Price and Volatility Spillovers in Australian Electricity Markets

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Summary

Electricity markets are significantly more volatile than other comparable financial or commodity markets. Extreme price outcomes, typically referred to as price spikes, as well as periods of substantial price volatility and their transmission between interconnected regional markets pose significant risks for market participants.

This study investigates spillover effects for electricity spot prices across different regions in the Australian National Electricity Market (NEM), aiming to provide a better understanding of price and volatility dynamics in a multi-regional context. This pioneering study is established in the econometric framework developed by Diebold and Yilmaz (2009, 2012), originally applied to equity markets. The research methodology is based on forecast error variance decomposition of vector autoregressive (VAR) models. We conduct both static and dynamic analyses to assess the systemically aggregated spillovers and their directional decomposition between regions. Using daily electricity spot market data from 2010 to 2015, we find that although spillover effects play an important role in the NEM, regional prices are still mostly influenced by local factors. In particular, greater spillover effects are observed between physically interconnected markets. Among all regions in the NEM, South Australia (SA) transmits the most net spillovers to others, while New South Wales (NSW) is the most significant net spillover receiver. The spillover effects show time-varying and event-dependent patterns.

Our findings provide insights to market participants for the development of cross-regional trading or risk management strategies in the Australian NEM. As the Australian Energy Regulator considers building new interconnectors to facilitate regional market integration, our findings regarding connectedness of regional markets through the applied spillover measures also provide important quantitative information to NEM policy makers.

Matlab and R code and the data used in the thesis can be provided upon request.

Statement

I, **LIN HAN**, certify that the work in this thesis entitled **'Price and Volatility Spillovers in Australian Electricity Markets'** has not been submitted for a higher degree to any university or institution other than Macquarie University.

I also certify that the thesis is an original piece of research and it has been written by me. Any help and assistance that I have received in my research have been acknowledged.

In addition, I certify that all information sources and literature used are indicated in the thesis.

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Chapter 1

Introduction

This study empirically assesses spillover effects in electricity spot prices and volatilities across regional markets in the Australian National Electricity Market (NEM). The aim is to provide a better understanding of electricity spot price dynamics in a multi-regional context.

Due to the non-storable nature of electricity, electricity markets are usually considered to be significantly more volatile than other comparable financial or commodity markets. Extreme price outcomes, typically referred to as price spikes, and periods of substantial price volatility are major sources of risks for electricity market participants. For example, The Australian Financial Review (Potter, 2016) reported that recently in July 2016, there were complaints from business about the extreme electricity prices in South Australia. Whereas the normal price levels are below $100 per megawatt hour (MWh), the spot prices frequently jumped above $1000 per MWh in that month, and even hit $14,000 per MWh at one point. ABC News (2016) reported that this highly volatile price period has cost South Australia $42 million. Interestingly, during this period also significant price spillover effects to the connected electricity market in Victoria could be observed. A more extreme situation was observed on 28 September 2016, when South Australia experienced a complete blackout of the state due to extreme weather events. The electricity spot prices jumped to and stayed at higher than $10,000 per MWh for several hours.

In a multi-regional context where electricity can be transmitted across different regions through interconnections, the spillovers of prices and volatilities are of great concern. By definition, spillovers are the effects that shocks or crises in one region have on another region through external links (Pesaran and Pick, 2007). A large part contained of the price and volatility spillovers is the transmission of those extreme price outcomes and substantial price volatilities. The analysis of these effects is important, especially for businesses that simultaneously operate in several electricity markets, since the probability of joint price spikes imposes significant risk on them.

This study focuses on the Australian NEM, which differs from the electricity markets in other countries and continents as a nationally interconnected system with strong linkages between regions. It comprises five state-based regional markets: New South Wales (NSW), Queensland (QLD), South Australia (SA), Tasmania (TAS) and Victoria (VIC) (Australian Energy Regulator, 2015). Wholesale trading in the NEM is conducted in a spot market where electricity supply and demand are matched in real time through a centrally-coordinated dispatch process. This process determines a market price for each region, which is known as the spot price. The NEM participants trade electricity at the spot prices and often protect themselves from spot price movements by entering into hedge contracts. In addition, electricity can be transmitted across different regions within the NEM through so-called interconnectors, which are high-voltage transmission lines between adjacent regional markets. This allows electricity to be imported from a low price region to a high price region.

The assessment of the spillover effects in electricity prices and price volatilities can be particularly important for the Australian NEM for two reasons. Firstly, electricity spot prices are even more volatile and spiky in the Australian NEM than in other comparable electricity markets partially due to the interconnection and electricity transmission (Higgs and Worthington, 2008a; Mayer and Trück, 2015). A better knowledge of the periodic price spikes and high volatility and their spillovers in this market is therefore of significance. Secondly, although the Australian NEM aims to provide a single integrated market with similar electricity prices across different states (Australian Energy Market Commission, 2013), so far the different regions in the NEM are still considered to be relatively isolated, which is reflected by the sizeable price differences across regions (Higgs, 2009; Ignatieva and Trück, 2016; Nepal et al., 2016). Stakeholders have raised one concern about the potential problem of underinvestment in interconnectors (Productivity Commission, 2013; Garnaut, 2011; Ignatieva and Trück, 2016; Nepal et al., 2016), although the Productivity Commission (2013) argues that new investment in interconnectors at the current stage is not cost efficient. In this context, there is a strong incentive for regulators to seek more evidence of the current market integration level, and to evaluate the efficiency of existing market interconnections and the potential of the NEM to achieve integration. According to Ciarreta and Zarraga (2015), spillover effects in prices and price volatilities are required features for market integration. Thus, from this perspective, the spillover analysis in the NEM is again of great interest.

The worldwide restructuring and deregulation of electricity markets since the 1990s have fostered a small but rapidly growing literature on spot price modelling in electricity markets, including univariate studies which investigate the intra-relationship of spot prices within each region (e.g. Bessembinder and Lemmon, 2002; Higgs and Worthington, 2005, 2008a; Janczura et al., 2013; Lucia and Schwartz, 2002), and multivariate studies which consider the inter-relationship of prices among different regions. However, to date the analyses of electricity price dynamics in a multivariate context are still limited. These studies typically include two groups: long-run interregional relationship and short-run relationship analyses. Cointegration analyses are normally employed in long-run relationship analyses (e.g. Apergis et al., 2016; De Menezes and Houllier, 2014; De Vany and Walls, 1999a; Dempster et al., 2008; Nepal et al., 2016; Zachmann, 2008). These analyses focus on revealing long-term trends in, for example, market integration and price convergence, and are usually inadequate to capture the time-varying dynamics. Short-run relationship analyses typically consider the time path of innovation or volatility transmission in electricity prices. The generalised autoregressive conditional heteroskedasticity (GARCH) type models are most popular in these analyses, especially when considering volatility spillovers (e.g. Ciarreta and Zarraga, 2015; Higgs, 2009; Higgs et al., 2015; Worthington et al., 2005), given that electricity prices are usually characterised by persistence and volatility clustering (Higgs and Worthington, 2008b)[1]. Vector autoregressive (VAR) models together with impulse response functions and forecast error variance decompositions are also widely used for analysing electricity price dynamics within an interconnected system (e.g. De Vany and Walls, 1999b; Le Pen and Sévi, 2010; Park et al., 2006). These techniques based on VAR models are also the foundation of the spillover analysis in this study. There are other methods which have been applied in recent studies, focusing on particular features or phenomena, such as tail dependence, in electricity price dynamics, for example, copulas (Aderounmu and Wolff, 2014a,b; Ignatieva and Trück, 2016; Smith, 2015; Smith et al., 2012) and multivariate point process model (Clements et al., 2015). This study builds on and extends the existing work of Aderounmu and Wolff (2014a,b), Clements et al. (2015), Higgs (2009) and Ignatieva and Trück (2016) by providing a more detailed analysis of the price and volatility spillover effects in the Australian NEM with more recent evidence.

Our analysis is based on the following research questions. Firstly, in general, the previous literature focuses more on testing the existence of the spillover effects or price interdependence across different electricity markets, while the detailed pattern of these effects is missing. This motivates us to examine electricity price and price volatility spillovers in more details: in particular, what are the degrees of price and volatility spillover effects in the Australian NEM; what are the directions of the spillovers between the regional markets; are certain markets transmitting or receiving more price or volatility spillovers? Secondly, Higgs (2009) and Ignatieva and Trück (2016) suggest that the level of the interdependence between regional prices varies over time. Meanwhile, in recent years significant events have taken place in the Australian NEM,

[1] Multivariate GARCH methods might have disadvantages in practice since they sometimes suffer from convergence problems (i.e. when more variables are included the model may not converge, especially when the number of variables is more than three) (Hassan and Malik, 2007).

including long-run evolution and short-run or mid-run events. For example, a carbon taxation system was established in 2012 and removed in 2014; the whole electricity industry is moving towards renewable energy generation; the NEM is under an ongoing reform aiming for a more integrated and efficient market (Productivity Commission, 2013); and electricity markets are usually significantly influenced by events such as extreme weather and technical issues in generation and networks. These facts motivate us to examine whether the level of various spillovers is changing in nature and, if so, how the time variation in spillover effects can be related to market structure or specific events (seasonality, regulatory changes, extreme weather, etc.) in the NEM. Thirdly, although the periodic occurrence of price spikes and the substantial price volatility in electricity markets are highly interrelated, the spillover effects in these two market properties can be different (see Worthington et al., 2005). As argued by Diebold and Yilmaz (2009), the divergent spillover patterns of different market properties can be due to the fact that they capture different information in the considered market. This motivates us to investigate whether there is any divergence in the degree and the time-varying pattern between price spillovers and volatility spillovers in the NEM.

A major novelty of this study is that we employ a relatively new econometric framework (Diebold and Yilmaz, 2009, 2012) to analyse the nature of spillover effects across regional markets in the NEM. This framework combines the elements of long-run and short-run interregional relationship analyses. Based on forecast error variance decompositions in a vector autoregressive (VAR) model, this framework allows us to quantify pairwise spillovers between two regions, gross directional spillovers from/to each region, net directional spillovers from each market, and the system-wide aggregated spillover index over a certain time horizon. By using a rolling-window technique, the applied analysis can monitor different types of spillovers at varying points in time.

In practice, the Diebold and Yilmaz (2009, 2012) method (hereafter, DY method) has three main advantages in examining price and volatility spillovers across regional electricity markets. Firstly, the nature of the DY method is similar and closely related to impulse response function analysis which is widely used to explore time-paths of shock transmissions across an economic system (see e.g. De Vany and Walls, 1999b; Park et al., 2006). However, compared with the standard application of impulse function analysis, the DY spillover measures have the advantage that they can be easily aggregated so that the overall level of spillover effects in the whole system can be estimated and monitored. Secondly, the DY method is superior in analysing the directional spillover flows across markets. Compared with some structural models, it can conveniently provide such information without having to conduct a priori analysis on the relative importance of all considered markets or to select particular independent variables beforehand (Conefrey and Cronin, 2015). Thirdly, this method is also advantageous in capturing the time variations of spillovers. It produces a continuously time-varying index, allowing the spillover effects to be tractable without having to pre-specify a series of breakpoints (for example, the peak/off-peak state in electricity markets specified in Bollino and Polinori (2008) and De Vany and Walls (1999a,b)).

To the best of our knowledge, this framework has never been used to examine the dynamics of electricity prices across different regions. Therefore, the successful application of the DY method to other financial markets such as equity, bond and foreign exchange markets in assessing spillover effects (e.g. Allen et al., 2014a,b; Antonakakis and Vergos, 2013; Claeys and Vašíček, 2014; Cronin, 2014; Maghyereh et al., 2015; McMillan and Speight, 2010; Narayan et al., 2014; Sugimoto et al., 2014) motivates us to test the approach for electricity markets as well.

We investigate price and volatility spillover effects in all five regional electricity markets in the Australian NEM, namely, NSW, QLD, SA, TAS and VIC. We investigate both market aggregated spillovers and directional spillovers for specific markets. Both static and dynamic analyses are conducted. By using daily electricity price and price volatility data from 1 January 2010 to 31 December 2015, we cover the periods before, during and after the implementation of an important policy – the carbon taxation policy between July 2012 and July 2014 – and we are able to assess the evolution of the spillover effects in these three stages.

Our findings suggest that although spillover effects play an important role in electricity price formulation in the NEM, regional prices are still mostly influenced by local factors. Among the five regions in the NEM, SA is the most influential market, while NSW is the most dependent on others. On the other hand, the magnitude and directions of those spillover effects all exhibit time variations. A large part of these time variations could be related to events in the NEM. In addition, the patterns of price and volatility spillovers are influenced by the physical interconnecting structure of the NEM. More spillovers can be observed where physical interconnections exist. Furthermore, divergent behaviour can be observed between price and volatility spillovers. Finally, our findings are robust when separate assessments are conducted for sub-periods with regard to the introduction and repeal of the Australian carbon taxation policy. All results are also relatively robust to the choice of model specification.

Overall, our results contribute to the existing literature in three ways. First, we conduct a pioneer study by applying the DY spillover method to electricity spot markets. By doing this we test the usefulness of this approach for electricity markets. Our results suggest that this method can efficiently capture the price dynamics across wholesale electricity markets. Second, we provide a deep analysis of price and volatility spillover effects in the Australian NEM, including detailed patterns of these effects, such as magnitude, directions and time variations. Finally, by using more recent data, our results add important empirical evidence to the limited multivariate studies in the Australian electricity market. In particular, we provide important evidence on the impacts of the recent introduction and abolishment of the carbon taxation system on spillover effects in the NEM, which has not been documented in the literature yet.

From a practical perspective, our results provide important information for participants in the NEM who are concerned about the extreme outcomes and high volatility periods of spot prices and the transmission of these events across regions. For example, retailers who are operating simultaneously in several different regions have to take spillover effects into consideration when making risk management and hedging decisions. Our results are also of great interest to electricity traders and so-called merchant interconnectors who earn revenue by making purchases in a lower-priced region and selling electricity to a higher-priced region, because the price differences and joint price behaviours between regions are highly relevant to their revenue. Furthermore, our results also provide important information for regulators who aim to evaluate the current market interconnection, systemic risks as a result of extreme events in a singular or multiple markets, and the potential of the NEM to achieve integration.

The rest of this thesis is structured as follows. Chapter 2 reviews the related literature. Chapter 3 provides a description of the Australian NEM, including its institutional background and some stylised facts regarding electricity spot prices. Chapter 4 introduces our methodological framework, while Chapter 5 summarises the properties of the data used in this study. Empirical findings are provided in Chapter 6. These include the results of both static and dynamic spillover analyses, as well as the robustness assessment of the results to different sub-periods and choice of model specifications. Finally, Chapter 7 concludes and discusses possible directions for future research.

Chapter 2

Literature Review

This chapter provides an overview of the existing literature related to this research, including multivariate studies[2] of electricity markets (Section 2.1) and literature on our major methodological framework: Diebold and Yilmaz's (DY) (2009, 2012) spillover method (Section 2.2).

2.1 Multivariate Analysis in Electricity Markets

Although this study focuses on the spillover effects in Australian electricity markets, more international studies have been conducted in this field, mostly based on the United States (US) and European electricity markets. Therefore, the evidence in the international context and in the Australian context is separately discussed in Section 2.1.1 and Section 2.1.2.

[2] Univariate analyses in electricity markets generally aim to model or forecast prices in a single market. The key issue in these studies is to deal with the unique features (stylised facts) of electricity prices and the own spillovers. These are discussed in Chapter 3, Section 3.3.

2.1.1 Literature in the International Context

The multivariate studies of electricity markets are roughly divided into two streams. The first stream focuses on the long-term market trend, while the second stream investigates short-term price interactions between markets.

In the first stream, De Vany and Walls (1999a) were the first to study the pricing transmission in decentralised electricity markets. The authors examine the joint behaviour of daily electricity spot prices in 11 regional spot markets in the western US from 1994 to 1996. By testing the price series for cointegration, the existence of arbitrage opportunities, and the equivalence in expectation, they find evidence of a highly integrated and efficient wholesale power market. On the other hand, contrary to De Vany and Walls (1999a), based on the Granger causality test and cointegration analysis results on an extended data set from 1994 to 1999 in the same markets, Dempster et al. (2008) suggest only a moderate degree of market integration.

Zachmann (2008) studies the integration of European electricity markets by analysing both static market integration levels and dynamic market convergence, accounting for the congestion and congestion management effects. The Principle Component Analysis results reject the existence of a single integrated market. However, using a Kalman filter, the author finds pairwise price convergence between several countries after considering congestion costs. More recently, De Menezes and Houllier (2014) reassess the European electricity market integration using both daily spot prices and month-ahead prices. They test the price convergence and conduct a time-varying fractional cointegration analysis. In particular, the authors argue that the prevalent unit root tests are not adequate for assessing convergence of electricity spot prices, which are fractionally integrated and mean-reverting.

In the second stream, De Vany and Walls (1999b) use impulse-response analysis and variance decompositions based on a VAR model to estimate the price dynamics in a network composed of five regional markets in the western US. They find that during off-peak periods, a larger proportion of price shocks can be absorbed locally, and only a small proportion of shocks are transmitted to other regions through the market interconnection. However, during peak periods, a large proportion of price shocks will propagate to other markets due to the limited local generation capacity. Later, Park et al. (2006) use the similar techniques based on the VAR model to analyse the transmission of price dynamics across the US national electricity markets. In an approach different to De Vany and Walls (1999b) who employ an unrestricted VAR model, Park et al. (2006) use an acyclic graphical method to impose identifying restrictions on VAR innovations. Their results suggest that the interrelationship between markets varies across time. Although the western US markets are separated from the other markets in contemporaneous time, in a longer time horizon (1 day or 30 days), the separation disappears, and regional prices become interdependent.

In the European context, Haldrup and Nielsen (2006) examine the dynamics of electricity price and price interdependence between pairs of regional markets in the Nordic countries by developing a Markov switching fractional integration model. They find that bilateral prices are identical during some periods but are divergent during other periods. Thus, they argue that a regime switching model is effective in forecasting relative prices based on Monte Carlo forecasting. Furthermore, Bollino and Polinori (2008) conduct a contagion analysis of regional electricity markets in Italy. They identify contagion effects in those markets and conclude that contagion and price interdependence can be identified separately.

Le Pen and Sévi (2010) use data from electricity forward markets to estimate a VAR-BEKK (Baba, Engle, Kraft and Kroner) model. They show the return and volatility spillovers in three major European electricity markets: Germany, the Netherlands, and the UK. The authors also investigate the impact of shocks on volatilities in each market by quantifying the impact through volatility impulse response functions. They find significant but short-lived positive impacts only when a shock has a large size compared to the current volatility level. Ciarreta and Zarraga (2015) use multivariate Generalised Autoregressive Conditional Heteroscedasticity (MGARCH) models to investigate mean and volatility spillovers of electricity prices between six European countries (Spain, Portugal, Austria, Germany, Switzerland and France). They find significant mean and volatility spillovers as well as increasing price convergence between each pair of countries except between Spain and France, and between Germany and France, and thus conclude that the considered markets are in a process of market integration. In addition, De Menezes and Houllier (2015) investigate the influence of the recently higher penetration of wind power in electricity generation (in particular, in Germany) on interconnected European markets. This study conducts both short-run and long-run interrelationship analyses to investigate changes in the market integration level. Two MGARCH models are used in the short-run analysis and a fractional cointegration method is used in the long-run analysis. Their results illustrate that greater price and volatility transmission can be observed in the short-run due to the market interconnection; however, in the long-run higher wind power penetration in Germany tends to make it less integrated with its neighbouring markets.

2.1.2 Literature in the Australian Context

In the Australian context, more studies focus on modelling short-term price and volatility dynamics in electricity markets. For example, Worthington et al. (2005) employ a MGARCH model to investigate the daily electricity spot price transmission and price volatility spillover in five regional markets (NSW, QLD, SA, SNO[3] and VIC) in the Australian NEM. Their results suggest insignificant price transmission across these markets. However, significant volatility spillovers are present in all five markets, indicating that shocks in one market have an influence on price volatility in other markets. This study is extended by Higgs (2009) by further assessing the effects of interregional electricity price volatility spillovers through three conditional correlation MGARCH models. Higgs (2009) finds significant positive conditional correlations between all pairs of regional markets. These correlations are strongest between interconnected

[3] SNO denotes the Snowy regional market in the NEM, which was abolished on 1 January 2008. Its electricity demand was then redistributed between NSW and VIC (Australian Energy Regulator, 2015).

markets.

Instead of examining volatility transmissions, several more recent studies conduct analyses on the interdependence of electricity prices. A number of studies have proposed the employment of copula models to measure the nonlinearity in multivariate electricity price modelling. In particular, Smith et al. (2012) construct a skew t copula to capture electricity spot price dependence. Their analysis of Australian electricity market integration suggests strong nonlinear price dependence between different regional markets. They show that the skew t copula coupled with Bayesian inference constructs a powerful model for this dependence. Smith (2015) employs a vine copula model to estimate the high level of nonlinear serial and cross-sectional price interdependence in the NEM. Aderounmu and Wolff (2014a,b) use copulas and the so-called tail dependence coefficient (TDC) to show significant dependence of price spikes in the NEM. Ignatieva and Trück (2016) employ a group of copula models to analyse price dependence structure in the NEM. They find a positive dependence structure between each pair of regions, while prices between well-connected markets exhibit the strongest dependence. They also show that copula mixture models are superior in capturing asymmetric tail dependence. Manner et al. (2016) propose a copula-based multivariate dynamic binary choice model to estimate and forecast joint spikes in the NEM. Dynamic spillover effects are evidenced through this model. Furthermore, Clements et al. (2015) model price spikes simultaneously in several interconnected regions in the NEM with a multivariate point process. They find transmissions of spikes across regions, which are proven to be influenced by interconnector capacities.

From the long-run market integration perspective, Nepal et al. (2016) employ pairwise unit root tests, a Johansen cointegration test, and time-varying coefficient estimations to examine the market integration level. Overall, the results suggest that the Australian NEM has not achieved full integration. Furthermore, Apergis et al. (2016) test the price convergence across states in Australia with a clustering group approach, including all five regions in the NEM as well as the Western Australia (WA) market. They find three groups: NSW, QLD and VIC; SA; and TAS and WA. According to

Apergis et al. (2016), the electricity generation mix and ownership structure of electricity generation are important factors that contribute to the separation of these three groups.

2.1.3 Electricity Market Interconnections in the Literature

Noticeably, while analysing market interdependence, various studies have emphasised the important role of market interconnections (i.e. physical interconnections of power lines between regions and their capacity). Some studies illustrate that the interconnector capacity is a key factor that influences the degree of market integration. Haldrup and Nielsen (2006) find that with the existence or absence of bottlenecks in network transmission, the electricity price behaviours in single markets are different. Micola and Bunn (2007) analyse the role of interconnector congestion in the split of local energy spot markets. They suggest that a threshold of interconnector capacity deployment exists. The interconnected local markets split after this threshold is reached. By analysing the data from the Bacton (the United Kingdom) to Zeebrugge (Belgium) natural gas pipeline, they find an increasing and convex relationship between the interconnector capacity utilisation and the market split level. In the Australian NEM, Nepal et al. (2016) illustrate that the limitation of transmission capacities of interconnectors prevents the overall market integration. Higgs (2009), Ignatieva and Trück (2016) and Smith (2015) find stronger electricity price interdependence between physically well-connected markets and weaker interdependence between markets that are not so well-connected. Higgs (2009) argues that interconnected markets in the NEM are integrated and informationally efficient, while it is unreasonable to expect markets that are geographically distant and isolated to become integrated.

In addition, several studies assess the influence of market interconnections on the specific patterns of electricity price dynamics. As highlighted in De Menezes and Houllier (2015), although higher electricity market integration and efficiency level can be achieved through market interconnection, when prices are positively correlated, the overall price volatility is higher than the sum of volatilities in every individual market. It means that higher price risks from the interconnections are imposed on market participants. Furthermore, Füss et al. (2015) theoretically show the important implication of different allocation mechanisms for cross-border transmission capacity for pricing in interconnected electricity markets. A fundamental multi-market model is developed to price the electricity spot and derivatives. Through this model, the authors show how the set-ups for cross-border trades impact the key stylised facts of electricity spot prices, such as price spikes and high price volatility. Finally, Clements et al. (2015) illustrate the significant impacts of interconnector capacities on the size of price spikes and thus the spillover effects of these spikes in interconnected regional electricity markets.

2.2 Diebold and Yilmaz's (DY) (2009, 2012) Spillover Measure

Our major methodological framework in this study is formed based on the spillover method of Diebold and Yilmaz (2009, 2012). The DY method provides several spillover measures, allowing us to conduct detailed analyses on the transmission of price and volatility in the Australian NEM.

2.2.1 Development and Advancements of the DY Framework

The DY measure was firstly developed in 2009 based on the forecast error variance decompositions from a vector autoregressive (VAR) model that was originally introduced by Sims (1980). Diebold and Yilmaz (2009) apply this measure to 19 global equity markets and assess the return and volatility spillovers in these markets. Their study shows divergent behaviour in return and volatility spillovers. Return spillovers display a gently upward trend, which is, as explained by Diebold and Yilmaz (2009), associated with the increasing integration level of the global financial markets. In comparison, volatility spillovers are more eventful than return spillovers, with bursts during crisis episodes, but display no trends.

Despite the efficiency of the DY method (2009) in analysing the aggregated market spillover effects, Diebold and Yilmaz (2012) and Gaspar (2012) point out that it has two main limitations. Firstly, its VAR variance decomposition relies on the Cholesky-factor identification which is dependent on variable ordering. The results generated with this method are thus sensitive to variable ordering by nature. Therefore, the application of this version (2009) requires a priori analysis on the comparative influential power of the considered variables. Secondly, the original version of the DY method only addresses the measure of total market spillovers, while in practice it might be of more significance to look at directional spillovers (spillovers from and to a particular market).

To address the two limitations above, Diebold and Yilmaz (2012) propose an improved spillover measure based on a generalised variance decomposition (GVD) framework that was introduced by Koop et al. (1996) and Pesaran and Shin (1998). The new method is invariant to the variable ordering and introduces the concept of directional spillovers, which can be used to analyse the transmission flow of spillovers without a priori identification of the relative importance of markets. Diebold and Yilmaz (2012) apply this new version of the DY method to assess the volatility transmission among four asset classes: stocks, bonds, commodities and foreign exchange. Further, Diebold and Yilmaz (2014) show that by combining it with network theories, the DY method can provide a variety of information on market connectedness.

In addition, to address the sensitivity of the original DY measure (2009) to variable ordering, Klößner and Wagner (2012, 2014) introduce another improvement. They develop an algorithm for fast calculation of the spillover index. Based on this algorithm all possible ordering can be explored, and the minimum and maximum values of the spillover index can be computed. Klößner and Wagner (2012) use this algorithm to assess the robustness of the DY measure (2009). They suggest that the aggregated spillover index is relatively robust; however, its decompositions (i.e. directional spillovers) are severely impacted by reorderings of the input variables.

In this study, identifying the directions of spillovers across the five regions in the NEM and the relative influencing power of these regions is one of the major research objectives. Therefore, the order-invariant version of the spillover measure (Diebold and Yilmaz, 2012) is more appropriate.

2.2.2 Application of the DY Framework

Although the DY (2009, 2012) framework is proposed to be appropriate for assessing spillover effects in any market, its application so far is limited mainly to equity, bond and foreign exchange markets (e.g. Allen et al., 2014a,b; Antonakakis and Vergos, 2013; Claeys and Vašíček, 2014; Cronin, 2014; Maghyereh et al., 2015; McMillan and Speight, 2010; Narayan et al., 2014; Sugimoto et al., 2014). The DY method is commonly used to investigate the transmission of shocks among different markets or asset classes. It provides implications on portfolio construction and risk management in financial markets. For example, Maghyereh et al. (2015) investigate equity return and volatility spillovers between the US and the Middle East and North African markets. They use the DY method to evaluate the diversification potential of the Middle East and North African equities before and after the global financial crisis in 2008. Allen et al. (2014b), in their analysis of volatility spillover from a group of Australia's trading partners to Australia's stock market, apply the DY model as a preliminary analysis for a further GARCH analysis. In particular, they first use the DY method to identify the two most influential markets (the US and Hong Kong). Next, they fit the data from these two markets and Australia into a GARCH framework. In addition, the DY method is able to generate a variety of time series data that measure dynamic spillover levels. Krause et al. (2014) use these time series as the dependent variable in Fama and MacBeth (1973) regressions, while Lau and Bilgin (2013) use the time series of an aggregated spillover index as an independent variable in the GARCH specification. Lau and Bilgin (2013) and Tokat and Tokat (2010) suggest that including a volatility spillover measure into the conditional variance equation in the GARCH model can help investors improve the hedging strategy in currency markets.

A few studies apply the DY measure in energy commodity markets. The DY framework based on structural VAR variance decompositions is used for oil markets in Antonakakis et al. (2014) and Kang et al. (2014). Rather than using Cholesky decomposition or GVD, they conduct variance decomposition by separating three types of structural oil price shocks. Zhang and Wang (2014) apply the DY (2012) method to show the bi-directional and asymmetric patterns in return and volatility spillovers between China and global oil markets. Their dynamic spillover analysis further illustrates the intensified influence of China's oil market on others in recent years. Furthermore, in the study of Baruník et al. (2015), the DY method is extended to detect and measure the spillover asymmetries (spillovers due to negative returns and positive returns) in petroleum markets. They use five-minute data and point out that when the focus of interest is the price movements (in their study, positive and negative returns), high-frequency data can be more informative for the analysis of the transmission mechanism. Finally, only one study (Jaeck and Lautier, 2015) has employed the DY framework to investigate the electricity derivative markets. The study analyses the volatility spillovers across electricity futures with different maturities.

However, to the best of our knowledge, the DY method has not been applied to analyse either electricity spot prices or the interrelationship between regional electricity markets.

2.3 Summary of Literature Review

In summary, Chapter 2 presents the rationale of this study in the context of the literature. There are limited multivariate studies focusing on electricity spot markets, especially in the Australian NEM. Furthermore, the existing literature focuses more on testing the existence of the spillover effects, while the specific pattern of these effects is missing. A detailed assessment of the spillovers in the NEM can therefore add important empirical evidence in this field. In particular, given the important role of electricity market interconnections in a multi-regional context, their impacts on price and volatility spillovers should be evaluated.

In addition, the DY method, which is efficient in capturing spillovers and connectedness in financial markets, has yet to be applied in a multivariate context in electricity spot markets. This encourages an assessment of the efficiency of the DY method in electricity markets.

Chapter 3

The Australian National Electricity Market

Because of the non-storable nature of electricity, electricity markets have a strong demand and supply relationship, resulting in special features, namely, seasonality, mean-reversion and short-lived spikes in electricity prices (Bessembinder and Lemmon, 2002; Kaminski, 2004). These stylised facts have to be considered in modelling electricity spot prices and price dynamics. Meanwhile, since the institutional set-ups have important influence on the formulation of electricity prices (Füss et al., 2015; Park et al., 2006), understanding the market mechanisms is significant in analysing electricity markets' interrelationship. Therefore, this chapter provides an overview of the structure and operation mechanism of the Australian NEM (Sections 3.1 and 3.2), as well as stylised facts of electricity prices (Section 3.3). The aim is to build a foundation for the following spillover analysis. Furthermore, the role of an important policy in Australia in recent years, the carbon taxation policy, is also discussed.

3.1 Overview of the NEM

The Australian NEM began operating as a wholesale market in December 1998 (Australian Energy Regulator, 2015). Prior to it, the electricity market in Australia was separated, with each state operating its own vertically integrated state-owned business for electricity generation, transmission and distribution. Electricity prices were determined by state government regulations in order to cover costs with any required return for the government. With the aim of increasing the market efficiency of the electricity industry, the Australian government commenced the reform in the 1990s to restructure the electricity market in three ways. Firstly, it separated the supply industry into generation, transmission, retail and distribution segments. Secondly, while transmission and distribution segments remained in a regulated monopoly, competition was introduced to the generation and retail markets. Private participants could enter the competitive generation and retail markets, and customers could choose their retail suppliers. Thirdly, the states' power systems were extended to be interconnected to form a national electricity wholesale market.

The following sections introduce the current characteristics of the NEM, including the structure, generation, spot pricing, interregional trade and market interconnection issues.

3.1.1 Structure of the NEM

The NEM operates one of the longest interconnected power systems in the world, covering 4,500 kilometres, and supplying electricity for five states which are NSW, QLD, SA, VIC and TAS (Australian Energy Regulator, 2015). Networks in each state are linked to others via interconnecting transmission lines. This nationally interconnected grid provides electricity supply to retailers and end-users.

The NEM differs significantly from other commodity markets since electricity is non-storable and indistinguishable according to its generator or consumer. Because of these features, the NEM uses a pool where the electricity output from all generators can be centrally pooled and scheduled to meet the forecasted demand. The Australian Energy Market Operator (AEMO) manages this pool, following the National Electricity Rules.

3.1.2 Spot Pricing

Unlike many other markets in the US and Europe (ACER (Agency for the Cooperation of Energy Regulators), 2013; Ciarreta and Zarraga, 2012; Füss et al., 2015), the electricity spot market in Australia is not a day-ahead market. Instead, supply and demand for electricity are matched in real time through a centrally-coordinated dispatch process (Australian Energy Regulator, 2015). Generators submit bids every five minutes, specifying the amount and the price they offer. AEMO then determines the generators to produce electricity to meet the forecasted demand based on a least-cost optimisation. Thus, generators with lower marginal costs will be given priority when scheduling a dispatch. Every five minutes AEMO determines a dispatch price for each region. The final half-hourly electricity spot price is the average of six dispatch prices. Similarly, a daily average spot price can be calculated based on the half-hourly prices[4]. Remarkably, although all of the supply of electricity is centrally pooled to meet the demand, spot prices are determined separately for each region after considering transmission loss factors and interconnector capacities, and therefore can vary significantly in different regions.

[4] Unlike electricity markets in many European countries (see ACER (Agency for the Cooperation of Energy Regulators), 2013; Ciarreta and Zarraga, 2012; Füss et al., 2015), the Australian NEM is an 'energy only' market where spot prices are 'energy only' without any price component for capacity. Namely, the NEM does not comprise a separate capacity market. In theory, this market mechanism leads to efficient generation and spot market pricing (Nepal et al., 2016).

3.1.3 Electricity Generation

The generation of electricity in the Australian NEM predominantly relies on fossil fuels, such as coal and gas. For example, in 2015, about 88% of the overall electricity generation were from fossil fuels, with around 76% from black and brown coal and 12% from gas (Australian Energy Regulator, 2015). However, encouraged by the government policies due to concerns regarding climate changes and energy generation independence, the source of electricity generation in the NEM is moderately transferring from fossil fuels to renewables. For example, the share of coal generation dropped by approximately 6% from 2010 to 2015, while on the other hand, the share of renewable energy increased from 9.6% to 12% (Clean Energy Council, 2011, 2015). In particular, hydropower and wind power represented the largest shares of the renewable generations in the NEM (40.1% and 33.7%) in 2015 (Clean Energy Council, 2015). Other renewable energy sources include solar, bioenergy and geothermal.

In reference to energy use by region, VIC, NSW and QLD rely more heavily on coal generation than other regions. On the other hand, TAS and SA have larger shares of renewable energy generation. In 2015, 99.9% of TAS's generation and 43% SA's generation came from renewable energy (Clean Energy Council, 2015). In particular, the majority of the TAS generation is hydroelectric, while the penetration of wind generation is especially strong in SA (Clean Energy Council, 2015). As suggested by Higgs et al. (2015), the type of generation has a strong impact on both electricity prices and price volatilities.

3.2 Interconnectors and Interregional Trade

The NEM allows electricity to be traded across different regions. In fact, a key objective of the continuing reform of the Australian NEM is to provide a nationally integrated electricity market with efficient delivery of network services and electricity infrastructure, limiting the market power of generators in each regional market (Productivity Commission, 2013). This is supported by interconnectors, which are the physical transmission lines connecting adjacent regions. The following sections introduce the role of these interconnectors in the NEM and discuss the current issues related to them.

3.2.1 Role of Interconnectors in Interregional Trade

On the one hand, those physical interconnections between regions facilitate market integration (Nepal and Jamasb, 2012) and promote competition in electricity wholesale markets, especially in a concentrated market with limited market participants. Specifically, electricity is imported into one region through the interconnectors when the output of local generators is insufficient to meet demand, or when the electricity price in the adjoining market is low enough to replace the local supply. Optimally, if the market operates efficiently, prices align across regions, with the difference only to account for physical transmission losses during the delivery of electricity (Australian Energy Regulator, 2015).

On the other hand, the efficient scheduling of generators to meet demand across different regions is limited by the physical transfer capacity of interconnectors (Australian Energy Regulator, 2015). When the interconnector is constrained (the limit of its capacity is reached), AEMO has to schedule a more expensive generator from within a region to meet the local demand, even if electricity supply with a lower price is available in another region. This results in substantial price differences between two regions, as well as extreme price outcomes in high demand areas, indicating the isolation of two markets. In addition, in the presence of transmission congestion, the higher spot price encourages strategic bidding behaviour by those generators constrained by interconnector capacity (Productivity Commission, 2013). These strategic biddings lead to further inefficient market generation and regional spot pricing.

The importance of interconnectors and interregional electricity transmission is evidenced by the recent extreme price scenarios in SA in July 2016. Those extreme spot prices and high price volatilities are partially due to the planned outage of a main interconnector (Heywood) between VIC and SA (Uhlmann, 2016). They also had a spillover effect to the VIC market, where periods of relatively high price volatility were observed[5]. In addition, in the recent blackout in SA at the end of September 2016, the failure of interconnectors between SA and VIC which cut off SA's supply from VIC is also a main contributing factor to this event (Charis, 2016). The important role of interconnectors is also evidenced by another recent event related to the outage of the interconnector between VIC and TAS (Basslink). Basslink went down on December 20, 2015, which isolated TAS from the NEM[6]. As a result, electricity spot prices in TAS spiked 400% from a normal level of around $40 per MWh to higher than $200 per MWh. These high prices were maintained over four months (Australian Energy Market Operator, 2016).

3.2.2 Interconnectors in the NEM

As shown in Figure 3.1, currently there are six interconnectors linking five jurisdictions in the NEM: QNI and Terranora between NSW and QLD, Heywood and Murraylink between VIC and SA, VIC-NSW interconnector between NSW and VIC, and Basslink between VIC and TAS. Notably, no direct interconnections exist between NSW and SA or between QLD and SA.

Except for Basslink between VIC and TAS, all of these interconnectors operate

[5] Those periods of high volatility in VIC include, for example, most half-hourly intervals on July 6 and July 7 (Australian Energy Market Operator, 2016).
[6] Basslink interconnector was back in operation in June 2016.

as regulated interconnectors. A regulated interconnector receives fixed revenue determined by the regulator based on the asset's value. The actual interconnector usage is not considered in calculating this revenue. In comparison, an unregulated interconnector, which is also called a market network service provider or merchant interconnector, derives revenue by participating in interregional trades in the spot market (Australian Energy Regulator, 2015). Therefore, the analysis of price difference and spillover effects between regions is especially of interest for unregulated interconnectors.

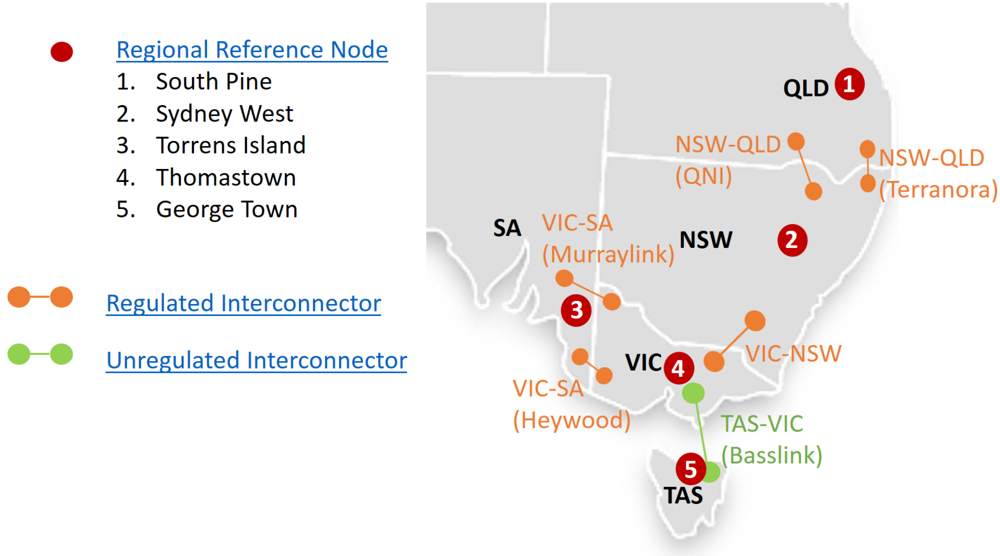


Figure 3.1: Interconnectors in the NEM (Australian Energy Regulator, 2015). Regulated interconnectors are interconnectors that have passed the Australian Competition and Consumer Commission (ACCC)-devised regulatory and add net market value to the NEM. Unregulated interconnectors do not undergo regulatory test.

3.2.3 Investigation of the Use of Interconnectors

Figure 3.2 illustrates the quarterly interregional trade as a percentage of regional electricity consumption. For the period considered in this study (January 2010 to December 2015), with only four exceptions out of 120 datapoints, the percentage of interregional trade for each region is limited below 30% (in absolute value). Most of these percentages are below 20%. Among the five states, NSW and SA typically import electricity, while QLD and VIC are typically electricity exporters. For TAS, the trade position fluctuates depending on the market and weather conditions (Australian Energy Regulator, 2015).

Overall, electricity generation from interstate trades still represents a relatively small fraction of the overall market generation. Accordingly, there is a concern about underinvestment in interconnectors in the Australian NEM (Productivity Commission, 2013; Garnaut, 2011). This potential underinvestment problem is reflected by the substantial price differences between regions, and the occurrence of unnecessarily high price outcomes. In particular, Nepal et al. (2016) investigate the use of the interconnectors in the NEM, and their hypothesis test results show that the existing interconnector capacities are not underutilised. The results, together with the isolated regional markets in the NEM, suggest the existence of significant transmission constraints (or bottlenecks) in all interconnectors. Nepal et al. (2016) thus propose more investments in the current interconnector capacities and new interconnectors.

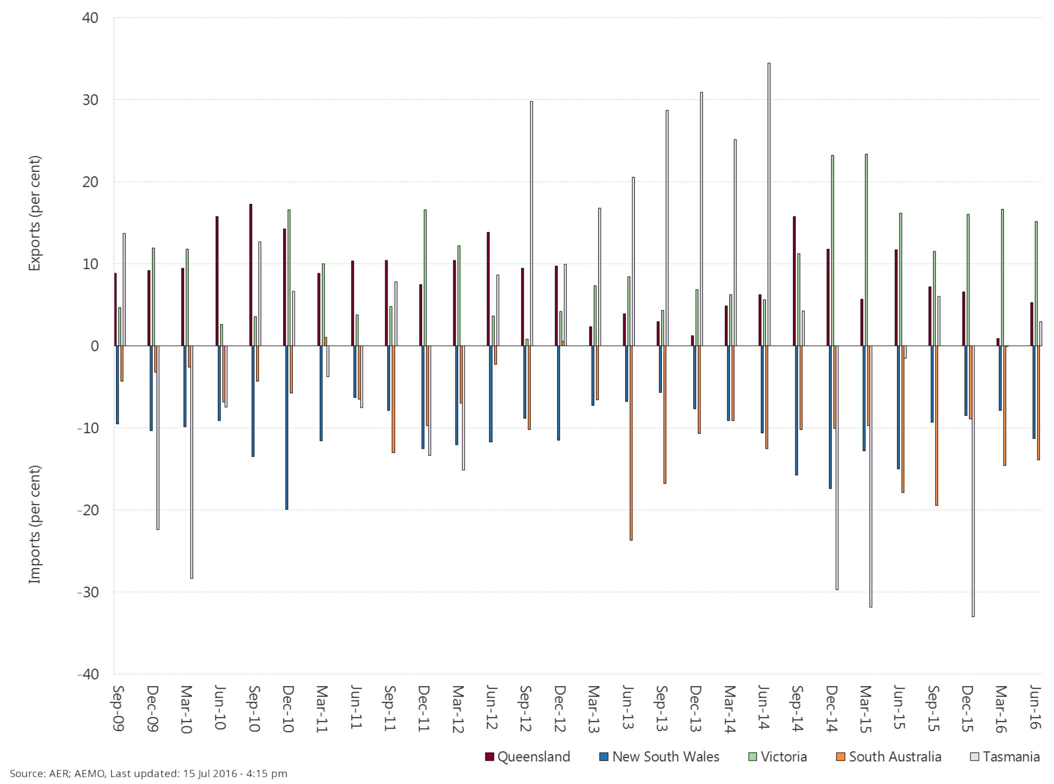


Figure 3.2: Quarterly interregional trade as a percentage of regional electricity consumption from July 2009 to June 2016 (Australian Energy Regulator, 2016)

3.3 Stylized Facts of Electricity Prices

Because of its non-storability, electricity has to be consumed when it is produced. This means that the electricity to be distributed in a particular time horizon is not substitutable for power that is available shortly before or after that time (Weron, 2006). This pushes the demand and supply balance in electricity markets to a knife-edge; namely, the electricity demand is highly inelastic. Even small changes in electricity load and generation may result in substantial changes in spot prices. In addition to the tight electricity demand and supply relationship, there are various factors (including seasonal factors and extraordinary events) imposing significant influences on the load of electricity. As a result, electricity prices can be far more volatile than prices in other commodity markets. In particular, three well-documented stylised facts, seasonality, mean-reversion and short-lived spikes, contribute to those high volatilities, which are discussed in this section.

3.3.1 Seasonality

Seasonality in electricity prices is stronger than in any other commodity market. This seasonal component is mainly driven by cyclical fluctuations in electricity demands (Kaminski, 2004; Pilipovic, 2007). These fluctuations correspond to changes in climate conditions and business or household activities such as working hours. Accordingly, different cycles (daily, weekly and yearly) can be observed in electricity prices. For example, electricity prices tend to be higher during summer and winter or weekdays which are usually high demand periods.

Given the significance of the seasonal component, a number of studies (e.g. Clements et al., 2015; Hadsell et al., 2004; Higgs et al., 2015; Higgs and Worthington, 2005; Koopman et al., 2007; Lucia and Schwartz, 2002) choose either to include seasonal factors in modelling electricity prices, or to remove the seasonality (Aderounmu and Wolff, 2014a,b; Ignatieva and Trück, 2016) before further analysing the stochastic part of electricity prices. Typical techniques for removing the seasonal component from electricity prices include differencing, moving average, spectral decomposition, the rolling volatility technique and wavelet decomposition (Weron, 2006).

3.3.2 Mean-Reversion

In a mean-reversion process, the value of a variable is always brought back to the equilibrium level. The stronger the mean-reversion effect is, the faster the variable returns when deviating from the equilibrium. Mean-reversion can be observed in most financial markets. However, this effect generally appears to be much stronger in electricity markets than in most other markets (Weron, 2006). In storable commodity markets, such as oil and gas markets, the mean-reversion process is usually related to annual cycles in supply and demand or economic cycles, which can take months or even years. In comparison, in electricity markets, it is common to observe extreme price values followed by fast reversion to the previous levels (Benth et al., 2008; Pilipovic, 2007). For example, when there is an increase in electricity demand due to extreme weather conditions, more expensive generators enter the pool on the supply side and push up the spot prices. As soon as the weather conditions and electricity demand return to normal afterwards (usually within several hours or days), those expensive generators leave the pool and the prices fall. This market operating mechanism, together with the multiple cyclical demand-drivers, results in the significant mean-reversion effect in electricity spot prices.

3.3.3 Price Spikes

Another pronounced feature of the electricity market is known as price spikes, referring to those infrequent, short-lived, and generally unanticipated extreme outcomes of spot prices. Within a period of as little as one hour, the electricity price can increase tenfold and then fall back to the previous level. As suggested by Bessembinder and Lemmon

(2002), price spikes reflect a convex relationship between demand and supply cost in the electricity market. Thus, during those unexpected high demand periods, there is a substantial increase in the marginal cost of electricity generators. In contrast, on some rare occasions, because of the non-storable nature of electricity, when electricity demand is reduced, generators fail to adjust to the new demand level due to operating costs or generation constraints. Consequently, negative prices spikes can be observed (see Fanone et al., 2013).

In the Australian NEM, electricity prices are even more volatile and spiky than other comparable markets (Higgs and Worthington, 2008a; Mayer and Trück, 2015). The current market price cap that limits the highest possible electricity spot price is \$13,800 per MWh (Australian Energy Regulator, 2015). The regional spot price has been close to or reached the market price cap on several occasions (e.g. extreme prices in SA in July 2016). Furthermore, the price dependence between regions in the NEM is especially strong for those price spikes (Aderounmu and Wolff, 2014a,b; Ignatieva and Trück, 2016; Smith et al., 2012).

Given the important role of price spikes in any electricity market, a number of studies have applied various techniques to deal with them in the analysis of electricity prices. For example, some authors use fixed or variable price and price change thresholds to identify spikes (Bierbrauer et al., 2004; Fanone et al., 2013; Trück et al., 2007; Weron, 2008), while others employ wavelet decomposition to filter out the extreme values (Stevenson et al., 2001, 2006). Furthermore, Green et al. (2014) and Schmidt (2008) use a generalised filtered Poisson Process to model electricity price spikes. Bierbrauer et al. (2004), Deng (2000) and Huisman and Mahieu (2003) show the interactions between the degree of the mean-reversion effect and price spikes. Other univariate studies on electricity price spikes include, for example, Christensen et al. (2012), Clements et al. (2013), Eichler et al. (2014), Herrera and González (2014) and Korniichuk et al. (2012).

3.4 Dynamics in Electricity Price Interdependence

The interrelationship between regional markets in the Australian NEM is not constant, and the level of the interdependence between regional prices varies over time. As described by Higgs (2009) and Ignatieva and Trück (2016), while significant electricity price differences can be observed between regional markets during certain periods, indicating a relatively low price interdependence, there have been occasions when joint price spikes and high volatilities appeared in several regions and price interdependence has been much higher. These observations indicate a time-varying pattern in both price and volatility spillover effects in the NEM. The issue of dynamic price intedependence in the NEM has been addressed in, for example, Aderounmu and Wolff (2014a,b), Higgs (2009), Ignatieva and Trück (2016) and Manner et al. (2016).

Furthermore, one would intuitively expect the spillover patterns to be time-varying due to a series of changes or specific events happening to the NEM. For example, in the long-term, the continuing reform aiming for a more efficient and integrated market (Australian Energy Regulator, 2015) may increase the spillover level by creating a closer relationship between different regions. In the short-term, shocks caused by issues such as extreme weather conditions or temporary generation outages in a particular market may spill over into other regions. In addition, regulatory changes such as the carbon taxation introduced in 2012 impact the NEM in various typical aspects, including the generation activity and interregional electricity flows. They are also expected to influence the pattern of spillover effects across all regions.

3.5 The Role of the Carbon Taxation Policy

The Australian NEM is constantly experiencing regulatory changes that may have an impact on the interaction between electricity spot prices in different regions. One important change that is relevant to our sample period is the carbon tax policy that operated between 1 July 2012 and 30 June 2014. This policy was introduced by the Australian Labor Government in order to reduce carbon emissions and mitigate climate change (Australian Energy Regulator, 2015). Central to this policy was the mechanism that a fixed price (or tax), starting at $23, was placed on each tonne of carbon dioxide equivalent emission. This policy had a significant influence on the electricity sector because electricity generation contributes a large proportion to overall carbon emissions in Australia.

The major impacts of the carbon pricing scheme can be summarised in three points. First, the carbon tax increased the cost of electricity generators during the two-year carbon pricing period between July 2012 and July 2014. As a result, although the electricity demand declined in this period, spot prices in the NEM generally exhibited a substantial rise. However, the increases in electricity spot prices were not even across all regions in the NEM. In particular, the increase in electricity prices in TAS was much less than in the other four NEM regions (Australian Energy Regulator, 2015; Apergis et al., 2016), because hydro generation had a large share in the TAS market. Second, the carbon taxation also altered the composition of the electricity generation in the NEM. The market share of coal generation largely dropped and even reached a historical low in the 2013-2014 financial year, while the share of generation from renewables significantly increased (Australian Energy Regulator, 2015). In particular, carbon taxation increased returns for hydro generation, and the share of hydropower generation thus grew to a record high level in the carbon pricing period. Finally, the changes in regional prices and the generation mix in the NEM further altered the interregional electricity flows. This is especially true for TAS. Due to the increased local hydro output and the relatively low electricity prices, TAS became a major electricity exporter during the carbon pricing period. In the 2013-2014 financial year, it even recorded the highest ratio for exports of all regions since the NEM operation (Australian Energy Regulator, 2015).

After the repeal of carbon taxation on 1 July 2014, the share of electricity generations based on fossil fuels became high again. The overall spot prices in the NEM fell back to lower levels. In contrast, the share of generation from renewables dropped. In particular, hydro generation in TAS significantly decreased due to its reduced profitability. As a result, TAS became a net electricity importer after July 2014.

Due to the impacts of carbon taxation on various aspects in the NEM operation, the interregional relationships across regions are expected to have been altered during the implementation of this policy. For example, Apergis et al. (2016), in their clustering group analysis for market integration, find that over recent years, although the prices of SA are converging towards those of QLD, NSW and VIC through investments in renewable energy, the carbon taxation policy between July 2012 and July 2014 slowed this process, because QLD, NSW and VIC were more sensitive to this policy than SA due to their higher reliance on coal-fired electricity generation. This motivates us to pay particular attention to the influence of carbon taxation on the spillover effects in prices and price volatilities in the NEM when conducting our dynamic spillover analysis.

3.6 Summary of the Australian NEM

In summary, Chapter 3 discusses the features of electricity prices and the institutional background in the Australian NEM. Electricity prices are generally characterised by seasonality, mean-reversion and periodic occurrence of spikes. The Australian NEM is a highly volatile and spiky electricity spot market. The market interconnection among the five regional markets is one of the contributors to the high volatilities and their transmissions.

Although one objective of establishing the Australian NEM is to provide a single integrated market with similar electricity prices across different states (Australian Energy Market Commission, 2013), due to the limited capacity of the interconnectors, the different regions in the NEM are still relatively isolated and sizeable price differences exist. These encourage a spillover analysis to evaluate the potential of the NEM to achieve market integration.

Meanwhile, the interrelationships between different regions in the NEM tend to vary across time. This encourages a dynamic spillover analysis where the time variations of the spillover effects are monitored and related to the changes in the market conditions. In particular, the important role of the recent establishment and abolishment of the carbon taxation policy encourages a particular attention to its impacts on the spillover effects in the NEM.

Chapter 4

Methodology

This chapter presents the methodology to assess the spillover effects based on the five regional markets in the Australian NEM. Our methodology in this study is composed of the following three steps:
(i) Deseasonalisation (4.1);
(ii) VAR modelling (4.2.1);
(iii) Decomposition of the linear forecast error variance (4.2.2-4.2.3).

4.1 Deseasonalisation

The electricity spot price (P_t) is typically modelled as Equation 4.1,

$$P_t \;=\; f_t \;+\; X_t, \tag{4.1}$$

where f_t is a deterministic (trend-seasonal) component, and X_t is a stochastic component (e.g. Ignatieva and Trück, 2016; Janczura and Weron, 2010; Janczura et al., 2013; Weron, 2006). Furthermore, the deterministic component f_t of electricity prices contains both a short-term (s_t) and a long-term (T_t) seasonal component, i.e., $f_t = s_t + T_t$.

This section introduces our approach to modelling and removing the seasonality in electricity prices. According to Ignatieva and Trück (2016), Janczura et al. (2013) and Weron (2009), three types of approaches are widely applied in the literature to model the trend-seasonal component (f_t) in electricity prices. The first is the piecewise constant function (e.g. Fanone et al., 2013; Higgs and Worthington, 2008a; Knittel and Roberts, 2005; Lucia and Schwartz, 2002). This method is flexible with regard to modelling seasonality in different time periods. However, the modelled seasonal component lacks smoothness, and thus requires additional processing. The second type of model consists of sinusoidal functions (e.g. Bierbrauer et al., 2007; Cartea and Figueroa, 2005; Clements et al., 2015; Geman and Roncoroni, 2006; Green et al., 2014; Pilipovic, 2007). Although the sinusoidal function can be a good approximation of the cyclical pattern for electricity prices in many countries (Pilipovic, 2007; Weron, 2006), for the Australian NEM it is too regular in periodicity to be used. As shown in Figure 5.1 in the following chapter on data, irregular long-term seasonal patterns of price changes can be observed throughout the sample period. These patterns rather reflects non-periodic factor, such as the fuel price level, changing climate conditions, consumer behaviour and strategic bidding practices by generators (Ignatieva and Trück, 2016). Therefore, sinusoidal functions are not used in this study.

Instead, we follow Aderounmu and Wolff (2014a,b), Ignatieva and Trück (2016), Janczura and Weron (2010) and Weron (2006, 2009) to apply a third approach: wavelet decomposition. Specifically, in this study a wavelet analysis is conducted for the long-term seasonal component in electricity prices, while a moving average technique is used for the short-term seasonal component. This method yields a flexible smoothing for the estimated seasonal component and is a less periodic alternative to the sinusoidal functions. Sections 4.1.1 and 4.1.2 introduce the detailed steps of this approach.

4.1.1 Removal of Long-term Seasonal Component: Wavelet Analysis

The first step of our deseasonalisation is to estimate and remove the long-term seasonal component (T_t) from electricity prices (P_t) through wavelet analysis. Wavelet analysis involves two procedures: the decomposition of the original data and a reconstruction process.

Wavelet decomposition projects a signal onto a series of so-called wavelets, which are an orthonormal set of components. Wavelets belong to different families. The choice of the wavelet family involves making trade-offs between the smoothness of the wavelets and the compactness of their localisation in time (Weron, 2006). In this study, the Daubechies wavelet family is used following Ignatieva and Trück (2016), Janczura et al. (2013) and Weron (2006). A wavelet family contains a father wavelet (denoted by ϕ) and a mother wavelet (denoted by ψ). The father wavelet is used to represent the trend or cycle component ('low frequency' smooth components) in a signal, while the mother wavelet is used to represent the deviations from the trend ('high frequency' detail components). In wavelet analysis, any signal $f(t)$ (or P_t here) can be decomposed as the sum of one father wavelet (S) and a sequence of mother wavelets (D),

$$f(t) = S_J + D_J + D_{J-1} + ... + D_1, \tag{4.2}$$

where

$$S_J = \sum_k s_{J,k}\phi_{J,k}(t) \text{ and } D_j = \sum_k d_{j,k}\psi_{j,k}(t), \quad k = 0, 1, 2, ... \; and \; j = 0, 1, 2, ..., J. \tag{4.3}$$

Mother wavelets are indexed by k and $s = 2^j$, where 2^J is the maximum scale that is sustainable with the number of observations. The coefficients $s_{J,k}$ and $d_{j,k}$ in Equation 4.3 measure the contribution of each corresponding wavelet function to the overall approximation, where the approximating father and mother wavelet functions are

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right) \text{ and } \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right). \tag{4.4}$$

After decomposing $f(t)$ with Equation 4.2, an approximation of the original signal is obtained by inverting the decomposition procedure (i.e. reconstruction of the signal). Specifically, the father wavelet S_J provides a rough approximation of $f(t)$, while $S_{J-1} = S_J + D_J$ yields a higher level of refinement in the approximation. Furthermore, in each step when a mother wavelet D_j of a lower scale $(j = J-1, J-2, ...)$ is added, a better estimation of $f(t)$ is obtained. This reconstruction process continues until the desired accuracy is achieved. The final estimation obtained is de-noised or smoothed. This procedure is also called a wavelet lowpass filtering, and the obtained estimation represents the long-term seasonal component T_t, which can subsequently be removed from the original data.

4.1.2 Removal of Short-term Seasonal Component: Moving Average Technique

The second step of our deseasonalisation is to remove the short-term (weekly) periodicity (s_t) in electricity prices. A moving average technique (see Aderounmu and Wolff, 2014a,b; Brockwell and Davis, 2002; Ignatieva and Trück, 2016; Weron, 2006) is applied to the data series from which the long-term seasonal component has been removed (i.e. $x_t = P_t - T_t$). This includes two procedures.

First, for the daily price series $x_t = x_1, x_2, ..., x_n$, the weekly trend is estimated through a moving average filter:

$$\hat{m}_t = \frac{1}{7}(x_{t-3} + \ldots + x_{t+3}), \quad where\ t = 4, 5, ..., n-3. \tag{4.5}$$

Next, the seasonal component within a week is estimated. Specifically, for each day of a week ($k = 1, 2, ..., 7$), the average of the deviations ($x_{k+7j} - \hat{m}_{k+7j}, 3 < k+7j \leq n-3$) is calculated to represent the seasonal fluctuations. These average deviations are denoted by $w_k, k = 1, 2, ..., 7$. Since the sum of these average deviations is not necessarily equal to zero, the weekly seasonal component s_k is further estimated as:

$$\hat{s}_k = w_k - \frac{1}{7}\sum_{i=1}^{7} w_i, \quad where\ k = 1, 2, ..., 7. \tag{4.6}$$

Finally, the deseasonalised price data are obtained after removing both long-term and short-term seasonal components, i.e., $X_t = P_t - T_t - S_t$.

4.2 Diebold and Yilmaz's (DY) (2009, 2012) Spillover Method

To estimate the spillover effect in electricity markets, we apply the DY method to the deseasonalised electricity prices and price volatilities.

Specifically, in this methodological framework, the first step involves a VAR model estimation for the considered market property (i.e. price and volatility). Next, a generalised variance decomposition is applied to the forecast error term of the VAR estimation. Based on the forecast error variance decomposition, various types of spillovers can be calculated, conveying a wealth of market information. Sections 4.2.1 to 4.2.3 introduce the details of these steps.

4.2.1 Vector Autoregressive (VAR) Model Estimation

Our spillover analysis starts from a covariance stationary N-variable VAR(p) model (in this study, $N = 5$ for five regional markets) for vector $\boldsymbol{x}_t = (x_{1t}, ..., x_{Nt})$ (here $\boldsymbol{x}_t$ is the electricity price or price volatility):

$$\boldsymbol{x}_t = \boldsymbol{\Psi} + \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{4.7}$$

where p is the lag length, $\boldsymbol{\varepsilon} \sim (0, \boldsymbol{\Sigma})$ is a vector of independently and identically distributed error terms, $\boldsymbol{\Sigma}$ is the variance matrix for $\boldsymbol{\varepsilon}$, and $\boldsymbol{\Psi}$ is an intercept vector . According to Greene (2003) and Park et al. (2006), one advantage of such a VAR model is that it captures regularities in the data without imposing as many prior restrictions as structural models may impose.

The moving average representation of the covariance stationary VAR exists, which is

$$\boldsymbol{x}_t = \boldsymbol{A}_0 \boldsymbol{\varepsilon}_t + \boldsymbol{A}_1 \boldsymbol{\varepsilon}_{t-1} + \boldsymbol{A}_2 \boldsymbol{\varepsilon}_{t-2} + ... = \sum_{i=0}^{\infty} \boldsymbol{A}_i \boldsymbol{\varepsilon}_{t-i}. \tag{4.8}$$

The $N \times N$ coefficient matrices follow the recursion:

$$\boldsymbol{A}_i = \boldsymbol{\Phi}_1 \boldsymbol{A}_{i-1} + \boldsymbol{\Phi}_2 \boldsymbol{A}_{i-2} + ... + \boldsymbol{\Phi}_p \boldsymbol{A}_{i-p}, \tag{4.9}$$

where $\boldsymbol{A}_0$ is an $N \times N$ identity matrix and $\boldsymbol{A}_i = 0$ for $i < 0$. The moving average coefficients and their transformations (variance decompositions in this study) are the key to analysing the dynamics of the considered system.

Since the definition of our spillover measures relies on the forecast error variance decomposition, we look at the H-step-ahead forecast at time t:

$$\boldsymbol{x}_{t+H,t} = \boldsymbol{A}_H \boldsymbol{\varepsilon}_t + \boldsymbol{A}_{H+1} \boldsymbol{\varepsilon}_{t-1} + \boldsymbol{A}_{H+2} \boldsymbol{\varepsilon}_{t-2} + ... = \sum_{i=0}^{\infty} \boldsymbol{A}_{H+i} \boldsymbol{\varepsilon}_{t-i}. \tag{4.10}$$

The corresponding forecast error is:

$$\boldsymbol{e}_{t+H,t} = \boldsymbol{x}_{t+H} - \boldsymbol{x}_{t+H,t} = \sum_{i=0}^{\infty} \boldsymbol{A}_i \boldsymbol{\varepsilon}_{t+H-i} - \sum_{i=0}^{\infty} \boldsymbol{A}_{H+i} \boldsymbol{\varepsilon}_{t-i} = \sum_{i=0}^{H-1} \boldsymbol{A}_i \boldsymbol{\varepsilon}_{t+H-i}. \tag{4.11}$$

The variance matrix of the forecast error is thus calculated as:

$$\boldsymbol{\Sigma}_{e,H} = \boldsymbol{A}_0\boldsymbol{\Sigma}\boldsymbol{A}_0' + \boldsymbol{A}_1\boldsymbol{\Sigma}\boldsymbol{A}_1' + \boldsymbol{A}_2\boldsymbol{\Sigma}\boldsymbol{A}_2' + ... + \boldsymbol{A}_{H-1}\boldsymbol{\Sigma}\boldsymbol{A}_{H-1}' = \sum_{h=0}^{H-1} \boldsymbol{A}_h\boldsymbol{\Sigma}\boldsymbol{A}_h', \tag{4.12}$$

where $\boldsymbol{A}_0 = \boldsymbol{I}_N$, which is an $N \times N$ identity matrix. $\boldsymbol{A}_h'$ $(h = 0, ..., H-1)$ stands for the transpose of $\boldsymbol{A}_h'$.

4.2.2 Forecast Error Variance Decomposition

The next step of our spillover analysis is to decompose the forecast error variance (i.e. the diagonal elements of $\boldsymbol{\Sigma}_{e,H}$) into parts that are attributable to different system shocks. More precisely, the variance decomposition answers the following question: what fraction of the H-step-ahead error variance in forecasting variable x_i $(i = 1, 2, ..., N)$ is due to exogenous shocks (typically include surged demand, generation outage and transmission failure in electricity markets) to variable x_j $(j = 1, 2, ..., N)$? In particular, the fraction of the H-step-ahead error variance in forecasting variable x_i due to shocks to x_i itself is defined as own-variance share; and the fraction of the H-step-ahead error variance in forecasting variable x_i due to shocks to x_j $(j \neq i)$ is defined as cross-variance share. The cross-variance share then measures the spillover effects.

The calculation of the forecast error variance decomposition requires orthogonal innovations (or shocks). However, as with electricity price data, our VAR model innovations are generally contemporaneously correlated. With contemporaneously correlated innovations, examining a shock to a single variable in isolation can yield misleading results (Park et al., 2006). To address this issue, Diebold and Yilmaz (2009) used an identification scheme based on Cholesky factorisation to achieve orthogonality in their original paper. Nevertheless, in a Cholesky-based orthogonalisation of correlated shocks, it is assumed that the first variable in the ordering is only contemporaneously influenced by its own innovations, that the second variable is only contemporaneously influenced by innovations of itself and the first variable, and so on (Sims, 1980). Under these assumptions, the first version of the DY method (2009) is sensitive to variable ordering by nature.

Later, Diebold and Yilmaz (2012) proposed a generalised version of the above method based on a generalised variance decomposition (GVD) framework that was introduced by Koop et al. (1996) and Pesaran and Shin (1998). The identification scheme in the GVD framework is largely data based. Instead of orthogonalising shocks, GVDs allow for correlated shocks but account for those correlations simultaneously based on historically observed distribution of the forecast errors (Diebold and Yilmaz, 2012). An appeal of GVDs is that the decomposition results are insensitive to the ordering of variables because, as opposed to Cholesky based variance decomposition, GVDs treat every variable as the first one in the ordering. Our spillover analysis with regards to variance decompositions therefore relies on the 2012 version of the DY method, rather than the 2009 version[7].

Using the 2012 version of the DY framework, the H-step-ahead error variance decompositions are calculated as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(\boldsymbol{s}_i'\boldsymbol{A}_h\boldsymbol{\Sigma}\boldsymbol{s}_j)^2}{\sum_{h=0}^{H-1}(\boldsymbol{s}_i'\boldsymbol{A}_h\boldsymbol{\Sigma}\boldsymbol{A}_h'\boldsymbol{s}_i)}. \tag{4.13}$$

In Equation 4.13, $\theta_{ij}^{g}(H)$ denotes the ij^{th} element of the variance decomposition matrix, where g refers to the generalised variance decomposition method. $\boldsymbol{\Sigma}$ is the variance matrix of the error vector $\boldsymbol{\varepsilon}$; σ_{jj} is the standard deviation of the error term for the j^{th} equation of the VAR model; and $\boldsymbol{s}_i, \boldsymbol{s}_j$ are selection vectors, i.e., the i^{th} element of $\boldsymbol{s}_i$ and j^{th} element of $\boldsymbol{s}_j$ are one, and other elements are zero. Each element of the variance decomposition matrix is then normalised as in Equation 4.14:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}, \tag{4.14}$$

[7] It should be noted that the 2009 version of the DY method is applied in the robustness assessment, which provides results in a similar pattern as those of Diebold and Yilmaz (2012).

so that the sum of each row equals one (i.e. $\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(H) = 1$) and $\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H) = N$.

Table 4.1 below is called a spillover table (Diebold and Yilmaz, 2012). The upper left $N \times N$ block provides the H-step-ahead forecast error variance decomposition matrix. Based on the decomposition matrix, this table describes various spillovers as explained in Section 4.2.3.

Table 4.1: Methodology: spillover table derived from VAR variance decomposition

		From				
		x_1	x_2	$\cdots$	x_N	From others
To	x_1	$\widetilde{\theta}_{11}^{g}(H)$	$\widetilde{\theta}_{12}^{g}(H)$	$\cdots$	$\widetilde{\theta}_{1N}^{g}(H)$	$\sum_{j=1}^{N} \widetilde{\theta}_{1j}^{g}(H), j \neq 1$
	x_2	$\widetilde{\theta}_{21}^{g}(H)$	$\widetilde{\theta}_{22}^{g}(H)$	$\cdots$	$\widetilde{\theta}_{2N}^{g}(H)$	$\sum_{j=1}^{N} \widetilde{\theta}_{2j}^{g}(H), j \neq 2$
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
	x_N	$\widetilde{\theta}_{N1}^{g}(H)$	$\widetilde{\theta}_{N2}^{g}(H)$	$\cdots$	$\widetilde{\theta}_{NN}^{g}(H)$	$\sum_{j=1}^{N} \widetilde{\theta}_{Nj}^{g}(H), j \neq N$
	To others	$\sum_{i=1}^{N} \widetilde{\theta}_{i1}^{g}(H)$, $i \neq 1$	$\sum_{i=1}^{N} \widetilde{\theta}_{i2}^{g}(H)$, $i \neq 2$	$\cdots$	$\sum_{i=1}^{N} \widetilde{\theta}_{iN}^{g}(H)$, $i \neq N$	Aggregated Spillover Index $= \frac{1}{N} \sum_{i=1}^{N} \widetilde{\theta}_{ij}^{g}(H)$, $i \neq j$

Notes: x_1, ..., x_N are the considered variables from N markets. $\widetilde{\theta}_{ij}^{g}(H)$, i, $j = 1$, ..., N is defined in Equations 4.13 and 4.14.

4.2.3 Spillover Measures

Pairwise Net Spillover

In the forecast error variance decomposition matrix in Table 4.1, the ij^{th} entry is considered to be the spillover of shocks received by market i which are transmitted by market j (i.e., $S_{i \leftarrow j}^{g}(H) = \widetilde{\theta}_{ij}^{g}(H)$, $\widetilde{\theta}_{ij}^{g}(H)$ is defined in Equations 4.13 and 4.14). That is, the elements of this matrix measure the pairwise directional spillovers. Hence the pairwise net directional spillover from market j to market i can be defined as:

$$S_{ij}^{g}(H) = S_{i \leftarrow j}^{g}(H) - S_{j \leftarrow i}^{g}(H) = \widetilde{\theta}_{ij}^{g}(H) - \widetilde{\theta}_{ji}^{g}(H) \tag{4.15}$$

Gross Directional Spillovers

The off-diagonal row and column sums measure the gross directional spillovers for each market. In particular, the gross directional spillover received by market i (i.e. the 'From others' column) is measured as the i^{th} off-diagonal row sum:

$$S^g_{i\leftarrow\bullet}(H) = \sum_{j=1,j\neq i}^{N} \widetilde{\theta}^g_{ij}(H). \tag{4.16}$$

Similarly, the gross directional spillover transmitted from market i (i.e. the 'To others' row) is measured as the i^{th} off-diagonal column sum:

$$S^g_{\bullet\leftarrow i}(H) = \sum_{j=1,j\neq i}^{N} \widetilde{\theta}^g_{ji}(H). \tag{4.17}$$

Total Net Directional Spillover

Next, by calculating the difference between the gross spillovers transmitted from and received by a certain market i, a net spillover from market i to all other markets is obtained:

$$S^g_i(H) = S^g_{\bullet\leftarrow i}(H) - S^g_{i\leftarrow\bullet}(H). \tag{4.18}$$

Aggregated Spillover Index

Finally, an aggregated spillover index is calculated where the sum of all off-diagonal elements is divided by the sum of all elements:

$$S^g(H) = \frac{\sum_{i,j=1;i\neq j}^{N} \widetilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ij}(H)} * 100 = \frac{\sum_{i,j=1;i\neq j}^{N} \widetilde{\theta}^g_{ij}(H)}{N} * 100. \tag{4.19}$$

In this equation, the numerator measures the total cross-variance shares or spillovers, and the denominator refers to the total forecast error variance. This aggregated spillover index measures the overall degree of spillover effects in the whole system.

In practice, different parties may be more interested in different measures. For example, market participants who aim to hedge risk or earn revenue might be more interested in the spillovers between particular regions. In contrast, regulators could be more concerned with monitoring the overall spillover magnitude, or identifying the most systemically influential market.

Chapter 5

Data

This chapter introduces the data used in this study. In particular, Chapter 5 is concerned with the data description and its preliminary statistical analysis.

5.1 Electricity Price Data

In the price spillover analysis, the data used are daily spot prices of the five regional electricity markets (NSW, QLD, SA, TAS and VIC)[8] in the Australian NEM from 1 January 2010 to 31 December 2015. The original data are recorded on a half-hourly basis, obtained from the Australian Energy Market Operator[9]. A series of daily prices for each regional market (2,191 observations) is then yielded by calculating the arithmetic mean of 48 half-hourly spot prices for each day. This treatment could lose some information contained in intra-day data; however, as argued by Worthington et al. (2005), daily average prices are important for electricity markets, especially with re-

[8] These regions have been considered by, for example, Clements et al. (2015); Higgs et al. (2015); Ignatieva and Trück (2016); Nepal et al. (2016); Smith (2015); Smith et al. (2012); and four of them (except TAS) have been used in Higgs (2009); Higgs and Worthington (2005); Worthington et al. (2005).

[9] Australian Energy Market Operator (AEMO) website, https://www.aemo.com.au/, accessed April 2016.

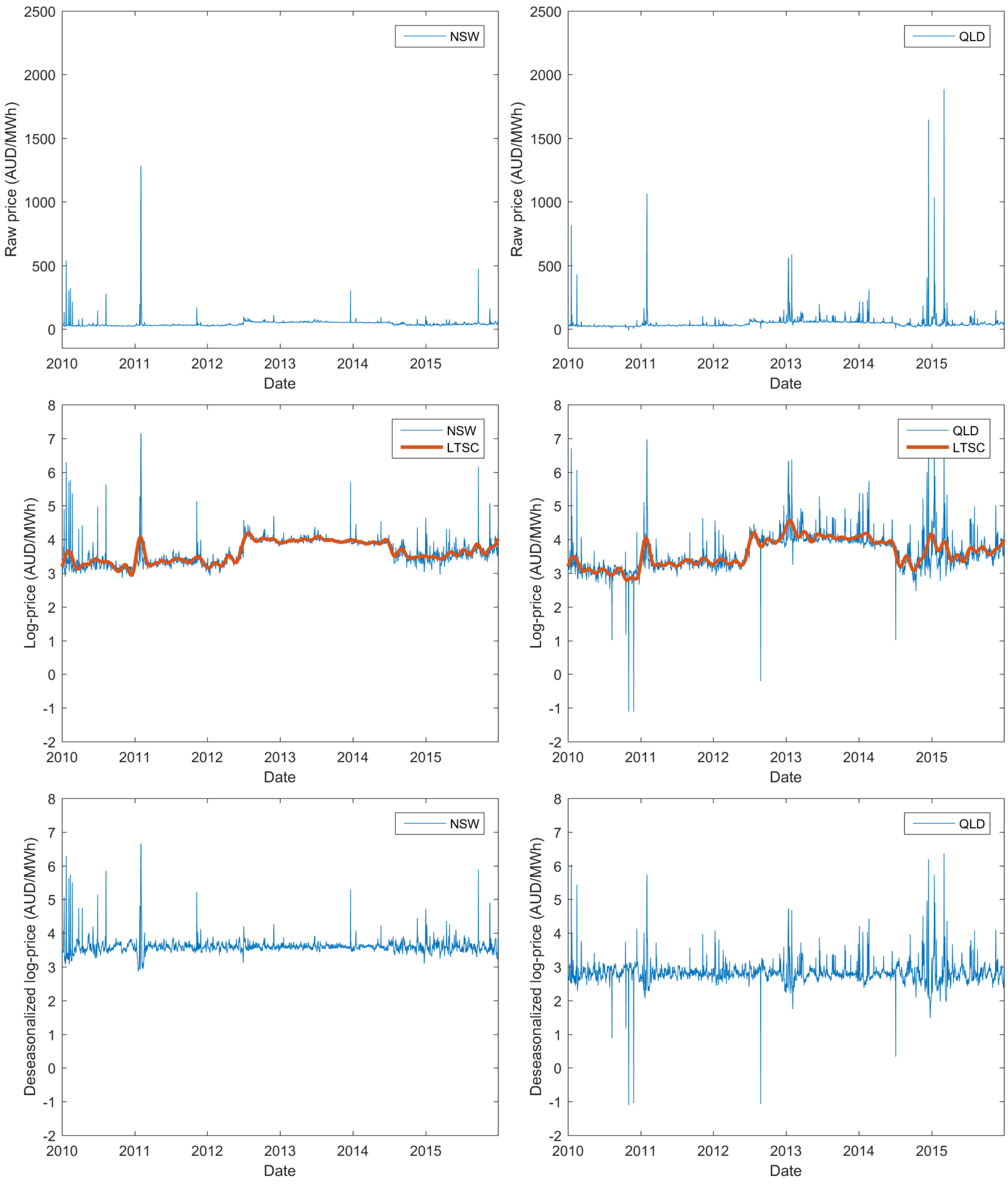
gard to financial contracts[10]. Logarithm transformation is then applied to normalise the data. As introduced in Chapter 4, wavelet decomposition is used to remove long-term seasonality, while a moving-average filter is used to subtract the short-term seasonal component (weekly). We choose $2^5 = 32$ ($J = 5$) as maximum scale in wavelet decomposition, which roughly corresponds to a monthly smoothing[11].

Accordingly, Figure 5.1 plots the raw daily electricity prices P_t (top panel), the log-prices together with the fitted long-term seasonal pattern obtained by the wavelet filter (middle panel), and the deseasonalised log-prices after removal of both long-term and short-term seasonal components (bottom panel) for the NSW and QLD electricity markets[12]. The stylised facts of electricity prices as discussed in Chapter 3, Section 3.3 are reflected in the figure. Specifically, significant price spikes can be observed in raw prices. There are also several joint spikes that appear at similar locations in different markets (for example, the joint spike in NSW and QLD on 31 January 2011). Because of the logarithm transformation, electricity price features such as mean-reversion and seasonality can be more easily observed in the middle panel of Figure 5.1. The fitted long-term seasonal patterns appear irregular. They contain several cycles with different periods (monthly, half-yearly, yearly, etc.). In addition, similarities can be found in the long-term seasonal pattern for NSW and QLD. After deseasonalisation, most seasonal components are removed, and the stochastic component of the price data is extracted for further spillover analysis.

[10] Daily electricity spot prices are also used in, for example, De Vany and Walls (1999a,b); Higgs (2009); Ignatieva and Trück (2016) and Worthington et al. (2005).

[11] Higher scales (e.g. $2^8 = 256$ ($J = 8$)) sometimes introduce a large deviation from the long-term seasonal pattern from the actual price series, see, for example, Ignatieva and Trück (2016). On the other hand, if J is too low, the approximation is too close to the actual price series. Some stochastic components would be eliminated together with seasonality. Therefore, J=5 referring to monthly smoothing could be the most appropriate choice.

[12] To reserve space, only the graphs for two regional markets are presented here. The graphs for SA, TAS and VIC are provided in Figure A1 in Appendix A.1.



(a) NSW (b) QLD

Figure 5.1: Daily raw prices, log-prices and deseasonalised log-prices of NSW and QLD from 1 January 2010 to 31 December 2015. The top panel plots raw daily prices. The middle panel plots log-prices with a long-term seasonal component (LTSC) obtained through wavelet decomposition. The bottom panel plots the deseasonalised log-prices (both long-term and short-term seasonal components are removed).

5.2 Electricity Price Volatility Data

In the volatility spillover analysis, we use realised or historical volatility calculated from high frequency (half-hourly) intra-day prices[13] of the Australian NEM.

We define our daily volatility of electricity price as the standard deviation of log-prices over the 48 half-hour intervals during each day, as represented in equation 5.1:

$$\sigma_i = \sqrt{\frac{\Sigma_{t=1}^{N}(p_{it} - \bar{p}_i)^2}{N}}, \tag{5.1}$$

where σ_i measures the market volatility on day i, p_{it} is the half-hourly log-price at time t on day i, $\bar{p}_i$ is the average half-hourly log-price on day i, and N equals 48. The calculated volatility for each day is only relevant to the intra-day prices on this day[14].

Figure 5.2 depicts the daily volatilities of prices for the NSW, QLD, SA, TAS and VIC electricity markets. From a visual inspection, three facts can be observed. Firstly, the SA market is generally more volatile than the other markets. This is due to several unique market conditions in this region, including a relatively high concentration of generator ownership, strategic rebidding behaviours by generators aiming for more favourable electricity prices, and the tight demand-supply balance due to limited import capacity and the recent thermal plant withdrawals (Australian Energy Regulator, 2015). The high penetration of wind generation in SA also contributes to the volatile spot prices in this market, because of the intermittent nature of wind energy. Secondly, volatilities appear to be highly persistent or serially correlated, which justifies the use of autoregressive models. Thirdly, for all five regional electricity markets, price volatilities are positively skewed and leptokurtic. Hence, we take the natural logarithm to obtain approximate normality, which is consistent with Diebold and Yilmaz (2014).

[13] In the calculation of volatility, the input price data are not deseasonalised because the seasonal components are mostly removed when calculating the standard deviation of prices.

[14] We choose to use the standard deviation of prices as the volatility estimator rather than that of price changes (or returns), because price-based functions contain information on the present price level. For electricity spot markets, our analysis is more concerned with the price jumps during extreme price periods, whereas volatility during low or normal price periods is not of such concern.

This transformation is helpful not only because of the superior statistical properties of the normal distribution, but also because normality is invoked by generalised variance decompositions that are applied in the following spillover analysis (Koop et al., 1996; Pesaran and Shin, 1998).

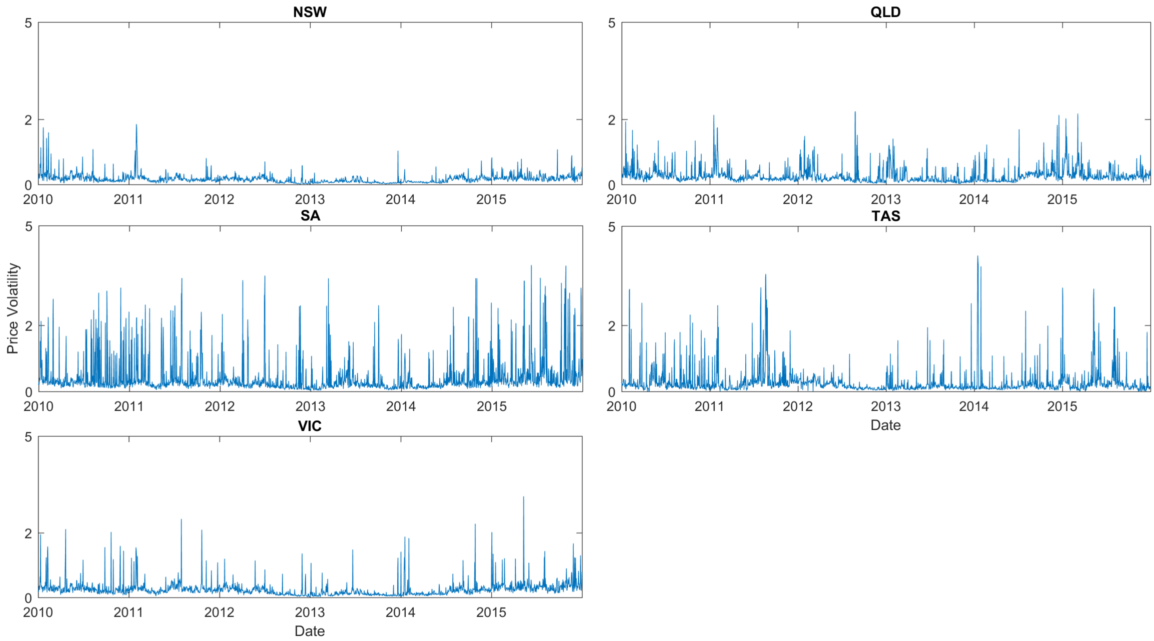


Figure 5.2: Daily volatilities of prices in NSW, QLD, SA, TAS and VIC electricity spot markets, from 1 January 2010 to 31 December 2015

5.3 Summary of Descriptive Statistics

Table 5.1 presents the summary of descriptive statistics for electricity prices (raw prices, log-prices and deseasonalised log-prices in Panel (a)) and volatilities (before and after log transformation in Panel (b)) for each regional market in the Australian NEM.

Price

For price data shown in Panel (a) of Table 5.1, although the average electricity price is around $40 per MWh, extreme price outcomes can be observed in the 'Maximum' column, which can be as high as $2,437.70 per MWh, as seen in SA. Meanwhile, during the considered period, negative price spikes (observed in the 'Minimum' column) appear in SA, TAS and VIC due to the failure of generators to adjust to reduced demand levels. Over the sample period, the standard deviations of the price series in SA and QLD are much higher than those of the other markets, indicating that these two markets are more volatile than the rest. In addition, the distributions of all price series generally are positively skewed (except for log-prices and deseasonalised log-prices in SA and log-prices in TAS) with fat tails. Accordingly, the Jarque-Bera statistics and corresponding p-values strongly reject the null hypothesis of normality (at the 1% significance level) for each data series[15]. Although both skewness and kurtosis are substantially reduced after the logarithm transformation and the deseasonalisation step, in Panel (a) of Table 5.1, p-values for the J-B test for these price data remain smaller than the significance level $\alpha = 0.01$.

Furthermore, given that the application of a VAR model requires stationarity of the input data series, the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) is used to assess the stationarity of the data series[16]. The null hypothesis of the ADF test is that a unit root exists in the univariate time series or the data series is non-stationary. The test is based on an ordinary least squares (OLS) regression, where the first differences of the prices (or volatilities) for each regional market are regressed on a lag of the price (or volatility) variable in level, and a series of lags of the dependent variable. An intercept is included in the ADF regression. The lag length is determined by the significance of the coefficients of the lagged terms. As shown in Table 5.1, Panel (a), the respective p-value of the ADF test for each price data series is much lower than $\alpha = 0.01$. The null hypothesis of the ADF test (unit root and non-stationarity) can be rejected at the 1% significance level. This indicates that the data series of electricity price for the five Australian regional markets are all stationary. This result on the stationarity of electricity prices in the NEM is consistent with results in Higgs (2009) and Worthington et al. (2005) who also use the Australian NEM data.

[15] Jarque-Bera test (Jarque and Bera, 1987) is a goodness-of-fit test (H_0: The data distribution matches a normal distribution. H_1: The data distribution does not match a normal distribution). It has a joint hypothesis that the data is from a distribution where skewness equals zero and kurtosis equals three. Under the null hypothesis, the J-B statistic asymptotically follows a χ^2 distribution with two degrees of freedom.

[16] The outputs of the ADF tests are provided in Appendix A.1, Table A1

Volatility

For volatility data shown in Panel (b) of Table 5.1, SA has the highest mean and median volatility among the five Australian regional electricity markets, as well as the highest standard deviation.

In addition, all volatility series are positively skewed and leptokurtic. After the natural logarithm transformation, the skewness and kurtosis of volatility are reduced; and the data distributions are closer to normal distribution. However, for both raw and log- volatilities in all regions, Jarque-Bera tests reject the null hypothesis that the data series are normally distributed at the 1% significance level. Furthermore, based on ADF tests with p-values less than $\alpha = 0.01$ we reject the null hypothesis of non-stationarity. In other words, the raw volatility and log-volatility data used in this study for all regions in the NEM are stationary.

Further in this study we will concentrate on the deseasonalised log-price and log-volatility data of the five regional electricity markets (NSW, QLD, SA, TAS and VIC) from 1 January 2010 to 31 December 2015.

Table 5.1: Descriptive statistics

		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	J-B test [1]	ADF test [2]
Panel (a) : Price										
NSW	raw	41.4487	35.0140	1282.0	17.3610	44.3571	20.0651	509.6698	23905000 (<0.001)	-14.9220 (<0.001)
	log.	3.6161	3.5557	7.1562	2.8542	0.3872	1.6420	9.5408	9315.90 (<0.001)	-6.5548 (<0.001)
	des.	3.6003	3.5816	6.6642	2.8542	0.2368	5.6323	54.7999	286270 (<0.001)	-19.9014 (<0.001)
QLD	raw	45.7805	33.4370	1885.9	-13.9790	73.7870	15.8358	320.6543	9495900 (<0.001)	-12.5474 (<0.001)
	log[3].	3.6033	3.5097	7.5422	-1.1106	0.5576	0.5438	10.7114	10607 (<0.001)	-6.8387 (<0.001)
	des.	2.8215	2.7908	6.3674	-1.1106	0.3766	0.8389	33.1443	100750 (<0.001)	-26.1694 (<0.001)
SA	raw	48.5463	37.0300	2347.7	-103.1600	81.2063	18.6110	442.4623	18032000 (<0.001)	-14.9019 (<0.001)
	log.	3.6546	3.6117	7.7612	0.1102	0.6085	-0.2225	9.0103	7447.80 (<0.001)	-7.7857 (<0.001)
	des.	3.7206	3.7108	7.7610	0.1102	0.4553	-0.2747	22.4240	46026 (<0.001)	-20.2696 (<0.001)
TAS	raw	39.1508	36.6040	805.06	-94.6700	27.5360	14.3794	339.1757	10597000 (<0.001)	-7.0703 (<0.001)
	log.	3.5762	3.6002	6.6909	1.1935	0.4118	-0.0543	7.2903	4865.80 (<0.001)	-4.5366 (<0.001)
	des.	3.5519	3.5424	6.8357	1.1935	0.2698	0.8121	37.6522	129910 (<0.001)	-13.8845 (<0.001)
VIC	raw.	39.4260	33.1970	1276.9	-4.8887	46.6428	17.8835	406.9201	15261000 (<0.001)	-14.3397 (<0.001)
	log.	3.5393	3.5025	7.1522	1.9012	0.4383	1.2508	7.3898	5570.30 (<0.001)	-6.3573 (<0.001)
	des.	3.1165	3.1025	6.8676	1.9012	0.2674	4.7289	51.4999	250760 (<0.001)	-20.1187 (<0.001)
Panel (b) : Volatility										
NSW	raw	0.1682	0.1412	1.8564	0.0081	0.1478	4.6242	35.4444	122740 (<0.001)	-8.7650 (<0.001)
	log.	-2.0345	-1.9572	0.6186	-4.8114	0.7136	-0.1763	0.5288	37.2102 (<0.001)	-6.0599 (<0.001)
QLD	raw	0.2720	0.2034	2.2486	0.0226	0.2498	3.2395	14.9928	24404 (<0.001)	-9.8414 (<0.001)
	log.	-1.5726	-1.5927	0.8103	-3.7892	0.7075	0.3047	0.3696	46.6218 (<0.001)	-8.2656 (<0.001)
SA	raw	0.4141	0.2389	3.8103	0.0299	0.5395	3.2267	11.2902	15471 (<0.001)	-11.6007 (<0.001)
	log.	-1.3164	-1.4316	1.3377	-3.5095	0.8368	0.8194	0.8447	311.1946 (<0.001)	-8.6215 (<0.001)
TAS	raw	0.2747	0.1626	4.1082	0.0002	0.4154	4.8712	29.0344	85790 (<0.001)	-12.6814 (<0.001)
	log.	-1.7646	-1.8168	1.4130	-8.5344	0.9114	-0.1674	5.3076	2589.40 (<0.001)	-9.3495 (<0.001)
VIC	raw	0.2521	0.2067	3.1316	0.0153	0.2395	4.4293	29.2312	8533.40 (<0.001)	-9.2576 (<0.001)
	log.	-1.6455	-1.5764	1.1415	-4.1797	0.7190	-0.0078	0.7064	46.0120 (<0.001	-6.5998 (<0.001)

Notes: Descriptive statistics for the electricity market data of NSW, QLD, SA, TAS and VIC, from 1 January 2010 to 31 December 2015. Panel (a) summarises raw prices ($/MWh), log-prices and deseasonalised log-prices. Panel (b) summarises raw volatilities and log-volatilities (raw volatilities are calculated as the standard deviation of half-hourly prices over each day). There are 2191 daily observations for each data series.

[1] This column shows the results of Jarque-Bera (J-B) test for the normality of each data series. The test statistics as well as the corresponding p-values (in the parentheses) are presented.
H_0: normal; H_1: non-normal.
[2] This column shows the results of augmented Dickey-Fuller (ADF) test for the stationarity of each data series. The test statistics as well as the corresponding p-values (in the parentheses) are presented.
H_0: a unit root (non-stationary); H_1: no unit root (stationary).
Critical values: -2.57% (10%), -2.87 (5%), and -3.44 (1%).
[3] In our sample period there are negative prices in QLD, SA, TAS and VIC. These negative values are replaced by the minimum positive price value of the corresponding market before taking the natural logarithm.

Unconditional Pairwise Correlation

Table 5.2 reports the pairwise correlation coefficients of deseasonalised log-prices (Panel (a)) and log-volatilities (Panel (b)) among the five markets. Overall, all pairwise correlations are positive according to the table. In addition, volatility data generally have higher correlations than price data do. In particular, there are two key results to note.

Firstly, the pairwise correlations for price data observed here are much lower than those found in Aderounmu and Wolff (2014a,b), Higgs (2009), Ignatieva and Trück (2016) and Smith et al. (2012), where the same regions are investigated. There are three possible reasons to explain these lower correlations. The first reason is that the Pearson correlations calculated here have a poor performance in measuring tail dependence (Aderounmu and Wolff, 2014a,b). Given that the pairs of regional markets in the Australian NEM are considered to be asymptotically dependent (Aderounmu and Wolff, 2014a,b; Ignatieva and Trück, 2016; Smith et al., 2012), the Pearson correlations could have underestimated the risk of joint tail events (spikes) in electricity spot prices, and therefore generate lower correlations. The second reason is that, in contrast to Aderounmu and Wolff (2014a,b), Higgs (2009) and Smith et al. (2012), the price data used here are unfiltered data. No region-specific stochasticity has been removed from these data[17], which could result in the correlations being low. The third reason is that the sample period used in this study is more recent compared to the cited literature. The correlations between different regional spot markets in the NEM could have decreased in this time period.

Secondly, higher correlations are found between regions where there are direct interconnections. For both price and volatility data, the highest correlations are found between NSW and VIC, SA and VIC, and NSW and QLD, which are well interconnected (refer to Chapter 3, Section 3.2.2). With one undersea interconnector in place,

[17] In comparison, for example, GARCH-type models are used in Aderounmu and Wolff (2014a,b); Higgs (2009); Ignatieva and Trück (2016); Smith et al. (2012), which filter out spike clusters caused by volatility persistence.

the correlation between VIC and TAS is also relatively high. In contrast, the lowest and second lowest correlations for both prices and volatilities are between QLD and TAS, and between QLD and SA, which are relatively distant in the NEM and not physically connected.

Table 5.2: Unconditional Pairwise Correlation

Panel (a) : Price					
	NSW	QLD	SA	TAS	VIC
NSW	1.0000				
QLD	0.2918	1.0000			
SA	0.2458	0.0835	1.0000		
TAS	0.1610	0.0746	0.2248	1.0000	
VIC	0.3866	0.1780	0.5895	0.2163	1.0000
Panel (b) : Volatility					
NSW	1.0000				
QLD	0.6012	1.0000			
SA	0.4986	0.2427	1.0000		
TAS	0.3507	0.1760	0.3425	1.0000	
VIC	0.7930	0.4406	0.6492	0.4511	1.0000

Notes: This table shows unconditional pairwise correlations (Pearson correlation coefficients) between each pair of regional electricity markets in the NEM. Panel (a) shows correlations of deseasonalised log-prices. Panel (b) shows correlations of log-volatilities. The sample period is from 1 January 2010 to 31 December 2015.

Chapter 6

Empirical Results

The previous chapter introduces the data in this study. Deseasonalised daily log-prices and daily log-volatilities are used in the further analysis. This chapter provides the main empirical findings of this study. First, based on the specified model (Section 6.1), static levels of spillover effects of prices and volatilities in the NEM are assessed through a full-sample spillover table (Section 6.2). Second, by rolling the sample period, time variations of the price and volatility spillovers in the NEM are tracked and discussed (Section 6.3). Finally, the robustness of the empirical findings is assessed in Section 6.4.

6.1 Model Specification

As the first step of the spillover analysis, the specification of the VAR model is required. Overall, there are three main parameters to be decided: the optimal lag length (p) of the VAR model (Section 6.1.1), the forecasting horizon (H) in VAR forecast error variance decompositions (Section 6.1.2), and the window length (w) in the dynamic spillover analysis (Section 6.1.3).

6.1.1 Choice of VAR Lag Length p

The optimal lag length (p) is selected based on Bayesian information criterion (BIC) (Schwarz et al., 1978). BIC provides a relative estimate for the information lost when fitting a data series to a given model, as shown in Equation 6.1:

$$BIC = \frac{-2}{T} \times ln(L) + \frac{ln(T)}{T} \times q, \tag{6.1}$$

where T is the sample size, L is the maximum likelihood estimates, and q denotes the number of parameters in the fitted model. The first term of BIC function ($\frac{-2}{T} \times ln(L)$) rewards the goodness-of-fit, and the latter term ($\frac{ln(T)}{T} \times q$) gives penalty for increased model complexity. Model selection based on BIC provides a trade-off between the two terms. When the number of parameters of a model increases, the value of goodness-of-fit term decreases and a higher penalty is imposed. Therefore, the optimal model should minimise the BIC value.

Based on BIC values, a VAR model with one lag (i.e. VAR (1)) is chosen for the price spillover analysis, while a VAR (2) model is chosen for the volatility spillover analysis. However, alternative choices of p are used for the robustness check.

6.1.2 Choice of Forecasting Horizon H

The choice of the forecasting horizon H in variance decomposition allows us to decide whether 'long-run' or 'short-run' spillover effects are to be assessed. As H lengthens, the conditioning information is becoming less valuable; and an unconditional variance decomposition will be obtained if $h \to \infty$ (Diebold and Yilmaz, 2014). Intuitively, there are more chances for spillovers to appear in a relatively longer horizon. However, in this study we choose $H = 1$ because we are more interested in short-term price and volatility transmissions in highly volatile electricity markets[18]. Longer forecasting

[18] As explained in Diebold and Yilmaz (2014), the selection of H usually relates to specific considerations in certain contexts. For example, $H = 10$, which corresponds to the 10-day Value-at-Risk required by the Basel accord, is commonly used in the risk management context. Similarly, H might be related to the rebalancing period in the portfolio management context.

horizons are explored in the robustness assessment.

6.1.3 Choice of Window Length w

In order to track the dynamics of the various spillover effects in real time, a rolling-window approach is employed, which requires a choice of window length w. The optimal window length reflects a trade-off between the reliability of the estimated results and the amount of information obtained. On the one hand, a longer sample provides more robust estimates. On the other hand, by using more windows with shorter samples, more information could be gained (i.e. information on the build-up of spillovers across time) (Alter and Beyer, 2014). We choose a window length $w = 365$ days (one calendar year) in the main analysis, and use a shorter window (180 days) and a longer window (540 days) to examine the robustness of the results. In particular, we use a one sided estimation window of 365 days to sweep through the entire sample. In each window, the same VAR model is estimated and the spillover measures are calculated so that time series data can be generated and indexed by the end date of each window.

6.2 Static Spillover Analysis

6.2.1 Full Sample Spillover Table

Table 6.1 provides a full-sample analysis of the static spillover patterns for both prices (Panel (a)) and volatilities (Panel (b)) of the five regional electricity markets in the Australian NEM. In each panel, an aggregated spillover index is shown in the lower right corner of the table. It measures the overall spillover level of the whole NEM over the entire sample period as explained in Section 4.2.

The other elements of Table 6.1 can be viewed as an 'input-output' decomposition of the total spillovers. Specifically, the 5×5 upper left block is the one-step-ahead VAR forecast error variance decomposition matrix. The off-diagonal elements of this matrix measure pairwise directional spillovers. The ijth element is the estimated spillover from market j to market i ($S^g_{i \leftarrow j}$). It should be noted that since the forecast error variance decomposition matrix is normalised by rows, each row sum of this matrix equals 100%, which is not the case for each column sum. Furthermore, the row sums of pairwise spillovers estimate gross directional spillovers received by each of the five Australian regional electricity markets from all other markets. These results are given in the last column ('From Others') of Table 6.1. Similarly, the 'To Others' row refers to the column sums of pairwise spillovers, and estimates gross directional spillovers transmitted by each of the five Australian regional electricity markets to all other markets.

Spillover Table: Price

In Table 6.1 Panel (a), the aggregated price spillover index in Australian electricity markets equals 21.64%. Thus, on average, spillover effects contribute 21.64% of the price forecast error variance in the Australian NEM across the full sample period. In terms of the pairwise decomposition of the total spillover, the highest spillover is from SA to VIC ($S^g_{VIC \leftarrow SA} = 35.69\%$), which is much higher than any other pairwise price spillover. That means that a 35.69% error variance in forecasting VIC prices comes from shocks to SA. In turn, the spillover from VIC to SA is also relatively high ($S^g_{SA \leftarrow VIC} = 14.06\%$). However, the difference between the two spillover measures indicates that net spillover is from SA to VIC, rather than from VIC to SA. The second highest pairwise price spillover is from VIC to NSW ($S^g_{NSW \leftarrow VIC} = 14.43\%$); and another relatively high pairwise spillover is from SA to NSW ($S^g_{NSW \leftarrow SA} = 12.42\%$). In contrast, much lower pairwise price spillovers are observed between QLD and TAS ($S^g_{TAS \leftarrow QLD} = 0.48\%$, $S^g_{QLD \leftarrow TAS} = 0.25\%$), and between QLD and SA ($S^g_{SA \leftarrow QLD} = 0.22\%$, $S^g_{QLD \leftarrow SA} = 0.63\%$).

According to the 'From Others' column and the 'To Others' row of Table 6.1 Panel (a), VIC and NSW are identified as two major spillover receivers because these two markets receive much higher spillovers ($S^g_{VIC \leftarrow \bullet} = 41.40\%$, $S^g_{NSW \leftarrow \bullet} = 33.55\%$) than other markets do. Meanwhile, SA and VIC are major price spillover givers, transmitting 54.58% ($S^g_{\bullet\leftarrow SA}$) and 33.45% ($S^g_{\bullet\leftarrow VIC}$) spillovers to other markets, respectively. Relating the total gross directional spillovers to pairwise spillovers, price spillovers received by NSW mainly come from VIC and SA; and price spillovers received by VIC mainly come from SA. On the other hand, price spillovers from VIC mostly flow to NSW and SA; and price spillovers from SA mainly flow to VIC.

With regard to the 'Net Spillover' row, SA (37.51%) and QLD (1.80%) are net price spillover givers, while NSW (-26.09%), TAS (-5.27%) and VIC (-7.95%) are net price spillover receivers. In particular, SA is the largest net price spillover giver. The positive net positions of SA and QLD are reasonable given the spiky and volatile spot prices in these two markets[19].

Spillover Table: Volatility

For the volatilities of electricity price (Table 6.1 Panel (b)), overall a 36.61% forecast error variance comes from spillover effects. Specifically, the highest pairwise volatility spillover is from SA to VIC ($S^g_{VIC\leftarrow SA} = 23.05\%$). That is followed by spillovers from VIC to NSW ($S^g_{NSW\leftarrow VIC} = 22.99\%$), while the opposite is the third highest ($S^g_{VIC\leftarrow NSW} = 17.28\%$). In addition, relatively high pairwise volatility spillovers can also be observed from VIC to SA ($S^g_{SA\leftarrow VIC} = 16.39\%$), and between NSW and QLD ($S^g_{QLD\leftarrow NSW} = 17.19\%$, $S^g_{NSW\leftarrow QLD} = 13.70\%$). In contrast, much lower pairwise volatility spillovers are observed between QLD and TAS ($S^g_{TAS\leftarrow QLD} = 0.52\%$, $S^g_{QLD\leftarrow TAS} = 1.19\%$), and between QLD and SA ($S^g_{SA\leftarrow QLD} = 1.07\%$, $S^g_{QLD\leftarrow SA} = 1.77\%$).

With regard to gross directional spillovers, the major volatility spillover receivers are VIC and NSW ($S^g_{VIC\leftarrow\bullet} = 54.25\%$, $S^g_{NSW\leftarrow\bullet} = 52.52\%$), while the major volatility spillover givers are VIC ($S^g_{\bullet\leftarrow VIC}$=54.65%), SA ($S^g_{\bullet\leftarrow SA}$=44.05%), and NSW ($S^g_{\bullet\leftarrow NSW}$ =43.74%). More specifically, volatility spillovers received by NSW mainly come from VIC, and volatility spillovers received by VIC mainly come from SA and NSW. In

[19] See time series plots for SA and QLD prices in Figure A1

contrast, volatility spillovers from VIC mostly flow to NSW and SA, volatility spillovers from SA mainly flow to VIC, and those from NSW mainly flow to QLD and VIC.

In net terms, SA (14.56%), TAS (0.85%), and VIC (0.40%) are net volatility spillover givers, while NSW (-8.78%) and QLD (-7.03%) are net volatility spillover receivers.

Table 6.1: Full sample spillover table

			From				
		NSW	QLD	SA	TAS	VIC	From Others
Panel (a) : Price spillover (in percentage)							
	NSW	66.45	5.56	12.42	1.14	14.43	33.55
	QLD	2.91	94.28	0.63	0.25	1.93	5.72
To	SA	0.87	0.22	82.93	1.92	14.06	17.07
	TAS	1.10	0.48	5.84	89.55	3.03	10.45
	VIC	2.58	1.26	35.69	1.87	58.60	41.40
	To Others	7.46	7.52	54.58	5.18	33.45	108.19
	Net Spillovers	-26.09	1.80	37.51	-5.27	-7.95	
	Spillover Index					$= \frac{108.19}{500.00}$	$= 21.64\%$
Panel (b) : Volatility spillover (in percentage)							
	NSW	47.48	13.70	11.47	4.36	22.99	52.52
	QLD	17.19	73.51	1.77	1.19	6.35	26.49
To	SA	6.18	1.07	70.51	5.85	16.39	29.49
	TAS	3.09	0.52	7.76	79.70	8.92	20.30
	VIC	17.28	4.17	23.05	9.75	45.75	54.25
	To Others	43.74	19.46	44.05	21.15	54.65	183.05
	Net Spillovers	-8.78	-7.03	14.56	0.85	0.40	
	Spillover Index					$= \frac{183.05}{500.00}$	$= 36.61\%$

Notes: Spillover table for NSW, QLD, SA, TAS and VIC electricity markets, 1 January 2010 to 31 December 2015, generated based on the generalised forecast error variance decomposition of VAR (1) (for prices in Panel (a)) and VAR (2) (for volatilities in Panel (b)). The ij^{th} entry estimates the fraction of 1-day ahead error variance in forecasting market i due to exogenous shocks to market j (i.e. the spillover from market j to market i: S^g_{ij}).

6.2.2 Static Spillover Analysis: Summary and Indications

In summary, for Australian electricity markets, spillover effects are on average more significant in volatilities than in prices. Compared to price spillovers, the aggregated volatility spillovers and most of the pairwise volatility spillovers are of a higher magnitude. This suggests more transmissions of price volatilities than transmissions of price shocks in the NEM.

For directional spillovers, SA and VIC transmit out the most price spillovers, indicating the most significant influence on prices in other markets. On the other hand, the most significant volatility spillover givers are VIC, SA and NSW.

In net terms, for both price and volatility spillovers, SA is the most important net giver, while NSW is the most significant net receiver.

Also of note in the full-sample static analysis is that the spillover effects in electricity prices and volatilities generally appear in a similar pattern. The interaction between adjoining markets that are physically connected tends to be higher since more spillover effects can be observed, such as the high price spillovers between the pairs NSW–VIC (one interconnector) and VIC–SA (two interconnectors), and the high volatility spillovers between the pairs VIC–SA (two interconnectors), NSW–VIC (one interconnector) and NSW–QLD (two interconnectors).

6.3 Dynamic Spillover Analysis

The analysis based on the full-sample spillover table in the previous section has provided a summary of the average pattern of spillover effects among different regional markets in the Australian NEM. This analysis is static because it assumes that the intensity of interdependence between markets remains constant. However, during our sample period (January 2010 to December 2015), many events took place in the Australian NEM. These included long-term evolutions, such as changes in market policies and integration level, and also short-term extraordinary events, such as temporary generation outages and transmission failures. These changes or market events are likely to cause variations (both long-term and event-specific) in the patterns of both price and volatility spillovers over time. Therefore, it is inadequate to assume that spillovers are time-invariant. Thus, in the following sections, a series of dynamic analyses are conducted to investigate the time-varying patterns of various spillover effects. In particular, we summarise the general patterns of the spillover dynamics and relate these patterns to the market structure and events. We also consider the important policy of the carbon pricing scheme in our dynamic spillover analysis, because this regulatory change triggered various effects (such as alternations of the generation mix in the NEM and the import/export position of each regional market) during its two-year period from July 2012 to June 2014.

6.3.1 Aggregated Spillover Plots

Figure 6.1 presents the time-varying plots of the aggregated spillover index for price (Panel (b)) and volatility (Panel (c)) respectively, which allows the time-variations of the overall market spillover effects to be assessed graphically against the raw log-prices (Panel (a)). These results are generated by dynamically estimating the aggregated price and volatility spillover indexes with a VAR (1) model for prices and a VAR (2) model for volatilities, a 1-day forecasting horizon, and a 365-day rolling window. As shown in the figure, the levels of both price and volatility spillover effects are not constant but time-varying. Overall, the intensity of both price spillovers and volatility spillovers can largely deviate from the average (static) spillover index (21.64% for price and 36.61% for volatility). Several major patterns can be identified from those time variations, including short-term fluctuations and long-term trend and cycles.

Some short-term fluctuations of the spillover plots could be related to significant market events. In particular, the daily log-price plots in of Figure 6.1(a) identify several extreme price outcomes and high volatility periods in the NEM. They are typically caused by extraordinary market events such as extremely high demand, congestion of transmission lines and generation outages (Events A to K). The spillover plots (Figures 6.1(b) and 6.1(c)) are found to indicate responses to these market events. We can correspondingly identify several periods of increased spillover effects that lasted for one to two months, as well as some so-called short-lived 'bursts' that occurred and subsequently subsided, usually within several hours or days.

In particular, price spillover plots are more efficient in capturing events during which there were joint price spikes among different markets (e.g. Events A, B and E), while volatility spillover plots more efficiently capture occasions of highly volatile prices in the NEM (e.g. Events C, D, J and K).

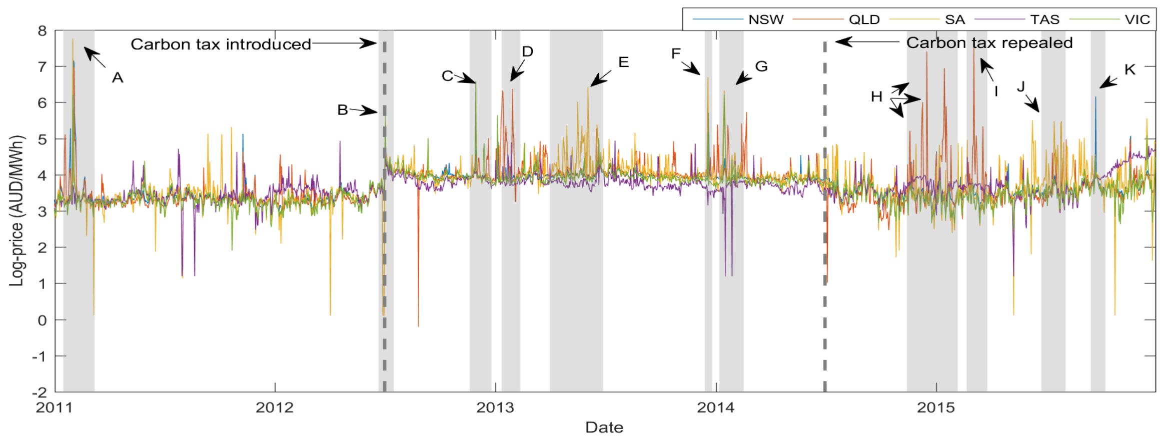
The long-term trends of price and volatility spillovers are described as follows.

In Figure 6.1(b), the aggregated price spillover index started from approximately 17% in the first window (ended on 31 December 2010), and ranged between 13% and 40%. Overall, the index had a marginally increasing trend over the entire sample. This may indicate a slight increase in the whole market integration level of the NEM. In addition, there were roughly three big cycles in the plot. Before the launch of the carbon taxation system in Australia (July 2012), the price spillover index experienced a first big cycle from February 2010 to March 2012. In this cycle, the index began at around 25% and peaked at almost 40% around the end of 2011 before sharply dropping back to the original level. The second cycle of price spillover index started at the beginning of the carbon pricing period and ended by the end of 2013. The third cycle was during 2015, ranging between 30% and 38%. In between these cycles, there were some tranquil periods with several small cycles.

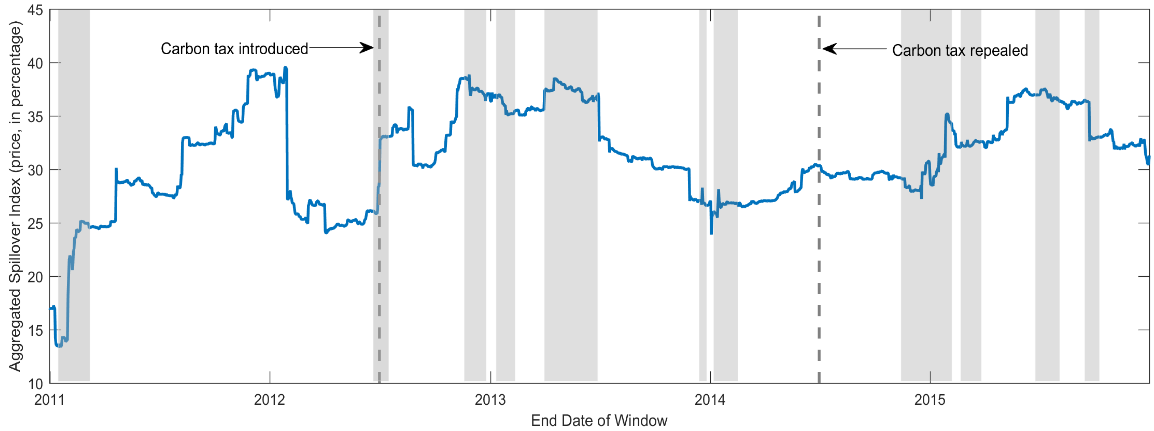
The aggregated volatility spillover index (Figure 6.1(c)) initiated at 39% in the first window, and ranged between 28% and 45%. Across the sample period, no obvious trend is observed from the aggregated volatility spillover plot; however, three large cycles are identified before, during and after the carbon pricing period. The first cycle took place in the pre-carbon pricing period and began in April 2011 when the aggregated spillover index of the NEM was around 37% (which is close to the unconditional spillover level). The spillover index peaked at almost 45% in mid-2011 and dropped back to 37% until the beginning of 2012. Noticeably, the period before the establishment of carbon pricing in Australia (January 2012 to June 2012) witnessed a significant drop in the level of the aggregated spillover index. In June 2012, this index reached the lowest level (28%) across our sample period. The second cycle was from July 2012 to December 2013, which was during the carbon pricing period. In this cycle, the aggregated volatility spillover index moved between 30% and 35%. After the cycle, the index jumped to above 35% in January 2014 and remained at around 36% for the first half of 2014. The third cycle began in July 2014 when the carbon taxation system was removed. The aggregated volatility spillover index climbed from 35% to 43% by the end of 2014. It then went back to 35% in mid-2015 and remained at around this level for the second half of 2015.

It is worth noting that at the overall market level, price spillovers and volatility spillovers appeared differently in the carbon taxation period. The index of price spillovers varied in a relatively similar pattern and range before, during and after the carbon pricing period, despite the fact that it dropped and remained at a lower level only around the beginning and the end of the period. In comparison, the level of the aggregated volatility spillover in the NEM was generally lower during the carbon pricing period than during the periods before and after. In particular, given the unconditional aggregated volatility spillover index (36.61%) calculated from the entire sample (Table

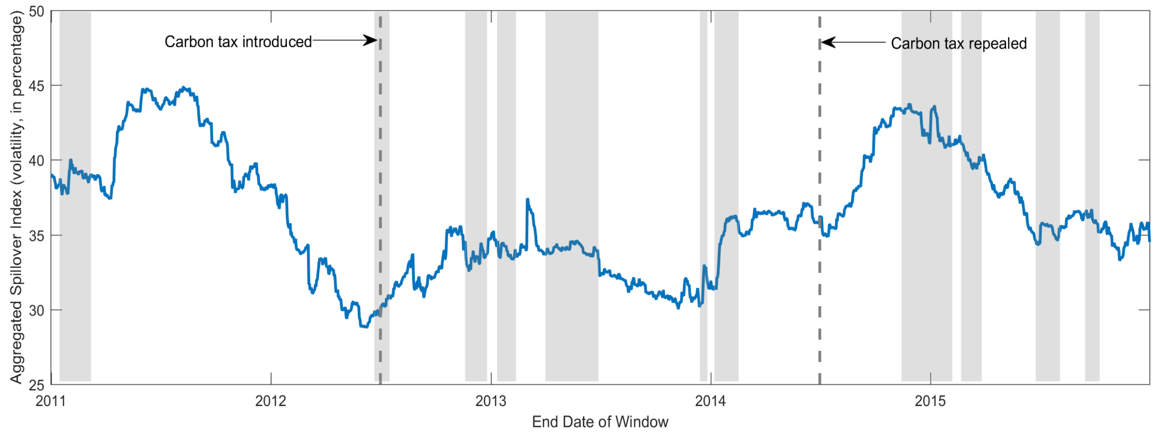
6.1), in the periods before and after the carbon taxation, the index mostly fluctuated well above this average level, while during the carbon taxation period, the index was mostly below this level.



(a) Log-prices



(b) Aggregated spillover index (price)



(c) Aggregated spillover index (volatility)

Figure 6.1: Plots of log-prices, aggregated price spillover index, and aggregated volatility spillover index. The shaded areas (A to K) represent identified short-term events in the NEM according to Australian Energy Regulator (2015), which are specified as follows:
A: record demand (NSW and SA); B: outages of Basslink interconnector (VIC-TAS); C: high demand (SA and VIC); D: congestion (QLD); E: temporary shutdown and tight supply conditions (SA); F: high demand and rebidding (SA), high demand and network issue (NSW); G: high demand (SA and VIC); H: rebidding (QLD); I: record demand (QLD); J: tight supply conditions and rebidding (SA); K: network issues (NSW)

6.3.2 Net Directional Spillover Plots

In this section we investigate the dynamic spillovers for each single regional market in the Australian NEM, including the pairwise net spillovers between each pair of regional markets and the total net directional spillovers contributed by each region. These results are generated by dynamically estimating the spillover table with a 365-day rolling window. Panel (a) of Figure 6.2 plots the time-variations of total net directional price spillovers for each of the five regional markets in the NEM. It corresponds to the dynamic estimation of the 'Net Spillovers' row of the spillover table (Table 6.1), which is the difference between the 'To Others' row and the 'From Others' column[20]. Below this, Panel (b) of Figure 6.2 provides the time-varying plots of pairwise net price spillovers between each pair of regional markets, which are calculated using Equation 4.15. Similarly, the plots of total and pairwise net spillovers for volatility are shown in Figure 6.3.

From a visual inspection, for both prices and volatilities in the Australian NEM, three main features are noticeable. Firstly, both the level and direction of the spillover effect are not constant but time-varying. Secondly, the transmission of shocks between markets is asymmetric. For example, the total net spillovers from SA are always positive with relatively large magnitude. This means that the interactions between SA and other markets are dominated by the transmission of price and volatility shocks from SA to others. In contrast, NSW is always a net receiver of price and volatility shocks with negative net spillovers. Thirdly, some temporary market events can still be captured and reflected as short-term bursts by directional spillover plots (both for price and volatility spillovers) in net terms, although these effects are less obvious compared to those in aggregated spillover plots[21].

[20] The dynamics of gross directional spillovers received from other markets and transmitted to other markets by each regional market are also provided in Appendix Appendix section:grossSI. Gross and net spillovers are substitutes, but should be considered as complements. However, in this study we focus more on net spillovers because they are informative on the relative influencing power of different markets.

[21] These effects can be observed even more clearly in gross directional spillover plots. The reason is that during those temporary market events, both the gross spillover from a market and the gross spillover to it tend to increase. A part of these increases is thus offset, see Appendix A.2.

In the following, the dynamic pattern of total net spillovers for each market is discussed together with the pairwise net spillovers, since pairwise net spillovers can be viewed as decompositions of total net directional spillovers.

Net Directional Spillovers: Price

According to Figure 6.2, NSW was always a net price spillover receiver over the sample period (Figure 6.2(a)), mainly from SA and VIC (Figure 6.2(b)). These spillovers were especially high between July 2012 and December 2014, which was within the carbon taxation period.

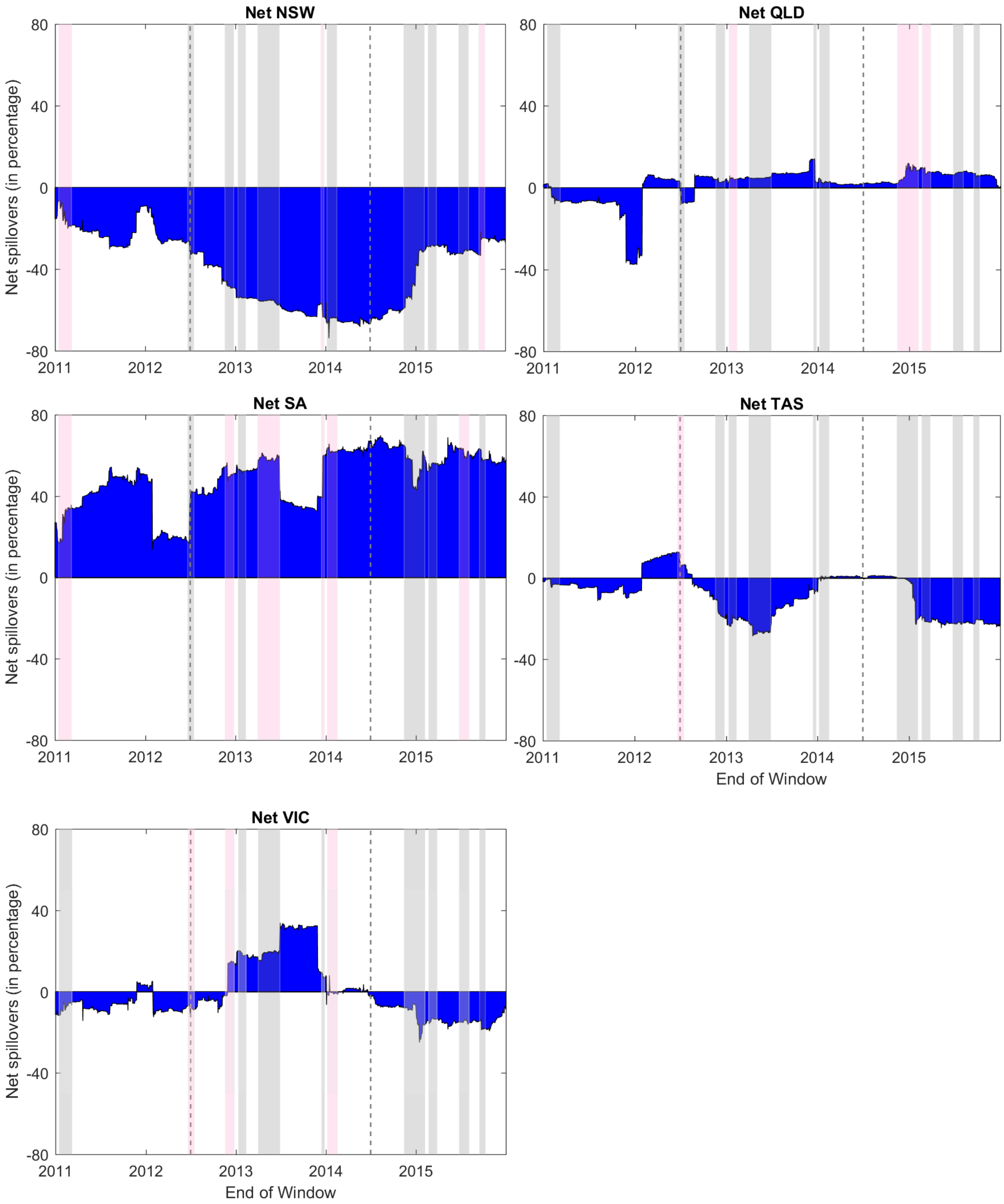
QLD was a net price spillover receiver before 2012 and a net giver after that. In particular, the magnitude of net spillovers for QLD, both in total and in pairwise levels, was relatively higher before 2012, and especially high around the end of 2011. From 2012 onward, all net spillovers continued to fluctuate at a low level.

As a typical net price giver (Figure 6.2(a)), SA mainly transmitted price shocks to NSW and VIC, which were physically connected to SA. However, the price shocks also flowed from SA to TAS, especially during the periods of July 2012 to December 2014 and January 2015 to December 2015 (Figure 6.2(b)).

TAS typically received a relatively low level of price shocks from other markets (Figure 6.2(a)). There were only two episodes during which TAS transmitted net spillovers out, which were the periods around the introduction of the carbon taxation system (around July 2012) and its abolishment (around June 2014). These net price spillovers from TAS mainly flowed to VIC (Figure 6.2(b)).

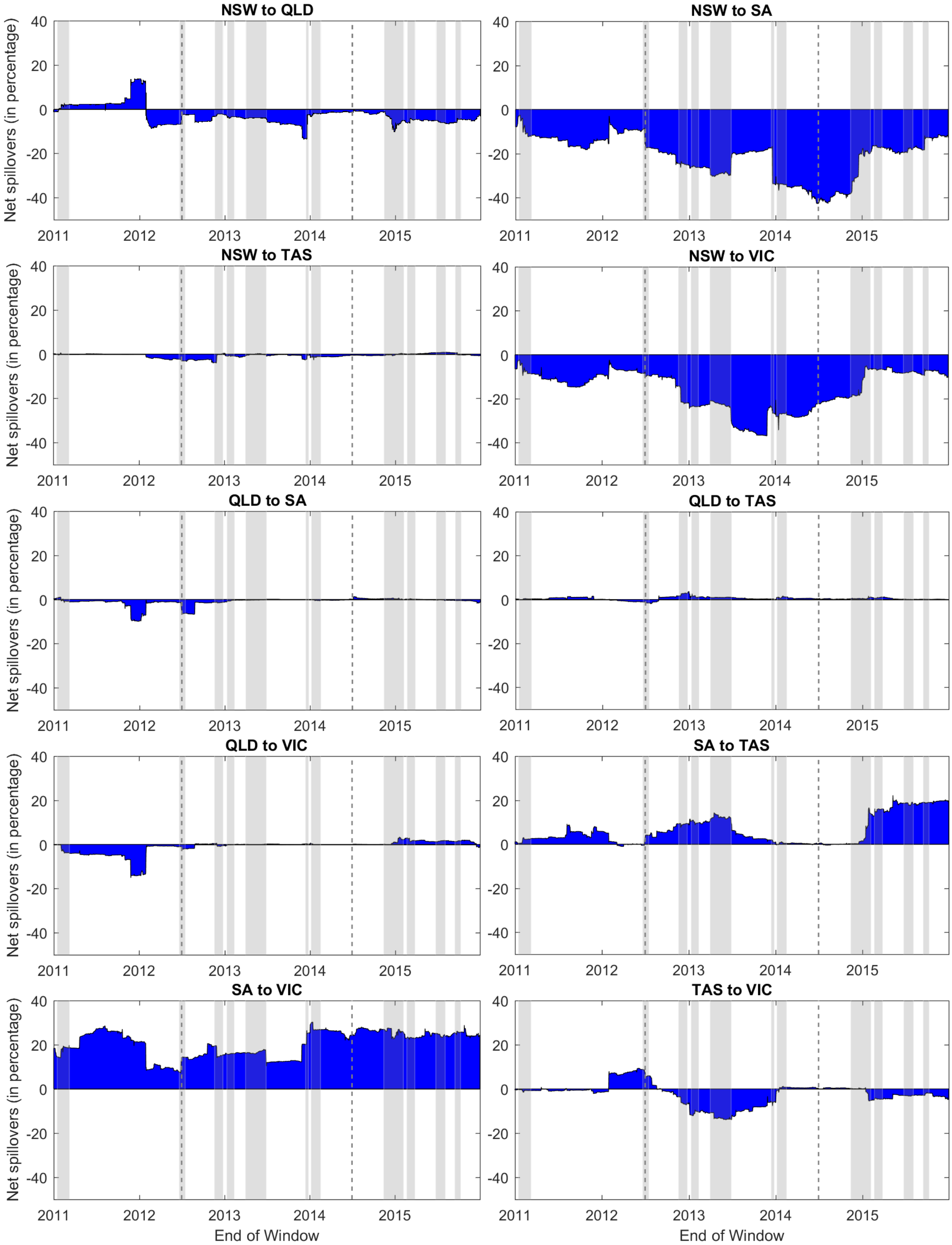
The net position of price spillovers for VIC was also influenced by the carbon taxation policy. Before and after the carbon taxation period, VIC was typically a net spillover receiver (Figure 6.2(a)). However, during the carbon taxation period, VIC was mainly a net spillover giver, transmitting price shocks to NSW and TAS (Figure 6.2(b)).

Overall, the total net price spillovers ranged widely between -80% and 80% (Figure 6.2(a)). The magnitude of these spillovers varied quite significantly for different regions. For example, the net price spillovers of NSW and SA could have a magnitude as large as 80%, while the magnitude for QLD net spillovers was typically below 10%. A similar pattern is also observed in pairwise net price spillovers (Figure 6.2(b)).



(a) Total net price spillovers

Figure 6.2: continued on next page



(b) Pairwise net price spillovers

Figure 6.2: Total net price spillovers and pairwise net price spillovers in the NEM over 1 January 2010 to 31 December 2015, estimated from a VAR(1) model with a 1-day forecasting horizon and a 365-day rolling window. Positive net spillovers from a market mean that the spillovers transmitted by that market are higher than the spillovers received by it. Negative net spillovers from a market mean that the spillovers transmitted by that market are lower than the spillovers received by it. The two dashed lines on each plot refer to the beginning and end dates of the carbon taxation policy. The shaded areas indicate identified temporary market events. For each market in Panel (a), the events that originated in that market are coloured pink. From left to right, these events are:
1: record demand (NSW and SA); 2: outages of Basslink interconnector (VIC-TAS); 3: high demand (SA and VIC); 4: congestion (QLD); 5: temporary shutdown and tight supply condition (SA); 6: high demand and rebidding (SA), high demand and network issue (NSW); 7: high demand (SA and VIC); 8: rebidding (QLD); 9: record demand (QLD); 10: tight supply conditions and rebidding (SA); 11: network issues (NSW).

Net Directional Spillovers: Volatility

Compared to net directional spillovers for price, the net volatility spillovers varied within a relatively small range between -15% and 20% (Figure 6.3(a)). Meanwhile, the ranges of the spillover magnitude for different regions were similar.

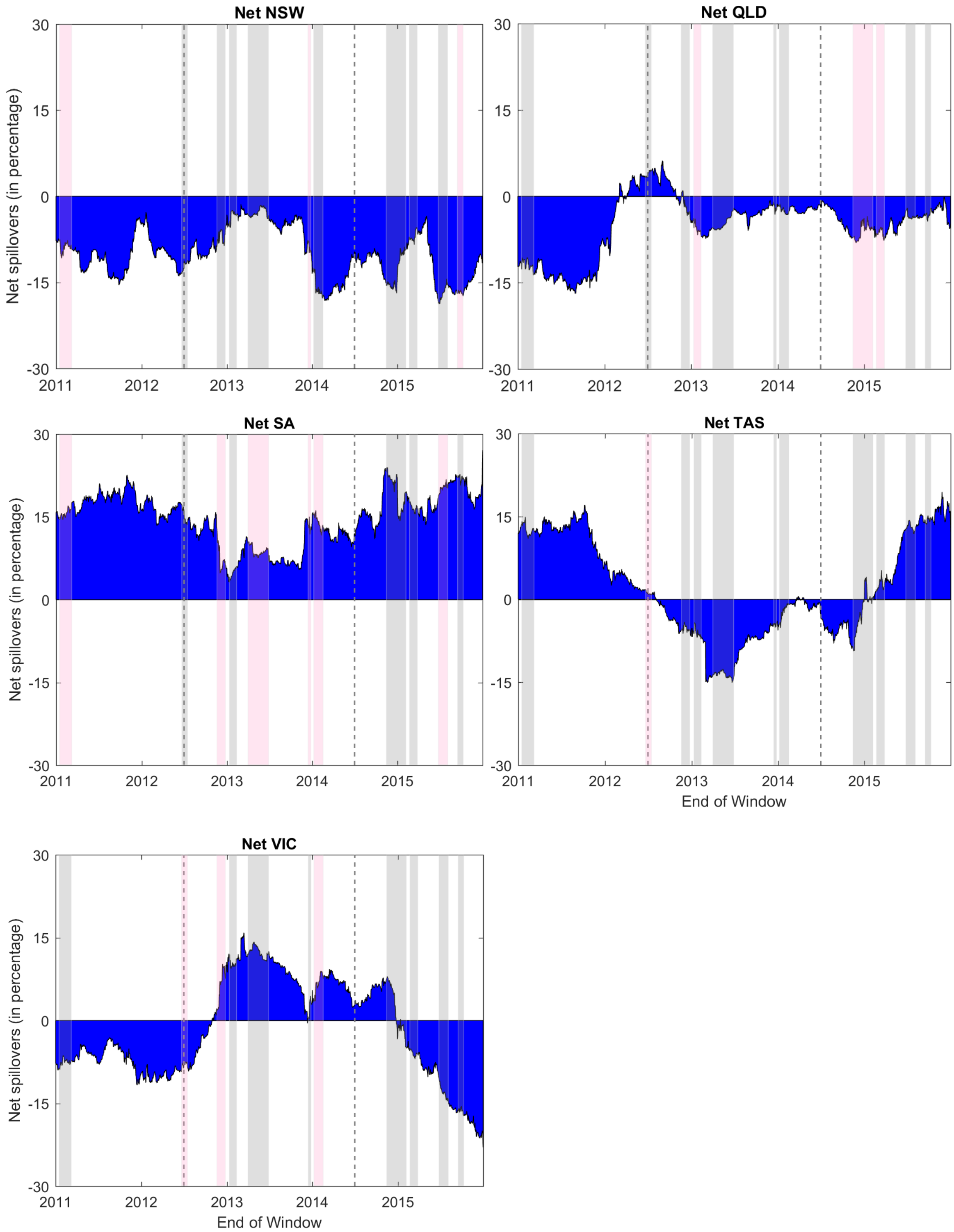
More specifically, according to Figure 6.3(a), NSW was a net volatility spillover receiver across the sample period. However, in pairwise spillover plots (Figure 6.3(b)), while NSW typically received volatility spillovers from SA and VIC, there were several episodes during which NSW transmitted net positive volatility spillovers to certain markets (QLD and TAS). Specifically, the volatility spillovers were always transmitted from NSW to QLD, except in 2012. Furthermore, NSW transmitted some net volatility spillovers to TAS throughout 2013 (during the carbon pricing period).

Typically, QLD was a volatility spillover receiver (Figure 6.3(a)). The magnitude of spillovers received by QLD was much higher during 2011 (around 15%) than during the rest of the studied period, where it was below 8%. Furthermore, only one episode can be identified (from April 2012 to December 2012) during which QLD was a net volatility spillover giver. During this period, the volatility shocks to QLD mostly spilled over to NSW (Figure 6.3(b)). While the magnitude of spillovers between QLD and NSW remained relatively stable, the interactions between QLD and each other market reduced significantly from the beginning of 2012.

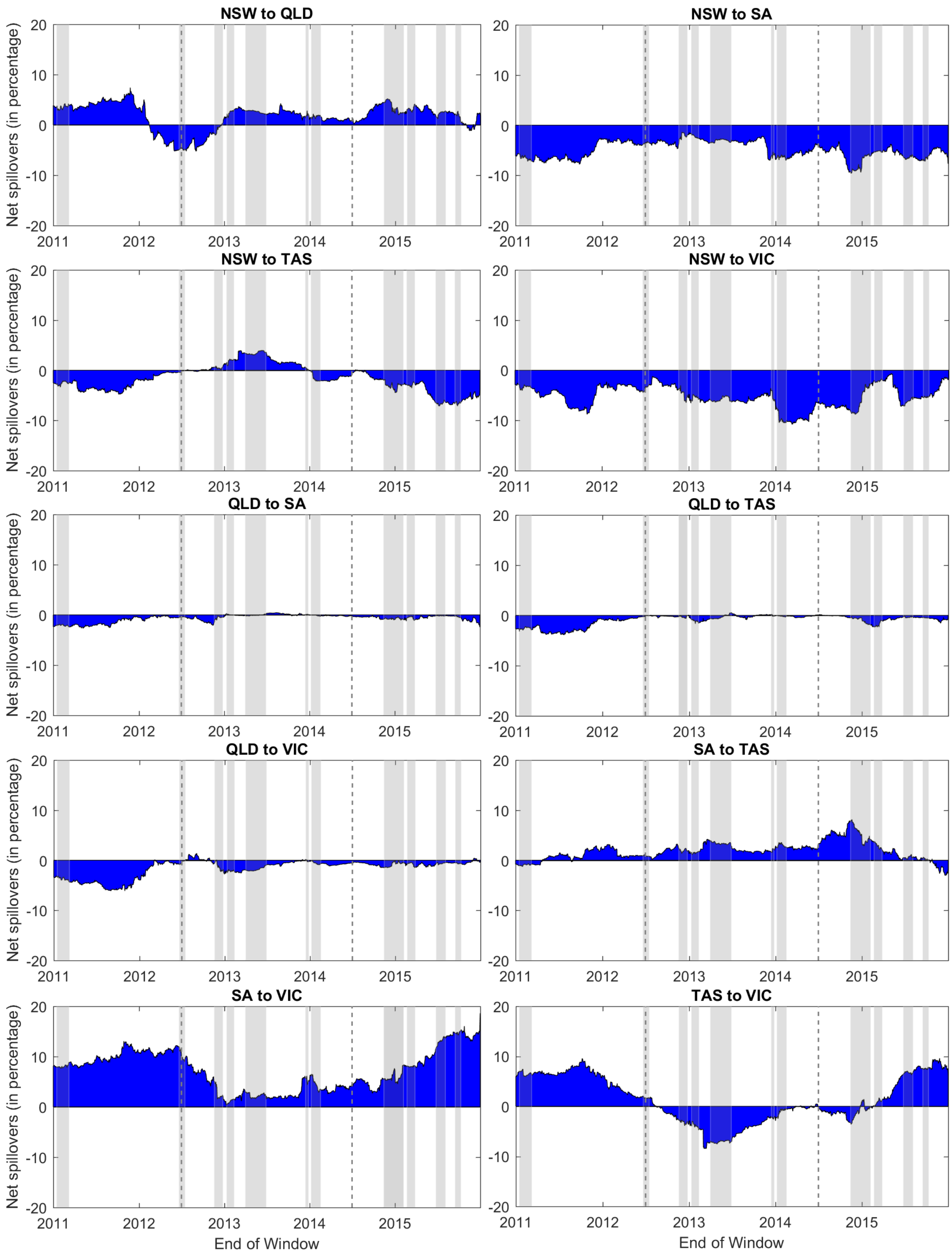
Much as in the case of price spillover effects (Figure 6.2(a)), SA transmitted out net volatility spillovers throughout the sample period (Figure 6.3(a)). In particular, the total net spillovers of volatility transmitted from SA to other markets were relatively higher in the periods before and after the carbon taxation. According to Figure 6.3(b), before the carbon taxation period, volatility shocks from SA were mainly transmitted to VIC (around 10%) and NSW (around 8%). After the carbon taxation period, although VIC and NSW were still the major net recipients of volatility shocks from SA, there was a period (the second half of 2014) during which the volatility spillovers from SA to TAS were relatively high. In comparison, during the carbon taxation period, the volatility spillovers (both net total and net pairwise) transmitted from SA were much lower. Furthermore, volatility spillovers between SA and QLD were typically the lowest. This conforms to the fact that they are located at the extremities of the NEM and not physically connected.

For TAS, there were two periods during which the net volatility spillovers were positive (Figure 6.3(a)). The first period was from January 2011 to July 2012. Net volatility spillovers from TAS mostly went to VIC, but also flowed to NSW and QLD (Figure 6.3(b)). The second period was during 2015. Net volatility spillovers from TAS mostly went to NSW and VIC. The net volatility spillovers from TAS were more obviously impacted by the establishment and abolishment of the carbon taxation policy. While TAS was typically a net spillover transmitter before and after the carbon taxation period, during carbon taxation, the position of TAS was reversed to be a net receiver.

For VIC, there was one episode of positive net volatility spillover (Figure 6.3(a)): from October 2012 to December 2014. During this period, TAS and NSW were the major net recipients of volatility shocks from VIC (Figure 6.3(b)). During other periods, VIC generally received volatility spillovers from SA and TAS, and transmitted spillovers to NSW and QLD. Similarly to TAS, net spillovers from VIC appeared different during and outside the carbon taxation period. While VIC was typically a net volatility spillover receiver before and after the carbon pricing period, during that period its position was reversed to be a net transmitter. In particular, the launch of the carbon taxation system seemed to exert a significant influence on the interaction between VIC and TAS. During the carbon taxation period, volatility shocks spilled over from VIC to TAS, while before and after this period the net volatility spillovers between these two markets were in the opposite direction.



(a) Total net volatility spillovers
Figure 6.3: continued on next page



(b) Pairwise net volatility spillovers

Figure 6.3: Total net volatility spillovers and pairwise net volatility spillovers in the NEM over 1 January 2010 to 31 December 2015, estimated from a VAR(2) model with a 1-day forecasting horizon and a 365-day rolling window. Positive net spillovers from a market mean that the spillovers transmitted by that market are higher than the spillovers received by it. Negative net spillovers from a market mean that the spillovers transmitted by that market are lower than the spillovers received by it. The two dashed lines on each plot refer to the beginning and end dates of the carbon taxation policy. The shaded areas indicate identified temporary market events. For each market in Panel (a), the events that originated in that market are coloured in pink. From left to right, these events are:
1: record demand (NSW and SA), 2: outages of Basslink interconnector (VIC-TAS), 3: high demand (SA and VIC), 4: congestion (QLD), 5: temporary shutdown and tight supply condition (SA), 6: high demand and rebidding (SA), high demand and network issue (NSW), 7: high demand (SA and VIC), 8: rebidding (QLD), 9: record demand (QLD), 10: tight supply conditions and rebidding (SA), 11: network issues (NSW).

6.3.3 Dynamic Spillover Analysis: Summary and Indications

Important findings from the above dynamic spillover analysis are summarised below.

Firstly, the dynamic analysis is able to capture some information that cannot be conveyed in the static analysis. For example, while the static analysis (Table 6.1 Panel (a)) identifies QLD as a net price spillover giver, the dynamic analysis can denote episodes wherein QLD received net price spillovers from other markets (Figure 6.2(a)). Similarly, although the static analysis in Section 6.2 suggests two net price spillover givers (SA and QLD) and three net volatility spillover givers (SA, TAS and VIC) on a full-sample basis, according to the dynamic examination, only SA is always found to have transmitted out net price and volatility spillovers, while the net spillover position for QLD, TAS and VIC varied over different periods. In contrast, NSW always received net price and volatility spillovers over time. Moreover, among the five regions in the NEM, the net price and volatility spillovers from SA both have time-varying patterns that are the closest to those of the corresponding aggregated spillovers. It indicates that overall spillover pattern in the NEM is largely dominated by the shocks transmitted from SA to other markets.

Secondly, the patterns of directional spillovers appear similar in static and dynamic analyses. Whether on an average or on a time-varying basis, a higher level of spillover effects exists between markets that are well interconnected, for example, between the pairs NSW–VIC, SA–VIC, and VIC–TAS. However, QLD is a special regional market in the NEM. Both price and volatility spillovers from and to QLD are low compared to other markets, which is especially obvious in the conducted dynamic analysis. Although there are two interconnectors in place between QLD and NSW, price and volatility transmissions between these two markets are relatively low. The interactions between QLD and other markets are even lower. A possible reason is the local structural factors in the QLD market in recent years. The electricity generation sector in QLD is more concentrated than in any other region in the NEM. The high degree of local generator power makes QLD relatively isolated from other markets, which explains the low level of spillover effects from and to QLD. The degree of QLD electricity market concentration increased even further in 2011 (Australian Energy Regulator, 2015) due to the integration of two local generators; this could also explain the decrease of the spillover magnitude for QLD from 2012 onwards.

Thirdly, the carbon taxation system had impacts on the spillover effects in the NEM, possibly by influencing interregional trade. The changing direction of net volatility spillovers between TAS and VIC during and outside the carbon pricing period is a clear example (Figure 6.3(b)). In particular, before the establishment of carbon taxation, TAS typically imported electricity from VIC. During that period, TAS was a net volatility spillover giver that transmitted volatilities mainly to VIC, while VIC was a net spillover receiver. When carbon taxation was in place, TAS became a net electricity exporter because of its relatively low regional prices, exporting electricity to VIC as well as other regions. Along with the reverse of trade positions of TAS and VIC, between July 2012 and June 2014, TAS became a net volatility spillover receiver, while VIC became a net transmitter. After the abolition of the carbon taxation policy, the trade position and net spillover direction between TAS and VIC both returned to those before July 2012. Another example is the net volatility spillover received by NSW. Due to high local fuel costs, NSW is typically an electricity importer. However, carbon taxation reduced the reliance of NSW on imports. Accordingly, with a lower level of electricity imports, NSW received lower levels of volatility transmissions from other markets during the carbon pricing period.

Furthermore, there are other time variations of the spillover effects which could be related to specific events in the NEM. For example, the minor upward trend in the aggregated price spillover plots (Figure 6.1(b)) could reflect a gradual increase in the integration level of the NEM. In addition, the eventful bursts reflect specific issues such as increased electricity demand, generation outage and transmission failure.

6.4 Robustness Assessment

Finally, we investigate the robustness of the results in this study. This assessment includes two parts. Firstly, we examine the reliability of our findings regarding the impacts of the carbon taxation (Section 6.4.1). Secondly, we check the robustness of our results to different choices of the parameters of the model (Section 6.4.2).

6.4.1 Carbon Taxation Period

In this section, the static spillover analysis introduced in Section 6.2 is re-performed for the three subperiods (before, during and after carbon taxation) separately. It is worth noting that all the data transformation including logarithm transformation and deseasonalisation are re-performed for the three periods. The corresponding descriptive data are provided in Appendix (Tables A2 and A3) to preserve space. As discussed in Section 3.5, it can be observed from Table A2 that during the carbon pricing period, electricity spot prices in all regions were generally high, with a higher mean and median compared to other periods. The TAS market had relatively low spot prices during this period, which made it the major net electricity exporter.

In the following, the price and volatility spillover effects for the periods before, during and after the carbon taxation periods are discussed.

Price

Table 6.2 shows the static spillover analysis results for price, where the overall spillover patterns for the entire sample (Panel (a), January 2010 to December 2015) can be compared with the patterns in three subperiods: before carbon taxation (Panel (b), January 2010 to June 2012), during carbon taxation (Panel (c), July 2012 to June 2014), and after taxation (Panel (d), July 2014 to December 2015).

Overall, the aggregated price spillover indexes in the three periods before, during and after the implementation of carbon pricing are 20.36%, 29.08% and 31.25% respectively. This confirms our finding that over our sample period, the aggregated price spillover index depicts an increasing trend.

With regard to directional price spillovers, for all three subperiods, the patterns are similar to that for the entire sample. SA and VIC are the largest price spillover transmitters that are the most influential in the Australian NEM, while NSW and VIC are the largest spillover receivers that are the most vulnerable. However, the price spillovers received by TAS are worth noting. Although the price shocks received by TAS from others were lower than 10% before and during the carbon taxation period, in the last period TAS received price spillovers as high as 36.15%, mainly due to the increased level of influence of SA (21.79%) and VIC (12.96%) on TAS. This pattern is also observed previously in Figure 6.2 in dynamic spillover analysis.

In net terms, the patterns of price spillovers for the entire sample are closer to those for the periods before and after carbon taxation. In particular, for all periods, NSW received the most net price spillovers, while SA spilled over the most. Before and after carbon taxation, TAS and VIC were net price spillover receivers; however, during the carbon taxation period the net spillover positions of TAS and VIC were reversed. Again, these patterns are consistent with Figure 6.2 in dynamic spillover analysis.

Table 6.2: Spillover table for prices before, during and after the carbon taxation period

		From				
	NSW	QLD	SA	TAS	VIC	From Others
Panel (a) : Price spillovers (in percentage) during the full sample (01/2010 - 12/2015)						
NSW	66.45	5.56	12.42	1.14	14.43	33.55
QLD	2.91	94.28	0.63	0.25	1.93	5.72
To SA	0.87	0.22	82.93	1.92	14.06	17.07
TAS	1.10	0.48	5.84	89.55	3.03	10.45
VIC	2.58	1.26	35.69	1.87	58.60	41.40
To Others	7.46	7.52	54.58	5.18	33.45	108.19
Net Spillovers	-26.09	1.80	37.51	-5.27	-7.95	
Spillover Index					$= \frac{108.19}{500.00}$	$= 21.64\%$
Panel (b) : Price spillovers (in percentage) before the carbon taxation (01/2010 - 06/2012)						
NSW	70.25	6.35	10.13	1.34	11.93	29.75
QLD	5.26	89.79	1.19	0.98	2.77	10.21
To SA	0.44	0.44	84.29	1.79	13.04	15.71
TAS	1.45	1.08	4.17	91.26	2.04	8.74
VIC	1.58	1.00	33.42	1.37	62.63	37.37
To Others	8.73	8.87	48.91	5.48	29.79	101.78
Net Spillovers	-21.02	-1.34	33.20	-3.26	-7.58	
Spillover Index					$= \frac{101.78}{500.00}$	$= 20.36\%$
Panel (c) : Price spillovers (in percentage) during the carbon taxation (07/2012 - 06/2014)						
NSW	32.87	4.54	31.84	1.25	29.50	67.13
QLD	1.01	98.56	0.00	0.10	0.33	1.44
To SA	0.74	0.00	75.01	0.40	23.85	24.99
TAS	0.95	0.82	1.70	92.38	4.16	7.62
VIC	1.75	0.32	41.14	1.01	55.78	44.22
To Others	4.45	5.68	74.68	2.77	57.84	145.42
Net Spillovers	-62.68	4.24	49.69	-4.85	13.62	
Spillover Index					$= \frac{145.42}{500.00}$	$= 29.08\%$
Panel (d) : Price spillovers (in percentage) after the carbon taxation (07/2014 - 12/2015)						
NSW	56.81	7.58	16.87	1.28	17.46	43.19
QLD	3.37	93.18	1.33	0.01	2.11	6.82
To SA	2.66	0.31	82.47	3.65	10.92	17.53
TAS	1.36	0.03	21.79	63.85	12.96	36.15
VIC	8.13	2.05	35.58	6.81	47.43	52.57
To Others	15.52	9.97	75.58	11.75	43.45	156.27
Net Spillovers	-27.67	3.15	58.05	-24.40	-9.12	
Spillover Index					$= \frac{156.27}{500.00}$	$= 31.25\%$

Volatility

Table 6.3 shows the static spillover analysis results for volatility, where the overall spillover patterns for the entire sample (Panel (a), January 2010 to December 2015) can be compared with the patterns in three subperiods: before carbon taxation (Panel (b), January 2010 to June 2012), during carbon taxation (Panel (c), July 2012 to June 2014), and after taxation (Panel (d), July 2014 to December 2015).

The aggregated volatility spillover indexes in the three periods before, during and after the implementation of carbon pricing are 35.62%, 33.81% and 34.17% respectively. This confirms our findings that the aggregated volatility spillover index was lower during the carbon pricing period compared to other time horizons.

For all three subperiods, the patterns of directional volatility spillovers are similar to those of the entire sample. NSW, SA and VIC are the largest volatility spillover transmitters, while NSW and VIC receive the most volatility spillovers.

In net terms, the positions of NSW, QLD, and SA were the same for all subperiods. However, consistent with Figure 6.3 in dynamic volatility analysis, Table 6.3 also indicates that the net spillover positions of TAS and VIC during the carbon taxation period were contrary to those during other periods.

In summary, the separate assessment of electricity price and volatility spillover effects before, during and after the carbon taxation period confirms the empirical findings of this study presented in Sections 6.2 and 6.3.

Table 6.3: Spillover table for price volatility before, during and after the carbon taxation period

		From					
		NSW	QLD	SA	TAS	VIC	From Others
Panel (a) : Volatility spillovers (in percentage) during the full sample (01/2010 - 12/2015)							
	NSW	47.48	13.70	11.47	4.36	22.99	52.52
	QLD	17.19	73.51	1.77	1.19	6.35	26.49
To	SA	6.18	1.07	70.51	5.85	16.39	29.49
	TAS	3.09	0.52	7.76	79.70	8.92	20.30
	VIC	17.28	4.17	23.05	9.75	45.75	54.25
	To Others	43.74	19.46	44.05	21.15	54.65	183.05
	Net Spillovers	-8.78	-7.03	14.56	0.85	0.40	
	Spillover Index					$= \frac{183.05}{500.00}$	$= 36.61\%$
Panel (b) : Volatility spillovers (in percentage) before the carbon taxation (01/2010 - 06/2012)							
	NSW	52.53	20.00	9.38	2.56	15.53	47.47
	QLD	21.93	64.97	2.66	1.09	9.35	35.03
To	SA	4.18	1.35	74.99	5.13	14.35	25.01
	TAS	1.44	0.47	5.72	84.93	7.44	15.07
	VIC	11.98	6.83	24.40	12.30	44.50	55.50
	To Others	39.52	28.65	42.16	21.08	46.68	178.09
	Net Spillovers	-7.95	-6.38	17.15	6.01	-8.82	
	Spillover Index					$= \frac{178.09}{500.00}$	$= 35.62\%$
Panel (c) : Volatility spillovers (in percentage) during the carbon taxation (07/2012 - 06/2014)							
	NSW	49.36	9.85	9.88	3.72	27.19	50.64
	QLD	11.36	84.88	0.23	0.82	2.71	15.12
To	SA	6.07	0.26	73.48	3.44	16.76	26.52
	TAS	4.29	0.68	6.94	74.93	13.14	25.07
	VIC	20.45	2.06	20.10	9.09	48.31	51.69
	To Others	42.17	12.85	37.16	17.06	59.80	169.05
	Net Spillovers	-8.47	-2.27	10.64	-8.01	8.11	
	Spillover Index					$= \frac{169.05}{500.00}$	$= 33.81\%$
Panel (d) : Volatility spillovers (in percentage) after the carbon taxation (07/2014 - 12/2015)							
	NSW	48.36	12.72	12.57	9.00	17.35	51.64
	QLD	15.77	80.48	1.01	1.00	1.74	19.52
To	SA	4.58	0.29	72.13	9.90	13.11	27.87
	TAS	2.85	0.11	10.13	81.45	5.47	18.55
	VIC	13.11	1.19	27.99	11.00	46.71	53.29
	To Others	36.31	14.30	51.70	30.90	37.66	170.87
	Net Spillovers	-15.33	-5.22	23.83	12.35	-15.63	
	Spillover Index					$= \frac{170.87}{500.00}$	$= 34.17\%$

6.4.2 Different Model Specification

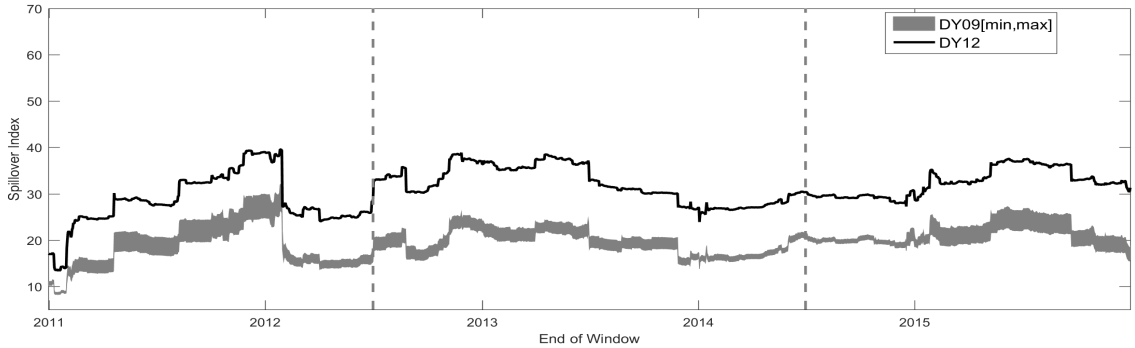
In this section the robustness of our findings to different model specifications is assessed. These different specifications include alternative choices of the identification method of shocks for the forecast error variance decomposition, VAR lag length p, forecasting horizon H, and window length w. Each of the following sections shows the effect of the choice of one parameter, while more explorations of robustness are found in Appendix A.3.2.

Choice of Identification Method

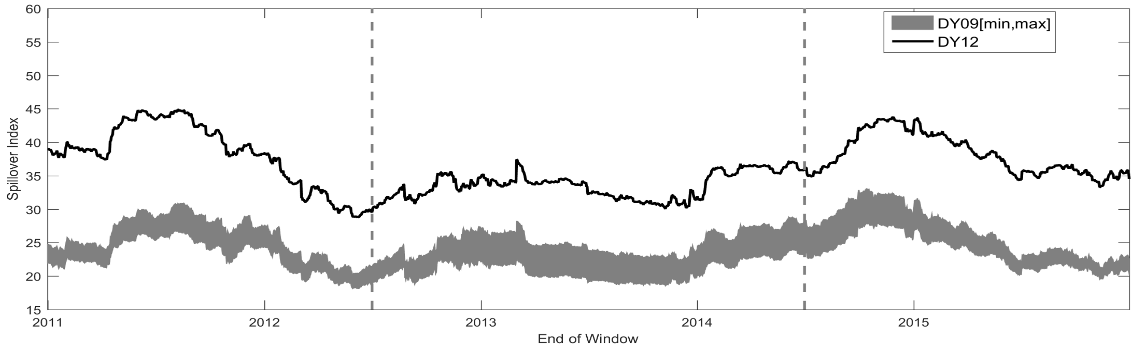
We assess the robustness of our results to the choice of shock identification method in this section. In particular, we compare the earlier version of the DY method (2009) with the version (Diebold and Yilmaz, 2012) that is employed in the main analysis of this study. The 2009 version of the DY method uses Cholesky decomposition to identify shocks, while the 2012 version uses the generalised variance decomposition (GVD).

Figure 6.4 plots the aggregated price and volatility spillover indexes generated by the two versions (i.e. 2009 and 2012) of the DY method. The Cholesky decomposition is sensitive to the variable ordering; therefore, for the 2009 version, we employ the 'fast spillover method' developed by Klößner and Wagner (2014) to compute the results for all possible orderings in each window, and show the interval between the minimum and maximum values of the spillover index in the plots.

The dynamic moves of the spillover indexes generated by the two versions of the DY method are in accordance with each other over time. However, it is observed that the aggregated spillover index obtained from the DY method (2012) is at a higher level than that obtained from the DY method (2009). This is because the generalised forecast error variance decomposition treats each variable as the first variable in the Cholesky-based decomposition and thus tends to give higher spillover estimations (Diebold and Yilmaz, 2014; Klößner and Wagner, 2014). In addition, as can be seen in Figure A4 in Appendix A.3.2, with the decrease of the window length w or the increase of the forecasting horizon H, the gap between the spillover indexes based on the two versions of the DY methods narrows.



(a) Price

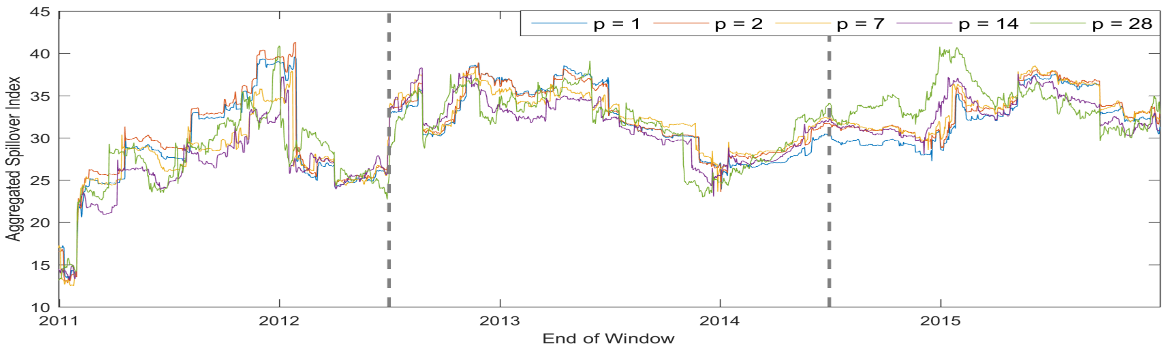


(b) Volatility

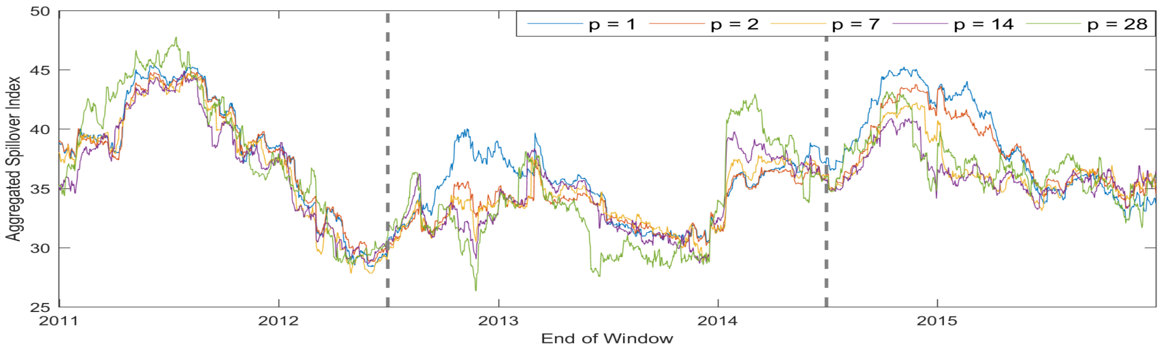
Figure 6.4: Robustness to the choice of identification method. The solid line refer to the spillover indexes calculated from generalised variance decomposition (Diebold and Yilmaz, 2012). The grey band corresponds to a interval between the minimum and maximum values of the spillover index calculated from Cholesky decomposition (Diebold and Yilmaz, 2009) based on all possible orderings.

Choice of VAR Lag Length p

In addition to $p = 1$ for the price VAR model (and $p = 2$ for volatility VAR), we examine alternative lag orders 1 (for volatility), 2 (for price), 7, 14 and 28. The results are plotted in Figure 6.5. It is observed that the change in VAR lag length does not make a significant difference in the spillover pattern for p=2, 7, 14, whereas for p = 1 and 28 the spillover plots are more volatile and the extreme patterns tend to be more frequent. This is particular for the volatility spillover analysis as indicated in the bottom panel of Figure 6.5. However, the overall qualitative patterns of spillover plots are similar for different VAR lag lengths.



(a) Price



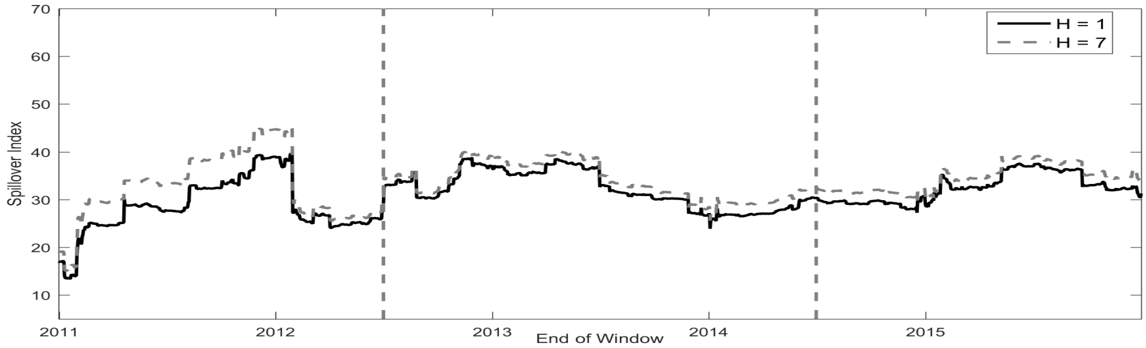
(b) Volatility

Figure 6.5: Robustness to the choice of VAR lag length p (p = 1, 2, 7, 14 and 28)

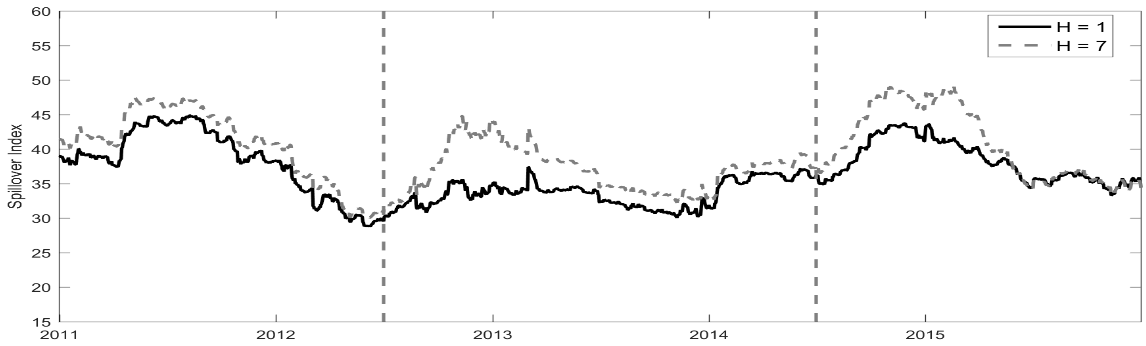
Choice of Forecasting Horizon H

In addition to a one-day predictive horizon in forecast error variance decomposition, we consider a 7-day horizon. According to Figure 6.6, both price and volatility spillover patterns are not sensitive to the choice of the forecasting horizon H, despite the fact that spillover effects are slightly higher when H is larger. Similar results are found in, for example, Diebold and Yilmaz (2009, 2014) and Maghyereh et al. (2015). Intuitively, more spillover effects are expected to be observed when the forecasting horizon is higher. The reason is that shocks in one market could spill over to others contemporaneously, with a short lag, or only with a long lag. With a short forecasting horizon, only contemporaneous and short-term spillover effects are considered. As the forecasting horizon lengthens, more spillover effects, which might only happen in a longer term, could be captured. Therefore, as indicated by Diebold and Yilmaz (2014), there is no reason why the spillover effects should be 'robust' to different forecasting horizons[22].

[22] Furthermore, we also provide the results generated by using a 30-day horizon in Figure A4 of Appendix A.3.2, which illustrate the same patterns.



(a) Price

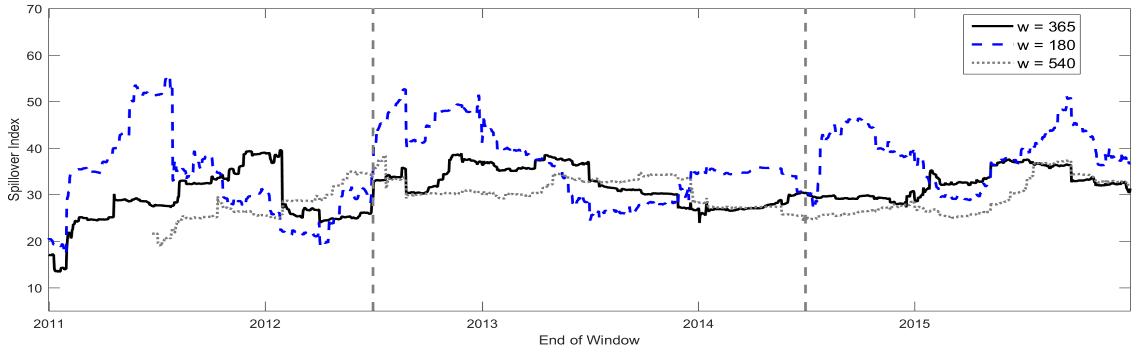


(b) Volatility

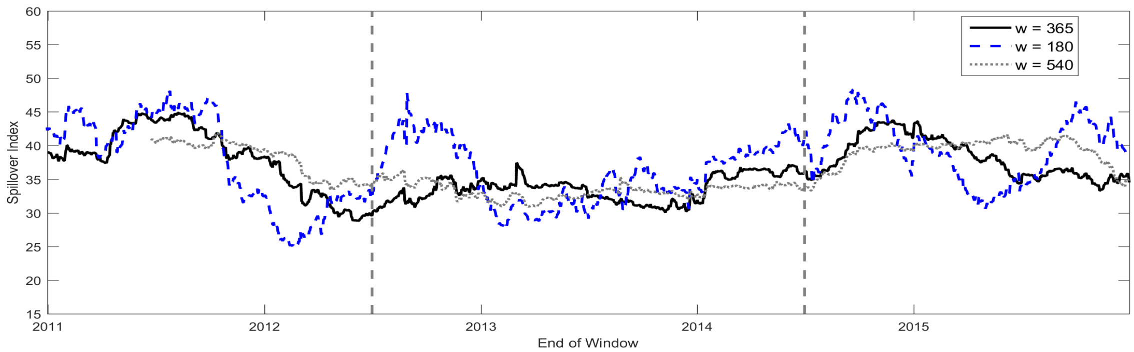
Figure 6.6: Robustness to the choice of forecasting horizon H ($H = 1$ and 7)

Choice of Window Length w

In addition to w = 365 days, we consider a shorter window length (180 days) and a longer window length (540 days) for rolling-sample analyses. The results are plotted in Figure 6.7. It is observed that spillover plots are more volatile for a shorter window and more stable for a longer window. Overall, for the window lengths w = 180, 365 and 540 days, the qualitative features of spillover plots are relatively similar. However, it should be noted that due to a different window length (backward-looking), different time intervals may be classified as periods with high (low) spillover effects. This is particular for the price spillover analysis as indicated in the upper panel of Figure 6.7. Thus, the applied window length for model estimation has to be considered as an important factor when interpreting the results.



(a) Price



(b) Volatility

Figure 6.7: Robustness to the choice of window length w (w = 180, 365 and 540)

6.4.3 Summary of Robustness Assessment

Overall, the reassessment of spillover effects in different time periods with regard to the carbon taxation policy confirms the findings presented in Chapter 6. In particular, the results of static spillover analyses for three separate periods present similar time-varying patterns that are captured in dynamic spillover analyses (Sections 6.3.1 and 6.3.2). This confirms the ability of the dynamic spillover plots to continuously track the changes in spillover levels over time.

Meanwhile, our results are robust to different settings of the identification method (Cholesky factorisation versus GVD), the lag length p of the VAR model, the forecasting horizon H, and up to a certain degree also to the sample window length w.

Chapter 7

Conclusion and Discussion

This study conducts a detailed examination of price and volatility spillovers in the five regional markets of the Australian NEM with a sample period from 1 January 2010 to 31 December 2015. The objective is to provide a better understanding of electricity spot price dynamics in a multi-regional context. In particular, we empirically assess the specific patterns of those spillover effects, including the degree of these effects, the direction of spillovers between regions, the time-variations in these effects, the impacts of changing market conditions on these effects, and the divergent patterns between price spillovers and volatility spillovers.

We employ a methodological framework that was developed by Diebold and Yilmaz (2009, 2012). Based on forecast error variance decomposition of VAR models, it allows us to quantify and monitor different types of spillovers (i.e. static and dynamic, aggregated and pairwise, gross directional and net directional).

We find that across our sample period, on average, the overall magnitude of spillover effects in the NEM is 21.64% for prices and 36.61% for volatilities. They are relatively low compared to those in equity markets. For example, the calculated return and volatility spillovers among nineteen global stock markets are respectively 36% and 40% in Diebold and Yilmaz (2009). The volatility spillovers among major US financial institutions' stocks aggregate to 78.3% in Diebold and Yilmaz (2014). Furthermore, our calculated spillovers in the NEM are also lower than those in Zhang and Wang (2014) among three oil markets (China, the US and UK) where return spillovers are 50.1% and volatility spillovers are 43.3%. The results indicate that although spillover effects play an important role in electricity price formulation in the NEM, regional prices are still mostly influenced by local factors.

For directional spillovers for both prices and volatilities, the static analysis suggests that SA is the most significant net spillover giver, while NSW is the most significant net spillover receiver in the NEM. This indicates that among the five regions in the Australian NEM, SA is the most influential market, while the spot prices in NSW are the most vulnerable.

In addition, we find that the spillover effects are indeed time-varying. The aggregated spillover index for both price and volatility changes in level over time. The magnitude and direction of spillover effects between different regions and the net spillover position of each region also vary in different time periods. In particular, SA is constantly a net spillover giver, while NSW is constantly a net spillover receiver over time. In comparison, the net spillover positions of QLD, VIC and TAS fluctuate.

The patterns of price and volatility spillovers could be related to market events and market structures. In particular, some of the periods of increased spillover effects correspond to significant market events, such as extremely high demand, congestion of transmission lines, and generation outages. These can be reflected in the dynamic spillover analysis. The dynamic analysis also points out the differences in spillover patterns with regard to the three episodes: before, during and after carbon taxation periods. On the other hand, the physical interconnecting structure of the NEM also influences the patterns of price and volatility spillovers. More spillovers can be observed where physical interconnections exist, for example, between the pairs NSW–VIC, SA–VIC, and VIC–TAS. In contrast, the lowest levels of spillover effects are always found between the pairs QLD–TAS and QLD–SA, which are geographically distant and not well connected. These results regarding interconnectors confirm the findings of Higgs (2009), Ignatieva and Trück (2016) and Smith (2015).

Furthermore, although the overall patterns of price and volatility spillovers are quite similar, there are some divergences. This confirms the findings of Diebold and Yilmaz (2009) that price (or return) and volatility spillovers could capture different information in the considered markets. Firstly, the static spillover analysis suggests that, on average, more spillover effects can be observed for volatilities than for prices. Secondly, the aggregated spillover index for prices shows a slightly increasing trend, while this is not the case for volatilities. In addition, during the carbon taxation period, the aggregated spillover index for volatility is lower compared to other periods. However, this is not observed for the price spillover index.

Finally, our results are robust when separate assessments are conducted for sub-periods with regard to the introduction and repeal of the Australian carbon taxation policy. Our results are also robust to the choice of model specification such as the shock identification method, lag length of VAR, predictive horizon of forecast error variance decomposition, and with some limitations also the rolling-window length.

Overall, to the best of our knowledge, this is the first study that applies the Diebold and Yilmaz (2009, 2012) method to assess the interregional transmission of price and volatility in the Australian NEM. We conclude that this approach can efficiently capture the dynamics across this wholesale electricity market system.

Our results provide a detailed examination of the spillover mechanism across the Australian NEM, including the level of price and volatility spillovers contributed by each market and the time variations of these effects. These results are of significance to market participants, especially those who operate in different regional markets simultaneously. In particular, the detailed patterns of spillover effects between different regional markets provide important insights for those participants on the strategies of transferring risks between the considered markets. Furthermore, the results will enable regulators to examine the impacts of market interconnection and current market mechanisms on the transmission of shocks across regions, which helps to make investment decisions on, for example, construction of new generation plants and interconnectors. The results also provide implications for market integration of the NEM. For example, the overall magnitude of spillover effects seems to suggest a still relatively low degree of integration; however, the slightly upward trend in price spillovers could indicate a gradual increase in the whole market integration level. In addition, compared to the previous literature, with more recent data, we consider the influence of the carbon taxation system on electricity price and volatility spillover effects in the NEM. This could provide regulatory indications with regard to other climate change policies that may also exert influences on the transmission of price and price volatility shocks by influencing electricity generation and interregional electricity flows in the NEM.

We do recognise some limitations of this study, which also present directions for future research.

First, theoretically, the generalised forecast error variance decompositions used in this study require VAR errors to follow a multivariate normal distribution (Koop et al., 1996; Pesaran and Shin, 1998). However, this requirement is rarely satisfied for electricity markets where the price data are highly skewed and leptokurtic. Therefore, multivariate analysis of VAR error terms is recommended for refinement of generalised variance decomposition (GVD) techniques used in the study.

Second, as for volatility spillovers, different volatility measures may exert an influence on the spillover estimates. A comparison between the spillover analyses using various volatility measures could be of interest. For example, volatilities of the electricity prices extracted from the GARCH or other heteroscedastic models could be an alternative in future research.

In addition, in this study we used daily electricity prices and volatilities. Given that the electricity spot prices in the NEM are originally recorded on a half-hourly basis, it is possible that the current choice of data frequency may miss some relevant information, especially on the short-term transmission of price dynamics. Thus, another possible extension would be to use high-frequency data as the input, to better capture the market information and to provide more accurate estimations for spillover effects.

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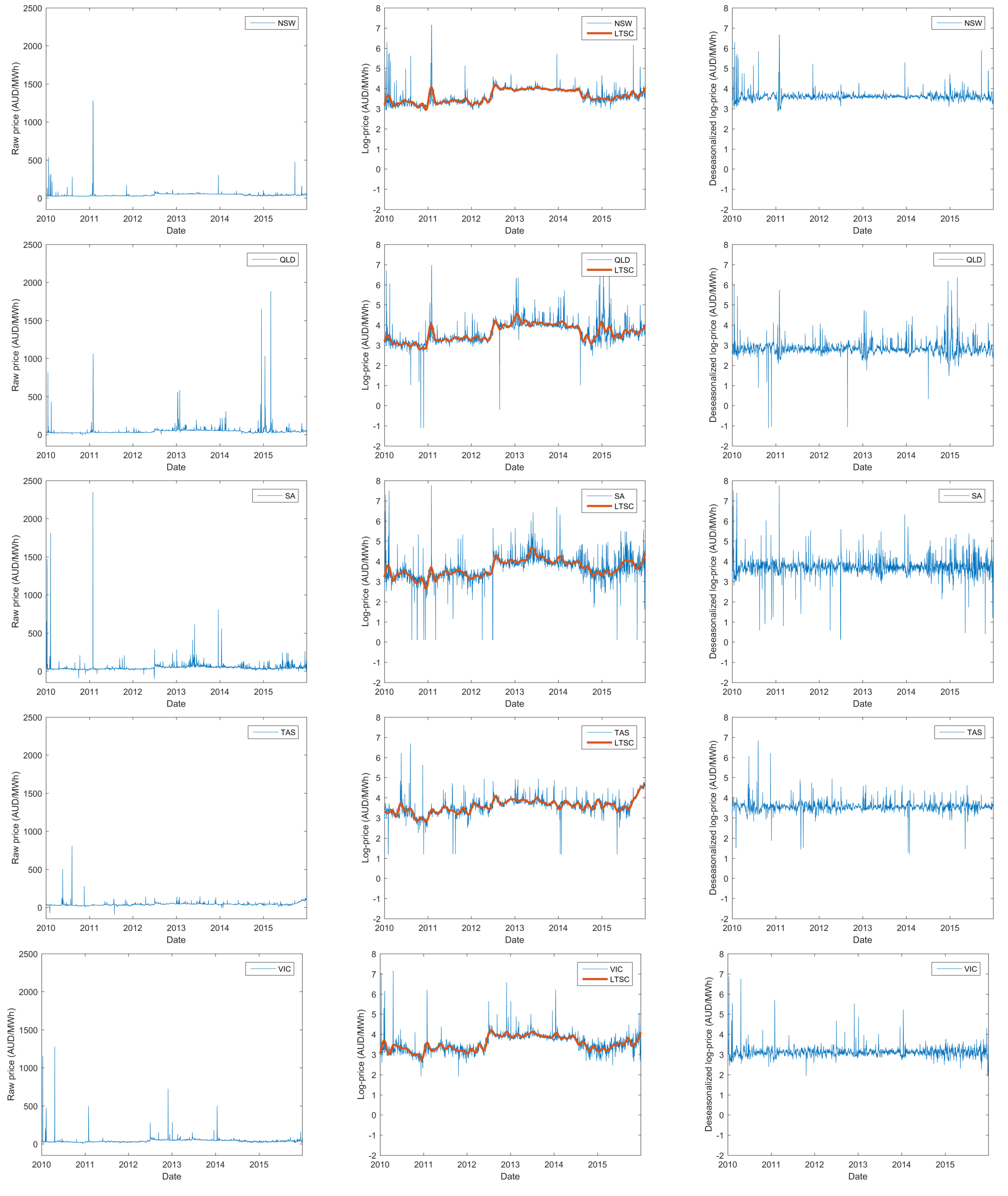
Appendix A

Supplementary Results

A.1 Data



(a) Raw prices

(b) Log-prices with a long-term seasonal component (LTSC)

(c) Deseasonalised log-prices

Figure A1: Daily raw prices, log-prices and deseasonalised log-prices of NSW, QLD, SA, TAS and VIC from 1 January 2010 to 31 December 2015. Panel (a) plots raw daily prices. Panel (b) plots log-prices with a long-term seasonal component (LTSC) obtained through wavelet decomposition. Panel (c) plots the deseasonalised log-prices (both long-term and short-term seasonal components are removed).

Table A1: Augmented Dickey-Fuller (ADF) test

	lag length	ADF statistic	Δy_{t-1}	Δy_{t-2}	Δy_{t-3}	Δy_{t-4}	Δy_{t-5}	Δy_{t-6}	Δy_{t-7}	Δy_{t-8}
Panel (a) : Deseasonalised log-prices										
NSW	2	-19.9014	0.0461	0.0343						
		(<0.001)***	(0.0534)*	(0.1086)						
QLD	1	-26.1694	-0.0488							
		(<0.001)***	(0.0224)**							
SA	3	-20.2696	0.1113	0.0328	0.0375					
		(<0.001)***	(0.0001)***	(0.1905)	(0.0797)*					
TAS	4	-13.8845	1.6819	0.9851	1.9427	3.2136				
		(<0.001)***	(0.0927)*	(0.3247)	(0.0522)*	(0.0013)***				
VIC	3	-20.1187	0.1249	0.0425	0.0349					
		(<0.001)***	(0.0000)***	(0.0734)*	(0.1048)					
Panel (b) : Log-volatility										
NSW	6	-6.0599	-17.3099	-13.3257	-11.0107	-9.6964	-8.0000	-5.4407		
		(<0.001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		
QLD	6	-8.2656	-14.5629	-11.1824	-9.1567	-8.4839	-5.7390	-4.7043		
		(<0.001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		
SA	8	-8.6215	-11.5816	-10.8754	-8.8864	-7.7320	-7.1302	-6.5219	-3.3820	-2.5991
		(<0.001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0007)***	(0.0094)***
TAS	7	-9.3495	-12.1825	-9.0819	-7.8273	-6.5819	-5.5337	-3.9861	-2.0120	
		(<0.001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0443)**	
VIC	6	-6.5998	-16.5567	-14.0181	-10.6180	-10.6799	-8.1309	-5.0347		
		(<0.001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		

Notes: The ADF test is based on an ordinary least square (OLS) regression: $y_t = c + \phi y_{t-1} + \sum_{l=1}^{p} \beta_l \Delta y_{t-l} + \varepsilon$, where y_t is the data series to be tested, y_{t-1} is a lag term of the data series in level, and Δy_{t-l} $(l = 1, 2, ..., p)$ are lagged difference terms. An intercept c is included, and the lag length is determined by the significance of the coefficients of the lagged terms.
$H_0 : \phi = 1$, which means that a unit root exists in the univariate time series, or the data series is non-stationary.
$H_1 : \phi < 1$, which means that no unit root exists in the univariate time series, or the data series is stationary.
The ADF test statistics are t-statistics of the estimated coefficient ϕ. These test statistics do not follow standard distributions under the null hypothesis. The critical values for various sample sizes are tabulated based on simulation techniques and the algorithm is provided by MacKinnon et al. (1990), which are -2.57% (10%), -2.87 (5%), and -3.44 (1%).
Column three shows the results of augmented DickeyFuller (ADF) test for the stationarity of each data series. The test statistics as well as the corresponding p-values (in the parentheses) are presented.
Columns four to eleven test the significance of the coefficients of included lag terms. The t statistics as well as the corresponding p-values (in the parentheses) are presented.
*** denotes that the data are significant at the 1% level.
** denotes that the data are Significant at the 5% level.
* denotes that the data are Significant at the 10% level.

A.2 Gross Directional Price and Volatility Spillovers

Gross spillovers measure all shocks transmitted out by one market or all shocks received by one market from others. Overall, the plots for gross directional spillovers (Figure A2 and Figure A3) express similar information compared with net spillovers. There are three noticeable points in these plots.

Firstly, in gross terms, for price spillovers, SA and VIC were always the major transmitters of shocks over the sample period, indicating that these two markets are more influential compared to other regions in the NEM. Meanwhile, NSW and VIC were the two major price spillover receivers, indicating that the prices in these two markets are more dependent on conditions in other regions. For volatility spillovers, the major gross transmitters were NSW, SA and VIC, while NSW and VIC were at the same time the major receivers of volatilities.

Secondly, for TAS, the change in net spillover position during the carbon taxation period can be traced to gross spillovers. During this period, two changes were significant in gross spillovers for the TAS market. The price spillovers flowing to TAS (Figure A2) substantially increased, while the volatility transmitted from TAS to others (Figure A3) largely dropped. These effects led TAS to become a net receiver for both price and volatility spillovers. It indicates that during the carbon taxation period, TAS's more exports to other markets made it more dependent.

Thirdly, VIC is a noteworthy market. Although the magnitude of net spillovers for VIC has been relatively low, the gross spillover effects transmitted from and received by this market were both large, indicating that VIC has been largely influenced by other regions but at the same time significantly impacting other markets. During the carbon taxation period, VIC has been transmitting out both more price shocks and higher volatilities while those spillovers flowing to it have became much lower. These effects have led VIC to become a net price and volatility spillover giver.

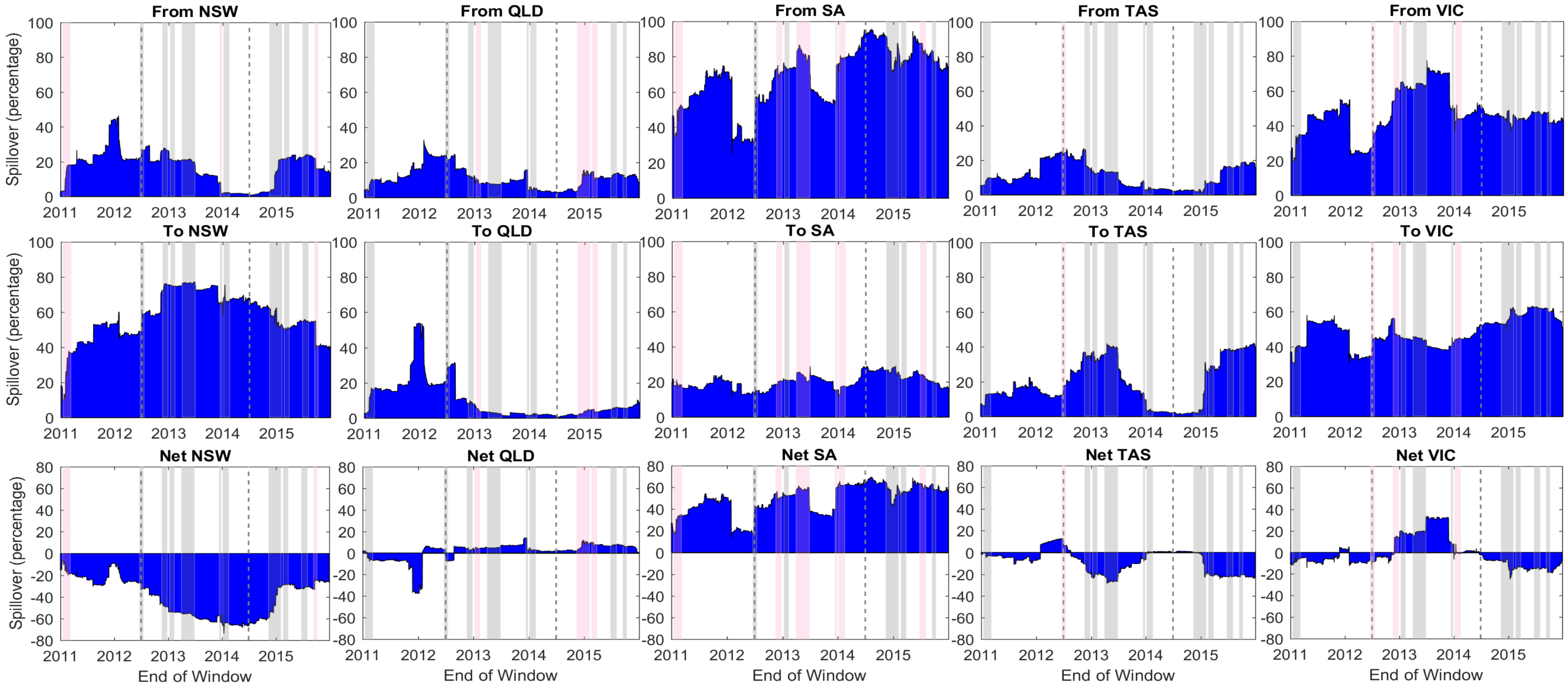


Figure A2: Gross and net directional price spillovers for each regional market in the NEM over the period from 1 January 2010 to 31 December 2015, obtained by dynamically estimating the 'To Others' row, 'From Others' column and 'Net Spillovers' row of Table 6.1, Panel (a) with a rolling window of 365 days. The upper panel shows the gross price spillovers transmitted by each region to other markets. The middle panel shows the gross price spillovers received by each region from other markets. The bottom panel shows the net price spillovers transmitted by each region to other markets. The two dashed lines on each plot refer to the beginning and end dates of the carbon taxation policy. The shaded areas indicate identified temporary market events. For each market, the events originated in this market are coloured pink. From left to right, these events are:
1: record demand (NSW and SA), 2: outages of Basslink interconnector (VIC-TAS), 3: high demand (SA and VIC), 4: congestion (QLD),
5: temporary shutdown and tight supply condition (SA), 6: high demand and rebidding (SA), high demand and network issue (NSW),
7: high demand (SA and VIC), 8: rebidding (QLD), 9: record demand (QLD), 10: tight supply conditions and rebidding (SA), 11: network issues (NSW)

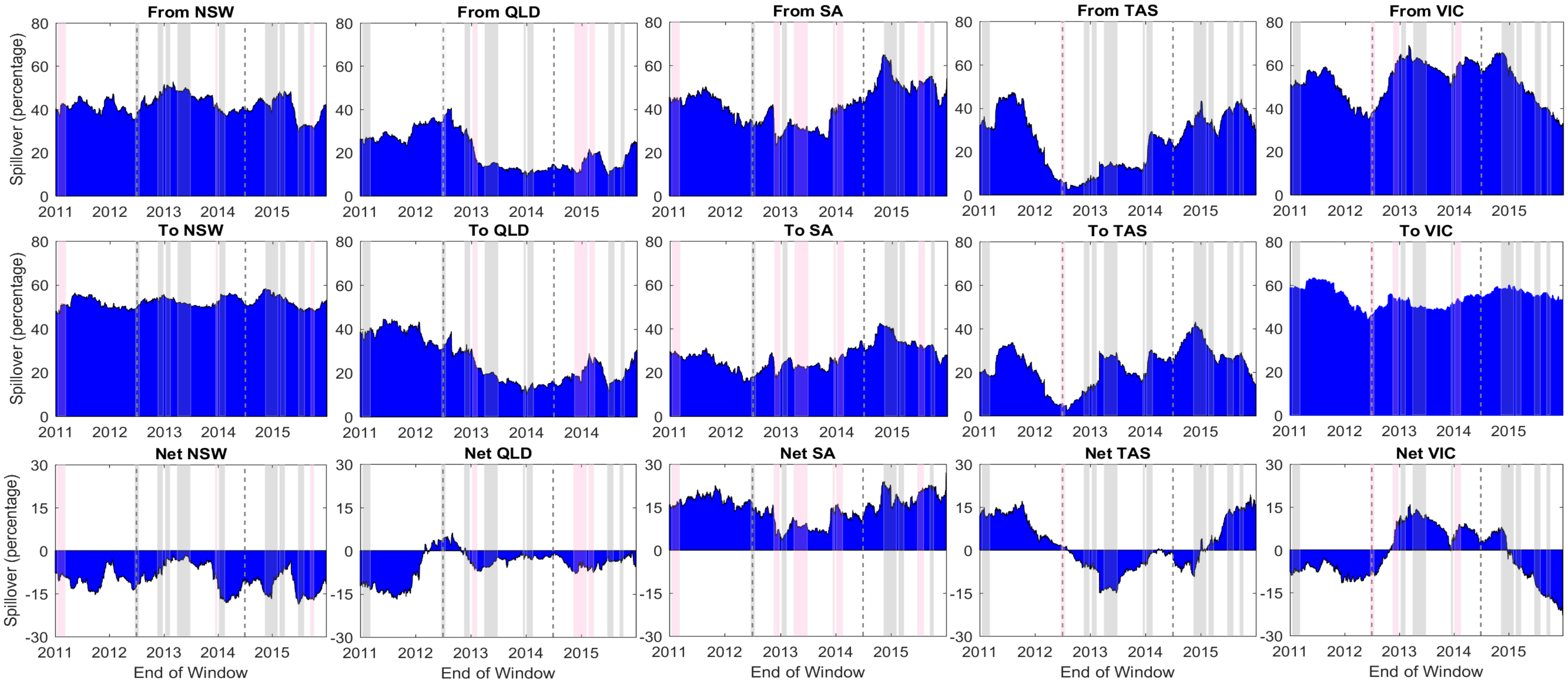


Figure A3: Gross and net directional volatility spillovers for each regional market in the NEM over the period from 1 January 2010 to 31 December 2015, obtained by dynamically estimating the 'To Others' row, 'From Others' column and 'Net Spillovers' row of Table 6.1, Panel(b) with a rolling window of 365 days. The upper panel shows the gross volatility spillovers transmitted by each region to other markets. The middle panel shows the gross volatility spillovers received by each region from other markets. The bottom panel shows the net volatility spillovers transmitted by each region to other markets. The two dashed lines on each plot refer to the beginning and end dates of the carbon taxation policy. The shaded areas indicate identified temporary market events. For each market, the events that originated in this market are coloured pink. From left to right, these events are:
1: record demand (NSW and SA), 2: outages of Basslink interconnector (VIC-TAS), 3: high demand (SA and VIC), 4: congestion (QLD),
5: temporary shutdown and tight supply condition (SA), 6: high demand and rebidding (SA), high demand and network issue (NSW), 7: high demand (SA and VIC),
8: rebidding (QLD), 9: record demand (QLD), 10: tight supply conditions and rebidding (SA), 11: network issues (NSW)

A.3 Robustness Assessment

A.3.1 Empirical Analysis for the Periods Before, During and After the Carbon Taxation Policy

Table A2: Descriptive statistics for prices before, during and after the carbon taxation period

		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	J-B test	ADF test
Panel (a) : Full sample (January 2010 to December 2015, 2191 observations)										
NSW	raw	41.4487	35.0140	1282.0	17.3610	44.3571	20.0651	509.6698	23905000 (<0.001)	-14.9220 (<0.001)
	log.	3.6161	3.5557	7.1562	2.8542	0.3872	1.6420	9.5408	9315.90 (<0.001)	-6.5548 (<0.001)
	des.	3.6003	3.5816	6.6642	2.8542	0.2368	5.6323	54.7999	286270 (<0.001)	-19.9014 (<0.001)
QLD	raw	45.7805	33.4370	1885.9	-13.9790	73.7870	15.8358	320.6543	9495900 (<0.001)	-12.5474 (<0.001)
	log.	3.6033	3.5097	7.5422	-1.1106	0.5576	0.5438	10.7114	10607 (<0.001)	-6.8387 (<0.001)
	des.	2.8215	2.7908	6.3674	-1.1106	0.3766	0.8389	33.1443	100750 (<0.001)	-26.1694 (<0.001)
SA	raw	48.5463	37.0300	2347.7	-103.1600	81.2063	18.6110	442.4623	18032000 (<0.001)	-14.9019 (<0.001)
	log.	3.6546	3.6117	7.7612	0.1102	0.6085	-0.2225	9.0103	7447.80 (<0.001)	-7.7857 (<0.001)
	des.	3.7206	3.7108	7.7610	0.1102	0.4553	-0.2747	22.4240	46026 (<0.001)	-20.2696 (<0.001)
TAS	raw	39.1508	36.6040	805.06	-94.6700	27.5360	14.3794	339.1757	10597000 (<0.001)	-7.0703 (<0.001)
	log.	3.5762	3.6002	6.6909	1.1935	0.4118	-0.0543	7.2903	4865.80 (<0.001)	-4.5366 (<0.001)
	des.	3.5519	3.5424	6.8357	1.1935	0.2698	0.8121	37.6522	129910 (<0.001)	-13.8845 (<0.001)
VIC	raw.	39.4260	33.1970	1276.9	-4.8887	46.6428	17.8835	406.9201	15261000 (<0.001)	-14.3397 (<0.001)
	log.	3.5393	3.5025	7.1522	1.9012	0.4383	1.2508	7.3898	5570.30 (<0.001)	-6.3573 (<0.001)
	des.	3.1165	3.1025	6.8676	1.9012	0.2674	4.7289	51.4999	250760 (<0.001)	-20.1187 (<0.001)
Panel (b) : Before carbon taxation (January 2010 to June 2012, 912 observations)										
NSW	raw	33.7707	27.0210	1282.0	17.3610	64.4992	15.6125	277.3314	2972800 (<0.001)	-6.7712 (<0.001)
	log	3.3460	3.2966	7.1562	2.8542	0.3669	5.5650	41.4570	70341 (<0.001)	-12.7193 (<0.001)
	des.	3.5888	3.5596	6.6236	2.8542	0.3142	4.8409	36.1526	53477 (<0.001)	-15.5144 (<0.001)
QLD	raw	30.1364	24.9900	1062.4	-13.9790	53.2818	15.4321	257.0136	2557600 (<0.001)	-6.8016 (<0.001)
	log	3.2468	3.2185	6.9683	-1.1106	0.4209	0.1625	44.8143	76678 (<0.001)	-10.3640 (<0.001)
	des.	2.8102	2.7934	5.9868	-1.1106	0.3499	-0.5545	53.7337	110274 (<0.001)	-17.7327 (<0.001)
SA	raw	36.5095	27.3490	2347.7	-103.1600	113.2392	16.0921	283.1934	3100600 (<0.001)	-8.3242 (<0.001)
	log	3.3023	3.3087	7.7612	0.1102	0.5676	0.0608	22.3664	19105 (<0.001)	-14.4930 (<0.001)
	des.	3.3169	3.3148	7.3412	0.1102	0.5103	0.5957	20.5594	16197 (<0.001)	-17.2187 (<0.001)
TAS	raw	31.2369	27.8395	805.06	-94.6700	36.8423	14.7080	265.2052	2717600 (<0.001)	-18.6718 (<0.001)
	log	3.3318	3.3264	6.6909	1.1935	0.3980	1.0553	17.0676	11297 (<0.001)	-10.1621 (<0.001)
	des.	3.2976	3.2888	6.5982	1.1935	0.3314	1.7133	31.0801	37332 (<0.001)	-16.9594 (<0.001)
VIC	raw	31.1482	25.6990	1276.9	-4.8887	62.4322	16.2328	292.7558	3311500 (<0.001)	-10.8343 (<0.001)
	log	3.2658	3.2465	7.1522	1.9012	0.3774	4.3439	36.4427	53585 (<0.001)	-8.1180 (<0.001)
	des.	3.0797	3.0650	6.7972	1.9012	0.3137	5.6595	54.9537	120173 (<0.001)	-17.7202 (<0.001)

Continued on next page

Table A2 – continued from previous page

		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	J-B test	ADF test
Panel (c) : During carbon taxation (July 2012 to June 2014, 730 observations)										
NSW	raw	53.6792	51.8420	303.12	44.3210	11.2575	15.5157	329.4433	3348900 (<0.001)	-5.3909 (<0.001)
	log	3.9731	3.9482	5.7141	3.7915	0.1226	5.3542	59.0249	110084 (<0.001)	-9.6776 (<0.001)
	des.	3.9339	3.9200	5.6387	3.7915	0.1001	8.2859	120.8305	454974 (<0.001)	-14.4985 (<0.001)
QLD	raw	62.7191	53.7605	585.63	0.8140	42.2847	8.1764	84.3174	225640 (<0.001)	-5.9758 (<0.001)
	log	4.0591	3.9845	6.3727	-0.2059	0.3491	0.0142	40.0831	49158 (<0.001)	-11.5419 (<0.001)
	des.	3.8047	3.7736	5.7087	-0.2059	0.3089	-1.3137	44.9846	62123 (<0.001)	-13.4970 (<0.001)
SA	raw	65.7300	54.5730	806.26	31.9280	50.6302	8.4496	95.9185	290150 (<0.001)	-5.3064 (<0.001)
	log	4.0871	3.9996	6.6924	3.4635	0.3648	2.6066	10.5618	4247 (<0.001)	-9.8860 (<0.001)
	des.	4.2802	4.2493	6.8826	3.4635	0.3055	2.6578	14.3923	7205 (<0.001)	-15.6145 (<0.001)
TAS	raw	45.1369	43.0045	139.96	-11.0680	12.5293	3.1639	18.5008	11700 (<0.001)	-13.4646 (<0.001)
	log	3.7848	3.7613	4.9414	2.9196	0.2173	1.3810	6.1333	1387 (<0.001)	-5.5858 (<0.001)
	des.	3.7102	3.6897	4.7349	2.9196	0.1754	2.1291	10.1770	3727 (<0.001)	-15.3428 (<0.001)
VIC	raw	54.4629	49.3650	722.65	36.9530	34.9531	13.4162	221.0629	1516700 (<0.001)	-8.1041 (<0.001)
	log	3.9468	3.8992	6.5829	3.6097	0.2450	4.8812	36.9078	44590 (<0.001)	-13.1060 (<0.001)
	des.	3.9531	3.9280	6.3836	3.6097	0.2156	5.6812	48.1501	74874 (<0.001)	-14.4730 (<0.001)
Panel (d) : After carbon taxation (July 2014 to December2015, 549 observations)										
NSW	raw	37.9405	35.0140	472.77	19.2430	21.6536	15.3959	296.3540	2045700 (<0.001)	-5.0645 (<0.001)
	log	3.5900	3.5557	6.1586	2.9572	0.2523	2.9585	22.6606	12649 (<0.001)	-10.0065 (<0.001)
	des.	3.4445	3.4244	5.6928	2.9572	0.2051	3.9124	32.7522	26143 (<0.001)	-11.7418 (<0.001)
QLD	raw	49.2456	33.6660	1885.9	2.7548	117.7227	12.6548	175.7182	726300 (<0.001)	-5.7243 (<0.001)
	log	3.5895	3.5165	7.5422	1.0133	0.5455	2.5270	13.8050	4986 (<0.001)	-9.4006 (<0.001)
	des.	3.4760	3.4437	7.0503	1.0133	0.4666	2.3956	16.3530	6698 (<0.001)	-11.0799 (<0.001)
SA	raw	45.6930	36.9170	259.59	-5.8235	31.3656	3.1399	13.7416	5265.10 (<0.001)	-3.2407 (0.0184)
	log	3.6702	3.6087	5.5591	1.6204	0.5298	0.2184	2.4803	147 (<0.001)	-9.3884 (<0.001)
	des.	4.2166	4.2017	5.8380	1.6204	0.4576	-0.0470	4.2191	413 (<0.001)	-14.4325 (<0.001)
TAS	raw	44.3377	39.0180	120.88	-0.0560	19.6451	1.6063	2.2640	356.6375 (<0.001)	-3.4283 (0.0105)
	log	3.7128	3.6640	4.7948	2.2142	0.3864	0.4472	1.0353	44 (<0.001)	-1.6352 (0.1026)
	des.	3.3522	3.3469	4.4259	2.2142	0.1985	-0.1032	6.5352	988 (<0.001)	-12.5187 (<0.001)
VIC	raw	33.1828	31.9670	160.94	11.6280	11.6199	3.2004	27.6322	18550 (<0.001)	-4.8058 (<0.001)
	log	3.4519	3.4647	5.0810	2.4534	0.3124	0.1167	1.5196	55 (<0.001)	-4.9695 (<0.001)
	des.	3.6403	3.6509	4.7383	2.4534	0.2304	-0.5477	3.6529	337 (<0.001)	-11.4516 (<0.001)

Notes: This table gives a summary of descriptive statistics for raw prices ($/MWh), log-prices and deseasonalised log-prices of NSW, VIC, QLD, TAS and VIC, for the full sample period (Panel(a)) and for the periods before, during, and after carbon taxation (Panel (b), (c) and (d)). In augmented Dickey-Fuller (ADF) test for the stationarity of each data series, we find a unit root for the log-prices of TAS for the period after carbon taxation (Panel (d)).

Table A3: Descriptive statistics for volatilities before, during and after the carbon taxation period

		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	J-B test	ADF test
Panel (a) : Full sample (January 2010 to December 2015, 2191 observations)										
NSW	raw	0.1682	0.1412	1.8564	0.0081	0.1478	4.6242	35.4444	122740 (<0.001)	-8.7650 (<0.001)
	log.	-2.0345	-1.9572	0.6186	-4.8114	0.7136	-0.1763	0.5288	37.2102 (<0.001)	-6.0599 (<0.001)
QLD	raw	0.2720	0.2034	2.2486	0.0226	0.2498	3.2395	14.9928	24404 (<0.001)	-9.8414 (<0.001)
	log.	-1.5726	-1.5927	0.8103	-3.7892	0.7075	0.3047	0.3696	46.6218 (<0.001)	-8.2656 (<0.001)
SA	raw	0.4141	0.2389	3.8103	0.0299	0.5395	3.2267	11.2902	15471 (<0.001)	-11.6007 (<0.001)
	log.	-1.3164	-1.4316	1.3377	-3.5095	0.8368	0.8194	0.8447	311.1946 (<0.001)	-8.6215 (<0.001)
TAS	raw	0.2747	0.1626	4.1082	0.0002	0.4154	4.8712	29.0344	85790 (<0.001)	-12.6814 (<0.001)
	log.	-1.7646	-1.8168	1.4130	-8.5344	0.9114	-0.1674	5.3076	2589.40 (<0.001)	-9.3495 (<0.001)
VIC	raw	0.2521	0.2067	3.1316	0.0153	0.2395	4.4293	29.2312	8533.40 (<0.001)	-9.2576 (<0.001)
	log.	-1.6455	-1.5764	1.1415	-4.1797	0.7190	-0.0078	0.7064	46.0120 (<0.001	-6.5998 (<0.001)
Panel (b) : Before carbon taxation (January 2010 to June 2012, 912 observations)										
NSW	raw	0.2068	0.1693	1.8564	0.0308	0.1779	4.9869	33.1114	45654 (<0.001)	-5.2122 (<0.001)
	log.	-1.7547	-1.7759	0.6186	-3.4805	0.5456	0.7500	2.2492	279.9884 (<0.001)	-3.9514 (<0.001)
QLD	raw	0.2885	0.2196	2.1398	0.0523	0.2345	3.3365	14.9407	10225 (<0.001)	-4.5902 (<0.001)
	log.	-1.4370	-1.5160	0.7607	-2.9514	0.5749	0.7778	1.0962	138.6714 (<0.001)	-4.1211 (<0.001)
SA	raw	0.4501	0.2568	3.4918	0.0484	0.5555	2.8247	7.9478	3631.80 (<0.001)	-7.1917 (<0.001)
	log.	-1.1921	-1.3596	1.2504	-3.0282	0.7721	1.2167	1.1522	277.0225 (<0.001)	-6.5322 (<0.001)
TAS	raw	0.3364	0.2217	3.5501	0.0002	0.4356	3.9985	19.0177	16252 (<0.001)	-12.6742 (<0.001)
	log.	-1.5097	-1.5064	1.2670	-8.5344	0.9107	-0.8713	8.9435	3173.10 (<0.001)	-11.8709 (<0.001)
VIC	raw	0.2934	0.2407	2.4301	0.0470	0.2370	4.5938	26.7195	30480 (<0.001)	-7.8243 (<0.001)
	log.	-1.3834	-1.4240	0.8879	-3.0574	0.5030	1.0107	3.0701	517.0612 (<0.001)	-6.1984 (<0.001)

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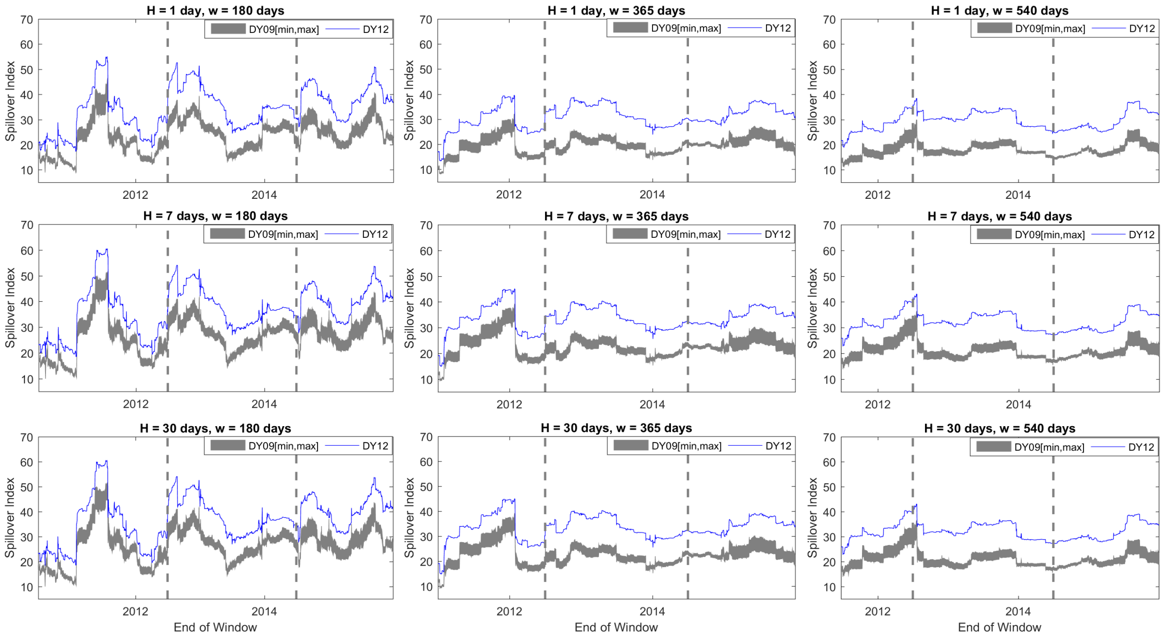
Table A3 – continued from previous page

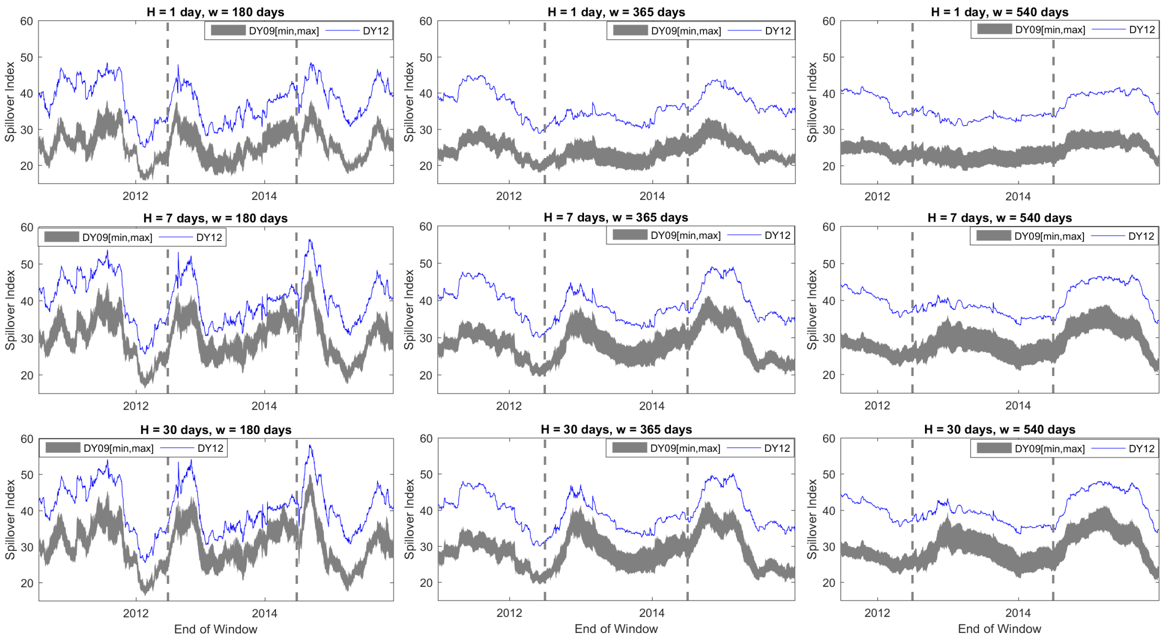
		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	J-B test	ADF test
Panel (c) : During carbon taxation (July 2012 to June 2014, 730 observations)										
NSW	raw	0.0867	0.0672	1.0372	0.0081	0.0781	5.0442	41.9912	57057 (<0.001)	-4.9868 (<0.001)
	log.	-2.6669	-2.6995	0.0365	-4.8114	0.6307	0.3743	1.0000	48.2001 (<0.001)	-3.5772 (<0.001)
QLD	raw	0.1992	0.1162	2.2486	0.0226	0.2412	3.6455	18.4181	12008 (<0.001)	-5.3860 (<0.001)
	log.	-1.9874	-2.1528	0.8103	-3.7892	0.7722	0.9504	0.8208	131.3654 (<0.001)	-4.9108 (<0.001)
SA	raw	0.2598	0.1569	3.4076	0.0299	0.3479	4.3544	23.8774	19765 (<0.001)	-4.9222 (<0.001)
	log.	-1.7377	-1.8519	1.2260	-3.5095	0.7791	0.9123	1.3022	154.2072 (<0.001)	-3.6575 (0.0050)
TAS	raw	0.1842	0.1106	4.1082	0.0148	0.3706	7.8199	70.1821	158150 (<0.001)	-11.3344 (<0.001)
	log.	-2.1128	-2.2022	1.4130	-4.2101	0.7138	1.6283	4.8580	1048.10 (<0.001)	-10.8069 (<0.001)
VIC	raw	0.1349	0.0973	1.8833	0.0153	0.1726	6.1185	45.7440	68594 (<0.001)	-7.6715 (<0.001)
	log.	-2.2850	-2.3296	0.6330	-4.1797	0.6503	0.9626	2.8731	367.1077 (<0.001)	-5.6712 (<0.001)
Panel (d) : After carbon taxation (July 2014 to December 2015, 549 observations)										
NSW	raw	0.2123	0.1875	1.0785	0.0440	0.1150	2.8574	13.1385	4735.4 (<0.001)	-4.6154 (<0.001)
	log.	-1.6583	-1.6738	0.0756	-3.1247	0.4542	0.1997	1.2762	41.8468 (<0.001)	-4.1289 (<0.001)
QLD	raw	0.3415	0.2687	2.1816	0.0576	0.2612	3.3887	15.6444	6703.90 (<0.001)	-4.5205 (<0.001)
	log.	-1.2465	-1.3141	0.7801	-2.8542	0.5396	0.8713	1.2227	104.9054 (<0.001)	-4.0266 (0.0018)
SA	raw	0.5595	0.3131	3.8103	0.0770	0.6589	2.8171	7.9249	2181.30 (<0.001)	-4.7993 (<0.001)
	log.	-0.9624	-1.1612	1.3377	-2.5643	0.7825	0.9714	0.5825	94.9349 (<0.001)	-3.7896 (0.0039)
TAS	raw	0.2925	0.1798	3.1386	0.0003	0.4169	4.1047	19.2157	10068 (<0.001)	-8.9395 (<0.001)
	log.	-1.7250	-1.7161	1.1438	-8.2729	0.9959	-0.6426	4.8918	591.8576 (<0.001)	-8.1610 (<0.001)
VIC	raw	0.3394	0.2829	3.1316	0.0592	0.2598	4.8817	35.5194	31281 (<0.001)	-5.8089 (<0.001)
	log.	-1.2307	-1.2627	1.1415	-2.8263	0.5011	0.8273	2.4614	203.8071 (<0.001)	-4.9116 (<0.001)

Notes: This table gives a summary of descriptive statistics for raw volatilities and log-volatilities of NSW, VIC, QLD, TAS and VIC, for the full sample period (Panel (a)) and for the periods before, during, and after carbon taxation (Panel (b), (c) and (d)).

A.3.2 Robustness Check with Different Model Specification



(a) Robustness assessment for price spillovers ($H = 1$, 7 and 30 days; $w = 180$, 365 and 540 days)



(b) Robustness assessment for volatility spillovers ($H = 1$, 7 and 30 days; $w = 180$, 365 and 540 days)

Figure A4: Robustness to different model specifications of the aggregated spillover index plots for price (Panel(a)) and volatility (Panel(b)). This figure explores various combinations of the choice with regard to the forecasting horizon ($H = 1$, 7 and 30 days) and rolling-window length ($w = 180$, 365 and 540 days). A VAR(1) model for price and a VAR(2) model for volatility are constantly applied. The blue solid lines refer to the spillover indexes calculated from Diebold and Yilmaz (2012). The grey band corresponds to a interval between the minimum and maximum values of the spillover index calculated from Diebold and Yilmaz (2009) based on all possible orderings.