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Keywords

Australian National Electricity Market, Higher moments, Spillovers, Interconnectedness, Long memory

JEL Classification

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Interconnectedness in the Australian National Electricity Market: A Higher Moment Analysis

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Abstract

We examine the risk transmission mechanisms in the interconnected Australian National Electricity Market (NEM). We illustrate that the transmission of extreme events in terms of their magnitude (via skewness) and the likelihood of their occurrence (via kurtosis) should be considered when promoting NEM interconnectedness. Our empirical findings suggest that interconnectedness costs can be limited by providing sufficient transmission capacities as it can expand generation capacity. Our results suggest that a one percent increase in NEM generation capacity can decrease the transmission of these risks by between 0.9 percent and 1.7 percent, depending on the moment of the electricity return distribution.

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1. Introduction

The theoretical benefits of improving market integration through increased electricity markets interconnectedness are well established and include improved security of supply, enhanced competition and greater economic efficiency, as well as environmental benefits (Newbery et al. 2016). However, the potential costs of interconnectedness beyond those captured through volatility spillovers are relatively less explored in the literature. In interconnected electricity markets, shocks in one region are expected to transmit to other regions through external links, commonly known as spillovers (Pesaran and Pick, 2007). Shocks in electricity markets are more common than in other commodity markets with abrupt jumps that can be several orders of magnitude greater than the mean, due to electricity, as a product, being non-storable, demand being inelastic and supply being inelastic at high output levels. Therefore, price spikes above a certain price threshold represent one of the main risks faced by electricity market participants in interconnected electricity markets (see e.g., Becker et. al., 2007; Clements et al., 2015; Christensen et al. 2012; Manner et al., 2016 for applications to the Australian market).

The existence of abnormally high price spikes raises the issue of whether there is sufficient transmission capacity. As discussed by Clements et al. (2015) in the context of the National Electricity Market (NEM), an important aspect influencing the inter-regional transmission of price spikes is the availability of spare capacity on the interconnectors between the regions. As they note (at p. 384) " if spare import capacity is (not) available, [price] spikes should be smaller (larger) in size as generation capacity from the nearby region can (cannot) be transmitted to meet the local demand." Prior research on electricity price linkages and information transmission in the NEM has identified the existence of spillovers of volatility (or second moment) risk (e.g., Apergis et al., 2017a; Han et al., 2017; Ignatieva and Truck, 2016; Higgs, 2009; Worthington et al., 2005; Higgs and Worthington, 2005). However, focusing on volatility alone ignores that the distribution of electricity prices is skewed and heavily tailed and what this implies for risks due to transmission of extreme events in terms of their magnitude (via skewness spillover) and the likelihood of their occurrence (via kurtosis spillover). We show that it is equally important to monitor the transmission of these extreme risks, alongside transmission of volatility risk, in an interconnected electricity market.

In addition, building on the reasoning in Clements et al. (2015), we address the question of whether there is sufficient transmission capacity between the states, given that greater transmission capacity would reduce the incidence and magnitude of the transmission of extreme events; hence, reducing the prevalence of higher moments risk for market participants. The benefit of focusing on higher moment channels, and not just volatility risk, is that higher moment risks contain more predictive information about underlying network constraints and future evolution of electricity market prices, given that regional energy markets exhibit significant tail dependence and asymmetries (Ignatieva and Truck, 2016). For instance, the fatter the tail, the greater the probability of obtaining price changes that are extreme. Studies of skewness and kurtosis linkages can provide insights into the spread of fat tail risks across electricity markets since they respectively capture the magnitude and occurrence of extreme events, such as high impact-low frequency events that are becoming more common in the NEM.

The remainder of the paper is structured as follows. Section 2 discusses the existing literature on electricity market interconnectedness based on dynamics of moments. The data and construction of realized moments are discussed in section 3. Section 4 describes the econometrics framework. Section 5 presents the results, while section 6 concludes.

2. Overview of the NEM and Relevant Literature

2.1. Interconnections in the NEM

The NEM was created as a wholesale market for electricity in the Eastern states (Victoria (VIC), New South Wales (NSW), South Australia (SA) and Queensland (QLD)) in 1998 with Tasmania (TAS) joining in 2005. The NEM is an energy-only gross pool with a real-time uniform first-price auction clearing mechanism and forward derivative markets traded both on-exchange and Over-the-Counter (OTC) at 300–400% of physical trade (Simshauser, 2018b). The NEM operates as a nationally interconnected system, physically connecting the five state-based regional markets (TAS, SA, VIC, NSW and QLD), covering about 40,000 kilometres (km) of transmission lines with a combined customer base of 9 million people.

In liberalised electricity markets, such as the NEM, retailers purchase electricity at an unregulated spot price and sell to consumers at a regulated price leading to extreme price spikes, which is a major source of risk for electricity retailers (Christensen et al. 2012). Therefore, retailers and generators enter into hedging contracts in order to manage price volatility in the NEM. Electricity generators and retailers trade through a spot market operated by the Australian Energy Market Operator (AEMO) (Nepal and Foster, 2016). To price this hedging accurately requires an understanding of the wholesale price linkages and the nature of risks between interconnected regional markets in the NEM. The central problem lies in the actual quantification of the full range of risks. As Levy (1969) pointed out, expected utility depends on all of the moments of the distribution and higher moments cannot be neglected.

There are only six regional operational interconnectors among the five electrically connected regional markets in the NEM (see Figure A1). There are two interconnectors operating between NSW-QLD and SA-VIC. However, VIC-TAS and NSW-VIC are connected by one interconnector. There is no direct physical interconnection between QLD-SA and NSW-SA. The regional interconnectors largely follow the state boundaries covering a distance of more than 5,000 kms, running from Port Douglas in QLD to Port Lincoln in SA (Nepal and Foster, 2016), making the NEM one of the longest interconnected power systems in the world.

The occurrence of extreme price spikes in the NEM spot electricity price represents a major source of risk for electricity retailers, and the forecasting of these extreme price spikes is important for effective risk management (Christensen et al. 2012). This is especially necessary because tail risks arising from policy uncertainty and extreme events can have a catastrophic impact on the stability of interconnected electricity markets.

For example, in 2016, SA experienced three major blackouts including a total grid collapse – Australia's first black system event since the early 1960s (Simshauser, 2018b). This catastrophic event led to questioning of the ability of the NEM to deliver energy security and reliability, prompting calls for SA to quit the NEM (Finkel et al., 2017).

2.2. Review of Literature

Interconnectedness between energy and energy commodity markets through volatility spillovers has been extensively explored (Sadorsky, 2012; Apergis et al. 2017a). However, focusing on volatility alone ignores that the distribution of electricity prices is skewed and heavily tailed and what this might imply for other risks of interconnectedness; specifically risks due to transmission of extreme events in terms of their magnitude (via skewness spillover) and the likelihood of their occurrence (via kurtosis spillover). Improved prediction of the extreme price spikes is important for market participant risk management (Becker et al. 2007).

One set of studies have focused on examining the degree of integration of European electricity markets. An early correlation analysis showed that returns in European electricity markets appear to be independent of each other (Bower, 2002). Another study, performing a Principal Component Analysis (PCA) on cross-border capacity auctions, rejected the assumption of full market integration (Zachmann, 2008). The application of fractional cointegration analysis led to the conclusion that a month day ahead prices are more resilient to system shocks than spot prices, which are more event dependent (Menezes and Houllier, 2016).

A recent study uses cointegration and error correction modelling to show that there is large potential for improving market integration in European electricity markets (Gugler et al. 2018). The application of multivariate GARCH (MGARCH) models and volatility impulse response functions (VIRF) to quantify the impact of shocks on return volatility is limited in the European context. The impact of shocks is usually not persistent, owing to the non-storability characteristics of electricity, while large increases in expected conditional volatilities are possible even if their probability is low based on the application of MGARCH and VIRF (Le Pen and Sevi, 2010). An application of impulse response techniques to study the shock transmission in European electricity forward markets, found the size and proximity of neighbouring markets to have little influence (Bunn and Gianfreda, 2010). Results from hidden Markov regime switching models conclude that the frequency of extreme events is positively related to the amount of renewable energy sources in the power system, while dependence measures across markets are asymmetrical (Lindstrom and Regland, 2012).

Another strand of the literature has examined the degree of integration in North American electricity markets. For the U.S. a bivariate cointegration test, a price-difference test and a causality test failed to reject the null hypothesis of market integration and price competition among wholesale electricity submarkets in the Pacific Northwest region of the Western System Coordinating Council (WSCC) (Woo, Lloyd-Zanetti and Horowitz, 1997). On the other hand, the application of unit root tests and cointegration techniques found pairwise cointegration among 11 regional U.S. western markets (De Vany and Walls, 1999). Another study also showed that a relationship exists between prices of distant regions in the U.S. using acyclic graphical methods (Park et al. 2006). In the Canadian context, an application of a MGARCH model found linear and non-linear bivariate relationships between deregulated natural gas and electricity markets in Alberta (Serletis and Shahmoradi, 2006).

In the Australian context, cointegration tests and Kalman filter analysis concluded that there was a lack of integration in the NEM due to significant transmission constraints among regional interconnectors (Nepal and Foster, 2016). The application of Phillips and Sul (2007) transition modelling and econometric convergence tests identified a long run, common price growth pattern in the cluster formed by the three Eastern States (NSW, QLD, VIC), which share common market characteristics and limited physical interconnection (Apergis et al. 2017b). The application of MGARCH models to electricity returns showed that price transmission is low, but that volatility spillovers are present across the five markets (Worthington et al. 2005). An analysis of the intraday price volatility processes in the NEM showed significant innovation and volatility spillovers in the conditional standard deviation equation, even when market and calendar effects were included (Higgs and Worthington, 2005). Intraday prices exhibited significant asymmetric responses of volatility to the flow of information in the NEM. The application of a MGARCH model with time-varying correlations to model price and volatility inter-relationships in the Australian wholesale spot electricity market confirmed the presence of positive own mean spillovers in all four markets studied and little evidence of lagged mean spillovers from other markets (Higgs, 2009). A Copula method applied to model dependence between regional Australian electricity markets found significant positive dependence between each of the markets (Ignatieva and Truck, 2016).

The majority of previous studies on electricity volatility spillovers make use of low frequency data (daily or aggregated daily prices) and employ MGARCH models. However, due to the increasing availability of intraday data, recent studies have constructed realized volatility non-parametrically from intraday returns and employed the Diebold and Yilmaz (2009, 2012) spillover index within a VAR framework (e.g., Han et al. 2017; Apergis et al., 2017a). Han et al. (2017) found that spillover effects are more pronounced in the physically interconnected regions, exhibiting time and event dependent patterns. Apergis et al. (2017a) applied VAR to quantify asymmetries in volatility spillover emerging from good and bad volatility and showed that Australian regional electricity markets are linked asymmetrically. However, addressing many of the important questions in which policymakers are interested, such as whether the introduction, and subsequent abolishment of carbon pricing or payments for closure policy in the NEM have played a significant role in the transmission of extreme price movements between interconnected electricity markets requires a skewness (or third moment) linkage analysis, which is currently missing in the literature.

To summarize, there are relatively few studies that have examined volatility spillovers between electricity markets and these do not consider the dynamics of higher moments such as skewness and kurtosis. Becker et al. (2007) is the only study in the NEM context that allowed for skewness in the distribution of electricity prices during high-price episodes by examining Queensland electricity prices. We show, in section 3, that the realized volatility; skewness and kurtosis, constructed non-parametrically from intraday Australian electricity returns, consistently display long-memory characteristics. Using data from the NEM, our study contributes to the extant literature by applying a fractionally integrated VAR (FIVAR) model in order to capture the data generating process of these higher moments.

3. Data and construction of realized moments

3.1 Data

We collect half-hour interval spot electricity prices for NSW, QLD, SA and VIC from the AEMO.[2] In the NEM, demand and supply are matched simultaneously in real time via a centrally coordinated dispatch system, with spot prices used for settlement set at five-minute intervals by the AEMO. The half-hour spot prices employed for settlement are the average of the five-minute spot prices. Our sample covers the period from 01 January 1999 0:00 to 31

[2] Data are publicly available at http://www.aemo.com.au/.

December 2017 23:30, comprising 1,332,424 half-hour prices observed in the four regional markets.[3] For the purpose of calculating the logarithmic returns, we drop those observations with non-positive prices.[4] As we aggregate intraday returns in order to get the daily realized moments, our final sample consists of prices for 6,940 trading days in each market.

3.2 Construction of realized moments

We capture the return distributions of the Australian electricity markets by constructing their four realized moments nonparametrically based on half-hour logarithmic returns. The daily realized returns are calculated as the sum of half-hour logarithmic returns during the day,

$$RR_t = \sum_{i=1}^{M} r_{i,t} \tag{1}$$

where $r_{i,t}$ (measured in percentage) is the ith half-hour logarithmic return in day t and M is the number of the intraday returns in trading day t. By construction, the daily realized return is identical to the daily return calculated using daily close to close prices. Following Andersen et al. (2003) and Amaya et al. (2015), we define the realized higher moments of returns, including the realized variance ($RVar_t$), realized skewness (RS_t) and realized kurtosis (RK_t) as,

$$RVar_t = \sum_{i=1}^{M} r_{i,t}^2 \tag{2}$$

[3] We do not include Western Australia or the Northern Territory in our analysis since there a direct lack of interconnection capacity between these two jurisdictions and the rest of Australia and they are not part of the NEM. The lack of direct physical interconnection does not allow for arbitrage of electricity prices, at least in the short run (Apergis et al. 2017a). Due to the limited availability of data for Tasmania (available since mid-2005) compared to other markets (available since 1999), we similarly do not include Tasmania in our main analysis. However, we do include Tasmania in a robustness check focusing on a shorter period of time.

[4] Negative prices occur as coal fired generators are too costly to shut down and thus bid negative prices in order to maintain capacity. Typically, these negative prices are rarely the market settlement price received by suppliers.

$$RS_t = \frac{\sqrt{M}\sum_{i=1}^{M} r_{i,t}^3}{RVar_t^{3/2}} \tag{3}$$

$$RK_t = \frac{M\sum_{i=1}^{M} r_{i,t}^4}{RVar_t^2} \tag{4}$$

The realized volatility (RV_t) represents the standard deviation of the return distribution, which is calculated by taking the square root of $RVar_t$, $RV_t = \sqrt{RVar_t}$. Note that the four realized moments $(RR_t, RV_t, RS_t$ and $RK_t)$ are all in percentage terms.

Table 1 presents summary statistics for the four daily realized moments in each market. SA exhibits higher level of deviation across all moments in RV, RS and RK primarily owing to the heavy reliance on renewables. The daily return distributions of all four electricity markets not only display a very high level of volatility, but also show some degree of asymmetry (RS deviates from 0) and fat tail (RK deviates from 3). It is, however, not clear from examining Table 1 alone the risk transmission mechanisms across all moments between highly interconnected markets (NSW-QLD and SA-VIC) in the NEM. This implies that it is necessary to analyse the risk transmission mechanism of market interconnectedness not only via RV, but also via higher moments of the return distribution; namely, RS and RK.

Table 1: Summary statistics

State	Mean	Std. Dev.	Skewness	Kurtosis	Max	Min
			Panel A: Realized Return (RR)			
NSW	0.22	24.43	1.16	80.75	512.53	-435.87
QLD	0.67	35.17	0.88	50.73	606.20	-520.96
SA	-0.66	64.82	1.84	102.42	1,553.37	-993.62
VIC	0.30	38.48	0.31	102.54	829.93	-830.66
			Panel B: Realized Volatility (RV)			
NSW	96.43	77.28	3.69	24.11	1,064.84	6.96
QLD	130.71	130.89	2.96	14.08	1,228.03	10.28
SA	143.47	132.60	2.75	12.34	1,371.29	14.53
VIC	113.10	82.56	3.49	23.81	1,330.23	8.88
			Panel C: Realized Skewness (RS)			
NSW	0.33	0.80	-0.06	6.08	6.68	-5.29
QLD	0.27	0.92	-0.07	7.05	6.15	-5.95
SA	0.19	0.98	-0.38	10.53	6.44	-6.48
VIC	0.30	0.81	-0.16	7.16	6.02	-6.39
			Panel D: Realized Kurtosis (RK)			
NSW	6.13	3.63	2.40	11.42	45.08	2.04
QLD	7.01	4.66	2.04	7.93	40.27	2.02
SA	6.89	5.02	2.47	10.81	42.93	1.93
VIC	5.99	3.66	2.52	12.09	42.43	1.99

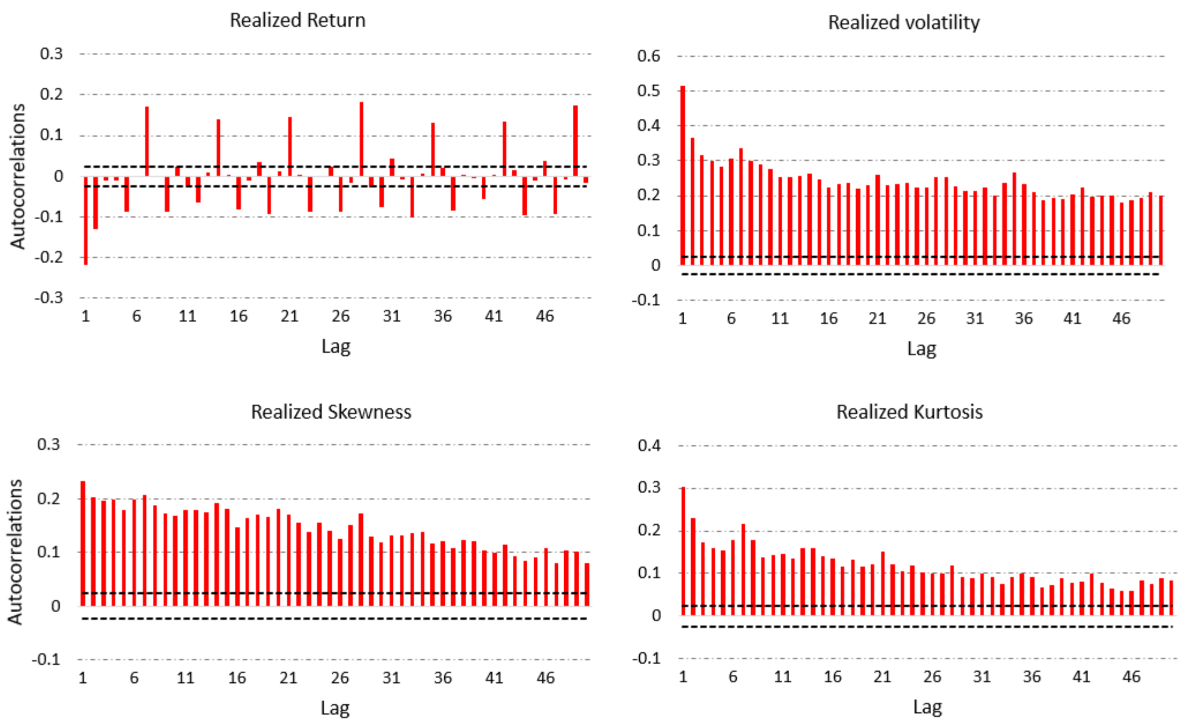
Note: This table shows the descriptive statistics for the daily realized return (RR), realized volatility (RV), realized skewness (RS) and realized kurtosis (RK) of Australian electricity markets over the period 01 January 1999 to 31 December 2017.

We first examine the characteristics of each moment of the electricity return distribution. Figure 1 shows the autocorrelation (ACF) structures up to lag 50 (nearly two and a half months) for four moments of the NSW electricity return distribution.[5] We find clear evidence that RV, RS and RK of all four electricity markets display long-memory characteristics with a slowly decaying ACF. Meanwhile, we find mixed results of long- and short-memory behaviour regarding RR. The RRs of NSW and QLD show evidence of long memory behaviour, which is reflected in the rejection of a unit root process based on the Augmented Dickey-Fuller (ADF)

[5] We do not show the ACF of RR, RV, RS and RK for other markets in order to conserve space. The ACF of RV, RS and RK show similar patterns across four states. The ACF of QLD's RR is similar to NSW's, whereas the RRs of SA and VIC shows an abrupt die out of the ACF. Details are available upon request.

test, but the ACFs do not die out quickly. Conversely, the RRs of SA and VIC exhibit short-memory behaviour illustrated by the abrupt die out of the ACF.

Figure 1: Autocorrelations of realized moments in the NSW electricity market



Note: This figure shows the autocorrelation functions (ACF) of the four realized moments in the NSW electricity market up to 50 lags (nearly two and a half months). The dashed line illustrates the 95% confidence interval bounds for the ACF of a white noise process.

We present estimates of fractional degrees of the four realized moments using the Shimotsu (2007) approach in Table 2. The results are consistent with our preliminary analyses using ACFs. That is, the degrees of integration of RRs of SA and VIC are very close to zero, which is indicative of short-memory behaviour, whereas, that for RV, RS and RK deviate significantly from zero, but are less than 1, implying long-memory behaviour.

Table 2: Fractional degrees of realized moments in the four markets

	RR	RV	RS	RK
NSW	0.04***	0.32***	0.29***	0.26***
	[7.07]	[78.51]	[68.18]	[63.04]
QLD	0.11***	0.31***	0.32***	0.28***
	[18.57]	[58.16]	[65.35]	[54.31]
SA	0.00	0.32***	0.22***	0.20***
	[-0.34]	[70.23]	[43.47]	[41.65]
VIC	0.00	0.30***	0.24***	0.23***
	[-0.82]	[76.09]	[54.03]	[54.32]

Note: The fractional degrees of realized moments are estimated using the Shimotsu (2007) approach. The cross-market realized moments are grouped to perform the multivariate estimation. The brackets contain t-statistics. ***, **, and * denote statistical significance at 1%, 5% and 10% level, respectively.

4. Methodology

4.1 Fractionally integrated VAR model

Evidence of a mixture of long and short-memory in the four realized moments of the electricity return distribution motivates the use of a multivariate fractionally integrated process. We analyse risk transmission mechanism of the market interconnectedness via all four realized moments. As Table 2 shows different long memory degrees regarding higher moments of different markets, we require our multivariate system to be able to capture a flexible, rather than a fixed, set of degrees of integration. Therefore, we employ a fractionally integrated VAR (FIVAR) model for the empirical analysis. Previous studies have shown a FIVAR specification to be effective in capturing long-memory behaviour in economics, finance and commodity markets (e.g., Andersen et al., 2003; Chiriac and Voev, 2011; Do et al., 2016; Yip et al., 2017).

We consider FIVAR models for a vector of four endogenous variables, $R_t = (R_{1t}, R_{2t}, R_{3t}, R_{4t})'$. To examine the risk transmission across markets via four realized moments, we form four (*4*) systems; one for each type of realized moment, across four markets. For example, in a FIVAR model of RV, the *4*-dimensional vector R_t has the form $R_t = (RV_{NSW,t}, RV_{QLD,t}, RV_{SA,t}, RV_{VIC,t})'$.

In general, a FIVAR model of R_t can be specified as,

$$A(L)B(L)R_t = u_t, \qquad t = 1,2,\dots,T \tag{5}$$

with L denotes the lag operator and $u_t \sim (0, \Sigma_u)$ is an identically and independently distributed error term. $\Sigma_u = \{\sigma_{ij};\, i,j = 1,\dots,4\}$ represents the variance-covariance matrix of u_t. $A(L) = I_4 - \sum_{i=1}^{p} A_i L^i$, where A_i is the (4×4) coefficient matrix and I_4 is the (4×4) identity matrix. p is the lag order determined using the Schwarz Information Criterion (SIC).[6]

$B(L)$ is a diagonal matrix of memory degrees, d_i, for $i = 1,\dots,4$, such that, $B(L) = \text{diag}\,\{(1-L)^{d_1}, (1-L)^{d_2}, \dots, (1-L)^{d_K}\}$. The inverse diagonal element, $(1-L)^{-d_i}$, can be generated using a binomial expansion as follows:

$$(1-L)^{-d_i} = \sum_{j=0}^{\infty} \frac{\Gamma(j+d_i)}{\Gamma(d_i)\Gamma(j+1)} L^j = \sum_{j=0}^{\infty} \xi_j^{(d_i)} L^j \tag{6}$$

where $\Gamma(.)$ is the gamma function; $\xi_0^{(0)} = 1$, and $\xi_j^{(0)} = 0$, for $j \neq 0$.

We estimate our FIVAR models using the maximum likelihood procedure proposed by Nielsen (2004). We employ the Nielsen (2004) approach for three main reasons. First, this approach allows one to estimate the fractional degrees and coefficient matrices A_i in one step. This helps avoid potential complexity faced when fractional differencing a long-memory process with a small sample size with the two-step estimation method.[7] Second, it allows endogenous variables in the FIVAR system to have different fractional integration degrees. Third, the Nielsen (2004) approach is efficient with a finite sample as small as T=100. This feature allows us to estimate the spillover index using a rolling window sample.

Nielsen (2004) estimates the FIVAR model by maximizing the likelihood function,

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[6] Based on the SIC, the lag orders (p) of FIVAR systems for RR, RV, RS and RK are 1, 1, 2, and 1, respectively.

[7] FIVAR models can also be estimated using a two-step estimation method, which has commonly been employed in previous studies (e.g., Do et al., 2014; Yip et al., 2017). With the two-step method, the first stage estimates the vector of memory degrees (d) in a multivariate framework such as Shimotsu (2007). In the second stage, the FIVAR model is transformed to the VAR model by applying the relationship $Y_t = B(L)R_t$ to Eq. (5) and then using Multivariate Least Square to estimate the coefficient matrices A_i for $i = 1,\dots,p$. We also perform the two-step approach to estimate our FIVARs as a robustness check. Our main results remain consistent.

$$l(d) = -\frac{T}{2}\ln\left(1 - \frac{|\Omega(d_0)| - |\Omega(d)|}{|\Omega(d_0)|}\right)$$

where, $\Omega(d) = T^{-1}\sum_{t=1}^{T}[B(L)u_t][B(L)u_t]'$. d_0 denotes the initial values of fractional degrees for numerical optimization. In our study, we employ Shimotsu (2007) to obtain d_0.

4.2 The generalized spillover index in a FIVAR model

We follow the approach in Diebold and Yilmaz (2012) to construct the generalized spillover indices within our FIVAR models. The *H*-step-ahead generalized forecast-error variance decomposition (FEVD) within a FIVAR model can be represented as:

$$\omega_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i'\Lambda_h\Sigma_u e_j)^2}{\sum_{h=0}^{H-1}(e_i'\Lambda_h\Sigma_u\Lambda_h' e_i)} \tag{7}$$

with e_i being a (4×1) vector that has one as its ith element and zeros elsewhere, and Λ_h can be generated as, $\Lambda_h = \sum_{j=0}^{h}\Xi_j^{(d)}\Phi_{h-j}$ with $\Lambda_0 = I_4$ if $h = 0$. $\Xi_j^{(d)}$ is the diagonal (4×4) matrix with $\xi_j^{(d_i)}$ as the ith diagonal element.[8] Φ_i is the ith coefficient matrix in the moving average representation of Equation (5), which can be calculated recursively as $\Phi_i = \sum_{j=1}^{p}\Phi_{i-j}A_j$ with $\Phi_0 = I_4$. Each entry of the FEVD matrix can be normalized by its row sum, as follows:

$$\tilde{\omega}_{ij}^{g}(H) = \frac{\omega_{ij}(H)}{\sum_{j=1}^{4}\omega_{ij}(H)} \tag{8}$$

with $\sum_{j=1}^{4}\tilde{\omega}_{ij}(H) = 1$ and $\sum_{i,j=1}^{4}\tilde{\omega}_{ij}(H) = 4$ by construction.

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[8] We note that the effect of *d* values on the FEVD is captured by $\xi_j^{(d_i)}$. We perform a simulation exercise to understand the relationship between *j* (*j* runs from 0 to *h*), the *d* values and $\xi_j^{(d_i)}$. We find that $\xi_j^{(d_i)}$ is bounded between 0 and 1. When *j* increases the $\xi_j^{(d_i)}$ decreases for a given *d* value. We conclude that the diagonal matrix $\Xi_j^{(d)}$ (with $\xi_j^{(d_i)}$ as its elements) acts as an adjustment factor when the variables exhibit long-memory behavior. Its impact on the FEVD (and therefore the spillover indices) is marginal. The FEVD is mainly driven by the coefficient matrices A_i and the variance-covariance matrix of the error term, Σ_u. However, we note that accommodation of the fractional degrees in econometrics modelling is essential to capture the underlying data generating process of the variables, which helps to avoid potential biases in estimating the A_i and Σ_u.

Using the normalized FEVD matrix, calculated in (8), we construct the spillover indices as proposed by Diebold and Yilmaz (2012). The total spillover index describes the contribution of spillover across all the variables to the total forecast error variance,

$$S^g(H) = \frac{\sum_{i,j=1,i\neq j}^{4} \widetilde{\omega}_{ij}(H)}{4} \times 100 \tag{9}$$

The directional spillover from all other variables j to a variable i are computed as:

$$S_{i\leftarrow j}^{g}(H) = \frac{\sum_{j=1,j\neq i}^{4} \widetilde{\omega}_{ij}(H)}{4} \times 100 \tag{10}$$

The directional spillover from one variable i to all other variables j is defined as:

$$S_{i\rightarrow j}^{g}(H) = \frac{\sum_{j=1,j\neq i}^{4} \widetilde{\omega}_{ji}(H)}{4} \times 100 \tag{11}$$

Finally, net spillover from a variable i to all other variables determines whether it is a net transmitter or net receiver of spillover,

$$S_{i}^{g}(H) = S_{i\rightarrow j}^{g}(H) - S_{i\leftarrow j}^{g}(H) \tag{12}$$

5. Empirical results

In this section, we examine how higher moment risks are transmitted across the NEM's four regional markets (NSW, QLD, SA and VIC). Using the whole sample, we construct overall spillover indices based on the 10-step-ahead FEVD. The dynamic spillover indices are generated by utilizing a 200-day rolling window with 10-step-ahead FEVD.[9]

5.1 Transmission of higher moment risks across markets

This subsection summarizes the results of risk transmission mechanism via each realized higher moment. Table 3 presents the overall spillover among the four market components of

[9] Our choice of window size (200 days) and forecasting horizon (10 days) is standard in many markets (e.g., see Apergis et al., 2017a, for the electricity market; Baruníck et al., 2015, for the petroleum market; Diebold and Yilmaz, 2012, for the stock market). We check the sensitivity of the window size by doing the analysis with 150-day and 250-day windows. We also try different forecasting horizons of 1 day, 5 days and 7 days. We find that our results are robust regarding different choices of window size or forecasting horizon.

the NEM over the whole period 01st Jan 1999 to 31st Dec 2017. We find that not only volatility, but also the effects of skewness and kurtosis spillovers in the NEM are significant, given that their total spillover effects are all greater than 30%. Shocks emanating from NSW and VIC have the largest influence on the NEM's spillover via all four realized moments.[10] That NSW and VIC contribute most in terms of volatility spillover within the NEM is consistent with previous findings by Apergis et al. (2017a). Our results additionally show that NSW and VIC also contribute most to the NEM's spillover via other moments of the electricity return distribution; namely, return, skewness and kurtosis. In this respect, our findings are consistent with previous studies for stock markets showing that higher order moment risks are transmitted across markets (see e.g., Del Brio et al., 2017; Do et al., 2016).

The finding that shocks emanating from NSW and VIC have the largest influence on the NEM's spillovers via all four realized moments can be explained by several factors. First, these two states have the largest electricity generation and consumption in the NEM. Second, both states have the largest export share of electricity to other markets. Third, there is also a convergence in generation technologies between these two states reflected in the significant reliance on coal for baseload electricity generation. Both NSW and VIC source more than 75 percent of their electricity generation from coal, while electricity generation from black and brown coal exceeds more than 70 percent in the NEM as a whole. Our findings, in this respect, are consistent with earlier studies on electricity market integration, such as Zachmann (2008), which suggest that convergence in electricity generation and consumption patterns are crucial factors in facilitating market integration. Overall, our results are consistent with findings in Lindstrom and Regland (2012) for European electricity markets that dependence can be explained by both geography and types of energy used. Our results are also consistent with

[10] The "To others" column in Table 3 shows that spillover contributions from NSW's RR, RV, RS and RK to other markets are 42.18%, 35.44%, 51.33% and 44.92%, respectively. Meanwhile, the spillover contributed by VIC's RR, RV, RS and RK are 36.74%, 48.96%, 40.68%, and 40.34%, respectively.

studies for currency and stock markets that more developed markets exhibit greater evidence of higher moments spillovers than emerging markets (see Do et al., 2016) and that the world's leading stock markets, such as the United States, are the dominant source of global spillovers at second, third and fourth moments (see Del Brio et al., 2017).

Table 3: Overall spillover (%) among four regional markets of the NEM via each moment: Row (From), column (To)

	NSW	QLD	SA	VIC	To others
Panel A: Realized Return (RR)					
NSW	68.10	14.16	6.33	21.70	42.18
QLD	10.71	77.97	1.37	3.96	16.04
SA	4.13	1.16	78.04	8.96	14.25
VIC	20.20	4.99	11.55	67.21	36.74
From others	35.04	20.31	19.25	34.62	**Total**
Net spillover	7.15	-4.27	-5.00	2.12	27.30
Panel B: Realized Volatility (RV)					
NSW	62.80	13.37	5.91	16.15	35.44
QLD	9.42	76.59	0.83	2.55	12.79
SA	6.45	1.16	71.08	18.11	25.72
VIC	21.73	4.66	22.57	67.59	48.96
From others	37.60	19.19	29.31	36.81	**Total**
Net spillover	-2.16	-6.40	-3.60	12.15	30.73
Panel C: Realized Skewness (RS)					
NSW	63.46	20.70	8.07	22.55	51.33
QLD	14.78	68.62	2.32	4.98	22.08
SA	5.38	2.35	72.53	10.85	18.59
VIC	20.03	6.29	14.35	63.70	40.68
From others	40.20	29.35	24.74	38.39	**Total**
Net spillover	11.13	-7.27	-6.15	2.29	33.17
Panel D: Realized Kurtosis (RK)					
NSW	63.65	17.59	7.38	19.94	44.92
QLD	13.30	72.69	1.74	4.70	19.75
SA	5.89	1.81	74.13	12.14	19.83
VIC	19.52	5.79	15.03	65.18	40.34
From others	38.71	25.20	24.15	36.78	**Total**
Net spillover	6.21	-5.45	-4.32	3.56	31.21

Note: This table summarises the electricity market's spillover effect across Australian markets (NSW, QLD, SA and VIC) via the four moments of the electricity return distribution over the period 1st Jan 1999 to 31st Dec 2017. The row **"From others"** summarises the directional spillover from all other markets to one market. The column **"To others"** summarises the directional spillover from one market to all other markets. The cell **"Total"** shows the total spillover among all four markets via each moment. Other columns show the pairwise directional spillover between two relevant markets.

Between NSW and VIC, we observe that shocks emanating from NSW have a notably larger impact on RS spillover (10.65% gap), while shocks emanating from VIC have a stronger effect on the RV spillover in the NEM (13.52% gap). A likely explanation for this result is that NSW, as the largest regional electricity market in the NEM, has limited peaking capacity at times of high demand, while the market is interconnected to VIC and QLD with varied resource mix in electricity generation. There are three interconnectors with relatively high capacity interconnecting NSW with QLD and VIC. VIC, meanwhile, significantly benefits from low cost baseload capacity and has excess capacity relative to its peak demand (AER, 2018). Furthermore, VIC is directly physically interconnected with three regional markets (SA, NSW and TAS) with four interconnectors, implying that it has access to a more varied energy generation mix. Higgs et al. (2015) and Worthington and Higgs (2017) demonstrate the important role that energy mix plays in significantly influencing electricity price volatility in the NEM. Consistent with our findings, the aggregated interconnector capacity for interregional electricity transmission to, and from, VIC is the highest among all regions in the NEM (AEMO, 2017).

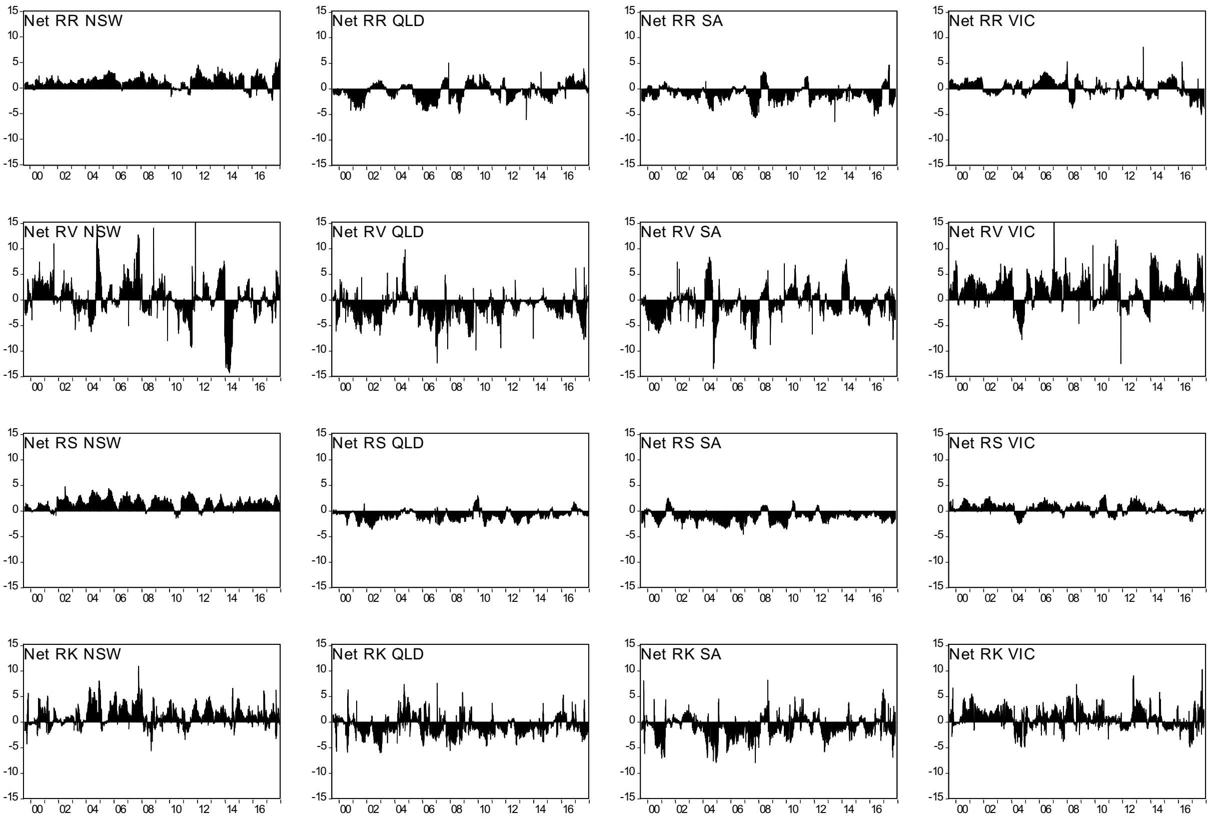
A shock emanating from SA has the lowest effect on the RR (14.25%) and RS (18.59%) spillover effect and a shock stemming from QLD has the lowest impact on the NEM's RV (12.79%) and RK (19.75%) spillover effect. Both SA and QLD maintain direct physical interconnection with just one adjoining market, VIC and NSW, respectively. The wholesale electricity market structure in QLD in terms of generation market concentration is also more concentrated than any other regional electricity market in the NEM (AEMO, 2017). This implies that the possibility of a high degree of local generator market power makes QLD relatively isolated from other markets in the NEM. Previous studies such as Clements et al. (2016) have documented the presence of strategic bidding, and rebidding, in the QLD market.

As Apergis et al. (2017b) note, there has also been a high degree of uncertainty associated with the development of QLD's natural gas resources.

SA has historically been a net importer of electricity, only becoming a net exporter of electricity for the first time in 2018. It is rich in renewables, investing heavily in wind generation, and only generates around 10% of its electricity from coal. Electricity generation from renewables is already de-risked in SA through the renewable energy target, which not only offers a price subsidy, but also guarantees market share and sales. Apergis et al. (2017b) note that SA's connection to the NEM network is very limited. Nepal and Foster (2016) also show the presence of a significant network constraint in the SA and VIC interconnector. Underlying network constraints in the presence of increasing wind penetration in SA explains the fact that a shock emanating from SA has the lowest effect on the RR.

Dynamic analyses of the net spillover from each market to the other markets in the NEM for the four realized moments support our empirical findings about the overall spillover effects (see Figure 2). Consistent with the results in Apergis et al. (2017a), we find that NSW and VIC have played primary roles in transmitting volatility risks in the NEM over time. But, in addition, even more so than in the volatility case, these two markets have almost always had dominant roles in return, skewness and kurtosis risk transmission in the NEM.

Figure 2: Net spillover from one market to other markets

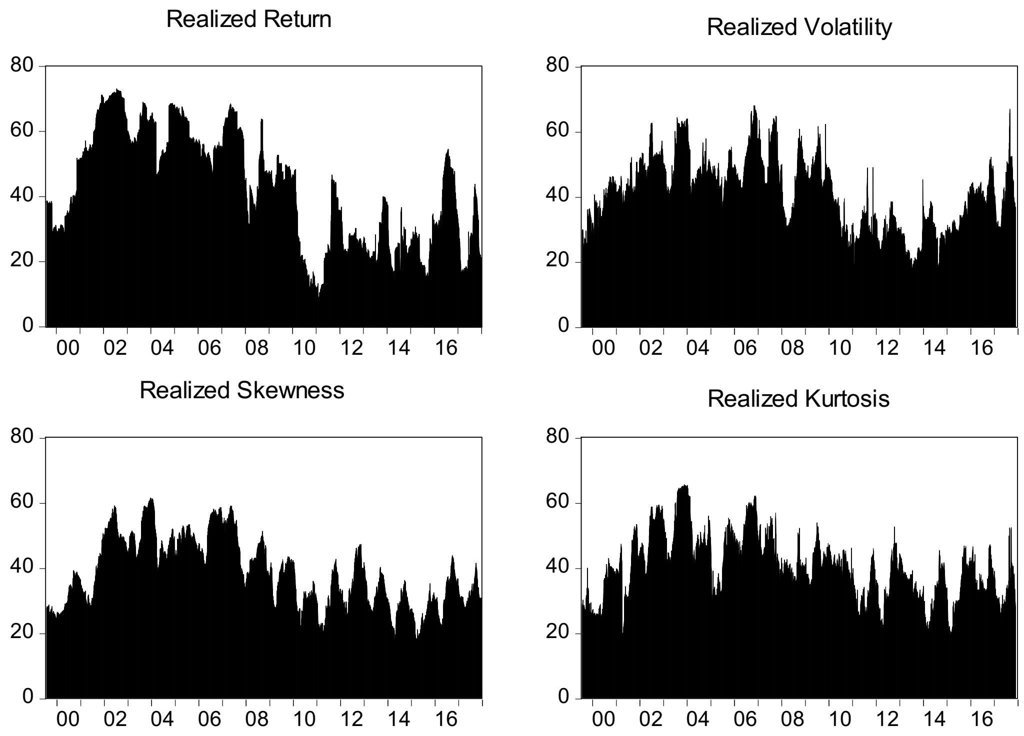


Note: The figure shows the net directional spillover from one market to all other markets via realized return (row 1), realized volatility (row 2), realized skewness (row 3) and realized kurtosis (row 4).

Figure 3 shows how the total spillover index for each of the four realized moments have varied over time. It suggests a significant, and time-varying, spillover effect via each moment. These total spillover indices experienced an increase between 2000 and 2002, followed by a period of decreasing trend until around mid-2013/early-2014 and then gradually rose again until the end of the sample.

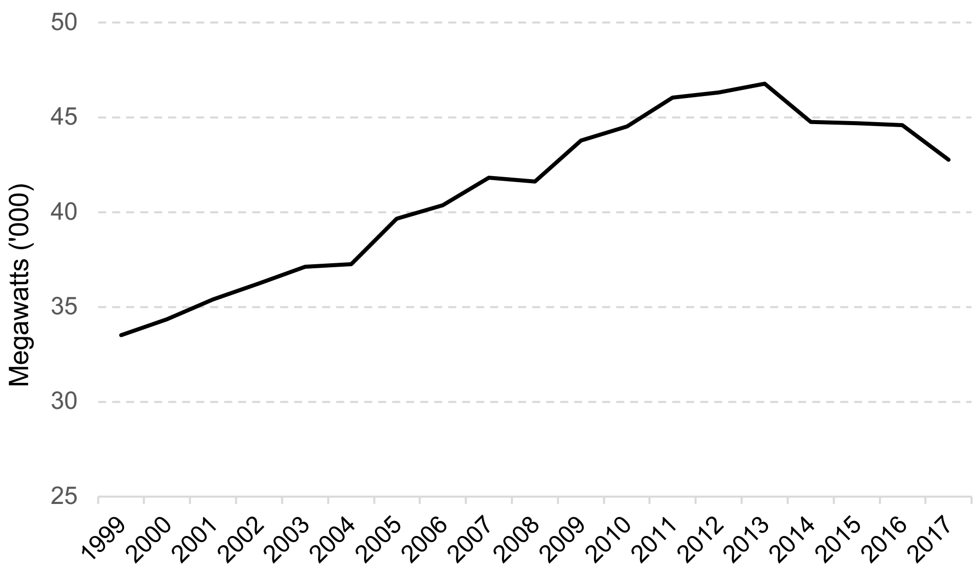
The initial increase in the indices reflects the process of market integration of the NEM from 1999, when it started operating as a wholesale spot electricity market (see Apergis et al., 2017a). After the market became more integrated, the behaviour of the higher moment spillover indices may have been driven by the market's generation capacity. Our conjecture is motivated by Clements et al. (2015), who find that the spare capacity of the interconnectors can limit transmission of price spikes because excess demand in one region can be matched by spare capacity in neighbourhood regions. As can be seen from Figure 4, the generation capacity of the NEM was increasing between 1999 and 2013, then declining from 2014.

Figure 3: Total spillover effect among markets via each moment



Note: This figure shows total spillover via each moment of Australian electricity price return among VIC, NSW, QLD and SA.

Figure 4: Annual generation capacity of the NEM



Source: Australian Energy Regulator, available at https://www.aer.gov.au/wholesale-markets/wholesale-statistics/annual-generation-capacity-and-peak-demand-nem.

A carbon price was in place in Australia during 2012, but was subsequently abolished in 2014 in favour of an Emissions Reduction Fund, which is a government funded scheme to subsidize agreed actions to reduce emissions, and the Renewable Energy Target (a portfolio standard with tradable certificates) (Jotzo and Mazouz, 2015). The Australian Government also announced a "Contracts for Closure" approach in 2012 with the intention of providing an orderly exit of older, high emission, coal-fired generation plants from the NEM. This scheme sought to permanently close around 2000 MW of highly emissions intensive generation capacity by 2020 via negotiated payments to particular plant owners from the Federal Government (Reisz et al. 20013). The Government received the closure proposals from eligible electricity generators in early 2012, but negotiations ceased on 5 September 2012 with the announcement that no agreement had been reached due to failed negotiations (Reisz et al. 2013). As Apergis et al. (2019, p. 140) describe the fallout from the failed negotiation: 'The upshot was that the period 2013-16 left the energy industry with huge uncertainty about what is in store, at a time when it [craved] reassurance more than ever'.

The NEM still significantly relies on coal-based electricity for baseload generation. Unlike renewables, coal-fired generation receives no guarantees in terms of market share and sales implying that there are no de-risking mechanisms for electricity generated from coal. Ageing coal-fired plants in the context of volatile gas prices, falling electricity demand, emission reductions targets and the transition to a low-carbon electricity industry have meant that the operation of dirty coal-fired plants have always been controversial in the NEM (Reisz, 2013; Nelson et al. 2015). The average capacity utilization factors for black coal plants also fell from 63% to 53% and for brown coal from 79% to 70% between 2007 and 2014, inducing surplus capacity (Jotzo and Mazouz, 2015). In recent years, the electricity generation risks from coal have been amplified by the 2017 decommissioning of the brown coal fuelled Hazelwood power station in VIC and the proposed 2022 decommissioning announcement of the Liddell coal-fired power station in NSW.

Our results also highlight that limited interconnector capacity or underlying network constraints may hinder the market integration process in the NEM, especially after 2010 with the rise of renewables. In this light, increased penetration of renewable electricity in the wholesale market will only facilitate market integration to the extent that there are no physical constraints in the transmission of electricity cross-borders. This may require improving the regulatory framework to prevent regulatory failures of regulated transmission or attracting private investment in networks by removing the barriers to merchant transmission and private initiatives (Littlechild, 2012).

5.2 Impact of generation capacity on higher moments' spillover

In this section, we examine our conjecture about the effect of the NEM's generation capacity on the dynamic behaviour of the higher moments' spillover among four regional markets (NSW, QLD, SA, and VIC). We collect yearly data on the NEM generation capacity from the Australian Energy Regulator from 1999 to 2017. The total dynamic spillovers of higher moments among four regional markets are estimated using Eq. (9) and averaged by year to obtain the yearly data. We run the following log-log regression:

$$\log(TSPI_t) = \alpha_0 + \alpha_1 \log(TSPI_{t-1}) + \beta_C \log(Capacity_{t-1}) + v_t \qquad (13)$$

where TSPI denotes the total spillover effect of each moment, Capacity represents the NEM generation capacity. We include the AR(1) term of the logged TSPI to control for its serial correlation. As a result, we have four equations, each for one moment of the electricity return distribution. We present the estimated results in Table 4.

Table 4: Effects of NEM generation capacity on total spillover effects of each moment

Variables	$\log(TSPI_t)$ of RR	$\log(TSPI_t)$ of RV	$\log(TSPI_t)$ of RS	$\log(TSPI_t)$ of RK
$\log(TSPI_{t-1})$	0.463**	0.548***	0.674***	0.537***
	(0.191)	(0.147)	(0.132)	(0.180)
$\log(Capacity_{t-1})$	-1.688**	-1.156**	-0.858**	-1.02**
	(0.680)	(0.428)	(0.332)	(0.450)
Adj-R^2	59%	61.36%	70.66%	51.06%
No. of Obs.	18	18	18	18

Note: This table shows the estimated coefficients of Eq. (13). Intercepts are omitted. Standard errors are presented in parentheses. *** and ** denote that the estimated coefficients are statistically significant at the 1% and 5%level. No. of Obs. is the number of observations.

As expected, the spillover effects of higher moments among regional markets are significantly and positively driven by their autoregressive term. An increase of 1% in NEM generation capacity decreases the spillover effects among the four regional markets between 0.9% and 1.7%, depending on the moment of the electricity return distribution. All these negative impacts are statistically significant at 5% level. This result is consistent with our conjecture, based on the findings in Clements et al. (2015), discussed in section 5.1.

5.3 Robustness checks

5.3.1 The NEM with Tasmanian market

In this subsection, we present a robustness check on the NEM's spillover effect via each realized moment by including TAS in the analysis. As TAS's electricity data is only available from mid-2005, our sample is restricted to the period from 16 May 2005 to 31 December 2017. Using the same econometrics methodology as discussed in section 3, we construct a measure of overall spillover effect among the five regional markets composing the NEM, based on the 10-step-ahead FEVD which is presented in Table 5.

Table 5: Overall spillover effect (%) among the five regional markets of the NEM via each moment: Row (From), column (To)

	NSW	QLD	SA	VIC	TAS	To others
	Panel A: Realized Return (RR)					
NSW	71.82	18.46	4.26	14.23	1.56	38.52
QLD	14.54	73.83	1.22	3.99	0.70	20.45
SA	2.84	1.06	81.64	8.11	2.19	14.20
VIC	12.88	4.90	9.32	72.12	3.61	30.70
TAS	1.03	0.46	2.08	2.90	90.67	6.47
From others	31.30	24.88	16.88	29.23	8.06	**Total**
Net spillover	7.22	-4.43	-2.68	1.48	-1.59	22.07
	Panel B: Realized Volatility (RV)					
NSW	65.12	12.83	4.04	12.15	2.22	31.24
QLD	8.98	78.41	0.46	1.79	0.16	11.39
SA	4.99	0.74	71.65	17.51	3.51	26.75
VIC	18.83	3.49	21.52	68.46	7.75	51.59
TAS	1.93	0.25	3.46	5.51	85.50	11.15
From others	34.73	17.31	29.49	36.96	13.63	**Total**
Net spillover	-3.49	-5.92	-2.74	14.64	-2.48	26.42
	Panel C: Realized Skewness (RS)					
NSW	55.10	21.90	13.51	24.21	1.75	61.38
QLD	14.87	60.64	4.02	6.85	1.34	27.09
SA	9.53	4.07	56.85	17.19	1.15	31.94
VIC	23.54	10.04	23.61	54.07	2.88	60.06
TAS	0.90	1.23	0.73	1.35	90.56	4.21
From others	48.84	37.23	41.87	49.61	7.12	**Total**
Net spillover	12.54	-10.14	-9.94	10.45	-2.92	36.93
	Panel D: Realized Kurtosis (RK)					
NSW	56.83	21.98	10.30	26.61	0.71	59.60
QLD	14.15	64.02	2.47	6.40	0.21	23.23
SA	6.84	2.61	64.54	13.08	0.66	23.20
VIC	26.04	8.73	19.41	57.03	1.06	55.25
TAS	0.30	0.05	0.60	0.69	96.49	1.64
From others	47.33	33.38	32.77	46.78	2.65	**Total**
Net spillover	12.27	-10.15	-9.57	8.47	-1.01	32.58

Note: This table summarises the electricity market's spillover effect among five Australian regional markets (NSW, QLD, SA, VIC and TAS) via the four moments of the electricity return distribution over the period from 16th May 2005 to 31st Dec 2017. The row **"From others"** summarises the directional spillover from all other markets to one market. The column **"To others"** summarises the directional spillover from one market to all other markets. The cell **"Total"** shows the total spillover among all five markets via each moment. Other columns show the pairwise directional spillover between two relevant markets.

Our main findings are robust in that NSW and VIC have played a central role in contributing the spillover effect to the NEM electricity market via all four realized moments.

TAS, rather than QLD or SA, contributes least to the spillover effect of the NEM for all four realized moments. This finding primarily reflects TAS relative isolation as an island state. Tasmania has only a 500 MW interconnector (Basslink) arrangement in place, which links the TAS regional markets with VIC directly, and the rest of the NEM indirectly. Tasmania is also heavily hydro reliant, making it vulnerable to rainfall conditions (Apergis et al., 2019). The vulnerability in energy supply security was exposed through a power crisis, which occurred in TAS in 2015 when the Basslink interconnector required maintenance together with TAS having low water storage. Overall, our results support our earlier conclusion that transmission of the higher moment risks can be explained primarily by direct physical interconnections.

5.3.2 Bi-power variation

For the electricity market, RV, as calculated from Eq. (2), might contain extreme values due to large price spikes experienced in a relatively short period of time. These significant discontinuities in the electricity prices can be considered as jumps. As RV consists of two components: continuous and jumps, a significant presence of jumps can affect the reliability of our volatility spillovers findings. We check the robustness of the NEM's volatility spillovers effect by using a jump-robust volatility estimate, called the bi-power variation (BV) proposed by Barndorff-Nielsen and Shephard (2004). Basically, BV consistently measures the continuous component of the RV. The BV for each regional market can be constructed from its intraday electricity returns as:

$$BV_t = \sqrt{\left(\frac{\pi}{2}\right)\sum_{i=1}^{M} |r_{i,t}||r_{i-1,t}|} \qquad (14)$$

We then construct the Diebold and Yilmaz (2012) volatility spillover indices within a FIVAR model of BV across the four regional markets, NSW, VIC, SA and QLD. We present the overall BV spillover effect (%) among these four markets in Table 6.

Table 6: Overall BV spillover effect (%) among the four regional markets of the NEM via each moment: Row (From), column (To)

	NSW	QLD	SA	VIC	To others
Bi-power variation (BV)					
NSW	63.92	13.53	6.40	18.41	38.34
QLD	8.69	76.84	0.72	2.43	11.83
SA	6.22	0.93	69.94	16.93	24.08
VIC	22.80	4.38	22.38	66.54	49.56
From others	37.70	18.83	29.50	37.77	**Total**
Net spillover	0.64	-7.00	-5.43	11.79	30.95

Note: This table summarises the electricity market's spillover effect among four Australian regional markets (NSW, QLD, SA, and VIC) via the BV of the electricity return distribution over the period from 16th May 2005 to 31st Dec 2017. The row **"From others"** summarises the directional spillover from all other markets to one market. The column **"To others"** summarises the directional spillover from one market to all other markets. The cell **"Total"** shows the total spillover among all four markets via each moment. Other columns show the pairwise directional spillover between two relevant markets.

We find that the volatility spillover results using BV measures (Table 5) are consistent with the RV measures in Table 3. NSW and VIC are the largest transmitters of the volatility spillover effect in the NEM. Between the two, VIC is larger than NSW by 11.22%, which is relatively close to the corresponding figure obtained from the RV measure (i.e., 13.52%).

5.3.3 Seasonality

One notable characteristic of the electricity market is that there are often extreme prices during the summer months. Therefore, one might be worried that the results for the spillover effect may be mainly driven by market behaviour in the summer months. To explore this concern, we perform a robustness check in which we control for the summer months. First, we create a seasonal dummy variable S_t, which is equal to 1 if in summer months and zero otherwise. We then control for the effect of the summer seasonality using the FIVAR with exogeneous variable (FIVARX) model, which can be specified as follows:

$$A(L)B(L)R_t = \beta_S S_t + u_t, \qquad t = 1,2,\dots,T \qquad (15)$$

We present the spillover effect among the four regional markets of the NEM (NSW, VIC, SA and QLD) after controlling for the summer season in Table 7.

Table 7: Overall spillover (%) among four regional markets of the NEM via each moment after controlling for the summer season: Row (From), column (To)

	NSW	QLD	SA	VIC	To others
Panel A: Realized Return					
NSW	69.40	14.09	6.45	22.15	42.69
QLD	10.31	78.09	1.28	3.69	15.28
SA	3.93	1.06	78.39	8.80	13.80
VIC	19.98	4.84	11.09	67.07	35.92
From others	34.22	20.00	18.83	34.65	**Total**
Net spillover	8.47	-4.71	-5.03	1.27	26.92
Panel B: Realized Volatility					
NSW	63.70	13.18	5.40	15.69	34.27
QLD	9.43	77.48	0.71	2.43	12.57
SA	5.97	0.98	72.26	17.78	24.73
VIC	21.15	4.35	21.98	68.39	47.48
From others	36.55	18.51	28.10	35.90	**Total**
Net spillover	-2.27	-5.94	-3.37	11.58	29.76
Panel C: Realized Skewness					
NSW	64.24	20.07	7.61	22.16	49.84
QLD	14.42	69.96	2.06	4.63	21.10
SA	5.12	2.08	73.59	10.67	17.87
VIC	19.80	5.85	14.06	64.59	39.71
From others	39.34	27.99	23.73	37.46	**Total**
Net spillover	10.50	-6.89	-5.86	2.25	32.13
Panel D: Realized Kurtosis					
NSW	63.71	17.36	7.37	19.86	44.59
QLD	13.02	72.93	1.69	4.51	19.22
SA	6.01	1.82	74.42	12.31	20.14
VIC	19.55	5.62	15.02	65.28	40.20
From others	38.58	24.80	24.08	36.68	**Total**
Net spillover	6.00	-5.58	-3.94	3.52	31.03

Note: This table summarises the electricity market's spillover effect across Australian markets (NSW, QLD, SA and VIC) via the four moments of the electricity return distribution over the period 1st Jan 1999 to 31st Dec 2017. These spillover effects are obtained after controlling for the summer seasons using FIVARX models as presented in Eq. (14). The row **"From others"** summarises the directional spillover from all other markets to one market. The column **"To others"** summarises the directional spillover from one market to all other markets. The cell **"Total"** shows the total spillover among all four markets via each moment. Other columns show the pairwise directional spillover between two relevant markets.

We find that our main conclusions discussed in section 5.1 hold after controlling for the effect of summer. It should be noted that there is a difference in the magnitude of the spillover effect. However, we note that these differences are trivial (around 1%).

5.4 Implications

Improving electricity market interconnectedness among separate regional electricity markets is important in order to gauge progress towards electricity market integration. The creation of competitive, and integrated, electricity markets was one of the foremost objectives of electricity market reforms initiated during the early 1990s. Increasing interconnectedness has several benefits in terms of greater economic efficiency and improved security of supply. However, as "every coin has two sides", policymakers also need to be aware of the costs of electricity market interconnectedness through transmission of higher moment risks.

Previous studies show that market interconnectedness can facilitate the transmission of the volatility risk (e.g., Apergis et al. 2017a; Han et al, 2017; Ignatieva and Truck, 2016; Higgs, 2009; Worthington et al. 2005; Higgs and Worthington, 2005). Yet, while volatility risk is normally regarded as a "standard" risk (since it is related to a standard dispersion from the long-run return), the risk of extreme events can be considered extreme risks, or tail risks, encountered by markets, as they appear in the tail of the return distribution. Our study presents new evidence on the transmission of these extreme risks in the interconnected NEM market.

Of course, an extreme event, by definition, rarely occurs, but when it happens it can cause dramatic destruction and the adverse effect can be made even worse if it spreads across markets. This was evident, for example, in the case of Long-Term Capital Management (LTCM) in the U.S. stock market.[11] In the electricity market, failing to recognise the existence of extreme risks, and dampen the transmission of these risks, can cause catastrophic damage to the stability of electricity market interconnectedness and possibly even energy security.

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[11] The LTCM was a hedge fund, whose investment portfolio exhibited excessive tail risks that was overlooked. Under adverse effects of extreme events, including the 1997 Asian financial crisis and the 1998 Russian financial crisis, the LTCM almost collapsed in 1998 with a loss of US$4.6 billion in less than four months. As many other financial institutions had invested in the LTCM, the problem of LTCM (which was rooted by tail risks) had a tragic influence on the stability of the whole financial world, which required a launch of a bailout program of US$3.6 billion to save the U.S banking system.

How to mitigate the transmission of these risks is a complex problem for wholesalers and policymakers. The use of electricity derivatives, such as electricity forward and futures contracts, can partly help to solve the issue by hedging the risks of price spikes in spot electricity markets (see e.g., Kalantzis and Milonas, 2013). Our findings, discussed in section 5.1 and 5.2, suggest an alternative, and perhaps more direct, solution to mitigate the transmission of these risks is to increase transmission capacity.

Returning to the question we posed at the beginning of this paper of whether there is sufficient transmission capacity between the states, our results suggest that the availability of additional spare capacity on the interconnectors between the regions would reduce the prevalence, and magnitude, of extreme events because generation capacity from nearby states could be transmitted to meet the extra demand associated with extreme events. In this sense, our results should not be viewed as an argument against having the NEM. The NEM brings with it several benefits for the states as discussed above. Rather, it is important for policymakers to take steps to mitigate the risks associated with the incidence and magnitude of extreme events on market participants. Adding interconnector capacity could help to mitigate the potential risks to market participants associated with extreme events and costs associated with network constraints such as persistent higher average wholesale prices, power outages and barriers to entry for new power generators.

6. Conclusions

We study the risk transmission mechanism of the NEM's interconnectedness via all four realized moments of the return distribution, including return, volatility, skewness and kurtosis. We find strong evidence of a mixture of short- and long-memory characteristics in the four realized moments. To examine the dynamic patterns of risk spillovers, we examine the generalized spillover index, proposed by Diebold and Yilzma (2012), within FIVAR systems.

Our results show that shocks emanating from NSW and VIC have the largest influence on NEM's risk spillover via all four realized moments. At the other end of the spectrum, shocks from SA have the lowest impact on RR and RS spillover, whereas, shocks from QLD have the lowest effect on the NEM's RV and RK spillover. These results can be explained by the coverage of the physical interconnectors and existing interconnector capacities. We find that not only the standard risk (i.e., volatility) transmits more, but also the spillovers of extreme risks (i.e., risk of extreme events captured by skewness and kurtosis) are more pronounced when market interconnectedness increases. An important factor influencing the transmission of extreme risks is the availability of spare capacity on the interconnectors between the states, with spare capacity in nearby states being imported to meet local demand and dampen the impact of skewness and kurtosis on market participants. Thus, one way for policymakers to mitigate the risk of extreme events would be by investing in additional capacity.

References

AEMO (2017). Interconnector Capabilities: For the National Electricity Market, Australian Energy Market Operator, https://www.aemo.com.au/-/media/Files/Electricity/NEM/Security_and_Reliability/Congestion-Information/2017/Interconnector-Capabilities.pdf.

AER (2018). State of Energy Market 2018, Australian Energy Regulator, Australian Government, https://www.aer.gov.au/publications/state-of-the-energy-market-reports/state-of-the-energy-market-2018

Amaya, D., Christoffersen, P., Jacobs, K., and Vasquez, A. (2015). Does realized skewness predict the cross-section of equity returns. *Journal of Financial Economics, 118*, 135-167.

Andersen, T., Bollerslev, T., and Diebold, F. (2003). Modeling and forecasting realized volatility. *Econometrica, 71*, 579-625.

Apergis, N., and Tsoumas, C. (2012). Long memory and disaggregated energy consumption: Evidence from fossils, coal and electricity retail in the U.S. *Energy Economics, 34*, 1082-1087.

Apergis, N., Baruník, J., and Chi Keung Lau, M. (2017a). Good volatility, bad volatility: what drives the asymmetric connectedness of Australian electricity markets? *Energy Economics, 66*, 108-115.

Apergis, N., Fontini, F., and Inchaupse, J. (2017b). Integration of regional electricity markets in Australia: A price convergence assessment. *Energy Economics, 62*, 411-418.

Australian Energy Regulator. (2015). *State of the energy market.* Retrieved from https://www.aer.gov.au/publications/state-of-the-energy-market-reports

Barndorff-Nielsen, O., and Shephard, N. (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics, 2*, 1-48.

Baruníck, J., Kočenda, E., and Vácha, L. (2015). Volatility spillovers across petroleum markets. *The Energy Journal, 36*, 309-329.

Becker, R., Hurn, A., and Pavlov, V. (2007). Modelling spikes in electricity prices. *Economic Record, 83*, 371-382.

Bell, W., Wild, P., Foster, J., and Hewson, M. (2017). Revitalising the wind power induced merit order effect to reduce wholesale and retail electricity prices in Australia. *Energy Economics, 67*, 224-241.

Borenstein, S. (2002). The trouble with electricity markets: understanding California's restructuring disaster. *Journal of Economic Perspectives, 16*, 191-211.

Bower, J. (2002). *Seeking the single European electricity market: evidence from an empirical analysis of wholesale market prices.* Washington University in St. Louis : Working paper.

Bunn, D., and Gianfreda, A. (2010). Integration and shock transmissions across European electricity forward markets. *Energy Economics, 32*, 278-291.

Chiriac, R., and Voev, V. (2011). Modelling and forecasting multivariate realized volatility. *Journal of Applied Econometrics, 26*, 922-947.

Chkili, W., Hammoudeh, S., and Nguyen, D. (2014). Volatility forecasting and risk management for commodity markets in the presence of asummetry and long memory. *Energy Economics, 41*, 1-18.

Christensen, T., Hurn, S., and Lindsay, K. (2012). Forecasting spikes in electricity prices. *International Journal of Forecasting, 28*, 400-411.

Clements, A. E., Hurn, A. S., and Li, Z. (2016). Strategic bidding and rebidding in electricity markets. *Energy Economics, 59*, 24-36.

Clements, A. E., Hurn, A. S., and Li, Z. (2017). The effect of transmission constraints on electricity prices. *The Energy Journal, 38*, 145-163.

Clements, A., Herrera, R., and Hurn, A. (2015). Modelling interregional links in electricity price spikes. *Energy Economics, 51*, 383-393.

Crampton, P. (2017). Electricity market design. *Oxford Review of Economic Policy, 33*, 589-612.

De Vany, A., and Walls, W. (1999). Conintegration analysis of spot electricity prices: insights on transmission efficiency in the Western US. *Energy Economics, 21*, 435-448.

Diebold, F. X., and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers with application to global equity markets. *The Economic Journal, 119*, 158-171.

Diebold, F. X., and Yilmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*, 57-66.

Do, H. X., Brooks, R., Treepongkaruna, S., and Wu, E. (2014). How does trading volume affect financial return distribution? *International Review of Financial Analysis, 35*, 190-206.

Do, H. X., Brooks, R., Treepongkaruna, S., and Wu, E. (2016). Stock and currency market linkages: new evidence from realized spillovers in higher moments. *International Review of Economics and Finance, 42*, 167-185.

Ergemen, Y. E., Haldrup, N., and Rodríguez-Caballero, C. V. (2016). Common long-range dependence in a panel of hourly Nord Pool electricity prices and loads. *Energy Economics, 60*, 79-96.

Finkel, A., Moses, K., Munro, C., Effeney, T., and O'Kane, M. (2017). *Independent review into the future security of the National Electricity Market: Blueprint for the future.* Canberra: Commonwealth Government Publication.

Gugler, K., Haxhimusa, A., and Liebensteiner, M. (2018). Integration of European electricity markets: evidence from spot prices. *The Energy Journal, 39*, 41-66.

Han, L., Kordzakhia, N., and Truck, S. (2017). *Volatility spillovers in Australian electricity markets.* Sydney: Working paper 17-02, Macquarie Univesrity, Centre for Financial Risk.

Higgs, H. (2009). Modelling price and volatility inter-relationships in the Australian wholesale spot electricity markets. *Energy Economics, 31*, 748-756.

Higgs, H., and Worthington, A. (2005). Systematic features of high-frequency volatility in Australian electricity markets: intraday patterns, information arrival and calendar effects. *The Energy Journal, 26*, 23-42.

Higgs, H., and Worthington, A. (2008). Stochastic price modelling of high volatility, mean reverting, spike-prone commodities: the Australian wholesale spot electricity market. *Energy Economics, 30*, 3172-3185.

Higgs, H., Lien, G., and Worthington, A. C. (2015). Australian evidence on the role of interregional flows, production capacity, and generation mix in wholesale electricity prices and price volatility. *Economic Analysis and Policy, 48*, 172-181.

Ignatieva, K., and Truck, S. (2016). Modelling spot price dependence in Australian electricity markets with applications to risk management. *Computers and Operational Research, 66*, 415-433.

Jotzo, F., and Mazouz, S. (2015). Brown coal exit: a market mechanism for regulated closure of highly emissions intensive power stations. *Economic Analysis and Policy, 48*, 71-81.

Kalantzis, F. G., and Milonas, N. T. (2013). Analyzing the impact of futures trading on spot price volatility: Evidence from the spot electricity market in France and Germany. *Energy Economics, 36*, 454-463.

Le Pen, Y., and Sevi, B. (2010). Volatility transmission and volatility impulse response functions in European electricity forward markets. *Energy Economics, 32*, 758-770.

Lindstrom, E., and Regland, F. (2012). Modelling extreme dependence between European electricity markets. *Energy Economics, 34*, 899-904.

Littlechild, S. (2012). Merchant and regulated transmission: theory, evidence and policy. *Journal of Regulatory Economics, 42*, 308-335.

Manner, H., Türk, D., and Eichler, M. (2016). Modeling and forecasting multivariate electricity price spikes. *Energy Economics, 60*, 255-265.

Menezes, L. D., and Houllier, M. (2016). Reassessing the integration of European electricity markets: a fractional cointegration analysis. *Energy Economics, 53*, 132-150.

Nelson , T., Reid, C., and McNeill, J. (2015). Energy-only markets and renewable energy targets: Complementary policy or policy collision? *Economic Analysis and Policy, 46*, 25-42.

Nepal, R., and Foster, J. (2016). Testing for market integration in the Australian national electricity market. *The Energy Journal, 37*, 215-237.

Nielsen, M. (2004). Efficient inference in multivariate fractionally integrated time series models. *Econometrics Journal, 7*, 63-97.

Park, H., Mjelde, J. W., and Bessler, D. A. (2006). Price dynamics among U.S. markets. *Energy Economics, 28*, 81-101.

Pesaran, M. H., and Pick, A. (2007). Econometric issues in the analysis of contagion. *Journal of Economic Dynamics and Control, 31*, 1245-1277.

Phillips, P. C., and Sul, D. (2007). Transition modelling and econometrics convergence tests. *Econometrica, 75*, 1771-1855.

Qu, H., Duan, Q., and Niu, M. (2018). Modeling the volatility of realized volatility to improve volatility forecasts in electricity markets. *Energy Economics, 74*, 767-776.

Riesz, J., Noone, B., and MacGill, L. (2013). *Payments for closure? Should direct action include payments for closure of high emission coal-fired power plans?* University of New South Wales, Centre for Energy and Environmental Markets Working paper 2013, Sydney.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics, 34*, 248-255.

Serletis, A., and Shahmoradi, A. (2006). Measuring and testing natural gas and electricity markets volatility: evidence from Alberta's deregulated markets. *Studies in Nonlinear Dynamics and Econometrics, 10*, 1-20.

Shimotsu, K. (2007). Gaussian semiparametric estimation of multivariate fractionally integrated processes. *Journal of Econometrics, 137*, 177-310.

Simshauser, P. (2018a). On intermittend renewable generation and the stability of Australia's national electricity market. *Energy Economics, 72*, 1-19.

Simshauser, P. (2018b). *Missing money, missing policy and resource adequacy in Australia's national electricity market.* University of Cambridge, Faculty of Economics. Cambridge working papers in economics 1840.

Woo, C. K., Lloyd-Zanetti, D., and Horowitz, I. (1997). Electricity market integration in the Pacific Northwest. *The Energy Journal, 18*, 75-101.

Worthington, A., and Higgs, H. (2017). The impact of generation mix on Australian wholesale electricity prices. *Energy Sources, Part B: Economics, Planning, and Policy, 12*, 223-230.

Worthington, A., Kay-Sprately, A., and Higgs, H. (2005). Transmission of prices and price volatility in Australian electricity spot markets: a multivariate GARCH analysis. *Energy Economics, 27*, 337-350.

Yip, P., Brooks, R., and Do, H. (2017). Dynamic spillover between commodities and commodity currencies during United States Q.E. *Energy Economics, 66*, 399-410.

Zachmann, G. (2008). Electricity wholesale market prices in Europe: Convergence? *Energy Economics, 30*, 1639-1671.

Appendix:

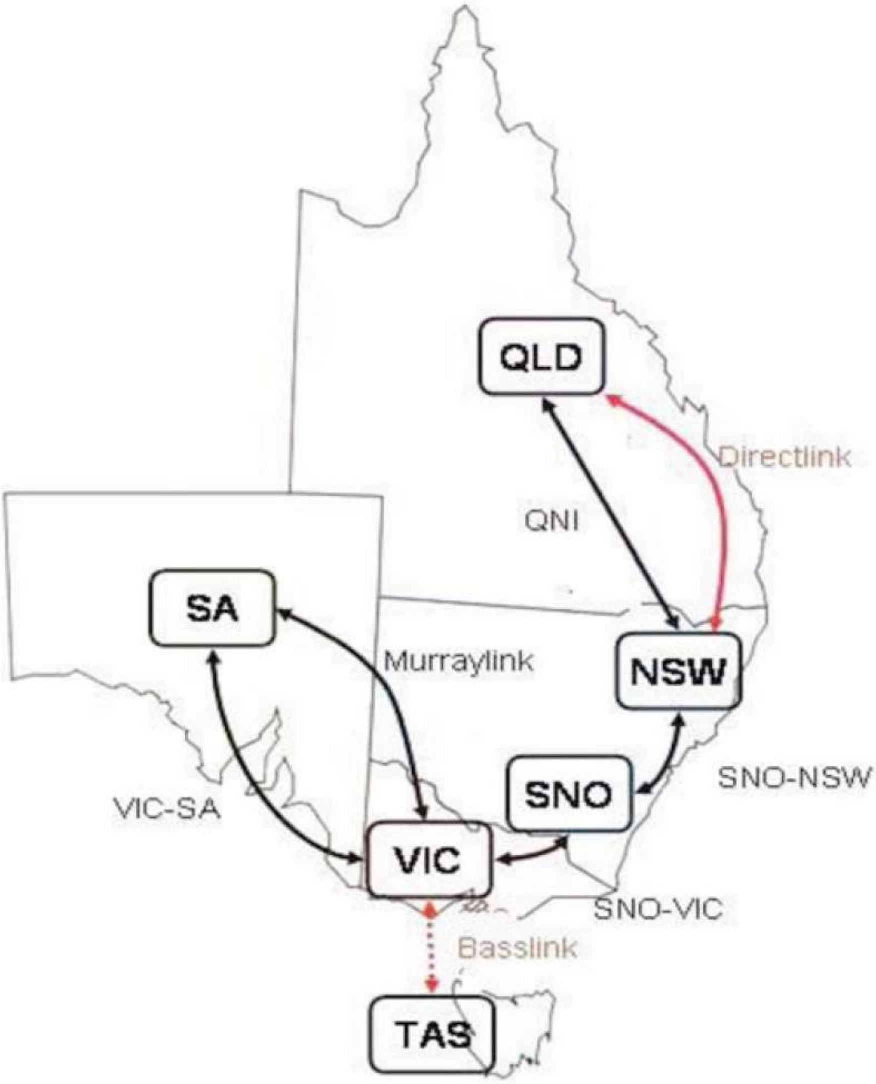

Figure A1: Interconnectors in the NEM

Source: Nepal and Foster (2016)

Note that Basslink is a merchant interconnector.