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## **Systematic features of high-frequency volatility in Australian electricity markets: Intraday patterns, information arrival and calendar effects**

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### Abstract

This paper investigates the intraday price volatility process in four Australian wholesale electricity markets; namely New South Wales, Queensland, South Australia and Victoria. The data set consists of half-hourly electricity prices and demand volumes over the period January 1, 2002 to June 1, 2003. A range of processes including GARCH, RiskMetrics, normal Asymmetric Power ARCH or APARCH, Student APARCH and skewed Student APARCH are used to model the time-varying variance in prices and the inclusion of news arrival as proxied by the contemporaneous volume of demand, time-of-day, day-of-week and month-of-year effects as exogenous explanatory variables. The skewed Student APARCH model, which takes account of right skewed and fat tailed characteristics, produces the best results in all four markets. The results indicate significant innovation (ARCH effects) and volatility (GARCH effects) spillovers in the conditional standard deviation equation, even with market and calendar effects included. Intraday prices also exhibit significant asymmetric responses of volatility to the flow of information.

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# Systematic Features of High-Frequency Volatility in Australian Electricity Markets: Intraday Patterns, Information Arrival and Calendar Effects

*Helen Higgs\* and Andrew C. Worthington\*\**

*This paper investigates the intraday price volatility process in four Australian wholesale electricity markets; namely New South Wales, Queensland, South Australia and Victoria. The data set consists of half-hourly electricity prices and demand volumes over the period January 1, 2002 to June 1, 2003. A range of processes including GARCH, RiskMetrics, normal Asymmetric Power ARCH or APARCH, Student APARCH and skewed Student APARCH are used to model the time-varying variance in prices and the inclusion of news arrival as proxied by the contemporaneous volume of demand, time-of-day, day-of-week and month-of-year effects as exogenous explanatory variables. The skewed Student APARCH model, which takes account of right skewed and fat tailed characteristics, produces the best results in all four markets. The results indicate significant innovation (ARCH effects) and volatility (GARCH effects) spillovers in the conditional standard deviation equation, even with market and calendar effects included. Intraday prices also exhibit significant asymmetric responses of volatility to the flow of information.*

## **INTRODUCTION**

Australia has been at the forefront of global efforts to introduce competition into the electricity industry. Where electricity was once supplied by state government-owned entities, the market is now characterized by separation of the generation, transmission and distribution functions across commercialized and privatized companies. The ongoing process of restructuring and deregulation has already gone far in promoting a competitive national electricity market in Australia. And on the whole, the spot markets integral to this restructuring process have achieved the key objective of lowering the wholesale price of electricity. But while lower prices for electricity are an encouraging sign, they have been accompanied by higher price volatility.

The prospect that this increased volatility will persist and likely increase in the future is a matter of interest to market participants. When prices are volatile there can be uncertainty about generators' revenues and suppliers' costs. Measures of risk are equally important to those managing energy commodity portfolios. Similarly, for those valuing derivatives, forecasts of volatilities over

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the life of an instrument are required, while extreme observations imply changes to option values. Value-at-risk calculations can also benefit from a more thorough knowledge of price variance. Lastly, higher price volatility is a concern for industry regulators and market management companies because of unease that it may be, at least partly, an outcome of regulatory failure associated with inadequacies in market design and the exercise of market power.

All the same, it is accepted that the inherent characteristics of these newly competitive electricity markets also have a role to play in the higher observed price volatility. Given the non-storability of electricity, higher-than-expected demand, poorly developed transmission networks, changes in purchasing and contracting behavior, inappropriately designed market mechanisms, market power and information asymmetry, among others, can provide a load-matching problem so that electricity shows seasonal, week-day and even intraday patterns in price level and volatility. Any satisfactory explanation of price volatility in electricity markets must be able to accommodate these striking empirical regularities.

It is also necessary to take into account the pronounced volatility clustering observed in these markets. Autoregressive conditional heteroscedasticity (ARCH) models allow volatility shocks to cluster and persist over time and to revert to some more normal level and so may offer potentially interesting insights on the volatility observed in electricity markets. Unfortunately, few ARCH-type studies of electricity prices have been undertaken in Australia or elsewhere [for exceptions see Escibano et al. (2002), Solibakke (2002) and Worthington et al. (2005) for spot prices and Walls (1999) for futures prices], and as far as the authors are aware, none which attempt to capture the arrival of intraday information effects

Accordingly, the purpose of this paper is to investigate the intraday price volatility process in Australian electricity markets by employing five different ARCH processes: namely, GARCH (generalised ARCH), RiskMetrics (normal integrated GARCH), normal APARCH (asymmetric power ARCH), Student APARCH and skewed Student APARCH (following Ding et al. 1993; and Giot and Laurent, 2003a, 2003b). By including systematic features – intraday, interday and monthly patterns (calendar effects), intraday innovation and volatility spillovers (ARCH and GARCH effects) and market activity (demand and information asymmetry effects) – such an approach provides a comprehensive characterization of the volatility process. It thereby provides both a starting point for understanding the intrinsic price volatility in electricity markets, distinguishing it from changes in volatility that are thought to arise, say, from regulatory design and the exercise of market power. The remainder of the paper is divided into four sections. The second section explains the data employed in the analysis and presents some brief descriptive statistics. The third section

discusses the methodology employed. The results are dealt with in the fourth section. The paper ends with some brief concluding remarks in the final section.

## **DATA AND DESCRIPTIVE STATISTICS**

In brief, the Australian National Electricity Market (NEM) encompasses the four state-based regional markets of New South Wales (NSW), Queensland (QLD), South Australia (SA) and Victoria (VIC) operating as an interconnected grid coordinated by the National Electricity Market Management Company (NEMMCO). For the most part these regional markets operate separately because while power can be transmitted between regions, it is very much constrained by the physical transfer capacity of the regional interconnectors. In each market, generators are required to submit bidding schedules on a half-hourly day-before basis. Matching expected demand in the next five minutes against the bid stack for that half-hour period sets prices and the price offered by the last generator (plant are dispatched on a least-cost basis) to meet total demand sets the five-minute price. The pool price is the time-weighted average of the six five-minute periods comprising each half-hour trading period. This is the price generators receive for the electricity they dispatch into the pool, and is the price customers pay to receive generation in that half hour period [for details see Dickson and Warr (2000), IEA (2001) and NEMMCO (2001, 2003)].

The data employed in the study consists of electricity prices and demand volumes for the half-hourly intervals from January 1, 2002 to June 1, 2003 for each of the four wholesale electricity markets. All data is obtained from NEMMCO on a half-hourly basis representing 48 trading intervals in each 24-hour period (NEMMCO, 2003). The prices are in Australian dollars per megawatt hour (MWh). By way of comparison, De Vany and Walls (1999a; 1999b), Robinson (2000), Wolak (2000), Lucia and Schwartz (2001), Escribano et al. (2002), Solibakke (2002) and Worthington et al. (2005) employ daily 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. The natural log of the price for each half-hourly interval is used to produce a time series of price relatives, such that  $p_t = \log(g_t/g_{t-1}) \times 100$  where  $g_t$  and  $g_{t-1}$  represent the half-hourly pool generation prices at time  $t$  and  $t-1$ , respectively.

<TABLE 1 HERE>

Table 1 presents the summary of descriptive statistics of the price relatives for the four electricity markets. Sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis and the Jarque-Bera (JB) statistic are reported. The table shows that while the price

relatives in all four markets are very small, the maximum, minimum and standard deviation of price relatives indicate much variability. The highest average price relatives are in QLD and VIC, while the greatest positive price relatives are in QLD and VIC with the largest negative price relatives in NSW and SA. The standard deviations of price relatives range from 22.4033 (NSW) to 29.4379 (QLD). For the four markets, the coefficient of variation shows VIC to be the most variable while NSW is the least variable.

<FIGURE 1 HERE>

The distributional properties of the price relative series appear non-normal. All of the markets are significantly positively skewed ranging from 0.2788 (SA) to 1.0585 (VIC) indicating the greater likelihood of large price increases than price falls. The kurtosis, or degree of excess, is also large, ranging from 76.4694 for SA to 84.3674 for NSW, thereby indicating leptokurtic or heavy-tailed distributions with many extreme observations. The calculated Jarque-Bera statistic and corresponding  $p$ -value in Table 1 is used to test the null hypotheses that the intraday distribution of price relatives is normally distributed. All  $p$ -values are smaller than the 0.01 level of significance indicating the null hypothesis is rejected. These intraday price relatives are then not well approximated by the normal distribution. One means of accommodating such non-normality is the use of the ARCH-type volatility models. Visual inspection of the price relative series in Figure 1 is also suggestive of the volatility clustering expected in these markets.

## MODEL SPECIFICATION

The distributional properties of Australian spot electricity prices indicate that generalized autoregressive conditional heteroscedastic (GARCH) models can be used to examine the dynamics of the electricity price volatility process. Autoregressive conditional heteroscedasticity (ARCH) models [as introduced by Engle (1982)], generalized ARCH (GARCH) models [as proposed by Bollerslev (1986)] and asymmetric power ARCH (APARCH) introduced by Ding et al. (1993) that take into account the time-varying variances of time series data have already been widely employed in financial markets. Suitable surveys of ARCH modeling in general and/or its widespread use may be found in Bera and Higgins (1993) and Bollerslev et al. (1992). Ding et al. (1993), Pagan (1996), Giot and Laurent (2003a, 2003b) and Laurent (2004) also discuss developments in this ever-expanding literature.

To start with, a basic requirement is to remove the predictable component of the electricity price relatives so as to produce price relative 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 half-hourly price relatives is to assume that they follow an AR(1) process:

$$p_t = \tau_0 + \tau_1 p_{t-1} + e_t \quad (1)$$

where  $p_t$  is the price relative for each electricity market in the current period and  $p_{t-1}$  is the price relative lagged one period,  $\tau_0$  represents the long-term drift coefficient and  $\tau_1$  is the degree of mean spillover effect across time, or put differently, the extent to which the lagged price relative can be used to predict the current price relative, and  $e_t$  is the random error or innovation at time  $t$ .

The next requirement is to model the variance of the price relative innovation process. A GARCH process of order 1 and 1, denoted as GARCH(1,1), for the random error term,  $e_t$ , is specified as:

$$e_t = h_t \varepsilon_t \quad \varepsilon_t \sim iid N(0,1) \quad (2)$$

with

$$h_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 h_{t-1}^2 \quad (3)$$

where  $h_t$  is the conditional standard deviation of volatility of  $e_t$  at time  $t$ ,  $\alpha_0$  is a constant,  $\alpha_1$  and  $\beta_1$  are coefficients that are associated with the degree of innovation from previous period,  $e_{t-1}^2$  (ARCH term) and previous period's volatility spillover effects,  $h_{t-1}^2$  (GARCH term) respectively.

A concern with the volatility generation process as defined is that current volatility is only related to the past values of innovation and volatility spillovers from previous periods. For example, Lamoureux and Lastrapes (1990) Engle and Ng (1993), Foster (1995), Andersen (1996), Andersen and Bollerslev (1997, 1998), Wang and Yau (2000) and Rahman et al. (2002), amongst others, argue that an appealing explanation for the presence of GARCH effects in financial markets is that the rate and timing of information arrival is the stochastic mixing variable that generates financial market returns. That is, market information, however defined, is strongly correlated with price volatility (Andersen and Bollerslev 1998). It is also likely that some important electricity market information is reflected in the time-of-day, day-of-week and month-of-year in much the same manner. In this paper, and with the high-frequency data used, it is hypothesized that at least some relevant information is included in the contemporaneous volume of demand, the direction of price relatives and the time-of-day, week and month. Solibakke (2002), for example, found that price volatility in the Nordic spot electricity market increased strongly on Mondays and Saturdays and was especially strong during May, June and July. Herbert (2002: 34) also presented evidence that "...there is seasonality in (electricity) price risk. Not surprisingly, price risk increases in the

summer...power prices also increase in the winter". And Hadsell et al. (2004) found that volatility behavior differed by month across five US electricity markets.

The next methodological requirement, then, is to include such information effects in the volatility model. The conditional variance equation, rather than the conditional mean equation, should take account of the time-varying conditional heteroscedasticity caused by changes in the contemporaneous volume of demand and seasonal and random fluctuations since the variance measures the risk generated by new information. For example, Hadsell et al. (2004) included monthly dummies in the conditional variance equation describing US electricity markets, while Rahman et al. (2002) introduced contemporaneous and lagged volume of demand and bid-ask spread in the conditional variance equation describing US financial markets. Five different GARCH volatility processes, namely GARCH, RiskMetrics, normal APARCH, Student APARCH and skewed Student APARCH models are employed, all of which include information effects as defined, but vary according to the assumed distribution of the random error term and/or the conditional standard deviation equation.

To start with, and to take account of the incidence of the time varying conditional heteroscedasticity that could be due to an increase in market information in the form of the contemporaneous volume of demand and time-of-day, day-of-week and month-of-year effects following the simultaneous arrival of new information, the random error term,  $e_t$  as previously defined in (2) and the GARCH conditional variance equation in (3) is reformulated as:

$$h_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 h_{t-1}^2 + \psi_1 v_t + \sum_{i=2}^{48} \varphi_i d_i + \sum_{i=2}^7 \eta_i w_i + \sum_{i=2}^{12} \zeta_i m_i \quad (4)$$

where  $v_t$  represents the contemporaneous volume of demand,  $d_i$  are dummy variables for the time-of-day having values of one for the second half hour  $d_2$  (0:30-1:00 hours) and zero otherwise, having values of one for the third half hour  $d_3$  (1:00-1.30 hours) and zero otherwise, ...having values of one for the last half hour  $d_{48}$  (23.30-24.00) and zero otherwise;  $w_i$  are dummy variables for each day of the week having values of one for  $w_2$  (Tuesday) and zero otherwise, having values of one for  $w_3$  (Wednesday) and zero otherwise, ...having values of one for  $w_7$  (Sunday) and zero otherwise;  $m_i$  are dummy variables for each month of the year having values of one for  $m_2$  (February) and zero otherwise, having values of one for  $m_3$  (March) and zero otherwise, ...having values of one for  $m_{12}$  (December) and zero otherwise, and  $\varphi_i$ ,  $\eta_i$  and  $\zeta_i$  are coefficients. The midnight half-hour, Monday and January are the reference categories in the calendar effects and all other variables are as previously defined.

Second, the RiskMetrics model is equivalent to a normal integrated GARCH (IGARCH) model where the autoregressive parameter of the conditional variance equation is preset to a

specified value of  $\lambda = 0.94$  and the parameter of the squared random error or innovation term is  $1-\lambda$ . The RiskMetrics model has the random error term,  $e_t$ , as specified in (2) and the conditional variance equation in (4) is reformulated as:

$$h_t^2 = \alpha_0 + (1-\lambda)e_{t-1}^2 + \lambda h_{t-1}^2 + \psi_1 v_t + \sum_{i=2}^{48} \varphi_i d_i + \sum_{i=2}^7 \eta_i w_i + \sum_{i=2}^{12} \zeta_i m_i \quad (5)$$

The RiskMetrics model is a special case of the GARCH model with  $(1-\lambda) = \alpha_1$  and  $\lambda = \beta_1$  and is then more limited in its ability to capture price spikes than the GARCH model.

Third, the normal APARCH model (Ding et al. 1993) is yet another extension of the GARCH model (Bollerslev 1986). In the normal APARCH the random error term,  $e_t$ , is specified as in (2) and the conditional standard deviation,  $h_t$ , in (4) is respecified as:

$$h_t^\delta = \alpha_0 + \alpha_1(|e_{t-1}| - \gamma_1 e_{t-1})^\delta + \beta_1 h_{t-1}^\delta + \psi_1 v_t + \sum_{i=2}^{48} \varphi_i d_i + \sum_{i=2}^7 \eta_i w_i + \sum_{i=2}^{12} \zeta_i m_i \quad (6)$$

where  $\alpha_0 > 0$ ,  $\alpha_1$ ,  $\beta_1$  and  $\delta \geq 0$  and  $-1 < \gamma_1 < 1$  are parameters to be estimated and all other variables are as previously defined. This model introduces a non-linear relationship between the conditional standard deviation and the lagged and lagged absolute random errors by imposing a Box-Cox transformation,  $\delta$  ( $\delta > 0$ ). The asymmetric volatility response to negative and positive shocks such that volatility tends rise in response to ‘bad news’ and fall in response to ‘good news’ is reflected in a positive value of the parameter  $\gamma_1$ . This APARCH process encompasses Bollerslev’s (1986) GARCH with  $\delta = 2$  and  $\gamma_1 = 0$ , the Taylor (1986)/Schwert (1990) model with  $\delta = 1$  and  $\gamma_1 = 0$  and five other GARCH processes (Ding et al. 1993).

Fourth, the Student APARCH model is an extension of the normal APARCH model (Ding et al. 1993). The Student APARCH is introduced to take account of the fat-tailed characteristic of Australian electricity markets (Bauwens and Giot, 2001, Alexander, 2001 and Giot and Laurent, 2003a and 2003b). The Student APARCH where the random error term is defined as  $e_t = h_t \varepsilon_t$  and  $\varepsilon_t \sim iid t(0, 1, \nu)$  and  $\nu$  is the degrees of freedom and the conditional standard deviation,  $h_t$ , is as previously defined in (6).

Finally, the skewed Student APARCH model is re-formulated by Lambert and Laurent (2001) with the skewed Student density expressed in terms of the mean and variance and the random error term is specified as  $e_t = h_t \varepsilon_t$  and  $\varepsilon_t$  is *iid* SKST(0, 1,  $\xi$ ,  $\nu$ ) ie the standardized skewed Student distribution and  $\xi$  is the asymmetric coefficient of the Student distribution. The conditional standard deviation of the skewed Student APARCH model is defined in (6). The sign of the distributional asymmetry coefficient or third moment,  $\xi$ , represents the direct of skewness. If the third moment is

positive (negative) then the density is skewed to the right (left). Full specifications of the APARCH models are presented in Giot and Laurent (2003a, 2003b).

## EMPIRICAL RESULTS

The estimated coefficients, standard errors and  $p$ -values for the conditional mean and variance equations for the five different GARCH processes are presented in Table 2. All of these models include the impact of news arrival as proxied by the contemporaneous volume of demand, time-of-day, day-of-week and month-of year (calendar) effects as exogenous variables in the conditional variance equation. However, due to the very large number of estimated calendar effects, the tabled conditional variance equations do not include all coefficients, but these are graphically represented. In brief, on the basis of the log-likelihood, Akaike Information (AIC) and Schwartz Criteria (SC), the skewed Student APARCH is the best model for all four markets. Clearly, this process has the ability to accommodate the skewed and fat-tailed or non-normal characteristics of Australian electricity markets. Only the skewed Student APARCH model is used to provide graphical representations of the calendar effects in Figures 2-4. All results are obtained using G@ARCH 3.0 an Ox package for estimating different ARCH models (Laurent and Peters, 2002).

<TABLE 2 HERE>

To start with, the estimated coefficients, standard errors and  $p$ -values for the conditional mean return equations ( $\tau_0$  and  $\tau_1$ ) for the GARCH model are presented in the uppermost panel of Table 2. All electricity markets exhibit a significant own mean spillover from their own lagged price relative ( $\tau_1$ ). In all cases, the mean spillovers are positive ranging from 0.1570 (QLD) to 0.1722 (NSW). The uppermost panel of Table 2 also presents the estimated coefficients, standard errors and  $p$ -values for the conditional variance equation. The own-innovation or ARCH spillovers ( $\alpha_1$ ) in all four markets are significant indicating the presence of significant ARCH effects, while the lagged volatility or GARCH spillovers ( $\beta_1$ ) are also significant and larger in magnitude. The respective innovation and volatility spillovers are 0.4319 and 0.5345 in the NSW market, 0.1607 and 0.8803 in the QLD market, 0.3913 and 0.6751 in the SA market and 0.0485 and 0.9473 in the VIC market respectively. The sum of the ARCH and GARCH effects is greater than one in the QLD and SA markets, suggesting that the shocks are permanent, while the values of less than one in the NSW and VIC markets implies a mean reverting conditional volatility process. That is, the shocks are transitory in nature. It should be noted that NSW and VIC are the largest, longest-established and most competitive markets among all Australian electricity markets.

The uppermost panel of Table 2 also includes the estimated coefficients and standard errors for the variable used to proxy the arrival of new information; that is, the contemporaneous volume of demand ( $\psi_1$ ). There is a significant positive relationship between price relative volatility and contemporaneous volume of demand for all four markets ranging from 0.0616 (VIC) to 0.4063 (NSW). This would suggest that the arrival of new information in the form of the volume of demand has the role of increasing price volatility. The Ljung-Box Q-statistics,  $Q^2(10)$ , and  $p$ -values are computed on the squared standardized residuals to test the null hypothesis that there is no remaining heteroscedasticity. The significance of the Ljung-Box Q-statistics in SA and VIC for the GARCH model implies that some residual heteroscedasticity remains in these markets.

The next-to-uppermost panel of Table 2 provides the estimated coefficients, standard errors and  $p$ -values for the RiskMetrics model. The magnitude and significance of the estimated RiskMetrics parameters are very similar to that of the GARCH process with the exception that the innovation and volatility spillover effects sum to one. The significance of the Ljung-Box Q-statistics in all markets for the RiskMetrics model once again suggests that this process has not overcome the problem of heteroscedasticity. Of course, it is well known that the RiskMetrics process can model the volatility clustering but not the non-normal characteristics of many time series. The middlemost panel of Table 2 presents the estimated parameters for the normal APARCH model. Once again, all markets exhibit a significant own mean spillover from their own lagged price relative ( $\tau_1$ ) with the mean spillovers ranging from 0.1664 (QLD) to 0.2596 (VIC). The innovation and volatility spillovers are significant with the volatility spillovers generally larger in magnitude. The respective innovation and volatility spillovers are 0.3630 and 0.3676 for NSW to 0.3081 to 0.6606 for SA. There is also a significant positive relationship between price relative volatility and contemporaneous volume of demand for all four markets ranging from 0.0835 (QLD) to 0.4061 (NSW).

The asymmetric volatility response ( $\gamma_1$ ) in the normal APARCH model is negative and significant for all four markets indicating an asymmetric response for positive price relatives in the conditional standard deviation equation and reflects the condition that volatility tends rise in response to ‘good news or positive spikes’ and fall in response to ‘bad news or negative spikes’. This lies counter to the usual expectation in stock markets where downward movements (falling returns) are followed by higher volatility than upward movements (increasing returns). The power coefficients ( $\delta$ ) of the standard deviation process are significant for all markets ranging from 1.0365 (QLD) to 1.5556 (NSW). These coefficients are significantly different from two and one indicating it is more relevant to model the conditional standard deviation of electricity markets in a non-linear

form. However, the Ljung-Box Q-statistics calculated on the squared standardized residuals are still significant for the NSW, SA and VIC markets indicating that this model has still not eliminated the problem of heteroscedasticity.

The next-to-lowermost panel of Table presents the estimated parameters for the Student APARCH model. Here, the mean spillovers are significant for all four markets, range from 0.1462 (QLD) to 0.3092 (VIC). The innovation and volatility spillovers are also significant across the four markets with the volatility spillovers greater in magnitude than the innovation spillovers. There is a significant positive relationship between the contemporaneous volume of demand and volatility for all markets. Once again, and in contrast to many stock markets, the asymmetric volatility response ( $\gamma_1$ ) is negative and significant for all markets indicating an asymmetric response for positive price relatives in the conditional standard deviation equation, i.e. volatility rises in response to ‘good news or positive spikes’ and falls in response to ‘bad news or negative spikes’. The power coefficients ( $\delta$ ) of the standard deviation process are also significant for all markets ranging from 1.0191 (VIC) to 1.6070 (NSW). As before, a non-linear conditional standard deviation equation is required. The tail coefficients ( $\nu$ ) are also significant and together with the insignificance of the Ljung-Box Q-statistics for the squared standardized residuals in all markets indicate that the Student distribution has taken account of the fat tailed and heteroscedastic characteristics of the electricity price relative series.

Finally, the lowermost panel of Table 2 presents the estimated coefficients, standard errors and p-values for the skewed Student model. All markets are shown to exhibit a significant own mean spillover from their own lagged price relative ( $\tau_1$ ). In all cases, the mean spillovers are positive ranging from 0.1811 (SA) to 0.2462 (VIC). Put differently, according to the skewed Student APARCH model, a ten percent increase in the VIC electricity price in the current period Granger causes an increase of 2.462 percent over the next half-hour. Likewise, a ten percent increase in prices for SA will Granger cause a 1.811 percent increase over the next half-hour. The own-innovation ( $\alpha_1$ ) in all four markets is also significant indicating the presence of significant ARCH effects. The lagged volatility or GARCH spillovers ( $\beta_1$ ) are also significant. For the skewed Student APARCH specification, the ARCH effects are larger in magnitude than the GARCH effects in the NSW (0.4376 and 0.3677) and VIC (0.5761 and 0.3057) markets while the reverse is true for QLD (0.3858 and 0.4337) and SA (0.2530 and 0.5422). This implies that for NSW and VIC the last period’s volatility shocks in electricity price relatives have a lesser effect on its future volatility than the memory of previous surprises or innovations. This is comparable to the only known study

(though using daily data) by Solibakke (2002) which discovered “...high past shock effects (ARCH) and rather low past volatility effects (GARCH)”.

The estimated coefficients for  $\psi_1$  indicates a significant positive relationship between price relative volatility and the contemporaneous volume of demand for all four markets ranging from 0.0621 (VIC) and 0.2605 (SA). This would suggest that the role of new information in the form of demand load has a greater role of increasing price relative volatility in the SA market than any other market. The estimated asymmetric volatility response coefficients to market news ( $\gamma_1$ ) in the skewed Student model are significant and negative for all markets. This lies counter to the results of the Student APARCH model. But by way of comparison, Solibakke (2002: 28) found “...insignificant asymmetric volatility coefficient for all specifications in the (Nordic) spot market suggesting equal reaction patterns to positive and negative shocks” while Hadsell et al. (2004) estimated that the asymmetric effect was also significant and negative thus capturing a strong market response to ‘negative’ news in US electricity markets when employing a Threshold ARCH model.

The power coefficient ( $\delta$ ) of the standard deviation process for VIC is significantly different from one, while the power coefficients for NSW, SA and QLD are all significantly different from two and one, thus indicating it is more appropriate to model a non-linear conditional standard deviation equation. The asymmetric coefficients ( $\xi$ ) are positive and significant for the markets and range from 0.0703 (NSW) to 0.1036 (SA). The positive asymmetry coefficients represent the price relative series are skewed to the right. The tail coefficients ( $\nu$ ) in the skewed Student APARCH specification are also significant for the four markets representing that the skewed Student distribution has again taken account of the fat right-skewed characteristic of all series. The insignificance of the Ljung-Box Q-statistics on the squared standardized residuals for the four markets would indicate that the skewed Student distribution (like the Student APARCH) has overcome the problem of heteroscedasticity in the series.

Figures 2 to 4 depict the volatility effects of the arrival of new information for the time-of-day ( $\phi_i$ ), day-of-week ( $\eta_i$ ) and month-of-year ( $\zeta_i$ ) effects in the skewed Student APARCH model. Tests in Table 3 of the null hypotheses that all time-of-day coefficients (not shown) are jointly zero reject the null hypotheses at the 0.10 level or lower in three markets with the exception of the NSW market, indicating that the time-of-day has a systematic influence on electricity price volatility in Australia. Some interesting patterns are illustrated in Figure 2, with price volatility increasing from midnight and reaching a maximum between 5:30 and 7:30, falling and increasing again until another maximum is reached between 17:00 and 18:30 and then falling again and peaking again between 21:30 to 23:00. The day-of-week effects are depicted in Figure 3. Hypothesis tests of joint

insignificance are likewise rejected with the exception of the SA market. Volatility in the QLD and SA markets is shown to be highest on Monday, falling progressively through the week. In the NSW market, however, volatility increases during the week and falls over the weekend. Volatility is lowest on Wednesday in SA, on Friday in QLD and VIC and on Saturday in NSW.

<TABLE 3 HERE>

The month-of-year volatility effects as estimated by the skewed Student APARCH process are presented in Figure 4. Joint tests for month-of-year effects in Table 3 are once again significant for all four markets. A familiar price volatility pattern emerges with volatility being highest in June, July and August (winter) and December and January (summer). By way of comparison, Solibakke's (2002) analysis of the Nordic spot electricity market also indicated that peaks in price volatility corresponded with peak demand, though just in summer. However, Hadsell et al. (2004) found that while calendar months exhibited different volatility behavior in US electricity markets, none was unique with respect to magnitude or volatility. The month-of-year effects are also jointly significant in explaining price relative volatility in the four markets.

<FIGURES 2-4 HERE>

In summary, and according to all five models, all four markets exhibit a significant own mean spillover from their own lagged price relative ( $\tau_1$ ). In all cases, the mean spillovers are positive. The own-innovation or ARCH spillovers ( $\alpha_1$ ) are also all significant indicating the presence of strong ARCH effects, while the lagged volatility or GARCH spillovers ( $\beta_1$ ) are also significant and larger in magnitude for the first four models. In the skewed Student APARCH models for QLD and SA the GARCH effects are also larger, but the reverse is true for NSW and VIC. In most cases, the power coefficients ( $\delta$ ) of the standard deviation processes are all positive and significantly different from one and two, thus indicating it is more relevant to model the conditional standard deviation in a non-linear form. The asymmetric coefficients of the Student distribution ( $\xi$ ) are positive and significant for the four markets indicating the price relative series are skewed to the right, and the estimated coefficients for news arrival denoted by the contemporaneous volume of demand are all positive and significant thus implying that increases in demand increase price volatility.

Finally, the three APARCH models indicate that the estimated asymmetric coefficients ( $\gamma_1$ ) are significant and negative for all four markets indicating that positive shocks (good news) are associated with higher volatility than negative shocks (bad news). This certainly lies counter to the prevailing stock market evidence and does open the issue whether the essential difference between the two markets is not market power. Stock markets are commonly regarded as competitive,

meaning many players are caught short by crashes (negative ‘price relatives’) and so there are disturbed periods of trading until non-strategic players find some new anchor. By contrast, electricity markets have relatively few players, many with market power and greater strategic options. Unexpected price falls can then quickly be dealt with from the supply side by, say, cutting back offers of generation. Players also hold shared expectations of the longer-run price at which the spot price is then expected to settle following such manipulation. On the other hand, upward price spikes occur for two main reasons: unforeseen contingencies or a strategic move by one or more key players. In either case, the strategic response is likely to generate greater volatility in subsequent periods precisely because there are positive rents created by the price spikes for which players compete.

## **CONCLUDING REMARKS**

This study presents an analysis of intraday 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 January 1, 2002 to June 1, 2003. Five different GARCH volatility processes consisting of the GARCH, RiskMetrics, normal, Student and skewed Student APARCH models are estimated. The results indicate that intraday price volatility in all four Australian electricity markets is best described by an asymmetric skewed Student APARCH specification. This accommodates both the right-skewed, fat-tailed properties of the observed data and the contemporaneous volume of demand, time-of-day, day-of-week and month-of-year effects as proxies for the arrival of new market information. In sum, an increase in the volume of demand, positive price spikes, early-morning, late afternoon and early evening hours, Mondays and peak winter and summer months are all associated with significantly higher volatility than low demand volumes, negative price spikes and other times of the day, week and year. This suggests that systematic influences on electricity price volatility can be easily quantified from readily available market information.

However, the market, information and calendar effects examined are at best only a partial explanation for the price volatility found in Australian electricity markets. Fortunately, other influences have been put forward and these provide fruitful avenues for further research, especially building upon the range of GARCH models used in this study. One distinct possibility is market power. Robinson and Baniak (2002), for example, have argued that generators with market power might have the incentive to create volatility in the spot market in order to benefit from higher risk premiums in the contract market. Proxying changes in the competitive environment may then be

able to provide empirical evidence whether competition increases or decreases price volatility. Another potential factor affecting volatility is regulatory change. Robinson and Taylor (1998a, 1998b), for example, have linked changes in regulation and regulatory risk with regional electricity company shares in the United Kingdom and it is feasible that changes in regulatory regimes could be included as exogenous factors in a study of electricity prices more directly.

Similarly, changes in purchasing or contracting behavior by large purchasers of electricity may also have an influence on price volatility. Smith (2003), for instance, argues that the US spot electricity markets lost much of their volatility as large consumers, like California, moved out of electricity purchases to long-term contracts. Finally, there is the prospect to examine volatility interactions between geographically close and linked markets using variants of the GARCH models used in the current analysis. For example, Herbert (2002) discusses the interactions between the electricity and gas markets as substitutable sources of energy. Worthington et al. (2005) examine the volatility interactions between regional electricity markets, though using only basic GARCH models with no allowance for systematic influences on electricity price volatility.

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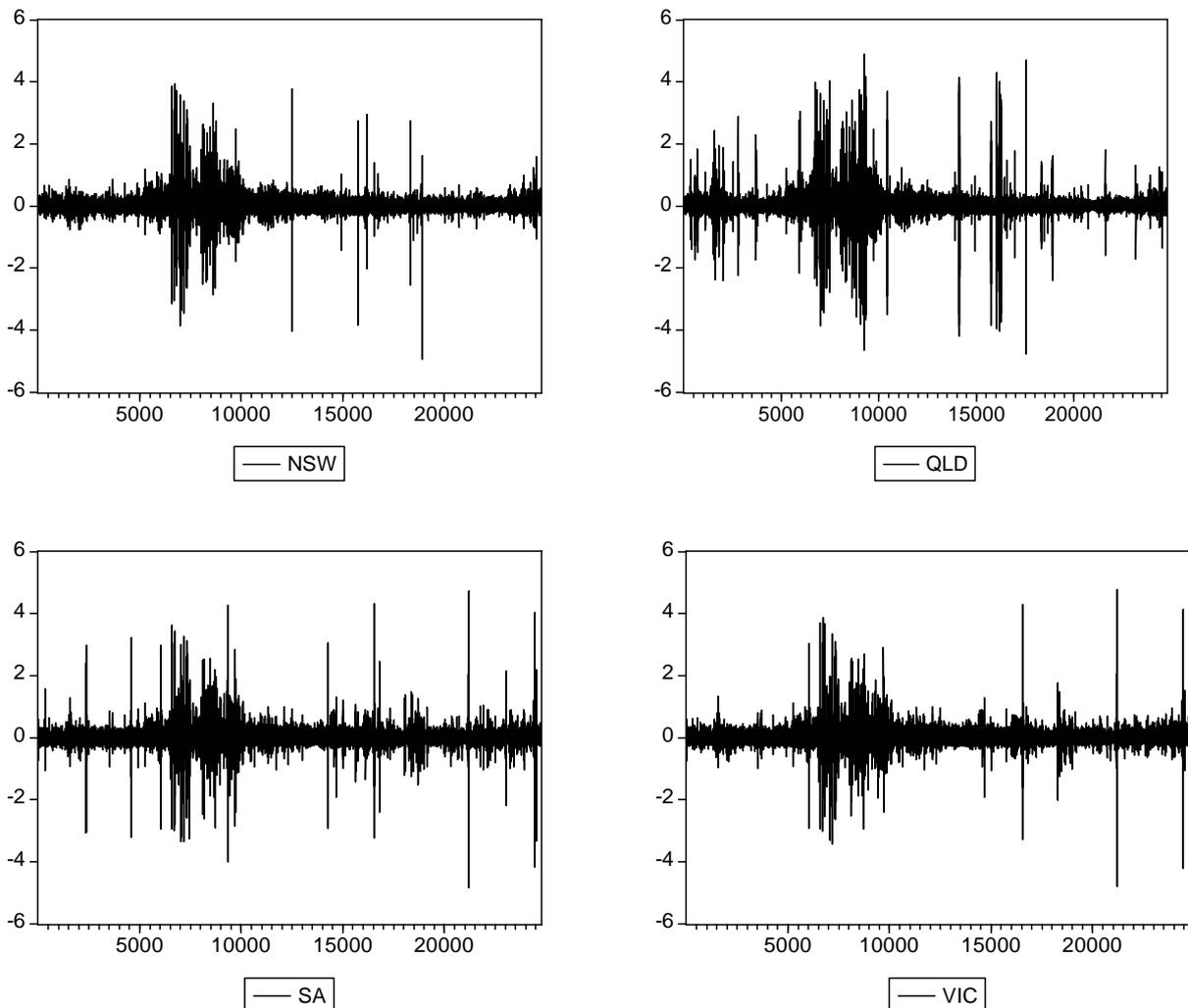
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**Table 1. Descriptive Statistics for Price Relatives by Market**

	NSW	QLD	SA	VIC
Observations	24767	24767	24767	24767
Mean	-8.69E-04	-1.08E-03	-8.98E-04	-8.03E-04
Median	-0.5786	-0.6237	-0.1833	-0.7168
Maximum	394.2530	489.1307	472.6716	477.6408
Minimum	-494.5365	-476.5178	-483.8354	-479.5675
Standard deviation	22.4033	29.4379	24.3649	22.5804
CV	2.58E+04	2.72E+04	2.71E+04	2.81E+04
Skewness	0.5556	0.6545	0.2788	1.0585
Kurtosis	84.3674	80.5308	76.4694	77.9228
Jarque-Bera statistic	6.83E+06	6.20E+06	5.57E+06	5.80E+06
JB <i>p</i> -value	0.0000	0.0000	0.0000	0.0000

This table provides measures of central tendency, dispersion and shape for the changes in the half-hourly spot prices for NSW - New South Wales, QLD - Queensland, SA - South Australia and VIC - Victoria. The sample period is from 1 January 2002 to 1 June 2003. The critical values of significance for skewness and kurtosis at the .05 level are 0.0305 and 0.0610, respectively. CV - Coefficient of Variation. JB - Jarque-Bera.

**Figure 1. Price Relatives by Market (y-axis), January 1, 2002 to June 1, 2003 (x-axis)**



**Table 2. Estimated Coefficients for Conditional Mean Price Relative and Variance Equations**

	NSW			QLD			SA			VIC		
	Coefficient	Std. error	p-value									
<b>GARCH</b>												
$\tau_0$	-0.7950	0.0844	0.0000	0.0059	0.1325	0.9644	-0.3086	0.0912	0.0007	0.0448	0.1148	0.6966
$\tau_1$	0.1722	0.0052	0.0000	0.1570	0.0059	0.0000	0.1706	0.0054	0.0000	0.1606	0.0053	0.0000
$\alpha_0$	-2.0587	13.4810	0.8786	0.0515	31.6030	0.9987	2.2818	9.3900	0.8080	-0.3828	24.1760	0.9874
$\alpha_1$	0.4319	0.0050	0.0000	0.1607	0.0014	0.0000	0.3913	0.0028	0.0000	0.0485	0.0007	0.0000
$\beta_1$	0.5345	0.0041	0.0000	0.8803	0.0005	0.0000	0.6751	0.0020	0.0000	0.9473	0.0005	0.0000
$\psi_1$	0.4063	0.0433	0.0000	0.1265	0.0574	0.0276	0.1497	0.0126	0.0000	0.0616	0.0109	0.0000
LL	-100790			-108259			-104932			-105934		
AIC	8.1447			8.7479			8.5482			8.5601		
SC	8.1676			8.7708			8.5713			8.5831		
$Q^2(10)$	4.9288		0.7652	12.8316		0.1178	97.0253		0.0000	179.1110		0.0000
<b>RiskMetrics</b>												
$\tau_0$	0.0105	0.1545	0.9458	0.0100	0.1151	0.9307	-0.3727	0.0908	0.0000	0.0102	0.1333	0.9392
$\tau_1$	0.1215	0.0055	0.0000	0.0153	0.0048	0.0016	0.1879	0.0050	0.0000	0.0302	0.0057	0.0000
$\alpha_0$	0.0500	25.3560	0.9984	0.0507	21.0750	0.0024	3.5282	4.7641	0.4590	0.0507	24.1960	0.9983
$\alpha_1$	0.0529	0.0005	0.0000	0.0574	0.0003	0.0000	0.2589	0.0017	0.0000	0.0504	0.0005	0.0000
$\beta_1$	0.9471			0.9426			0.7411			0.9496		
$\psi_1$	0.0468	0.0198	0.0182	0.0494	0.0260	0.0572	0.9336	0.0959	0.0000	0.0485	0.0251	0.0531
LL	-104917			-108631			-105092			-107379		
AIC	8.4779			8.7778			8.5611			8.6767		
SC	8.5005			8.8004			8.5836			8.6993		
$Q^2(10)$	128.8050		0.0000	26.4380		0.0009	20.3747		0.0090	114.7580		0.0000
<b>Normal APARCH</b>												
$\tau_0$	-0.4153	0.0940	0.0000	-0.9534	0.0686	0.0000	-0.0214	0.0814	0.7930	-0.9319	0.0890	0.0000
$\tau_1$	0.2253	0.0062	0.0000	0.1664	0.0043	0.0000	0.1828	0.0057	0.0000	0.2596	0.0057	0.0000
$\alpha_0$	-8.8317	5.6310	0.1168	-2.7865	1.0742	0.0095	2.5766	1.8487	0.1634	0.9629	2.5855	0.7096
$\alpha_1$	0.3630	0.0064	0.0000	0.3261	0.0038	0.0000	0.3081	0.0029	0.0000	0.3315	0.0041	0.0000
$\beta_1$	0.3676	0.0060	0.0000	0.5930	0.0037	0.0000	0.6606	0.0035	0.0000	0.4659	0.0061	0.0000
$\psi_1$	0.4061	0.0351	0.0000	0.0835	0.0061	0.0000	0.2094	0.0156	0.0000	0.1188	0.0092	0.0000
$\gamma_1$	-0.5471	0.0109	0.0000	-0.6359	0.0081	0.0000	-0.2936	0.0076	0.0000	-0.3285	0.0097	0.0000
$\delta$	1.5556	0.0295	0.0000	1.0365	0.0147	0.0000	1.2752	0.0151	0.0000	1.1596	0.0203	0.0000
LL	-98115			-100654			-102352			-100817		
AIC	7.9288			8.1339			8.3383			8.1471		
SC	7.9524			8.1575			8.3621			8.1707		
$Q^2(10)$	45.1336		0.0000	10.1465		0.2549	15.6308		0.0480	23.3778		0.0029
<b>Student APARCH</b>												
$\tau_0$	-0.4977	0.0954	0.0000	-0.9022	0.0716	0.0000	-0.7331	0.0570	0.0000	0.0020	0.0707	0.9775
$\tau_1$	0.2483	0.0066	0.0000	0.1462	0.0064	0.0000	0.2064	0.0059	0.0000	0.3092	0.0055	0.0000
$\alpha_0$	0.1568	6.3817	0.9804	4.5537	4.1324	0.2705	7.2333	2.2140	0.0011	5.6732	2.9878	0.0576
$\alpha_1$	0.3147	0.0109	0.0000	0.3584	0.0131	0.0000	0.4117	0.0141	0.0000	0.4380	0.0216	0.0000
$\beta_1$	0.4709	0.0140	0.0000	0.4512	0.0142	0.0000	0.5162	0.0245	0.0000	0.4416	0.0153	0.0000
$\psi_1$	0.1879	0.0624	0.0026	0.1137	0.0492	0.0209	0.4056	0.0394	0.0000	0.0223	0.0109	0.0409
$\gamma_1$	-0.4668	0.0227	0.0000	-0.4120	0.0241	0.0000	-0.4796	0.0226	0.0000	-0.7528	0.0241	0.0000
$\delta$	1.6070	0.0713	0.0000	1.3757	0.0573	0.0000	1.1110	0.0401	0.0000	1.0191	0.0431	0.0000
$\nu$	4.5667	0.1092	0.0000	3.3471	0.0674	0.0000	2.5766	0.0531	0.0000	2.6288	0.0622	0.0000
LL	-97815			-97517			-97859			-98582		
AIC	7.9047			7.8806			7.9726			7.9666		
SC	7.9286			7.9045			7.9967			7.9906		
$Q^2(10)$	4.5802		0.8014	4.2745		0.8315	0.4445		0.9999	4.5917		0.8002
<b>Skewed Student APARCH</b>												
$\tau_0$	0.6508	0.1097	0.0000	0.1745	0.0746	0.0194	0.3681	0.0779	0.0000	0.0740	0.0629	0.2392
$\tau_1$	0.2401	0.0067	0.0000	0.2091	0.0059	0.0000	0.1811	0.0055	0.0000	0.2462	0.0054	0.0000
$\alpha_0$	5.7889	3.6619	0.1139	6.1363	3.3238	0.0649	8.7298	4.5844	0.0569	0.7168	0.7766	0.3560
$\alpha_1$	0.4376	0.0191	0.0000	0.3858	0.0141	0.0000	0.2530	0.0107	0.0000	0.5761	0.0251	0.0000
$\beta_1$	0.3677	0.0166	0.0000	0.4337	0.0133	0.0000	0.5422	0.0133	0.0000	0.3057	0.0143	0.0000
$\psi_1$	0.0842	0.0307	0.0061	0.0674	0.0192	0.0004	0.2605	0.0629	0.0000	0.0621	0.0088	0.0000
$\gamma_1$	-0.4538	0.0244	0.0000	-0.7173	0.0242	0.0000	-0.6565	0.0317	0.0000	-0.4013	0.0223	0.0000
$\delta$	1.3470	0.0565	0.0000	1.2272	0.0455	0.0000	1.3222	0.0492	0.0000	0.7704	0.0330	0.0000
$\nu$	3.3812	0.0924	0.0000	3.1602	0.0670	0.0000	2.8959	0.0581	0.0000	2.6149	0.0608	0.0000

	NSW			QLD			SA			VIC		
	Coefficient	Std. error	p-value									
$\xi$	0.0703	0.0102	0.0000	0.0891	0.0087	0.0000	0.1036	0.0081	0.0000	0.0877	0.0074	0.0000
LL	-96662			-96542			-97645			-98064		
AIC	7.8117			7.8020			7.9553			7.9249		
SC	7.8359			7.8262			7.9797			7.9491		
$Q^2(10)$	11.8230		0.1593	2.0073		0.9808	1.6953		0.9890	0.0790		1.0000

This table provides the estimated coefficients, standard errors and  $p$ -values for the mean and conditional standard deviation equations for the NSW - New South Wales, QLD - Queensland, SA - South Australia and VIC - Victoria electricity markets.  $\tau_0$  is the constant in the conditional mean equation,  $\tau_1$  is the degree of mean spillover,  $\alpha_0$  is the constant in the conditional standard deviation equation,  $\alpha_1$  is the ARCH coefficient,  $\beta_1$  is the GARCH coefficient,  $\gamma_1$  is the leverage effect,  $\psi_1$  is the coefficient to the contemporaneous volume of demand,  $\delta$  is the power of the conditional standard deviation process,  $\nu$  is the degrees of freedom,  $\xi$  is the asymmetric coefficient. LL is the log likelihood, AIC and SC are the Akaike Information Criterion and Schwartz Criteria, respectively.  $Q^2(10)$  is the Ljung-Box  $Q$ -statistic on the squared standardized residuals of order 10.

**Table 3. Joint Hypothesis Tests for Estimated Variance Covariance Coefficients**

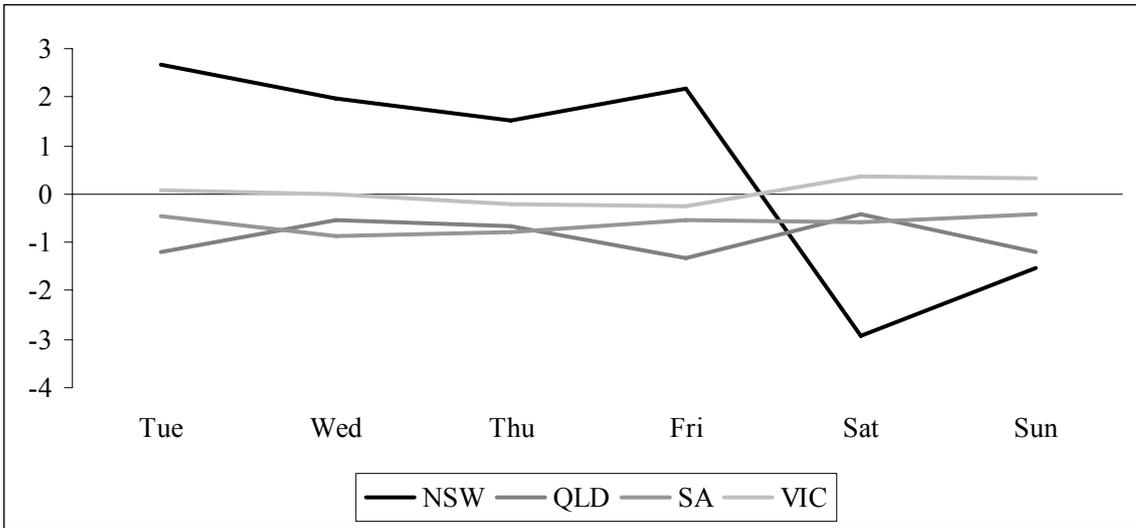
	df	NSW		QLD		SA		VIC	
		$\chi^2$	p-value	$\chi^2$	p-value	$\chi^2$	p-value	$\chi^2$	p-value
Time-of-day	47	29.8545	0.9758	62.0277	0.0698	61.6563	0.0742	65.6096	0.0376
Day-of-week	6	27.9899	0.0001	33.8892	0.0000	9.7213	0.1369	39.4242	0.0000
Month-of-year	11	29.3993	0.0020	41.4733	0.0000	35.9321	0.0002	53.5040	0.0000

This table presents joint hypothesis tests for the estimated conditional standard deviation coefficients in Table 2 for NSW - New South Wales, QLD - Queensland, SA - South Australia and VIC - Victoria. The joint significance tests are  $\chi^2$  tests that all coefficients are jointly zero for the skewed Student APARCH model, demand volume, time-of-day, day-of-week and month-of-year coefficients.

**Figure 2. Time-of-Day Effects for the Skewed Student APARCH Model by Market**



**Figure 3. Day-of-Week Effects for the Skewed Student APARCH Model by Market**



**Figure 4. Month-of-Year Effects for the Skewed Student APARCH Model by Market**

