{S}_{[T_1,T_2]})$, under a no-carbon tax scenario for delivery period $[T_1, T_2]$, based on the applied model for the seasonal pattern and the stochastic dynamics of spot electricity prices. Futures quotes for the period of the carbon tax and the post-tax period are again obtained from the Australian Securities Exchange (ASX). The difference between observed futures quotes for the quarterly delivery periods and $\left\{\mathbb{E}_t(\bar{S}_{[T_1,T_2]}) + \pi^F_{t,[T_1,T_2]}\right\}$, i.e., the sum of the expected average spot price levels and the ex-ante forward premiums, then allows us to extract estimates for the additional carbon premium.

The premiums should be interpreted with the background of political developments regarding the tax between 2011 and 2014. The final version of the *Clean Energy Bill* was released by the Labor government on 10 July 2011. It passed the Australian House of Representatives on 12 October 2011 and the Australian Senate on 8 November 2011 and became effective on 1 July 2012. An interesting landmark was also that the next federal election was to be held in September 2013, while the opposition, i.e., the Liberal/National coalition, had promised to abolish the carbon tax once they got into power. From 2013 onwards, opinion polls suggested that there was a relatively high chance of this going to happen. The federal election took place on 7 September 2013 and the centre-right Liberal/National coalition was elected into power.

In Table 5 we provide the estimated market implied carbon premiums at seven different points in time, starting in April 2011 and ending in April 2014. The corresponding estimates for the implied carbon premiums for the other three markets QLD, SA and VIC are reported in the Appendix in Tables 6, 7 and 8, respectively. Our results suggest that in particular for April 2011 but also for October 2011, futures-implied carbon premiums are typically much lower than the expected cost increase due to the tax. For the NSW market, the estimated average carbon premium for Q3 2012 – Q2 2014 contracts on 1 April 2011 was only 2.36 AUD/MWh, while on 1 October 2011 it was as high as 12.52 AUD/MWh. This makes perfect sense, given that in these six months details on the intended CPM were confirmed by the Labor government and the introduction and first reading of the Bill had already been held at the House of Representatives. So by October 2011, the market had already included a carbon premium in electricity futures prices from Q3 2012 onwards. This becomes obvious, when comparing futures-implied premiums for contracts with delivery in 2011 and the first two quarters of 2012. The estimated carbon premiums for these quarters are typically close to zero, suggesting that no additional adjustment for a carbon price had occurred.

With regards to the magnitude of the expected pass-through costs of the carbon tax, recall that following Nazifi (2016), we define the *carbon pass-through rate* as the ratio of change in the price of electricity to the change in marginal costs due to the carbon tax. Effectively we can think of it as the proportion of higher costs incurred by consumers in the form of higher electricity prices

Table 5: Estimated market implied carbon premiums, i.e., $\pi^C_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \left\{E(\bar{S}_{[T_1,T_2]}) + \pi^F_{t,[T_1,T_2]}\right\}$, at seven time points ranging from 1 April 2011 to 1 April 2014 for available futures contracts from Q2 2011 to Q4 2015. Results are reported for the NSW market. The tax only became effective for Q3 2012, and was abolished in Q3 2014.

Contract	1.04.2011	3.10.2011	2.04.2012	1.10.2012	2.04.2013	1.10.2013	1.04.2014
Q2 2011	-1.65						
Q3 2011	-0.60						
Q4 2011	-1.24	-2.21					
Q1 2012	-1.62	-2.88					
Q2 2012	-1.75	-2.57	-2.50				
Q3 2012	2.60	15.16	21.80				
Q4 2012	3.71	13.76	20.23	26.19			
Q1 2013	-0.08	12.24	16.11	19.58			
Q2 2013	2.38	14.02	19.61	17.90	26.56		
Q3 2013	0.28	10.80	16.71	19.47	25.56		
Q4 2013	-1.43	10.66	16.35	18.83	23.70	21.48	
Q1 2014	6.09	15.67	9.68	15.48	17.35	15.04	
Q2 2014	5.30	7.84	13.42	21.49	24.65	25.49	22.66
Q3 2014	2.22	0.73	11.75	14.51	12.27	15.51	9.92
Q4 2014	1.75	1.07	8.54	14.51	12.65	12.18	4.32
Q1 2015	6.29	2.39	6.97	-7.06	3.44	1.59	-5.54
Q2 2015		3.27	3.43	5.08	9.04	10.70	5.61
Q3 2015		0.08	2.07	0.64	2.53	5.92	-0.47
Q4 2015			2.59	-1.85	0.89	4.27	-0.90

attributable to the carbon tax (Nelson et al., 2012; Sijm et al., 2012; Huisman and Kilic, 2015). We find that by October 2011, our estimated premiums would only suggest a price increase of ca. 55% of the expected additional costs based on emission intensities for NSW. This estimate is computed as the ratio of the mean carbon premium for futures contracts expiring in the carbon tax period (i.e., Q3 2012 to Q2 2014; see Table 5) to the mean emission intensity for NSW (see Table 4):

$$\frac{15.16 + 13.76 + 12.24 + 14.02 + 10.80 + 10.66 + 15.67 + 7.84}{21.71 + 22.80 + 23.98} = \frac{12.52}{22.83} \approx 55\%. \tag{8}$$

A possible explanation for these results is that the Bill had not passed the House of Representatives and the Senate yet.

Considering our results for 2 April 2012 and 1 October 2012, we find that carbon premiums for Q3 2012 – Q2 2014 futures contracts had further increased on these dates. The estimated average carbon premium on 2 April 2012 was 16.74 AUD/MWh, while on 1 October 2012 it had further increased to 19.85 AUD/MWh. At this stage, market quotes for futures contracts clearly included a significant portion of emission intensity based additional cost estimates. Our results would suggest expected pass-through rates of ca. 75% for 2 April 2012 and ca. 85% for 2 October 2012. Interesting results can also be observed for the Q3 2014 – Q4 2015 contracts on 2 April 2012. There is a clear tendency for a decline in futures implied premiums for contracts with later delivery periods: while for the Q3 2014 contract, we still observe an estimated carbon premium of 11.75 AUD/MWh, for the contracts referring to Q3 and Q4 2015 futures-implied premiums are less than 3 AUD/MWh based on our approach. Similar results can be observed on 2 October 2012: for Q3 and Q4 2014 contracts, premiums are still estimated to be greater than 14 AUD/MWh, while for Q3 and Q4 2015 contracts, we observe premiums around zero. These results most likely indicate market expectations on a possible repeal of the tax or at least a significantly lower price of carbon once an Australian emissions trading scheme was in place.

Our results for futures-implied carbon premiums change again, when considering the dates of 2 April 2013, 1 October 2013 and 1 April 2014. While carbon premiums for Q2 2013 – Q2 2014 contracts, the period when the tax was actually effective, are typically greater than 20 AUD/MWh (suggesting expected pass-through rates of ca. 95%), we observe a very different picture for contracts with delivery from Q3 2014 onwards. In April 2013, the Liberal/National coalition had a lead in the opinion polls and had promised to abolish the tax in case they were elected. We observe that this information is clearly reflected in the futures prices for contracts with longer maturities: on 2 April 2013 average carbon premiums for these contracts are only 6.80 AUD/MWh. Interestingly, even on 1 October 2013, i.e., after the election that had been won by the Liberal/National coalition, we still find positive carbon premiums for contracts with delivery in the post-tax period. This might still reflect some uncertainty about what was going to happen to the CPM in the near future even after the September 2013 election. However, in April 2014 market-implied carbon premiums for post-Q2 2014 contracts had dropped significantly, indicating that prices now reflected a strong belief in the abolishment of the tax by July 2014.

For the other regional markets we find a similar behavior with regards to the dynamics of initially increasing and later decreasing futures-implied carbon premiums, see Tables 6-8. Premiums and pass-through rates for Q2 2013 – Q2 2014 contracts were typically very low on 1 April 2011 and then increased significantly until 2 April 2013. At the same time, for contracts with delivery after the actual tax period, i.e., Q3 2014 – Q4 2015, estimated carbon premiums were always of significantly lower magnitude and typically approached values below 10 AUD/MWh once it became clear that the tax would be abolished by the new government.

However, we can also observe some less expected results with regards to the pass-through rates in these markets. For VIC, namely the market with the highest emission intensity of approximately 1.20 tCO_2e/MWh (see Table 4), we find that the futures-implied expected price increase for contracts with delivery during the carbon tax period was not as substantial as suggested by emission intensities. For the dates from 1 October 2012 to 1 April 2014 we observe forward-looking average carbon premiums of ca. 20 AUD/MWh, i.e., expected carbon pass-through rates of only 65%. This suggests overall significantly lower pass-through for VIC than for NSW. On the same dates, for QLD (emission intensities of ca. 0.83 tCO_2e/MWh) we find average forward-looking carbon premiums of ca. 27 AUD/MWh for contracts with delivery during the tax period, while for SA (the market with the lowest emission intensity of ca. 0.55 tCO_2e/MWh) the average expected carbon premium is almost 22 AUD/MWh. These figures relate to expected average pass-through rates of 133% for QLD and 142% for SA, based on futures quotes for contracts with delivery during the tax period. Therefore, our results suggest that expected carbon pass-through rates seemed to be inversely related to emission intensities and were relatively low for the market with the highest emission intensity (VIC), while they were the highest for the market with the lowest emission intensities (SA). At the same time, expected pass-through rates seemed to be positively related to average price levels, since VIC typically exhibited the lowest wholesale prices during the sample

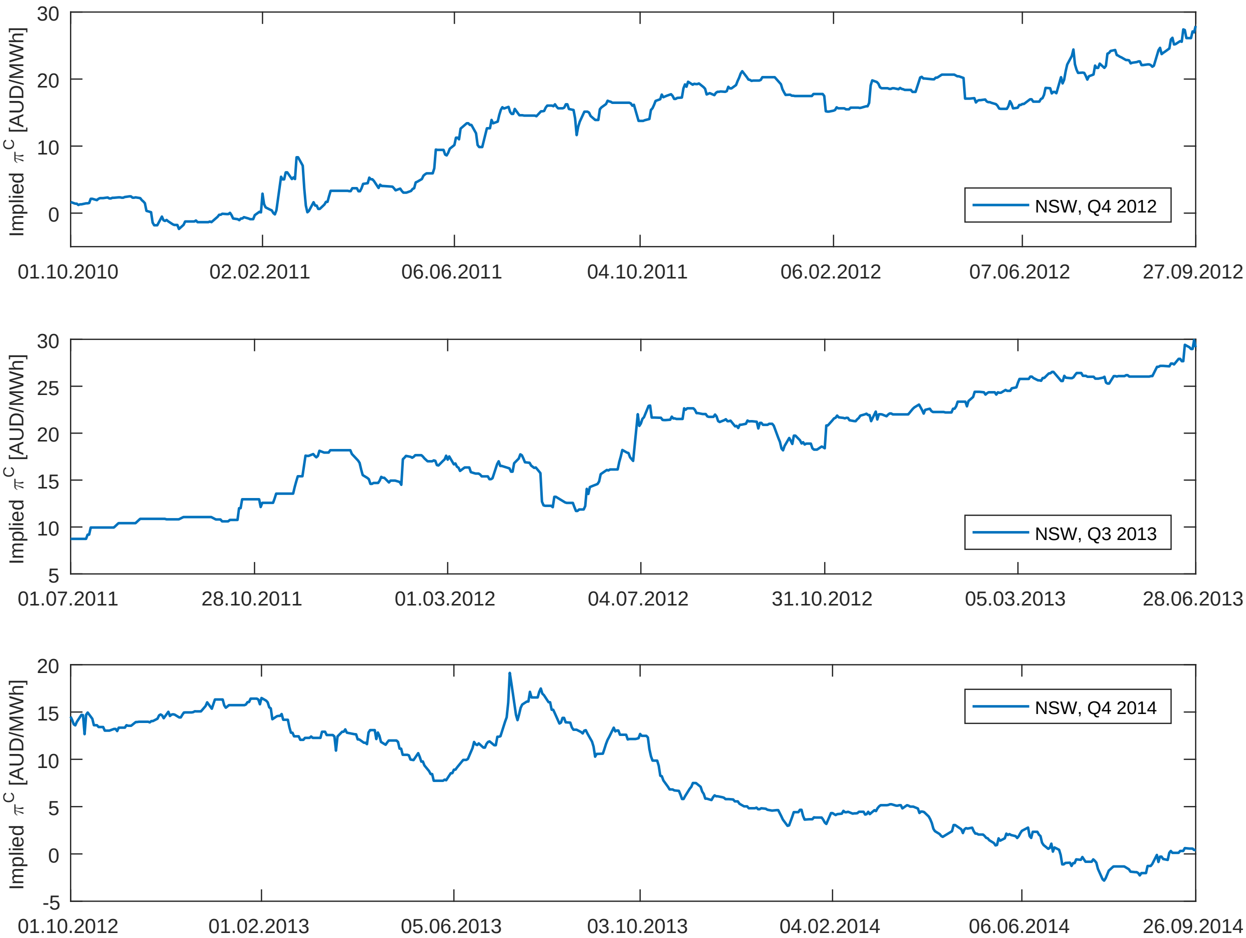

Figure 5: Implied carbon risk premium for Q4 2012 futures contract from 1 October 2010 to 27 September 2012 (*upper panel*), Q3 2013 futures contract from 1 July 2011 to 28 June 2013 (*middle panel*) and Q4 2014 futures contract from 1 October 2012 to 26 September 2014 (*lower panel*) for the NSW market.

period, and SA the highest price levels.

4.4. The Dynamics of Carbon Premiums

To further investigate the dynamic process of futures-implied carbon premiums, in Figure 5 we plot the market-implied carbon premiums extracted from three futures contracts: Q4 2012 from 1 October 2010 to 27 September 2012, Q3 2013 from 1 July 2011 to 28 June 2013, and Q4 2014 from 1 October 2012 to 26 September 2014. Note that for each contract a two-year time frame before the beginning of the delivery period is examined.

Let us first consider the results for the Q4 2012 futures contract (upper panel in Fig. 5) that illustrates a clear upward trend in the futures-implied carbon premium from around zero up to nearly 28 AUD/MWh just before the beginning of the delivery period. In 2010 the Labor government had brought forward the notion of introducing a CPM, however had not proposed the Clean Energy Act yet. According to our results the Q4 2012 futures contract does not indicate a mark-up for this tax before April 2011. However, between April 2011 and November 2011 we find a continuous

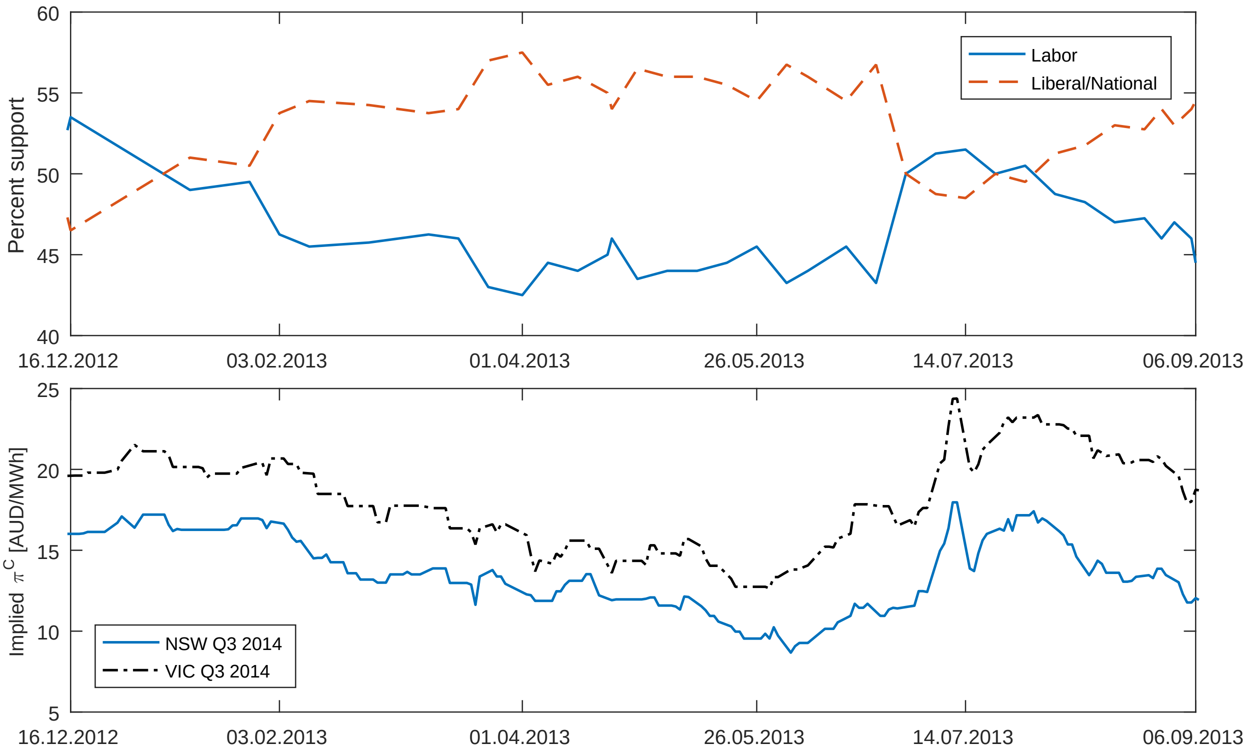

Figure 6: Results for opinion polls (*upper panel*) and implied carbon risk premiums, π^C, for Q3 2014 futures contracts in NSW and VIC (*lower panel*) for the time period 16 December 2012 – 6 September 2013. Note that the implied carbon risk premiums to a large extent mimic the support for the then ruling government (i.e., the Labor party).

increase in the carbon premium from around 4 AUD/MWh up to a level of almost 20 AUD/MWh. Interestingly, we find a second period of increase in the premium up to 28 AUD/MWh once the tax became effective in July 2012. This may also be a result of an increase in wholesale spot electricity prices in NSW during Q3 2012 that was actually far higher than the emission intensity based estimate of 22 AUD/MWh.

The Q3 2013 contract (middle panel in Fig. 5) shows a very different pattern. Note that the contract was hardly traded between July and September 2011 such that the implied carbon premium remains relatively constant for this period. However, given that the notion of a CPM had been published by the government already, we observe a carbon premium of approximately 10 AUD/MWh for this time period. In October-November 2011 the implied carbon premium hikes to 18 AUD/MWh, once the bill passes the Lower and the Upper house. Interestingly, after this event, the premium drops to a level of 15 AUD/MWh in late January 2012 and then to 12 AUD/MWh in May 2012. However, similar to the Q4 2012 contract, once the tax became effective in July 2012 and spot prices in NSW increased substantially, also the carbon premium rose back to a level of almost 23 AUD/MWh, more or less reflecting the expected additional costs based on the emission intensities for the NSW market, see Table 4.

Now let us consider the lower panel in Figure 5 that refers to the contract with maturity in December 2014. Implied carbon premiums for this contract are particularly interesting, since they may be driven by expectations about the outcome of the federal election in September 2013.

From the beginning of 2013, opinion polls drifted towards a majority for the Liberal/National coalition that had promised to abolish the tax once they were elected, see the top panel in Fig. 6. Interestingly, the controversial carbon tax was actually one of the key topics determining the election campaign of the Liberal/National coalition. By 22 June 2013, opinion polls suggested that 42% would vote for the Labor party, while 58% preferred the Coalition to take over the government. This tendency is also clearly reflected in the dynamics of the futures-implied carbon premium. From an initial value of 15 AUD/MWh, the premium drops continuously to a level of ca. 7-8 AUD/MWh by early June.

In a last effort to turn the polls, on 26 June 2013 the Labor party decided to replace Prime Minister Gillard with former Labor Prime Minister Kevin Rudd, since it was believed that Rudd had a much better chance to win the election for the Labor party. Opinion polls suggested a possible swing towards Labor with a preference of 48% Labor vs. 52% Coalition on 27 June 2013 and even 51% Labor vs. 49% Coalition on 5 July 2013. However, in the end, the swing did not last very long and Labor lost the election on 7 September 2013. The new Coalition government then decided to abolish the Carbon Tax with the effect of Q3 2014.

The political situation, i.e., the probability of an abolishment of the tax (Coalition) against a continuation of the scheme also in 2014-2015 (Labor), is clearly reflected in the carbon premium dynamics for the Q3 2014 contract. As illustrated in Figure 6, once the opinion polls started to change during the second half of June 2013, also the implied premium increased again up to a level of 15-18 AUD/MWh. However, when it became clear that most likely the Labor government would be replaced, the premium quickly dropped back to a level of ca. 12 AUD/MWh; the dynamics of the carbon premiums in VIC was nearly identical, only the levels were 3-5 AUD/MWh higher. After the election, starting in October 2013, we see another rather rapid decline to a level of below 5 AUD/MWh in NSW, see the lower panel in Fig. 5. Finally, from then on the premium keeps declining until it reaches a value very close to zero just before the delivery period of the contract.

5. Conclusions

In this paper we have examined carbon premiums and pass-through rates in the Australian National Electricity Market (NEM) during the pre-tax, carbon tax (July 2012 – July 2014) and post-tax periods. We have developed a novel framework which consists of computing ex-ante forward risk premiums in the pre-tax period using state-of-the-art econometric techniques for modeling and forecasting electricity spot prices (Hodrick-Prescott filter based trend-seasonal pattern, Markov regime-switching driven stochastic component), then using them to derive market-implied carbon premiums in the carbon tax and post-tax periods.

We have found the obtained term structures of the forward premiums to be increasing with time to maturity: initially 10-20 AUD/MWh (for the first, most spiky quarter of the year) or close to zero (for quarters 2-4), then increasing respectively to 45-55 AUD/MWh or 10-15 AUD/MWh for distant maturities (third and fourth year). Interestingly, these results resemble the findings for the Nord Pool market, but contradict the results for the German EEX market where the term structure was rather downward sloping with time to maturity. Apparently, the forward premium may exhibit different dynamics depending on the characteristics of the market and the behavior of market participants.

Using futures prices instead of spot prices has allowed us to take a forward-looking approach, and to thoroughly examine the impact of key policy events on observed carbon premiums in the electricity markets. Hereby, we have analyzed the impact of announcements about the introduction of the tax, opinion polls on upcoming federal election, as well as the actual change of the federal government that was accompanied by the promise to repeal the tax. Our results clearly indicate the impact of political news on the carbon premiums. We find that the market reacted relatively quickly to the passing of the *Clean Energy Bill* by the Labor government in July 2011. Even more striking is the inclusion of news about opinion polls for the 2013 Australian federal election with regards to the existing Labor government vs. the Liberal/National opposition.

Finally, having derived the carbon premiums and given the approximate emission intensities of generation in the considered regional markets, we have been able to compute carbon pass-through rates. During the period where market participants could be relatively certain that the tax would be effective, we have found expected carbon pass-through rates to be between 65% and 140%. Interestingly, they seem to be inversely related to emission intensities – they are relatively low for the market with the highest emission intensity (VIC) and the highest for the market with the lowest emission intensities (SA). At the same time, they seem to be positively related to average price levels, since VIC typically exhibited the lowest wholesale prices during the sample period, and SA the highest price levels.

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Appendix: Observed Carbon Premiums in the States of QLD, SA and VIC

Table 6: Estimated market implied carbon premiums, i.e., $\pi^{C}_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \left\{E(\bar{S}_{[T_1,T_2]}) + \pi^{F}_{t,[T_1,T_2]}\right\}$, at seven time points ranging from 1 April 2011 to 1 April 2014 for available futures contracts from Q2 2011 to Q4 2015. Results are reported for the QLD market. The tax only became effective for Q3 2012, and was abolished in Q3 2014.

Contract	1.04.2011	3.10.2011	2.04.2012	1.10.2012	2.04.2013	1.10.2013	1.04.2014
Q2 2011	-0.12						
Q3 2011	-0.02						
Q3 2011	-2.49	-0.75					
Q1 2012	-2.44	-2.60					
Q2 2011	0.81	4.00	3.23				
Q3 2012	4.05	21.03	24.32				
Q4 2012	1.49	18.61	20.28	32.77			
Q1 2013	1.75	18.50	19.73	26.16			
Q2 2013	7.06	21.20	24.13	30.09	26.32		
Q3 2013	4.23	19.25	21.53	30.60	31.63		
Q4 2013	0.69	17.08	18.13	26.07	25.45	32.05	
Q1 2014	7.51	22.05	14.34	25.54	21.19	26.93	
Q2 2014	8.13	10.09	13.46	29.28	27.46	32.64	21.56
Q3 2014	1.70	4.35	15.8	22.29	18.80	22.06	11.29
Q4 2014	2.05	3.86	10.20	18.73	14.08	18.66	7.71
Q1 2015	7.72	9.16	19.93	3.10	6.54	16.47	7.27
Q2 2015		9.60	15.56	8.94	10.44	18.68	11.05
Q3 2015		4.98	7.35	2.87	5.15	13.96	6.37
Q4 2015			8.36	2.44	2.02	10.70	4.19

Table 7: Estimated market implied carbon premiums, i.e., $\pi^{C}_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \left\{E(\bar{S}_{[T_1,T_2]}) + \pi^{F}_{t,[T_1,T_2]}\right\}$, at seven time points ranging from 1 April 2011 to 1 April 2014 for available futures contracts from Q2 2011 to Q4 2015. Results are reported for the SA market. The tax only became effective for Q3 2012, and was abolished in Q3 2014.

Contract	1.04.2011	3.10.2011	2.04.2012	1.10.2012	2.04.2013	1.10.2013	1.04.2014
Q2 2011	1.12						
Q3 2011	-3.93						
Q4 2011	-7.91	-16.04					
Q1 2012	-16.84	-13.56					
Q2 2012	-6.56	-2.13	-15.09				
Q3 2012	-10.49	14.27	14.27				
Q4 2012	-5.48	15.30	13.49	4.20			
Q1 2013	0.54	-0.43	0.40	-9.78			
Q2 2013	9.47	17.10	17.23	30.35	38.22		
Q3 2013	10.45	1.99	7.91	31.83	41.66		
Q4 2013	8.84	-3.75	5.74	9.76	23.17	2.44	
Q1 2014	7.08	6.29	4.05	5.93	2.18	-1.03	
Q2 2014	7.31	4.14	2.31	17.58	39.51	43.38	29.89
Q3 2014	10.49	6.43	14.67	16.65	28.63	31.30	23.88
Q4 2014	10.63	12.2	11.79	7.74	14.49	12.14	4.44
Q1 2015	3.41	7.83	11.26	8.47	-2.24	1.08	-17.14
Q2 2015		8.52	8.64	16.41	7.38	22.25	18.12
Q3 2015		16.38	12.07	12.42	3.62	11.44	11.75
Q4 2015			5.87	21.29	1.94	6.19	0.25

Table 8: Estimated market implied carbon premiums, i.e., $\pi^C_{t,[T_1,T_2]} = F_{t,[T_1,T_2]} - \left\{E(\bar{S}_{[T_1,T_2]}) + \pi^F_{t,[T_1,T_2]}\right\}$, at seven time points ranging from 1 April 2011 to 1 April 2014 for available futures contracts from Q2 2011 to Q4 2015. Results are reported for the VIC market. The tax only became effective for Q3 2012, and was abolished in Q3 2014.

Contract	1.04.2011	3.10.2011	2.04.2012	1.10.2012	2.04.2013	1.10.2013	1.04.2014
Q2 2011	1.03						
Q3 2011	-0.03						
Q4 2011	-0.04	1.09					
Q1 2012	-9.15	-3.79					
Q2 2012	-0.66	1.97	2.22				
Q3 2012	4.01	19.97	25.37				
Q4 2012	4.57	19.71	24.56	29.53			
Q1 2013	-2.11	9.34	11.73	13.43			
Q2 2013	0.28	18.52	22.83	26.97	26.40		
Q3 2013	2.19	17.73	19.32	27.06	28.32		
Q4 2013	0.92	12.17	19.56	24.19	27.02	28.20	
Q1 2014	4.08	18.10	9.50	10.55	11.92	12.83	
Q2 2014	9.32	14.35	14.84	25.35	26.38	31.44	26.51
Q3 2014	0.29	3.62	9.89	19.17	15.93	21.40	14.38
Q4 2014	-1.08	3.67	11.88	18.03	15.14	15.68	9.88
Q1 2015	5.22	6.36	7.66	-4.29	-0.01	1.18	-9.23
Q2 2015		11.79	12.18	8.42	12.08	15.27	7.65
Q3 2015		3.54	2.39	-1.27	0.97	11.49	3.64
Q4 2015			1.49	-0.83	0.61	10.25	2.81