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H. Higgs  
*Griffith University*

A. C. Worthington  
*University of Wollongong*

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Helen Higgs

Andrew C Worthington

School of Accounting & Finance  
University of Wollongong  
Wollongong NSW 2522  
Australia

Tel +61 (2) 4221 3718  
Fax +61 (2) 4221 4297  
eMail [george@uow.edu.au](mailto:george@uow.edu.au)  
[www.uow.edu.au/commerce/accy/](http://www.uow.edu.au/commerce/accy/)

# Stochastic price modelling of high volatility, mean-reverting, spike-prone commodities: The Australian wholesale electricity market

Helen Higgs

*Department of Accounting, Finance and Economics, Griffith University, Logan QLD 4131, Australia*

Andrew C. Worthington

*School of Accounting and Finance, University of Wollongong, Wollongong NSW 2522, Australia*

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## Abstract

It is commonly known that wholesale spot electricity markets exhibit high price volatility, strong mean-reversion and frequent extreme price spikes. This paper employs a basic stochastic model, a mean-reverting model and a regime-switching model to capture these features in the Australian national electricity market (NEM), comprising the interconnected markets of New South Wales, Queensland, South Australia and Victoria. Daily spot prices from 1 January 1999 to 31 December 2004 are employed. The results show that the regime-switching model outperforms the basic stochastic and mean-reverting models. Electricity prices are also found to exhibit stronger mean-reversion after a price spike than in the normal period, and price volatility is more than fourteen times higher in spike periods than in normal periods. The probability of a spike on any given day ranges between 5.16 percent in NSW to 9.44 percent in Victoria.

JEL classification: C32, D40, Q40

Keywords: wholesale spot electricity markets, volatility, price spikes, regime-switching, mean-reversion

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## 1. Introduction

The restructuring and deregulation of electricity markets in Australia has brought about fundamental changes in the behaviour of wholesale spot prices. As in like economies, these prices are invariably characterised by high volatility (the variance of prices is very large), strong mean-reversion (prices tend to fluctuate around a long-term equilibrium), and abrupt and unanticipated upward price jumps or spikes which quickly decay (associated with shocks to price-inelastic demand and supply) [electricity prices technically ‘spike’ rather than ‘jump’, since they do not move to a new level and remain there, instead quickly revert to the earlier level (Blanco and Soronow 2001)]. In turn, these reflect the inherent characteristics of competitive electricity markets: seasonality, low marginal production costs, the impact of

system breakdowns or outages, constraints on interconnection between markets, limited storability, and even market manipulation [for interesting perspectives on market power in electricity markets see Brennan and Melanie (1998), Joskow and Kahn (2001), Wilson (2002) and Robinson and Baniak (2002)]. As a result, major participants in these markets, including generators, retailers and large industrial users, are exposed to significant market risks and are obliged to undertake costly risk management measures.

In point of fact, the Australian electricity market is regarded as significantly more volatile and spike-prone than many comparable systems. To start with, it is well known that electricity is among the most volatile of commodities. A report by the US Federal Energy Regulatory Commission (2004) comparing the annualised historical volatility of the electricity market (Cinergy hub), with natural gas prices (Henry hub), oil (NYMEX) and the stock market (S&P 500) found electricity volatilities approaching 300 percent, never more than 100 percent in other energy commodities, and 20 percent or lower in equity markets. In Australia, and using similar techniques, Booth (2004) calculated historical volatilities in the Australian market in excess of 900 percent. At least part of this volatility is a direct result of price spikes, with 20-30 percent of average annual pool prices in the Australian National Electricity Market (NEM) coming from price spikes occurring for less than one percent of hours in a year (Booth 2004).

Observing fewer spikes in the US (Pennsylvania-New Jersey-Maryland pool), Bushnell (2003) explained it as a consequence of US regulators being more willing to modify the behaviour of suppliers, while Australia, "...which also uses a uniform price auction, places fewer restrictions on suppliers, and [as a consequence] price spikes, are a standard feature" (Mount et al. 2006: 63). Moreover, half-hourly spot prices in Australia can and do approach the price cap of \$10,000 per megawatt-hour (MWh), as compared to a cap of US\$1,000 per MWh in the US, a feature Booth (2004: 1) links with generators exploiting "...the freedom afforded them under the National Electricity Code to arrange their price bids, and/or withhold capacity in various ways, causing a small number of very large price spikes, and increasing the annual average pool prices to more acceptable levels".

Clearly, knowledge of the dynamics of spot prices, particularly the spike process, is of importance for real and financial asset valuation and risk management for electricity generators, retailers and end-users. For example, modelling price spikes accurately is important for generation assets, particularly peaking plants, whose value is entirely dependent on the existence of price spikes that facilitate the recovery of high marginal costs and the recouping of fixed costs over very short running periods (Blanco and Soronow 2001). Large

industrial users are also concerned with the better modelling of prices because of cost efficiencies associated with load shedding during peak periods, while retailers can benefit from improved forecasting of volatility and price spikes to hedge against upside price risk. A White Paper issued by the Australian Government (2004) highlights the economic impact of price spikes: “These peaks in demand, while generally being of short duration, can impose high costs on the supply system...peaks lasting for only 3.2 percent of the annual duration of the market accounted for 36 percent of total spot market costs”. More realistic appraisals of the volatility of spot prices can also be used to determine the financial value of electricity derivatives. For instance, even with deep out-of-the-money options, it is still necessary to model price spikes directly in order to price and hedge effectively (Blanco and Soronow 2001).

Accordingly, the purpose of this paper is to model Australian spot electricity prices with allowances for high volatility, strong mean-reversion and frequent price spikes. While a nascent literature is already concerned with Australian electricity prices [see, for example, Higgs and Worthington (2003), Worthington and Higgs (2004), Worthington and Higgs (2005) and Worthington et al. (2005)] none has yet fully addressed these stylised features of contemporary electricity markets. In this regard, past studies in the US and elsewhere have attempted to capture some characteristics of electricity spot prices with mean-reverting specifications [see, for instance, Lucia and Schwartz (2002)]. Unfortunately, while these models are useful for modelling storable commodities, such as oil and gas (Schwartz 1997; Pindyck 1999), they are less useful for electricity, where there is little opportunity for direct or indirect storage to smooth price spikes (except in the presence of substantial hydropower capacity) (de Jong 2005).

A common solution is to add a stochastic jump process to the mean-reverting specification to allow for spikes [see, for example, Deng (2000) and Knittel and Roberts (2001)]. The mean-reversion component in these models is used to force electricity prices back to the normal level after a jump or spike has occurred: that is, mean-reversion is directly associated with the jump process (Huisman and Mahieu 2003). However, mean-reverting stochastic jump processes are limited in two respects. First, while these models are well suited to foreign exchange and equity markets where jumps are ordinarily sustained and revert slowly to some long-run equilibrium, the spikes in electricity markets are typically short-lived and die out in a matter of days or even hours. This can only be achieved with an unrealistically high mean reversion parameter (de Jong 2005). Second, the jump process is assumed to be constant over

time, whereas in electricity markets we typically observe alternating periods of high and low jump frequency. If the mean-reversion exists only in the ‘normal’ price process, Huisman and Mahieu (2003: 426) argue that a “...stochastic jump process with mean-recession [may] lead to an erroneous specification of the true mean-reversion process”.

In response, Deng (2000), Huisman and De Jong (2003), Bierbrauer et al. (2003), Huisman and Mahieu (2003) and De Jong (2005) specify regime-switching models to disentangle the mean-reversions from the spikes. Deng (2000) and Huisman and Mahieu (2003), for example, propose a three regime-switching model to accommodate a first (or normal) regime with moderate mean-reversion and volatility, a second (or spike) regime when prices suddenly increase, and a third (or jump-reversal) regime when prices are forced back to the normal regime. The main benefit of this model is that the prominent features of electricity spot prices, mean-reversion and spikes are included, with the spikes treated as truly independent disruptions from the (normally) stable price process. One limitation, however, is that there is no allowance for the multiple consecutive spikes that are sometimes observed in electricity markets.

The remainder of the paper is structured as follows. Section 2 explains the data employed in the analysis and presents some brief descriptive statistics. Section 3 discusses the methodology employed. The results are dealt with in Section 4. The paper ends with some concluding remarks in the final section.

## **2. Data and Descriptive Statistics**

The data employed in the study are daily spot prices of the Australian National Electricity Market (NEM) comprising the (partially) interconnected regional markets of New South Wales (NSW), Queensland (QLD), South Australia (SA) and Victoria (VIC) [for details of the NEM’s regulatory background, institutions and operations see NEMMCO (2001; 2005), ACCC (2000) and IEA (2001)]. The sample period is from 1 January 1999 to 31 December 2004. All price data is obtained from the National Electricity Market Management Company (NEMMCO 2005) originally on a half-hourly basis representing 48 trading intervals in each 24-hour period. A series of daily arithmetic means is drawn from the trading interval data, yielding 2,192 observations for each market. While Deng (2000), Lucia and Schwartz (2002), Knittel and Roberts (2001) and Huisman and Mahieu (2003) also employ daily prices in their respective analyses of the western United States and United Kingdom spot electricity markets, this specification invariably involves some loss of information on price spikes. For example,

price-spikes are sometimes most pronounced in peak hourly prices, but are usually averaged away in weekly and monthly data. Daily observations are a good compromise given the unwieldiness of intraday data.

<TABLE 1 HERE>

Table 1 presents summary of descriptive statistics of the daily spot prices for the four markets. Samples means, minimums, maximums, standard deviations, coefficients of variation, percentile values, skewness, kurtosis and the Jarque-Bera and Augmented Dicky-Fuller statistics and their  $p$ -values are reported. Between 1 January 1999 and 31 December 2004, the highest spot prices are in QLD and SA averaging \$38.66 and \$42.71 per MWh, respectively. The lowest mean spot prices are in NSW (\$33.82) and VIC (\$32.74). The standard deviations range between \$47.23 in VIC to \$66.08 in QLD. Of the four markets NSW and VIC are the least volatile, while QLD and SA are more volatile. 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. A visual perspective on the volatility of the spot prices can be gained from the plots of each series on the left-hand side of Figure 1. These plots clearly indicate the strong mean-reversion and infrequent and the price spikes so characteristic of electricity spot prices. In terms of spikes,

<FIGURE 1 HERE>

All of the spot electricity markets are significantly positively skewed, and since the kurtosis, or degree of excess, in all of these electricity markets exceeds three, leptokurtic distributions are indicated. The fat-tailed distributions are also very characteristic of electricity spot prices, while positive skewness indicates that the upward jumps are more intense than the jump reversals (Huisman and Mahieu 2003). The null hypothesis of distributional normality is rejected at the .01 level for all series using the Jarque-Bera statistic. Finally, each price series is tested for the presence of a unit root using the Augmented Dickey-Fuller (ADF) test. Contrary to some earlier empirical work [see, for example, de Vany and Walls (1999a; 1999b) in the US context] which found that spot electricity prices contain a unit root, this study concurs with Worthington et al. (2005) that spot electricity prices, at least in Australia, are stationary. Table 1 presents the same statistics for the natural logarithms of the prices, with the series plotted on the right-hand side of Figure 1.

### 3. Model Specification

The methodology used in this paper models the spot price as the sum of two components. The first is predictable and is represented by a known deterministic function  $f(t)$ . The second is stochastic and is represented by  $X(t)$ . Let  $P(t)$  be the natural logarithm of the spot price at time  $t$  such that the sum of the two components is given by:

$$P(t) = f(t) + X(t) \quad \text{where } t = 1, 2, \dots, T \quad (1)$$

#### 3.1 The deterministic component

The deterministic component aims to capture any predictable variation in electricity price behaviour arising from regularities over time. The simplest deterministic function is a constant function of time,  $t$ , which reflects a constant mean-reverting process for the daily spot price (or the natural logarithm of the daily spot price). This implies that a linear trend for a log spot price variable is an exponential trend for the spot price itself. A time trend was initially included in the deterministic function, but while the estimated coefficient was significant it was very small in magnitude and was excluded from the final analysis.

It is more likely that important spot price variation is reflected in day-of-week and month-of-year effects. In this paper, it is hypothesized that spot electricity prices are higher during weekdays and during warmer and colder months. Solibakke (2002), for example, found that price volatility in the Nordic spot electricity market increased strongly on Mondays and Saturdays, especially 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". Finally, Worthington and Higgs (2005) also concluded that Mondays and peak winter and summer months were associated with higher spot electricity prices.

Seasonal behaviour can be incorporated in these models as either dummy variables (Lucia and Schwartz 2002; Huisman and Mahieu 2003) or sinusoidal cosine functions (Lucia and Schwartz 2002). However, dummy variables are generally preferred as they are intuitive and relatively easy to interpret (Lucia and Schwartz 2002). Three sets of dummy variables are included. The first captures the variation in spot prices between working and non-working days, while a second reflects seasonal fluctuations throughout the year. A final dummy variable is included to incorporate the inception of two new interconnectors between the mainland regional markets: the Queensland and New South Wales Interconnector (QNI) began operation on 18 February 2001 while the Murraylink interconnector between South



Australia and Victoria commenced on 2 September 2002 [a third interconnector, the Basslink between Tasmania (not included) and Victoria, was completed in 2005]. The inclusion of interconnection dummy variables draws upon evidence by Worthington et al. (2005) that the presence and size of regional interconnectors plays an important role in Australian electricity price dynamics.

The deterministic component  $f(t)$  is then specified as:

$$f(t) = \mu_0 + \beta_1 D_t + \sum_2^{12} \beta_i M_{it} + \gamma_1 INT \quad (2)$$

where  $D_t$  are dummy variables for the day-of-the-week having values of one when  $t$  is a holiday or weekend and zero otherwise (weekdays are the reference category),  $M_i$  are eleven dummy variables for each month with a value of one for  $M_2$  (February) and zero otherwise, having a value of one for  $M_3$  (March) and zero otherwise, and so on (January is the reference category),  $INT$  is an interconnector dummy variable having a value of one after 18 February 2001 for QLD and NSW and after 2 September for SA and VIC and zero otherwise, and  $\beta_i$  for  $i = 1, 2, \dots, 12$  and  $\gamma_1$  are parameter coefficients. Parameter  $\mu_0$  represents the mean spot price.

### 3.2 The stochastic component

The change in the stochastic component of the spot price is defined as:

$$dX(t) = dP(t) - df(t) \quad \text{where } t = 1, 2, \dots, T \quad (3)$$

The operator  $d$  measures the change in the value of the variable that is  $dX(t) = X(t) - X(t-1)$ . In the current analysis, three alternatives are used to measure the dynamics of the stochastic component of electricity spot prices: (i) a basic stochastic model: (ii) a mean-reverting model; and (iii) a Markov regime-switching model. To start with, the basic stochastic model is a simplistic approach where it assumed that the stochastic change in the spot price is normally distributed, such that:

$$dX(t) = \sigma_0 \xi(t) \quad \text{where } \xi(t) \sim N(0,1) \quad (4)$$

In this model, the volatility of changes in the spot electricity price is measured by the parameter  $\sigma_0$ .

The mean-reverting model reflects findings by Pilipovic (1998), Clewlow and Strickland (2000), Lucia and Schwartz (2002) and Huisman and Mahieu (2003), amongst others, that spot electricity prices tend to fluctuate around some long-term equilibrium price level,  $\mu_0$  in equation (1), which reflects the marginal cost of producing electricity. The rate of mean-

reversion is introduced as prices are forced back to their long-run equilibrium after the actual price has deviated from this equilibrium; negatively if the spot price is higher than the mean-reversion level and positively if lower. The mean-reverting model is defined as:

$$dX(t) = -\alpha_0 X(t-1) + \sigma_0 \xi(t) \quad \text{where } \xi(t) \sim N(0,1) \quad (5)$$

where  $\alpha_0$  is the rate of mean-reversion and all other variables are as previously defined.

Finally, the unique behaviour of spot electricity prices can be thought of as being divided into separate regimes with different underlying processes where a spike can be considered as a change or temporal level shift to an abnormally high price. This potentially arises from a number of factors, including generator breakdowns or abnormally high or low temperatures. In these instances, the price will return to the equilibrium level very quickly when the generator is repaired or supply is obtained from another generator or temperatures return to more normal levels. Since the sudden up-jump in spot prices is followed rapidly by a down-jump, it assumes that mean-reversion forces high prices back to the long-run equilibrium price.

This paper follows Huisman and Mahieu (2003) who propose a Markov regime-switching model to separate mean reversion in the normal (non-spike) and spike price periods. The regime framework assumes that on any day the electricity spot price lies in one of three regimes: (i) a normal (regime 0) when prices follow ‘normal’ electricity price dynamics; (ii) an initial jump regime (regime +1) when prices suddenly increase (decrease) during a price spike; and (iii) a downturn regime (regime -1) when electricity prices revert to normal after a spike has occurred. The deseasonalised stochastic component,  $dX(t)$ , of the regime switching model used to capture the three regimes is specified as:

$$dX(t) = -\alpha_0 X(t-1) + \sigma_0 \xi(t) \quad \text{in regime 0} \quad \text{where } \xi(t) \sim N(0,1) \quad (6)$$

$$dX(t) = \mu_1 + \sigma_1 \xi(t) \quad \text{in regime +1} \quad \text{where } \xi(t) \sim N(0,1) \quad (7)$$

$$dX(t) = -\alpha_{-1} X(t-1) + \sigma_{-1} \xi(t) \quad \text{in regime -1} \quad \text{where } \xi(t) \sim N(0,1) \quad (8)$$

The mechanism that allows the price level to move from one regime to another is achieved through a Markov transition matrix which contains the probabilities of jumping from one regime on a given day to another regime on the next day. Maximum likelihood estimates are used to determine the parameters and regimes given the conditions for each regime.

The switches between the regimes are assumed to have one-period transmission probabilities. Let  $\pi(i,j)$  be the probability that the electricity price process switches regime  $j$  in period  $t$  to regime  $i$  in period  $t + 1$ . The probabilities are set according to any normal day; that is, the probability of a spike tomorrow. Let  $\pi(0,0)$  represent the probability that no spike will occur and  $\pi(+1,0) = 1 - \pi(0,0)$  be the probability of a spike. As there cannot be a process of switching from the normal regime to the spike reverting regime, then  $\pi(-1,0)$  is set to zero. Being in the spike regime +1 at day  $t$ , the model assumes that spikes are only short-lived, say, today, and the reverting regime begins tomorrow. This is represented by  $\pi(-1,+1)$  equals one and  $\pi(0,+1)$  and  $\pi(+1,+1)$  are zero. Being in a mean reverting regime -1 at day  $t$ , the price process is expected to be back in the normal regime the next day, thus  $\pi(0,-1)$  equals one and  $\pi(+1,-1)$  and  $\pi(-1,-1)$  are equal zero. Given these combinations of the different regimes, only the Markov probability  $\pi(0,0)$  is estimated. To keep the Markov probability estimates between 0 and 1, the Markov probability is calculated as:

$$\pi(0,0) = \frac{\exp(p)}{1 - \exp(p)} \quad (9)$$

where  $p$  is the parameter to be estimated,  $\exp$  is the exponential and all other variables are as previously defined.

#### 4. Empirical Results

The estimated coefficients and standard errors for the three different models (basic stochastic, mean-reverting and regime-shifting) in this study are presented in Table 2. All models share a deterministic component and this is included in the uppermost panel of Table 2. The stochastic component is represented in turn by a basic stochastic function (next-to-uppermost panel), mean-reverting function (next-to-lowermost panel) and regime-shifting function (lowermost panel).

To start with, the estimated coefficients, standard errors and  $p$ -values of the deterministic function  $f(t)$  are presented in the uppermost panel in Table 2. The average log price level ( $\mu_0$ ) is 3.3319 for NSW, 3.3536 for VIC, 3.7156 for SA and 3.7615 for QLD. This indicates that average equilibrium prices range from \$27.99 per MWh (NSW) [i.e.  $\$27.99 = \exp(3.319)$ ] to \$43.01 per MWh (QLD). The weekend and public holidays' effect ( $\beta_1$ ) is significant and negative in all four markets indicating that Saturday, Sunday and public holiday electricity prices are lower than weekday prices. In dollar terms, prices on weekends and public holidays

are generally lower by \$0.73-\$0.74/MWh in QLD, SA and VIC and \$0.85/MWh in NSW. Most monthly effects are also significant. Generally (and relative to January), prices are higher in most regional markets (except QLD) in February and the peak winter months of May-August and lower in September-December. The highest (lowest) monthly prices by state are June (March) in NSW, January (April) in QLD, February (March) in SA and June (April) in VIC. The interconnector dummy variable (*INT*) is also significant for all markets excluding VIC. The respective negative and positive *INT* coefficients for QLD (-0.2313) and NSW (0.0544) suggest that after the introduction of the QNI interconnector, spot prices in QLD have fallen (\$0.79/MWh), while those in NSW have increased (\$1.05/MWh). The introduction of the Murraylink interconnector appears to have reduced prices only in SA (-0.3336) by (\$0.71/MWh) with no significant change in VIC.

<TABLE 2 HERE>

The next-to-uppermost panel in Table 2 presents the estimated coefficients and standard errors of the basic stochastic model. The estimated volatility of the daily changes in the spot price is significant in all four markets, with daily volatilities ranging from 0.0140 for VIC to 0.0179 for QLD. As indicated, daily prices are most volatile in QLD (0.0179) and NSW (0.0171) and least volatile in SA (0.0161) and VIC (0.0140). The next-to-lowermost panel of Table 2 contains the parameter estimates of the mean-reverting model. This extends the basic stochastic model by including mean-reversion in the dynamic price process. The mean-reversion parameter  $\alpha_0$  is significant and positive for all spot markets and ranges from 0.3213 for VIC to 0.4115 for SA. Electricity prices exhibiting strong mean-reversion suggests that spot price returns rapidly from some extreme position, such as a price spike, to equilibrium. That is, price spikes are short lived. In terms of a comparison with international spot prices, the strength of mean-reversion (short-livedness of spikes) in Australian electricity markets is less than the Dutch APX market (0.473) but higher than either the German LPX (0.284) or the UK Telerate (0.206) markets (Huisman and Mahieu 2003).

The estimated volatility coefficient of price changes is again significant for all markets. The daily prices are more volatile in SA (0.0156) and QLD (0.0136) and least volatile in NSW (0.0127) and VIC (0.0102). However, the volatility estimates are lower than in the basic stochastic model, and this suggests that at least some of the volatility in prices (about 25 percent) is linked with the strong mean reversion. Put differently, if spikes (read mean-reversion) are excluded from prices, daily volatility is lower. Moreover, the volatility ranking

of the markets has changed, with SA, for instance, moving from the second least volatile to most volatile. This suggests that SA has a higher level of normal-period volatility, whereas volatility in NSW, QLD and VIC owes much to the presence of volatility in spike-periods. The log likelihoods for the mean-reversing models are lower than the basic stochastic model for all series, indicating a better fit.

Finally, the lowermost panel of Table 2 presents the estimated parameters of the Markov regime-switching model. The probability of a spike is low for all markets with the parameter  $\pi(0,0)$ , being the probability of the process in the normal regime today will again be in the normal process tomorrow are 0.9056 (VIC), 0.9197 (SA), 0.9206 (QLD) and 0.9484 (NSW). The probability of a spike therefore varies from 9.44 percent (VIC), 8.03 percent (SA), 7.94 percent (QLD) and 5.16 percent (NSW). In the normal regime (regime 0) the mean-reversion parameter  $\alpha_0$  is significant and positive for all Australian electricity markets and ranges from 0.2802 (QLD) to 0.3854 (VIC). Once again, this reveals the importance of mean-reversion in electricity price dynamics and the quicker the return of prices from some extreme position to equilibrium. The estimates of mean reversion in the normal regime are also substantially smaller in magnitude than the mean-reverting models, suggesting that failure to account for price spikes as independent departures from the normal price process significantly overestimates the strength and speed of return to equilibrium prices. The estimated volatility coefficients of price changes ( $\sigma_0$ ) in the normal regime range from 0.0008 (VIC) to 0.0046 for both QLD and SA. This indicates that volatility in electricity markets, once price spikes are excluded, is actually quite low.

In the spike regime (regime 1), the size of a price jump ( $\mu_1$ ) is significant for all markets being the lowest for QLD (0.5799) and VIC (0.5878) and the highest for SA (0.8273) and NSW (0.9169). That is, the average magnitude of price spikes is greatest in SA and NSW. However, the standard error of the size of the spikes in the spike regime is greater in QLD (0.0687) than in any of the other markets. This suggests that the size of price spikes in QLD is more uncertain. The mean-reversion coefficients in the spike regime are much higher than those in the normal regime indicating the more rapid the return of the spike price to equilibrium. Price spikes are clearly short lived. The estimated volatility of price changes ( $\sigma_1$ ) is significant for all markets and ranges from 0.0574 for VIC to 0.0981 for QLD. These volatilities as expected are somewhat magnified as compared to the estimated volatility estimates in the normal regime. The volatilities in the spike regime as compared to that in the normal regime are respectively 0.0605 and 0.0023 for NSW, 0.0981 and 0.0046 for QLD, 0.0638 and 0.0046 for

SA and 0.0574 and 0.0008 for VIC. Broadly speaking, daily volatilities exceed seven percent in spike periods, but are less than half of one percent in normal periods.

In the back-to-normal regime (regime -1), the mean-reversion coefficients are significant for all markets ranging from 0.2961 (QLD) to 0.5146 (SA) and are stronger than the mean-revision coefficients in the normal regime. While all prices return to the equilibrium position more rapidly after a spike than in the normal regime in all markets, the adjustment to equilibrium is quickest and the spikes generally most short-lived in SA. Finally, since the log-likelihood is lower again, the mean-reverting model with regime jumps has the highest explanatory power for all four spot markets as compared to either basic stochastic or mean-reverting models.

## **5. Concluding Remarks**

This study uses basic stochastic, mean-reverting and Markov regime-switching models to examine the price dynamics in the Australian wholesale electricity spot markets. While all of these models are useful in modelling spot prices, only the regime-shifting model fully accounts for the high volatility, mean-reversion and spike-prone behaviour so characteristic of electricity markets. A number of salient features are found in this model and these are useful for understanding the price dynamics in the Australian market.

First, the probability of a price spike on any particular day ranges between five percent in NSW to nearly ten percent in VIC. However, while these spikes are frequent, they are short-lived. In fact, prices generally revert faster when returning from spike periods than in normal periods. Second, price spikes account for much of the volatility in electricity spot prices. Daily volatility in normal periods is actually quite low, and appears to cluster closely around the marginal cost of production. Third, there is great variation in the magnitude of spikes in the Australian market, with spikes being generally largest in SA and smallest in QLD. However, price spikes are less uniform in the QLD market, suggesting a higher degree of uncertainty.

Finally, apart from stochastic variation, there is a great deal of deterministic disparity among the various regional markets, in which equilibrium prices, seasonal and day-of-the-week effects and the impact of regional interconnectors diverge. All other things being equal, equilibrium prices are highest in QLD and SA, the differential between weekday and weekend prices is lowest in NSW, and prices are lowest in autumn in NSW, SA and VIC, highest in winter in NSW and VIC, highest in summer in QLD and SA and lowest in spring in QLD.

The presence of new interconnectors appears to have most benefited QLD and SA with lower prices, but prices have risen in NSW and are unchanged in VIC.

The main limitation of this study is the rather restrictive assumption regarding spike behaviour and this suggests possible research extensions. First, the methodology employed follows the three-regime structure proposed by Huisman and Mahieu (2003): that is, a normal regime, a jump regime created by the spike and a jump reversal regime where the price returns to the normal level. Accordingly, there is no allowance for consecutive spikes that may arise. One solution is a two-regime model following De Jong and Huisman (2002), Bierbrauer *et al.* (2003) and De Jong (2005) which permits a spike regime of log-normal prices with consecutive spikes.

Second, through the use of daily data, this methodology also sets the shortest duration of a spike to one day. In many instances, short-duration spikes may also occur in half-hourly prices, but these are often averaged away in daily prices. This is especially important because the spiking behaviour in electricity markets appears to exhibit strong time variation, with spikes being relatively more common in peak daylight times. Specification of intraday data would provide a logical resolution to these as yet unexplored features.

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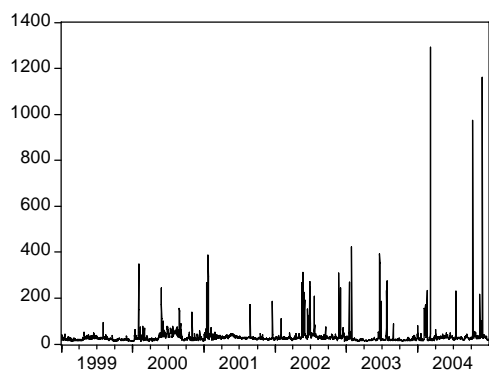


Table 1. Selected descriptive statistics of daily spot prices (\$/MWh) and natural logarithms of spot prices, 1 January 1999–31 December 2004

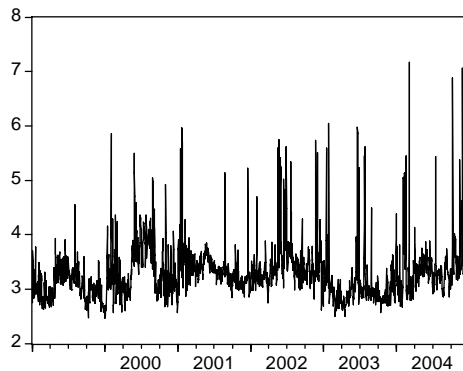
Statistic	New South Wales (NSW)		Queensland (QLD)		South Australia (SA)		Victoria (VIC)	
	Price	lnPrice	Price	lnPrice	Price	lnPrice	Price	lnPrice
Number	2192	2192	2192	2192	2192	2192	2192	2192
Mean	33.822	3.301	38.660	3.371	42.707	3.515	32.743	3.290
Minimum	11.653	2.456	11.171	2.413	10.607	2.362	4.979	1.605
Maximum	1293.003	7.165	1379.269	7.229	1152.575	7.050	1239.197	7.122
Standard deviation	57.275	0.497	66.077	0.583	67.630	0.529	47.234	0.499
Coefficient of variation	1.693	0.150	1.709	0.173	1.584	0.151	1.443	0.152
Tenth percentile	16.724	2.817	16.492	2.803	20.569	3.024	15.982	2.771
Twentieth percentile	18.817	2.935	19.128	2.951	23.247	3.146	18.805	2.934
Thirtieth percentile	20.832	3.037	21.393	3.063	25.506	3.239	21.162	3.052
Fortieth percentile	23.155	3.142	23.851	3.172	27.616	3.318	23.057	3.138
Fiftieth percentile	25.531	3.240	26.093	3.262	29.955	3.400	25.434	3.236
Sixtieth percentile	27.595	3.318	28.590	3.353	33.406	3.509	27.939	3.330
Seventieth percentile	30.451	3.416	32.085	3.468	37.706	3.630	30.987	3.434
Eightieth percentile	34.734	3.548	38.185	3.642	44.735	3.801	35.023	3.556
Ninetieth percentile	44.440	3.794	56.194	4.029	60.311	4.100	45.059	3.808
Skewness	14.560	2.482	11.801	2.058	10.066	2.228	14.136	1.916
Kurtosis	271.672	13.846	190.617	9.504	123.466	11.738	282.539	11.145
J-B statistic	6.67E+06	1.30E+04	3.27E+06	5.41E+03	1.36E+06	8.79E+03	7.21E+06	7.40E+03
J-B <i>p</i> -value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF <i>t</i> -statistic	-33.350	–	-24.814	–	-33.347	–	-31.034	–
ADF <i>p</i> -value	0.000	–	0.000	–	0.000	–	0.000	–

Notes: ADF – Augmented Dickey-Fuller; coefficient of variation is standard deviation divided by mean; J-B – Jarque-Bera. Hypothesis for ADF test:  $H_0$ : unit root (non-stationary),  $H_1$ : no unit root (stationary).

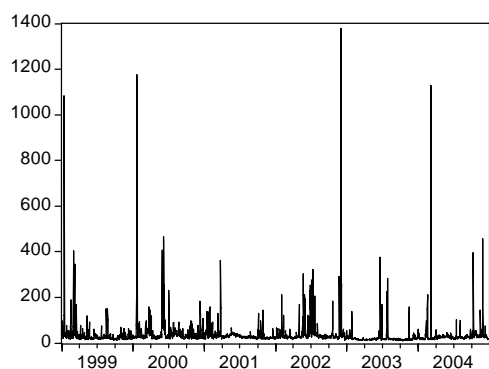
Figure 1. Daily spot prices (\$/MWh) and natural logarithms of spot prices, 1 January 1999–31 December 2004



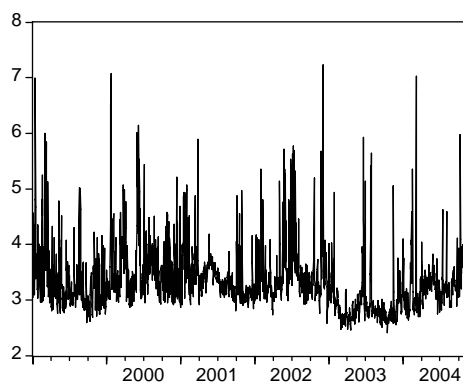
— NSW - from January 1999 to 31 December 2004



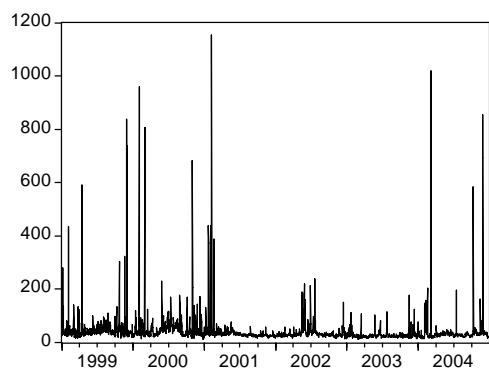
— Log NSW - from 1 January 1999 to 31 December 2004



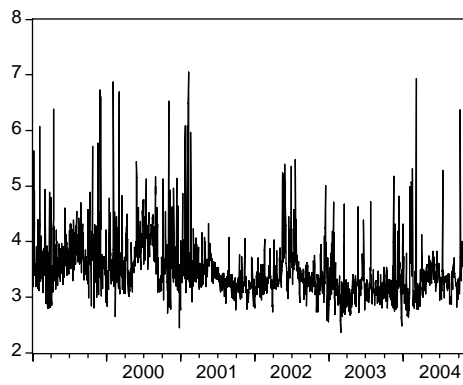
— QLD - from 1 January 1999 to 31 December 2004



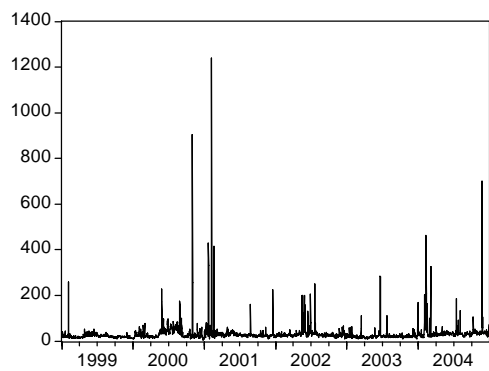
— Log QLD - from 1 January to 31 December 2004



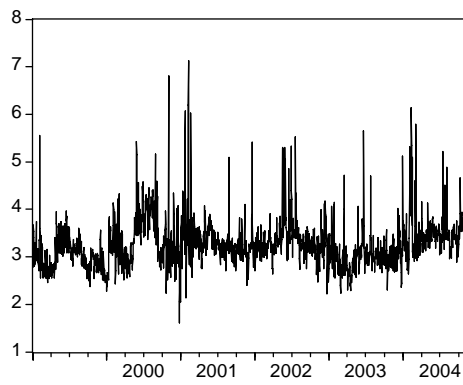
— SA - from 1 January 1999 to 31 December 2004



— Log SA - from 1 January to 31 December 2004



— VIC - from 1 January 1999 to 31 December 2004



— Log VIC - 1 January 1999 to 31 December 2004

Table 2. Estimation results for basic stochastic, mean-reverting and regime-switching models

		New South Wales (NSW)		Queensland (QLD)		South Australia (SA)		Victoria (VIC)	
		Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Deterministic component	$\mu_0$	3.3319***	0.0369	3.7615***	0.0431	3.7156***	0.0368	3.3536***	0.0355
	Eq.Pr	27.9902		43.0137		41.0829		28.6063	
	$\beta_1$	-0.1494***	0.0217	-0.2599***	0.0254	-0.2694***	0.0222	-0.2634***	0.0215
	$\beta_2$	0.0082	0.0500	-0.1380**	0.0584	0.1200**	0.0510	0.1162**	0.0493
	$\beta_3$	-0.2037***	0.0490	-0.0741	0.0572	-0.1110**	0.0498	-0.1127**	0.0482
	$\beta_4$	-0.1889***	0.0494	-0.2971***	0.0577	-0.0918*	0.0502	-0.1744***	0.0486
	$\beta_5$	0.1358***	0.0490	-0.1282**	0.0572	0.1004**	0.0498	0.1805***	0.0482
	$\beta_6$	0.2635***	0.0494	-0.0130	0.0577	0.1128**	0.0502	0.2623***	0.0486
	$\beta_7$	0.1712***	0.0490	-0.0812	0.0572	0.1049**	0.0498	0.1797***	0.0482
	$\beta_8$	0.0413	0.0490	-0.2021***	0.0572	-0.0063	0.0498	0.1044**	0.0482
	$\beta_9$	-0.1294***	0.0494	-0.3713***	0.0577	-0.1065**	0.0504	-0.0948*	0.0487
	$\beta_{10}$	-0.1018**	0.0490	-0.1973***	0.0572	0.0211	0.0499	-0.0657	0.0483
	$\beta_{11}$	-0.1092**	0.0494	-0.2666***	0.0577	0.0791	0.0504	-0.0449	0.0487
	$\beta_{12}$	-0.1166**	0.0490	-0.1608***	0.0572	-0.0537	0.0499	-0.1237**	0.0483
$\gamma_1$	0.0544**	0.0211	-0.2313***	0.0247	-0.3336***	0.0213	-0.0008	0.0206	
Basic stochastic component	$\sigma_0$	0.0171***	0.0021	0.0179***	0.0038	0.0161***	0.0028	0.0140***	0.0022
	LnL	-1102.0470		-1435.7030		-1396.1200		-939.6626	
Mean- reverting stochastic component	$\alpha_0$	0.3622***	0.0165	0.3466***	0.0162	0.4115***	0.0173	0.3213***	0.0157
	$\sigma_0$	0.0127***	0.0046	0.0136***	0.0039	0.0156***	0.0055	0.0102***	0.0026
	LnL	-883.1969		-1227.3200		-1140.6150		-748.4933	
Regime- switching stochastic component	$\alpha_0$	0.3747***	0.0166	0.2802***	0.0233	0.3841***	0.0174	0.3854***	0.0166
	$\sigma_0$	0.0023**	0.0011	0.0046***	0.0008	0.0046***	0.0011	0.0008***	0.0002
	$\mu_1$	0.9169***	0.0285	0.5799***	0.0687	0.8273***	0.0247	0.5878***	0.0226
	$\sigma_1$	0.0605*	0.0319	0.0981***	0.0319	0.0638***	0.0235	0.0574***	0.0213
	$\alpha_{-1}$	0.4803***	0.0276	0.2961**	0.1241	0.5146***	0.0268	0.4514***	0.0332
	$\sigma_{-1}$	0.0058*	0.0032	0.0400***	0.0131	0.0278**	0.0129	0.0201**	0.0082
	p	2.9118***	0.1792	2.4505***	0.4951	2.4379***	0.3763	2.3147***	0.5444
	$\pi$	0.9484		0.9206		0.9197		0.9056	
	LnL	-209.9161		-913.8360		-410.8549		-290.9938	

Notes: Asterisks indicate significance at the \*\*\* – 0.01, \*\* – 0.05 and \* – 0.10 level. LnL – Log-likelihood. EqPr – equilibrium price.