Modeling Price and Volatility Relationships in the Australian Wholesale Spot Electricity Markets Using Constant and Dynamic Conditional Correlation Multivariate GARCH Models

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ABSTRACT

This paper examines the inter-relationship of wholesale spot electricity prices among the four regional electricity markets in the Australian National Electricity Market (NEM): namely, New South Wales, Queensland, South Australia and Victoria using the constant conditional correlation and Tse and Tsui's (2002) and Engle's (2002) dynamic conditional correlation multivariate GARCH models. Tse and Tsui's (2000) dynamic conditional correlation multivariate GARCH model which takes account of the Student *t* specification produces the best results. At the univariate GARCH(1,1) level, the mean equations indicate the presence of positive own mean spillovers in all four markets and little evidence of mean spillovers from the other lagged markets. In the dynamic conditional correlation equation, the highest conditional correlations are evident between the well-connected markets indicating the presence of strong interdependence between these markets with weaker interdependence between the not so well-interconnected markets.

JEL classifications: C32, C51, L94, Q40

Keywords: wholesale spot electricity price markets, constant and dynamic conditional correlation, multivariate GARCH

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1. INTRODUCTION

The Australian National Electricity Market (NEM) was established on 13 December 1998. It currently comprises four state-based [New South Wales (NSW), Victoria (VIC), Queensland (QLD) and South Australia (SA)] and one non-state based [Snowy Mountains Hydroelectric Scheme (SNO)] regional markets operating as a nationally interconnected grid. Within this grid, the largest generation capacity is found in NSW, followed by QLD, VIC and SA, while electricity demand is highest in NSW, followed by VIC, QLD and SA. The NEM, encompasses privately and publicly owned generators, transmission and distribution network providers and traders (for details of the NEM's regulatory background, institutions and operations see ACCC, 2000; IEA, 2001 and NEMMCO, 2008a). However, each state's

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network was (and still is) characterised by a very small number of participants and sizeable differences in electricity prices were found. One of the objectives in establishing the NEM was to provide a nationally integrated and efficient electricity market.

However, a defining characteristic of the NEM is the limitations of physical transfer capacity. QLD has two interconnectors that together can import and export to and from NSW, NSW can export to and from the SNO and VIC can import from the SNO and SA and export to the SNO and to SA. There is currently no direct connector between NSW and SA and QLD is only directly connected to NSW. As a result, the NEM itself is not yet strongly integrated. During periods of peak demand, the interconnectors become congested and the NEM separates into its regions, promoting price differences across markets and exacerbating reliability problems of regional utilities (IEA, 2001; ACCC, 2000 and NEMMCO, 2008a).

While the appropriate regulatory and commercial mechanisms do exist for the creation of an efficient national market, and these are expected to have an impact on the price of electricity in each region, it is argued that the complete integration of the separate regional electricity markets has not yet been realised. In particular, the limitations of the interconnectors between the member states suggest that, for the most part, the regional spot markets are relatively isolated.

There are many studies that use various univariate generalised autoregressive conditional heteroskedasticity (GARCH) models to asses the dynamics within spot electricity markets. This is then extended to multivariate GARCH (MGARCH) models to capture volatility clustering between spot electricity prices. The univariate autoregressive conditional heteroskedasticity (ARCH) models [as introduced by Engle (1982)] and GARCH models [as proposed by Bollerslev (1986)] have already been widely employed in modeling the dynamics of spot electricity markets. Suitable surveys of GARCH modeling in the spot electricity markets may be found in Knittel and Roberts (2001), Solibakke (2002), Hadsell at al. (2004), Higgs and Worthington (2005) and Chan and Gray (2006).

The only studies to date that have extended the univariate GARCH analyses to MGARCH applications as proposed by Bollerslev (1990) are De Vany and Walls (1999a), Bystrom (2003) and Worthington et al. (2005). De Vany and Walls (1999a) use cointegration analysis between pairs of US regional electricity markets to assess market integration while Bystrom (2003) applies the constant correlation bivariate GARCH model to the short-term hedging of the Nordic spot electricity prices with electricity futures. Worthington et al. (2005) employ the multivariate GARCH (MGARCH) BEKK (Baba, Engle, Kraft and Kroner) model to capture the price and volatility spillovers among five spot electricity markets in Australia.

The disadvantage of the MGARCH BEKK model is that the estimated coefficients for the variance covariance matrix cannot be interpreted on an individual basis: "instead, the functions of the parameters which form the intercept terms and the coefficients of the lagged variance, covariance, and error terms that appear are of interest" (Kearney and Patton, 2000: 36). So far Worthington et al. (2005) produce the only study that utilizes the MGARCH model to assess the inter-relationships among five Australian spot electricity markets.

The aim of this research is to extend on the paper by Worthington et al. (2005) by employing an up-to date family of constant and dynamic conditional correlation MGARCH models to capture the effects of cross-correlation volatility spillovers between the four Australian spot electricity markets. This permits a greater understanding of pricing efficiency and cross-correlation volatility spillovers between these interconnected markets. To the author's knowledge a detailed study of the applications of constant and dynamic correlation MGARCH models to spot electricity markets has not been undertaken. It is within the context of previous limited empirical work that the present paper is conducted.

Accordingly, the purpose of this paper is to investigate the price volatility and inter-relationships in four Australian regional electricity markets by employing three conditional correlation MGARCH models namely: the constant conditional correlation, Tse and Tsui's (2002) and Engle's (2002) dynamic conditional correlation MGARCH models. If there is a lack of significant inter-relationships between regional markets then doubt may then be cast on the ability of the NEM to foster a nationally integrated and efficient electricity market. The reminder of the paper is divided into four sections. The second section explains the data employed in the analysis and presents some brief summary statistics. The third section discusses the methodology employed. The results are dealt with in fourth section. The paper ends with some brief concluding remarks in the final section.

2. DATA AND DESCRIPTIVE STATISTICS

The data employed in this study consists of daily spot electricity prices from January 1, 1999 to 31 December 2007 for each of the four wholesale electricity markets. All data is obtained from National Electricity Market Management Company (NEMMCO, 2008b) originally on a half-hourly basis representing 48 trading intervals in each 24-hour period. A series of daily arithmetic means is calculated from the 48 trading interval data, yielding 3,287 observations for each regional market. The prices are in dollars per megawatt hour (MWh). By way of comparison, De Vany and Walls (1999a; 1999b), Robinson (2000), Wolak (2000), Lucia and Schwartz (2002), Escribano et al. (2002), Solibakke (2002), Higgs and Worthington (2005), Worthington et al. (2005), Chan and Gray (2006), Koopman et al. (2007)

and Becker et al. (2007) employ daily spot prices in their respective analyses of the western United States, United Kingdom, Scandinavian and Australian electricity markets. Importantly, the use of daily prices may lead to the loss of at least some 'news' impounded in the more frequent trading interval data.

<TABLE 1 HERE>

Table 1 presents the summary of descriptive statistics of the daily spot electricity prices and the natural logarithm of the daily spot electricity prices for the four Australian electricity markets. Sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis, the Jarque-Bera (JB) statistic and the Augmented Dickey-Fuller test and *p*-values are reported. The spot electricity prices for the four markets range from $34.10/MWh (VIC) to $42.99/MWh (SA). The highest average spot electricity prices are in SA ($42.99/MWh) and QLD ($38.89/MWh). The standard deviations of spot electricity prices range from $47.09 (VIC) to $65.88 (NSW). The coefficient of variation measures the degree of variation relative to the mean. On this basis, SA and VIC are less variable than either NSW or QLD.

The distributional properties of the spot electricity price series appear non-normal. All of the markets are significantly positively skewed ranging from 10.3449 (SA) to 15.7461 (VIC) indicating the greater likelihood of large price increases than price falls. The kurtosis, or degree of excess, is also large, ranging from 144.0229 for SA to 384.4721 for VIC, and since the kurtosis, or degree of excess, in all of these electricity markets exceeds three, leptokurtic distributions are indicated. The calculated Jarque-Bera statistic and corresponding *p*-value in Table 1 is used to test the null hypotheses that the distribution of spot electricity prices is normally distributed. All *p*-values are < 0.01 level of significance indicating the null hypothesis is rejected. These spot electricity prices are then not well approximated by the normal distribution. The respective Augmented Dickey-Fuller (ADF) *t*-statistic and *p*-value are -13.4736 and <0.01 for NSW, -14.4815 and <0.01 for QLD, -30.6863 and <0.01 for SA and -15.3856 and <0.01 for VIC. The ADF *t*-statistics reject the null hypothesis of non-stationarity or unit root at the 0.01 level of significance. The spot electricity price series in the four markets are stationary. Contrary to previous empirical work by De Vany and Walls (1999a; 1999b), which found that spot electricity prices contained a unit root, this study concurs with Lucia and Schwartz (2001), Higgs and Worthington (2005), Worthington et al. (2005) that electricity prices are stationary.

3. MODEL SPECIFICATION

The distributional properties of Australian spot electricity prices indicate that multivariate generalised autoregressive conditional heteroskedastistic (MGARCH) models can be used to examine the dynamics of the price volatility process between spot electricity markets. A family of MGARCH models uses the conditional correlations to assess the volatility spillovers between markets. The condition variance hence conditional correlation matrix for this family of models is specified in two stages. At the first stage, the conditional variances are obtained from a univariate GARCH process for each market. At the second stage, the conditional variances are used to determine the conditional correlation matrix imposing a positive definiteness for all t in the optimisation process. Engle et al. (1984) presented the necessary conditions for the conditional variance of a bivariate ARCH model to be positive definite.

Bollerslev (1990) proposes a constant conditional correlation MGARCH model (CCC) where the computational simplicity of this model has been widely used in empirical research. Although the constant correlation assumption provides a convenient process for estimation, this assumption does not hold for many economic and financial applications. There is a need to extend to the MGARCH model to take account of time-varying correlations and yet retaining the positive definite optimisation condition for the conditional correlation matrix.

Tse and Tsui (2002) and Engle (2002) extend the CCC to dynamic conditional correlation models (DCC) by including a time dependent conditional correlation matrix. Tse and Tsui's (2002) dynamic conditional correlation (TTDCC) and Engle's (2002) dynamic conditional correlation (EDCC) models include information effects and can vary according to the assumed distribution of the random error term and/or the conditional variance-covariance and conditional correlation equations. The TTDCC and EDCC models assume that each conditional variance term follows a univariate GARCH process. These DCC model have the flexibility of univariate GARCH processes and not the complexity of the MGARCH processes. An autoregressive moving average process is applied to the conditional correlation matrix. By imposing some suitable restrictions on the conditional correlation matrix, this ensures the conditional correlation matrix is positive definite for each point in time during the optimisation. The DCC models retain the insight and interpretation of the univariate GARCH model while satisfying the positive definite condition as required in the conditional correlation MGARCH models. The following section formulates the three conditional correlation MGARCH models.

The first stage starts with the definition of the univariate GARCH process. A basic requirement is to remove the predictable component of the electricity prices so as to produce the price innovation, e_t, with a conditional mean of zero before a GARCH equation is specified for the variance. One common method to produce an uncorrelated process in the daily prices is to assume that they follow an AR(1) process. The following MGARCH model is developed to examine the processes relating to the spot prices for the K electricity markets. The following conditional mean price equation accommodates each market's own prices and the prices of its own and other markets lagged one period:

$$P_{it} = \alpha_0 + \sum_{i=1}^{K} \alpha_i P_{it-1} + \varepsilon_{it} \qquad (1)$$

where P_{it} is the natural logarithm of the daily prices of market i (i = 1,…, K) at time t and $\varepsilon_{it} | I_{it\text{-}1} \sim N(0, h_{it})$, ε_{it} is the random errors or innovation with its corresponding conditional variance, h_{it} for market i at time t. The market information available at time t - 1 is represented by the information set $I_{t\text{-}1}$. The α_0, represent the long-term drift coefficients. The elements α_i are the degree of mean spillover effect across markets, or put differently, the current prices in market i that can be used to predict future prices (one day in advance) in market j. The estimates of these elements can provide measures of the significance of the own and cross mean spillovers. This univariate structure then enables the measurement of the effects of the innovations in the mean spot prices of one series on its own lagged prices and those of the lagged prices of other markets.

The conditional variance of a univariate GARCH process of order 1 and 1 is denoted as GARCH(1,1) and the random error term, $\varepsilon_{it,}$ is specified as:

$$\varepsilon_{it} = h_{it} e_{it} \qquad e_{it} \sim iid\ N(0,1) \qquad (2)$$

with

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 h_{it-1} \qquad (3)$$

where h_{it} is the conditional variance of volatility of ε_{it} for market i at time t, β_0 is a constant, β_1 and β_2 are coefficients that are associated with the degree of innovation from previous period, ε_{it-1}^2 (ARCH term) and previous period's volatility spillover effects, h_{it-1} (GARCH term) for each market respectively.

At the second stage, the conditional variances obtained from the univariate GARCH(1,1) process are then used to estimate the conditional correlation matrix for the CCC, TTDCC and EDCC models. The conditional correlation matrix has to be positive definite for all *t*.

First, the constant conditional correlations (CCC) MGARCH model is presented by Bolleslev (1990). Under the assumption of constant conditional correlations the maximum likelihood estimate of the correlation matrix is equivalent to the sample correlation. As the sample correlation is always positive definite, the optimisation can be achieved as long as the conditional variances are positive. The CCC MGARCH model has been introduced because of its computational simplicity (Tse, 2000 and Lien and Tse, 2002). The conditional covariance matrix of the CCC model (Bollerslev, 1990) is specified as:

$$H_t = D_t R D_t = \rho_{ij} \sqrt{h_{iit} h_{jjt}} \tag{4}$$

where

$$D_t = diag(h_{11t}^{1/2} ... h_{KKt}^{1/2}) \tag{5}$$

$$R = \rho_{ij} \tag{6}$$

h_{iit} is defined as the conditional variance of the univariate GARCH model for market *i* and *R* is the symmetric positive definite constant conditional correlations matrix with $\rho_{ii} = 1$ for all *i*. The CCC model with a GARCH(1,1) specification for each conditional variance in D_t is specified as:

$$h_{iit} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 h_{iit-1} \tag{7}$$

The conditional covariance matrix H_t is positive definite and only if all the *K* conditional variances are positive and *R* is positive definite.

Although the assumption that the conditional correlations are constant provides a very convenient MGARCH model for estimation, this assumption may not hold for many economic and financial time series. Tse and Tsui (2002) and Engle (2002) extend the CCC model to dynamic conditional correlation models (DCC) by including a time dependent component in the conditional correlation matrix. In addition, the time dependent conditional correlation matrix has to be positive definite for all *t*. This condition is upheld in DCC models under simple conditions on the parameters.

Second, the conditional covariance matrix of Tse and Tsui's (2002) dynamic conditional correlation model (TTDCC) is defined as:

$$H_t = D_t R_t D_t \tag{8}$$

where D_t is defined in (5) and h_{iit} is defined as any univariate GARCH process with the time-varying conditional correlation matrix R_t is generated from the recursion:

$$R_t = (1-\theta_1-\theta_2)R + \theta_1 \Psi_{t-1} + \theta_2 R_{t-1} \tag{9}$$

where θ_1 and θ_2 are non-negative parameters with $\theta_1 + \theta_2 < 1$, R is the $K \times K$ symmetric positive definite constant parameter matrix with $\rho_{ii} = 1$ for all i, R_t, is a weighted average of R, R_{t-1} and Ψ_{t-1} and Ψ_{t-1} is the $K \times K$ correlation matrix of ε_τ for $\tau = t - M, t - M + 1, \ldots, t - 1$. If R and Ψ_{t-1} are well-defined correlation matrices (ie positive definite with unit diagonal elements), then R_t will also be a well-defined correlation matrix. Ψ_{t-1} depends on the lagged standardised residuals ξ_t and its ijth elements can be denoted as:

$$\psi_{ij,t-1} = \frac{\sum_{m=1}^{M} \xi_{i,t-m}\xi_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} \xi_{i,t-m}^2\right)\left(\sum_{m=1}^{M} \xi_{j,t-m}^2\right)}} \qquad 1 \le i \le j \le K \tag{10}$$

where $\xi_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$. The matrix Ψ_{t-1} can be expressed as:

$$\Psi_{t-1} = B_{t-1}^{-1} L_{t-1} L_{t-1}^{'} B_{t-1}^{-1} \tag{11}$$

where B_{t-1} is a $K \times K$ diagonal matrix with the ith diagonal element given by $\left(\sum_{h=1}^{M} \xi_{i,t-h}^2\right)^{1/2}$

for $i = 1, \ldots K$ and L_{t-1} is a $K \times M$ matrix given by $L_{t-1} = (\xi_{t-1}, \ldots \xi_{t-M})$.

A necessary condition for Ψ_{t-1} and also R_t to be positive definite is $M \ge K$.

Finally, Engle (2002) proposes a dynamic conditional correlation model (EDCC) which defines equation (8) with R_t specified as:

$$R_t = \text{diag}(q_{11t}^{-1/2} \ldots q_{KKt}^{-1/2})\, Q_t\, \text{diag}(q_{11t}^{-1/2} \ldots q_{KKt}^{-1/2}) \tag{12}$$

where $Q_t = (q_{ijt})$ is a $K \times K$ symmetric positive definite matrix given by:

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} + \theta_1 \xi_{t-1}\xi_{t-1}^{'} + \theta_2 Q_{t-1} \tag{13}$$

where $\overline{Q}$ is the $K \times K$ unconditional correlation matrix of ξ_t where θ_1 and θ_2 are non-negative parameters with $\theta_1 + \theta_2 < 1$.

Engle (2002) presents the conditional correlation as a weighted sum of past correlations. In addition, Engle (2002) specifies the matrix Q_t as a GARCH equation, and then transforms it to a correlation matrix. For both DCC models, the null hypothesis of $\theta_1 = \theta_2 = 0$ is tested to determine whether imposing constant correlations is relevant.

The disadvantage of the DCC models is that θ_1 and θ_2 are scalars, therefore the conditional correlations feature the same dynamics. This is a necessary condition to ensure that R_t is positive definite for all t. Since the data indicate that all four markets are non-normally distributed, the Student t specification is introduced into the MGARCH process to take account of the fat-tailed characteristics in the spot price series.

4. EMPIRICAL RESULTS

At the first stage, the parameters of the univariate GARCH(1,1) model are calculated for each spot electricity market. The estimated coefficients, standard errors and p-values for the conditional mean equation of the univariate GARCH(1,1) model for each spot electricity market are presented Table 2. The average daily log price (α_0) is 0.4565 for NSW, 0.2865 for QLD, 0.9270 for SA and 0.6042 for VIC. This indicates that average equilibrium prices range from \$1.33/MWh (QLD) [i.e. \$1.33 = exp(0.2865)] to \$2.53/MWh (SA). All four electricity spot markets exhibit a significant own mean spillover from their own lagged electricity price. In all cases, the mean spillovers are positive. For example, in NSW a \$1.00/MWh increase in its own spot price will Granger cause an increase of \$2.24/MWh (0.8063) in its price over the next day. Likewise, a \$1.00/MWh increase in the VIC lagged spot price will Granger cause a \$2.15/MWh (0.7671) increase the next day. As a comparison, Worthington et al. (2005) found only two of the five Australian spot electricity markets exhibit a positive significant own mean spillover from their own lagged electricity price.

There appears to be a significant positive relationship between the mean price in the SA market and the lagged mean price in the QLD market. There is no logical reason for this relationship as there are no direct interconnectors between these two markets. The relationship may results from both QLD and SA markets are relatively poorly interconnected and have higher spot electricity prices than the other markets. There is a negative and significant relationship between mean price in the VIC and the lagged mean price in the SA market. A \$100/MWh increase in the SA spot price will Granger cause a decrease of \$0.96/MWh in the VIC market over the next day. In terms of the relationship between the mean price of a market and that of the other market lagged one period, only two out of 12 markets are significant. This indicates that on average short-run price changes in the four spot

electricity markets are not associated with price changes in any of the other spot electricity markets, despite the connectivity offered by the NEM. Worthington et al. (2005) obtained similar results with no significant mean spillovers from other lagged markets.

<TABLE 2 HERE>

Table 2 also presents the estimated coefficients, standard errors and *p*-values for the conditional variance equation of the univariate GARCH(1,1) for all four markets. The own-innovation or ARCH spillovers (β_1) in all four markets are significant indicating the presence of significant ARCH effects, while the lagged volatility or GARCH spillovers (β_2) are also significant and larger in magnitude for NSW, SA and VIC markets. The respective innovation and volatility spillovers are 0.4672 and 0.5320 in the NSW market, 0.6648 and 0.4119 in the QLD market, 0.0615 and 0.9216 in the SA market and 0.1108 and 0.8563 in the VIC market. This implies that for all markets the last period's volatility shocks in the spot electricity price have a great effect on its future volatility than the memory of previous surprises or innovations with the exception of QLD. As a comparison, Higgs and Worthington (2005) concluded that the GARCH effects were larger in magnitude than the ARCH effects in QLD and SA while the reverse was true for NSW and VIC.

One important and well-founded characteristic of electricity spot prices is the tendency for volatility clustering to be found, such that large changes in spot prices are often followed by other large changes, and small changes in daily spot prices are often followed by yet more small changes. The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility in the future. The persistence coefficient is defined as the sum of the ARCH and GARCH effects ($\beta_1 + \beta_2$). The persistence coefficient is less than one for NSW (0.9992), SA (0.9830) and VIC (0.9671), thus implies that these markets experience a mean-reverting conditional volatility process in which the shocks are transitory in nature. The degree of persistence is greater than one in QLD (1.0768). This suggests that the positive shocks in the QLD market exhibit a permanent impact, indicating the daily spot electricity price exceeding the normal or mean level of volatility lead to an increase in conditional volatility that do not die down. As a comparison, Higgs and Worthington (2005) found the degree of persistence to be less than one for each of the Australian spot electricity markets, employing the skewed Student asymmetric power ARCH model.

At the second stage, the conditional variances from the univariate GARCH(1,1) models are used to calculate the conditional correlation matrix. Table 3 presents the estimated coefficients, standard errors and *p*-values for the conditional correlations between the four

markets employing the CCC, TTDCC and EDCC models. The estimated conditional correlations are all positive and significant at <0.01 level for all three models, indicating the presence of significant strong positive spillover relationship between the spot electricity markets. In the CCC model, the conditional correlations are the highest between NSW and VIC (0.8801); SA and VIC (0.7577); and NSW and QLD (0.7428), whereas the conditional correlations are the lowest between NSW and SA (0.6550); QLD and VIC (0.6531); and QLD and SA (0.5241). The conditional correlations for the former three pairs of spot electricity markets are the strongest for the well-interconnected markets thus exhibiting the presence of interconnectivity between these markets. The low conditional correlations between the latter three pairs of markets are consistent with the fact that there is currently no direct interconnector linkage between these pairs of spot electricity markets. In general, the conditional correlations are higher for the EDCC model than the TTDCC model which in turn is higher than those of the CCC model. For example the conditional correlation between NSW and QLD increased dramatically from 0.7428 in the CCC model to 0.9149 in the TTDCC model and 0.9256 in the EDCC model, with smaller changes in the conditional correlations between the other pairs of markets across the three methods.

<TABLE 3 HERE>

Table 3 also presents the likelihood ratio statistic (LR) testing for the restriction H_0: $\theta_1 = \theta_2 = 0$ or whether the constant correlations are relevant. The LR test is distributed as a χ^2_P with $P = K(K - 1)/2$ degrees of freedom. The LR statistics, for the TTDCC and EDCC models are respectively 1636.25 and 1515.66 and the χ^2 critical value is 12.5916. This indicates that the constant correlation assumption is rejected. On the basis of the log-likelihood, Akaike Information (AIC) and Schwartz Criteria (SC), the TTDCC is the best model for all four markets. Clearly, the dynamic conditional correlation process has the ability to accommodate the time-varying conditional correlation volatility spillovers across the four Australian electricity markets. In brief, the discussion of the estimated conditional correlation matrix is only presented for the TTDCC model.

In the TTDCC model, the conditional correlations are all positive and significant at the <0.01 level. The conditional correlations are highest between NSW and QLD (0.9149); NSW and VIC (0.8654); and SA and VIC (0.7847), thus suggesting interdependence between these markets over the sample period. The conditional correlations are lowest between QLD and VIC (0.7597); NSW and SA (0.6127); and QLD and SA (0.5368). The high interdependence of the conditional correlation spillovers are evident between the well-interconnected markets

while the contrary is found between the not so well-interconnected markets such as QLD and SA which are located at the extremities of the NEM.

Plots of the dynamic correlations for the TTDCC model are depicted in Figure 1. Between 1999 and 2001, the conditional correlations between the NSW and QLD markets reveal that they are very volatile ranging from below 0.0 to 0.8 and after 2001, the conditional correlations are still very volatile (ranging between 0.1 to 0.9) but are mean-reverting. This is the result of the inception of the Queensland and New South Wales Interconnector which began operation on 18 February 2001. The amplitude of the conditional correlations narrows towards the end of the sample period. Similar patterns are exhibited between the SA and VIC markets with evidence of mean-reverting conditional correlation spillovers after 2002 with the introduction of the Murraylink interconnector.

Another interesting plot is the one between the long-standing spot electricity markets of NSW and VIC which are linked by the Snowy Mountains Hydroelectric Scheme (SNO) from the beginning of the sample period. These markets generate the largest interconnected capacity in the NEM. The conditional correlations between these markets are mean-reverting with the amplitude of the conditional correlations becomes narrower towards the end of the sample period. This plot shows that the conditional correlations between the long-standing electricity spot markets between NSW and VIC are interdependent and mean-reverting over this sample period.

In sum, the strong significant positive conditional correlation volatility spillovers between the well-connected electricity markets together with the mean-reverting plots of the dynamic conditional correlations over the sample period suggest the NEM has fostered a nationally integrated and stable spot electricity market, thus indicating that the interconnected markets are informationally efficient.

<FIGURE 1 HERE>

Table 3 also presents the degrees of freedom (df) for the Student *t* specification. The df are also significant for the three models ranging from 2.6008 (CCC) to 2.7076 (EDCC). The significance of the Student *t* coefficients indicates that this specification has taken account of the fat-tailed characteristic of the four spot price series. The estimated coefficients for the conditional correlation equation (θ_1 and θ_2) for both TTDCC and EDCC models are significant and sum to less than one which implies the dynamic conditional correlations are mean-reverting.

5. CONCLUSIONS

This study presents an analysis of inter-relationships in the wholesale electricity price volatility in the four Australian electricity markets of New South Wales, Queensland, South Australia and Victoria. The data consists of half-hourly prices for the period 1 January 1999 to 31 December 2007. Three different conditional correlation MGARCH models namely: the constant conditional correlation (CCC), Tse and Tsui's (2002) and Engle's (2002) DCC MGARCH models are estimated. The results indicate that the price and price volatility inter-relationships in the Australian wholesale electricity markets are best described by the Tse and Tsui (2002) DCC MGARCH specification. This model has the ability to capture the time-varying dynamics of the conditional correlations across pairs of electricity markets. The Student *t* specification is also included to accommodate the fat-tailed properties of the observed data.

These findings make a significant contribution in estimating the volatility and the efficiency of the wholesale electricity markets by employing time-varying multivariate techniques that have not been previously explored in the Australian context. The assessment of these prices and volatility between regional markets allows for better understanding of the spot electricity dynamics by electricity producers, transmitters and retailers and the efficient distribution of energy on a national level.

At the first stage, the univariate GARCH(1,1) models are used to identify the source and magnitude of the mean, innovation and volatility spillovers of each market. All four markets exhibit a significant own mean spillover. Only two of the markets exhibit a significant mean spillover from other lagged markets. This suggests, for the most part, that Australian spot electricity prices could not be usefully forecast using lagged price information from other markets. The results of the univariate GARCH(1,1) also show the presence of strong ARCH and GARCH effects with the exception of the QLD market. This indicates that for all regional markets volatility shocks are persistent over time. This persistence suggests that high (low) volatility of price changes is followed by high (low) volatility price changes; that is, like magnitudes of price changes cluster over time. This price clustering captures the non-normality and non-stability of Australian electricity spot prices.

At the second stage, the conditional correlation volatility spillovers of the TTDCC model are positive and significant for all pairs of markets, indicating the presence of positive volatility effects between pairs of markets. The highest conditional correlations are evident between the well-connected markets namely: NSW and QLD; NSW and VIC; and SA and VIC. This indicates that the interconnectivity between the separate regions in the NEM has

fostered a nationally integrated and stable spot electricity market, thus indicating that the interconnected markets are informationally efficient. The lowest conditional correlation is evident between the not directly interconnected QLD and SA markets. As a general rule, the less direct the interconnection between regions, the lower the conditional correlations volatility spillover effects between these regions. This suggests that the main determinant of the interaction between regional electricity markets is geographical proximity and the number and size of interconnectors. Accordingly, it may be unreasonable to expect that prices in electricity markets that are geographically isolated market will ever become fully integrated.

REFERENCES

Australian Competition and Consumer Commission (2000). *Infrastructure industries: Energy*, Commonwealth of Australia, Canberra.

Becker, R., S. Hurn and V. Pavlov (2007). "Modelling Spikes in Electricity Prices." *Economic Record* 83(263): 371-382.

Bera, A.K. and M.L. Higgins (1993). "ARCH models: properties, estimation and testing." *Journal of Economic Surveys* 7(4): 305-366.

Bollerslev, T. (1986). "Generalised autoregressive condition heteroskedasticity." *Journal of Econometrics* 31(3): 307-327.

Bollerslev, T. (1990). "Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model." *Review of Economics and Statistics* 72(3): 498-505.

Bystrom, H.N.E. (2003). "The hedging performance of electricity futures on the Nordic power exchange." *Applied Economics* 35(1): 1-11.

Chan, K.F. and P. Gray (2006). "Using extreme vale theory to measure value at risk for daily electricity spot prices." *International Journal of Forecasting* 22(2): 283-300.

De Vany, A.S. and W.D. Walls (1999a). "Cointegration analysis of spot electricity prices: Insights on transmission efficiency in the western US." *Energy Economics* 21(3): 435-448.

De Vany, A.S. and W.D.Walls (1999b). "Price dynamics in a network of decentralized power markets." *Journal of Regulatory Economics* 15(2): 123-140.

Engle, R. (2002) "Dynamic conditional correlation: A sample class of multivariate generalized autoregressive conditional heteroskedasticity models." *Journal of Business and Economic Statistics* 20(3): 339-350.

Engle, R., C.W.J. Granger and D. Kraft (1984). "Combining competing forecasts of inflation: Using a bivariate GARCH model." *Journal of Economic Dynamics and Control* 8(1): 151-165.

Escribano, A., J.I. Pena and P. Villaplana (2002). "Modeling electricity prices: International evidence." Working paper 02-27, Economics Series 08, Departamento de Economía, Universidad Carlos III de Madrid.

Hadsell, L., A. Marathe and H.A. Shawky (2004). "Estimating the volatility of wholesale electricity spot prices in the US." *Energy Journal* 25(4): 23-40.

Higgs, H. and A.C. Worthington (2005). "Systematic features of high-frequency volatility in the Australian electricity market: Intraday patterns, information arrival and calendar effects." *The Energy Journal* 26(4): 1-20.

International Energy Agency (2001). *Energy policies of IEA Countries: Australia 2001 Review*, Organisation for Economic Cooperation and Development (OECD), Paris.

Kearney, C. and A.J. Patton (2000). "Multivariate GARCH modeling of exchange rate volatility transmission in the European monetary system." *Financial Review* 41(1): 29-48.

Knittel, C.R. and M.R. Roberts (2001). "An empirical examination of deregulated electricity prices." University of California Energy Institute Working Paper PWP-087.

Koopman, S.J., M. Ooms and M.A. Carnero (2007). "Periodic seasonal reg-ARFIMA-GARCH models for daily electricity spot prices." *Journal of American Statistical Association* 102(477): 16-27.

Lien, D. and Y.K. Tse (2002). "Evaluating the hedge performance of the constant correlation GARCH model." *Applied Financial Economics* 12(11): 791-798.

Lucia, J.J. and E.S. Schwartz (2002). "Electricity prices and power derivatives: Evidence from the Nordic power exchange." *Review of Derivatives* Research 5(1): 5-50.

National Electricity Market Management Company Limited (2008a). *An Introduction to Australia's National Electricity Market*, NEMMCO, Melbourne.

National Electricity Market Management Company Limited Website (2008b). WWW site: http://www.nemmco.com.au/. Accessed March 2008.

Robinson, T. (2000). "Electricity pool series: A case study in non-linear time series modelling." *Applied Economics* 32(5): 527-532.

Solibakke, P. (2002). "Efficient estimated mean and volatility characteristics for the Nordic spot electricity power market." *International Journal of Business* 7(2): 17-35.

Tse, Y.K. (2000). "A test for constant correlation in a multivariate GARCH." *Journal of Econometrics* 98(1): 107-127.

Tse, Y.K. and A.K.C. Tsui (2002). "A multivariate generalised autoregressive conditional heteroscedasticity model with time-varying correlations." *Journal of Business and Economic Statistics* 20(3): 351-362.

Wolak, F.A. (2000). "Market design and price behavior in restructured electricity markets: An international comparison." NBER-East Asia Seminar on Economics, vol. 8. Chicago and London: University of Chicago Press.

Worthington, A.C., A. Kay-Spratley and H. Higgs (2005). "Transmission of prices and price volatility in Australian electricity spot markets: A multivariate GARCH analysis." *Energy Economics* 27(2): 337-350.

Table 1. *Summary statistics of daily spot prices ($/MWh) and natural logarithms of spot prices, 1 January 1999 – 31 December 2007*

	Spot electricity prices				Log spot electricity prices			
Statistics	NSW	QLD	SA	VIC	NSW	QLD	SA	VICA
Mean	37.4255	38.8852	42.9947	34.1017	3.328	3.3595	3.3656	3.5588
Median	26.0396	25.3046	31.5856	25.8392	3.2519	3.2596	3.231	3.4527
Maximum	1293.064	1378.986	1152.575	1499.753	7.3131	7.1648	7.2291	7.0498
Minimum	11.7585	0.5392	10.6142	4.934	1.5961	2.4646	-0.6177	2.3622
Std. Dev.	65.8795	65.0153	56.0917	47.0939	0.5153	0.5425	0.6027	0.5109
Skewness	11.6013	10.6917	10.3449	15.7461	1.7445	2.382	1.868	1.9315
Kurtosis	171.9408	160.301	144.0229	384.4721	9.2277	12.2122	9.1874	9.7555
CV	1.7603	1.672	1.3046	1.381	0.1548	0.1615	0.1791	0.1436
J-B	3982658	3451468	2782379	20066136	6979	14731	7155	8294
J-B *p*-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	-13.4736	-14.4815	-30.6863	-15.3856	-6.6693	-9.5956	-9.6958	-7.4436
ADF *p*-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	3287	3287	3287	3287	3287	3287	3287	3287

Notes: Prices are in dollars per megawatt-hour; J-B–Jarque-Bera test statistic; ADF–Augmented Dickey-Fuller test: H_0: unit root (non-stationary), H_1: no unit root (stationary); NSW–New South Wales, VIC–Victoria, QLD–Queensland, SA–South Australia; CV–Coefficient of variation.

Table 2. *Estimated coefficients for GARCH(1,1) conditional mean and variance equations*

	NSW			QLD			SA			VIC		
	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value
α_0	0.4565	0.0787	0.0000	0.2865	0.1055	0.0066	0.9270	0.0745	0.0000	0.6042	0.0802	0.0000
α_1	0.8063	0.061	0.0000	0.0996	0.0592	0.0928	0.0410	0.0556	0.4612	0.0817	0.0582	0.1602
α_2	0.004	0.013	0.7570	0.8062	0.035	0.0000	0.0665	0.028	0.0178	0.008	0.0185	0.6639
α_3	-0.0234	0.0177	0.1867	0.0415	0.0328	0.2066	0.6369	0.0358	0.0000	-0.0369	0.0152	0.0153
α_4	0.0777	0.0559	0.1644	-0.0356	0.0469	0.4478	-0.0033	-0.0526	0.9499	0.7671	0.0478	0.0000
β_0	0.0221	0.0075	0.0030	0.0325	0.0149	0.0298	0.0032	0.0019	0.0932	0.0056	0.0056	0.321
β_1	0.4672	0.1255	0.0002	0.6648	0.2295	0.0038	0.0615	0.0193	0.0015	0.1108	0.0559	0.0474
β_2	0.532	0.0851	0.0000	0.4119	0.1561	0.0084	0.9216	0.0278	0.0000	0.8563	0.0941	0.0000
LnL	-928.8710			-1421.2770			-1339.4030			-871.9180		
Persist	0.9992			1.0768			0.9830			0.9671		

This table provides the estimated coefficients, standard errors and *p*-values for the mean and conditional variance equations for the NSW, SA and VIC electricity markets. α_0 is the constant in the conditional mean equation, α_1 is the degree of mean spillover lagged one period with NSW, α_2 is the degree of mean spillover lagged one period with QLD, α_3 is the degree of mean spillover lagged one period with SA, α_4 is the degree of mean spillover lagged one period with VIC, β_0 is the constant in the conditional variance equation, β_1 is the ARCH coefficient, β_2 is the GARCH coefficient, LnL is the log likelihood, Persist is the degree of persistence.

Table 3. *Estimated coefficients for conditional correlations of CCC, TTDCC and EDCC models*

	CCC			TTDCC			EDCC		
	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value
$\rho_{NSW\ QLD}$	0.7428	0.0125	0.0000	0.9149	0.0135	0.0000	0.9256	0.0081	0.0000
$\rho_{NSW\ SA}$	0.655	0.0111	0.0000	0.6127	0.0309	0.0000	0.7207	0.0159	0.0000
$\rho_{NSW\ VIC}$	0.8801	0.0051	0.0000	0.8654	0.0128	0.0000	0.9099	0.0065	0.0000
$\rho_{QLD\ SA}$	0.5241	0.0127	0.0000	0.5368	0.0341	0.0000	0.6505	0.0182	0.0000
$\rho_{QLD\ VIC}$	0.6531	0.0113	0.0000	0.7597	0.0201	0.0000	0.8192	0.0109	0.0000
$\rho_{SA\ VIC}$	0.7577	0.0095	0.0000	0.7847	0.0240	0.0000	0.8516	0.0128	0.0000
df	2.6008	0.0209	0.0000	2.6703	0.0252	0.0000	2.7076	0.0260	0.0000
θ_1				0.0966	0.0190	0.0000	0.1049	0.0111	0.0000
θ_2				0.8602	0.0306	0.0000	0.8225	0.0195	0.0000
Parameters	39			41			41		
LnL	3904.15			4722.28			4661.98		
LR Test				1636.25			1515.66		
AIC	-7806.30			-9362.55			-9241.96		
SC	-7492.50			-9112.56			-8991.97		

This table provides the estimated coefficients, standard errors and *p*-values for the conditional correlations for the CCC-Constant Conditional Correlation, TTDCC-Tse and Tsui's (2002) Dynamic Conditional Correlation and EDCC-Engle's (2002) Dynamic Conditional Correlation, ρ_{ij} is the correlation between market i and market j, df is the degrees of freedom, LnL is the log likelihood, LR Test: $\theta_1 = \theta_2 = 0$ (constant correlation assumption); AIC and SIC are the Akaike Information Criterion and Schwartz Criteria, respectively.

FIGURE 2. *Time-varying conditional correlations between markets of TTDCC model*