Good volatility, bad volatility: What drives the asymmetric connectedness of Australian electricity markets?

Abstract

Efficient delivery of network services and the electricity infrastructure to meet the long-term consumer's interests are the main objectives and the strategies of a national electricity market, while the main interests of generators are to maximize their profit through pricing strategies. Therefore, the objective of this study is to explore whether electricity prices across the four Australian States display symmetric price volatility connectedness. The study is the first attempt in the literature to make use of intraday 5-minute Australian dispatch electricity prices, spanning the period December 8th, 1998 to May 5th, 2016 to quantify asymmetries in volatility connectedness emerging from good, and bad volatility. The results provide supportive evidence that the Australian electricity markets are connected asymmetrically implying the presence of some degree of market power that is exercised by generators across regional electricity markets.

Keywords: Electricity prices; volatility spillovers; semivariance; asymmetric effects; Australia National Electricity Market

JEL Classifications: Q41; Q50

1. Introduction

The literature has extensively explored volatility spillovers across energy (or energy commodity) markets. According to Sattary et al. (2014), there is a rapidly growing literature which addresses linkages across oil and stock markets in terms of volatility spillovers. Certain studies focus on such spillovers across regions like Asia, the U.S. and the U.K. Their findings provide supportive evidence of the presence of volatility spillover linkages, mostly over the post-crisis period (In, 2007; Alsubaie and Najand, 2009; Moon and Yu, 2010; Arifin and Syahruddin, 2011; Gebka, 2012; Zheng and Zuo, 2013; among others). There is also a strand of literature that corroborates the significance of volatility spillovers across European stock markets in the light of oil prices (Giannellis et al., 2010; Arouri et al., 2012; Antonakakis, 2012; Tamakoshi and Hamori, 2013; Reboredo, 2014), while a third strand explores extensive volatility spillover comparisons among different countries (Serra, 2011; Korkmaz et al., 2012; Krause and Tse, 2013; Salisu and Mobolaji, 2013). A number of recent studies investigate the behavior of U.S. stock markets and sector indices depending on oil behavior, while they provide positive evidence of the presence of transmissions of volatility and shocks across oil markets and relevant sectors (Malik and Ewing, 2009; Du et al., 2011; Diebold and Yilmaz, 2012; Liu et al., 2013). Finally, there is a methodological strand of the literature that focuses on the comparison of econometric methodologies used to measure volatility spillovers, along with the presence of asymmetric effects across and within energy, such as oil and natural gas, markets (Chang et al., 2010; Sadorsky, 2012; Ewing and Malik, 2013).

It is important to examine the dynamics of volatility spillovers across electricity markets to add knowledge of the information transmission channels on Australian national electricity markets. According to Higgs (2009), the Australian electricity markets are characterized by the limitations of the interconnectors across the member states, indicating that the Australian regional electricity markets are relatively isolated. The absence of convergence has been also confirmed by the study of Apergis et al. (2017). It is generally accepted that in electricity markets, supply or demand shocks, say due to the presence of unexpected outages of generation units or transmission constraints cannot be fully compensated in the short run. As a result, sudden jumps in prices (i.e., spikes) usually occur, especially in the cases when reserve capacity is limited, which is the case for electricity markets across Australia (Apergis et al., 2017). Given that the electricity market is perceived to have a high level of exposure to external shocks, such market contains significant market risk level. Therefore, accurately measuring the downside market risk exposure represents a pivotally important and difficult practical problem for suppliers and consumers in the electricity market and, hence, electricity prices are expected to be very volatile and pose a huge risk for those market participants. In addition, such findings will allow further the study of the differences in volatility across the Australian electricity markets and to provide evidence on whether price volatility across those markets is high and/or persistent either in the real time market or in the day-ahead market. Furthermore, the findings will allow a more consistent manner in further forecasting electricity price volatility, while will also allow to measure the market risk level and to analyze the risk evolution which is expected not only to efficiently analyze the heterogeneous market structure, but also to improve the risk measurement accuracy (Deng and Oren, 2006; Pineda and Conejo, 2012). Therefore, it is expected that the documentation of volatility spillovers will shed further light on the understanding of the dynamics of electricity pricing, and further on the efficiency of pricing, given that the Australian state electricity markets are identified as centralized markets which still are primarily composed of commercialized and corporatized public sector entities. The findings in relevance to the presence of such spillovers will also benefit the proper evaluation as a step towards higher levels of regional electricity markets integration.

The Australian National Electricity Market (NEM) is currently operating as a nationally interconnected grid and interconnecting five state-based regional markets (i.e., Queensland, New South Wales, Victoria, South Australia and Tasmania) , while NEM covers about 40,000 km of transmission lines. The main domestic network is the *National Electricity Market* (NEM), which was established in 1998 and links regional markets in Queensland, New South Wales, Victoria and, more recently, Tasmania and South Australia. Both producers and retailers trade through a spot market operated by the Australian Energy Market Operator. Our study does not cover Western Australia (WA). WA's main wholesale market is the South West Interconnected System (SWIS), which covers the area of Perth and surroundings and is operated by WA's Independent Market Operator (IMO). In WA, there is no existing interconnection with any other power system outside the state. The lack of interconnection capacity between the SWIS and the rest of Australia does not allow for arbitrage of electricity prices, at least in the short run.

The goal of the paper is to extend Higgs' (2009) work and undertake a research effort for the first time, to the best of the authors' knowledge, the presence of asymmetries in volatility spillovers across Australian electricity markets. This is also the first study that uses 5-minute high frequency data to capture more information in relevance to the dispatched price data. Investigation towards the presence of asymmetric volatility spillovers seems to be substantially important because spillovers that are asymmetric tend to be a source of contagion, which could have important implications towards the implementation of energy and electricity policies. It is highly possible that in certain conditions, especially in the phase of expanding electricity demand, the electricity market in a certain region looks as if it is not related to the market of another region, which could be more advanced. The concept of asymmetric volatility spillovers comes from the financial literature. In particular, there have been two competing hypotheses that provide the theoretical background for the presence of such asymmetric volatility spillovers: the leverage hypothesis effect, according to which negative returns increase financial leverage, causing volatility to rise (Christie, 1982; Schwert, 1989), and the volatility feedback effect, according to which if the market risk premium is an increasing function of market volatility, anticipated increases in volatility raise the required returns on equity, leading to immediate declines of stock prices (Campbell and Hentschel, 1992). The findings in the case of electricity prices are expected to be very helpful in designing efficient electricity trading rules, leading to an efficient, as well as integrated electricity market.

Whereas asymmetric volatility in financial markets has long been recognized as a stylized fact (Black, 1976; Christie, 1982; Pindyck, 1984; French, Schwert, and Stambaugh, 1987), question if these asymmetries propagate to other assets, or markets, have not yet received the same attention. Since large literature documents how volatility transfers across different assets and markets, it is worth assuming that volatility spillovers exhibit asymmetries as well and such asymmetries might stem from qualitative differences due to bad and good uncertainty. Segal, Shaliastovich, and Yaron (2015) provide precise definitions, and coin bad uncertainty as the volatility that is associated with negative innovations to quantities (e.g., output, returns) and good uncertainty as the volatility that is associated with positive shocks to these variables. Barunik, Kocenda, and Vacha (2015, 2016) hypothesize that volatility spillovers might substantially differ depending on nature of these shocks. They suggest how to quantify the asymmetries in volatility spillovers originating due to bad and good uncertainty as defined by associated with negative and positive shocks to volatility (as defined by Segal, Shaliastovich, and Yaron, 2015). In addition, Barunik, Kocenda, and Vacha (2015, 2016) document asymmetries in volatility spillovers in financial assets as well as petroleum markets.

The remaining of the paper is organized as follows. Section 2 describes the data set used in the empirical analysis, and provides the description of the methodologies used. Section 3 reports the empirical results, and finally, Section 4 concludes the paper.

2. Data and methodology

The paper employs high frequency data on electricity dispatched price obtained from the Electricity Market Management Company, and the prices are in Australian dollars per megawatt hour (MWh). The time resolution of the data is 5 minute basis, representing 288 trading intervals in each 24-hour period. The spot price is where market generators are paid for the electricity they sell to the pool and market customers pay for their electricity consumption from the pool. All electricity is traded through the pool at the spot price. The pool is defined into a number of pre-defined regions. A dispatch price for each region is determined every 5 minutes, and the 6 dispatch prices in a half-hour period are averaged to determine the regional spot price for that half-hour trading interval.

AEMO uses the spot price to settle all energy traded in the NEM. In other words, the wholesale market of the NEM is operated as a real-time energy market through the centrally coordinated dispatch system to match demand and supply instantaneously in real time. The dispatch price for each 5 min interval is the one of the last bid that matches demand at time period t. The dispatch electricity prices, spanning the period from December 8th, 1998 to May 5th, 2016[i], are obtained and the asymmetric spillover effects between electricity markets across four Australian regions, i.e. Queensland, New South Wales, Victoria and South Australia, are examined using the squared realized variance (i.e. RV) time series in a logarithm form.

2.1.Measuring asymmetric volatility spillovers

This sub-section aims at defining a measure of asymmetries in volatility spillovers. In their seminal works, Diebold and Yilmaz (2009, 2012) developed a volatility spillover index based on forecast error variance decompositions from vector autoregressions (VAR) to measure extend of transfers among markets. Consecutive large strand of literature extended this approach in various ways incorporating covariances, or frequency dependent shocks to the analysis (among many see for example McMillan and Speight, 2010; Kumar, 2013; Fengler and Gisler, 2015; Barunik and Krehlik, 2016; and Krehlik and Barunik, 2017). Despite its versatility, the spillover measures do not distinguish the potential asymmetry in originating due to bad and good uncertainty associated with negative and positive shocks to volatility.

[i] Data can be downloaded from http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard

An important extension has been proposed in this direction by Barun ŀk, Kocenda, and Vacha (2016), who showed how to quantify asymmetries due to negative and positive shockls. A new spillover asymmetry measure (SAM) combines two methodological concepts (i.e. realized semi-variance and volatility spilover index) to capture asymmetric volatility spillovers using high-frequency data.

Under the assumption of continuous-time stochastic process for the dispatch price in the logarithm form (i.e. p_t) evolving over a time horizon $[0 \leq t \leq T]$, p_t contains a continuous component, as well as a pure jump component such that the data generating process (GDP) can be written as:

$$p_t = \int_0^t \mu_s \, ds + \int_0^t \sigma_s \, dW_s + J_t \tag{1}$$

where μ in Equation (1) denotes a locally bounded predictable drift process, σ represents a strictly positive volatility process (i.e. $\sigma>0$), and J_t jumps; note that all process is governed by the common filtration $\mathcal{F}$. The quadratic variation associated with the log-prices p_t is then:

$$[p_{t,} p_t] = \int_0^t \sigma_s^2 \, ds + \sum_{0<s<t} (\Delta p_s)^2 \tag{2}$$

where $\Delta p_s = p_s - p_{s-}$ are jumps in the above process. The measure for quadratic variation, formally termed as "realized variance" (RV),[ii] has been formalized as the sum of squared returns. Let us assume the intraday dispatch electricity log prices for a particular Australian state $p_{0,\ldots,}$ p_n are equally spaced on the $[0, t]$ interval, such that the realised variance can be defined as:

$$RV = \sum_{i=1}^{n} (p_i - p_{i-1})^2 \ . \tag{3}$$

[ii] For details please refer to Andersen et al. (2001) and Barndorff-Nielsen (2002).

RV converges in probability to the quadratic variation of log-prices p_t in Equation (2) with growing number of intraday observations, $n \to \infty$. Barndorff-Nielsen et al. (2010) further introduce measure that decomposes RV to components due to solely positive returns or negative returns, coined the name "realized semivariance" (RS) :

$$RS^{+} = \sum_{i=1}^{n}(p_i - p_{i-1})^2 \, I(p_i - p_{i-1} \geq 0) \tag{4}$$

$$RS^{-} = \sum_{i=1}^{n}(p_i - p_{i-1})^2 \, I(p_i - p_{i-1} < 0) \tag{5}$$

Note that the realized semivariances provide a complete decomposition of the realized variance, such that the summation of RS^{+} and RS^{-} is always equal to as RV (i.e. RV = RS^{+}+ RS^{-})[iii]. It is further proved for the limiting behavior of realized semivariance of convergence to $1/2 \int_0^t \sigma_s^2 \, ds$ and the sum of the jumps attributed to positive and negative returns. Table 1 reports the summary statistics for the estimated annualized realized variances. SA displays the highest price volatility while NSW the lowest (Panel A, Table 1). One interesting observation is that RV originated from positive price returns is higher than volatility originated from negative returns (Panels B-C, Table 1).

[Insert Table 1 about here]

2.2. Measuring volatility spillovers

This sub-section describes how to measure volatility spillovers by adopting the method of Diebold and Yilmaz (2009), hereafter DY09, and to measure the magnitude of volatility spillovers across Australian National Electricity markets. The measures introduced by the authors are based on forecast error variance decompositions from Vector Autoregressive regressions (VARs). This measure is a simple and direct way

iii We can treat RS+ and RS- measures of upside and downside risk respectively.

of quantifying the amount of volatility spillovers in the system (i.e., the Australian National Electricity markets). The methodology of variance decompositions quantify how much of the h-step ahead forecast error variance of some electricity market i is due to innovations in another market j. However, two crucial limitations of DY09 are first that the employment of Cholesky-factor identification of VARs leads to the resulting variance decompositions dependent on variable ordering, and second, this methodology allows measuring total spillovers in the system only (Barun ǩ, Kocenda, and Vacha, 2016). Subsequently, Diebold and Yilmaz (2012), hereafter DY12, address the above limitations by using a generalized VAR framework in which the forecast error variance decompositions are invariant to the variable ordering and the model is also capable of measuring directional volatility spillovers. The DY methodologies have been widely applied to the equity markets literature (Yarovaya, Brzeszczynski and Lau, 2016). The use of high-frequency data can further improve the understanding of the transmission mechanism on volatility spillovers. To the best of our knowledge there has been no study employing 5-min Australian electricity dispatch data to enhance our understanding of the geography of the market interconnectedness, as well as the time-varying nature of the spillover effects. Furthermore, our study is the first attempt to decompose daily volatility into positive and negative semivariance, offering a proxy for upside and downside, respectively, risk to measure the magnitude of spillovers across electricity markets from good and bad volatility. For the purpose of measuring the intensity of good and bad volatility we have total volatility spillovers denoted by $RV_t = \left(RV_{1t,\dots,}RV_{nt}\right)'$; $RS_t^+ = (RS_{1t}^+, \dots, RS_{nt}^+)'$ for positive semivariance; and $RS_t^- = (RS_{1t}^-, \dots, RS_{nt}^-)'$ for negative semivariance. In the following sections we will construct tables for volatility spillovers so as to visualise the channels and the dynamics of spillover effects across electricity markets. To this end, we consider a N-dimensional vector of realized variance, $RV_t = (RV_{1t,\cdots,}RV_{nt})'$ in N different markets, such that a covariance stationary of N-variable VAR (p) can be specified as:

$$\mathrm{RV_t} = \sum_{\mathrm{i=1}}^{\mathrm{p}} \Phi_{\mathrm{i}} \mathrm{RV_{t-i}} + \varepsilon_{\mathrm{t}} \tag{6}$$

where $\mathrm{RV_t}$ is a vector of realized variance of electricity markets, Φ_{i} is for $i = 1, \dots, p$ parameter matrices, and $\varepsilon_{\mathrm{t}} \sim (0, \Sigma_\varepsilon)$ is an independently and identically distributed disturbance. Given that the VAR process is invertible, the moving average representation of the VAR model yields:

$$\mathrm{RV_t} = \sum_{\mathrm{i=0}}^{\infty} \mathrm{A_i}\, \varepsilon_{\mathrm{t-i}} \tag{7}$$

where the NxN matrices holding parameters $\mathrm{A_i}$ can be retrieved from the recursion:

$\mathrm{A_i} = \sum_{j=1}^{p} \Phi_{\mathrm{j}}\, \mathrm{A_{i-j}}$ with $\mathrm{A_0}$ being the N×N identity matrix and $\mathrm{A_i}$= 0 for i < 0. The measure of DY12 spillovers index is built on the idea of computing the fraction of the h-step-ahead error variance in forecasting the ith variable that is attributed to the jth variable for $i \neq j$, for each i[iv]. The methodological framework of Diebold and Yilmaz (2012) examines how a variable $\mathrm{RV_i}$ depends on its own shocks, as well as on total volatility spillovers. The adopted generalized VAR process is built on Koop, Pesaran, and Potter (1998) and Pesaran and Shin (1998) h-step-ahead forecast errors (KPPS hereafter), which are invariant to variable ordering, and can be defined for h = [1, 2…+∞), as:

$$\vartheta_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{H}) = \frac{\sigma_{\mathrm{jj}}^{-1} \sum_{\mathrm{h=0}}^{\mathrm{H-1}} \left(\mathrm{e_i'} \mathrm{A_h} \Sigma_\varepsilon \mathrm{e_j}\right)^2}{\sum_{\mathrm{h=0}}^{\mathrm{H-1}} \left(\mathrm{e_i'} \mathrm{A_h} \Sigma_\varepsilon \mathrm{A'_h} \mathrm{e_i}\right)} \tag{8}$$

[iv] Essentially, it follows the N-variable VAR variance decompositions methodology by Sims (1980) for each variable RV_{i} to be added to the fraction of its h-step-ahead error forecasting variance, associated with shocks in relevance to the variable RV_{j} (where ∀i ≠ j for each observation). The cross variance fraction contains information on spillovers from one market to another.

where Σ_{ε} is the variance matrix for the error vector ε; σ_{jj} is the standard deviation of the error term for the jth equation; e_i is the selection vector, with one as the ith element, and zero otherwise. $\sum_{j=1}^{N} \vartheta_{ij}^{g}(H) \neq 1$ as the shocks are not necessarily orthogonal in this framework. The normalization of each entry of the variance decomposition matrix by the row sum provides:

$$\tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{N} \vartheta_{ij}^{g}(H)} \tag{9}$$

where $\sum_{j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)= 1$ and $\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)= N$. Using the contributions from the variance decomposition, we can define the total spillover index as measures of the contribution of spillovers from volatility shocks across variables in the system to the total forecast error variance. The total volatility contributions from KPPS variance decompositions are used to calculate the Total Spillover Index:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{N} \times 100 \tag{10}$$

Note that the contributions of spillovers from volatility shocks are normalized by the total forecast error variance. The total spillover index, as defined by Equation (10), provides information not only on how much of the shocks to volatility spillovers across the Australian national electricity market, but also to identify directional spillovers using the normalized elements of the generalized variance decomposition matrix. The directional spillover indices are calculated to measure spillovers from market i to all markets j, as well as the reverse direction of transmission from all markets j to market i, using equations (11) and (12), respectively:

$$S_{\cdot\to i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{11}$$

$$S_{i\leftarrow\cdot}^{g}(\mathrm{H}) = \frac{\sum_{\substack{\mathrm{j}=1 \\ \mathrm{i}\neq\mathrm{j}}}^{\mathrm{N}} \tilde{\vartheta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{H})}{\sum_{\mathrm{i,j}=1}^{\mathrm{N}} \tilde{\vartheta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{H})} \times 100 \quad (12)$$

The difference between total shocks transmitted to market i and those transmitted from market i to all markets is defined as the net volatility spillover [Equations (11) and (12)]. Therefore, net pairwise spillovers indices are calculated for each K pairs of markets:

$$\mathrm{S}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{H}) = \frac{\tilde{\vartheta}_{\mathrm{ji}}^{\mathrm{g}}(\mathrm{H})}{\sum_{\mathrm{i,k}=1}^{\mathrm{N}} \tilde{\vartheta}_{\mathrm{ik}}^{\mathrm{g}}(\mathrm{H})} - \frac{\tilde{\vartheta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{H})}{\sum_{\mathrm{j,k}=1}^{\mathrm{N}} \tilde{\vartheta}_{\mathrm{jk}}^{\mathrm{g}}(\mathrm{H})} \times 100 = \frac{\tilde{\vartheta}_{\mathrm{ji}}^{\mathrm{g}}(\mathrm{H}) - \tilde{\vartheta}_{\mathrm{ij}}^{\mathrm{g}}(\mathrm{H})}{\mathrm{N}} \times 100 \quad (13)$$

The following sections report the Total Spillover Index to examine the volatility spillover indices across the four Australian electricity markets, while the directional spillovers are also used to illustrate the relative contribution of each market to the remaining markets.

2.3.Measuring asymmetric spillovers

This sub-section develops a methodology to differentiate volatility spillovers from positive returns S^{+} and negative returns S^{-} ; the same differentiation has to be made for directional spillovers from volatility due to negative returns $S_{i\leftarrow\cdot}^{-}$, $S_{i\rightarrow\cdot}^{-}$, and positive returns $S_{i\leftarrow\cdot}^{+}$, $S_{i\rightarrow\cdot}^{+}$. To estimate the asymmetric volatility spillovers we have to replace the vector of volatilities $RV_t = \left(RV_{1t,\cdots,}RV_{nt}\right)'$ either with the vector of negative semivariances $RS_t^{-} = (RS_{1t}^{-}, \dots, RS_{nt}^{-})'$ or with the vector of positive semivariances $RS_t^{+} = (RS_{1t}^{+}, \dots, RS_{nt}^{+})'$. We also use a moving window of 200 steps to take into account of the tie-varying behavior of the volatility spillover indices, while these spillovers are symmetric once $RS_t^{-} = RS_t^{+}$.

2.3.1. Spillover Asymmetry Measure

We can define a spillover asymmetry measure (*SAM*) to estimate the degree of volatility spillovers as:

$$SAM = 100 \times \frac{S^{+} - S^{-}}{1/_{2}(S^{+} + S^{-})} \tag{14}$$

where S^{+} and S^{-} are volatility spillover indices due to positive and negative semivariances, respectively, using h-step-ahead forecasts at time t. The magnitude of *SAM* as measured in Equation (14), quantifies the degree of asymmetry in spillovers due to the presence of RS_t^{+} and RS_t^{-} . The volatility spillovers associated with RS_t^{+} dominate those associated with RS_t^{-} at time t when *SAM* is positive, and vice versa. When the value of *SAM* is zero, it indicates that the spillovers from RS_t^{+} and RS_t^{-} are equal.

3. Empirical results

In this section we summarize the results of the volatility spillover analysis of the NEM. Our findings are presented and divided into three parts. We first present the dynamics of spillovers and show important features of volatility transmission in NEM. Secondly, we show the issues of understanding the informational content on asymmetric volatility transmission as resulted from negative and positive shocks (i.e., bad and good volatility). The last part investigates the validity of the asymmetric directional spillovers mechanism. Note that before accessing the empirical estimation, we have tested the realized volatility and semivariances at hand for unit roots using augmented Dickey-Fuller tests with augmentation lag length selected using information criteria, and allowing for linear trend under the alternative. We found overwhelming evidence against the unit root in all tested series, supporting the alternative hypothesis of stationarity of the electricity volatilities.[v]

3.1. Extent to which uncertainty spills over NEM

Table 2 decomposes total volatility spillovers indices for different regions in the Australian electricity market; it also displays values of net-spillover indices indicating net-contributors and net-recipients of volatility spillovers across different markets. The findings document that the Total Spillover Index for volatility is 52.445%. The contribution of volatility in New South Wales (NSW) to the rest of markets is the highest, as named in the row “Contribution to Others”, are 61.107%, while Queensland contributes the less to other markets, with contribution of 40.645%. Following New South Wales, the contribution of volatility spillovers to other regions are: 59.838% (Victoria), 48.194% (South Australia), and 40.645% (Queensland)[vi]. Hence, we can conclude that: shocks from QLD have the smallest influence, shocks from NSW have the largest effect, and QLD is also the one which is influenced less than the others by the presence of shocks. The significant role of NSW in terms of volatility spillover may be explained by the fact that the largest generation capacity is found in NSW. Worthinghton and Higgs (2017) find that the generation mix used for producing electricity exerts a strong influence on both the mean and the volatility of wholesale electricity prices, especially when these prices are expected to increase markedly with the increasing utilization of gas-fired generation used to support the intermittent and variable production from renewables and from the policy-driven use of renewables wind power associated with the current renewable energy target and carbon taxation scheme. Moreover, changes in the energy generation mix place

[v] These results are available upon request from authors.
[vi] Note that electricity consumption by region follows a similar pattern as of volatility spillover indices, where New South Wales is the highest and Victoria follows.

extreme pressure on the operation of this regional electricity market. Thermal generators have historically been relied upon for their capacity at times of peak demand and for their contribution to the management of system frequency, while their output has declined since it is the value of the energy they generate that is gradually being eroded by the substitution of coal and gas for wind and solar with their inherent ‘free energy’ characteristics (Nelson and Orton, 2016). Therefore, the electricity market should need a new wholesale pricing model that reflects the very high-fixed cost nature of technologies required for the electricity system to decarbonize.

Moreover, the column named “From others” shows volatility received from other regions. It is intriguing to note that New South Wales is not only the largest volatility contributor to the Australian NEM, but also receives 62.239% of volatility from the remaining markets[vii]. Two regions are net-contributors of volatility in the market, namely Queensland and South Australia. In particular, New South Wales contributes 61.107% of volatility to other markets, especially, to Victoria (27.169%), followed by Queensland (18.461%), and South Australia (15.474%). In return, New South Wales receives 62.379% of volatility from the markets, especially, from Victoria (27.027%)[viii], followed by Queensland (18.621%), and South Australia (16.749%). Overall, New South Wales receives 1.29% more than what it contributes to the remaining electricity markets.

Moreover, as pair-wise comparison of pattern on volatility spillovers across regions, we aware that regions contributing to volatility spillovers to New South Wales are similar to those in regions receiving spillovers from New South Wales (for

[vii] Volatility received from other regions, including Victoria (27.027%), Queensland (18.621%), and South Australia (16.749%).
[viii] For the pair of NSW-VIC, this highly interconnected market can be explained by the long-standing spot electricity markets of NSW and VIC, which are linked by the Snowy Mountains Hydroelectric Scheme (Higgs, 2009).

example New South Wales contributes 18.461% to Queensland , while at the same time it receives 18.624% from Queensland) [ix]. The same pattern holds for other regions as well.

[Insert Table 2 about here]

We also plot the Total Volatility Spillover index using a 200-day rolling window estimation, and horizon h=10. The total volatility spillover is presented in Figure 1, which shows the dynamics of the volatility spillovers across the NEM. As the time span is 16 year (i.e., using all-time series data available), the results contain rich dynamics and patterns. The rolling window estimation provides a comprehensive synthesis on the time-varying behavior of volatility spillovers. On average, spillovers from volatility are not so large, with a value of 50%, but the time-varying spillover index exhibits a great degree of fluctuation around the volatility spillover indices, ranging from about 30% to 70% (Figure 1). This result implies that shocks from one market do not necessarily and substantially impact the volatility of other electricity markets over the whole sample period, but the degree of volatility spillover varies over time.

The results also show a relatively weak connectedness of NEM from 1999 to 2001, as the national market commenced operation as a wholesale spot market for electricity just in December 1998 and it took two years for the NEM to become a better integrated single electricity market. Another intriguing observation on spillovers indices is that it varies between 50% - 70% from year 2002 to 2010, while these figures decreased to 30% - 60% starting from year 2010. This observation in the

[ix] Higgs (2009) examines the degree of electricity market integration across New South Wales, Queensland, South Australia and Victoria from 1 January 1999–31 to December 2007. Using the methodology of constant conditional correlation, the author finds evidence that two pairs of market (NSW- QLD and NSW-VIC) are highly interconnected vis- à-vis the remaining pairs. He further argues in favor of the introduction of Queensland and New South Wales Interconnector (QNI) on February 18, 2001.

later regime (i.e., from 2010 to 2016) may be due to the combination of an increased use of renewable energy and the introduction of the Carbon Pricing Mechanism (CPM) on the first of July 2012, with a planned transition to an emissions trading scheme (ETS) in July 2015[x]. We expect the degree of electricity market connectedness decreases in the future because of market barriers due to the presence of the ETS scheme that makes the market less competitive. We expect the degree of electricity market connectedness to decrease in periods where certain market barriers, i.e. the period in which the ETS scheme was in full operation, could make the market less competitive and/or less efficient. In addition, these results could also indicate not only the limited nature of the interconnectors across the Australian regional markets that prevents full integration, but also the fact that shocks in these markets could have an asymmetric nature and thus, affecting differently price volatility. For instance, in periods of abnormally high demand, the NEM may be offsetting the ability of regional participants to exert market power, while there exists an inability of the current network of interconnectors to lead to an integrated national electricity market, which may indicate the presence of sizeable differences in spot prices across the Australian regions, with such differences remaining either for a short or long term, validating the need for new regional interconnectors that will smooth out volatility spillovers across these regions. This suggests that the main drivers of the interaction between regional electricity markets are both any geographical proximity and the number and size of interconnectors, which also reinforces any calls for the privatisation of some electricity market participants to improve competition, given that the overwhelming majority of these remain under public sector control. At the same time, electricity prices, along with their volatility, are heavily influenced by their fuel costs. Given that

[x] The aim of this scheme was to encourage producers to switch away from coal-fired generation and adapt natural gas and renewable sources of energy.

the short-run cost of generation for renewable (i.e., solar and wind) power is very low (their fuel is essentially free once the plant is built), they generally bid at prices lower than fossil fuel generators. Therefore, it is possible that downward pressure is placed on the wholesale electricity market, because higher cost generators are prevented from being dispatched by lower cost renewable energy generators. Therefore, by increasing the use of renewables and, consequently, the supply of electricity volumes is expected to decrease dispatch price volatility.

The factors contributing to a less integrated market, as well as to lower connectedness and lower volatility spillover from 2010 to 2016 are complex, including uncertain demand and the use of renewable energy. Wind power is rapidly expanding as a form of renewable energy in Australian and it accounted for 4.9% of Australia's total electricity demand and 33.7% of total renewable energy supply in 2015[xi]. In particular, 26% of electricity was generated and consumed from wind power in South Australia and 54% of Australia installed wind capacity is located in South Australia.

Cutler et al. (2011) use 30-mins market data on electricity prices of South Australian from September 2008 to August 2010 to examine the potential implications of expanded wind generation in South Australia. Their findings suggest that electricity demand is the main factor affecting electricity spot prices in South Australia, while wind power also has an influence on its spot prices. An intriguing result is that there is an apparent negative correlation between wind generation and price in this electricity market. Additionally, they show that periods of high wind output are associated with negative price events. However, the authors also admit that wind power outputs may enhance our understanding of extreme price events, but the

[xi] For details, see https://www.cleanenergycouncil.org.au/technologies/wind-energy.html

use of wind power generation is difficult to be predicted in general[xii]. The above observations together with the use of a national green tradable certificate scheme imply a change in regional demand and prices, as well as regional price volatility transmission within other states within the NEM.

Figueiredo, da Silva, and Cerqueira (2016) use logit and non-parametric models to estimate the probability of market splitting occurrence between two Danish bidding areas; they conclude that market splitting probability between West and East Denmark increases (i.e., decreases in the degree of price convergence or market integration) when there is an increase of wind power generation share in both West and East Denmark. We pair the above insights and evidence with the time-varying total spillover index as presented in Figure 1. We can observe that the process of advancing renewable energy and emissions trading scheme is highly correlated with the decrease of spillovers from early 2010s on.

[Insert Figure 1 about here]

The directional spillovers FROM and TO a particular electricity market are indicated in Figure 2. The dynamic patterns of volatility flows from one market to another market are represented in the first row of Figure 2, while the degree and the direction of volatility that a specific market receives is indicated in the second row. We also provide the dynamic patterns of net directional spillovers that an electricity market receives or donates from/to other markets. Some new observations emerge: both New South Wales and Victoria play a major role in volatility transmission in the Australian NEM.

[Insert Figure 2 about here]

[xii] Factors affecting electricity prices include an uncertain demand and generator bidding strategies.

3.2. Asymmetric Transmission of Information in Electricity Markets

We examine the possibility of asymmetries in relevance to the electricity price volatility transmission mechanism, taking into account the argument of difference in the magnitude of volatility spillovers due to the originality of shocks (i.e., from positive or negative returns). Figure 3 computes negative and positive volatility spillovers and quantifies to what extent electricity markets process information asymmetrically. We aim to identify time episodes during which spillovers are attributed to negative and positive volatility. The Spillover Asymmetry Measure (SAM) is presented in Figure 3, with positive values suggesting that volatility spillovers for the sake of positive returns are larger than spillovers owing to negative returns. Negative values of SAM suggest that volatility spillovers for the sake of positive returns are larger than spillovers owing to negative returns. A zero SAM shows that the influence of both negative and positive spillovers is equivalent and they act against each other with the same magnitude. The SAM in Figure 3 reveals that asymmetries in total spillovers are driven by either negative or positive shocks, while even the extent of asymmetry is not substantial in magnitude[xiii].

The first period of prolonged positive returns drives volatility spillovers in electricity markets (2006-2011); this observation may be associated with an increase in electricity prices due to an escalating electricity demand, combined with a drought across most regions during the period 2006-2008, followed by a succession of hot summers caused the presence of peak demand during the period 2008-2009. The high demand for electricity was also reflected by historical peaks of almost 900 Terawatt hour's electricity traded in electricity futures contracts during the period

[xiii] This result implies that the regulations are efficient in controlling negative shocks on volatility spillovers across markets.

2009-2010. It is found that generators in South Australia exercised market power during 2008-2011 (Mountain, 2012). The 72 highest priced settlement periods (i.e., peak price) during the period 2007-2011 caused the average annual electricity prices in Victoria, New South Wales and Queensland to rise by 30%, 37% and 32%, respectively[xiv]. Moreover, it is also evident that higher spot prices have flowed into higher contract prices, hence, both generators and retailers have benefitted from higher spot prices that occurred in the period from 2008 to 2011.

The second period of prolonged negative returns drives volatility spillovers in electricity markets (2011 to date); this observation may be associated with several policy reforms, including the adoption of a carbon tax policy implemented from July 2012 to July 2014. This carbon scheme affected power production from fossil fuels, regardless of the specific physical location of the power plant. The impact of the introduction of a carbon tax altered the marginal cost of electricity in a homogeneous way across Australian markets, while it affected the electricity costs of those power supply systems that are more carbon intensive, and, thus, it enhanced the different costs of power supply. The rising uptake of wind energy from 2009–2010 combined with a falling demand drove spot prices to fall to their historical lows in 2011-2012. Barun k, Kocenda, and Vacha (2016) use the same econometric methodology to quantify asymmetries in volatility spillovers that emerge due to bad and good volatility across 21 U.S. stocks. The authors conclude that negative spillovers provide larger magnitudes of volatility transmission.

[Insert Figure 3 about here]

[xiv] Hu, Grozev, and Batten (2005) examine the strategic bidding and rebidding behavior of Australia's NEM for the period from May 1, 2002 to May 31, 2003. They conclude that larger generators are more likely to use capacity offers rather than price offers to control market prices. They also provide evidence that larger generators are capable of pushing market prices higher during peak periods by abusing or taking advantage of market rules and supply a shortage during these peak periods.

Conclusion

This study presented evidence on the presence of asymmetric inter-relationships of the presence of volatility spillovers across electricity markets in Australia. The data consisted of 5-minute electricity prices. The results indicated that such volatility spillovers exhibits asymmetries in total spillovers as driven by negative or positive shocks.

The findings make a significant contribution in estimating asymmetric volatility and the efficiency of the Australian electricity market in a study that had not been previously undertaken in the electricity market context. The assessment of these volatility spillovers across Australian regional electricity markets (except that of Western Australian) is expected to enhance our understanding of the spot electricity dynamics by electricity producers, transmitters and retailers, as well as the efficient distribution of energy on a national level. In a essence, the findings can be used in future research venues to easier identify how a range of shocks (usually related to the supply of various energy sources that help to generate electricity) can impact the provision of electricity and, thus, the forecasting of electricity prices, which is expected to minimize the impact of different risk factors embedded across these markets in the case of the Australian regions. The associated implications have to do with certain investment strategies the energy policy makers and regulators need to adopt. More specifically, regulators are expected to gain higher information on the reasons for why particular electricity markets are relatively more volatile than the others by exploring a number of potential factors for the presence of frequent and extreme volatility, including the abuse of market power, higher-than-expected demand, unexpected capacity bottlenecks, plant outages, poorly developed transmission networks, changes in purchasing and contracting behavior, fluctuant renewable electricity generation, inappropriately designed market mechanisms, and potential information asymmetries. Additionally, the satisfactory pricing performance in these markets requires a sufficient regulatory perspective, while accommodating certain price regularities and irregularities. The identification of asymmetries in these markets will also allow regulators to investigate the presence of volatility persistence, which will provide further information on why volatility in some markets may take a longer time to die out following a shock. Power generators may utilize the empirical findings to optimize the terms of agreed contracts and, hence, to efficiently participate in the day-ahead and real-time markets. As a result, power generators that wish to secure a stable flow of income may prefer to avoid adopting contracts for volatile hours. The findings will also let both small and large consumers create an optimal bidding strategy. In particular, risk-averse small and large consumers may choose to buy electricity capacity through bilateral contracts, rather than from spot markets if prices in the latter are highly volatile.

The results also illustrate that the NEM is not yet strongly integrated, with interstate trade representing only a small fraction of total generation. During periods of peak demand, the interconnectors can become congested and the NEM is separated into its regions, promoting price differences across markets and exacerbating reliability problems, as well as the market power of regional utilities. Ongoing challenges remain in implementing efficient transmission pricing strategies with a view to strengthening interconnection as a check on regional market power and extending retail access to all consumers.

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Table 1: Descriptive Statistics for electricity markets realized volatility, and semivariances over the sample period extending from December 8, 1998 through May 5, 2016.

	Mean	St.dev.	Skewness	Kurtosis	Minimum	Maximum

Panel A: Annualized RV^(1/2)

NSW	1034	1750.24	6.07303	53.2665	85.9215	26615.3
OLD	1778.9	3310.73	3.86584	20.4065	73.86	27316.9
SA	1807.1	2912.51	4.03002	23.8955	122.322	26450.3
VIC	1125.72	1916.21	6.35826	58.4933	81.1657	27336.3

Panel B Annualized RS+^(1/2)

NSW	741.558	1254.31	6.20579	56.5206	59.1111	20793.7
OLD	1261.29	2342.88	3.90873	20.9951	51.5242	20592.2
SA	1284.69	2062.92	4.06036	24.3357	79.5017	19235.9
VIC	805.008	1361.58	6.35123	58.2635	56.0554	17918.1

Panel C Annualized RS-^(1/2)

NSW	718.064	1222.16	5.98987	51.3097	61.8822	16613.1
OLD	1250.71	2341.2	3.84567	20.0789	52.9204	17949.2
SA	1266.61	2058.63	4.03358	23.9615	86.5498	20389.6
VIC	784.059	1349.97	6.42446	60.0948	58.6997	20644.9

Table 2: Volatility Spillover Table Rows(To), Columns (From)

	NSW	QLD	SA	VIC	From	Net	Conclusion

					Others		
NSW	37.603	18.621	16.749	27.027	62.397	-1.290	net-recipient
QLD	18.461	59.540	9.648	12.352	40.466	0.180	net-contributor
SA	15.474	9.088	54.979	20.460	45.022	3.172	net-contributor
VIC	27.169	12.937	21.796	38.098	61.902	-2.064	net-recipient
Contribution to others**	61.107	40.645	48.194	59.838			
Contribution including own***	98.710	100.185	103.172	97.936			
						TOTAL	52.445

Notes: *From Others - directional spillover indices measure spillovers from all regions j to region i; **Contribution to others - directional spillover indices measure spillovers from region i to all regions j; ***Contribution including own - directional spillover indices measure spillovers from region i to all regions j, including contribution from own innovations to region i; Other columns contain net pairwise (i,j)-th spillovers indices. NSW, QLD, SA, VIC represent New South Wales, Queensland, South Australia, and Victoria, respectively.

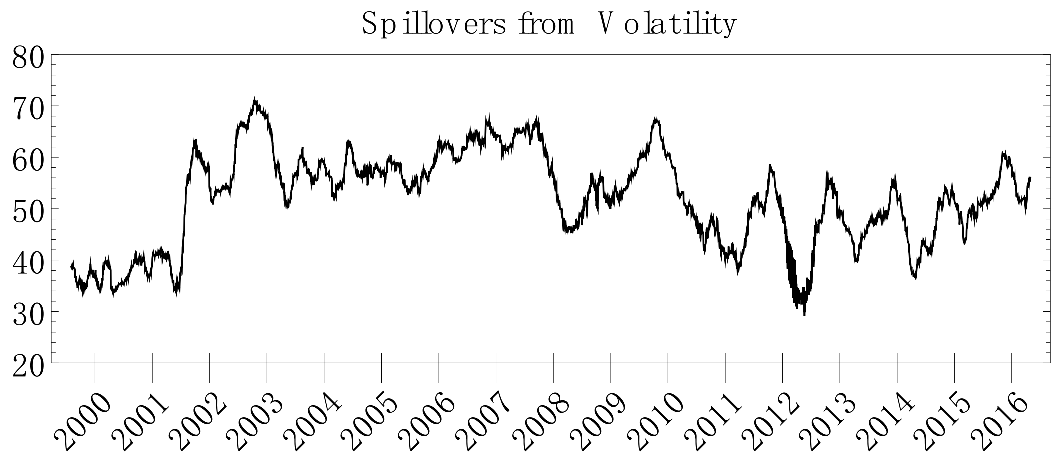

Figure 1: Total spillover plot: spillovers from volatility on the NEM market over the sample period spanning from December 8th, 1998 to May 5th, 2016.

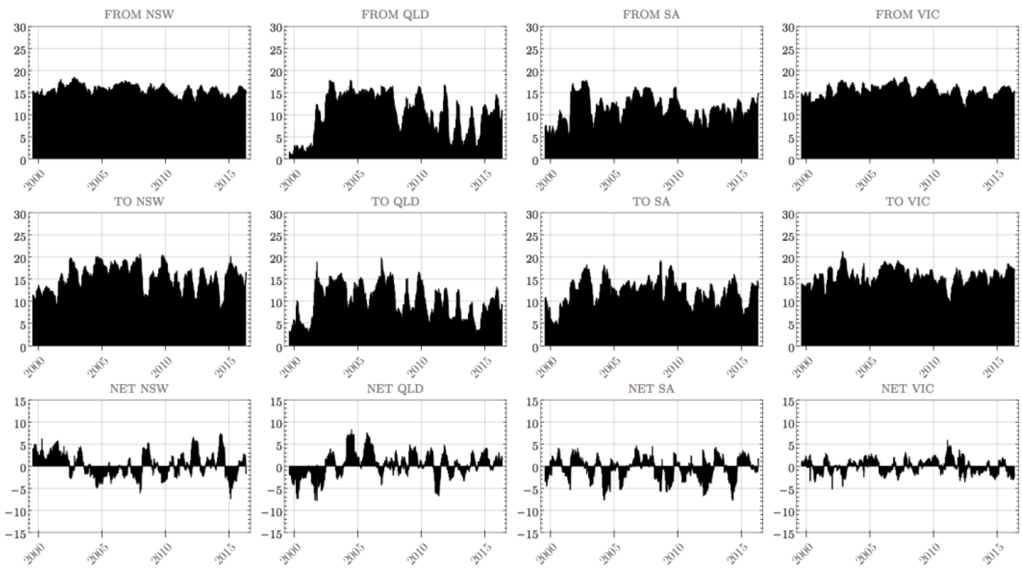

Figure 2: Directional spillover plots: Directional spillovers FROM (first row), TO (second row) and Net spillovers (third row) on RV).

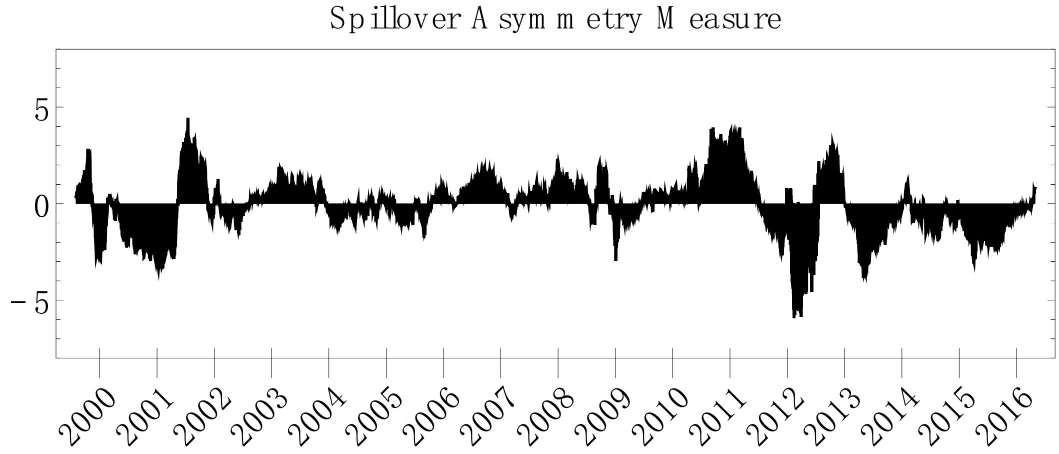

Figure 3: Spillover Asymmetry Measure