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Abstract

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. We investigate volatility spillover effects across different regions in the Australian National Electricity Market (NEM), aiming to provide a better understanding of the transmission of risks in electricity markets in a multi-regional context. Our analysis is based on the econometric framework originally proposed by Diebold and Yilmaz (2009, 2012). We conduct both a static and dynamic assessment of aggregated spillover effects as well as their directional decomposition between the individual regions. We find that spillover effects are typically more pronounced between physically interconnected markets. Our results further suggest that the markets in New South Wales, South Australia and Victoria all transmit and receive significant volatility spillovers, while Victoria is the market with the highest net spillovers to others. The observed spillover effects also show time-varying and event-dependent patterns. Our findings provide important insights to market participants with regards to cross-regional trading of electricity or developing risk management strategies in the Australian NEM. Further, as the Australian Energy Regulator considers building additional interconnectors to facilitate regional market integration, our results also provide important quantitative information on volatility transmission across regional electricity markets to policy makers.

Keywords: Electricity Markets, Volatility Modelling, Spillover Effects, Directional Spillovers, Time-Varying Effects
JEL: Q41, C32, C58, G32

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1. Introduction

This study assesses volatility spillover effects for spot electricity prices across regional markets in the Australian National Electricity Market (NEM). The objective is to provide a better understanding of risk and volatility transmission in electricity markets in a multi-regional context. In particular, we aim to examine patterns of volatility spillover effects in the NEM as well as how these patterns are related to specific market characteristics, events and regulatory policy.

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, for the regional South Australia electricity market, whereas normal price levels are below \$100 per megawatt hour (MWh), spot prices frequently jump above \$1000 per MWh, and even hit \$14,000 per MWh at rare occasions (Potter, 2016). Factors that have contributed to such price and volatility shocks typically include the maintenance of power plants, the congestion of interconnectors or main transmission lines between South Australia and Victoria as well as periods of no-wind scenarios, i.e. very low generation of renewable energy. Interestingly, during such periods, often also significant spillover effects of price volatility to the connected markets in the NEM can be observed (Australian Energy Market Operator, 2016).

By definition, spillovers are the effects that shocks or crises in one region have on another region through external links (Pesaran and Pick, 2007). For financial markets, these spillover effects are typically characterized by the transmission of extreme price outcomes and volatility. For the energy sector, the analysis of these effects is important, especially for businesses that simultaneously operate in several electricity markets, since the probability of joint price spikes and high volatility imposes significant risk.

This study focuses on the Australian NEM as a nationally interconnected system with strong linkages between the individual regions (Ignatieva and Trück, 2016). The NEM 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 to determine a price for each region, which is known as the spot price. 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. However, such transmission is limited by the physical transfer capacity of interconnecters.

The assessment of spillover effects for the volatility of spot electricity prices is of particular interest for the Australian electricity markets. Electricity spot prices in the Australian NEM are even more volatile and spiky than in other comparable electricity markets, partially due to the interconnection of regional markets (Higgs and Worthington, 2008; Mayer and Trück, 2015). The analysis of volatility spillovers may therefore provide further insights on the transmission of extreme outcomes in electricity prices for Australia. Further, a long-run objective of the NEM is to provide a single integrated market with similar electricity prices across the different states. Such an integrated market is expected to provide an efficient electricity network that meets the long-term interests of consumers (Australian Energy Market Commission, 2013). However, so far 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). One related concern that has been raised by stakeholders is the potential underinvestment in interconnectors (Garnaut, 2011; Nepal et al., 2016; Productivity Commission, 2013). Since volatility spillover effects are considered as required features for market integration (Ciarreta and Zarraga, 2015), the analysis of these effects is also relevant for evaluating the efficiency of existing market interconnections and the potential of the NEM to achieve further integration.

Since the 1990s there is a small but rapidly growing literature on deregulated electricity markets. However, to date more studies typically focus on analysing electricity prices in a single market (e.g. Christensen et al., 2012; Clements et al., 2013; Eichler et al., 2014; Herrera and González, 2014), while studies focusing on a multivariate analysis that considers the interrelationship of electricity price or volatility between different markets are still limited.

In the US context, De Vany and Walls (1999a) were the first to study the joint behaviour of electricity spot prices in decentralised electricity markets. Using cointegration analysis, the authors find evidence of a highly integrated and efficient wholesale power markets in the western US. Nevertheless, based on an extended and more recent data set in the same markets, Dempster et al. (2008) suggest only a moderate degree of market integration. De Vany and Walls (1999b) and Park et al. (2006) use impulse-response analysis and variance decompositions based on VAR models to assess the transmission of electricity price dynamics. De Vany and Walls (1999b) find that price shocks tend to transmit to other markets during peak periods rather than during off-peak periods. Park et al. (2006) find that the interrelationship between regional electricity markets varies across time. Although the western US markets are separated from the other markets in contemporaneous time, over a longer time horizon, the separation seems to disappear.

In the European context, Haldrup and Nielsen (2006) examine price interdependence between pairs of regional markets in the Nordic countries through a Markov switching fractional integration model. They find that bilateral prices are identical during some periods but are divergent during others. Micola and Bunn (2007) analyse the role of interconnector congestion and find a threshold of interconnector capacity deployment after which two interconnected markets split. Bollino and Polinori (2008) conduct a contagion analysis of regional electricity markets in Italy and suggest that contagion and price interdependence can be identified separately. Zachmann (2008) studies the integration of European electricity markets. Although results for a conducted Principle Component Analysis reject the existence of a single integrated market, using a Kalman filter, the author finds pairwise price convergence between several countries after considering congestion costs. Le Pen and Sévi (2010) estimate a VAR-BEKK (Baba, Engle, Kraft and Kroner) model and show the existence of return and volatility spillovers in three major European electricity forward markets. More recently, De Menezes and Houllier (2014, 2015) use fractional cointegration methods to assess integration across European electricity markets, suggesting that electricity spot prices in the considered markets are intermediate between non-stationary and stationary. Multivariate GARCH models are used in Ciarreta and Zarraga (2015) and De Menezes and Houllier (2015) to assess mean and volatility spillovers of electricity prices. Furthermore, Füss et al. (2015) develop a fundamental multi-market model to analyse the impacts of interconnectivity of electricity markets on spikes, high volatility of electricity spot prices as well as on the term structure of electricity futures prices.

Also in the Australian context, there are some existing studies focussing on the interdependence of regional electricity prices. From a long-run perspective, after conducting pairwise unit root tests, a Johansen cointegration test, and time-varying coefficient estimations, Nepal et al. (2016) 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. Considering all five regions in the NEM as well as the Western Australia (WA) market, they find three separate groups: NSW, QLD and VIC; SA; and TAS and WA. The authors propose that generation mix of electricity as well as the ownership structure of electricity generation are important factors that contribute to these separations. From a short-run perspective, Smith et al. (2012), Smith (2015), Aderounmu and Wolff (2014a,b), Ignatieva and Trück (2016) and Manner et al. (2016) apply a series of copula models to measure the nonlinearity in multivariate electricity price modelling, especially in assessing tail dependence of spot prices between different regions. Furthermore, Clements et al. (2015) find evidence of price spike transmissions across interconnected regions in the NEM using a multivariate point process model.

Other studies focus on price volatilities and their transmission or spillover effects in the Australian NEM. Worthington et al. (2005) employ a MGARCH model to investigate the daily spot price and volatility dynamics in the NEM. Their results suggest insignificant price transmission but significant volatility spillovers. This study is extended by Higgs (2009) by further assessing the effects of interregional electricity price volatility spillovers through three conditional correlation MGARCH models. Furthermore, Higgs et al. (2015) investigate the impacts of a series of demand and supply factors on electricity price volatility. Taking into account interregional electricity flows, they find that the generation mix exerts a strong influence on electricity price volatility.

Overall, the existing literature on volatility spillovers in electricity markets does not provide a complete picture on the strength, specific patterns or the direction of spillover effects through time. This motivates us to conduct a more detailed analysis of volatility spillover effects in the Australian NEM. In particular, we are interested to analyze the overall degree of volatility spillover in the Australian NEM, including the direction of spillovers between individual regional markets. We also investigate whether the markets typically transmit or receive more volatility spillovers as well as the changing nature of spillovers through time. We also aim to examine whether the time variation in spillover effects is influenced by specific events (e.g. extreme weather events, network congestion, etc.), the electricity generation mix, or regulatory changes.

A major novelty of this study is that we employ a relatively new econometric framework (Diebold and Yilmaz, 2009, 2012) to investigate spillover effects in the NEM to address the above questions. This framework was developed by Diebold and Yilmaz (2009) based on using forecast error variance decomposition from a vector autoregressive (VAR) model (Sims, 1980). The method has further been extended by Diebold and Yilmaz (2012) based on a generalised variance decomposition (GVD) framework (Koop et al., 1996; Pesaran and Shin, 1998). The chosen approach allows us to quantify various spillover effects, including pairwise spillovers between two regions, gross directional spillovers from/to each region, net directional spillovers from each market, as well as a system-wide aggregated spillover index over a specified time horizon. Furthermore, by using a rolling-window approach, the applied analysis can monitor different the magnitude of spillover effects through time.

The Diebold and Yilmaz (2009, 2012) method (hereafter, DY method) has some appealing features in assessing spillover effects. First, 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 economic systems (see, e.g. De Vany and Walls, 1999b; Le Pen and Sévi, 2010; Park et al., 2006). However, unlike standard applications of impulse response analysis, the DY spillover measure has the advantage that it can be easily aggregated so that the overall level of spillover effects in the whole system can be estimated and monitored. Second, the DY method can conveniently provide information on directional spillover flows across markets without having to conduct an a priori analysis on the relative importance of all considered markets as might be the case for other methodologies (Conefrey and Cronin, 2015). Third, the approach is also advantageous in capturing time variations of spillovers. Using a rolling window approach, a time-varying index can be specified, allowing to analyze spillover effects through time without having to pre-specify a series of breakpoints or scenarios.

To the best of our knowledge, the DY framework has not been applied to analyse spillover effects in spot electricity markets and its application 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). Few authors have applied the method to commodity markets (e.g. Antonakakis et al., 2014; Baruník et al., 2015; Kang et al., 2014; Zhang and Wang, 2014), while only one study (Jaeck and Lautier, 2016) has employed the DY method to electricity derivative markets and assesses volatility spillovers across electricity futures with different maturities. However, it is well-known that electricity spot prices exhibit an entirely different, more 'spiky' and volatile behaviour than derivatives contracts.

Overall, the successful application of the DY method to various financial markets motivates us to use the approach for analysing spillover effects and dynamics in electricity spot markets. We investigate volatility spillover effects in the five regional electricity markets in the Australian NEM, namely, NSW, QLD, SA, TAS and VIC. Hereby, we investigate both market aggregated and directionally decomposed spillovers for specific markets, while the analysis is also conducted using a dynamic setting. By using daily electricity price volatility from 1 January 2010 to 31 December 2015, we also cover the periods before, during and after the Australian carbon pricing mechanism that was in place between July 2012 and June 2014. Thus, our study also allows us to examine the evolution of volatility spillover effects across these three sub-periods.

Our findings suggest that although spillover effects play an important role in the overall market volatility in the NEM, regional market volatilities are still largely influenced by local factors. Among the five regions in the NEM, VIC, NSW and SA all transmit and receive significant volatility spillover effects, while VIC is the most important market in transmitting shocks to others. The magnitude and direction of spillover effects both exhibit time variations, and a large part of these time variations could be related to extraordinary events and policy changes in the NEM. In addition, patterns of volatility spillovers are highly influenced by the interconnector structure of the NEM: greater spillover effects are observed where physical interconnections exist, confirming the significant role of interconnectors in facilitating integration between regions. Finally, our findings are robust when separate assessments are conducted for sub-periods with regard to the introduction and repeal of the Australian carbon tax policy. All results are also relatively robust to the choice of alternative parameter or model specifications.

Overall, our results contribute to the literature in three ways. First, we conduct a pioneering study by applying the DY spillover method to electricity spot markets. Our results suggest that this method can efficiently capture the transmission of electricity price volatility. Second, compared with the existing literature, we provide a deeper analysis of volatility spillover effects in the Australian NEM by estimating more detailed patterns of these effects, such as their magnitudes, directions and time variations. Finally, by using more recent data, our results add important empirical evidence on the impacts of the recent introduction and abolishment of the carbon tax policy 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 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 profits by purchasing electricity in a market where prices are currently low, then selling it to a market with currently higher prices, because price differences and spillover effects across regions are highly relevant to their revenue. Furthermore, our results also provide important information for regulators who aim to evaluate current market interconnections and systemic risks as a result of extreme events in a singular or multiple markets, the potential of the NEM to achieve integration, and impacts of the inclusion of renewable resources on market volatility.

The remainder of this paper is structured as follows. Section 2 provides a brief overview of the institutional background and features of the Australian NEM. Section 3 introduces our research methodology, while Section 4 summarises the properties of data used in this study. Empirical findings are provided in Section 5. These include the results of both static and dynamic spillover analyses, as well as several robustness checks for different sub-periods and choice of model specifications. Finally, Section 6 concludes and discusses possible directions for future research.

2. The Australian National Electricity Market

The Australian NEM began operating as a wholesale market in December 1998 (Australian Energy Regulator, 2015). Prior to this, electricity markets in Australia were 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 market efficiency for the electricity sector, the Australian government commenced the reform in the 1990s to restructure the electricity market in three ways: the supply industry was separated into generation, transmission, retail and distribution segments; competition was introduced to generation and retail markets; and the states' power systems were extended to be interconnected (Australian Energy Regulator, 2015). The NEM now operates as a wholesale electricity market, supplying electricity to retailers and end-users for the five state-based regional markets in NSW, QLD, SA, VIC and TAS. Networks in each state are linked to others via interconnectors, which are the physical transmission lines connecting adjacent regions.

The electricity spot market in the NEM operates as a central pool managed by Australian Energy Market Operator (AEMO). It is an 'energy only' gross pool with mandatory participation (Australian Energy Regulator, 2015),i.e. all electricity generated has to be sold through this pool where the electricity output from all generators is aggregated to meet demand in real-time. Generators submit bids every five minutes, specifying the amount and the price they offer. AEMO then determines the generators to produce electricity based on a least-cost optimisation. Thus, generators with lower marginal costs will be given priority to supply electricity. Every five minutes AEMO determines a spot price for each region. The final half-hourly electricity spot price is then determined as the average of six five-minute interval prices.

Electricity spot prices are considered to be far more volatile than prices in other commodity markets. One major reason is the highly inelastic electricity demand due to the non-storable nature of electricity. 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 influence on electricity load. As a result, electricity prices exhibit infrequent but extreme price spikes, as well as mean-reversion behaviour and seasonality. Spikes in electricity spot prices are usually caused by demand shocks, for example, peak-load during extreme weather, or supply disruptions such as generation outages and transmission failures (Kaminski, 2004; Knittel and Roberts, 2005).

Within a period of as little as one hour, prices can increase tenfold and then fall back to the previous level. As pointed out in the literature, spot prices in the Australian NEM are even more spiky and volatile than in other comparable electricity markets (Higgs and Worthington, 2008; Mayer and Trück, 2015). During our sample period, the market price cap (the highest possible electricity spot price) has been increased from $10,000 to $13,800 per MWh (Australian Energy Regulator, 2015); and spot prices have been close to or reached the market price cap on several occasions. Furthermore, spot prices in different regional markets appear to exhibit tail dependence (Smith et al., 2012; Aderounmu and Wolff, 2014a,b; Ignatieva and Trück, 2016), which means price spikes and high price volatilities tend to occur jointly in different regions.

Electricity spot prices also exhibit strong mean-reversion. 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 prices followed by fast reversion to previous price 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 spot prices. As soon as the weather conditions and electricity demand return to their normal levels (usually within several hours or days), those expensive generators leave the pool and prices revert back to their normal levels.

In addition, seasonality in electricity prices is stronger than in any other commodity market, mainly driven by cyclical fluctuations in electricity demand, corresponding to, for example, changes in climate conditions and business or household activities (Kaminski, 2004; Pilipovic, 2007; Weron, 2006). For instance, electricity prices tend to be higher during summer and winter months and also exhibit intra-weekly and intra-daily patterns due to a higher demand on weekdays and during peak hours. Overall, all these features of electricity prices contribute to high volatility in general electricity markets and particularly in the NEM.

Electricity generation in Australia predominantly relies on fossil fuels. For example, in 2015, about 88% of the overall electricity generation was from fossil fuels, with around 76% from black and brown coal and 12% from gas (Australian Energy Regulator, 2015). However, encouraged by government policies with concerns regarding climate change and the dependence of the energy sector on fossil fuels, in recent years also an increasing share of electricity generation from renewable energy sources could be observed (Higgs et al., 2015; Ignatieva and Trück, 2016). Thus, during our sample period from 2010 to 2015, the share of generated renewable energy increased from 9.6% to 12% (Clean Energy Council, 2011, 2015). Hereby, in particular hydropower (40.1%) and wind power (33.7%) represent the largest share of renewable generation in the NEM for the year 2015. Regarding generation by region, NSW, QLD and VIC rely heavily on coal generation, while 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 with the majority of generation in TAS coming from hydropower, while the penetration of wind generation is especially strong in SA (Clean Energy Council, 2015).

In terms of electricity consumption, from 2010 to 2015, NSW accounted for the largest share (about 37%), followed by QLD (26%) and VIC (25%), while the shares of SA and TAS were around 7% and 5% (Australian Energy Regulator, 2016). In interregional trade, NSW, SA, and TAS were typically net electricity importers, with the exception of TAS being a net exporter during the carbon tax period from July 2012 to June 2014. At the same time QLD and VIC were typically net exporters (Australian Energy Regulator, 2015).

A key objective of establishing the Australian NEM is, in the long-run, 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 between adjacent regions. 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, the VIC-NSW interconnector between NSW and VIC, and Basslink (an undersea power cable) between VIC and TAS (Australian Energy Regulator, 2015). Except for Basslink, all of these interconnectors operate as regulated interconnectors[1]. Electricity can be imported into one region through interconnectors when the output of local generators is insufficient to meet demand, or when the electricity price in the adjoining market is

[1] 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 merchant interconnector, derives revenue by participating in interregional trades in the spot market (Australian Energy Regulator, 2015).

low enough to replace 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). This mechanism facilitates market integration (Nepal and Jamasb, 2012) and promotes competition in electricity wholesale markets, especially in a concentrated market with limited market participants. However, as pointed out before, the efficient transmission of electricity across regions is limited by the physical transfer capacity of the interconnectors.

The limitation of interconnecter capacity is one defining feature of the NEM (Higgs and Worthington, 2005; Higgs, 2009; Nepal and Jamasb, 2012), limiting much generation capacity to remain within the local market. As a result, regional markets in the NEM are still considered as isolated, which is reflected by the substantial price differences between regions, and the occurrence of unnecessarily high price and volatility regimes[2]. Accordingly, there is a concern about underinvestment in interconnectors in the Australian NEM (Garnaut, 2011; Productivity Commission, 2013). In particular, Nepal et al. (2016) investigate the usage of interconnector capacity in the NEM. They find the existence of significant transmission bottlenecks in all interconnectors and thus propose more investment in capacities of existing interconnector as well as into new interconnectors.

The Australian NEM has also experiencing several regulatory changes over the last decae: 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 in the electricity sector what could possibly help to 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 tax policy can be summarised as follows: first, the carbon tax significantly increased the cost of electricity generators during the two-year carbon pricing period between July

[2] The important role of interconnectors is evidenced by a recent event related to the outage of the interconnector between TAS and VIC (Basslink) on December 20, 2015, when TAS was isolated from the NEM and electricity spot prices in TAS spiked 400% from a normal level of around $40 per MWh to prices exceeding $200 per MWh. High price levels and volatility lasted for a period of over four months until Basslink was back in operation (Australian Energy Market Operator, 2016).

2012 and July 2014. As a result, although electricity demand declined during this period, spot prices in the NEM generally exhibited a substantial rise. However, 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 (Apergis et al., 2016; Australian Energy Regulator, 2015), because hydro generation had a large share in the TAS market. Second, the carbon tax also slightly altered the composition of electricity generation in the NEM. The market share of coal generation dropped and even reached a historical low in the 2013-2014 financial year, while the share of generation from renewables, especially hydro generation increased significantly (Australian Energy Regulator, 2015). Finally, changes in regional prices and the generation mix in the NEM further altered the interregional electricity flows, in particular for TAS. Typically, TAS was a net electricity importer, while during the carbon tax period, due to the increased local hydro output and the relatively low regional prices, TAS became a electricity exporter. 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). In our empirical analysis we will also investigate the impact of this major policy change on price spillover effects across the markets.

3. Methodology

We apply Diebold and Yilmaz's (DY) (2009, 2012) spillover method to estimate volatility spillover effects in the Australian NEM. Specifically, the first step involves a VAR model estimation for the price volatility. Next, based on H-step forecast error variance decompositions, various types of spillovers can be calculated, conveying a wealth of market information. The following sections 3.1 to 3.3 will introduce the details of these individual steps.

3.1. Vector Autoregressive (VAR) Model

Our spillover analysis starts from a covariance stationary N-variable VAR(p) model (in this study, $N = 5$ for five regional markets) for a vector $\boldsymbol{x}_t = (x_{1t}, ..., x_{Nt})'$ of price volatilities in the considered markets:

$$\boldsymbol{x}_t = \boldsymbol{\Psi} + \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{3.1}$$

where p is the lag length, $\boldsymbol{\varepsilon}_t \sim (0, \boldsymbol{\Sigma})$ is a vector of independently and identically distributed error terms, $\boldsymbol{\Sigma}$ is the variance-covariance matrix for $\boldsymbol{\varepsilon}_t$, 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.

Then the moving average representation of the covariance stationary VAR model can be denoted by

$$\boldsymbol{x}_t = \boldsymbol{A}_0\boldsymbol{\varepsilon}_t + \boldsymbol{A}_1\boldsymbol{\varepsilon}_{t-1} + \boldsymbol{A}_2\boldsymbol{\varepsilon}_{t-2} + ... = \sum_{i=0}^{\infty} \boldsymbol{A}_i\boldsymbol{\varepsilon}_{t-i}. \tag{3.2}$$

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

$$\boldsymbol{A}_i = \boldsymbol{\Phi}_1\boldsymbol{A}_{i-1} + \boldsymbol{\Phi}_2\boldsymbol{A}_{i-2} + ... + \boldsymbol{\Phi}_p\boldsymbol{A}_{i-p}, \tag{3.3}$$

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 are the key to analysing the dynamics of the considered system, because they measure the effects of shocks at different time points on the value of variables in the future.

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

$$\boldsymbol{x}_{t+H,t} = \boldsymbol{A}_H\boldsymbol{\varepsilon}_t + \boldsymbol{A}_{H+1}\boldsymbol{\varepsilon}_{t-1} + \boldsymbol{A}_{H+2}\boldsymbol{\varepsilon}_{t-2} + ... = \sum_{i=0}^{\infty} \boldsymbol{A}_{H+i}\boldsymbol{\varepsilon}_{t-i}. \tag{3.4}$$

The corresponding forecast error is

$$\boldsymbol{e}_{t+H,t} = \boldsymbol{x}_{t+H} - \boldsymbol{x}_{t+H,t} = \sum_{i=0}^{\infty} \boldsymbol{A}_i\boldsymbol{\varepsilon}_{t+H-i} - \sum_{i=0}^{\infty} \boldsymbol{A}_{H+i}\boldsymbol{\varepsilon}_{t-i} = \sum_{i=0}^{H-1} \boldsymbol{A}_i\boldsymbol{\varepsilon}_{t+H-i} \tag{3.5}$$

and the variance-covariance matrix of the forecast error can then be calculated as:

$$\boldsymbol{\Sigma}_{e,H} = \boldsymbol{A}_0\boldsymbol{\Sigma}\boldsymbol{A}_0' + \boldsymbol{A}_1\boldsymbol{\Sigma}\boldsymbol{A}_1' + \boldsymbol{A}_2\boldsymbol{\Sigma}\boldsymbol{A}_2' + ... + \boldsymbol{A}_{H-1}\boldsymbol{\Sigma}\boldsymbol{A}_{H-1}' = \sum_{h=0}^{H-1} \boldsymbol{A}_h\boldsymbol{\Sigma}\boldsymbol{A}_h'. \tag{3.6}$$

3.2. 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 aims to examine what fraction of the H-step-ahead error variance in forecasting variable x_i ($i = 1, 2, ..., N$) can be attributed to exogenous shocks (typically including rising 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. This decomposition of forecast error variance requires isolated shocks. However, economic data generally exhibit contemporaneously correlated shocks or innovations (Park et al., 2006). To address this issue, identifying uncorrelated shocks is necessary.

Diebold and Yilmaz (2009, 2012) propose two identification schemes to deal with this issue. Diebold and Yilmaz (2009) use a Cholesky-based VAR variance decomposition (Sims, 1980) to orthogonalise shocks. Nevertheless, this first version of the DY method (2009) is sensitive to variable ordering by nature, because Cholesky-based orthogonalisation assumes a recursive ordering, i.e. it assumes that the first variable in the ordering is only contemporaneously influenced by its own innovations, while the second variable is only contemporaneously influenced by innovations of itself and the first variable, and so on (Diebold and Yilmaz, 2012; Gaspar, 2012). Therefore, in later applications Diebold and Yilmaz (2012) propose an alternative 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). Instead of orthogonalising shocks, GVDs allow for correlated shocks but accounts for their correlations based on an assumed multivariate normal distribution of the shocks. Like Cholesky-based decomposition, GVD is largely data based. However, GVD has the advantage that the decomposition results are insensitive to the ordering of variables. Our spillover analysis with regard to variance decompositions therefore relies on the approach proposed in Diebold and Yilmaz (2012), rather than Diebold and Yilmaz (2009).

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

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\boldsymbol{s}_i' \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{s}_j)^2}{\sum_{h=0}^{H-1} (\boldsymbol{s}_i' \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{A}_h' \boldsymbol{s}_i)}. \tag{3.7}$$

Hereby, $\theta^g_{ij}(H)$ denotes the ij^{th} element of the variance decomposition matrix, where g refers to the generalised variance decomposition method. $\mathbf{\Sigma}$ is the variance-covariance matrix of the error vector $\boldsymbol{\varepsilon}_t$; σ_{jj} is the j^{th} element of $\mathbf{\Sigma}$; 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 all other elements are zero. Each element of the variance decomposition matrix is then normalised,

$$\widetilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}, \tag{3.8}$$

such that the sum of each row equals one (i.e. $\sum_{j=1}^{N} \widetilde{\theta}^g_{ij}(H) = 1$) and $\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ij}(H) = N$. The resulting Table 1 is then the so-called spillover table (Diebold and Yilmaz, 2009, 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 allows to examine various spillover effects as will be explained in the following section.

Table 1: Spillover table based on forecast error variance decomposition.

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

Notes: x_1, ..., x_N are the considered variables from N markets. $\widetilde{\theta}^g_{ij}(H)$, i, j $=$ 1, ..., N is defined in Equations 3.7 and 3.8.

3.3. Spillover Measures

Pairwise Net Spillover

In the forecast error variance decomposition matrix in Table 1, the ij^{th} entry is considered to be the spillover of shocks transmitted by market j and received by market i (i.e., $S^g_{i \leftarrow j}(H) = \widetilde{\theta}^g_{ij}(H)$, based on equations 3.7 and 3.8). Thus, the off-diagonal elements of this matrix ($\widetilde{\theta}^g_{ij}(H), i \neq j$) measure pairwise directional spillovers. Hence the pairwise net directional spillover from market j to market i can be defined as:

$$S^g_{ij}(H) = S^g_{i\leftarrow j}(H) - S^g_{j\leftarrow i}(H) = \widetilde{\theta}^g_{ij}(H) - \widetilde{\theta}^g_{ji}(H) \tag{3.9}$$

Gross Directional Spillovers

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

$$S^g_{i\leftarrow\bullet}(H) = \sum_{j=1, j\neq i}^{N} \widetilde{\theta}^g_{ij}(H). \tag{3.10}$$

Similarly, gross spillovers transmitted by market j (i.e. the 'to others' row) is measured as the j^{th} off-diagonal column sum:

$$S^g_{\bullet\leftarrow j}(H) = \sum_{i=1, i\neq j}^{N} \widetilde{\theta}^g_{ij}(H). \tag{3.11}$$

Total Net Directional Spillover

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

$$S^g_i(H) = S^g_{\bullet\leftarrow i}(H) - S^g_{i\leftarrow\bullet}(H). \tag{3.12}$$

Aggregated Spillover Index

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

$$S^g(H) = \frac{\sum_{i,j=1; i\neq j}^{N} \widetilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ij}(H)} * 100 = \frac{\sum_{i,j=1; i\neq j}^{N} \widetilde{\theta}^g_{ij}(H)}{N} * 100. \tag{3.13}$$

This index measures the overall degree of spillover effects in the whole system.

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

4. The Data

The data used in this study are half-hourly spot prices for the five regional electricity markets (NSW, QLD, SA, TAS and VIC) in the Australian NEM from 1 January 2010 to 31 December 2015[3].

We apply two realized measures to estimate daily volatilities of electricity spot prices. The first measure is the standard deviation of spot prices[4,5] over the 48 half-hour intervals during each day, as represented in Equation 4.1:

$$SD_t = \sqrt{\frac{\Sigma_{i=1}^{N}(p_{it} - \bar{p_t})^2}{N}}, \tag{4.1}$$

where SD_t measures the market volatility on day t, p_{it} is the half-hourly spot price for the i^{th} half-hourly interval on day t, $\bar{p_t}$ is the average half-hourly price on day t, and N equals 48.

The second measure is the daily range of prices that takes into account the highest and lowest price on a day:

$$Range_t = H_t - L_t, \tag{4.2}$$

where H_t and L_t are the highest and lowest prices on day t, respectively[6].

---

[3] Half-hourly electricity spot prices are obtained from the Australian Energy Market Operator (AEMO) website, https://www.aemo.com.au/.

[4] We choose to use the standard deviation of prices as the volatility estimator rather than that of returns, because price-based functions have the advantage that they contain information on the present price level, and our analysis is also concerned with volatility during extreme price periods than volatility during low or normal price periods. For example, consider a low-price scenario where electricity price jumps from $5 to $10 and an extreme-price scenario where the price jumps from $500 to $1000, both scenarios give a return of 100%; however, for electricity market participants, only the second scenario is of concern. In comparison, price-based measures are much less sensitive to such scenarios. In addition, as pointed out in Chan et al. (2008) and Ullrich (2012), 'returns' in the traditional sense do not exist in electricity markets because electricity is non-storable and thus cannot be used as a store of value.

[5] Note that we also conducted the analysis by estimating volatility as the standard deviation of half-hourly price changes (i.e. $p_t - p_{t-1}$). Obtained results for this definition were very similar and are not reported here, but are available upon request to the authors.

[6] This daily price range has been used as volatility estimator in, for example, Frömmel et al. (2014); Reboredo (2014); Auer (2016); Hansen and Huang (2016). It differs from the original range-based estimator developed by Parkinson (1980) by not being scaled with the adjustment factor 4 ln 2. We omit the adjustment factor because this factor depends on the underlying data generating process (Patton, 2011; Frömmel et al., 2014), while the derivation of an appropriate adjustment factor for electricity market is beyond the scope of this study.

With either of these two measure, the calculated volatility for each day is based on intra-day prices for this day and we obtain a time series of daily price volatilities for each regional market (2,191 observations). The empirical results based on the two measures are very similar, suggesting that our spillover analysis is relatively robust to the choice of the volatility estimator[7].

Table 2 presents descriptive statistics for electricity price volatilities (SD) and log-volatility ($log(SD)$) for each regional market in the Australian NEM. Note that since the calculated volatility time series are positively skewed and strongly leptokurtic, following Diebold and Yilmaz (2014) we take the natural logarithm of these series to obtain approximate normality. The applied 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 (Koop et al., 1996; Pesaran and Shin, 1998) that are applied in the following spillover analysis. After the natural logarithm transformation, the skewness and kurtosis of volatility are largely reduced. In addition, the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) statistics suggest that for all volatility series a unit root can be rejected at the 1% significance level, i.e. each series is stationary. In the following, we will concentrate on log-volatility data.

According to Table 2, among the five markets in the NEM, price volatility in SA has the highest mean and median values, indicating that the electricity market in SA is the most volatile. The relatively high penetration of wind generation in SA can be considered as one of the factor contributing to this high volatility, because of the intermittent nature of wind energy. Other market conditions in SA also contribute to volatile prices, including a relatively high concentration of generator ownership, strategic rebidding by generators aiming for more favourable electricity prices, and the tight demand-supply balance due to limited import capacity and recent withdrawal of thermal power plant (Australian Energy Regulator, 2015). QLD is also a relatively volatile market, due to the high concentration level in its electricity generation sector as well as rebidding by generators in recent years (Australian Energy Regulator, 2015).

Figure 1 depicts daily logarithmic price volatilities estimated using the two realized mea-

[7] Since the results based on the two measures are very similar, most results reported in the following main text are generated with the first measure (i.e. SD), while the results based on the second measure (i.e. $Range$) can be found in Appendix B or are available upon request to the authors.

Table 2: Descriptive statistics for electricity price volatility for NSW, QLD, SA, TAS and VIC from 1 January 2010 to 31 December 2015 (2191 daily observations). Price volatility is estimated as the standard deviation of 48 half-hourly intraday prices on each day. Statistics for both raw and logarithmic volatility are reported.

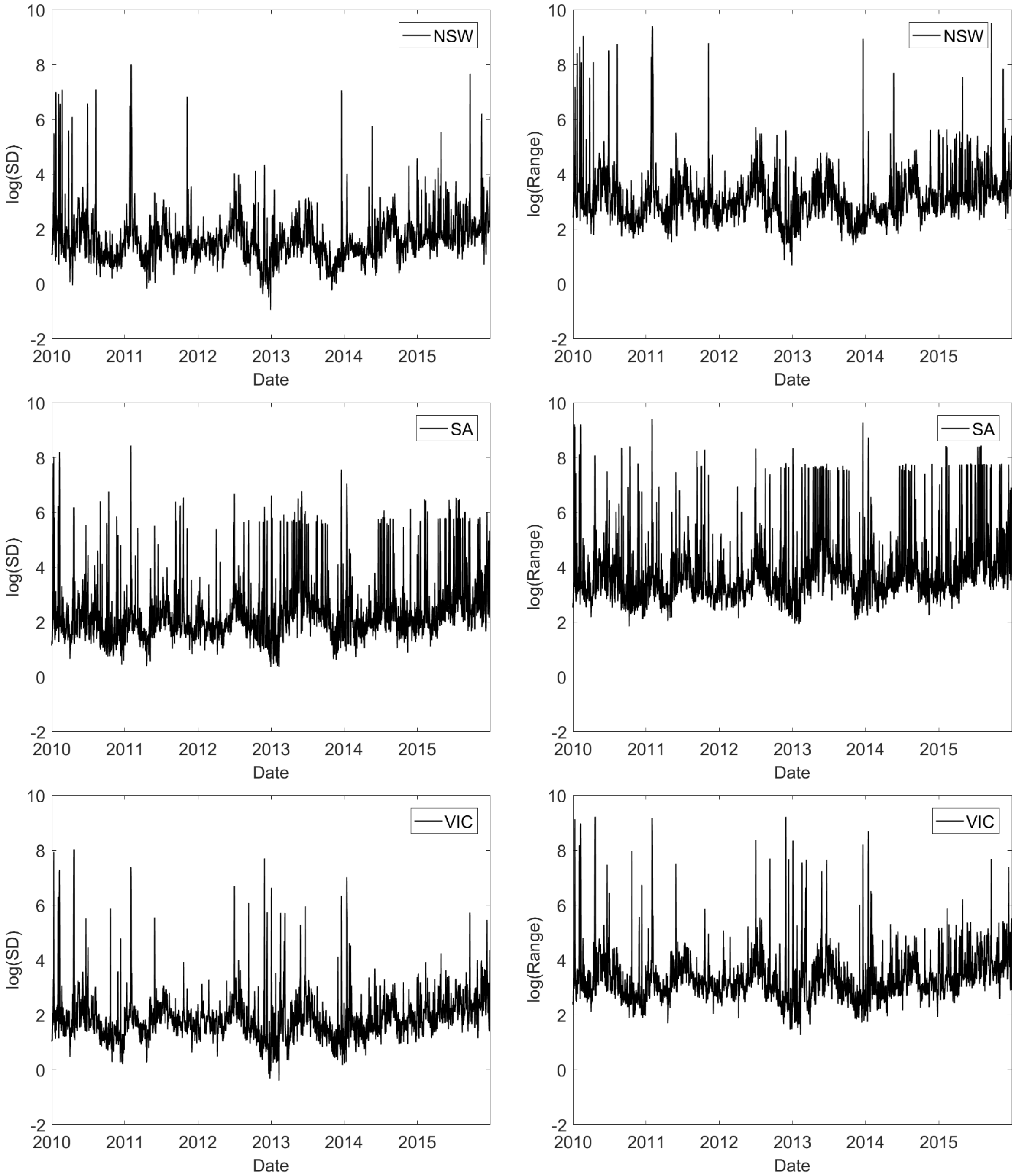
		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	ADF Stat.
NSW	raw	16.3617	4.4698	2959.2	0.3791	121.0935	17.0961	346.1559	-25.1293
	log.	1.6156	1.4973	7.9927	-0.9699	0.8858	2.2386	10.5955	-9.7339
QLD	raw	35.6339	6.1428	3677.8	1.2287	168.3130	13.3573	231.7753	-21.4077
	log.	2.1475	1.8153	8.2101	0.2060	1.1755	1.9615	4.3352	-10.2821
SA	raw	39.9123	7.9997	4561.0	1.4131	184.6812	14.6202	282.4003	-28.2617
	log.	2.3492	2.0794	8.4253	0.3458	1.1440	1.9548	4.4093	-12.1903
TAS	raw	17.5981	5.7353	2712.3	0.0040	95.6022	18.2822	422.1824	-30.1501
	log.	1.8260	1.7466	7.9055	-5.5223	1.0108	0.9720	7.7300	-12.0041
VIC	raw	18.2451	5.8989	3045.6	0.6644	124.0542	17.2056	344.8485	-29.4006
	log.	1.8818	1.7748	8.0214	-0.4088	0.8367	2.3015	11.1680	-10.8024

Notes: The hypotheses of the augmented Dickey-Fuller (ADF) test is H_0: a unit root (non-stationary); against H_1: no unit root (stationary). An intercept is included in the ADF regression; and the lag length is determined by Bayesian information criterion (BIC) (Schwarz et al., 1978). The null hypothesis is rejected for a given significance level when the test statistic is less than the corresponding critical value (-2.57 (10%), -2.86 (5%) and -3.44 (1%)).

sures (SD and $Range$) for the NSW, SA and VIC electricity markets[8]. In general, the time series plots based on the two volatility estimators show very similar patterns. For each market, especially SA, there are frequent peaks in the plot, suggesting the existence of regular price spikes in the considered markets. Meanwhile, some degree of co-movement between the volatility series for each market can be observed, indicating some extent of spillover effects. Furthermore, volatilities appear to be persistent or serially correlated, which justifies the use of autoregressive models.

Table 3 reports pairwise correlations (Pearson correlation coefficients) between log-volatilities ($log(SD)$) over the sample period. It provides an initial idea on the connectedness among different regional markets in the NEM. Overall, all pairwise correlations are positive; and higher correlations are typically found between regions where there are direct interconnections (e.g. NSW and VIC, VIC and SA, and VIC and TAS). In contrast, the lowest correlation coefficients can be observed between regions that are geographically distant and not physically connected (e.g. QLD and TAS, and QLD and SA). Interestingly, although there are two interconnectors in place between QLD and NSW, the correlation

[8] We chose to show the plots for these three regional markets because NSW and VIC are the two markets with the highest electricity consumption and high interconnection levels with other regions, while SA is the most volatile market in the NEM.



(a) Realized standard deviation of prices (b) Intraday price range

Figure 1: Logarithmic volatility (daily) of electricity prices for NSW, SA and VIC from 1 January 2010 to 31 December 2015. Price volatility is estimated as the standard deviation (left panel) and the intraday range (right panel) of half-hourly prices, respectively.

of volatility between these two markets is lower in comparison to the ther markets with direct intercnnection (NSW,VIC), (SA,VIC) and (TAS,VIC).

Since the interaction and transmission of shocks between markets in reality might be far more complex than what can be captured by a simple correlation analysis (for example, these effects have directions and may vary over time), in the following, we will further investigate volatility transmission by analysing specific patterns of spillover effects across the NEM.

Table 3: Unconditional pairwise correlation based on log-volatility ($log(SD)$) from 1 January 2010 to 31 December 2015.

	NSW	QLD	SA	TAS	VIC
NSW	1.0000				
QLD	0.3957	1.0000			
SA	0.3979	0.1376	1.0000		
TAS	0.3196	0.1616	0.2954	1.0000	
VIC	0.6376	0.2359	0.6357	0.4335	1.0000

5. Empirical Results

This section provides empirical findings on the constructed spillover indices as well as a thorough analysis of volatility spillovers between individual markets and through time. We also conduct several robustness checks in order to examine the sensitivity of the obtained results to alternative model specifications.

5.1. Model Specification

As the first step of our spillover analysis, the specification of a VAR model is required. Overall, there are three main parameters to be decided: the optimal lag length (p) of the VAR model, the forecasting horizon (H) in the VAR forecast error variance decomposition, as well as the choice of window length (w) for the dynamic spillover analysis.

A VAR model with one lags ($p = 1$) is selected based on Bayesian (Schwarz) information criterion (BIC) (Schwarz et al., 1978). However, alternative choices of p will also be assessed in the robustness check section.

The choice of the forecasting horizon H in variance decompositions allows us to decide whether 'long-run' or 'short-run' spillover effects are to be assessed. As H lengthens, the conditioning information in the short run is becoming less valuable; and an unconditional variance decomposition will be obtained if $H \rightarrow \infty$ (Diebold and Yilmaz, 2014). In this study we choose $H = 1$ because we are more interested in short-term volatility transmissions in highly volatile electricity markets[9], while a longer forecasting horizon is used for robustness assessment.

In order to track time variations of volatility spillover effects, a rolling-window approach is employed. In particular, a one sided estimation window is used to sweep through the entire sample. In each window, than a VAR model is estimated and spillover measures are calculated so that time series data can be generated and indexed by the end date of each window. The choice of optimal window length w 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, but also use a shorter window (180 days) and a longer window (540 days) to examine the robustness of the results.

5.2. Static Spillover Analysis

Results for a conducted static spillover analysis for price volatility (log(SD)) in the Australian NEM is are reported in Table 4. Note that these results are based on a VAR forecast error variance decomposition for the entire sample.

The aggregated index (32.09%) shown in the lower right corner of Table 4 measures the degree of volatility spillover effects at a system-wide level. THe interpretation of this result suggests that 32.09% of the one-day-ahead forecast error variance for the entire market can be attributed to spillover effects. At the same time, a significantly higher proportion (100% - 32.09% = 67.91%) is due to shocks within each of the regional markets. It indicates that it is typically local factors in each region that dominate the volatility in this market. In comparison to results reported in the literature for equity markets,

[9] As explained in Diebold and Yilmaz (2014), the selection of H usually relates to specific considerations in certain contexts. For example, for equity markets, $H = 10$ which corresponds to the 10-day Value-at-Risk required by the Basel Capital Accord is commonly used in a risk management context. Similarly, H might be related to the rebalancing period in a portfolio management context. In electricity markets, spillover effects estimated with $H = 1$ are of greater interest because the level of electricity price and volatility can change significantly within a very short period of time. In addition, in many electricity markets around the world generators typically submit bids one day ahead.

Table 4: Spillovers effects based on daily log-volatility ($log(SD)$) for the entire sample period from 1 January 2010 to 31 December 2015.

		From					
		NSW	QLD	SA	TAS	VIC	From Others ($S^g_{i\leftarrow\bullet}$)
	NSW	59.79	8.02	7.58	3.46	21.15	40.21
	QLD	12.10	81.79	0.97	1.17	3.97	18.21
To	SA	6.44	0.64	65.96	3.70	23.26	34.04
	TAS	4.53	1.17	5.24	76.90	12.15	23.10
	VIC	15.38	2.11	20.20	7.18	55.13	44.87
	To Others ($S^g_{\bullet\leftarrow j}$)	38.45	11.94	34.00	15.52	60.53	160.43
	Net ($S^g_{\bullet\leftarrow j} - S^g_{i\leftarrow\bullet}$, $i = j$)	-1.77	-6.27	-0.05	-7.58	15.66	
	Spillover Index (S^g)					$= \frac{160.43}{500.00}$	$= 32.09\%$

Notes: This spillover table is generated based on one-day-ahead generalised forecast error variance decomposition of a VAR(1) model. The ij^{th} entry estimates the fraction of one-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}).

the calculated volatility spillover index for the NEM is lower than the one reported in Diebold and Yilmaz (2009) for nineteen global stock markets (40%) and in Zhang and Wang (2014) for three oil markets (China, the US and UK, 43.3%). It is also significantly lower than the spillover index reported for thirteen major US financial institutions' stocks (78.3%) (Diebold and Yilmaz, 2014).

In terms of pairwise volatility spillover effects, the highest level of spillover can be observed from VIC to SA ($S^g_{SA\leftarrow VIC} = 23.26\%$). The spillover from SA to VIC is also relatively high ($S^g_{VIC\leftarrow SA} = 20.20\%$). However, the difference between these two indicates that net spillover is from VIC to SA, rather than from SA to VIC. High spillover effects can also be observed between NSW and VIC ($S^g_{NSW\leftarrow VIC} = 21.15\%$, $S^g_{VIC\leftarrow NSW} = 15.38\%$). In contrast, much lower pairwise volatility spillovers are observed between QLD and TAS ($S^g_{TAS\leftarrow QLD} = S^g_{QLD\leftarrow TAS} = 1.17\%$), and between QLD and SA ($S^g_{SA\leftarrow QLD} = 0.64\%$, $S^g_{QLD\leftarrow SA} = 0.97\%$).

Overall, as expected greater spillover effects are observed between adjoining markets that are physically connected. In particular, spillovers between the pairs SA–VIC (two interconnectors) and NSW–VIC (one interconnector) are of high magnitude. Relatively high spillovers can also be observed between the pairs NSW–QLD (two interconnectors) and TAS–VIC (one interconnector). In contrast, spillovers between geographically distant and unconnected markets are significantly lower (e.g. QLD–TAS and QLD–SA). This indicates the important role of interconnectors in facilitating price convergence and integration between regional markets and confirms the findings in Higgs (2009), Ignatieva and Trück (2016) and Smith (2015).

With regards to gross directional spillovers shown in the 'To Others' row and the 'From Others' column of Table 4, the major transmitters are VIC ($S^g_{\bullet\leftarrow VIC}$ = 60.53%), NSW ($S^g_{\bullet\leftarrow NSW}$ = 38.45%) and SA ($S^g_{\bullet\leftarrow SA}$=34.00%). These three regions are also the major gross spillover receivers in the NEM ($S^g_{VIC\leftarrow\bullet}$ = 44.87%, $S^g_{NSW\leftarrow\bullet}$ = 40.21%, $S^g_{SA\leftarrow\bullet}$=34.04%). Although VIC is not the most volatile market in the NEM, it is the most significant volatility spillover transmitter and receiver according to Table 4, possibly due to its large electricity consumption, its high degree of interconnection with other regions, and its relatively high share of generation and export of electricity to other markets. VIC is directly connected to three other regional markets with four interconnectors in place. The aggregated interconnector capacity for interregional electricity transmission to and from VIC is the highest among all regions in the NEM (Australian Energy Market Operator, 2015). Therefore, it is reasonable to expect VIC to have the highest connectedness and spillover effects with other regional markets. The high spillovers to and from NSW could be explained in a similar way. As the largest regional market in the NEM, there are three interconnectors with relatively high capacity between NSW and two other regions. For SA, the high gross spillover effects are not surprising because of the extremely high price volatility in this region, which is largely due to high reliance on wind generation and the intermittent nature of wind power.

In contrast, relatively low gross spillover effects are observed for QLD and TAS, indicating lower connectedness between either of these two regions and others. Particularly, spillovers from and to QLD are both the lowest ($S^g_{\bullet\leftarrow QLD}$=11.94%, $S^g_{QLD\leftarrow\bullet}$=18.21%), while its own shocks ($S^g_{QLD\leftarrow QLD}$) explain 81.79% of the forecast error variance. A possible reason for this may be the market structure in QLD: the electricity generation sector in QLD is more concentrated than in any other region in the NEM (Australian Energy Regulator, 2015) such that the high degree of local generator market power makes QLD relatively isolated from other markets.

Regarding the 'Net' row, for each market, positive net spillovers for a market indicate that spillover effects transmitted by that market are higher than spillover effects received by it, while negative net spillovers for a market suggest that spillover effects transmitted by that market are lower than spillover effects received. Only VIC (15.06%) is a net volatility spillover transmitter, while NSW (-1.77%), QLD (-6.27%), SA (-0.05%) and TAS (-7.58%) all receive net spillovers from others. The highest net spillover for VIC indicates that this market is the most influential in the NEM. In contrast, net spillovers transmitted by TAS are the lowest, indicating that TAS is the least influential market. This is not surprising because TAS is the smallest market in the NEM and relatively distant with other regions, connected only to VIC through a submarine cable.

5.3. Dynamic Spillover Analysis

The analysis based on the full-sample in the previous section has provided a summary of the average pattern of spillover effects in the Australian NEM. This analysis is static because it implies an assumption that spillover effects remain constant across the sample. However, during our sample period from January 2010 to December 2015, a number of events occurred in the Australian NEM that could be expected to impact on spillovers across the markets. These events include long-term evolutions, such as changes in market policies and structures, and also short-term extraordinary events, such as extreme weather, temporary generation outages and transmission failures. These changes or market events are likely to cause variations in spillover effects over time. Therefore, it may be inadequate to assume that spillovers are time-invariant. Thus, in the following sections, a series of dynamic analyses are conducted.

5.3.1. Aggregated Spillover Analysis

Figure 2 plots the time-varying aggregated volatility spillover index based on the two volatility measures with a 365-day rolling window. Since the results based on the two measures are very similar, only $log(SD)$-based results (Figure 2(a)) are discussed. As shown in the figure, the overall degree of volatility spillover effects in the NEM is not constant but time-varying, which can largely deviate from the average (static) level (32.09%). Initiated at 35% in the first window, the spillover index ranges from 25% and 45% across the sample period. Two major patterns can be observed from those time variations, which are described as follows.

First, some significant upward movements of the spillover index could be related to certain market events. In particular, the shaded areas in Figure 2 indicate periods when extraordinary market events (Events A to K) are recorded in Australian Energy Regulator

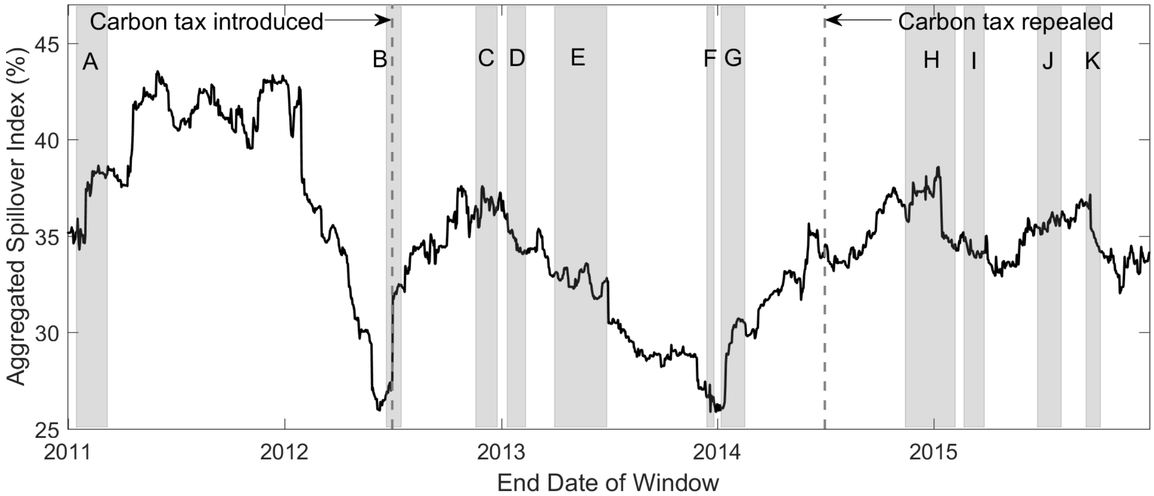
(2015). These events typically include extremely high demand, congestion of interconnectors and generation outages. The spillover plots are found to indicate responses to these market events. More precisely, the spillover index tends to jump during major market events, reflecting a higher likelihood of joint price spikes and high price volatility in different regions during significant market events. They typically drop once the rolling sample window leaves the period of events behind, given the absence of other shocks.

Second, volatility spillovers in the NEM appear to be impacted significantly by the carbon tax policy. The level of aggregated volatility spillover in the NEM was generally lower during the carbon pricing period than during the periods before and after. In particular, before the introduction of the carbon tax policy, the spillover index mostly stayed between 35% and 45%, except that the index experienced a significant drop from around 42.5% to 26% before the establishment of carbon pricing in Australia (January 2012 to June 2012). When the carbon tax was in place, the spillover index generally fluctuated within a lower band between 25% and 35%, except for a short period around the beginning of 2013 when the index was slightly higher. After the abolishment of the carbon tax, the spillover index typically fluctuated around 35%, with a range between 32% and 38%. A possible reason for this pattern is the non-even impact of the carbon tax on different regions, which is also discussed in Apergis et al. (2016). For example, electricity prices in NSW, QLD and VIC were more sensitive to the carbon tax due to their reliance on coal-based generation, while prices in TAS were most insensitive due to its large share of hydropower. These divergent reactions of regional prices might have lowered the connectedness and convergence level between regions, and thus the overall volatility transmission in the NEM during the carbon tax period.

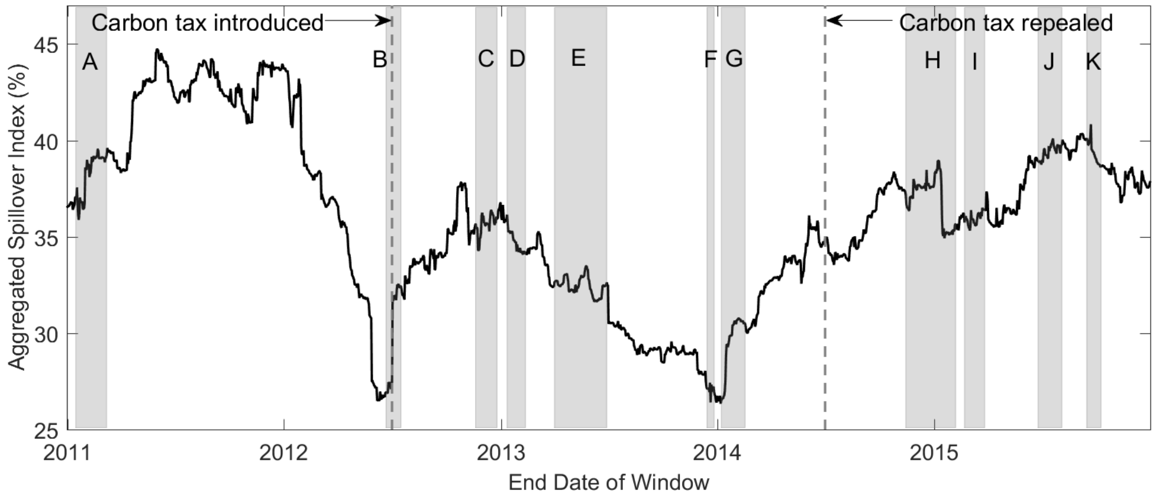
5.3.2. Net Directional Spillover Analysis

We now investigate dynamic spillovers ($log(SD)$-based) and their directions for particular regional markets in the NEM. Panel (a) of Figure 3 plots time variations of total net directional volatility spillovers contributed by each of the five regional markets in the NEM, corresponding to the dynamic estimation of the 'Net' row of the spillover table (Table 4)[10]. Panel (b) of Figure 3 provides the time-varying plots of pairwise net

[10] Gross spillovers (i.e. the 'To Others' row and the 'From Others' column of the spillover table) and net spillovers are not substitutes (Diebold and Yilmaz, 2014), but should be considered as complements.



(a) Aggregated spillover index based on $log(SD)$



(b) Aggregated spillover index based on $log(Range)$

Figure 2: Plots of aggregated volatility spillover index estimated based on one-day-ahead generalised forecast error variance decomposition of a VAR(1) model with a 365-day rolling window. The underlying data are log-volatilities ($log(SD)$ in Panel (a) and $log(Range)$ in Panel (b)). Shaded areas (A to K) represent recorded events in the NEM according to Australian Energy Regulator (2015), which are specified as follows:
A: record demand (NSW and SA); B: outages of the Basslink interconnector (VIC and 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)

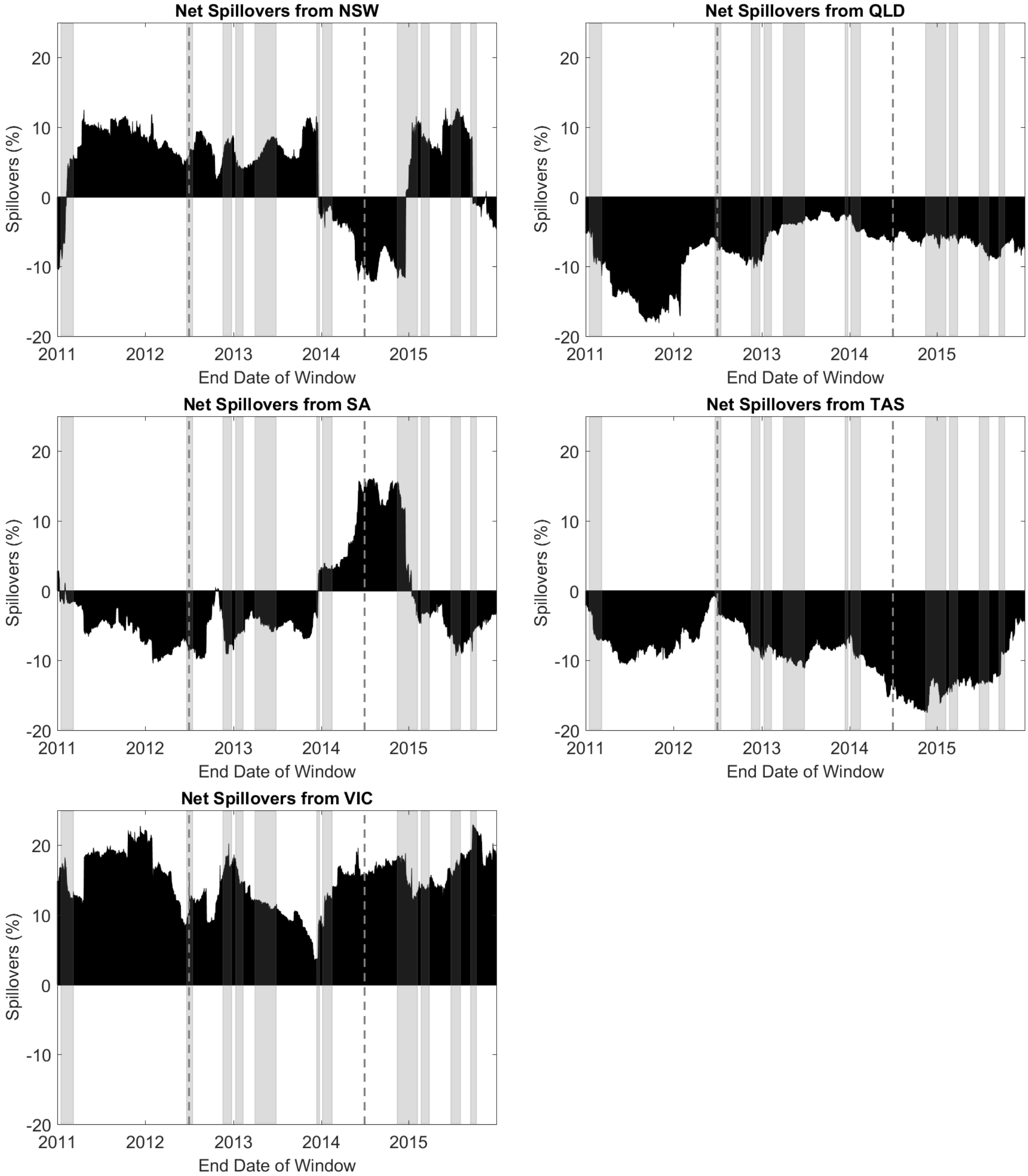
volatility spillovers between each pair of regional markets. Figure 3 indicates that both the degree and direction of spillover effects are not constant but clearly exhibit some variation through time. Some major events in the NEM are still reflected by significant upward or downward jumps in net directional spillover plots. Furthermore, directional spillover plots allow us to observe the influence of a certain event on each particular market. In the following, the dynamic pattern of total net spillovers for each market is discussed together with pairwise net spillovers, since pairwise net spillovers can be viewed as decompositions of total net directional spillovers.

Although NSW was identified as a net volatility spillover receiver in the static analysis, dynamic plots of net spillovers in Figure 3(a) indicate that NSW was typically a net transmitter across the sample period. In addition, this net position changed through time what could not be captured by the static analysis. There was one episode (over the year 2014) during which NSW received significant net volatility spillovers from other markets. Particularly, Figure 3(b) shows that during the year 2014, net spillovers received by NSW mainly came from SA and VIC. This episode could be relevant to the high electricity demand in NSW, SA and VIC around the beginning of 2014 (Events F and G in Figure 2). After the influence of these events disappears around the beginning of 2015, NSW changed back to being a net spillover transmitter. During other periods, NSW mainly received net volatility spillovers from VIC and transmitted net spillovers to QLD, SA and TAS. This indicates that based on a pairwise comparison, NSW is typically more influential than QLD, SA and TAS, but less influential than VIC.

QLD was a net volatility spillover receiver (Figure 3(a)) throughout the entire sample period. Noticeably, the magnitude of net spillovers received by QLD was much higher during 2011 (mainly between 10% and 20%) than during the rest of the studied period, where it was around 5%. These net spillovers to QLD mainly came from NSW and VIC (Figure 3(b)). Similarly, their magnitudes also was significantly reduced from the beginning of 2012 onwards. Furthermore, the same pattern was also observed in gross spillovers transmitted and received by QLD[11], indicating a decreased level of interactions between QLD and other regions in the NEM from 2012 onwards. A possible reason for

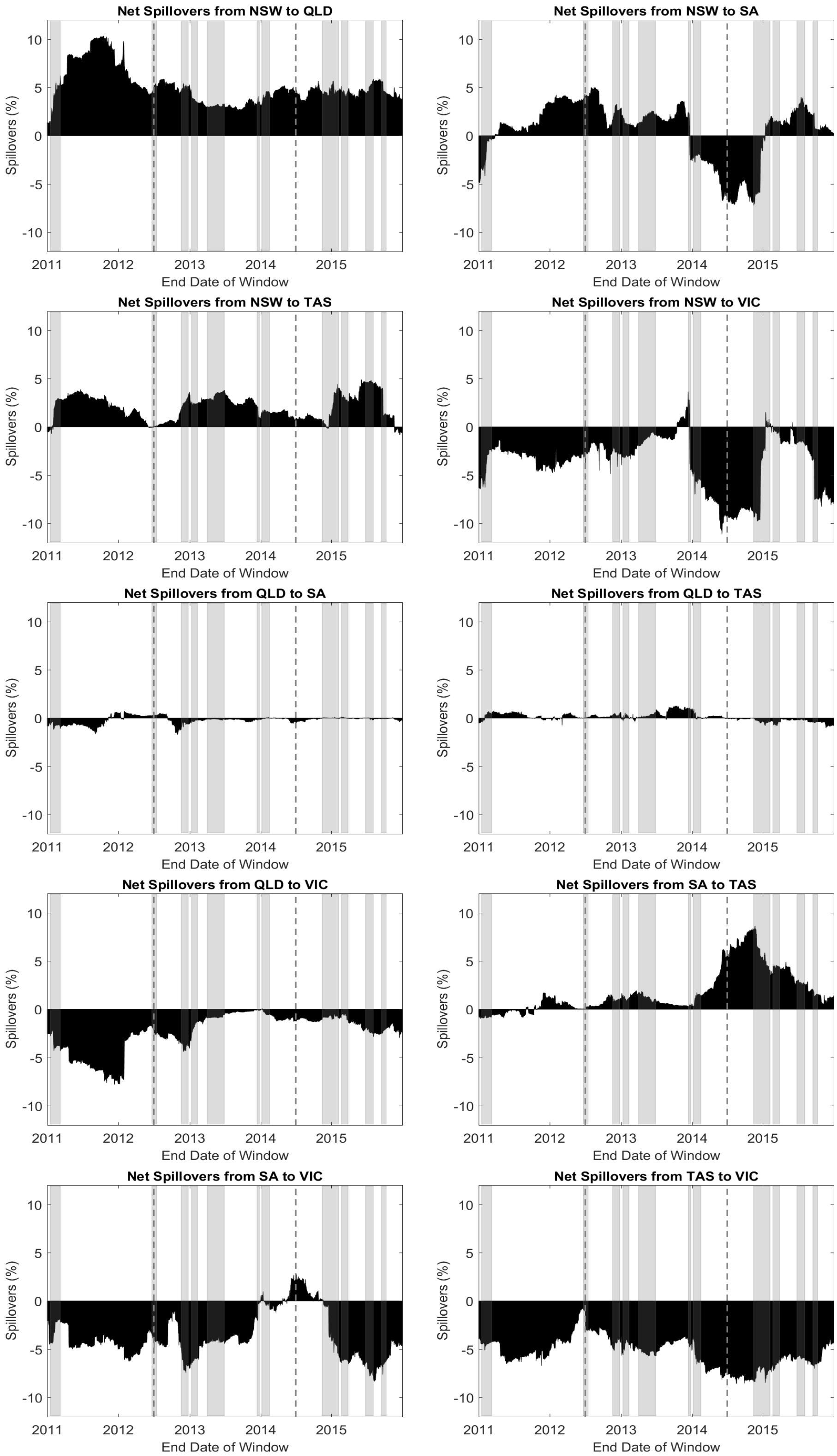
However, in this study we focus more on net spillovers because they are informative on the relative influencing power of different markets. For completeness, plots for gross spillovers are provided in Appendix A.

[11] See Appendix A.



(a) Total net volatility spillovers based on $log(SD)$

Figure 3: Total and pairwise net volatility spillovers, estimated based on $log(SD)$, one-day-ahead generalised forecast error variance decompositions of VAR(1) with a 365-day rolling window. The two dashed lines on each plot refer to the beginning and end dates of the carbon tax policy. Shaded areas represent recorded events in the NEM according to Australian Energy Regulator (2015), see also Figure 2.



(b) Pairwise net volatility spillovers based on $log(SD)$

Figure 3: Total and pairwise net volatility spillovers (continued)

this could be the integration of two local generators in QLD in 2011 (Australian Energy Regulator, 2015), which has increased the degree of QLD electricity market concentration.

SA was typically a net volatility spillover receiver over the sample period, except for 2014, when the market transmitted net spillovers to others (Figure 3(a)). Similar to the case of NSW, this reversion of net spillover position could be related to the high demand in NSW, SA and VIC around the beginning of 2014. According to Figure 3(b), over the year 2014, the positive net volatility spillover transmitted by SA mainly impacted on NSW and TAS. Meanwhile, VIC also received low but positive net spillovers from SA. During other periods, SA mainly received net spillover effects transmitted by NSW and VIC.

Similar to QLD, TAS was also a net volatility spillover receiver (Figure 3(a)) throughout the sample period, receiving spillover effects mainly from VIC but also NSW (Figure 3(b)). While net spillovers received by TAS were generally below 10%, its degree increased from the beginning of 2014 onwards and fluctuated between 10% and 20% until September 2015, mainly due to the increased spillover effects from VIC and SA to TAS[12].

Throughout the sample period VIC is always classified as a net volatility spillover transmitter, while net spillovers transmitted from VIC were generally higher than those for other markets (Figure 3(a)). For the pairwise analysis (Figure 3(b)), VIC typically had a positive net spillover position, indicating a higher influence in comparison to any of the other four markets.

Overall, the provided net directional spillover plots suggest that VIC is the most influential market with regards to spillover effects. NSW and SA also exert significant influence on other markets during certain subperiods with positive net spillover positions. In contrast, QLD and TAS appear to have the lowest impact on spillovers and always receive a net transmission of volatility shocks from other markets. Additionally, two patterns are worth noticing. First, although most findings based on Table 4 are supported by the time-varying net spillover plots, there are clear differences between the static and dynamic analysis (e.g. for NSW) since the dynamic analysis is based on a rolling window with smaller sample size. Second, certain extraordinary events can reverse the direction

[12] Note that directional spillover effects regarding TAS appeared to be influenced by the carbon tax significantly. During the carbon tax period from July 2012 to June 2014, both gross spillovers transmitted and received by TAS were lower than those estimated in other periods, see Appendix A. This influence of the carbon tax is not obvious in net spillover plots due to the calculation of the difference between spillovers from and to TAS.

of net spillover effects, which could be observed, for example, for NSW and SA at the beginning of 2014.

5.4. Robustness Assessment

Finally, we investigate the robustness of our results, including the reliability of our findings with regards to the impacts of the carbon tax and different choices of parameters for the applied model.

5.4.1. Carbon Tax Period

In this section, the static spillover analysis is conducted separately for three subperiods: these subperiods include the period before the implementation of the carbon pricing mechanism (January 2010 to June 2012), the period when the carbon tax was effective (July 2012 to June 2014), and the post-carbon tax period (July 2014 to December 2015). Results for each of these subperiods are presented in Table 5.

The aggregated volatility spillover indices for the three subperiods, i.e. before, during and after the carbon tax are 34.18%, 32.27% and 34.07%, respectively. This confirms our earlier finding that the aggregated volatility spillover index was slightly lower during the carbon tax period, in comparison to pre- and post-tax periods. In each subperiod, higher spillover effects were still observed between adjoining and interconnected markets, while significantly lower spillovers were found between distant and unconnected markets.

Regarding gross directional spillovers, in each subperiod, NSW, SA and VIC were still major gross volatility spillover transmitters and receivers. In addition, it is observed in Table 5 that for QLD, gross spillovers from and to others in the first subperiod (Panel (a)) were significantly higher than those in the following two subperiods (Panel (b) and (c)). This confirms our finding that the overall connectedness between QLD and other markets in the NEM has been reduced since 2012.

In net terms, Table 5 confirms that the net direction of spillover effects can change in different subperiods (e.g. NSW and SA). Additionally, it is noticeable that on average, net spillovers received by TAS during the carbon tax period were around twice the degree of those prio and after the carbon pricing mechanism was in place. This indicates that increased electricity imports of other markets from TAS during the carbon tax period (as discussed in Section 2) resulted in a higher net influence exerted by other markets on TAS.

Table 5: Spillovers based on daily log-volatility ($log(SD)$) before, during and after the carbon tax period.

		From					
		NSW	QLD	SA	TAS	VIC	From Others
Panel (a) : Volatility spillovers (in percentage) before the carbon tax period (01/2010 - 06/2012)							
	NSW	59.92	14.47	6.95	2.55	16.11	40.08
	QLD	17.74	71.09	1.87	1.64	7.66	28.91
To	SA	4.53	1.42	64.01	3.93	26.12	35.99
	TAS	3.05	1.71	4.23	79.24	11.76	20.76
	VIC	9.62	4.38	23.56	7.60	54.84	45.16
	To Others	34.94	21.98	36.62	15.71	61.65	170.90
	Net Spillovers	-5.14	-6.93	0.63	-5.05	16.49	
	Spillover Index					$= \frac{170.90}{500.00}$	= 34.18%
Panel (b) : Volatility spillovers (in percentage) during the carbon tax period (07/2012 - 06/2014)							
	NSW	58.07	4.55	11.04	2.77	23.57	41.93
	QLD	8.32	89.01	0.09	0.87	1.71	10.99
To	SA	9.96	0.08	63.19	2.53	24.24	36.81
	TAS	4.77	1.30	4.88	76.46	12.60	23.54
	VIC	19.08	0.92	21.88	6.19	51.93	48.07
	To Others	42.12	6.85	37.88	12.37	62.12	161.34
	Net Spillovers	0.18	-4.15	1.08	-11.17	14.06	
	Spillover Index					$= \frac{161.34}{500.00}$	= 32.27%
Panel (c) : Volatility spillovers (in percentage) after the carbon tax period (07/2014 - 12/2015)							
	NSW	53.15	7.25	5.84	6.81	26.95	46.85
	QLD	11.99	82.39	0.31	1.11	4.19	17.61
To	SA	6.17	0.12	68.94	5.85	18.92	31.06
	TAS	7.05	0.46	7.97	70.42	14.10	29.58
	VIC	20.17	1.88	13.95	9.27	54.74	45.26
	To Others	45.39	9.71	28.07	23.04	64.16	170.37
	Net Spillovers	-1.46	-7.90	-3.00	-6.54	18.90	
	Spillover Index					$= \frac{170.37}{500.00}$	= 34.07%

Notes: The spillover table for each subperiod is generated based on one-day-ahead generalised forecast error variance decomposition of VAR(1). The ij^{th} entry estimates the fraction of one-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}).

In summary, the separate assessment of volatility spillover effects in the NEM for periods before, during and after the carbon tax confirms empirical findings of this study presented in Sections 5.2 and 5.3. Our results also confirm the ability of dynamic spillover plots to continuously track the changes in spillover levels through time.

5.4.2. Alternative Model Specification

Finally, we assess the robustness of our findings to different model specifications, including alternative choices of the identification method of shocks in the forecast error variance decomposition, the lag length p for the VAR model, the forecasting horizon H, and the rolling window length w.

Choice of Identification Method

We assess the robustness of our results to the choice of the shock identification method, by comparing 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 a Cholesky decomposition to identify shocks, while the 2012 version uses a generalised variance decomposition (GVD).

Figure 4 plots the aggregated volatility spillover index generated by the two versions (i.e. 2009 and 2012) of the DY method. Recall that the Cholesky decomposition is sensitive to the variable ordering; therefore, for the 2009 version, we employ a 'fast spillover method' developed by Klößner and Wagner (2014) to compute the results for all possible orderings in each window, and show the intervals between the minimum and maximum values of the spillover index in the plots.

Overall, the dynamics of the spillover indices generated by the two versions of the DY method are quite similar. However, 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 decomposition and thus tends to yield higher estimates for spillover effects (Diebold and Yilmaz, 2014; Klößner and Wagner, 2014).

Choice of VAR Lag Length p

In addition to $p = 1$ that is used in the VAR estimation in the main analysis of this study, we examine alternative lag lengths $p = 2$, $p = 7$ and $p = 14$, i.e. referring to two days, one week and two weeks. The results are provided in Figure 5. We find that the overall

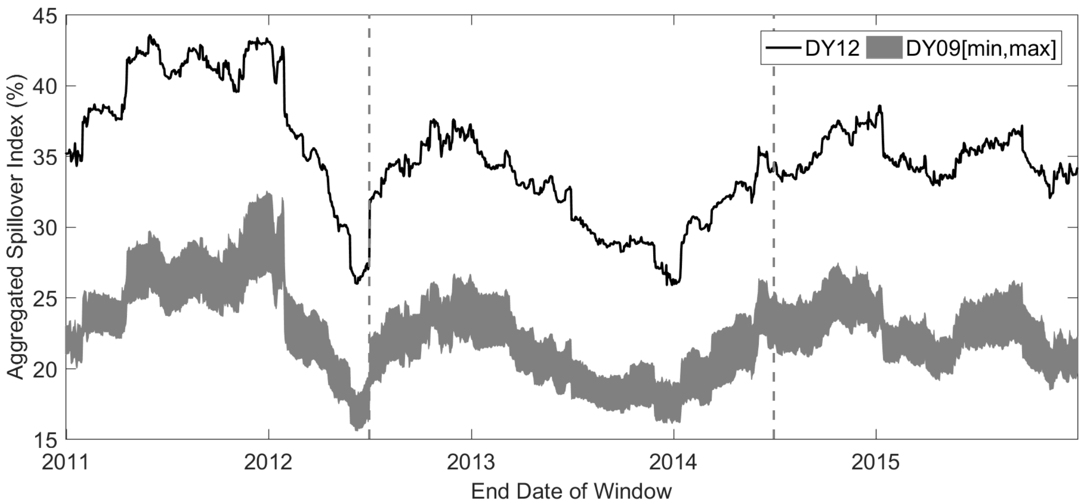


Figure 4: Robustness of the results to the choice of the identification method, based on $log(SD)$. The solid line refers to the spillover indices calculated from a generalised variance decomposition (Diebold and Yilmaz, 2012). The grey band corresponds to a interval between the minimum and maximum values of the spillover index calculated from a Cholesky decomposition (Diebold and Yilmaz, 2009) based on all possible orderings.

qualitative patterns of the spillover plots are similar for different VAR lag lengths.

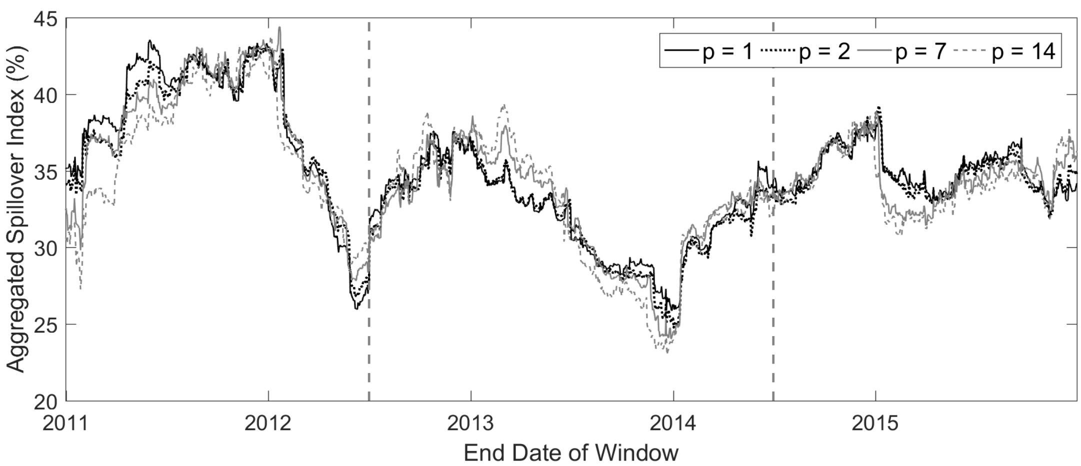


Figure 5: Robustness to the choice of VAR lag length p, based on $log(SD)$.

Choice of Forecasting Horizon H

In addition to a one-day horizon in the forecast error variance decomposition, we consider a seven-day horizon. According to Figure 6, spillover patterns are not particularly sensitive to the choice of the forecasting horizon H, despite the fact that the identified spillover effects are slightly higher when H is larger. Similar patterns are found in, for example, Diebold and Yilmaz (2009, 2014) and Maghyereh et al. (2015). Generally, 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 with a short lag or only with a long lag. With a short forecasting horizon, only short-term spillover effects are considered. As the forecasting horizon lengthens, also spillover effects which might only happen in the longer term are included. Therefore, as indicated by Diebold and Yilmaz (2014), there is no reason why the spillover effects should be 'robust' to different forecasting horizons.

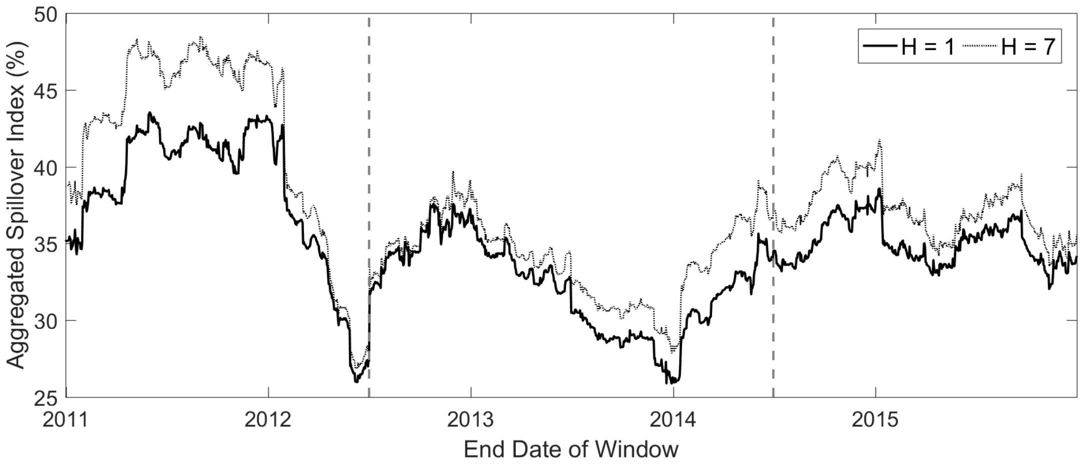


Figure 6: Robustness to the choice of forecasting horizon H, based on $log(SD)$.

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 the rolling-sample analysis. The results are plotted in Figure 7. As expected, the identified spillover effects exhibit higher variation for a shorter window length and more stable for a longer rolling window choice. 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 (or low) spillover effects. Similar results are found in Diebold and Yilmaz (2014). Thus, the applied window length for model estimation has to be considered as an important factor when interpreting the results.

6. Conclusions

This study provides a detailed examination of volatility spillover effects for five regional markets in the Australian NEM, based on a sample period from 1 January 2010 to 31 December 2015. In particular, we empirically assess the specific patterns of volatility

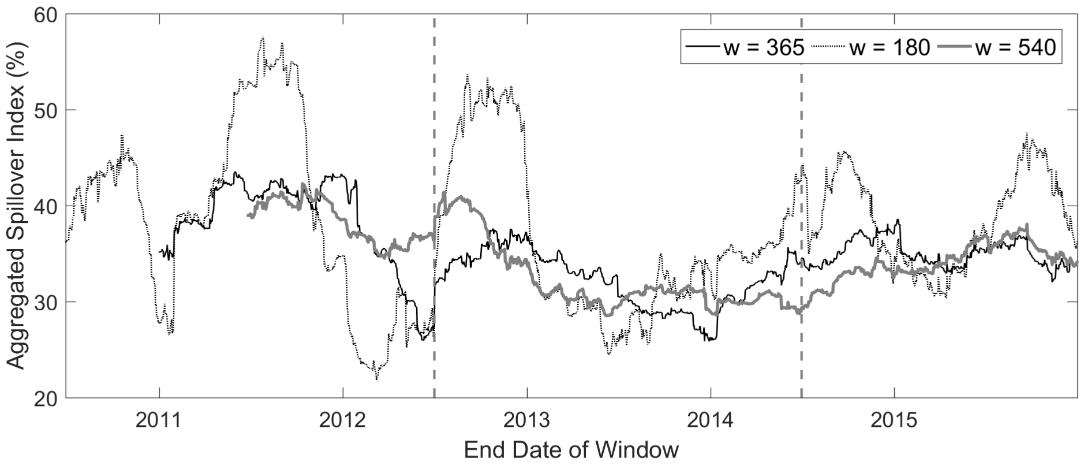


Figure 7: Robustness to the choice of window length w, based on $log(SD)$.

spillover effects, including their degree, direction between regions, time variation, and the impacts of changing market conditions on these effects, applying spillover indices that were originally proposed by Diebold and Yilmaz (2009, 2012). To the best of our knowledge, this is the first study to apply this relatively new econometric framework to interconnected spot electricity markets.

We find that for the entire sample period, the degree of a system-wide aggregated volatility spillover index for the NEM is 32.09%. Interestingly, despite several existing interconnectors between the regional markets, the overall level of volatility spillover across the electricity spot markets seems to be lower than results typically reported for equity and other financial markets. Our interpretation of these results is that in comparison to other financial markets, for electricity spot markets a significantly higher proportion of volatility is due to market-specific factors and shocks within each region. Thus, volatility spillover effects across markets seem to play an overall important role, regional market volatility is typically dominated by local effects. We also find that the degree of volatility spillovers is time-varying. During the carbon tax period from July 2012 - June 2014, spillovers are typically lower, possibly due to a different impact of the tax on regions with a higher share of fossil fuels (NSW, QLD and VIC) and those with a higher share of renewables (SA and TAS).

Regarding the direction of volatility spillovers, we find that VIC, NSW and SA can be classified as major volatility spillover transmitters and receivers, suggesting a higher importance as well as a higher level of connectedness with other regions in the NEM for these markets. In contrast, much lower spillover effects from and to QLD and TAS can be observed for these more isolated markets.

Interestingly, VIC is the only net spillover transmitter, indicating that VIC exerts the highest relative influence on other markets. This is in line with VIC's high share of electricity generation from fossil fuels resulting in typically lower price levels and its high share of electricity exports to other markets such as NSW and SA. However, we find that the direction of spillover effects across different regions is time-varying: NSW and SA exhibit both periods where the market can be classified as net spillover transmitter or net spillover receivers. On the other hand, VIC is a permanent net spillover transmitter, while QLD and TAS are net receivers throughout the entire sample period.

We also find that the patterns of spillover effects could be related to specific market events and market structures. In particular, some periods of increased spillover effects correspond to significant market events, such as extremely high demand, congestion of transmission lines, and generation outages. In addition to the magnitude, certain extraordinary market events also change the direction of spillovers between different regions. Meanwhile, factors such as the generation mix, electricity consumption, market policy and interregional electricity trade also exert influence on spillover effects. Furthermore, interconnectors are found to play an important role in facilitating higher connectedness and integration level between regional markets through greater spillover effects.

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

Overall, our results suggest that the framework by Diebold and Yilmaz (2009, 2012) is well suited to capture spillover dynamics across a system of wholesale electricity spot markets. Our results provide important insights for market participants, especially for those who simultaneously operate in different regional markets in the NEM. In particular we provide an analysis on the transfer of risks between the considered highly volatile markets. Compared to the previous literature on Australian electricity markets, using more recent sample period also allows us to consider the influence of the carbon tax period on volatility spillover effects in the NEM. Our analysis therefore also provides regulators with information on how climate change policies inpact on volatility transmission and the overall stability of the NEM. In addition, the conducted spillover analysis will enable regulators to examine the impacts of current market structure on volatility transmissions across regions, which is of significance for making investment decisions on, for example, inclusion of renewables and, in particular investment into new generation plants and interconnectors.

Finally, there are some directions for future research. First, a further exploration on the influence of using different volatility estimators could be of interest. Estimated spillover effects based on more alternative volatility measures could be compared to current results. A comparison between the spillover analyses using various volatility measures (e.g. volatilities extracted from a GARCH or alternative model) could be of interest. Second, in this study we use generate a daily time series of volatility calculated based on half-hourly prices. Given that electricity spot prices in the NEM are originally determined and recorded every five minutes, it is possible that the current choice of data frequency may miss some relevant information within shorter time horizons. Thus, another possible extension could be to look at spillover effects based on high-frequency data. Furthermore, additional factors could be considered in the VAR model, such as variations in electricity demand, weather and congestion of interconnectors or in other transmission lines.

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Appendix A. Gross Directional Spillovers

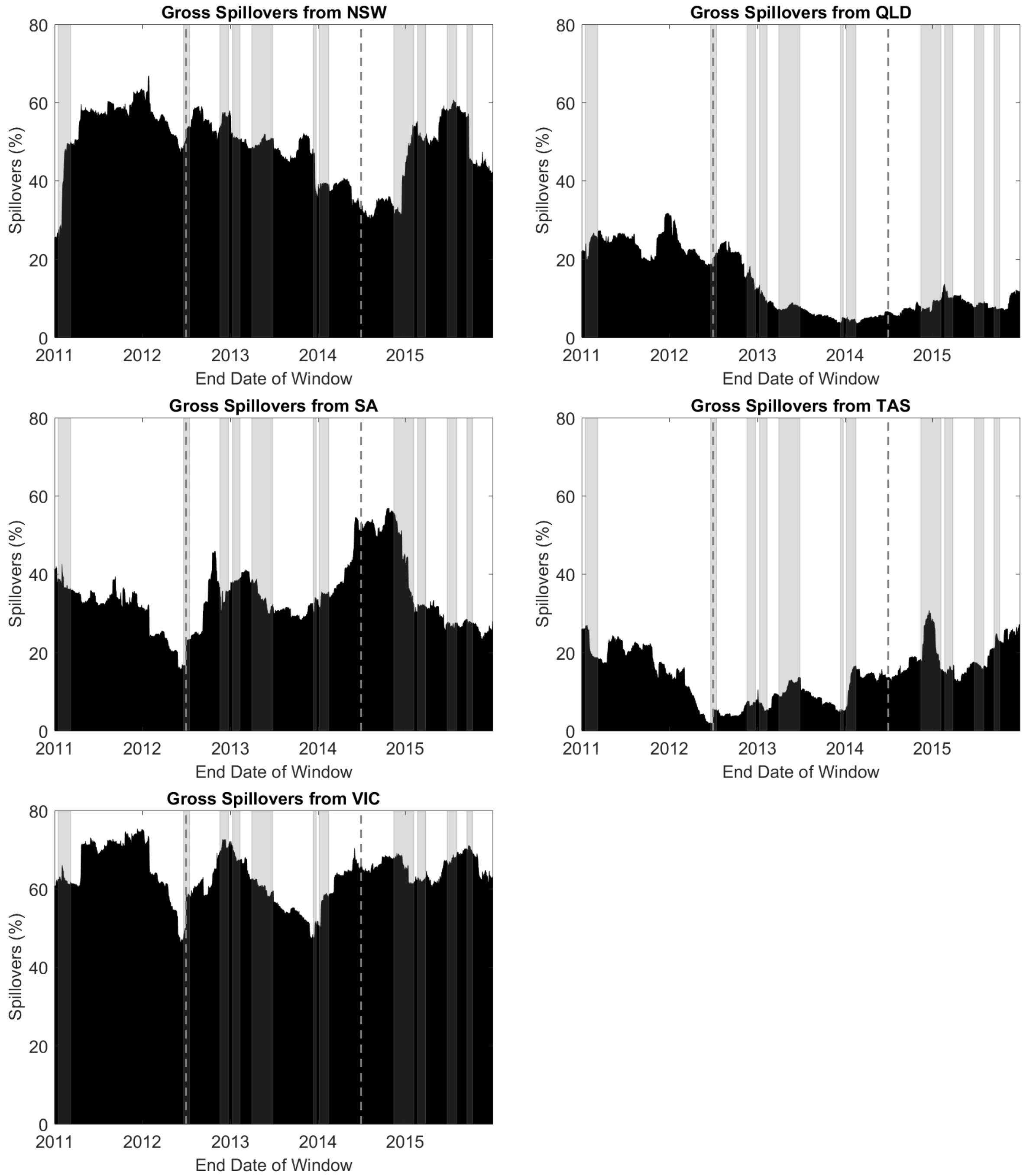


Figure A1: Gross volatility spillovers transmitted from each market, estimated based on $log(SD)$ data, one-day-ahead generalised forecast error variance decompositions of VAR(1) with a 365-day rolling window. The two dashed lines on each plot refer to the beginning and end dates of the carbon tax policy. Shaded areas represent recorded events in the NEM according to Australian Energy Regulator (2015), see Figure 2.

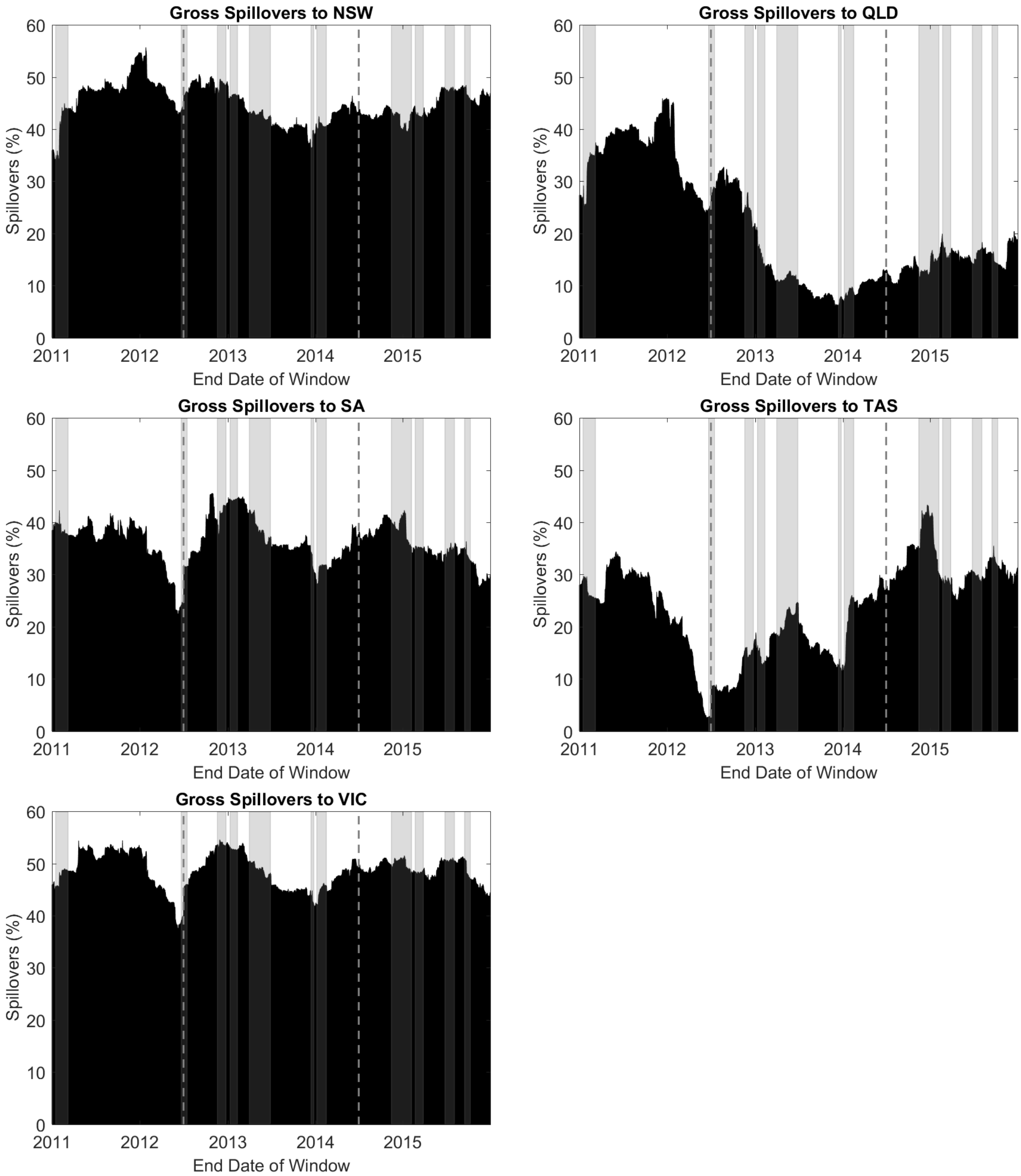


Figure A2: Gross volatility spillovers received by each market, estimated based on $log(SD)$ data, one-day-ahead generalised forecast error variance decompositions of VAR(1) with a 365-day rolling window. The two dashed lines on each plot refer to the beginning and end dates of the carbon tax policy. Shaded areas represent recorded events in the NEM according to Australian Energy Regulator (2015), see Figure 2.

Appendix B. Results for Range-based Volatility Measure

Table B1: Descriptive statistics for electricity price volatility for NSW, QLD, SA, TAS and VIC from 1 January 2010 to 31 December 2015 (2191 daily observations). Price volatility is estimated as the intraday price range on each day. Statistics for both raw and logarithmic volatility are reported.

		Mean	Median	Max.	Min.	Std.dev	Skew.	Excess Kurt.	ADF Stat.
NSW	raw	84.5376	19.5300	13383.0	1.9300	617.1803	14.5382	243.4082	-25.9667
	log.	3.1167	2.9720	9.5018	0.6575	0.9431	2.1718	9.6243	-9.7090
QLD	raw	192.2101	26.9400	13476.0	3.8200	784.4014	9.6310	127.2779	-19.5963
	log.	3.6732	3.2936	9.5087	1.3403	1.2870	1.8058	3.4561	-10.4321
SA	raw	207.3156	32.5700	12183.0	6.2400	775.5271	8.1033	88.4539	-27.2561
	log.	3.8261	3.4834	9.4078	1.8310	1.2491	1.8991	3.7843	-12.4883
TAS	raw	99.4686	26.2400	12388.0	0.0200	569.4338	15.7775	309.1479	-30.0995
	log.	3.3435	3.2673	9.4245	-3.9120	1.0767	1.1974	7.3115	-12.1461
	raw	88.3251	24.5000	9985.6	3.5200	549.9719	13.5911	207.8469	-29.0516
VIC	log.	3.3405	3.1987	9.2089	1.2585	0.9088	2.2305	9.3344	-10.8042

Notes: Hypotheses of the augmented Dickey-Fuller (ADF) test are H_0: a unit root (non-stationary); H_1: no unit root (stationary). An intercept is included in the ADF regression; and the lag length is determined by Bayesian information criterion (BIC) (Schwarz et al., 1978). The null hypothesis is rejected at a certain significance level when the test statistic is less than the corresponding critical value (-2.57 (10%), -2.86 (5%) and -3.44 (1%)).

Table B2: Unconditional pairwise correlation based on log-volatility ($log(Range)$) from 1 January 2010 to 31 December 2015.

	NSW	QLD	SA	TAS	VIC
NSW	1.0000				
QLD	0.3831	1.0000			
SA	0.4176	0.1320	1.0000		
TAS	0.3419	0.1789	0.3057	1.0000	
VIC	0.6604	0.2366	0.6369	0.4477	1.0000

Table B3: Full sample spillovers based on daily log-volatility ($log(Range)$) from 1 January 2010 to 31 December 2015.

		From					
		NSW	QLD	SA	TAS	VIC	From Others ($S^g_{i\leftarrow\bullet}$)
To	NSW	57.45	7.56	8.10	4.19	22.70	42.55
	QLD	11.64	81.57	0.92	1.60	4.27	18.43
	SA	7.73	0.65	64.23	4.00	23.39	35.77
	TAS	5.81	1.53	5.63	73.87	13.17	26.13
	VIC	17.51	2.24	19.42	7.68	53.14	46.86
	To Others ($S^g_{\bullet\leftarrow i}$)	42.69	11.99	34.06	17.47	63.54	169.74
	Net Spillovers ($S^g_{\bullet\leftarrow i} - S^g_{i\leftarrow\bullet}$)	0.14	-6.45	-1.72	-8.66	16.68	
	Spillover Index (S^g)					$= \frac{169.74}{500.00}$	= 33.95%

Notes: This spillover table is generated based on one-day-ahead generalised forecast error variance decomposition of VAR(1). The ij^{th} entry estimates the fraction of one-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}).

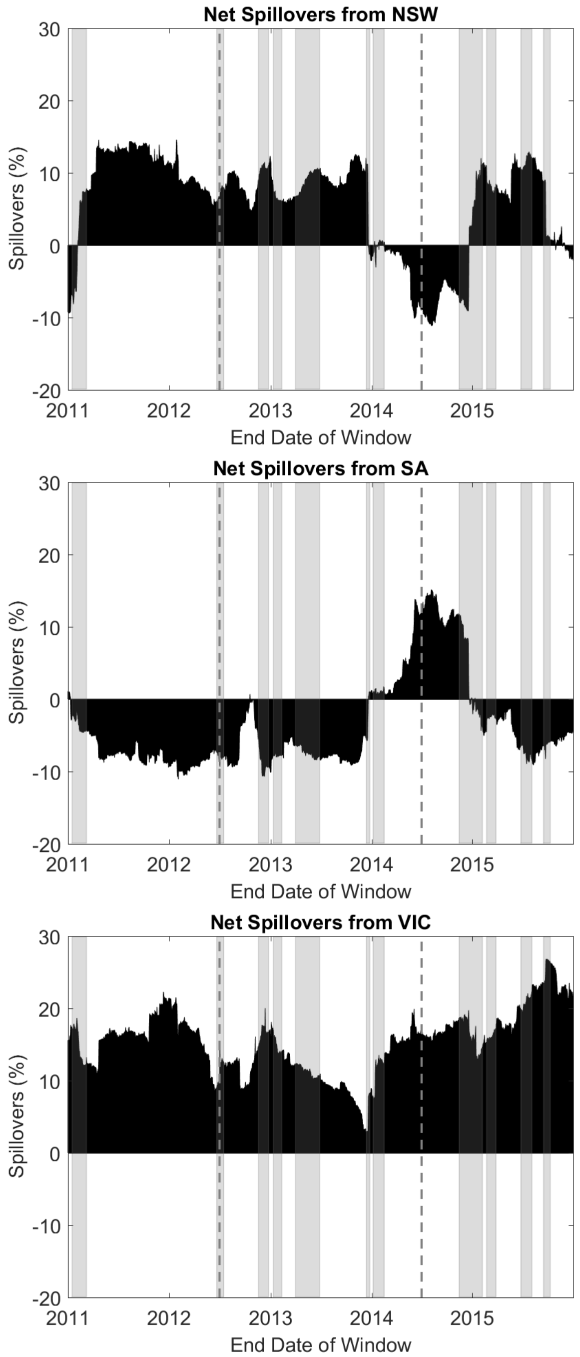
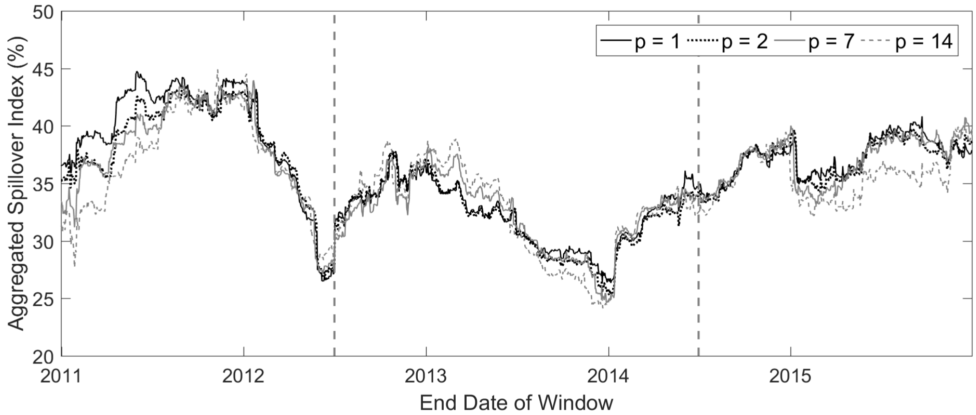
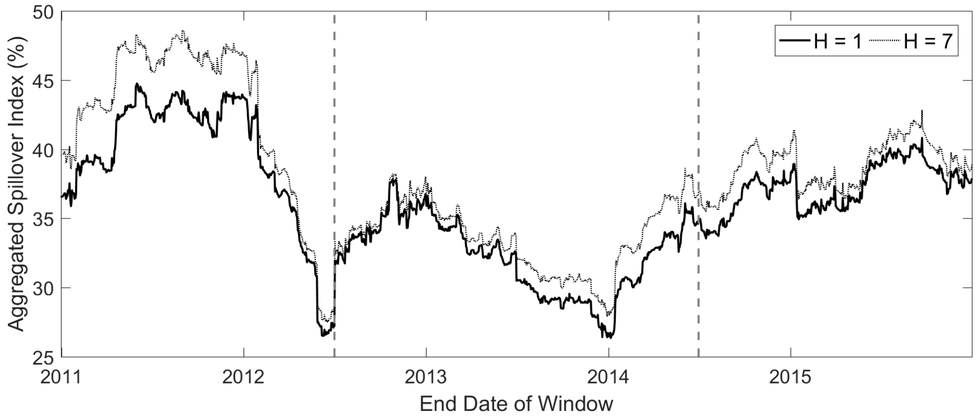


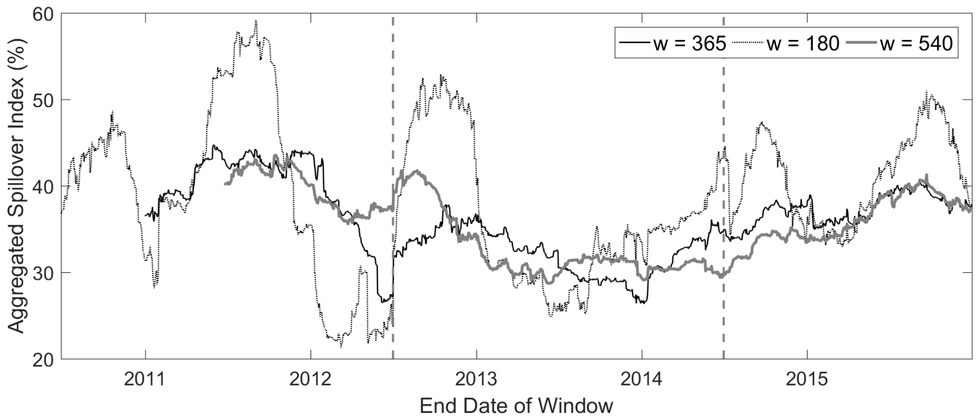
Figure B1: Total and pairwise net volatility spillovers, estimated based on $log(Range)$ data, one-day-ahead generalised forecast error variance decompositions of VAR(1) with a 365-day rolling window. The two dashed lines on each plot refer to the beginning and end dates of the carbon tax policy. Shaded areas represent recorded events in the NEM according to Australian Energy Regulator (2015), see Figure 2.



(a) Robustness to the choice of VAR lag length p.



(b) Robustness to the choice of forecasting horizon H.



(c) Robustness to the choice of window length w.

Figure B2: Robustness to alternative model specification based on $log(Range)$.

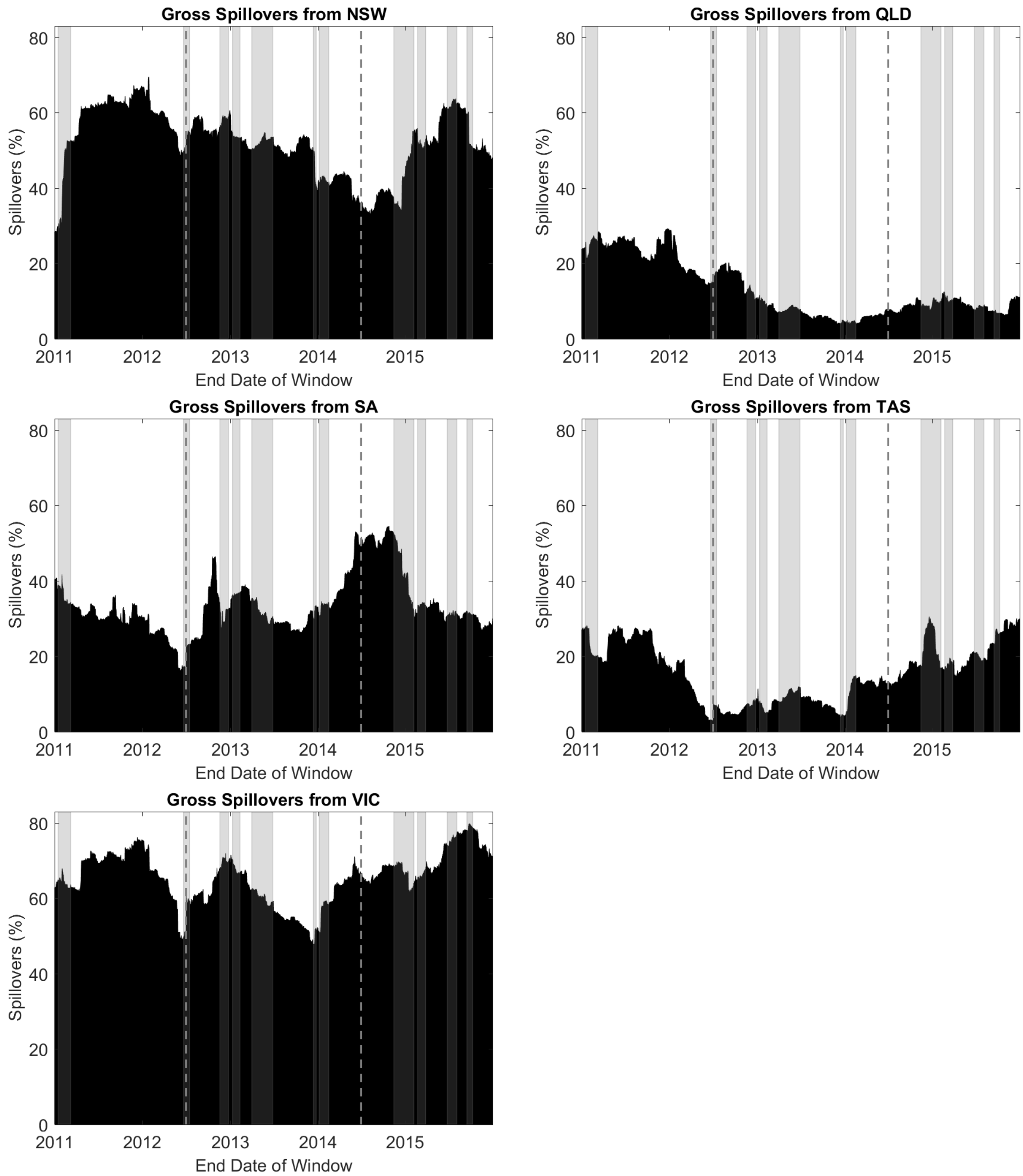


Figure B3: Gross volatility spillovers transmitted from each market, estimated based on $log(Range)$ data, one-day-ahead generalised forecast error variance decompositions of VAR(1) with a 365-day rolling window. The two dashed lines on each plot refer to the beginning and end dates of the carbon tax policy. Shaded areas represent recorded events in the NEM according to Australian Energy Regulator (2015), see Figure 2.

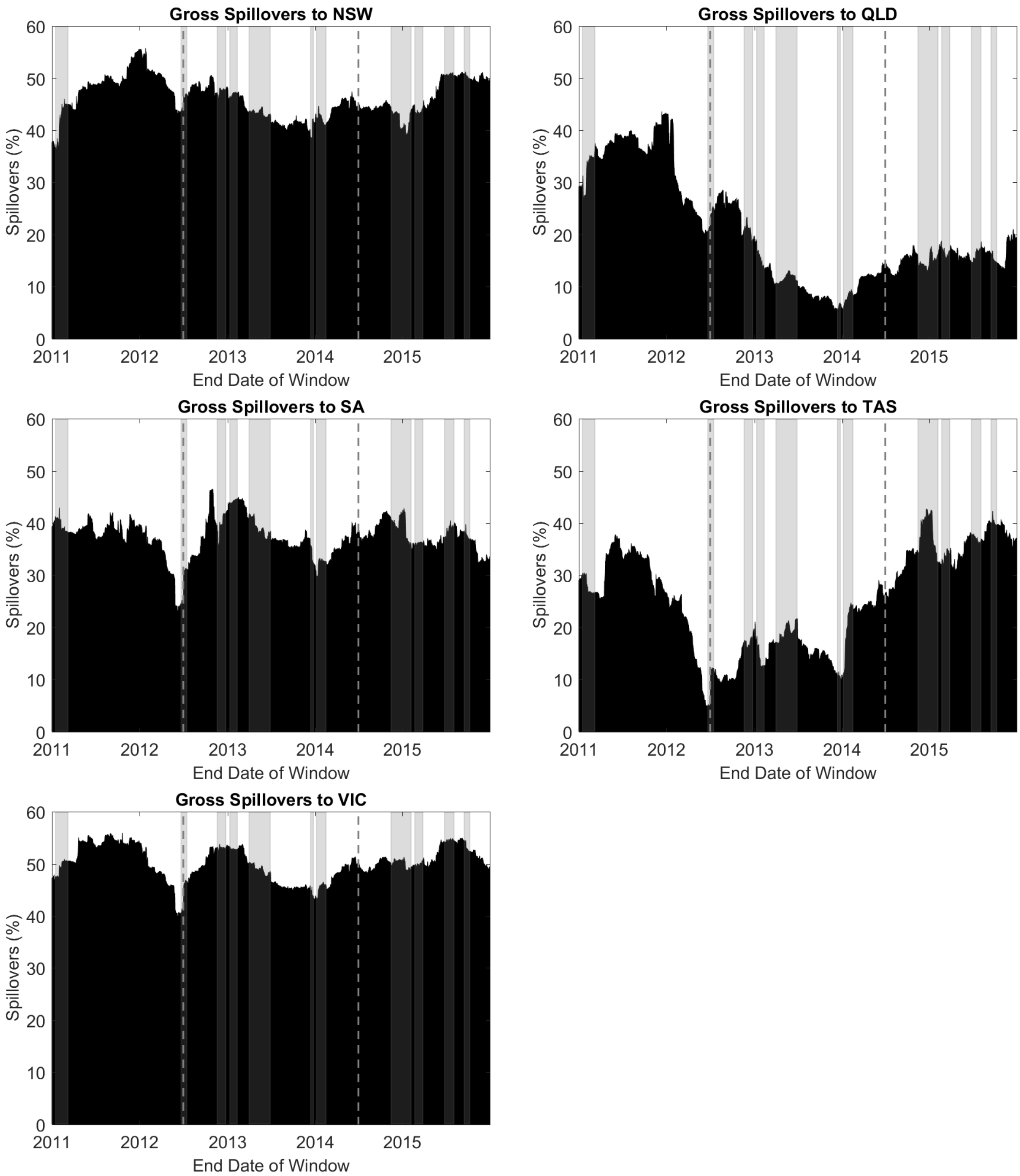


Figure B4: Gross volatility spillovers received by each market, estimated based on $log(Range)$ data, one-day-ahead generalised forecast error variance decompositions of VAR(1) with a 365-day rolling window. The two dashed lines on each plot refer to the beginning and end dates of the carbon tax policy. Shaded areas represent recorded events in the NEM according to Australian Energy Regulator (2015), see Figure 2.