MODELLING COMMODITY PRICES IN THE AUSTRALIAN NATIONAL ELECTRICITY MARKET

by

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DECLARATION

In compliance with the policies governing submission and examination of a thesis for the degree of Doctor of Philosophy at RMIT University, I hereby declare that except where due acknowledgement has been made the work herein is my own. This thesis contains no material that has been submitted previously, in whole or in part, to qualify for any other academic award. The work of the research program has been carried out since the official date of commencement of the program and all applicable ethics procedures and guidelines have been followed.

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Signed

Stuart Thomas
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Thesis Abstract

Beginning in the early 1990s several countries, including Australia, have pursued programs of deregulation and restructuring of their electricity supply industries. Dissatisfaction with state-run monopoly suppliers and a desire for increased competition and choice for consumers have been the major motivations for reform. In Australia, the reform process followed the recommendations of the 1993 “Report of the Independent Committee of Inquiry into the Australian Electricity Utilities Industry” (the Hillmer Report). The previously vertically integrated, government-owned electricity authorities were progressively separated into separate generation, transmission, distribution and retail sales sectors in each State and a competitive, wholesale market for electricity, the National Electricity Market (NEM) began operation in December 1998.

The goal of deregulation and this new market was (and remains) increased competition in electricity supply, so that consumers may enjoy wider choice of electricity supplier and lower prices. The first benefit has been delivered, at least in the major cities, but it is arguable whether the second benefit of lower prices has been realised. Increased competition has come at the price of increased wholesale price volatility, which brings with it increased cost as market participants seek to trade profitably and manage the associated increase in price risk. In the NEM, generators compete to sell into an electricity market pool and the distributors purchase electricity from the pool at prices determined by the intersection of demand and supply, on an hourly or half-hourly basis. These market-clearing prices can be extremely volatile.

The volatility arises because of the physical characteristics of electricity. Unlike other traded commodities, electricity cannot be stored – it is for all practical purposes instantly produced and consumed. This means that neither suppliers nor consumers can "stockpile" the commodity and use inventory to smooth short-run shocks to supply or demand.

Electricity price behaviour is highly idiosyncratic and there is much work needed in order to understand it. Electricity prices are generally characterised by significant seasonal patterns, on an intra-day, weekly and monthly basis, as demand and supply conditions vary. Electricity prices are also characterised by strong mean-reversion and are subject to extremely high spikes in price. While long-run mean prices typically range between $30 and $45 per megawatt hour, prices can spike to levels above $9,000, even reaching the NEM's price cap of $10,000 per megawatt hour from time to time. These spikes tend to be sporadic and very short-lived, rarely lasting for more than an hour or two. Although infrequent, spikes are the major contributor to price volatility and their evolution and causes need to be investigated and understood.

The purpose of this thesis is to investigate and model Australian electricity prices. The research work presented is mostly empirical, with the early analytical chapters focusing on investigating the presence and significance of seasonal factors and spikes in electricity price and demand. In subsequent chapters this work is extended into analysis of the underlying volatility processes and the interaction between extreme values in demand and price. The findings of the thesis are that the strong seasonal patterns and spikes that are generally observed in similar electricity markets are present in the NEM, in both price and demand, there is significant variation in their presence and effect between the regional pools. The study also finds that, while time-varying volatility is evident in the price series, there is again some variation in the way this is characterised between states. A further finding challenges the accepted wisdom that demand peaks drive price spikes at the extremes and shows empirically that price spikes are more likely to be caused by supply disruptions than extremes of demand. The findings provide useful insight into this economically important national market.

Chapter 1: Introduction

1.1 Background

Prior to the 1990s, the electricity supply industry in many countries was viewed as a natural monopoly and was typically operated as such with all stages in the electricity value chain, from fuel production through generation, transmission and retail distribution, under state control. Prices were generally fixed at levels reflecting the operator's short-run marginal cost, plus a required return to the state as owner. The late 1980s and early 1990s saw a growing dissatisfaction with state-owned and operated monopoly electricity supply and an emerging view worldwide that wherever technically feasible, competition should be introduced into the electricity supply industry[1]. To that end many national regulators have embarked on new regulatory schemes and programmes of industry reform, involving varying degrees of privatisation of electricity generation and distribution businesses, and the establishment of wholesale electricity markets, in which the price is determined by the interaction of demand and supply (Wolak, 1997).

In this new setting, generators compete to sell into an electricity market pool and distributors purchase electricity from the pool at prices set by the intersection of aggregated demand and supply on an hourly (or half-hourly) basis. Prices in these new, deregulated markets typically demonstrate extremely high volatility. When compared with financial markets (stocks, bonds) or with other commodities, the behaviour of electricity prices is quite complex and volatile (see Escribano *et al.*,

[1] Although outside the scope of this thesis, there is an extensive literature on the deregulation of electricity markets from a regulatory and industrial organization point of view. For an introduction to competitive electricity markets, see Hogan (1998), Borenstein (2001) and references therein.

2002, Bunn and Karakatsani, 2003). Deregulation has introduced new elements of price uncertainty to both the production and consumption sectors and tools for financial risk management in the form of derivatives such as futures contracts, options and commodity swaps are being developed by and for the industry. Electricity futures contracts are traded on the Sydney Futures Exchange, New Zealand Futures and Options Exchange, Eltermin (Scandinavia), NYMEX and others, and seemingly exotic "weather derivatives" have emerged on the major United States and Continental exchanges to assist firms in dealing with weather variation that affects demand conditions and therefore price.

Why are electricity prices so volatile? The principal reason derives from the physical properties of electricity. By its nature it is instantly produced and consumed and cannot be stored (at least not in any viable wholesale quantity). For this reason, shocks to demand and supply cannot be smoothed out using inventory. Another factor contributing to volatility is that electricity demand is highly inelastic to price. Commercial and industrial consumers as well as households tend not to moderate their consumption in response to price variation (Escribano *et al.*, 2002). The characteristics of the supply stack within each market can also contribute to the price volatility. At low levels of demand, generators supply electricity by using base-load units with low marginal costs. As higher quantities are needed to meet demand, new generators with higher marginal costs are called into production and the marginal price of supply rises. The relative insensitivity of demand to price fluctuations and the binding constraints of generation capacity at peak times contribute to the extreme volatility seen in the spot price. Further, electricity demand and price demonstrate significant seasonal behaviours at intra-daily, weekly and monthly levels.

The importance of regular patterns in the behaviour of electricity prices has been analysed by Lucia and Schwartz (2000) and by Bhanot (2000) among others. While the goals of restructuring and deregulation include increased competition and lower prices to consumers, according to Booth (2004), the increased price volatility that has come with it increases the risk of trading in the market and may lead to increased consumer prices as participants pay for various risk management measures to mitigate the consequences prices spiking to high levels. The characterisation and understanding of the behaviour of electricity prices is therefore a very necessary task that will help inform the trading and investment decisions of generators and distributors as well as the development of effective financial products to help mitigate risk.

1.2 Australian Electricity Prices

Following the 1993 report of the Independent Committee of Inquiry into the Australian Electricity Utilities Industry (the Hillmer Report), the Australian electricity industry has been progressively deregulated. The Hillmer reforms led to the disaggregation of the vertically integrated government-owned electricity authorities into separate generation, transmission, distribution and retail sales sectors in each State. As in other countries that have undertaken similar programmes of reform in their electricity supply industries, the deregulation and restructuring of electricity markets in Australia has brought about fundamental changes in the behaviour of wholesale spot prices. Australian wholesale electricity prices demonstrate high volatility, strong mean-reversion (prices tend to fluctuate around a long-term equilibrium, usually reflecting generators' short-run marginal costs), and abrupt and unanticipated price jumps or spikes[2] that are generally associated with shocks to demand or supply (Higgs & Worthington, 2006). In addition, Australian electricity prices exhibit sporadic occurrences of negative prices[3], which are not seen in other financial markets and are generally overlooked by the current electricity price literature. Figure 1.1 illustrates price spikes and negative prices in the VIC region over the sample period of the study.

The National Electricity Market in Australia (the NEM) is administered by the National Electricity Market Management Company (NEMMCO), under the auspices of the National Electricity Code. Pool prices in the NEM (NEM) exhibit extraordinary levels of volatility, even when compared to electricity prices in other deregulated markets (Booth, 2004). Pool prices in the NEM generally remain around the levels where generators bid their marginal costs, as would be expected in a competitive market, however half-hourly prices can and do approach the NEM price ceiling of \$10,000/MWh[4] during price spikes, compared to long-run mean levels around \$35-\$45 per megawatt hour. It should be noted that the Australian price cap of \$10,000 is itself high compared to overseas practice. For example in the USA, a price cap of \$US1,000/MWh is almost universally applied (Booth, 2004).

[2] Note that electricity prices 'spike' rather than 'jump'. A 'jump' process in financial markets usually suggests that prices move rapidly to a new level and remain there, however electricity process tend to move abruptly to an extremely high level and revert to mean levels just as abruptly (Blanco and Soronow, 2001).
[3] Negative prices occur as a result of the price bidding practices of generators. See Chapters Four and Five for further discussion.
[4] The National Electricity Code sets a maximum spot price of \$10,000 per megawatt hour as the maximum price at which generators can bid into the market.

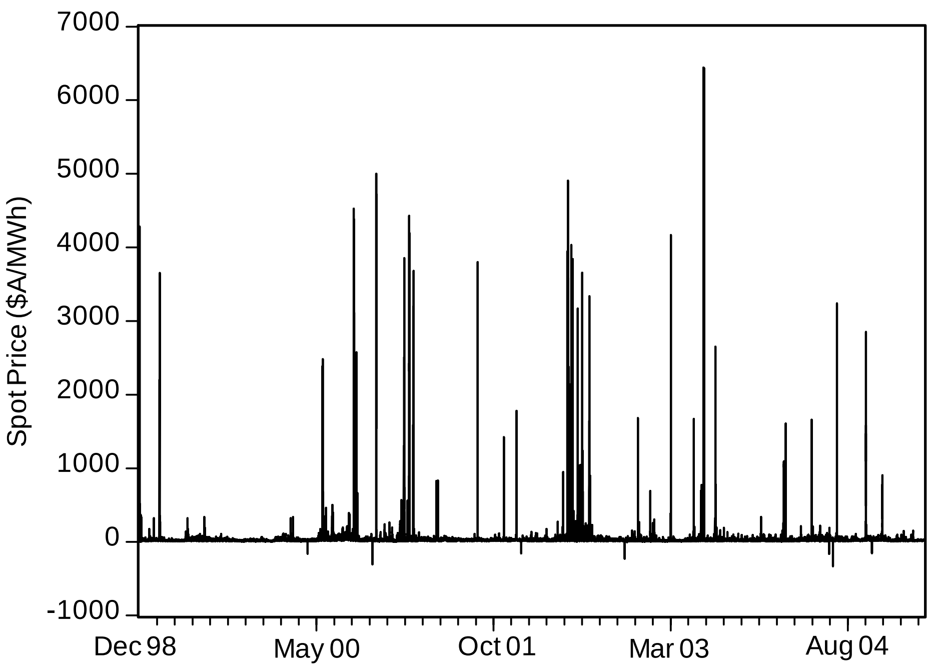


Figure 1.1 Half-Hourly Spot Prices in the VIC1 region, December 1998 to March 2005

An understanding of the dynamics of Australian spot prices, particularly the spike process, is of interest to generators, distributors, retailers and large-scale consumers end-users for risk management, for capacity investment decisions, and for valuation of real and financial assets.

The Australian Government's white paper "Securing Australia's Energy Future" (2004) recognises the significant economic impact of price spikes:

> "These peaks…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".

A report by the US Federal Energy Regulatory Commission (2004) compared 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). The report found that electricity volatilities approach 300 percent, which is markedly higher than

100 percent annualised volatility found in other energy commodities, and the 20 percent or lower volatility reported in equity markets. By applying similar techniques to Australian market data, 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 USA, Bushnell (2003) argues that this is 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).

It is easy to see why an understanding of the behaviour of spot prices, particularly the spike process, is critical to electricity generators, retailers and end-users. In particular, modelling price spikes is vitally 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 better modelling of prices because of the impact of load shedding during peak periods[5], while retailers can benefit from improved forecasting of volatility and price spikes to hedge their purchase price risk.

There is an emerging literature on Australian electricity prices (see, for example, and Strickland, 2000a & 200b; Higgs and Worthington 2003, 2005; among others),

[5] When prices reach the maximum level of $10,000 prescribed by the National Electricity Code, generators are directed to disrupt supply in order to give effect to the price cap and maintain physical system balance. This process is known as 'load shedding'.

however none has yet fully and specifically addressed these structural features of Australian electricity markets. Previous studies based on markets in the United States and Europe 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 like oil and gas (see Schwartz, 1997 and Pindyck, 1999), they are less useful for electricity, where there is little opportunity for direct (or indirect) storage to smooth price spikes (de Jong 2005).

Accordingly, the purpose of this thesis is to investigate the structural characteristics of Australian spot electricity prices, including the spike behaviour discussed so far, as well as the extent to which the strong seasonal patterns that are observed in other electricity markets are evident in the NEM. Much of the literature attempts to model spike behaviour using some generalised functional form [see Clewlow and Strickland, 2000a; Higgs and Worthington (2003, 2005); Bunn (2004); Alvaro, Peña, and Villaplana (2002); Hadsell, Marathe and Shawky (2004); and Goto and Karolyi (2004)]. This thesis takes a different approach by identifying and capturing *individual* spikes and modelling their effects, along with seasonal factors. Spikes are irregular and vary in magnitude, so it is useful to examine them individually. Much of the existing literature uses daily or hourly data, over samples spanning one or two years. This study's use of half-hourly prices over a six-year sample provides a useful extension of past work and is potentially significant for producers, regulators and researchers. The use of data sampled over a longer (six-year) time period is necessary in order to establish the extent to which these extreme within-day price spikes and negative prices are significant and regular features of the data. Knittel and Roberts

(2001) find that the forecasting performance of standard financial models is relatively poor in the presence of seasonal effects and extreme behaviour without adjustment for these effects. By explicitly investigating these effects this study may also be of significance for financial markets traders wishing to profitably operate in the electricity markets. A further contribution of this thesis is to extend the analysis into demand, to investigate the presence and effect of seasonal patterns and spikes in demand and the interaction between observed demand spikes and spikes in price.

1.3 Scope and Structure of Thesis

The remainder of this thesis is organised as follows. Chapter Two presents a review of the relevant literature. It is worth noting that the electricity market literature is very broad in scope and embraces the disciplines of engineering, mathematics, economics and finance. In the context of this thesis, only the latter are relevant and issues such as price and demand behaviour, price forecasting, and derivative pricing and contract design have been considered. As discussed earlier, the wholesale pool markets for electricity are a relatively new development. The economics and finance literature focussing on price behaviour in electricity markets is also relatively new and therefore less extensive than the literature in 'conventional' financial commodity markets. Relevant research on price formation in electricity markets is discussed, given the special nature of electricity as a traded commodity and special aspects of market design that it requires. The next section presents the literature on stochastic modelling of electricity prices, particularly the various adaptations of techniques from the "conventional" financial markets and their strengths and limitations when applied to modelling electricity prices. Next, the literature emphasising structural modelling, especially the complex mix of seasonality and outlier effects observed in electricity prices is discussed, followed by a brief overview of the emerging field of non-parametric modelling, which takes in the application of neural networks, fuzzy logic and fuzzy regression techniques for the purposes of price forecasting. The nascent Australian literature is discussed next, and the final section discusses opportunities for research emerging from the literature and the foci of this thesis.

Chapter Three provides an overview of the institutional characteristics of the Australian electricity market. It firstly provides background to the recent deregulation and restructuring of the Australian electricity supply industry. Second, it provides an overview of the important historical and operational aspects of Australia's National Electricity Market (NEM). Third, the nature of electricity and how the NEM is organised to accommodate distribution given its unique characteristics is discussed - electricity has physical characteristics unlike other traded commodities and these characteristics require that the wholesale markets for electricity must be conducted differently to other commodity markets. Fourth, it provides an overview of the markets in other countries that have undertaken similar restructuring of their electricity supply industry.

Chapter Four describes the data collection and collation procedures and sources of the electricity price and demand data used in this thesis. The summary descriptive statistics for each data set are also presented. In brief, the data sets used include time series data for demand and price for electric power in the NEM, collected directly from NEMMCO[6] for the period from commencement of the NEM at 2:00am December 7, 1998 to 11:30pm March 31, 2005. NEMMCO collates and reports half-

[6] Available for download from NEMMCO's website at http://www.nemmco.com.au/data/market_data.htm.

hourly trading interval observations for demand and price for the five NEM regions (NSW1, QLD1, SA1, SNOWY1 and VIC1)[7]. The sample size is 110,719 observations for each of price and demand for each of five regions in the NEM. This chapter also includes discussion of the process of determination of half-hourly demand and price values, which are necessarily different from pricing mechanisms in other financial markets.

Chapter Five documents seasonal patterns and other characteristics of electricity spot prices in the Australian National Electricity Market (NEM), over the six-year sample period. The goal is to more finely investigate the influence of seasonalities and outliers noted in the body of literature on electricity prices. Results confirm that electricity prices exhibit significant time-of-day and day-of-week effects. Monthly and yearly effects are significant to a lesser degree. Extremely high spikes in the price series are an important characteristic of electricity prices and are shown to be a highly significant component of returns behaviour. Negative prices are impossible in financial time series data but do occur in Australian electricity prices and are found to be influential. The implications of these findings confirm the view that seasonal and outlier effects should not be ignored in efforts to model electricity prices.

Chapter Six investigates whether the structural characteristics of electricity price are also present in electricity demand. Given that the spot market is always in equilibrium, these spikes could be caused by short-run spikes in demand or shocks to supply (such as breakdowns in generation plant or disruption to the transmission

[7] The five NEM regional pools are defined on state lines, but are designated within the NEM as NSW1, QLD1, SA1, SNOWY1 and VIC1. This naming scheme will be followed throughout this thesis. The TAS1 region based in Tasmania commenced operation in late 2005, after the sample period examined by this thesis.

grid). Analysis of the demand data may provide some insight into the spike behaviour observed in the price series. As a first step in this analysis, it is necessary to characterise any seasonal patterns that might be present and investigate the presence of spikes in the demand side of the spot market. Seasonal patterns in demand or system load are well documented in the literature and these patterns are incorporated into a variety of forecasting models. Harvey and Koopman (1993) document intra-day and intra-week effects and incorporate them into their demand model using splines. Earlier studies consider longer-term load forecasting horizons several months into the future, using monthly demand data (Engle, Granger and Hallman, 1989). In the Australian context, Smith (2000) and Cottet and Smith (2003) document intra-day patterns in demand in New South Wales.

While a number of studies have incorporated seasonal patterns into demand models, the presence of sudden and fast reverting spikes in demand have not been comprehensively documented. This chapter investigates if, like changes in the electricity spot price, changes in demand demonstrate a high incidence of spikes, as well as sensitivity to seasonal patterns. According to Knittel and Roberts (2001), the regular occurrence of these spikes accounts for the failure of conventional stochastic forecasting models and in light of this, I believe it is necessary to test if demand also exhibits evidence of spikes. With these objectives in mind the contribution of this chapter is twofold. First, the research examines a six-year sample of half hourly total system demand for five regions in Australia's National Electricity Market (NEM) and reports on the occurrence of outliers in the form of extreme spikes in demand returns. Second, a model that captures the sensitivity of demand returns to these outliers is presented, that controls for seasonal factors including time-of-day, day-of-week, monthly and yearly effects. The results show that seasonal effects are significant but vary across regions. Time-of-day effects are found to be more significant than other seasonalities. Further, like price spikes, spikes in demand are spikes that are present in the demand series and are found to be highly significant. Chapter Eight extends the work in Chapters five and six to examine the transmission of spikes in the demand data to price series.

Chapter Seven considers the underlying volatility process in Australian electricity prices and examines the applicability of a range of GARCH specifications to modelling volatility in the 5 regional NEM markets. The GARCH variants considered include the "basic" GARCH specification (Bollerslev, 1986), the Threshold GARCH (TARCH) model of Glosten, Jaganathan and Runkle (1993), Nelson's (1991) Exponential GARCH (EGARCH) and the Power ARCH (PARCH) model proposed by Ding *et al.* (1993). The approach used in this study differs from the previous Australian ARCH-based studies in that discrete half-hourly returns[8] are used rather than price relatives. The use of discrete returns is necessary to allow for the presence of negative prices which were identified in Chapter Five as a significant feature of the data. This study is further distinguished from previous work in that seasonal effects and individual spikes are treated by pre-whitening the data to remove seasonalities and outlier effects in an OLS framework before fitting the various GARCH models. The reasons for doing so are twofold: firstly, after accounting for spikes and seasonalities, significant residual ARCH effects are observed in the pre-whitened data (see section 7.3 for further discussion). I am interested in developing a better

[8] Electricity requires no initial investment and is not storable, therefore does not produce a return to an investor as it is generally understood in financial markets (ie: as a result of change in value of a held position). Here "return" means half-hourly percentage change in spot price, similar to Black's (1976) application of the term in futures markets.

understanding of underlying volatility process in the returns series *without* the noise contributed by seasonalities and outliers; and secondly, a model specified with a conditional mean and variance process that includes a very large number of explanatory variables (up to 260 variables to account for seasonalities, outlier effects and serial correlation) *and* over a very large sample size (>110,000 observations in each region), is too unwieldy for available computing capabilities and as such, a two-stage procedure is called for. Results show that based on ranking by Schwarz-Bayes and Akaike Information Criteria (see McKenzie and Mitchell, 2002), the PARCH(1,1) specification is favoured in all regions but in QLD1 and SA1, model parameters indicate that the PARCH (1,1) model may be unstable in QLD1 and SA1, in which case the EGARCH (1,1) specification is preferred as it more reliably describes the volatility processes in those two regions.

Chapter Eight extends the work on spike analysis in Chapters five and six and considers the interaction of the significant spikes in price and demand. Having identified all individual occurrences of extreme spikes in both demand and price, this study applies an event study methodology to investigate the extent to which shocks and extreme values in the demand series are reflected as extreme values in price. The research issue considered in this section is the extent to which extreme spikes in demand coincide with spikes in price and whether a spike in demand triggers a response in price. To date no other study in the electricity literature has used an event-study approach to answer this question and I believe it provides valuable insight into the relationship between extreme demand and price behaviour in electricity markets. A 'standard' parametric event study approach and a GARCH-based event study (following McKenzie, Thomsen and Dixon, 2004) are used and results show that there is negligible coincidence of demand and price spikes across the five NEM regions in the study, yet there is evidence of a small but significant price response to demand spikes in the New South Wales, Queensland and Victorian regional pools. This response is not evident in the South Australian and Snowy pools. These results suggest that supply effects might be more significant contributors to spike evolution and flags this possibility as a direction for future research.

Chapter Nine concludes the thesis by summarising the major findings of the empirical analysis, highlighting the major contributions of this research to the existing literature in the field of electricity price behaviour and suggests possible directions for future research.

Chapter 2: Literature Review

2.1 Introduction

The electricity market literature is very broad in scope and embraces the disciplines of engineering, mathematics, economics and finance. In the context of this thesis, only the latter are relevant and issues such as price and demand behaviour, price forecasting, and derivative pricing and contract design have all been considered. For example, one popular area of research has focused on the ex-ante economic modelling of electricity markets, using stylized game theory or simulation methods to understand the price implications of various market designs or equilibrium conditions (e.g. Guan *et al.*, 2001; Park *et al.*, 2001; Andersen and Xu, 2002). A second popular area of research has been in the area of electricity price forecasting (e.g. Green and Newbery, 1992; Joskow and Frame, 1998; Green, 1999; Batstone, 2000, Skantze *et al.*, 2000; Bunn and Oliveira, 2001; Routledge, Seppi and Spatt, 2001; Baldick, 2002; Day *et al.*, 2002; Bessembinder and Lemmon, 2002). The focus of this thesis is on the time-series modelling of electricity price behaviour, including the special structure and stochastic properties of electricity prices.

This chapter presents a review of the literature relevant to this thesis. It should be noted that the wholesale pool markets for electricity are a relatively new development. As such, the economics and finance literature focussing on price behaviour in electricity markets is also relatively new and therefore less extensive than the literature in ‘conventional’ financial commodity markets. Section 2.2 discusses relevant research on price formation in electricity markets, given the special nature of electricity as a traded commodity and special aspects of market design that it requires. Section 2.3 presents the literature on stochastic modelling of electricity prices, particularly the various adaptations of techniques from the "conventional" financial markets and their strengths and limitations when applied to modelling electricity prices. Section 2.4 discusses the literature emphasising structural modelling, especially the complex mix of seasonalities and outlier effects observed in electricity prices. Section 2.5 briefly introduces the emerging field of non-parametric modelling, which investigate the efficacy of neural networks, fuzzy logic and fuzzy regression techniques for the purposes of price forecasting. Section 2.6 considers the emerging Australian literature and section 2.7 discusses opportunities for research emerging from the literature and the particular foci of this thesis.

2.2 Models of Electricity Price Behaviour: Price Formation in Electricity Markets

The most significant characteristic of the wholesale electricity spot market relates to the nature of the product being sold[9]. The physical laws that govern the delivery of electricity via a "poles and wires" transmission grid require that the input of electricity by generators and offtake by consumers be in synchronous balance[10]. If production and consumption are different, even for a moment, the frequency and voltage of the power fluctuates (Bunn & Karakatasani, 2003) leading to breakdown of transmission infrastructure and damage to end-use equipment. Further, end-users treat electricity as a service at their convenience, and there is very little short term elasticity

[9] Chapter three presents a detailed discussion of the institutional characteristics of key markets and the price formation process in the Australian market.
[10] With some allowance for physical transmission losses across the transmission network.

of demand to price (Silk and Joutz, 1997). The task of a system operator, in the Australian case the National Electricity Market Management Company (NEMMCO) is to continuously monitor the demand process and to ensure that base load requirements of the system are met and that generators who have the capacity to respond quickly to periodic fluctuations in demand are called in when required.

Although many spot markets for electricity work on the basis of hourly trading intervals, the Australian (and British) spot markets are unique in that they trade based on half-hourly segments of time. At any given point in time, a variety of plants using different fuels and generation technologies will produce electricity. The marginal cost of this supply is coupled with demand to set prices at different times. Figure 2.1 presents a plot of the demand and price series for a selected week in 2000. The price series exhibits a high degree of structure and seasonality, which is a defining feature of spot electricity prices.

More specifically, a number of characteristics typical of electricity spot price series have been noted in the literature. Johnson and Barz (1999) report mean-reversion to a long-run level in various markets. Kaminski's (1997) study of United States power markets identifies multi-scale seasonalities on an intra-day basis, along with weekly, monthly and seasonal effects related to summer, autumn, winter and spring). Kaminski (1997) also notes erratic extreme behaviour with fast-reverting spikes as opposed to "smooth" regime-switching and non-normality, expressed as high positive skewness and leptokurtosis. Electricity prices typically 'spike' rather than 'jump'- a jump process typically suggests rapid movement to a new level which is subsequently maintained, whereas electricity prices increase rapidly to extremely high values and revert quickly to ‘normal’ levels (Blanco and Soronow, 2001). In their analysis of the Nordic market, which is centered on Norway and Sweden, Lucia and Schwartz (2002) identify seasonal patterns in the deterministic component of prices and in the degree of spike intensity.

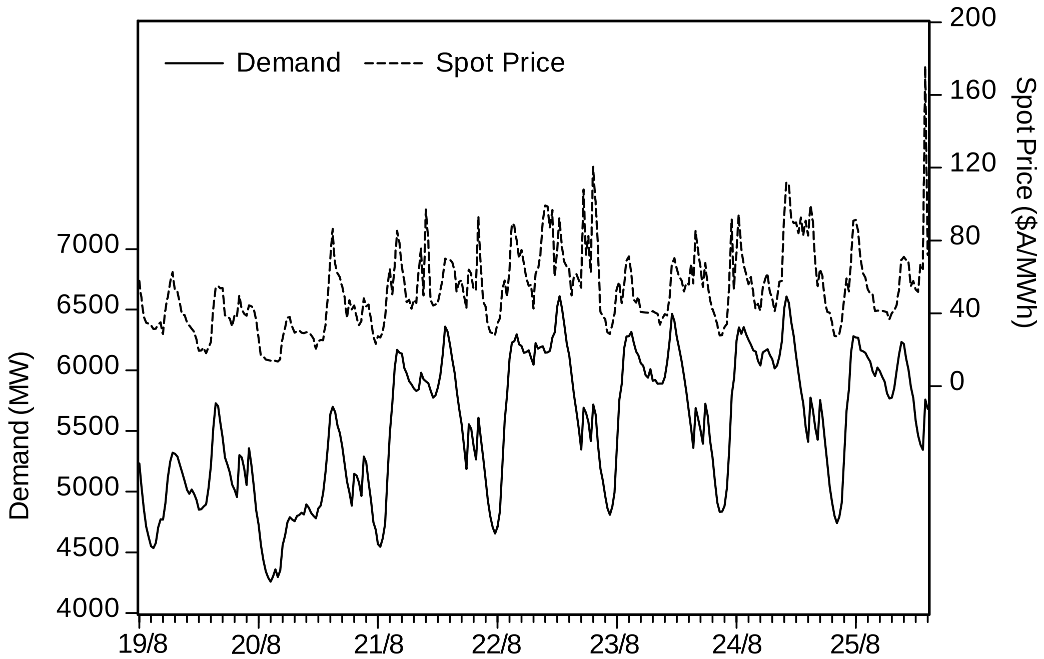


Figure 2.1: Victorian Half-Hourly Spot Price and Demand for the Week Commencing 19/8/2000

According to Escribano *et al.* (2001), the volatility of spot prices is typically orders of magnitude higher than for other commodities and financial assets, with annualised values of 200% or more. The authors further note that this volatility is time-varying, with evidence of heteroskedasticity both in the unconditional and conditional variance. They argue that the former reflects the influences of demand, capacity margin and trading volume on volatility levels and the latter describes the observed clustering of tranquil or unstable periods (GARCH effects), specifying volatility as a function of its lagged values and previous disturbances. There is also evidence in the literature that conditional variance reacts asymmetrically to positive and negative past shocks. Interestingly, electricity price volatility displays a response to leverage effects that is inverse to the response typically observed in conventional financial markets (Knittel and Roberts, 2001). Higgs and Worthington (2005) note a similar perverse asymmetry in the Australian markets.

Bunn and Karakatsani (2003) argue that there are a number of market microstructure elements that help to explain these unusual time series characteristics. They contend that with a diversity of plant employing different generation technologies and fuel efficiencies in the system, different plant will be setting the market-clearing price at different levels of demand. They further argue that a diversity of plant in the system is expected for two reasons. The first is obsolescence. With power plant lasting 40 years or more, new and more efficient generation technologies will be introduced during the productive life of existing plant. Prices will fluctuate because of the varying efficiencies of the set of plant being used for generation at any particular moment in time. The plant with the lowest marginal costs (the "base load" plant), will operate most of the time but during peaks in demand, other, "more expensive" power plants (the "peak load" plant) may only be operating for a few hours when demand exceeds base-load supply capacity and prices are sufficiently high. The recovery of capital costs on peak-load plant, through market prices, may have to be achieved over a relatively few hours of operation per year compared to the 8760 hours in a normal year that a base load plant could theoretically operate. The authors argue that this will favour both the construction of low capital/high operating cost plant for peaking purposes and the over-recovery of marginal costs when such plant is called into production, with a natural consequence that prices will be much higher in peak load periods. Blanco and Soronow (2001) put forward the view that modelling price peaks accurately is vitally important for generation assets, particularly peaking plants whose value is entirely dependent on the existence of price spikes that facilitate recovery of high marginal costs and recouping of fixed costs over very short running periods. This view is intuitively appealing and consistent with the experience in the Australian market, with base load generally being provided by relatively low-cost brown coal and black coal-fired generation plant that is in continuous operation, and high-priced peak load being provided by fast-start gas-fired and hydroelectric generators. Bunn and Karakatsani (2003) further contend that other factors may also come into play in the short term: there may be technical failures with plant, causing more expensive standby generators to come online; the transmission system may become congested or disrupted so that expensive but necessary local plant gets called into production; and unexpected fluctuations in demand may also be influential.

2.3 Stochastic Modelling of Spot Electricity Prices

Much of the literature on empirical price modelling attempts to adapt an established model of financial asset behaviour to the special characteristics of electricity. Typically this is done in order to provide better information for trading decisions and to aid in the design and valuation of electricity derivatives. An early example is Kaminski (1997), where the spiky characteristic observed in regional power markets in the United States is addressed through a random walk jump-diffusion model, adopted from Merton (1976). Kaminski's model does not incorporate another fundamental feature of electricity prices, that being rapid reversion to a mean level following the occurrence of a spike. Johnson and Barz (1999) identify this mean-reversion tendency, which is confirmed in the then newly-established national

Australian market by Clewlow and Strickland (2000b). Deng *et al.* (2000) extends this class of modelling to include regime-switching and stochastic volatility in the price dynamics, although they are not captured jointly in a single model. In the same paper, the authors propose a multivariate framework for the joint dynamics of electricity price and a range of correlated variables including demand, weather conditions (in particular, air temperature) and fuel prices, allowing richer dynamics to emerge.

Jump-diffusion models are superficially appealing but present some limitations when applied to electricity price data. Jump-diffusion models *a la* Clewlow and Strickland (2000a) assume that shocks affecting the price series die out at the same rate. This assumption is challenged by Huisman and Mahieu (2001). In their examination of daily price and price index data for the power markets in California, UK, Germany and the Netherlands, they find that stochastic jump models do not clearly disentangle mean-reversion from the reversal of spikes to normal levels. Secondly, model assumptions for jump intensity (constant or seasonal) are convenient for simulating the distribution of prices over several periods of time but are restrictive for actual short-term predictions for a particular time. Regime switching models offer an alternative framework to jump-diffusion that may be more suitable for actual price forecasting. Regime-switching can replicate price discontinuities observed in practice, and could detach the effects of mean-reversion and spike reversal that jump-diffusion attempts to replicate. Ethier and Mount (1999) consider two latent market states, an abnormal, “spike” state and a more “regular” state around a long-run mean. They model an AR(1) price process under both the regular and the abnormal regimes and constant transition probabilities, however their model specification imposes stationarity in the spike process which is sometimes found to be invalid (see de Jong and Huisman, 2002).

Huisman and Mahieu (2001) propose a model that isolates the mean state and spike effects by assuming three market regimes; a regular state with mean-reverting price, a jump regime that creates the spike and finally, a jump reversal regime that ensures reversion of prices to their previous long-run mean level. Their regime-transition structure is restrictive, as it does not allow for consecutive irregular prices. In de Jong and Huisman (2002), the spike states are found to be irregular and recurrent but not persistent. They propose a more relaxed, two-state model, assuming a stable mean-reverting regime and an independent spike regime of log-normal prices. Their model allows regime independence that can accommodate multiple consecutive regimes of either type. When applied to forecasting, their regime-switching price model typically overstates the 'normal' price level and generally predicts the normal regime, with predicted occurrence of spikes much less than the actual rate of occurrence and the predicted probabilities of the extreme state very rarely exceeding a conventional threshold level. This problem might be averaged out when simulating several periods ahead with the intention to price a financial instrument but it is critical for the precision required in a day-ahead prediction (Bunn & Karakatsani, 2003)

An interesting and potentially more accurate description of electricity prices is proposed in Bystrom (2005). Bystrom examines five years of hourly price changes in the Nordpool, noting that hourly price changes of 100% are commonplace and have been observed to exceed 600%. The price change data is first pre-filtered using a combined AR-GARCH time series model, taking into account autocorrelation in the returns themselves (AR) and in the squared returns, as well as seasonal effects and volatility clustering (GARCH). Extreme value theory (EVT) is then applied to the residuals using the *peaks over threshold* (POT) method, following McNeil and Frey (2000). Bystrom finds that the POT method models the extreme values with a high degree of accuracy, with in-sample and out-of-sample evaluation of forecasts providing strong support for conditional EVT-based modelling. This approach avoids the estimation complexities and forecasting limitations present in the previous stochastic models due to sudden and fast-reverting spikes.

Finally, it should be noted that the stationarity properties of electricity prices potentially differ across markets. If the modelling involves daily average or by-period spot prices, a mean-reverting process with a seasonal trend, proposed for instance in Lucia and Schwartz (2002), seems appealing for some markets, however, discrepancies exist. In Atkins and Chen (2002), time and frequency-domain tests reject the null hypotheses of I (1) and I (0) processes for the electricity prices in Alberta. Long memory features are subsequently identified in the price evolution and described with autoregressive fractional difference (ARFIMA) models. In Stevenson (2002), a unit root is identified in the Victorian market, possibly because all hourly prices are retained in the same data set and not divided by load period.

A common feature of the finance-inspired stochastic models reviewed in this section is their main intention to replicate the statistical properties of spot prices with the ultimate objective of derivatives evaluation. In order to retain simplicity and/or analytical tractability, the models include only a few factors and typically focus on daily average prices, which are sensitive to outliers. As noted earlier, trading in most markets is based on half-hourly or hourly intervals. According to Ait-Sahalia *et al.* (2003), when using high-frequency data it is desirable to sample as often as possible and it may be that some important information may be lost by the use of daily average data. Worthington *et al.* (2005) however, note that daily averages play an important role in electricity markets, particularly in the case of financial contracts. For example, the electricity futures contracts traded via the Sydney Futures Exchange (SFE) are settled against the arithmetic mean of half hourly spot prices in a given month.

Although useful for derivative contracts, the aggregation of intra-day information is likely to be restrictive from a forecasting perspective. Estimation complexities and forecasting limitations are further enhanced due to the abrupt and fast-reverting nature of price spikes. In many instances, short-duration spikes may 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 (see Higgs and Worthington, 2005 and Thomas *et al.*, 2006). Accurate and reliable price forecasting is crucial to generators when formulating their bidding strategies and specification of intra-day data would provide a logical resolution to these as yet unexplored features.

Stochastic models have been substantially adapted to the peculiarities of electricity, but still need much development in order to fully reveal the main components of price structure. Knittel and Roberts (2001) emphasised the need to explore this structure and include it in price specifications. A related challenge is to explore how the sensitivities of prices to influential factors vary throughout the day as a response to the fundamentals of intra-day variation in demand, plant-operating constraints, and the strategic actions of generators.

2.4 Structural Modelling

There is an emerging family of structural models of electricity prices that seek to uncover a richer structure for electricity prices in order to understand market performance and enable more accurate forecasting. They typically examine historic market prices in the context of fundamental influences such as system load (demand), weather and data on plant service. For example, a simple regression model that relates spot price in the Spanish and Californian markets to lagged price and demand values is suggested in Nogales *et al*. (2002). Their model was refined by adjusting the number of lags until the assumption of uncorrelated errors was satisfied, however the predictive ability of this model seems limited in the case of markets with strategic market power and complex trading environments.

Other structural formulations address non-linear aspects of electricity price dynamics, such as multiple price regimes and jumps. Vucetin *et al.* (2001) implement a discovery algorithm of regression regimes, which reveals multiple price-load relationships in spot trading. The assumption of a moderate switching rate between regimes, necessary for convergence, is unappealing for the sudden spikes in electricity but could describe smooth regime transitions in the medium term. As the regime-switching process is not modelled, the algorithm is constrained to the analysis of past data, rather than applied to forecasting.

Davison *et al*. (2002), posits a model in which prices are assumed to follow a mixture of two normal distributions and the 'regime' probabilities are related empirically to a variable with economic and strategic attributes, the ratio demand/supply. To derive a general formulation that allows medium-term forecasting, demand is specified as a sinusoidal function and capacity across the year as a two-level categorical variable. This approximation however ignores the interaction between prices and capacity availability. In Skantze *et al.* (2000), hourly price is specified as an exponential function of demand and supply. Both are assumed stochastic with a deterministic monthly component plus a random term. Due to the pronounced intra-day correlation, the random terms are derived from a Principal Component Analysis approach, similar to Wolak (1997). To capture stochastic effects, the loadings are specified as mean-reverting to a stochastic mean. A distinct feature of the model, compared to standard jump-diffusion, is the incorporation of data for plant outages affecting supply. A Markovian process is assumed for plant outages with parameters related to the various generation technologies. The set of outages examined only reflects ex-post knowledge of outages and does not consider the possibility of generators engaging in strategic capacity withholding, leading to price manipulation, which has been a major concern to regulators in electricity markets, and has strong implications for accurate price forecasting. In the Australian context, Booth (2004) suggests that generators actively exploit "…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".

The existence of multiple, different, components in electricity pricing is considered in Stevenson (2002). The price and demand series are decomposed into multiple levels of resolution with wavelet analysis and signal is differentiated from noise with a robust smoother-cleaner transformation. For the reconstructed data, a threshold autoregressive (TAR) model is suggested, with demand as a critical variable. Price changes are modelled in the presence of a unit root and assigned to one of two regimes depending on whether the change in demand is positive or negative. This restriction excludes the impact on prices of other fundamentals such as supply constraints. The model could possibly be enhanced by defining the threshold variable as a function of the ratio of demand to supply. The smoothing procedure eliminates the leakage of rapidly reverting price spikes to more fundamental resolution levels, where information takes progressively longer to be impounded into price. This allows a more reliable estimation of the baseline regime but treats price spikes as noise are effectively filtered out of the data despite their information content.

2.5 Non-Parametric Modelling.

Efforts to model electricity prices are gradually becoming more focussed on practical applications with a view to reliable forecasting. To that end, several non-parametric techniques, such as genetic algorithms and neural networks, have been adopted for price prediction. An indicative list includes neural networks applications for the England -Wales pool by Ramsay and Wang (1997), for the California market by Gao *et al.* (2000), Spain by Centano Hernandez *et al.* (2003) and Victoria by Szkuta *et al.* (1999); fuzzy regression models linking demand and price by Nakashima *et al.* (2000); and Fourier and Hartley transformations by Nicolaisen *et al.* (2000). Although non-parametric models tend to be flexible, can handle complexity and as a result are promising for short-term predictions, they do not provide structural insights or forecasts of the price distribution, which limits their application to risk management and longer-term capacity investment decisions.

2.6 Modelling Price Behaviour in the Australian National Electricity Market

Spikes in electricity prices are a common feature of the Australian market. For example, Lu *et al.,* (2005) observe regional spot prices as high as several thousands of Australian dollars per Megawatt Hour (MWh), several hundred times higher than the normal price level around $20–30 per MWh. For example, at 18.30 on 31 July 2003 New South Wales reached $8,622.63 per MWh and on January 16, 2007, prices in Victoria reached the market maximum level of $10,000 MWh for two hours during the afternoon. Booth (2004) estimates that some 20-30 percent of annual average price levels in the Australian National Electricity Market is attributable to extreme price spikes, which occur at fewer than one percent of the trading intervals in a year. Thomas *et al.* (2006) confirm this view and note some 516 occurrences of extreme spikes in returns across all NEM regions over a six-year sample period of half-hourly trading interval data representing approximately 0.1% of all observations.

Bushnell (2003) observes fewer price spikes in the US market (based on the Pennsylvania - New Jersey – Maryland pool) than in the Australian market and suggest that this is a consequence of US market regulators being more willing to constrain or modify the behaviour of generators, however the reason may be more to do with market design. Wolak (1997) observes that the occurrence of extreme price spikes is more prevalent in compulsory pool markets such as the NEM than it is in 'residual' spot markets like Nordpool[11] A report by the US Federal Energy Regulatory committee (2004) found electricity volatilities in the US approaching 300 percent, with other energy commodities (oil, natural gas) never more than 100 percent and equity markets (S&P500) demonstrating annual volatility of 20 percent or less. Booth (2004) calculated historical volatilities in the Australian electricity market in excess of 900 percent.

In the Australian context, only a small number of papers have been published that have focused on modelling volatility processes in electricity prices. For example, Worthington, Kay-Spratley and Higgs (2005) examine electricity prices and price volatility among the five Australian electricity markets in the NEM by applying a multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) model to identify the source and magnitude of spillovers, in a sample of half-hourly spot prices for the period December 1998 to June 1991. The authors find a large number of significant own volatility and cross-volatility effects in all five markets, indicating the presence of strong ARCH and GARCH effects. It should be noted that for the purposes of their analysis a series of daily arithmetic means is drawn from the trading interval data (following Lucia and Schwartz, 2002). The authors recognise that this treatment will entail the loss of at least some 'news' impounded in more frequent trading interval data, but correctly note that "…daily averages play an

[11] See chapter three for further discussion of institutional characteristics of different markets.

important role in electricity markets, particularly in the case of financial contracts…"[12].

This work is extended in Higgs and Worthington (2005), which presents an investigation of the intra-day price volatility process in Australian electricity markets under five different ARCH processes: GARCH (generalised ARCH), Risk Metrics (normal integrated GARCH), normal APARCH (asymmetric power ARCH), Student APARCH and skewed-Student APARCH (following Ding, Granger, and Engle, 1993; and Giot and Laurent, 2003a, 2003b). The authors include the documented systematic features – intra-day and monthly patterns (calendar effects), intra-day innovation and volatility spillovers (ARCH and GARCH effects) and market activity (demand and information asymmetry effects), with a view to providing a characterization of the volatility process. The data employed consists of electricity price relatives and demand volumes for the half-hourly intervals from 1 January 2002 to 1 June 2003 for NSW1, QLD1, SA1 and VIC1[13]. The natural log of the price for each half-hourly interval is used to produce a time series of price relatives for analysis. In their analysis, the inclusion of news arrival is indicated by the contemporaneous volume of demand, time-of-day, day-of-week and month-of-year effects as exogenous explanatory variables. The authors find that on the basis of the log-likelihood, Akaike Information (AIC) and Schwartz Criteria (SC), the skewed Student APARCH form is the best model for all four markets under consideration. Their results also indicate significant innovation (ARCH effects) and volatility (GARCH effects) in the conditional standard deviation equation, even with market

[12] For example, the electricity futures contracts traded via the Sydney Futures Exchange (SFE) is settled against the arithmetic mean of half hourly spot prices in a given month.
[13] The SNOWY region is not included in the Higgs and Worthington (2005) study.

and calendar effects included. They further observe significant asymmetric news responses in intra-day price volatility.

The previous Australian research typically confines its analysis to one regional market in the NEM over a relatively short time horizon (less than two years). This chapter extends the previous research by using data sampled over a much longer time horizon and includes five NEM regional markets, to better characterise the volatility process by examining the market over a wider range of conditions and broader market base. I examine the applicability of a range of GARCH specifications to modelling volatility in 5 regional NEM markets. Half-hourly trading-interval prices for the period from the commencement of the NEM in December 1998 to March 2005 are used and five NEM regions (NSW1, QLD1, SA1, SNOWY1 and VIC1) are included. The GARCH variants considered include the "basic" GARCH specification (Bollerslev, 1986), the Threshold GARCH (TARCH) model of Glosten, Jaganathan and Runkle (1993), Nelson's (1991) Exponential GARCH (EGARCH) and the Power ARCH (PARCH) model proposed by Ding *et al.* (1993).

2.7 Electricity Price Modelling: Research Opportunities

The price structure of electricity markets is highly idiosyncratic when compared to other more "conventional" financial markets. Many of the characteristics of electricity prices can be replicated with existing stochastic models, but their structure has not been fully represented adequately in the empirical research literature. A structural approach is appropriate but to date there are several unresolved modelling issues.

The finance-based stochastic models reviewed in this section generally intend to evaluate and replicate properties of spot prices with a view towards pricing and evaluating derivatives contracts. To retain simplicity and some degree of tractability, models include only a few factors and typically focus on daily average prices, which are sensitive to outliers. While convenient for derivative pricing, the aggregation of intra-day information can be restrictive from a forecasting prospective. Although some stochastic models are adaptable to the peculiarities of electricity, there is still much work to do in accounting for the main elements of electricity price structure.

The focus of this thesis is on modelling the structural characteristics of electricity prices in the Australian National Electricity Market. Seasonalities including time-of-day, day-of-week, monthly and yearly effects and large price spikes are a well-documented feature of electricity markets and several studies examine their effect in aggregate using various functional forms (e.g. Kaminski, 1997, Clewlow and Strickland, 2000a; De Jong and Huismann, 2002; and Goto and Karolyi, 2004). The literature on electricity price modelling frequently identifies the presence of extreme price jumps with rapid reversion to the mean as a cause of extreme volatility in electricity prices (Bunn (2004), Alvaro, Peña, and Villaplana (2002), Hadsell, Marathe and Shawky (2004)). Modelling electricity prices in the Australian and overseas markets is a difficult process and this provides a strong incentive for further research into the electricity price market. Various models developed in the study of financial time-series data have been applied to electricity time series but there is much work yet to be done to fully account for the main components of price structure. Knittel and Roberts (2001) highlight the need to explore this structure and include it in price specifications, as do Goto and Karolyi (2004).

Chapter 3: The Market for Electricity

3.1 Introduction

The purpose of this chapter is fourfold. First, it provides background to the recent deregulation and restructuring of the Australian electricity supply industry. Second, it provides an overview of the important historical and operational aspects of Australia's National Electricity Market (NEM). Third, the nature of electricity and how the NEM is organised to accommodate distribution given its unique physical characteristics is discussed. Fourth, it provides an overview of the significant markets in other countries that have undertaken similar restructures of their electricity supply industry.

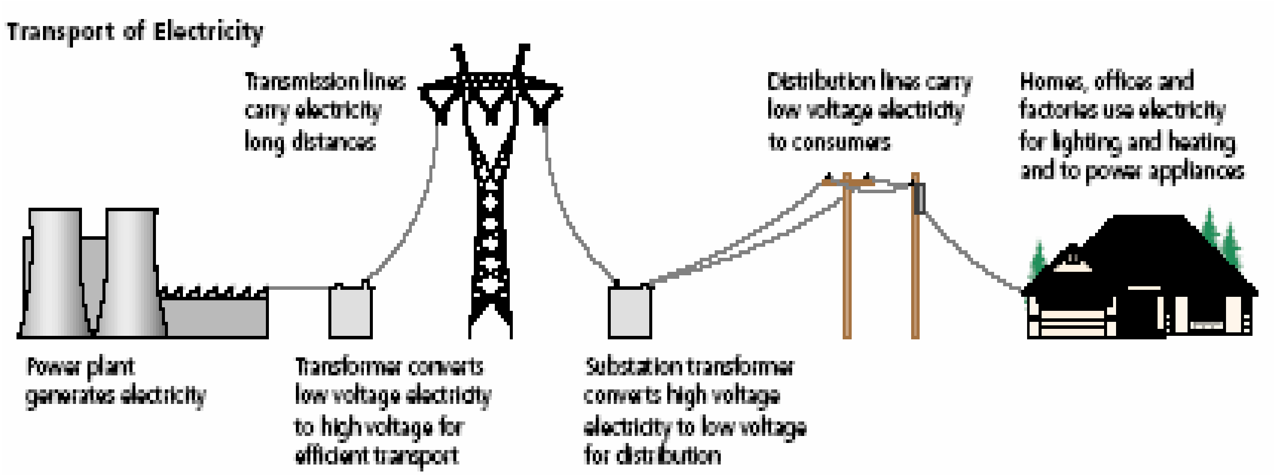
Electricity supply has traditionally been viewed as a natural monopoly, in which economies of scale and the need for an extensive transmission and distribution network seem to favour supply by a single firm within a given geographic region. One generally accepted characteristic of a natural monopoly is increasing returns to scale. According to Sweeney (2002), transmission of electricity, that is the provision of physical delivery services and infrastructure (poles, wires, transformers, and other equipment) provides a robust example of increasing returns to scale in the electricity supply industry. A customer could double the amount of electricity used with no increase in the cost of providing wires to a home. If two competing companies were each to run electric wires down the same streets to compete for customers, total cost and cost per customer would increase even with no change in the quantity of electricity delivered. Cost would be lowest if there were only one company providing the wires, transformers, and other physical equipment for local distribution of centrally generated electricity, therefore local distribution of centrally generated electricity is generally considered to be a natural monopoly and, as such, has historically been allowed to operate as a monopoly franchise, subject to regulatory oversight.

Unlike electricity distribution, retail electricity is not characterised by increasing returns to scale. In order to double the amount of electricity sold, a retailer would need to double the amount of electricity purchased at wholesale. If wholesale electricity prices were held fixed, doubling the acquisition of electricity would double the total cost of acquiring the electricity, therefore the cost per unit of electricity sold at retail neither increases nor decreases (at least not significantly) as the scale of retail operations changes. Retail sale of the commodity, electricity itself, is not characterized by increasing returns to scale and the retail electricity sales function cannot be viewed as a natural monopoly.

In principle, the regulatory system could separate transmission of electricity from retail sales. The retail sales function could be organised as a competitive industry even when transmission does not lend itself to competition. Although, in principle, delivery and sale of the electricity could be separated, they have typically been bundled: customers were charged a price for the combination of electricity and delivery services. In this way, the natural monopoly franchise for distribution was extended into a monopoly franchise for retail electricity supply.

Transmission of electricity demonstrates increasing returns to scale, up to a point. Electricity moves on high-voltage transmission lines integrated into an electricity grid. Figure 3.1 illustrates the transmission system for electricity from generator to consumer:

Figure 3.1: The Electricity Transport System



Source: NEMMCO

A significant cost of this transmission system is the costs of acquiring the right-of-way on which to build high-voltage transmission lines. Transmission rights-of-way are increasingly politically and environmentally sensitive and costs may include environmental impact assessments, animal relocation or habitat management among others, on top of land purchase or leasing costs. If transmission lines are operating below capacity, there is negligible additional cost for moving additional electricity through these lines. Even at capacity, installing additional high-voltage wires on an existing transmission route involves substantially less cost than establishing the link in the first place or establishing a new link in a new location. Transmission therefore seems to be appropriately organised as a monopoly, at least along a given transmission path.

Sweeney (2002) contends that electricity generation also seemed to have the increasing returns to scale characteristic of a natural monopoly. For many years the conventional wisdom was that the larger the electric generating plant, the lower the overall cost of electricity generation. This belief in an increasing-returns-to-scale reinforced the common view that electricity generation should be organised as a monopoly.

Given that all the components of the electricity supply system were operated as monopolies, they were typically (but not necessarily) vertically integrated into a single company. A fundamental reason for this was the need for coordinated planning for capital investments and operations. The amount of electricity sold by the distribution/retail firm determined the amount of generation and transmission capacity needed. The location of transmission infrastructure and generation facilities required coordination in order to minimise overall cost. This need for coordination throughout the supply chain and for appropriate information flows helped justify the combination of these three entities into one vertically integrated company. A second and related reason for vertical integration was based on reducing transaction costs. Three separate monopolies, all integrated into one supply chain, might choose to operate so as to each gain financial advantages over the other. Although this strategic problem could be controlled through the regulatory process, integrating the three entities into one company would reduce or eliminate those incentives and the resulting need for regulatory oversight (Sweeney, 2002).

For these reasons, in the early development of their electricity infrastructure many countries adopted the approach of establishing vertically-integrated “firms” as cost-of-service regulated or government-owned utilities with monopoly control of the electricity supply chain, from generation, through transmission and distribution to retail supply, usually within a geographic region. Historically, joint decision making processes between regulated utility, regulatory body and/or government have had difficulty making economically efficient investment decisions concerning new generation and transmission capacity. Wolak (1997) argues that under this kind of industry structure there are limited incentives for efficient operation or developing new supply capacity. Supporting this last contention is early work by Joskow (1987), who argues that returns to scale in electricity generation diminish and are exhausted at a unit size of about 500 Megawatts, a level of production generally well below industry output in most Organisation for Economic Cooperation and Development (OECD) member countries. Econometric work by Lee (1995) finds that constant returns to scale in the electricity supply industry (combining generation, transmission and distribution) in the Unites States of America are better supported when electricity utilities are owned by private investors rather than by states.

In summary, the desire for reform in the electricity supply industry has, over the last two decades, driven many regulators worldwide to develop new regulatory schemes and programmes of market reorganization. The prevailing view is that technologies for electricity generation and retailing are such that competition is feasible, but that transmission retains the features of a natural monopoly. Competition in transmission would require duplication of the existing physical network of poles and wires, which in most countries would not be economically viable. Several countries have in recent years formed wholesale markets for electricity and introduced varying degrees of competition in electricity retailing. For reasons discussed earlier, most countries that have embarked on programmes of electricity industry reform have kept the transmission sectors of the industry regulated and under state control. To varying degrees generation and retail businesses have been privatised, in some countries state and privately-owned companies compete with each other, some have municipally-owned distribution companies and a few have only privately-owned distribution companies (Wolak, 1997). The approach taken in Australia is discussed in section 3.2, and examples of countries that have taken similar steps towards integrated national markets are discussed in section 3.3.

3.2 The Australian National Electricity Market (NEM)

The Australian National Electricity Market (NEM) is a wholesale market for electricity supply, initially covering the states of Queensland, New South Wales (including the Australian Capital Territory), Victoria and South Australia. The NEM commenced operating at 2:00 am on 7 December 1998, to deliver electricity to market customers on an interconnected power system that stretches more than 4000 km from Port Douglas in Queensland to Port Lincoln in South Australia. At its inception, the NEM included four regions based on the mainland state boundaries (designated NSW1, QLD1, SA1 and VIC1), plus the Snowy Mountains Hydroelectric Scheme (SNOWY1) which is classified as a region in its own right. Tasmania became the sixth region of the NEM late in 2005. Queensland, New South Wales and Tasmania have largely corporatised the individual sectors of their electricity supply industry (while keeping them as government-owned entities), Victoria has fully privatised its generation, distribution and retail sectors and the bulk of electricity supply businesses in South Australia remain state-owned but are currently operated by private companies under long-term lease arrangements. Table 3.1 illustrates the breakdown of ownership of assets in the NEM by stage in the value chain.

Table 3.1: Breakdown of Public vs Private Ownership of Assets, by Stage in the Electricity Value Chain (as at 2003)

	Generation	Transmission	Distribution	Retail
Private	36%	57%	50%	55%
Public	64%	43%	50%	45%

Source: NEMMCO

3.2.1 Formation of the NEM

Since 1991 successive Australian Governments have introduced fundamental reforms to improve the performance of the electricity supply industry. Prior to 1990, vertically integrated, state-owned authorities responsible for the generation, transmission and distribution of electricity dominated the electricity supply industry. Electricity prices were set by the respective state governments to cover the industry's costs plus a prescribed return component required by the governments as owners.

Work undertaken by the Industry Commission in 1991 highlighted the idea that major increases in national productive output could be achieved from:

- Restructuring the electricity supply industry into separate elements of generation, transmission and distribution and retail supply;
- The introduction of competition into generation and retail supply; and
- The enhancement and extension of the three state interconnected power systems (between New South Wales, South Australia and Victoria) to eventually include Queensland and Tasmania.

Progressive deregulation and restructuring of the Australian electricity supply sector followed the recommendations of the 1993 report of the Independent Committee of Inquiry into the Australian Electricity Utilities Industry (the Hillmer Report). Prior to deregulation, each state's electricity industry was closed and governed by state legislation. This regime was dismantled and the national wholesale market was begun, initially being organised into two separate electricity "pools", centred in Victoria (Vicpool) and New South Wales (SEM). The Victorian Power Exchange (VPX) in Victoria and Transgrid in NSW operated these pools until December 1998. On 7

December 1998, VPX and Transgrid were amalgamated and joined by Queensland South Australia and the Snowy Hydroelectric Scheme to form the National Electricity Market (NEM). The NEM has been developed with the aims of achieving a competitive wholesale market for the supply and purchase of electricity by market participants in an open access regime, that provides for non-discriminatory access to electricity networks and a transparent and nationally consistent legal and regulatory framework. As an interim step towards a single, fully integrated national market, the NEM is segmented into 5 regions along state lines: VIC1, NSW1, QLD1, SA1, and SNOWY1. The SNOWY1 region is differs from the other regions in that it is not defined by state boundaries, rather it is a collection of hydroelectric power stations comprising the Snowy Mountains Hydroelectric Scheme and operated by Snowy Hydro, a corporation owned jointly by the State Governments of New South Wales, Victoria and the Commonwealth[14]. The majority of electric power generated in SNOWY1 services demand from New South Wales and Victoria. Physical transmission of power between regions is achieved via interconnectors that physically link VIC, NSW, SA, ACT and Queensland. The National Electricity Market Management Company (NEMMCO) operates the NEM on behalf of the participating states. Tasmania entered the NEM in late 2005 via the "Basslink" submarine cable interconnector under Bass Strait. Western Australia and the Northern Territory are not expected to join the NEM in the foreseeable future, primarily for reasons of geographic isolation.

[14] At the time of writing the Snowy Mountains Hydroelectric Scheme remains jointly owned by the State Governments of New South Wales and Victoria and the Commonwealth Government. A program for full privatisation via a public share offering was initiated in 2006 but failed as a result of public and political pressure to retain public ownership of the Scheme.

3.2.2 The Special Nature of Electricity

Electricity is a homogeneous commodity with physical characteristics that distinguish it from more conventional traded commodities. It is physically the same no matter when and where it is produced or consumed. Its generation and consumption are for all practical purposes simultaneous[15]. The "non-storability" of electricity ensures that electricity markets clear at each moment in time through an adjustment of prices. There is no possibility for generators to make use of productive capacity in hours when demand for electricity may be substantially less than supply, nor can distributors stockpile the commodity, for later use to "smooth" supply or demand shocks, resulting in market-clearing prices that can be extremely volatile, especially on an intra-day basis.

How is Electricity Produced?

Electricity can be produced by either chemical or mechanical action. Electricity produced using chemical means is stored in batteries. While this type of electricity production has many important applications in modern society, it is an expensive production process and can meet only limited specific requirements for electricity. In the NEM, electricity is produced by large-scale power stations that produce electricity by the mechanical action of turbine-driven generators - large, powerful magnets that spin very rapidly inside huge coils of conducting wire. More than 90 percent of Australia's electricity production relies on the burning of fossil fuels, primarily coal,

[15] To date no technology has been developed to provide a viable storage medium for wholesale quantities of electric power. While it can be argued that hydroelectric generation technologies can provide de-facto storage, it is not physical storage of the commodity as is traditionally defined and understood. Pumped water storage provides at best an indirect form of storage: when prices are low, water is cycled uphill into a reservoir and at peak price periods, water is released in high volume to generate electricity through a turbine. This is storage of potential energy rather than electrical energy and is only available when water levels are sufficient and the reservoir is ready for use (Bodily & Buono, 2002).

with some plant fired by natural gas or heating oil. The chemical energy stored in these fuels is released by burning to generate heat, which in turn is used to heat water and produce steam. The steam is then forced under great pressure through a turbine that drives a generator to produce electricity. The complete process involves the conversion of chemical energy to kinetic energy to electrical energy.

In hydroelectric power generation, water is stored in a reservoir behind a dam wall. Water is released from the dam and falls through large pipes to a generation plant at the foot of the dam wall. The kinetic energy of falling water drives turbine blades to produce electrical energy. In wind-powered generation, the action of wind on a propeller-like turbine spins a generator coil to produce electricity. Table 3.1 summarises the basic practical characteristics of commonly used generation technologies.

The basic unit of electric power is referred to as a Watt, representing consumption of one joule of energy per second. A joule is the quantity of energy required to raise the temperature of a kilogram of water by 1-degree Celsius. The “wattage” of an electrical appliance refers to the rate at which it converts electrical energy to heat or light. A typical electric kettle has wattage of 2400, indicating that its use consumes 2400 joules of electrical energy per second. One megawatt (MW), or one million watts, is the standard unit applied in the wholesale markets. In the NEM, the unit of price is Australian dollars per megawatt hour ($/MWh), where one Megawatt Hour can be defined as the quantity of energy required to power ten thousand 100W light globes for one hour.

Table 3.2 Characteristics of Electricity Generators

Characteristic	Type			
	Gas and Coal-fired Boilers	**Gas Turbine and Oil-Fired**	**Water (Hydro)**	**Renewable (Wind/Solar)**
Time to fire-up generator from cold	8–48 hours	20 minutes	1 minute	dependent on prevailing weather
Degree of operator control over energy source	high	high	medium (depending on available water levels)	low
Use of non-renewable resources	high	high	nil	nil
Production of greenhouse gases	high	medium-high	nil	nil
Other characteristics	medium-low operating cost	medium-high operating cost	low fuel cost with plentiful water supply; production severely affected by drought	suitable for remote and stand-alone applications; batteries may be used to store power

Source: Salomon Smith Barney 1998 – "Flipping the Switch".

Once electricity is dispatched to the distribution grid, it is not possible to distinguish which generator produced the electricity that is consumed by a particular customer. For this reason, the wholesale electricity market is organised as a centralised "pool" where all electricity output from generators is notionally pooled and coordinated to meet prevailing electricity demand.

3.2.3 NEMMCO Market Operation

As described in the previous section the wholesale market uses a pool system to centrally coordinate output from generators to meet consumer demand. The pool is not a centralised marketplace; rather it is a set of rules and procedures managed by NEMMCO. In order to understand how the spot price for electricity is determined in the NEM it is necessary to describe the workings of the pool.

The pool has two basic components, which are:

- The centrally coordinated dispatch process; and
- The spot market.

The Centrally Coordinated Dispatch Process:

The centrally coordinated dispatch process continually balances supply with demand by "dispatching" generators to produce sufficient electricity to meet customer demand. The process also attempts to provide sufficient reserve supply ("reserve margin") to handle potential failures in generation units and transmission networks. In the event that reserve margin is insufficient to cover a failure, NEMMCO may reduce a customer's load without reference to the customer to ensure that the power system achieves a balance between supply and demand. This process is referred to as "load shedding" and is only implemented as a measure of last resort.

The NEMMCO trading day is divided into half-hour trading intervals, each defined by the local time at the end of the trading interval. For example, the trading interval "1630" describes the trading period from 4:01 to 4:30 pm. Each generator provides NEMMCO with a "dispatch offer", an offer to supply electricity, for a given half-hour trading interval. Dispatch offers for a particular day's trading intervals are submitted no later than 24 hours ahead of time. The dispatch offer specifies a minimum level of generator output (the "self dispatch level") plus prices for incremental supply quantities above the self-dispatch level.

For example, a generator may make the following dispatch offer:

Dispatched Quantity	**Offer Price**
0-150MWh (self-dispatch level)	$5
150-250MWh	$15
250-350MWh	$30
350-500MWh	$45

This example indicates that the generator is willing to generate more as the spot price rises. The generator is offering to sell up to its self-dispatch level of 150MW at $5 per MWh and would like to be paid higher prices for load above 150MWh. The generator's self-dispatch price often corresponds to its marginal cost of production.

The Spot Market:

The spot electricity market in the NEM is the centralised market where all generators and market customers settle their electricity sales and purchases based on a spot price. The spot price is a derived price per trading interval, calculated by a two-step procedure based on the spot price offers and bids made by generators and customers in the pool. Each half-hour trading interval is further divided into five-minute "dispatch intervals". First, a "dispatch price" is recorded as the marginal price of supply to meet demand for each five-minute interval in a given half-hour period. This marginal price is typically the dispatch offer price of the last generator brought into production to meet demand at that interval. Second, the spot price is calculated as the arithmetic average of the six dispatch prices in a half hour and is expressed in dollars per megawatt hour. To illustrate the process of spot price calculation, consider an example half-hour trading interval, for which five generators submit the following offers:

Generator 1: 100MWh at a dispatch price of $20
Generator 2: 150MWh at a dispatch price of $28
Generator 3: 50MWh at a dispatch price of $35
Generator 4: 100MWh at a dispatch price of $37
Generator 5: 100MWh at a dispatch price of $38

At each 5 minute interval during the dispatch period the following might occur:

Time	**Demand**	**Generator Dispatch**	**Price**
4:05pm	260MWh	Generator 1: 100MWh (fully dispatched) Generator 2: 150MWh (fully dispatched) Generator 3: 10MWh (partly dispatched)	$35
4:10pm	330MWh	Generator 1: 100MWh (fully dispatched) Generator 2: 150MWh (fully dispatched) Generator 3: 50MWh (fully dispatched) Generator 4: 30MWh (partly dispatched)	$37
4:15pm	370MWh	Generator 1: 100MWh (fully dispatched) Generator 2: 150MWh (fully dispatched) Generator 3: 50MWh (fully dispatched) Generator 4: 70MWh (partly dispatched)	$37
4:20pm	405MWh	Generator 1: 100MWh (fully dispatched) Generator 2: 150MWh (fully dispatched) Generator 3: 50MWh (fully dispatched) Generator 4: 100MWh (fully dispatched) Generator 5: 5MWh (partly dispatched)	$38
4:25pm	470MWh	Generator 1: 100MWh (fully dispatched) Generator 2: 150MWh (fully dispatched) Generator 3: 50MWh (fully dispatched) Generator 4: 100MWh (fully dispatched) Generator 5: 70MWh (partly dispatched)	$38
4:30pm	380MWh	Generator 1: 100MWh (fully dispatched) Generator 2: 150MWh (fully dispatched) Generator 3: 50MWh (fully dispatched) Generator 4: 80MWh (partly dispatched)	$37*

* Dispatch price reverts to Generator 4's offer price as Generator 5 is no longer "called in" to meet prevailing demand. *Source*: NEMMCO (2001)

The spot price for 4:30pm is therefore:

$$\frac{(\$35 + \$37 + \$37 + \$38 + \$38 + \$37)}{6} = \$37$$

This spot price is the market price paid to contributing generators for the 1630 trading interval and the price paid by wholesale customers for the electricity they consume during the period 4:00pm to 4:30pm [for further discussion see Dickson and Warr (2000), and NEMMCO (2001)].

The National Electricity Code sets a maximum spot price of $10,000 per megawatt hour as the maximum price at which generators can bid into the market. Referred to as the Value of Lost Load (VoLL), it is the price at which NEMMCO directs network service providers to interrupt customer supply to maintain physical balance and stability in the grid.

3.3 Other National Electricity Markets

To date several countries in the OECD have embarked on programs of deregulation in their electricity industries, forming wholesale markets and introducing varying degrees of competition into the retail side of electricity supply[16]. The following sections discuss the significant characteristics of the major overseas electricity markets that have moved towards integrated, national wholesale markets in a broadly similar ways to Australia, including England and Wales; Norway and Sweden; and New Zealand.

[16] The U.S.A. has a large and diverse electricity supply industry sector that has undergone some degree of deregulation and restructuring and moved towards establishing wholesale pool markets in some states, most notably California. This section is concerned with discussing national industries that have moved towards integrated national markets in similar ways to Australia. The U.S. wholesale electricity markets are still somewhat disjoint, functioning on geographically separate, state-based lines. As such the U.S. national electricity supply is quite different from the type of nationally-integrated markets under discussion and is not discussed in detail here. Several other countries have undergone processes of electricity industry deregulation and restructuring to varying degrees, including Spain, Greece and Portugal among others.

3.3.1 England and Wales

A wholesale market for electricity commenced in April 1990, since which time all but a very small proportion of electricity consumed in England and Wales must be sold through a day-ahead spot market for electricity, with market-clearing prices set on a half-hourly basis. The market was formed as a result of the dissolution and privatisation of the state-owned Central Electricity Generation Board (CEGB) and 12 "Area Boards" which served as the local electricity distribution organisations.

The electricity supply industry was restructured into four segments[17]:

1. Generation;
2. Transmission;
3. Distribution; and
4. Retail Sales.

The distribution network was split into 12 regional electricity supply companies (RECs) and the National Grid Company (NGC) was formed. The NGC was originally jointly owned by the 12 RECs but has since been privatised and is now a publicly traded company. The NGC provides transmission services from the generators to the RECs, coordinates transmission and dispatch of generators and runs the electricity spot market. This arrangement differs from Australia's NEM in that NEMMCO coordinates the dispatch of generators and runs the wholesale spot market but does not manage transmission. NGC runs both the physical and financial markets for

[17] Almost all subsequent industry restructures have followed this same subdivision, with minor variation.

electricity in England and Wales, serving as both power exchange and as independent system operator.

The retail sector of the market was initially divided into franchise and non-franchise customers, with franchise customers being tied to a supplier within a geographic territory. Non-franchise customers were generally large-scale commercial consumers and were given their choice of supplier from any of the 12 RECs as well as selected generators directly. As of March 31, 1998 all customers, including residential consumers were given supplier choice and effectively became non-franchise customers.

3.3.2 Norway and Sweden

Nordpool began operation in Oslo, Sweden in 1996 and is the world's only international power exchange, integrating the electricity systems of Norway and Sweden, with some limited participation by neighbouring Russia, Finland and Denmark.

There are three major differences between Nordpool and the markets in England and Wales. The first relates to generation technology. In Norway, 99 per cent of installed capacity is provided by hydro-electric plant, with the remaining marginal capacity provided by oil and gas-fired plant. In Sweden, approximately half of total capacity is provided by hydropower, approximately thirty percent is provided by nuclear power and the remainder provided by oil and gas fired plant and some small marginal capacity provided by other renewable energy means (wind and solar). This contrasts with England and Wales, where some 80% of generation capacity is provided by higher marginal cost fossil-fuel powered plant.

The second difference is that Nordpool is not a mandatory pool. Generators and consumers are free to choose whether or not they wish to sell or buy electricity through Nordpool or by way of directly-negotiated bilateral contracts. To date the majority of electricity in Norway and Sweden is still traded via bilateral contract. In addition, there is a weekly financial futures market that offers contracts with maturities ranging from a week ahead to three years ahead.

The third difference is that the greater proportion of generation plant in Norway and Sweden is still state-owned. When the electricity market in Norway was "deregulated", Statkraft, the state-owned electricity supplier, was broken up into separate companies providing generation, transmission, and distribution services similar to the market structure in Australia, England and Wales, but was not privatised. Statkraft SF was created as the national grid company and system operator and retained all Statkraft generation assets. Statnett Marked AS was formed to run the spot electricity market. Statkraft owns approximately 40% of Norway's hydroelectric capacity and supplies approximately 30% of all Norwegian output. Norsk Hydro, a large industrial end-user of electricity, controls 10% of generation capacity through its subsidiary Hydro Energy. The remaining 60% of supply is provided by small firms, the majority of which are owned by municipalities. In total there are approximately 200 generation companies in Norway, many of whom do not participate in the wholesale spot market). In Sweden, Vatenfall, the Swedish state power board, generates approximately 50% of electricity supplied, nine other large generators share 40%, with small municipally-owned plants providing the remainder.

3.2.3 New Zealand

Up to 1994, the New Zealand Electricity Market had a system of monopoly providers of generation, transmission, distribution and retailing. Electricity Supply Authorities (ESAs) handled local distribution as governing bodies (power boards) Since then, a step-by-step process of industry reform has led to the separation of the monopoly elements to create competition in energy generation and electricity retailing. Reform of the New Zealand's electricity supply industry followed the passage of the Energy Sector Reform Bill in 1992, which corporatised the ESAs and removed franchise territories, starting in 1993 for small customers and for all customers in 1994. Ownership of the distribution network remained primarily in government hands through municipally owned trusts or other local government authorities.

The geographic separation of New Zealand into two main islands has resulted in a system consisting of two alternating current (AC) subsystems for the North and South Islands, connected by a submarine High Voltage Direct Current (HVDC) cable. All generation capacity on the South Island is hydroelectric and on the North Island there is a mix of hydroelectric (approximately 75%), geothermal (approximately 17%) and fossil fuel (approximately 8%) electricity generation plant. There is sufficient generation capacity on the South Island to serve its existing levels of local demand and export to the North Island. The annual consumption of electricity in New Zealand is typically about one tenth that of England and Wales, yet the land area of New Zealand is approximately the same size as the entire United Kingdom. With a relatively small population of approximately 3.5 million and a mountainous topography, transmission and distribution accounts for a relatively large proportion of the cost of delivered electricity compared to the other markets discussed. Another important aspect of the New Zealand system is that most of the population resides on the North Island, yet the bulk of the generation resources are on the South Island, therefore transmission constraints imposed by the HVDC submarine interconnector play an important role in electricity supply (Wolak, 1997).

A wholesale market for electricity commenced on October 1, 1996 and is administered by The Electricity Market Company (EMCO) on behalf of the Electricity Commission of New Zealand (ECNZ). The main participants are seven generator/retailers who trade at 244 nodes across the transmission grid. Similar to Nordpool, participation in the wholesale market is not mandatory. The generators offer their capacity at grid injection points and retailers bid for electricity "offtake" at grid exit points. EMCO reconciles all metered quantities, determines the prices at each node, and manages a clearing and settlement process by which generators are paid for their generation at the market clearing price and retailers are invoiced for their for their "offtake". Prices and quantities are determined half-hourly at each node. Because of concerns about the capacity of the HVDC interconnector, different spot prices are set for the North Island and the South Island. Market operation is similar to NEMMCO, in that generators submit bids as a function of price for all half-hours for the following day. Generator dispatch must meet actual loads and price is determined ex-post as a function of the market clearing dispatch solutions during each half-hour.

The transmission system is owned and operated by a state-owned enterprise, Transpower, that performs the functions of Grid Owner, Grid Operator, Scheduler and Dispatcher for the wholesale market. Distribution of electricity from the grid exit points to the end consumers' premises is the responsibility of 28 distributors who have monopoly control of the line services on their networks. Ownership of distributors, also known as lines companies, is through Trust Owned Companies or Public Companies. Full retail competition was introduced in 1999, with the result that consumers can choose from up to seven electricity retailers (who are also generators) for their energy supply.

3.4 Summary

In most countries the electricity supply industry has historically been controlled and operated by vertically-integrated, state-controlled enterprises with effective monopoly control over a geographic territory for the entire electricity supply chain, from generation, through transmission and distribution to retail sales to the end consumer. Limited or no competition, perceived inefficiencies, limited economies of scale and reduced incentives for investment in such a market environment has led many countries to embark on programmes of deregulation, restructure and privatization to varying degrees, with a view to providing improved pricing and services to consumers and industry and improved productivity within the industry itself.

In the Australian context the regime of state-controlled, vertically integrated suppliers has been progressively restructured since the early 1990s, with the component sectors of the electricity supply industry disaggregated into distinct generation, transmission and distribution businesses.

The generation and retailing ends of the supply chain lend themselves well to deregulation and increased competition, while the transmission and distribution sectors of the industry (the "poles and wires" network) exhibit traits of natural monopoly and have remained under regulated, state control. In Victoria, the generation and retail businesses have been fully privatised and the assets of these sectors in the other states have been corporatised but remain under state ownership.

The National Electricity Market (NEM), administered by the National Electricity Market Management Company (NEMMCO) was established in December 1998 as a wholesale market for electric power covering the states of South Australia, Victoria, New South Wales, Queensland and more recently Tasmania. Because of the special physical characteristics of electricity: that it cannot be stored; that it is for all practical purposes instantly produced and consumed; and supplied quanta cannot be identified to a particular producer, the NEM is based on a regional "pool" structure based on state boundaries, with the addition of the generation assets of the Snowy Hydroelectric Scheme as its own pool. The NEM trades continuously, with each calendar day divided into 48 half-hourly trading intervals. The NEM coordinates supply to meet demand through a mechanism of demand-driven generator dispatch and prices are determined as an average of market-clearing dispatch prices within each half-hour trading interval. All spot electricity trade between generators and retail/distributors is conducted via the pool system, but bilateral contracts are also traded between generators, retail companies and large-scale industrial and commercial customers.

Other OECD countries have successfully embarked on similar restructures, most notably England and Wales; Norway and Sweden; and New Zealand. Each of these countries has, like Australia, disaggregated the components of electricity supply into separate generation, transmission & distribution and retail business. Competition and varying degrees of corporatisation and privatisation have been introduced into electricity generation and retail. Transmission and distribution assets have remained monopolies, either retained under state control through the agency of a state-owned company, or fully privatised, as in England and Wales. Each has established a wholesale market for spot trade in electricity, administered by a corporate entity that also serves as an Independent System Operator (ISO).

Chapter 4: Description and Sources of Data

4.1 Introduction

The purpose of this chapter is to describe the data collection and collation procedures and sources of the data sets used in this thesis. The summary descriptive statistics for each data set are also presented. In brief, the data sets used include time series data for demand and price for electric power in the NEM collected from NEMMCO.

4.2 NEMMCO Electric Power Demand and Price Series

The demand and price data used in this study are half-hourly demand and pool price observations sourced directly from NEMMCO[18] for the period from commencement of the NEM at 2:00am December 7, 1998 to 11:30pm on March 31, 2005. NEMMCO collates and reports half-hourly trading interval observations for each of demand and price for the five NEM regions (NSW, QLD, SA, SNOWY1 and VIC1). The sample size is 110,719 observations for each of the five regions in the NEM.

4.2.1 Demand

This study uses NEMMCO's reported pre-dispatch total demand values for each region, expressed in Megawatts (MW) by half-hour trading interval for the sample period. Total demand is defined by NEMMCO as the total forecast regional demand

[18] Available for download from NEMMCO's website at http://www.nemmco.com.au/data/market_data.htm

against which a dispatch solution is performed. For any particular interval and region this is determined by NEMMCO as[19]:

$$D_T = \sum G_i - \sum L_i + NI_i + \sum AIL_i + F_i(D) + ADE$$

Where:

D_T is Total Demand per Trading Interval;

$\sum G_i$ is "*∑Generator Initial MW (SCADA)*", the sum of initial MW values for all scheduled generation units within the region, measured at their generator terminals and reported by SCADA – NEMMCO's Supervisory Control And Data Acquisition system;

$\sum L_i$ is "*∑Load Initial MW(SCADA)*", the scheduled base-load generation level for the interval;

NI_i is "*Net Interconnector Initial MW into Region*", the net of all interconnector flows into and out of the region;

$\sum AIL_i$ is "*Total Allocated Interconnector Losses*" is represented by *∑(MW losses X Regional Loss Allocation)* . "*MW losses*" represents actual power losses due to physical leakage from the transmission system. *Regional Loss Allocation* is a NEMMCO pre-determined static loss factor for each interconnector;

$F_i(D)$ *is Demand Forecast*, a per-interval demand adjustment that relates the demand at the beginning of the interval to the target at the end of the interval;

ADE is "*Aggregate Dispatch Error*", an adjustment value used by the NEM to account for disparities between scheduled and actual dispatch for all scheduled generation units in the region;

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[19] *Source*: NEMMCO Document "Regional Demand Definition" , Version 1.0, 17 June, 2004, available at http://www.nemmco.com.au/dispatchandpricing/140-0035.htm, accessed 25 June 2005. The demand determination model is here presented as it is in the NEMMCO demand definition document.

Summary statistics by region for each demand series are presented in Table 4.1.

Table 4.1: Descriptive Statistics for Total Demand (MW) by region 7/12/1998 to 1/4/2005

	NSW1	QLD1	SA1	SNOWY1	VIC1
Mean	8042.87	5118.64	1451.41	29.58	5355.72
Median	8106.43	5157.00	1454.71	18.76	5335.44
Maximum	12838.14	8231.95	2833.22	736.89	8524.07
Minimum	3294.38	2023.65	731.48	0.00	2239.46
St. Dev	1287.40	837.72	263.574	27.79	761.55
Skewness	0.01	0.07	0.75	1.40	-0.04
Kurtosis	2.65	2.62	4.44	10.69	2.94
Jarque-Bera	568.30	771.56	20003.84	309405.6	54.44
(p-value)	(0)	(0)	(0)	(0)	(0)
ADF Test Stat	-20.55	-16.50	-25.61	-16.73	-20.46
(1% crit.value)	(-3.43)	(-3.43)	(-3.43)	(-3.43)	(-3.43)
# Obs	110719	110719	110719	110719	110719

NSW1 has the highest mean, median and maximum demand observations of the five regions for the period. New South Wales is Australia's most populous state so we would expect that demand for electric power to be highest in the NSW1 region. The other regions follow generally in order of state population, with VIC1 next highest, followed by QLD1, SA1 and SNOWY1. It should be noted that SNOWY1 represents a cluster of hydroelectric generation assets in the snowy mountains regions of New South Wales, rather than a geographical region or state like the other 4 NEM regions. As such almost all of the electric power produced by generation plant in SNOWY1 services demand arising primarily in New South Wales. To a lesser extent Victoria and Queensland are serviced with power from SNOWY1 via the interconnectors joining those states with New South Wales.

The distributions of demand observations are slightly negatively skewed for VIC1, and positively skewed for NSW1, QLD1, SA1 and SNOWY1; and that the Demand series' for NSW1, QLD1, SA1, SNOWY1 and VIC1, demonstrate positive kurtosis. Jarque-Bera (JB) statistics reject the hypothesis of normal distribution at the 1% level of significance for all 5 regions. Augmented Dickey-Fuller statistics reject the hypothesis of a unit root at the 1% level of significance, indicating stationarity consistent with the findings of Worthington *et al.* (2003)[20].

An interesting characteristic of the SNOWY1 is the occurrence of zero demand from time to time, as illustrated by Figure one. Over the sample period, a zero level of demand is observed 1799 times. Figure 4.1 indicates that at times of zero demand we also observe a market-clearing price. This condition may be attributable to the business activities Snowy Hydro Pty Ltd, the operator of the Snowy Hydroelectric Scheme. A significant component of Snowy Hydro's earnings derive from its activities in the sale of hedge contracts to demand-side market participants, primarily distributors and retailers, as protection against price spikes.

[20] Interestingly, De Vany and Walls (1999) find that electricity prices in 10 of 11 regional markets in the USA demonstrate significant non-stationarity. This difference may be a result of market operation and design - that the prices considered by their study were prices for supply determined by over-the-counter bilateral supply agreements.

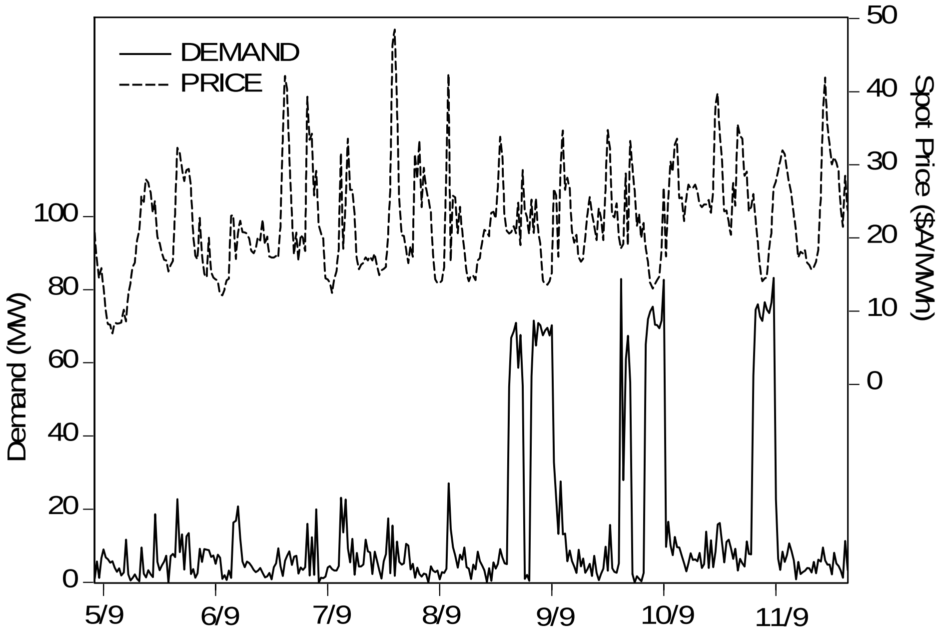

Figure 4.1: SNOWY1 Half-Hourly Demand and Spot Price for the Week Commencing 5/9/1999, Illustrating the Occurrence of Zero Demand Associated With a Market Clearing Spot Price.

The generator/operator sells cap-style option contracts on spot electricity with a specific exercise price over a specified quantity of electricity. In the first instance it receives premium income for the sold option. If the exercise price of the cap is exceeded, cap is in the money and the holder will exercise their right under the cap. On exercise the generator pays the contract holder the excess of the spot price over the exercise price for the specified quantity of electricity. Hydroelectric generation is described as a "fast-start" generation technology – hydroelectric generation plant can typically be called into production within one to two minutes of activation[21]. This capacity to generate and to commence production quickly provides a natural hedge

[21] In hydroelectric power generation, water is stored in a reservoir behind a dam wall. Water is released from the dam and falls through large pipes to a generation plant at the foot of the dam wall. The kinetic energy of falling water drives generator turbine blades to produce electrical energy. The flow of water can usually be started or stopped within one to two minutes. Other generation technologies, such as coal, oil or gas-fired plant, require that fuel be burned to heat water, producing steam that turns generator turbine blades to produce electricity. Gas turbine and some oil-fired plant can be called into production in the order of 20 to 30 minutes, with coal-fired plant requiring 8 to 48 hours for orderly start-up and shutdown. (*source: "Flipping the Switch", Salomon Smith Barney, 1998).*

against the exercise risk of the sold contract. The generator can bid its production capacity into the pool at the exercise price and quantity of its sold contracts to cover its exercise risk. If the spot price exceeds the exercise price of the sold cap, the operator will be called into production at its bid price and level of production, receiving the spot price over the production quantity specified by its sold contracts. As a result a quantity of electricity is produced by the SNOWY1 generation assets and sold at a prevailing spot market price, but that quantity sold is not necessarily associated with a level of physical demand in the SNOWY1 region. On this basis, Snowy Hydro effectively operates as a peak producer with its generation assets dormant for much of the time and only producing when prices are high but with a supplementary income stream of premiums earned from the sale of option contracts.

4.2.2 Price

This study uses half-hourly reported spot price[22] values for each region, expressed in Australian Dollars[23] per megawatt hour (MWh). Descriptive statistics by region for the price series' are presented in Table 4.2.

The SA1 region has the highest mean and median prices per megawatt hour at $45.99 and $28.05 respectively. This is most likely attributable to the nature of generation technology prevalent in each state. New South Wales, Queensland and Victoria rely on relatively low-cost brown and black coal fired generators for their base-load electricity needs, compared to South Australia's greater reliance on higher-cost gas-turbine generation.

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[22] The mechanism of spot price determination is described in section 3.1.3
[23] Spot prices are exclusive of Australian Goods and Services Tax (GST)

The distributions of price for all five regions demonstrate positive excess skewness with coefficients higher than 0.5, and extremely high positive kurtosis with some coefficients in the order of 1000 or more. This extreme fat-tailed character is consistent with the findings of earlier studies (see Huisman and Huurman, 2002; Higgs and Worthington, 2005; and Wolak, 1997) and is likely driven by the prevalence of extremely high prices (see Figure 1.1) and the occurrence of negative prices (see Figure 4.2). Consistent with these statistics, Jarque-Bera (JB) statistics are extremely high and reject the null hypothesis of normal distribution at the 1% level of significance for all five regions. Augmented Dickey-Fuller (ADF) statistics robustly reject the hypothesis of a Unit Root at the 1% level of significance for all five regions, consistent with the earlier findings of Goto and Korolyi (2004).

Table 4.2: Descriptive Statistics for Price ($/MWh) by region 7/12/1998 to 1/4/2005

	NSW1	QLD1	SA1	SNOWY1	VIC1
Mean	33.98	37.98	45.99	31.78	30.46
Median	23.18	21.95	28.05	23.44	23.11
Maximum	9909.03	8942.60	8999.98	7500.00	6444.19
Minimum	-3.10	-156.14	-822.45	-3.15	-329.91
St. Dev	167.22	159.51	201.08	119.01	102.66
Skewness	36.01	27.46	20.99	36.81	34.31
Kurtosis	1561.44	993.59	505.49	1652.50	1394.47
Jarque-Bera	1.12×10^{10}	4.54×10^{9}	1.17E $\times 10^{9}$	1.26×10^{10}	8.95×10^{9}
(p-value)	(0)	(0)	(0)	(0)	(0)
ADF Test Stat	-33.80	-30.01	-25.21	-33.64	-32.21
(1% crit.value)	(-3.43)	(-3.43)	(-3.43)	(-3.43)	(-3.43)
# Observations	110719	110719	110719	110719	110719

Negative Prices

An observed characteristic of the price series for all 5 regions (NSW1, QLD1, SA1, SNOWY1, and VIC1) is the occurrence from time to time of negative prices in the pool. Figure 4.2 illustrates an extreme occurrence of a negative price in the pool, where the pool price fell to -$161.48 at 12:30 am, 15/4/2000. Negative prices are not usually encountered in financial time series. In the NEM price series for the sample period they occur but are relatively rare, with NSW1 recording 6 occurrences, QLD1 9 occurrences, SA1 5 occurrences, including the most extreme value of -$822.45. SNOWY1 recording 6 negative price events (all of which coincide with occurrences in NSW1 and VIC1), and VIC1 records 15 occurrences for the period under study.

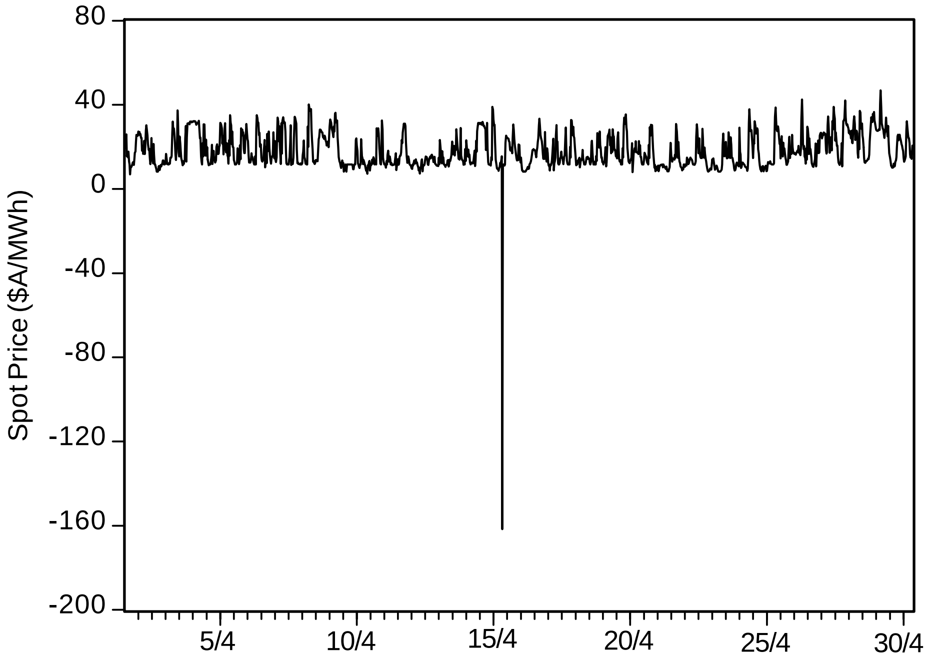

Figure 4.2: VIC1 Spot rice for the Month of April 2000, illustrating the Occurrence of an Extreme Negative Price Spike at 12:30a.m. on April 15, 2000.

Occurrences of negative price are rare and typically short-lived, usually persisting for ½ to 1 hour. The longest observed interval of negative price occurred simultaneously in NSW1, SNOWY1 and VIC1 for a period of 2½ hours, between 04:00am and 06:30

am on October 10, 1999. Table 4.4 lists all observed occurrences of negative price during the sample period by regions, and shows the date and time of the occurrence and the corresponding spot price.

Table 4.3: Occurrences of Negative Spot Price ($/MWh) by region 7/12/1998 to 1/4/2005

DATE	TIME (aest)	NSW1	QLD1	SA1	SNOWY1	VIC1
16-Jun-99	6:00:00 AM		-4.45			
29-Aug-99	4:00:00 AM		-3.52			
10-Oct-99	4:00:00 AM	-0.39			-0.39	-0.38
10-Oct-99	4:30:00 AM	-1.00			-1.02	-1.00
10-Oct-99	5:00:00 AM	-1.52			-1.55	-1.53
10-Oct-99	5:30:00 AM	-3.10			-3.15	-3.10
10-Oct-99	6:00:00 AM	-3.07			-3.11	-3.07
10-Oct-99	6:30:00 AM	-0.02			-0.02	-0.02
24-Oct-99	4:30:00 AM		-12.81			
15-Apr-00	8:30:00 AM		-2.91			-161.67
13-Jun-00	5:30:00 AM					
3-Jul-00	6:00:00 AM		-4.28			
22-Oct-00	6:00:00 AM					-305.78
28-Oct-00	3:00:00 AM		-84.39			
20-Jan-01	1:30:00 AM		-20.81			
3-Jan-02	4:30:00 AM					-155.94
3-Nov-02	5:00:00 AM			-246.57		-228.01
3-Nov-02	5:00:00 AM					
10-Nov-02	10:30:00 AM					-5.10
10-Dec-02	2:00:00 PM			-6.03		
12-Dec-02	5:00:00 PM			-9.99		
11-Jan-03	3:00:00 PM			-61.95		
25-Mar-03	6:00:00 AM		-156.14			
8-Mar-04	12:00:00 PM			-822.45		
24-Jun-04	1:00:00 PM		-150.46			
27-Jun-04	6:30:00 AM					-163.02
8-Jul-04	6:00:00 AM					-329.91
30-Oct-04	4:00:00 PM					-153.61
31-Oct-04	1:00:00 PM					-153.00

The occurrence of negative prices is attributable to the market practices of generators. As discussed previously, it is usual for generators to provide offers to supply electricity to the pool one day ahead of actual supply. The offer bid specifies a minimum level of generator output known as the "self-dispatch" level. A generator may lower its self-dispatch price to ensure that it is called in to generate. A generator may bid a negative price into the pool for its self-dispatch quantity (in effect, an offer to pay to generate) as a tactical move to ensure that they are among the first to be called in to generate. Demand usually outstrips the self-dispatch level of supply, so it is rare that generators actually pay to generate but on occasion a generator may not be called in and is "caught short", effectively paying to generate for a short period. Trades are settled in the NEM daily on a net basis, so "paying to generate" does not usually require a cash outlay on the part of the generator. The occurrence of a negative price may also be a function of the nature of technology used to generate electricity. In Victoria and New South Wales "base load" generation capacity employs what is generally referred to as "slow-start" generation technology, typically brown coal (VIC1) or black coal (NSW1) fired generation plant, usually located adjacent to a coalmine. The process of extracting coal from the earth, conveying it to a furnace, starting a furnace to boil water to make steam to ultimately turn a generator turbine, may require 8-48[24] hours for an orderly start-up and a similar time for an orderly shut-down, at great cost to the generator. Given that electricity is not storable and if demand does not meet the minimum base-load capacity of these generators for a short period, a generator may be prepared to risk having to "pay" the pool to take their excess capacity for a short time rather than incur the greater cost of shut-down and start-up and the opportunity cost of lost production.

[24] See table 3.1 and accompanying discussion.

4.3 Summary

In this chapter, electricity demand and price data sources and collection method are presented, along with a description of NEMMCO's method of deriving half-hourly demand values. Preliminary statistical analyses of demand and price are also presented.

The descriptive analyses in this chapter suggest that demand for electric power is greater in Australia's more populous states, a finding which is intuitively appealing. Demand in the SNOWY1 region is comparatively very low. This can be attributed to the nature of SNOWY1 as an artificially-defined region of hydroelectric power generation assets that primarily services demand from New South Wales and Victoria. Mean and median electricity prices are broadly consistent across the NSW1, QLD1 and VIC1 regions in which base generation technologies are similar and use relatively low-cost fuels. Mean and median prices appear higher in South Australia, where more costly fuels and generation technologies are used and the benefits of a direct interconnector with New South Wales and the SNOWY hydroelectric scheme are not available. It should also be noted that consistent with the extant literature, distributions of price and demand are significantly non-normal for all 5 NEM regions with all demonstrating broadly similar characteristics of positive skewness and high kurtosis, consistent with the established literature on electricity prices.

Chapter 5: Seasonal Factors and Outlier Effects in Rate of Return on Electricity Spot Prices in Australia's National Electricity Market

5.1 Introduction

As discussed in Section 3.2, the non-storability of electricity ensures that electricity markets clear at each moment in time through an adjustment of prices and there is no capacity for producers or consumers to use inventory to smooth out supply or demand shocks. Such shocks may be caused by unplanned generation unit outages, transmission network failure, generator pool price re-bidding, unexpected weather variation and physical constraints on transmission between regions. This particular feature of electricity means that market-clearing prices can be extremely volatile, especially within an intra-day time frame. Further, electricity price time series tend to exhibit a greater incidence of extreme price spikes than financial data and at times negative prices are observed.

The literature on electricity price modelling frequently identifies the presence of extreme price jumps with rapid reversion to the mean as a cause of extreme volatility in electricity prices (Bunn (2004), Alvaro, Peña, and Villaplana (2002), Hadsell, Marathe and Shawky (2004)). Modelling electricity prices in the Australian and foreign markets is a difficult process and this provides a strong incentive for further research into the electricity price market. Many stochastic models applied to conventional financial time-series data have been applied to electricity time series but they have some way to go in revealing the main components of price structure. Knittel and Roberts (2001) emphasised the need to explore this structure and include it in price specifications. Goto and Karolyi (2004) further note that their jump models fail to capture the significant effects of extreme price spikes and the effects of these spikes warrant further investigation.

The research contribution of this chapter is twofold. First, it examines a six-year sample of half hourly returns on spot prices for five regions in Australia's National Electricity Market (NEM) and reports on the occurrence of outliers in the form of extreme spikes and the incidence of negative prices. It is not contentious that seasonalities and large price spikes are a feature of electricity markets and several studies examine their effect in aggregate using various functional forms (e.g. Kaminski, 1997; Clewlow and Strickland, 2000a; De Jong and Huismann, 2002; Goto and Karolyi ,2004) This study differs from previous work in that it presents a model that captures individual large price spikes along with negative prices and seasonal factors including time-of-day, day-of-week, monthly and yearly effects. Much of the existing literature uses daily or hourly data, over samples spanning one or two years. This study's use of half-hourly prices over a six-year sample provides a useful extension of past work and is potentially significant for producers, regulators and researchers. The use of data sampled over a longer (six-year) time period is necessary in order to establish the extent to which these extreme within-day price spikes and negative prices are a regular feature of the data. Knittel and Roberts (2001) find that the forecasting performance of standard financial models is relatively poor in the presence of seasonal effects and extreme behaviour and without adjustment for these effects. By explicitly investigating these effects this study may also be of significance for financial markets traders wishing to profitably operate in the electricity markets.

The empirical results of this study show that seasonal effects vary between regions and time of day effects are generally more significant than other seasonalities. It is further shown that when examined individually the extreme values represented by spikes and negative prices are highly significant.

The rest of the chapter is organised as follows: Section 5.2 summarises the key related literature on electricity price behaviour to clearly distinguish contribution of this study. Data and preliminary statistical analysis is provided in section 5.3. Models and main estimation results are presented in sections 5.4 and 5.5. Section 5.6 summarises findings and suggests further related research.

5.2 Summary of Key Literature

The literature in the field of electricity price behaviour reveals several typical characteristics in its various markets. These characteristics include non-normality in the form of positive skewness and extreme leptokurtosis (e.g. Huismann and Huurman, 2003, Goto and Karolyi, 2004), mean-reversion to a long-run level (e.g. Johnson and Barz, 1999), multi-scale seasonality (intra-day, weekly, seasonal), calendar effects, and extreme behaviour with fast-reverting spikes (e.g. Kaminski, 1997, Clewlow and Strickland, 2000b). The majority of the literature treats electricity as a single commodity traded and delivered at different times of the day. An interesting alternative approach is proposed in Guthrie and Videbeck (2002). In a study of half-hourly prices in the New Zealand Electricity Market (NZEM), support is found for the treatment of electricity delivered at different times of the day as different commodities that trade on a small number of distinct intra-day markets, however in the interests of model parsimony, their approach ignores finer intra-day variation and other seasonalities.

Spot prices for electricity display excessive volatility when compared to other commodities and financial assets (Bunn and Karakatsani, 2003). Escribano *et al.* (2002) show volatility to be time-varying with evidence of heteroskedasticity in conditional variance for daily spot prices in Argentina, New Zealand, Nordpool (Norway and Sweden) and Spain. Much of the work on empirical price modelling attempts to adapt some of the familiar models from financial assets to the characteristics of electricity. Knittel and Roberts (2001), apply various financial models of asset prices to hourly prices in the California market, including mean-reversion, time-varying mean, jump-diffusion, time-dependent jump intensity, ARMAX and EGARCH. The author concludes that the forecasting performance is relatively poor for most standard financial asset models. Kaminski (1997) provides an early example where the spike characteristic is addressed through a random walk jump-diffusion model, adopted from Merton (1976), but this model ignores the persistent mean-reversion in electricity prices first identified by Johnson and Barz (1997) and explored further in Clewlow and Strickland (2000a and 2000b). One of the limitations of the jump-diffusion approach is the assumption that all shocks affecting the price series decay at the same rate. Escribano *et al.* (2002) suggests two additional price features; volatility clustering in the form of GARCH effects and seasonality (emphasised by Lucia and Schwartz, 2002), both in the deterministic component of prices and the jump intensity.

There is a branch of the literature that provides support for regime-switching as an alternative modelling framework to jump-diffusion and this may be more suitable for actual price forecasting. Huisman and Mahieu (2001) propose an isolation of two effects assuming three market regimes; a regular state with mean-reverting price, a jump regime that creates the spike and finally, a jump reversal regime that ensures that prices revert to their previous normal level. The advantage of this model is that the mean-reversion and spike features are included, with the spikes treated as truly independent disruptions from the (normally) stable price process. One limitation of this regime-transition structure is that it does not allow for the multiple consecutive spikes that are sometimes observed in electricity markets. De Jong and Huisman (2002) relax this constraint and propose a two-state model of lognormal prices that assumes a stable mean-reverting regime and an independent spike regime in spot price observed on the Dutch power exchange (APX) for the period January 2001 to June 2002. These models show that electricity spot prices demonstrate spikes that are truly time-specific events and are independent from the underlying mean-reverting price process.

Goto and Karolyi (2004) provide some insight into Australian electricity price in their comparison of electricity prices drawn from the US, NORDPOOL (Norway and Sweden) and Australia. Evidence in support of the existence of volatility jumps is found in their sample of data. Wolak (1997) and Goto and Karolyi (2004) in their comparative studies of markets note that jump characteristics appear to be closely related to the institutional structure of markets, with extreme price spikes more prevalent in markets with compulsory participation, as is the case in Australia's NEM. Higgs and Worthington (2005) estimate five different GARCH volatility processes

(GARCH, RiskMetrics, Normal, student and skewed student APARCH) over a sample of half-hourly price data for the period January 1, 2002 to June 1, 2003. Their results indicate that time-of-day, day-of-week and month-of-year effects proxy the arrival of new market information. They further find that positive price spikes, early-morning, late-afternoon and early evening hours are associated with high volatility and that negative price spikes, and other times of the day, week and year are associated with relatively lower volatility.

According to Bunn and Karakatsani (2003), a common feature of finance-inspired stochastic models is to capture the statistical properties of spot price behaviour in the context of derivatives pricing. In order to retain simplicity and/or analytical tractability, the models include only a few factors and typically focus on daily average prices, which are sensitive to outliers. While convenient for options pricing, disregarding evident seasonal and structural effects present in the market data is unhelpful from a forecasting perspective.

Much of the literature documents behaviour of daily or hourly price and returns series over sample periods of two years or less[25]. The Australian wholesale electricity market is based on prices determined at half-hourly trading intervals. According to Ait-Sahalia *et al.* (2003), when using high-frequency data it is desirable to sample as

[25] With the exception of Higgs and Worthington (2005) who use a sample period of from 1 January 1999 to 31 December 2004, however rather than using half-hourly trading interval data in their analysis, a series of daily arithmetic means is drawn from the trading interval data, yielding 2,192 observations for each market. The study presented here uses samples of more than 110,000 observations for each of five regions. 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 intra-day data would provide a logical resolution to these as yet unexplored features.

often as possible and I believe the use of daily data may lead to the loss of important information present in the higher-frequency time series. Many stochastic models applied to conventional financial time-series data have been applied to electricity time series but they have some way to go in revealing the main components of price structure. As noted in the introduction to this study, Knittel and Roberts (2001) emphasised the need to explore this structure and include it in price specifications. Goto and Karolyi (2004) further note that their jump models fail to capture apparently significant effects of extreme price jumps and the effects of these jumps warrant further investigation. This chapter extends the current body of empirical work by examining how half-hourly returns are sensitive to seasonalities and other structural factors over a six-year sample period. Seasonalities examined include time-of-day, day-of-week, monthly and yearly effects and structural effects examined include extreme-value influences such as price spikes and negative prices. The effects of price spikes are more closely examined in this paper and occurrences of negative price, which are generally not considered in the literature, but are explicitly investigated in this study.

5.3 Data

5.3.1 Price Data

The raw price data used to derive the returns series employed by this study are half-hourly pool price observations sourced directly from NEMMCO for the period from 7th December 1998 to 31st March, 2005[26]. Descriptive statistics and preliminary

[26] It is worth noting that the half-hourly spot price in the NEM is a derived price and the method used by the NEM to determine spot price is generally not generally discussed in the current body of literature. A description of the mechanism of spot price determination is presented in section 3.1.3.

analysis of the price series is presented in detail in section 4.2. The sample size is 110,719 observations for each of five NEM regions under examination, these being NSW1, QLD1, SA1, SNOWY1 and VIC1.

As discussed in Chapter Four, the existence of negative prices is a characteristic of the electricity market that is not commonly found in financial time series data and is most likely attributable to the market practices of generators. Figure 4.2 illustrates an extreme occurrence of negative price in VIC1, where the pool price fell to -$161.48 at 12:30a.m. on April 15, 2001. Figure 4.2 also suggests that negative prices exhibit similar rapid mean-reverting tendencies to the extreme high price spikes discussed in the existing literature. Occurrences of negative price are rare and typically short-lived, usually persisting for half to one hour. The longest observed interval of negative price occurred simultaneously in NSW1, SNOWY1 and VIC1 for a period of two and a half hours, between 04:00am and 06:30 am on October 10, 1999.

5.3.2 Half-Hourly Rate of Return

In general, attempts to model or forecast prices in financial markets should be based on successive variations in price and not on the prices themselves (see*, inter alia*, de Bodt, Rynkiewicz & Cottrell, 2001). In the context of commodity futures contracts, Black (1976) notes that because futures contracts require no initial investment, futures positions cannot be said to yield rates of return as they are generally understood, i.e. as a result of change in value of the holder's initial investment over time. Because there is no ability to hold a unit of electricity and there is no "initial investment" in the commodity as such, spot electricity also does not yield a rate of return to an investor in the traditional sense. In light of this characteristic the term "returns" is used to denote proportionate price change over a trading interval. The half-hourly rate of return series (hereafter referred to as “returns”) is of interest because there are a growing number of over-the-counter and exchange-traded derivative products available for hedgers and speculators in the Australian and overseas electricity markets and pricing models for derivatives are informed by the behaviour of returns. Figure 5.2 shows price and returns over a 10-day period in August 2000 and indicates that returns appear to exhibit some time-of-day effects but may not necessarily exhibit the seasonal effects evident in the price series.

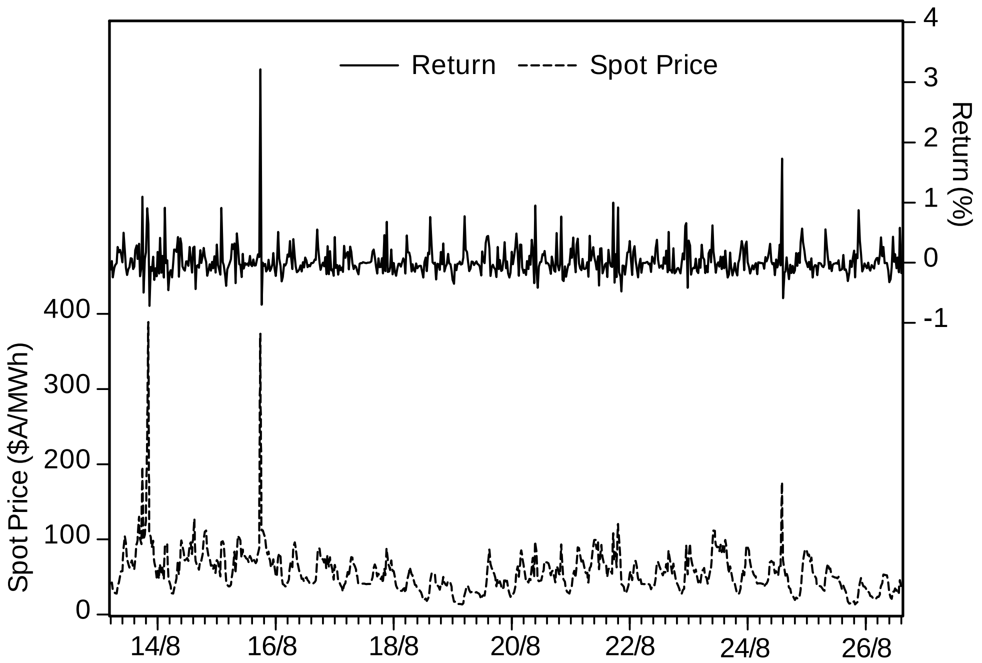

Figure 5.1: Half-Hourly VIC1 Price and Return for the period 14/8/2000 to 26/8/2000.

A discrete returns specification[27] is preferred over log returns because the spot market in the NEM trades at discrete half-hourly intervals – it is not a continuous market in the way of most conventional financial markets. Further, a log returns specification will dampen the extreme spike effects I am attempting to capture, and is not defined

[27] The analysis on returns reported in this chapter was also performed on first-difference (change in level) in the price series and the results were not found to be materially different from those found for the returns series.

in the presence of negative prices, the effects of which are also examined. With these market characteristics in mind, the returns series used in this study were generated as half-hourly discrete returns, ie:

$$RP_t = \frac{(P_t - P_{t-1})}{|P_{t-1}|}. \tag{5.1}$$

Where RP_t represents the half-hourly discrete proportionate change in price ("return") at time t, P_t is half-hourly price at time t and $|P_{t-1}|$ is the absolute value of the previous half-hourly price, i.e. at time $t-1$. The denominator is specified as the absolute value to allow for the presence of negative prices.

As discussed in Chapter 4, negative prices are a rare but real feature of electricity prices that do not occur in financial markets data. When working with returns, negative prices become problematic, as illustrated by Table 5.1, in which observation 4 is a negative price that occurred in the VIC1 regional pool at 10:30 am on November 10th, 2002:

Table 5.1: Illustration of the Arithmetic Treatment of Negative Prices

(1) Observation	(2) Date & Time	(3) P_t	(4) $RP_t = \frac{P_t - P_{t-1}}{P_{t-1}}$	(5) $RP_t = \frac{P_t - P_{t-1}}{\lvert P_{t-1}\rvert}$
1	10/11/2002, 09:30	6.49	_	_
2	10/11/2002, 09:30	7.12	10%	10%
3	10/11/2002, 10:00	10.38	46%	46%
4	10/11/2002, 10:30	-5.10	-149%	-149%
5	10/11/2002, 10:30	16.33	-420%	420%
6	10/11/2002, 10:30	5.67	-65%	-65%
7	10/11/2002, 10:30	5.59	-1%	-1%

The conventionally derived discrete return is shown in column (4). Arithmetically, this approach produces a *negative* return of -420% at observation 5, immediately following the occurrence of negative price, implying incorrectly that the price *falls* from -\$5.10 to +16.33. The magnitude of the change is correct but the sign is wrong. By applying the absolute value of P_{t-1} in the denominator, as in column 5, the sign of the return is corrected, and now reflects a price *increase* from -\$5.10 to +16.33.

Descriptive statistics for the half-hourly returns series are shown in Table 5.2. The mean, standard deviation, minimum, maximum, range, skewness, kurtosis and Augmented Dickey-Fuller statistics are reported for each region's returns series.

Table 5.2: Descriptive Statistics for Half-Hourly Returns
(by Region, December 1998 to March 2005).

Returns	**NSW1**	**QLD1**	**SA1**	***SNOWY1***	**VIC1**
Mean	0.0284	0.0643	0.0651	0.0955	0.0272
S.D.	1.22	1.72	1.77	17.00	1.11
Maximum	151.93	369.24	390.80	4542.50	142.43
Minimum	-222.00	-11.25	-32.94	-220.00	-209.50
Range	152.37	256.10	273.24	4300.99	157.29
Skewness	-0.44	113.14	117.56	241.51	-14.86
Kurtosis	15213.09	20540.27	22339.69	59676.37	16338.64
JB Stat					
P-Value	0.000	0.000	0.000	0.000	0.000
ADF Stat*	-38.16	-40.66	-341.20	-332.65	-39.84
N	110718	110718	110718	110718	110718

*All Augmented Dickey-Fuller test statistics reject the hypothesis of a Unit Root at the 1% level of confidence.

Mean half-hourly returns vary widely between regions, from 2.72% for VIC1 to 9.55% for SNOWY1. The standard deviation of returns is generally high, is widely dispersed across the regions and is consistent with the pattern of means, ranging from 111% for VIC1 to an extremely high 1700% for SNOWY1. The highest maximum return of 454250% is observed in SNOWY1 and lowest in VIC1 of 14,243%. SNOWY1 also exhibits a markedly wider range of returns than the other regions. The extreme character of returns evident for SNOWY1 is most likely attributable to the nature of generation technology employed. All generation plant in SNOWY1 is hydroelectric, whereas more than 80% of generation capacity in NSW1, VIC1 and QLD1 is provided by coal-fired plant. Coal-fired generation is described as a "slow-start" technology, with orderly shutdown and start-up procedures taking up to 48 hours. By contrast, hydroelectric plant is a "fast-start" technology that can be called into production and shut down within a few minutes, with the result that hydroelectric generators are able to behave more opportunistically than coal-fired generators, with the ability to opt out of supply when pool prices are low and respond rapidly when prices are high.

The distributions of returns for QLD1, SA1 and SNOWY1 demonstrate positive skewness with NSW1 and VIC1 demonstrating a relatively low degree of negative skewness. Distributions of returns in all regions demonstrate extremely high positive kurtosis. Jarque-Bera (JB) statistics reject the null hypothesis of normal distribution at the 1% level of significance for all five regions. This fat-tailed character is consistent with earlier studies (see Huisman and Huurman (2002), Higgs and Worthington (2005) and Wolak (2000)) and like price, is driven by the prevalence of extremely large spikes in returns. Augmented Dickey-Fuller (ADF) statistics clearly reject the hypothesis of a Unit Root at the 1% level of significance for all five regions, again consistent with the findings of the earlier studies.

5.3.3 Spike Behaviour

The presence of extreme spikes in prices is a widely recognised characteristic of electricity markets. Figure 5.3 illustrates the occurrence of extreme spikes in the price series over a four-day period in August 2000.

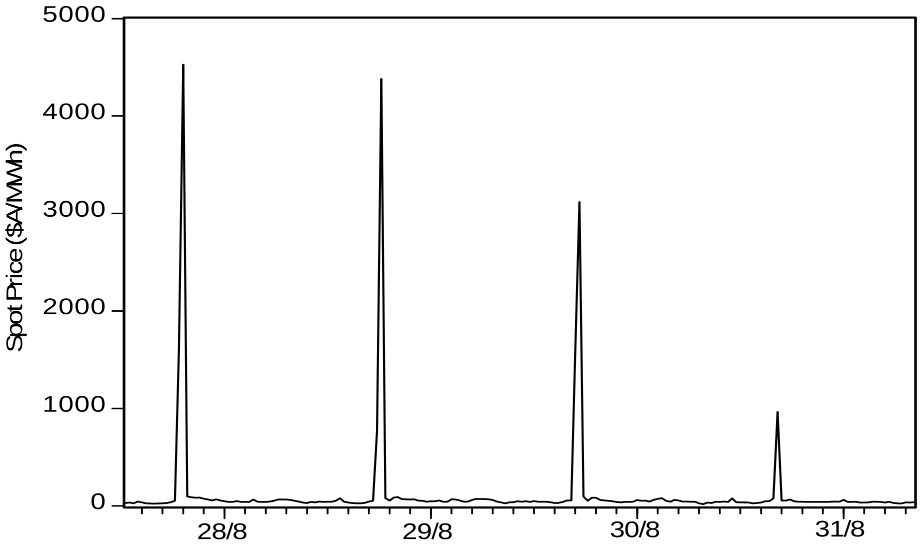

Figure 5.2: VIC1 Spot Price for the Period 28/8/00 to 31/8/00, Illustrating the Occurrence of Extreme Spikes in the Price series

For the purposes of this study a spike in returns is defined as any observed return more than four standard deviations larger than the mean. While the conventional practice is to apply a filter for outliers at three standard deviations from the mean, an initial survey of the data indicated that there is sufficient incidence of high prices and returns around and above the threshold at three standard deviations to justify applying a filter for outliers at four standard deviations. Table 5.3 collates the occurrences of spikes as defined. Panel (a) shows the occurrence of spikes by region and in aggregate for weekday, month and year. Panels (b) and (c) show the occurrence of spikes by half-hourly trading interval.

Table 5.3, Panel (a) shows that there are 566 extreme returns spikes observed across all regions during the sample period. QLD1 has the highest incidence of extreme price spikes by state with 190 occurrences (34% of the total sample of spikes), followed by SA1 with 162 (29%), both have a markedly higher incidence than VIC1 with 98 (17%), NSW1 with 90 (16%) and SNOWY1 with 26 occurrences (5%). By day of the week, Monday shows the highest incidence with 121 observations (21%) and Friday the lowest with 49 occurrences (9%).

Table 5.3: Panel (a) Summary of Occurrences of Extreme Spikes in Returns by Region, by Weekday, Month and Year.

	NSW	QLD	SA	Snowy	VIC	Total
Sun	16	24	10	8	19	77
Mon	23	30	36	5	27	121
Tue	14	40	25	6	18	103
Wed	18	24	27	5	10	84
Thu	8	27	20	2	14	71
Fri	2	19	23	0	5	49
Sat	9	26	21	0	5	61
Total	***90***	***190***	***162***	***26***	***98***	***566***
Jan	5	23	13	0	3	44
Feb	2	9	20	2	7	40
Mar	0	13	18	0	2	33
Apr	0	4	11	0	2	17
May	14	19	11	4	16	64
Jun	23	30	11	3	20	87
Jul	13	29	12	5	12	71
Aug	6	14	7	3	6	36
Sep	7	2	6	1	6	22
Oct	9	21	13	7	12	62
Nov	7	11	14	0	6	38
Dec	4	15	26	1	6	52
Total	***90***	***190***	***162***	***26***	***98***	***566***
1998	2	2	16	0	2	22
1999	10	34	32	8	10	94
2000	17	59	31	3	20	130
2001	4	15	19	0	13	51
2002	37	55	29	5	32	158
2003	15	15	11	6	16	63
2004	4	10	21	2	5	42
2005	1	0	3	2	0	6
Total	***90***	***190***	***162***	***26***	***98***	***566***

Table 5.3: Panel (b) Occurrence of Extreme Price Spikes by Half-Hourly Trading Interval (T.I.) 0000hrs to 2330hrs.

T.I.	NSW1	QLD1	SA1	SNOWY1	VIC1	Total
H0000	0	0	3	0	0	3
H0030	0	0	1	0	0	1
H0100	0	0	7	0	0	7
H0130	0	1	2	0	2	5
H0200	0	0	1	0	0	1
H0230	0	3	3	0	0	6
H0300	1	3	0	0	0	4
H0330	0	0	0	0	0	0
H0400	1	1	0	1	1	4
H0430	1	2	1	1	2	7
H0500	1	1	1	1	2	6
H0530	2	1	0	1	2	6
H0600	1	3	4	1	4	13
H0630	4	4	4	3	6	21
H0700	7	1	8	3	7	26
H0730	0	12	2	0	0	14
H0800	0	4	1	0	0	5
H0830	0	10	5	0	2	17
H0900	1	3	5	0	2	11
H0930	3	5	0	0	1	9
H1000	0	4	5	0	1	10
H1030	1	2	1	1	2	7
H1100	0	3	3	0	1	7
H1130	0	1	0	0	0	1
H1200	0	3	2	0	0	5
H1230	0	3	7	0	2	12
H1300	2	3	4	0	1	10
H1330	1	3	5	0	3	12
H1400	0	4	6	0	0	10
H1430	2	4	2	0	2	10
H1500	0	1	6	0	1	8
H1530	3	2	7	1	2	15
H1600	0	2	4	0	3	9
H1630	1	5	5	0	1	12
H1700	1	5	8	1	1	16
H1730	12	12	3	0	8	35
H1800	39	40	19	11	33	142
H1830	2	7	5	1	1	16
H1900	0	9	5	0	2	16
H1930	0	3	2	0	1	6
H2000	0	4	3	0	1	8
H2030	0	1	3	0	0	4
H2100	0	0	3	0	0	3
H2130	1	1	1	0	0	3
H2200	0	0	0	0	0	0
H2230	2	7	5	0	1	15
H2300	1	2	0	0	0	3
H2330	0	5	0	0	0	5

June shows the highest incidence by month with 87 (15%). The highest incidences by year occur in 2002 with 158 spikes (28%) and 2000 with 130 spikes (23%), both markedly higher than any other full year in the study period[28]. It should be noted that the incidence of extreme price spikes appears to be declining from 2003 onwards. At the time of writing it is believed that this "settling down" is a feature of a maturing market combined with the development and wider use of bilateral hedge contracts between generators and distributors/retailers.

Table 5.3, Panel (b) shows the incidence of extreme spikes in returns by half-hourly trading interval. There is evidence of a concentration of spikes occurring between the hours 06:30 to approximately 10:00 and between 15:30 and 19:00 hours, with a marked increase in frequency evident at the 18:30 trading interval. A sub-period analysis of returns shows that this high concentration at 18:30 may be transient. Figure 5.4 on the following pages shows the pattern of extreme returns for NSW1 from 1999 to 2004 and represents the apparent transient nature of the concentration of spikes around the 18:00 trading interval[29]. The concentration of extreme returns is not present in 1999-2001, arises in 2002 and 2003 in all regions and dissipates after 2003.

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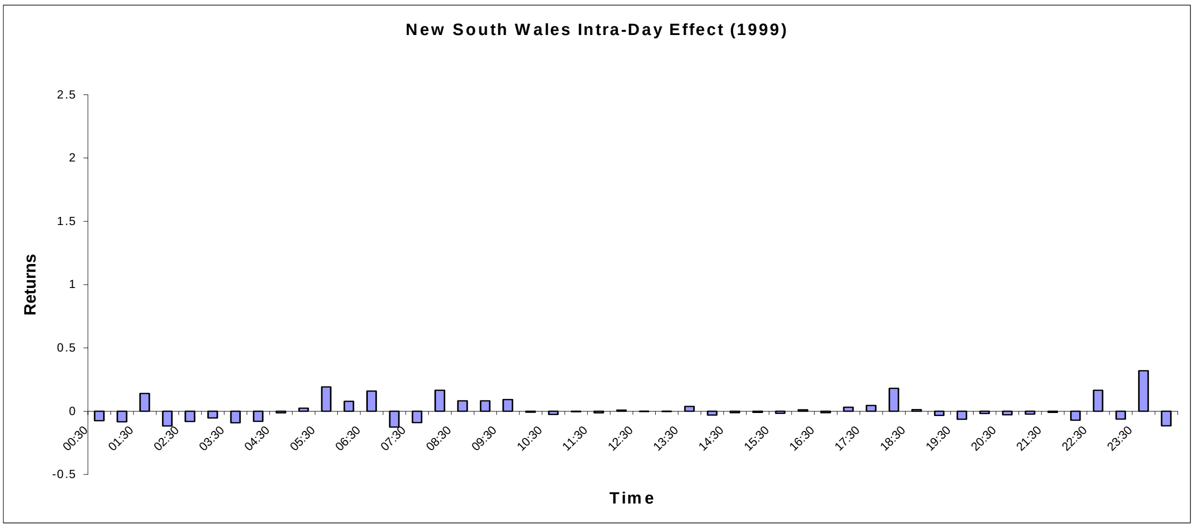
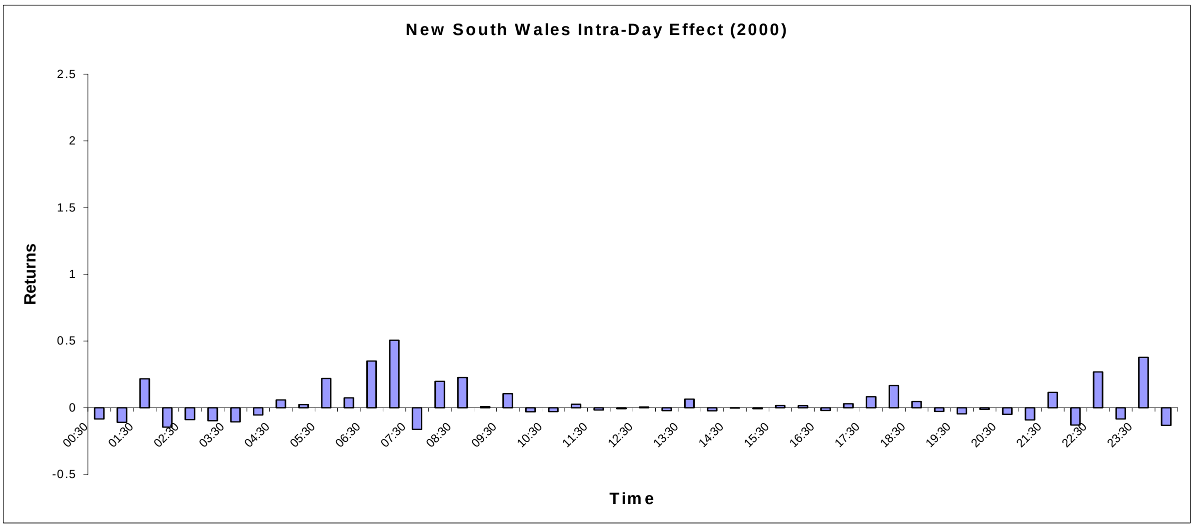
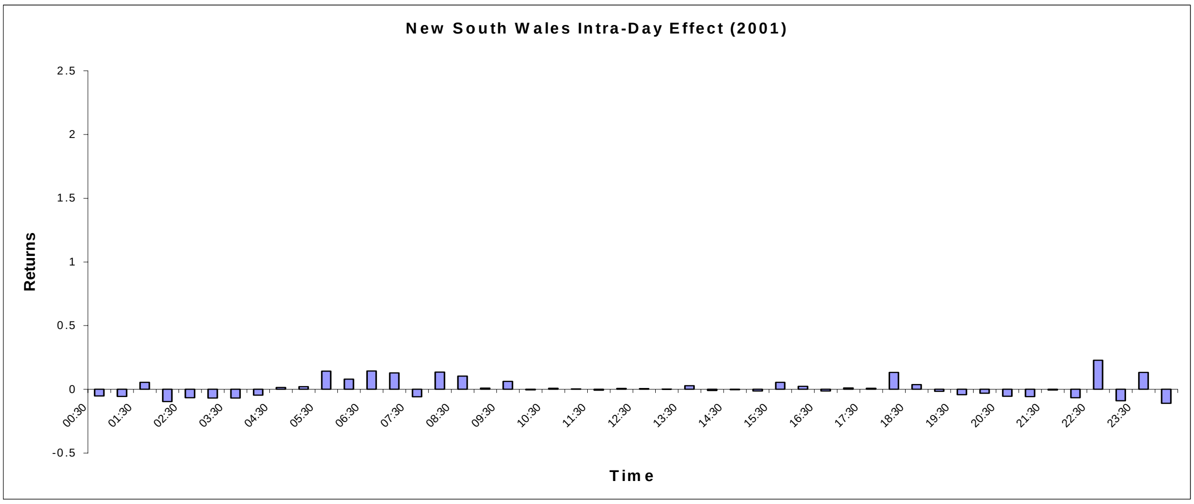
[28] The sample data set includes the full years 1999-2004. 1998 includes approximately three weeks of December, from the commencement of the market on 7th December 1998. 2005 only includes observations for the January to March period and is not likely to be representative of the full year.

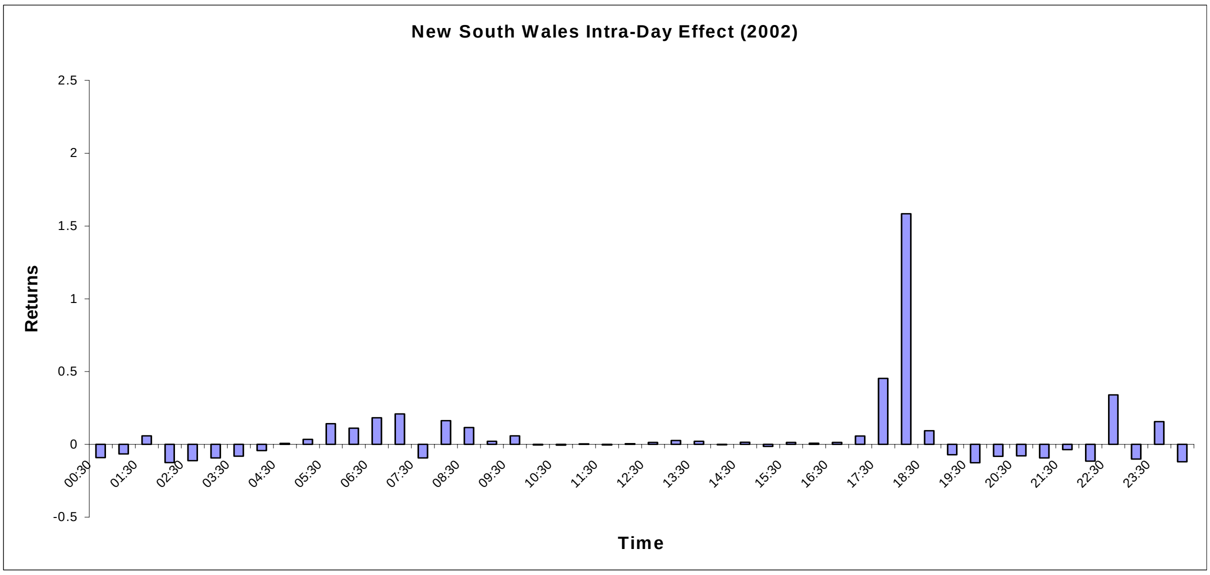
[29] This pattern of returns behaviour is illustrative of the patterns in the other regions.

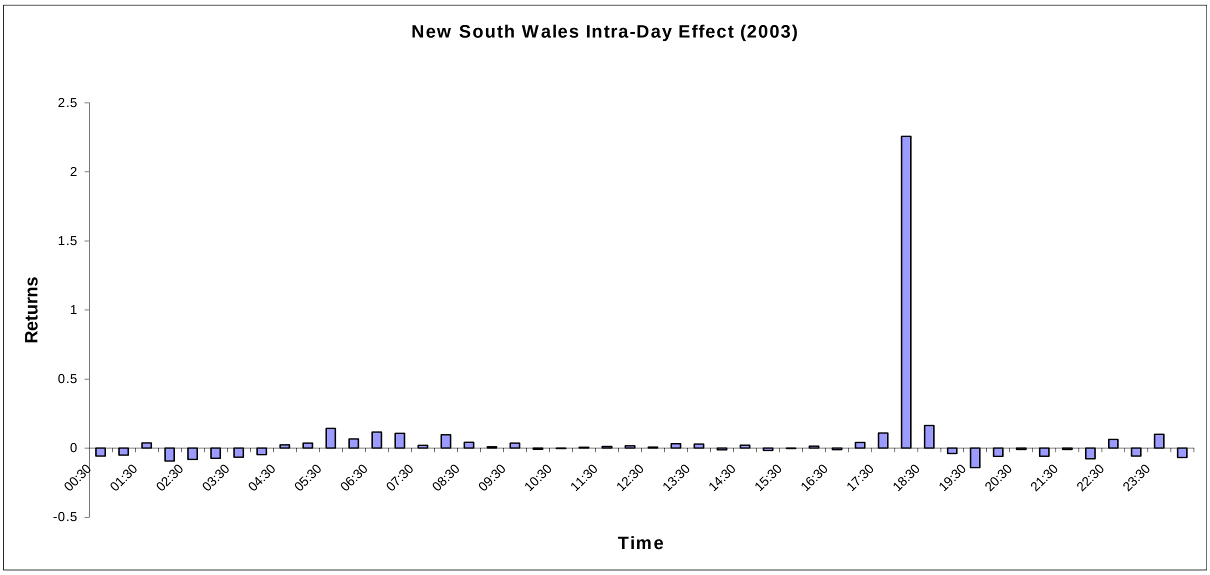
Figure 5.4: Half-Hourly returns for NSW1 for the years 1999-2005, illustrating the transient nature of the observed 6:00pm effect.

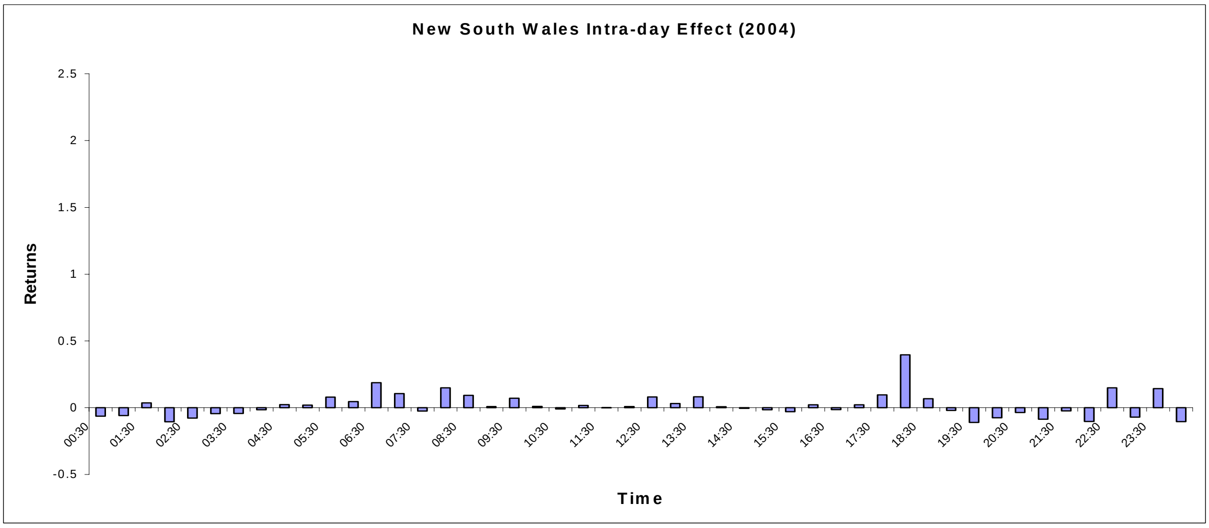







New South Wales Intra-Day Effect (2002)
Returns
Time
2.5
2
1.5
1
0.5
0
-0.5
00:30
01:30
02:30
03:30
04:30
05:30
06:30
07:30
08:30
09:30
10:30
11:30
12:30
13:30
14:30
15:30
16:30
17:30
18:30
19:30
20:30
21:30
22:30
23:30


New South Wales Intra-Day Effect (2003)
Returns
Time
2.5
2
1.5
1
0.5
0
-0.5
00:30
01:30
02:30
03:30
04:30
05:30
06:30
07:30
08:30
09:30
10:30
11:30
12:30
13:30
14:30
15:30
16:30
17:30
18:30
19:30
20:30
21:30
22:30
23:30


New South Wales Intra-day Effect (2004)
Returns
Time
2.5
2
1.5
1
0.5
0
-0.5
00:30
01:30
02:30
03:30
04:30
05:30
06:30
07:30
08:30
09:30
10:30
11:30
12:30
13:30
14:30
15:30
16:30
17:30
18:30
19:30
20:30
21:30
22:30
23:30

5.4 Methodology

The summary of key literature on electricity prices presented in section 5.2 suggests that furthering our understanding of the nature and significance of seasonalities and extreme values in electricity prices is justified. To that end an autoregressive model is developed in which the dependent variable is half-hourly return and the explanatory variables are half-hourly lagged returns and dummy variables[30] representing trading interval (half-hourly time of day), day of the week, and month of the year for NSW1, QLD1, SA1, SNOWY1 and VIC1. The model also incorporates dummy variables for "spikes", as defined in section 5.3.3, and dummy variables are set for each occurrence of a negative value in the price series.

The model employed by this study is presented as equation (5.2) and provides a relatively simple but highly effective method for satisfying the objective of capturing the effects of individual spikes while controlling for seasonalities and serial correlation in the returns series.

$$RP_{R,t} = \alpha_0 + \sum_{i=1}^{5} \beta_{1,i} RP_{R,t-i} + \sum_{j=1}^{6} \beta_{2,j} DAY_j + \sum_{k=1,\neq 9}^{12} \beta_{3,k} MTH_k + \sum_{l=1999,\neq 2001}^{2006} \beta_{4,l} YR_l$$
$$+ \sum_{m=1,\neq 23}^{48} \beta_{5,m} HH_m + \sum_{o=1}^{N_{R,S}} \beta_{6,o} SPIKE_{R,o} + \sum_{p=1}^{N_{R,N}} \beta_{7,p} NEG_{R,p} + \varepsilon_t \tag{5.2}$$

[30] 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).Lucia and Schwartz (2002) favour dummy variables as they are intuitive and are relatively easy to interpret.

Where:

$RP_{R,t}$ represents the discrete return for region *R* at time *t*;

DAY_j represents the dummy variable for each day of the week (*j*=1 for Monday, 2 for Tuesday,…,6 for Saturday). MTH_k represents the dummy variable for each month (*k*=1 for January, 2 for February,…,12 for December).

YR_l represents the dummy variable for each year included in the sample period (*l*=1999,…,2006).

HH_m represents the dummy variable for each half-hourly trading interval (*m*= 1 for 00:00hrs, 2 for 00:30hrs…,48 for 23:30hrs) $SPIKE_{R,S}$ represents a set of $N_{R,S}$ dummy variables, one for each extreme spike as previously defined, with $N_{R,S}$ representing the number of extreme returns observed in region R for the period of the study (see Table 2);

$NEG_{R,N}$ represents the dummy variable for the return associated with an occurrence of a negative price (*p*=1,…,$N_{R,N}$), with $N_{R,N}$ representing the number of occurrences of a negative price for region *R* during for the period of the study.

To avoid the dummy variable trap, the dummy variables representing the trading interval at 1100hrs, Sunday, September and the year 2001 are dropped to avoid exact collinearity. These values were dropped because they reflect categories whose returns activity was consistently lowest in all five regions. As such, the constant term (α_0) embodies this omitted case and the estimates for the included dummy variables HH_m, DAY_j, MTH_k, and YR_l must be assessed relative to this base case.

The model presents a relatively simple but highly effective method for capturing the impact of individual price spikes and seasonalities. The equation was initially estimated for each region with 20 lagged returns (RET_{Rt-1}, …RET_{Rt-20}). *F*-Tests for redundant variables were performed for all regions and AIC and SBC values support the finding that lags 1 through 5 were significant. Lags 6 onwards were not found to be significant and were discarded. Standard tests and residual diagnostics revealed no misspecification in the above model.

5.5. Empirical Results

Results of the regression analysis are presented in Table 5.4. Coefficients and *p*-values are presented for each seasonal dummy variable and for lagged returns. In view of the very large number of individual spikes in returns (566 spikes identified for the sample period), results for individual outliers are discussed here but not reported in full detail. Note also that Lindley (1957) pointed out that in very large samples, test statistics may be biased in favour of "unfairly" accepting a parameter as significant. In view of Lindley's (1957) paradox and the need for conservatism that it suggests, a 1% level of significance is applied rather than the more usual 5%.

The results do not reveal a clear pattern in day-of-week effects for most days across regions. There is a positive and significant effect in returns for Monday observed in SA1 only. Friday demonstrates statistically significant negative returns across all 5 regions. Significant positive effect on returns is found for Saturday in QLD1 only. There appears to be no clear pattern in monthly effect across regions, although a small but significant positive effect is observed for April in VIC1, May in NSW1, SNOWY1 and VIC1, June in NSW1. Significant and positive effects are noted for December in NSW1, SNOWY1 and VIC1 but not in QLD1 and SA1. A possible explanation of the similarity in these monthly effects between NSW1 and VIC1 might be the broadly similar temperate climates in NSW and VIC, with relatively higher use of electricity for heating in these cooler states during the seasonal transition through late autumn and early winter as the population acclimatises to cooler seasonal temperatures; and an increase in the use of cooling systems in December as the population acclimatises to warmer summer temperatures. The commonality of these effects may also be due to the geographic proximity of NSW1 and VIC1, with the fact that these three regions are well serviced by large capacity interconnectors and that there is a high degree of inter-regional electricity sales between them.

There is no clear pattern evident in yearly effect, with wide variation in direction and significance between regions. Lagged returns exhibit variation in direction and significance of effect between regions, with individual lags 1, 3 and 5 generally significant.

Half-hourly time-of-day effects offer more interesting results and are broadly more consistent across regions than the seasonal effects previously discussed. In general significant negative returns are found for the small hours of the morning between 12:30 a.m. and approximately 4:30 a.m. in all regions. The hours between 5:00a.m. and 9:30a.m. inclusive exhibit significant positive effect in all regions. Negative returns are found during mid-afternoon but are generally not statistically significant during this period. Significant positive effects are observed for all regions in the early evening, generally between the hours of 5:00 to 7:00 pm, reverting to significant negative effects for the remainder of the evening, until positive effects emerge in the late evening at 10:30 p.m. and at midnight.

Table 5.4: Panel (a) - Results Of Regression Analysis For Returns Against Seasonal Dummy Variables, By Region For Day, Month, Year and Lagged Return ($RP_{R,t-i}$).

	NSW1		QLD1		SA1		SNO1		VIC1	
	Coeff	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**
C	-0.010	0.0206	0.013	0.0950	0.020	0.0067	-0.014	0.0592	-0.006	0.1869
MON	0.002	0.1637	0.001	0.9730	0.006	0.0186	0.009	**0.0014**	0.003	0.1172
TUE	0.001	0.6738	0.001	0.6583	0.004	0.1779	0.001	0.8105	0.001	0.9572
WED	0.003	0.1310	0.001	0.9599	0.004	0.1385	0.001	0.7191	0.001	0.8655
THU	-0.001	0.6689	-0.006	0.0802	0.002	0.5919	-0.003	0.3623	-0.002	0.2946
FRI	-0.009	**0.0000**	-0.016	**0.0000**	-0.009	**0.0013**	-0.012	**0.0002**	-0.010	**0.0000**
SAT	0.005	0.0668	0.022	**0.0000**	0.003	0.5603	0.003	0.4606	0.007	0.0147
JAN	0.005	0.0662	0.014	**0.0022**	0.008	0.0569	0.002	0.7064	0.007	0.0134
FEB	0.002	0.4887	0.027	**0.0000**	0.000	0.9188	-0.002	0.5877	0.002	0.4924
MAR	0.004	0.1400	0.003	0.5083	0.003	0.5692	0.001	0.9600	0.005	0.0602
APR	0.008	0.0042	0.016	0.0008	0.003	0.5684	0.009	0.0417	0.008	**0.0031**
MAY	0.009	**0.0010**	0.019	0.0001	0.003	0.4984	0.020	**0.0000**	0.010	**0.0004**
JUN	0.007	**0.0053**	0.012	0.0116	0.011	0.0168	0.009	0.0330	0.007	0.0131
JUL	0.004	0.1107	0.015	0.0015	0.007	0.1013	0.004	0.4105	0.005	0.0672
AUG	0.001	0.8883	0.010	0.0391	0.001	0.9247	-0.002	0.7251	0.001	0.9143
OCT	-0.001	0.8461	0.001	0.9582	0.009	0.0407	0.001	0.7889	-0.001	0.8014
NOV	0.000	0.8714	0.011	0.0251	-0.005	0.2730	-0.001	0.7730	0.002	0.5013
DEC	0.022	**0.0001**	-0.008	0.4289	0.041	**0.0000**	0.029	**0.0012**	0.013	0.0274
1999	0.005	0.0067	0.023	0.0000	0.040	**0.0000**	0.003	0.2803	-0.001	0.5457
2000	0.013	**0.0000**	0.038	0.0000	0.022	**0.0000**	0.017	**0.0000**	0.008	**0.0001**
2002	0.008	**0.0000**	0.009	0.0061	0.005	0.0934	0.018	**0.0000**	0.003	0.2025
2003	0.001	0.8298	-0.008	0.0191	-0.001	0.8623	0.001	0.9728	-0.004	0.0731
2004	0.004	0.0306	-0.005	0.1413	0.003	0.4083	0.003	0.3547	0.002	0.3039
2005	-0.003	0.2840	-0.021	0.0002	-0.005	0.3232	0.001	0.9947	-0.009	**0.0057**
2006	0.002	**0.0000**	-0.005	**0.0000**	-0.007	**0.0000**	0.001	**0.0000**	-0.001	0.0164
$RP_{R,t-1}$	-0.008	**0.0000**	-0.004	**0.0000**	-0.002	**0.0002**	0.002	**0.0000**	-0.008	**0.0000**
$RP_{R,t-2}$	-0.005	**0.0000**	-0.002	**0.0001**	-0.002	**0.0002**	0.001	**0.0033**	-0.006	**0.0000**
$RP_{R,t-3}$	-0.002	**0.0000**	-0.001	0.3134	0.001	0.6153	0.001	0.4172	-0.002	**0.0000**
$RP_{R,t-4}$	-0.001	0.1015	-0.001	0.3258	-0.001	0.0528	0.002	**0.0000**	-0.002	**0.0015**
$RP_{R,t-5}$	-0.010	0.0206	0.013	0.0950	0.020	0.0067	-0.014	0.0592	-0.006	0.1869
R^2	0.9788		0.9670		0.9717		0.9998		0.9720	
Adj R^2	0.9787		0.9669		0.9716		0.9997		0.9719	
DW Stat	2.0005		1.9942		1.9967		2.0573		1.9832	

Note: The equation was initially estimated for each region with 20 lagged returns. F-Tests for redundant variables were performed and for all regions AIC and SBC values indicated that lags 1 through 5 were significant. Lags 6 onwards were not found to be significant and were discarded. Standard tests and residual diagnostics revealed no misspecification in the above model. Bold type indicates significance at 1%. R^2 and Adj R^2 values shown are for the complete model incorporating all seasonal factors and outliers. Table 5.4 Panel (b) shows coefficients and p-values for trading interval (time of day). Coefficients for 566 spike dummies are not reported in detail – all were positive and significant.

Table 5.4 Panel (b): Results of regression analysis for returns against seasonal dummy variables, by half-hourly trading interval by region, 0000hrs to 2330hrs (excluding 11:00hrs).

	NSW1		QLD1		SA1		SNO1		VIC1	
	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val
H0000	-0.104	**0.000**	-0.168	**0.000**	-0.018	0.035	-0.099	**0.000**	-0.107	**0.000**
H0030	-0.064	**0.000**	-0.123	**0.000**	-0.033	**0.000**	-0.067	**0.000**	-0.082	**0.000**
H0100	-0.067	**0.000**	-0.098	**0.000**	-0.036	**0.000**	-0.070	**0.000**	-0.087	**0.000**
H0130	0.091	**0.000**	-0.038	**0.000**	-0.088	**0.000**	0.111	**0.000**	0.192	**0.000**
H0200	-0.112	**0.000**	-0.096	**0.000**	-0.186	**0.000**	-0.116	**0.000**	-0.141	**0.000**
H0230	-0.080	**0.000**	-0.075	**0.000**	-0.110	**0.000**	-0.088	**0.000**	-0.114	**0.000**
H0300	-0.066	**0.000**	-0.060	**0.000**	-0.155	**0.000**	-0.073	**0.000**	-0.100	**0.000**
H0330	-0.071	**0.000**	-0.057	**0.000**	-0.138	**0.000**	-0.076	**0.000**	-0.101	**0.000**
H0400	-0.043	**0.000**	-0.046	**0.000**	-0.105	**0.000**	-0.045	**0.000**	-0.065	**0.000**
H0430	0.022	**0.000**	-0.013	0.144	-0.031	**0.000**	0.022	**0.009**	0.012	0.034
H0500	0.031	**0.000**	-0.008	0.406	-0.006	0.511	0.033	**0.000**	0.032	**0.000**
H0530	0.155	**0.000**	0.052	**0.000**	0.122	**0.000**	0.162	**0.000**	0.172	**0.000**
H0600	0.079	**0.000**	0.010	0.300	0.072	**0.000**	0.092	**0.000**	0.116	**0.000**
H0630	0.158	**0.000**	0.091	**0.000**	0.179	**0.000**	0.174	**0.000**	0.222	**0.000**
H0700	0.173	**0.000**	0.118	**0.000**	0.214	**0.000**	0.197	**0.000**	0.214	**0.000**
H0730	-0.060	**0.000**	0.066	**0.000**	-0.048	**0.000**	-0.069	**0.000**	-0.065	**0.000**
H0800	0.152	**0.000**	0.133	**0.000**	0.130	**0.000**	0.147	**0.000**	0.171	**0.000**
H0830	0.113	**0.000**	0.120	**0.000**	0.149	**0.000**	0.113	**0.000**	0.137	**0.000**
H0900	0.015	**0.004**	0.044	**0.000**	0.030	**0.001**	0.017	0.041	0.029	**0.000**
H0930	0.065	**0.000**	0.060	**0.000**	0.015	0.087	0.066	**0.000**	0.072	**0.000**
H1000	-0.003	0.600	-0.031	**0.001**	-0.017	0.044	-0.003	0.707	0.002	0.703
H1030	-0.005	0.366	-0.029	**0.002**	-0.038	**0.000**	-0.001	0.920	-0.002	0.771
H1100	0.014	**0.006**	-0.025	**0.008**	-0.010	0.247	0.016	0.049	0.014	0.011
H1200	0.009	0.075	-0.010	0.261	-0.010	0.268	0.009	0.260	0.006	0.310
H1230	0.022	**0.000**	-0.029	**0.001**	0.018	0.034	0.022	**0.009**	0.015	**0.007**
H1300	0.001	0.793	-0.033	**0.000**	-0.004	0.663	0.011	0.182	0.002	0.669
H1330	0.041	**0.000**	0.010	0.297	-0.004	0.652	0.047	**0.000**	0.039	**0.000**
H1400	-0.006	0.223	-0.020	0.028	-0.015	0.080	-0.003	0.740	-0.010	0.059
H1430	0.005	0.353	-0.001	0.928	-0.030	**0.000**	0.005	0.546	-0.004	0.430
H1500	-0.007	0.172	-0.045	**0.000**	-0.025	**0.004**	-0.001	0.950	-0.003	0.582
H1530	0.000	0.994	-0.017	0.064	-0.049	**0.000**	0.010	0.230	-0.006	0.262
H1600	0.020	**0.000**	-0.003	0.768	-0.007	0.411	0.015	0.070	0.020	**0.000**
H1630	-0.013	0.012	-0.009	0.334	-0.040	**0.000**	-0.004	0.666	-0.007	0.192
H1700	0.029	**0.000**	0.045	**0.000**	0.002	0.788	0.039	**0.000**	0.036	**0.000**
H1730	0.074	**0.000**	0.121	**0.000**	0.035	**0.000**	0.097	**0.000**	0.060	**0.000**
H1800	0.217	**0.000**	0.267	**0.000**	0.146	**0.000**	0.296	**0.000**	0.193	**0.000**
H1830	0.047	**0.000**	0.079	**0.000**	0.059	**0.000**	0.044	**0.000**	0.049	**0.000**
H1900	-0.022	**0.000**	0.046	**0.000**	-0.042	**0.000**	-0.024	**0.004**	-0.025	**0.000**
H1930	-0.074	**0.000**	-0.102	**0.000**	-0.096	**0.000**	-0.072	**0.000**	-0.068	**0.000**
H2000	-0.038	**0.000**	-0.086	**0.000**	-0.038	**0.000**	-0.033	**0.000**	-0.025	**0.000**
H2030	-0.039	**0.000**	-0.122	**0.000**	-0.071	**0.000**	-0.034	**0.000**	-0.035	**0.000**
H2100	-0.066	**0.000**	-0.088	**0.000**	-0.084	**0.000**	-0.062	**0.000**	-0.066	**0.000**
H2130	0.005	0.328	-0.054	**0.000**	-0.044	**0.000**	0.012	0.161	-0.021	**0.000**
H2200	-0.091	**0.000**	-0.097	**0.000**	-0.097	**0.000**	-0.088	**0.000**	-0.101	**0.000**
H2230	0.195	**0.000**	0.145	**0.000**	0.050	**0.000**	0.198	**0.000**	0.140	**0.000**
H2300	-0.075	**0.000**	-0.081	**0.000**	-0.060	**0.000**	-0.068	**0.000**	-0.069	**0.000**
H2330	0.205	**0.000**	0.129	**0.000**	0.146	**0.000**	0.224	**0.000**	0.319	**0.000**

All occurrences of extreme outliers captured by the model are statistically significant and as noted in the Australian Government's (2004) white paper "securing Australia's Energy Future", represent a significant economic cost to the community with price spikes accounting for greater than 30% of total spot market costs[31]. As discussed in Section 1.2 and in later chapters, spikes also contribute excess volatility and its attendant costs. All occurrences of negative prices have a statistically significant negative effect on returns in QLD1, SA1 and VIC1 with fewer instances having effect in NSW1 and SNOWY1. That said, negative prices have negligible economic effect. As noted in Chapter 4, occurrences of negative prices are rare and very short-lived, with occurrences rarely lasting more than an hour. Given that sales are settled on a daily basis, it is unlikely that a generator would ever have to outlay cash to "pay" the pool for taking its excess capacity, nor would distributors or retailers receive cash for taking it.

5.6 Conclusion

The deregulation of the electricity supply chain and its reorganisation into wholesale markets offers a rich opportunity for researchers. The physical nature of electricity and the mode of organisation of its various markets give rise to price characteristics and behaviours that are not widely found in more traditional financial markets. Several contributors to the current body of empirical work, including Knittel and Roberts (2001), Goto and Karolyi (2004) and Higgs and Worthington (2005) identify seasonal factors in electricity prices as a critical component of price behaviour and

[31] See Section 1.2 for further discussion.

therefore worthy of further study. A number of studies document and attempt to model extreme behaviour with fast-reverting spikes (e.g. Kaminski, 1997, Clewlow and Strickland, 2000a). Knittel and Roberts (2001) find that in the presence of these seasonal effects and extreme behaviour, the forecasting performance of standard financial models is relatively poor without adjustment for these effects.

This study investigates seasonalities and spike effects in Australian electricity prices in considerable detail and over a longer sample period than the existing literature. Over the six-year period of the study, time-of-day effects in returns are significant and generally consistent across all five regions of the NEM, with positive returns generally occurring at times of peak population activity in the morning and early evening and negative returns observed at most other times. There is also evidence of a transient, early evening spike effect in returns arising in 2002 and 2003 and dissipating quickly over subsequent years. Day-of-week effects generally appear stronger for Monday and Friday than for other days of the week. Monthly effects show some consistency between NSW1, SNOWY1 and VIC1 in late autumn to early winter and in early summer.

The physical nature of electricity and aspects of the organisation of the Australian market give rise to the occurrence of extreme spikes in prices and in the returns series. Extreme spikes in returns, although representing less than 0.1% of observations in any region, are found to have highly statistically significant positive effect on returns. The occurrence of negative prices, although relatively rare and unique to electricity markets are found to have a significant negative effect on returns. These findings reinforce the assertions of previous researchers that seasonal and price spike effects should be incorporated into stochastic models of electricity price behaviour.

Given the instantaneous market-clearing nature of prices in the NEM, a logical extension of this study is to investigate the prevalence of seasonal effects and spike behaviour in electricity demand, with a view to examining the extent to which these effects are transmitted from demand to price and how efficiently the spot market absorbs demand-side shocks. Planned further work also includes an examination of the influence of air temperature on electricity demand, and an investigation into the influence of supply-side shocks on price behaviour.

As a caveat on methodology I recognise that while the ordinary-least-squares approach to modelling adopted for this study is a simple but very effective tool for capturing these effects but with many variables it becomes cumbersome for forecasting purposes. A further proposed extension follows Bystrom (2005), who suggests a potentially more practical description of electricity prices involving extreme-value theory. Bystrom introduces an AR-GARCH price process with a seasonal component in volatility. The advantage of this approach is that the residuals are modelled with distributions from extreme value theory. Another extension is suggested by the apparent intra-day switching between positive and negative returns, which may provide support for further development of regime-switching models, and provide support for multiple intra-day markets such as proposed by Guthrie and Videbeck (2002).

Chapter 6: Structural Characteristics of Demand for Electricity in Australia's National Electricity Market

6.1 Introduction

Forecasting electricity spot price remains one of the most challenging tasks for energy traders. The spot market for electricity in the NEM differs from conventional financial markets, primarily because of the non-storable nature of electricity. This special characteristic implies that the spot market is always in equilibrium, i.e. demand is always equal to supply and that spot price is determined by the interaction of these two factors. Chapter Five of this thesis examined the seasonal patterns and sudden spikes in electricity spot price changes in the NEM, and showed that seasonal effects vary between regions and that time of day effects are generally more significant than other seasonalities. The extreme values represented by high price spikes and negative prices were shown to be highly significant.

Demand is a major driver of spot price (see Vucetic *et al.*, 2001 and references therein, and Lo and Wu, 2004) and this chapter investigates whether similar structural characteristics to those evident in electricity prices are present in electricity demand[32]. Results from chapter 5 show the presence of significant spikes in the price series, and given that the spot market is always in equilibrium, these spikes could be caused by short-run spikes in demand or shocks to supply such as breakdowns in generation plant or disruption to the transmission grid. Analysis of the demand data may provide some insight into the spike behaviour observed in the price series. As a first step in this analysis, it is necessary to characterise any seasonal patterns that might be

[32] Demand is also referred to as "load" or "system load". In practice and in the academic literature these terms appear to be used interchangeably.

present and investigate the presence of spikes in the demand side of the spot market. Chapter Eight will examine the transmission of spikes in the demand data to price series.

Understanding the behaviour of demand for electricity is central to operation of and planning for electric utilities and is central to the forecasting function of electricity producers and consumers that participate in electricity markets. Accurate load forecasting holds great saving potential for electric utility corporations. According to Bunn and Farmer (1985), these savings are realised when demand forecasting is used to control operations and decisions such as dispatch, commitment of generation plant, fuel allocation, maintenance scheduling and off-line network analysis. The accuracy of demand forecasts has a significant effect on power system operations, as economy of operations and control of power systems may be quite sensitive to forecasting errors. Haida and Muto (1994) observed that both positive and negative forecasting errors resulted in increased operating costs. Hobbs *et al*. (1999) quantified the dollar value of improved demand forecasting for a typical utility; a 1% reduction in the average forecast error can save hundreds of thousands or even millions of dollars.

Seasonal patterns in demand or system load are reported in the literature and these patterns are incorporated into a variety of forecasting models. Harvey and Koopman (1993) document intra-daily and intra-week effects and incorporate them into their demand model using splines. Earlier studies considered longer-term load forecasting horizons several months into the future, using monthly demand data (Engle, Granger and Hallman, 1989). Pardo, Meneu and Valor (2002) employ daily data in a study of Spanish electricity demand and emphasise the importance of daily and monthly seasonal structures. More recent studies consider modelling and forecasting demand over shorter periods using intra-day data. In the Australian context, Smith (2000) and Cottet and Smith (2003) document intra-day patterns in demand in New South Wales and incorporate diurnal variation into a Bayesian regression framework to model intra-day electricity load data and obtain short-term load forecasts.

While a number of studies have incorporated seasonal patterns into demand models, the presence of sudden and fast reverting spikes in demand have not been comprehensively documented. I am interested in investigating if, like changes in the electricity spot price, half-hourly changes in demand demonstrate a high incidence of spikes, as well as sensitivity to seasonal patterns. According to Knittel and Roberts (2001), the regular occurrence of these spikes accounts for the failure of conventional the stochastic forecasting models. I believe it is necessary to test if demand also exhibits evidence of such spikes.

With these objectives in mind the contribution of this chapter is twofold. First a six-year sample of half hourly total system demand for five regions in Australia's National Electricity Market (NEM) is examined here and the occurrence of outliers in the form of extreme spikes in half-hourly proportionate demand change is reported. Second, a model is presented that captures the sensitivity of demand changes to these outliers, while controlling for seasonal factors including time-of-day, day-of-week, monthly and yearly effects. The results show that seasonal effects are significant but vary across regions. Time of day effects are found to be more significant than other seasonalities. Further, demand spikes are present in the series and are found to be highly significant.

The rest of the chapter is organised as follows. Demand change data and preliminary statistical analysis are presented in section 6.2. Models and main estimation results are presented in sections 6.3 and 6.4 and section 6.5 presents conclusions and suggests further related research.

6.2 Data

6.2.1 Demand data

The basic quantity of interest in demand modelling and forecasting is the periodic "total system demand" or "total demand". The total demand value reported by NEMMCO is a derived value, somewhat different from demand as it is understood in conventional financial markets (and as may be represented by traded volume). The NEM trading day is divided into 48 half-hour "trading intervals", each defined by the local time at the end of the trading interval. Suppliers and distributors lodge schedules and bids for the sale and purchase of electricity with NEMMCO at 12:30pm on the day prior to actual dispatch of electricity. NEMMCO compiles this data and mates it with a short-term forecast of system demand and grid capacity to determine a dispatch quantity and dispatch order of generators (Smith, 2000).

The demand data used in this study are half-hourly observations of total demand (as described in section 4.2.1), sourced directly from NEMMCO for the period from 2:00am on December 7, 1998, to 11:30pm on March 31, 2005. The sample size is 110,719 observations for each of the five NEM under study (NSW1, QLD1, SA1, SNOWY1 and VIC1). Descriptive statistics and preliminary analysis of the demand series is presented in Chapter Four, section 4.2.1.

6.3.2 Changes in Demand

The half-hourly pool price and its associated returns exhibit strong seasonal and outlier effects as a result of the occurrence of price spikes. As indicated earlier, demand is widely understood to be a major influence on price (and therefore returns) and I am interested in investigating the extent to which the seasonalities and spike effects observed in half-hourly returns on spot price are present in the equivalent changes in demand.

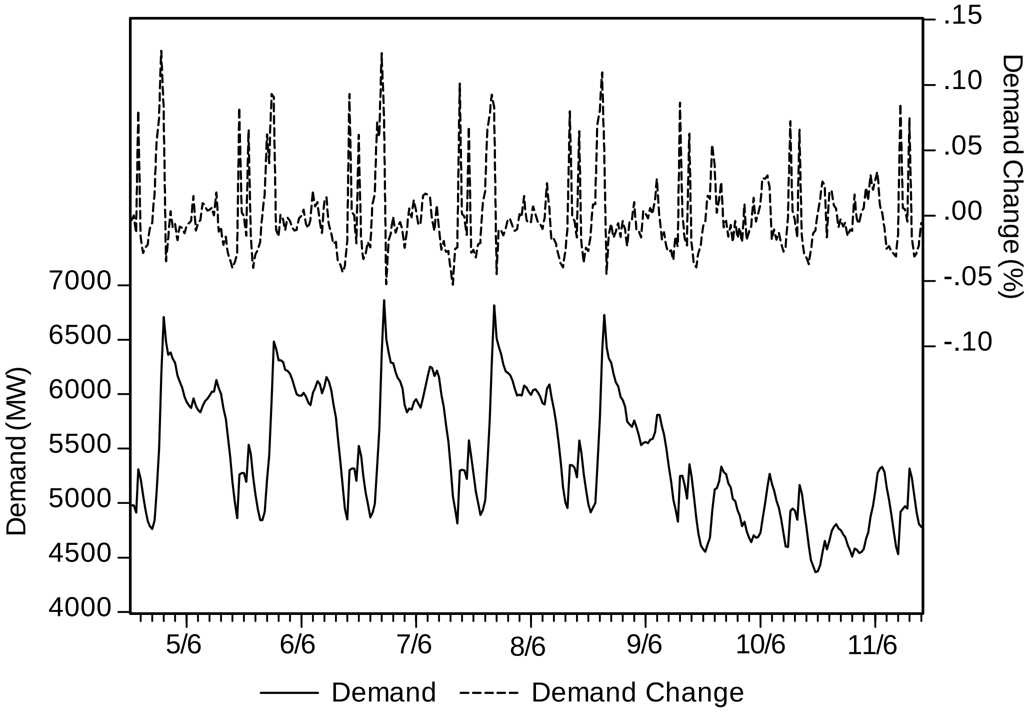


Figure 6.1: VIC1 Demand and Demand Change for the Week Commencing 5/6/00.

Figure 6.1 shows a snapshot of demand with demand change over a week during June 2000, indicating that demand and demand changes may exhibit some time-of-day effects, but also suggests the presence of sudden and fast-reverting spikes in demand change.

Like spot price, NEMMCO's total demand is reported at half-hourly intervals in discrete time. For this reason and for consistency with the approach taken in Chapter Five, the demand change series used in this study were generated as half-hourly discrete changes rather than log changes, according to equation 6.1:

$$CD_t = \frac{(D_t - D_{t-1})}{D_{t-1}}. \qquad (6.1)$$

Where CD_t is discrete proportionate change in demand at time t, D_t is half-hourly demand at time t and D_{t-1} is the previous half-hourly total demand, i.e. at time $t-1$. The results of tests for the presence of a unit root give us confidence that the demand and demand changes series are stationary. This discrete change specification is preferred over log changes, as a log specification will dampen the spike effects I am attempting to capture.

Descriptive statistics for the half-hourly demand change series are shown in Table 6.1. The mean, standard deviation, minimum, maximum, skewness, kurtosis and Augmented Dickey-Fuller statistics are reported for each region’s demand changes series. Mean, standard deviation, maximum and minimum are expressed in terms of half-hourly percentage change and are broadly consistent across NSW1, QLD1, SA1 and VIC1. SNOWY1 demonstrates extremely high mean, and standard deviation of demand changes when compared to the other regions. I believe that this is attributable to the unique nature of SNOWY1, as discussed in section 3.1.

Table 6.1: Descriptive Statistics for Half-Hourly Demand Change (CD_t), by Region, December 1998 to March 2005.

CD_t	NSW1	QLD1	SA1	SNOWY1	VIC1
Mean*	0.05	0.04	0.05	73.16	0.04
S.D.*	3.16	2.88	3.27	2210.41	3.02

Maximum*	44.50	76.38	38.41	357868.40	62.33
Minimum*	-26.55	-31.94	-38.97	-100.00	-100.00
Range	71.05	108.32	77.38	357968.40	162.33
Skewness	1.13	1.07	0.38	99.91	0.87
Kurtosis	5.05	9.97	4.57	12337.15	17.60
JB Stat	4.30×10^4	2.45×10^5	1.40×10^4	7.02×10^{11}	9.97×10^5
ADF **	-43.66	-43.67	-39.71	-333.16	-40.74
N	110718	110718	110718	110718	110718

*Mean, Standard Deviation, Maximum and Minimum are expressed as percentage values.

**Augmented Dickey-Fuller (ADF) Statistic rejects the hypothesis of a Unit Root at the 1% level of confidence.

Demand in SNOWY1 may maintain at zero or very low levels for some time, then increase markedly when Snowy Hydro's generation assets are called into production. As discussed earlier, the "fast-start" nature of hydroelectric generation allows plant to be called into production and shut down within a few minutes, with the result that hydroelectric generators are able to behave more opportunistically than coal-fired generators, with the ability to opt out of supply when pool demands are low and respond rapidly when demands and prices are high or when sold option contracts are in the money.

The distributions of demand change for all five regions demonstrate positive skewness and high kurtosis, with SNOWY1 demonstrating extremely high positive skewness and extreme leptokurtosis. Jarque-Bera (JB) statistics reject the null hypothesis of normal distribution at the 1% level of significance for all five regions. This fat-tailed character is consistent with studies on price behaviour (see Huisman and Huurman (2003), Higgs and Worthington (2005) and Wolak (1997)) and appears driven by the presence of spikes in demand change. Augmented Dickey-Fuller (ADF) statistics robustly reject the hypothesis of a Unit Root at the 1% level of significance for all five regions, again consistent with the findings of the earlier studies.

6.2.2 Spikes in Half-Hourly Demand Change

For the purposes of this study a spike in demand change is defined as any observed demand change greater than four standard deviations larger than the mean change, consistent with the spike definition applied to returns on price in Chapter Five. Table 6.2 collates the occurrences of spikes in demand change. Panel (a) shows the occurrence of spikes by region and in aggregate for weekday, month and year. Panels (b) and (c) show the occurrence of spikes by half-hourly trading interval.

Table 6.2 Panel (a) shows that in aggregate there are 377 spikes in demand change observed across all regions during the sample period. VIC1 shows the highest incidence of demand spikes with 113 (30%) of the 377 observed, followed by SNOWY1 with 109 (29%), NSW1 with 94 (25%) of observed spikes during the sample period.

By day of the week, Monday shows the highest incidence with 95 (25%) and Saturday the lowest with 30 occurrences (8%). March shows the highest incidence by month with 59 (16%) and of these 32 occur in VIC1. The next highest incidences by month are December (51) and August (49), with the majority of these spikes occurring in NSW1 and VIC1. The highest incidence by year occurs in 1999 with 178 spikes (47%), dropping markedly in 2000 (60) and 2001 (33). The incidence of spikes appears to be declining from 2001 onwards[33]. Interestingly, the sample data for 1998 only includes the period from 7th December when the NEM commenced to 31st December and includes 28 spikes, more than the number observed for each of the full

[33] Sample data for 2005 only includes the period from January to March inclusive and may not be representative of the full year.

years from 2002 to 2004 inclusive, which may be attributable to start-up effects in a new market.

Table 6.2, Panel (b) shows the incidence of extreme spikes in demand changes by half-hourly trading interval. There are concentrations of spikes occurring at the 06:30 trading interval (98 spikes, of which 80 occur in NSW1) and 23:30 (108 spikes, of which 98 occur in VIC1). The number and occurrence of spikes in the demand change series differs somewhat from the number and occurrence observed in returns on price (566 spikes are observed in returns on price, 377 are observed in demand change - see Table 5.2). Given the accepted wisdom that demand drives price this is an interesting comparative result that will be investigated further in Chapter Eight, in which a study of the interaction between demand spikes and price spikes will be undertaken and the effects of spikes in demand change on returns on price will be investigated.

Table 6.2: Panel (a) Summary of Occurrences of Extreme Spikes in Demand Change by Region, by Weekday, Month and Year.

	NSW1	QLD1	SA1	SNOWY1	VIC1	Total
Sun	4	6	8	11	9	**38**
Mon	40	8	11	13	23	**95**
Tue	13	3	3	11	22	**52**
Wed	16	5	4	19	18	**62**
Thu	14	0	6	16	18	**54**
Fri	5	2	1	21	17	**46**
Sat	2	2	2	18	6	**30**
Total	**94**	**26**	**35**	**109**	**114**	**377**
Jan	2	0	0	18	22	**42**
Feb	0	0	2	12	17	**31**
Mar	4	3	12	8	32	**59**
Apr	3	1	1	7	9	**20**
May	14	0	3	8	0	**25**
Jun	20	4	2	2	0	**28**
Jul	3	4	5	9	0	**21**
Aug	37	1	0	8	3	**49**
Sep	6	4	0	5	0	**15**
Oct	3	2	2	6	1	**14**
Nov	1	6	1	11	2	**21**
Dec	1	1	7	15	27	**51**
Total	**94**	**26**	**35**	**109**	**114**	**377**
1999	0	1	2	3	22	**28**
2000	20	4	13	61	80	**178**
2001	14	2	4	34	6	**60**
2002	21	1	4	3	4	**33**
2003	21	4	0	2	1	**28**
2004	10	6	5	5	0	**26**
2005	7	6	6	1	0	**20**
2006	1	0	5	0	0	**6**
Total	**94**	**26**	**35**	**109**	**114**	**377**

Table 6.2: Panel (b) Occurrence of Extreme Demand Spikes by Half-Hourly Trading Interval (T.I.) 0000hrs to 2330hrs

T.I.	NSW1	QLD1	SA1	SNOWY1	VIC1	Total
H0000	0	0	1	1	0	2
H0030	0	0	0	3	0	3
H0100	0	0	0	2	0	2
H0130	1	1	0	5	0	7
H0200	0	0	0	5	0	5
H0230	0	1	0	5	2	8
H0300	0	0	0	4	0	4
H0330	0	0	0	0	0	0
H0400	0	1	0	6	0	7
H0430	0	0	0	1	0	1
H0500	0	1	0	3	0	4
H0530	1	1	0	1	2	5
H0600	0	0	0	1	0	1
H0630	80	8	0	4	6	98
H0700	0	1	1	0	0	2
H0730	0	1	3	3	0	7
H0800	0	1	2	0	0	3
H0830	1	1	2	1	1	6
H0900	1	1	2	1	1	6
H0930	1	1	2	2	1	7
H1000	0	0	0	1	0	1
H1030	0	0	0	0	0	0
H1100	0	0	0	1	0	1
H1130	0	0	0	1	0	1
H1200	0	0	2	0	1	3
H1230	0	0	1	1	0	2
H1300	0	0	2	0	0	2
H1330	1	2	3	1	0	7
H1400	0	0	2	1	0	3
H1430	0	1	1	4	0	6
H1500	0	1	1	0	0	2
H1530	0	0	1	1	0	2
H1600	0	1	0	0	0	1
H1630	0	1	0	1	0	2
H1700	1	0	0	3	0	4
H1730	0	1	0	4	0	5
H1800	4	0	2	7	0	13
H1830	1	0	6	1	1	9
H1900	0	0	0	4	0	4
H1930	0	0	0	4	0	4
H2000	0	0	0	2	0	2
H2030	0	0	0	1	0	1
H2100	0	0	0	1	0	1
H2130	1	0	1	1	0	3
H2200	0	0	0	1	1	2
H2230	0	0	0	5	0	5
H2300	1	0	0	5	0	5
H2330	0	0	0	10	98	108

A sub-period analysis of demand changes suggests that sharp peaks in demand changes are persistent throughout the sample period, as illustrated by Figure 6.2. Figure 6.2 shows the pattern of demand changes for VIC1 from 1999-2005 and is broadly illustrative of the pattern observed in the other regions. The 06:30 peak in demand appears consistent with the commencement of the morning peak in activity in the population. The 23:30 peak appears to coincide with the activation of off-peak hot water systems set to take advantage of overnight off-peak retail electricity tariffs.

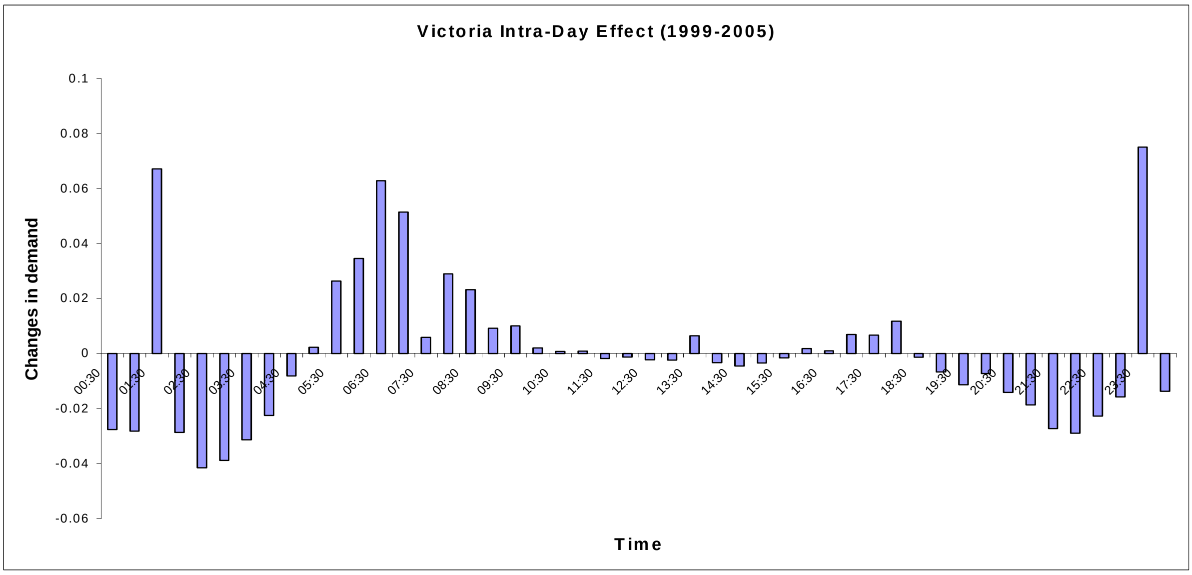


Figure 6.2: Half-Hourly Change in Demand for VIC1 for the years 1999-2005.

6.3 Methodology

The survey of the literature on electricity demand and the results reported in Chapter Five suggests that further exploration of the significance of seasonalities and extreme values in demand is justified. To that end an autoregressive model is developed in which the dependent variable is half-hourly demand changes and the explanatory variables are half-hourly lagged returns, dummy variables representing trading interval (half-hourly time of day), day of the week, and month of the year for NSW1, QLD1, SA1, SNOWY1 and VIC1. The model also incorporates dummy variables for "spikes", as defined in section 6.3. Unlike the model developed in Chapter Five, there are no dummy variables required to account for the presence of negative values in the base demand series, as demand level does not fall below zero.

The model used for this study captures seasonalities and controls for demand spikes and is specified in equation (6.2), as follows:

$$CD_{R,t} = \alpha_0 + \sum_{i=1}^{1} \beta_{1,i} CD_{R,t-i} + \sum_{j=1}^{6} \beta_{2,j} DAY_j + \sum_{k=1,\neq 9}^{12} \beta_{3,k} MTH_k + \sum_{l=1999,\neq 2001}^{2006} \beta_{4,l} YR_l$$
$$+ \sum_{m=1,\neq 23}^{48} \beta_{5,m} HH_m + \sum_{o=1}^{N_{R,S}} \beta_{6,o} SPIKE_{R,o} + \varepsilon_t \tag{6.2}$$

Where:

$CD_{R,t}$ represents the discrete demand change for region R at time t;

α_0 represents the constant term;

DAY_j represents the dummy variable for each day of the week (j=1 for Monday, 2 for Tuesday, ..., 6 for Saturday);

MTH_k represents the dummy variable for each month (K=1 for January, 2 for February, ..., 12 for December). ;

YR_l represents the dummy variable for each year included in the sample period (l=1999, …, 2006);

HH_m represents the dummy variable for each half-hourly trading interval (m=1 for 00:00hrs, 2 for 00:30hrs, ..., 48 for 23:30hrs);

$SPIKE_{R,o}$ represents a set of $N_{R,S}$ dummy variables, one for each extreme return as previously defined, with $N_{R,S}$ representing the number of extreme positive returns observed in region R for the period of the study (see Table 6.2);

Note that this model specification differs from that presented in Chapter Five in that a dummy variable series representing negative values in the base series is not included in the specification – there are no instances of negative demand observed in the base series.

As in Chapter Five, the trading interval at 11:30hrs, Sunday, September and the year 2001 were incorporated into the constant term α in the model as the base case for each dummy series. These base cases were selected as the trading interval, day, month and year in which demand changes activity was consistently lowest in all five regions. Standard tests and residual diagnostics revealed no misspecification in the above model.

6.4 Empirical Results

Results of the regression analysis are presented in Table 6.3. Coefficients and *p*-values are presented for each seasonal dummy variable and for lagged returns. In view of the very large number of individual spikes in demand changes (377 spikes identified for the sample period across all regions), coefficients are not reported in detail but the results for these outliers are discussed here.

Results are relatively consistent across the four geographic regions, namely NSW1, QLD1, SA1 and VIC1 but markedly different for SNOWY1. Day-of-week effects are positive and significant for Monday in the four geographic regions. These results most likely correspond to peak levels of activity in the population as the working week begins. Thursday shows significant negative effect in demand changes in SA1 only. There is a clear negative Friday effect in all regions, which is believed to correspond to the winding down of business activity at the end of the working week. Interestingly a Saturday effect is evident in SNOWY1. Anecdotal evidence suggests that this may be due to NSW and VIC generators scheduling plant maintenance on the weekend, but this was unable to be confirmed empirically.

With the exception of SNOWY1, which exhibits statistically significant effects in January, June, July, October and November there is no clear evidence of monthly effect nor yearly effect across the geographic regions (except for VIC1 in 1999). SNOWY1 demonstrates significant positive effect for 1998 and 1999; and significant negative effect in demand changes for 2002 to 2004. Lagged return is highly significant in all regions except SNOWY1.

Table 6.3: Panel (a) - Results Of Regression Analysis For Demand changes Against Seasonal Dummy Variables, By Region For Day, Month, Year and Lagged Demand change ($CD_{R,t-i}$).

	NSW1		QLD1		SA1		SNO1		VIC1	
	Coeff	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**	**Coeff**	**p-val**
C	0.0030	0.0000	0.0043	0.0000	0.0040	0.0000	0.1247	0.0665	-0.0016	0.0000
MON	0.0010	**0.0000**	0.0006	**0.0000**	0.0004	0.0173	-0.0238	0.3671	0.0002	0.2239
TUE	0.0001	0.9954	0.0001	0.9918	0.0001	0.8777	0.0242	0.4061	0.0001	0.3715
WED	-0.0001	0.6471	0.0000	0.9985	0.0001	0.8338	0.0030	0.9173	0.0001	0.2679
THU	-0.0003	0.0267	-0.0003	0.0079	-0.0004	0.0307	0.0013	0.9658	0.0000	0.8831
FRI	-0.0014	**0.0000**	-0.0008	**0.0000**	-0.0006	**0.0002**	-0.0762	**0.0091**	-0.0008	**0.0000**
SAT	0.0001	0.9205	0.0001	0.8791	0.0001	0.9848	0.1117	**0.0049**	-0.0001	0.7064
JAN	0.0001	0.8452	0.0001	0.9019	0.0002	0.9483	0.1420	**0.0005**	0.0001	0.8512
FEB	0.0002	0.7998	0.0001	0.9544	0.0001	0.9124	0.0306	0.4413	-0.0001	0.5626
MAR	0.0001	0.7342	0.0001	0.9576	0.0001	0.9627	0.0686	0.0944	0.0001	0.9798
APR	0.0001	0.6109	0.0001	0.7203	0.0001	0.8800	0.1022	0.0120	0.0001	0.7825
MAY	0.0001	0.6830	0.0001	0.8455	0.0001	0.5699	0.0412	0.3147	0.0001	0.8737
JUN	0.0002	0.4104	0.0001	0.6348	0.0001	0.8341	0.1097	**0.0070**	0.0001	0.9149
JUL	-0.0001	0.6659	0.0001	0.8630	0.0001	0.7031	0.1594	**0.0001**	0.0001	0.9543
AUG	0.0001	0.9752	0.0001	0.9122	0.0001	0.8822	0.0046	0.9092	0.0001	0.9942
OCT	0.0001	0.9096	0.0001	0.9521	0.0001	0.9934	0.0869	0.0342	0.0001	0.8170
NOV	0.0001	0.9153	-0.0001	0.7350	0.0001	0.9831	0.0867	0.0331	0.0001	0.9087
DEC	-0.0001	0.9072	0.0002	0.8991	0.0001	0.9961	-0.0240	0.7788	-0.0009	0.0164
1998	0.0001	0.9883	0.0001	0.7712	0.0001	0.8820	0.4632	**0.0000**	-0.0002	0.1829
1999	0.0001	0.9437	0.0001	0.7042	0.0001	0.9914	0.4613	**0.0000**	0.0001	0.9442
2000	0.0001	0.8559	0.0001	0.9346	0.0002	0.9881	-0.0139	0.6288	0.0001	0.9056
2002	0.0001	0.9811	0.0001	0.8750	0.0001	0.9621	-0.0390	0.1761	0.0001	0.8742
2003	0.0001	0.9398	0.0001	0.9173	0.0001	0.9778	-0.1581	**0.0000**	0.0001	0.8523
2004	0.0001	0.8533	0.0001	0.8637	0.0001	0.8743	-0.1866	**0.0001**	0.0001	0.6338
2005	0.0010	**0.0000**	0.0006	**0.0000**	0.0004	0.0173	-0.0238	0.3671	0.0002	0.2239
$CD_{R,t-1}$	0.6238	**0.0000**	0.5470	**0.0000**	0.6300	**0.0000**	-0.0006	0.0882	0.6109	**0.0000**
$CD_{R,t-2}$	-0.1186	**0.0000**	-0.0646	**0.0000**	0.0059	0.0911	0.0001	0.8528	-0.1158	**0.0000**
$CD_{R,t-3}$	0.0641	**0.0000**	-0.0716	**0.0000**	-0.0708	**0.0000**	-0.0002	0.6728	-0.0330	**0.0000**
$CD_{R,t-4}$	-0.1666	**0.0000**	-0.0223	**0.0000**	-0.0440	**0.0000**	0.0000	0.9920	-0.0412	**0.0000**
$CD_{R,t-5}$	0.0301	**0.0000**	-0.0287	**0.0000**	-0.0105	**0.0003**	-0.0003	0.4531	-	-
$CD_{R,t-6}$	-0.0040	0.2480	-0.0176	**0.0000**	-	-	-	-	-	-
$CD_{R,t-7}$	-0.1144	**0.0000**	-0.0122	**0.0002**	-	-	-	-	-	-
$CD_{R,t-8}$	-0.0422	**0.0000**	-0.0022	0.4940	-	-	-	-	-	-
$CD_{R,t-9}$	-	-	-0.0318	**0.0000**	-	-	-	-	-	-
R^2	0.8038		0.8427		0.7871		0.9852		0.8337	
Adj R^2	0.8035		0.8426		0.7869		0.9851		0.8334	
DW Stat	1.9943		1.9967		1.9937		2.0652		1.9844	

Note: The equation was initially estimated for each region with 20 lagged returns. F-Tests for redundant variables were performed and for all regions AIC and SBC values indicated that the appropriate number of significant lags on the dependent variable ranged from 4 to 9 as shown in the table. Standard tests and residual diagnostics revealed no misspecification in the above model. Bold type indicates significance at 5%. R^2 and Adj R^2 values shown are for the complete model incorporating all seasonal factors and outliers. Table 4 Panel (b) shows coefficients and p-values for trading interval (time of day). Coefficients and p-values for all 377 spikes outliers are not reported in detail here – all were significant.

Table 6.3 Panel (b): Results of regression analysis for Demand Changes ($CD_{R,t}$) against seasonal dummy variables, by half-hourly trading interval by region, 0000hrs to 2330hrs (excluding 11:00hrs).

	NSW1		QLD1		SA1		SNOWY 1		VICl	
	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val	Coeff	p-val
H0000	-0.028	**0.000**	-0.049	**0.000**	0.039	0.000	-0.205	**0.010**	-0.064	**0.000**
H0030	-0.014	**0.000**	-0.036	**0.000**	-0.033	**0.000**	0.091	0.254	-0.022	**0.000**
H0100	-0.026	**0.000**	-0.021	**0.000**	0.006	**0.000**	0.184	0.021	-0.002	**0.000**
H0130	-0.023	**0.000**	-0.027	**0.000**	-0.064	**0.000**	0.668	**0.000**	0.086	**0.000**
H0200	-0.028	**0.000**	-0.022	**0.000**	-0.036	**0.000**	-0.149	0.061	-0.068	**0.000**
H0230	-0.026	**0.000**	-0.020	**0.000**	-0.019	**0.000**	0.260	**0.001**	-0.027	**0.000**
H0300	-0.020	**0.000**	-0.015	**0.000**	-0.015	**0.000**	0.249	**0.002**	-0.006	**0.000**
H0330	-0.018	**0.000**	-0.012	**0.000**	-0.017	**0.000**	0.270	**0.001**	-0.008	**0.000**
H0400	-0.010	**0.000**	-0.009	**0.000**	-0.015	**0.000**	0.071	0.372	-0.005	**0.000**
H0430	-0.002	**0.000**	-0.004	0.000	-0.008	**0.000**	0.041	0.604	0.000	0.315
H0500	0.001	0.083	-0.001	0.029	-0.003	0.000	-0.166	0.036	0.003	**0.000**
H0530	0.028	**0.000**	0.017	**0.000**	0.002	**0.000**	-0.072	0.365	0.022	**0.000**
H0600	0.015	**0.000**	0.015	0.000	0.016	**0.000**	-0.199	0.012	0.017	**0.000**
H0630	0.028	**0.000**	0.046	**0.000**	0.013	**0.000**	0.060	0.450	0.042	**0.000**
H0700	0.026	**0.000**	0.029	**0.000**	0.035	**0.000**	-0.054	0.497	0.017	**0.000**
H0730	-0.001	**0.005**	0.032	**0.000**	0.014	**0.000**	-0.055	0.491	-0.021	**0.000**
H0800	0.032	**0.000**	0.012	**0.000**	0.001	0.180	-0.067	0.396	0.037	**0.000**
H0830	0.015	**0.000**	0.010	**0.000**	0.020	**0.000**	-0.081	0.310	0.017	**0.000**
H0900	0.007	**0.000**	0.006	**0.000**	0.006	**0.000**	-0.233	0.003	0.001	0.013
H0930	0.017	**0.000**	0.009	**0.000**	-0.002	0.000	0.029	0.714	0.012	**0.000**
H1000	0.005	0.000	-0.001	**0.004**	0.003	0.000	-0.087	0.273	0.001	0.000
H1030	0.008	0.000	0.000	0.873	-0.004	**0.000**	-0.035	0.655	0.004	0.000
H1100	0.001	0.020	-0.001	0.181	0.001	0.225	-0.078	0.327	0.005	0.000
H1200	0.002	0.000	-0.004	0.000	-0.003	0.000	-0.008	0.919	0.002	0.000
H1230	-0.003	**0.000**	-0.007	**0.000**	0.001	0.277	0.154	0.052	0.000	0.299
H1300	-0.005	0.000	-0.006	**0.000**	-0.002	0.000	-0.080	0.312	0.001	0.084
H1330	-0.004	**0.000**	-0.004	0.000	-0.004	0.000	0.297	**0.000**	0.009	**0.000**
H1400	-0.008	0.000	-0.006	0.000	0.005	0.000	-0.059	0.458	-0.006	0.000
HI 430	-0.004	0.000	-0.004	0.000	-0.014	**0.000**	0.017	0.832	-0.001	0.002
H1500	-0.006	0.000	-0.009	**0.000**	-0.003	**0.000**	-0.031	0.699	0.002	0.000
H1530	-0.003	0.000	-0.005	0.000	-0.008	**0.000**	-0.028	0.728	0.002	0.000
H1600	0.000	0.513	-0.001	0.001	-0.006	0.000	0.082	0.300	0.004	**0.000**
H1630	-0.004	0.000	-0.001	0.028	-0.002	**0.000**	-0.074	0.349	0.001	0.049
H1700	0.009	**0.000**	0.005	**0.000**	-0.003	0.000	0.127	0.111	0.007	**0.000**
H1730	0.001	0.202	0.004	**0.000**	0.003	**0.000**	0.185	0.020	0.003	**0.000**
H1800	0.016	**0.000**	0.008	**0.000**	0.005	**0.000**	0.163	0.041	0.008	**0.000**
H1830	-0.014	**0.000**	-0.007	**0.000**	0.007	**0.000**	-0.018	0.822	-0.006	**0.000**
H1900	-0.006	**0.000**	-0.001	**0.006**	-0.008	**0.000**	-0.083	0.294	-0.003	**0.000**
H1930	-0.011	**0.000**	-0.015	**0.000**	-0.010	**0.000**	0.082	0.302	-0.003	**0.000**
H2000	-0.005	**0.000**	-0.009	**0.000**	-0.009	**0.000**	0.100	0.206	0.002	**0.000**
H2030	-0.016	**0.000**	-0.017	**0.000**	-0.004	**0.000**	0.122	0.125	-0.009	**0.000**
H2100	-0.012	**0.000**	-0.012	**0.000**	-0.014	**0.000**	0.048	0.547	-0.010	**0.000**
H2130	0.001	0.075	-0.015	**0.000**	-0.015	**0.000**	0.064	0.419	-0.016	**0.000**
H2200	-0.019	**0.000**	-0.019	**0.000**	-0.013	**0.000**	-0.023	0.777	-0.013	**0.000**
H2230	0.020	**0.000**	-0.007	**0.000**	-0.016	**0.000**	0.718	**0.000**	-0.006	**0.000**
H2300	-0.031	**0.000**	-0.018	**0.000**	0.010	**0.000**	-0.032	0.687	-0.004	**0.000**
H2330	-0.007	**0.000**	0.000	0.709	-0.011	**0.000**	0.938	**0.000**	0.081	**0.000**

Results for trading interval (time of day) are shown in Table 6.3 Panel (b). Half-hourly time-of-day effects offer more interesting results than the broader seasonalities and are more consistent across regions than the seasonal effects previously discussed. In general, significant negative demand changes are found for the small hours of the morning from 12:30 a.m. until approximately 4:00 – 5:00 a.m. in all regions except SNOWY1. VIC1 exhibits an unexplained highly significant positive return at 1:30 a.m., reverting to negative returns for the remainder of the early morning. There is some small variation in the pattern of demand changes during the waking day. NSW1 and VIC1 show broadly similar intra-day patterns, with significant positive demand changes dominating between 04:30 and 18:00 and with minor variation reverting to negative demand changes for the remainder of the evening. QLD1 and SA1 are also broadly similar to each other; demonstrating significant positive effect between 04:30 and 10:30, predominantly negative effect from 10:30 to 15:30, reverting to positive effect from 16:00 to 19:30 when there is apparent reversion to negative effect for the remainder of the evening. No clear pattern is discernible in intra-day demand changes for SNOWY1. The periods of positive return in the early morning and early evening are consistent with peaks in activity in the population. One would expect to observe positive demand changes arising from off-peak hot water systems generally switching on around 11:00 pm, but curiously returns appear to be significant and negative at around that hour in all regions except SA1. The periods of positive return in the morning and early evening are economically sensible, coinciding with peaks in activity in the population. For example, the morning peaks are broadly consistent with people rising, breakfasting, traveling to work, and turning on office and factory equipment at the start of the working day. The late afternoon and evening peaks are consistent with people traveling home from work, turning on heating or cooling depending on the season, preparing evening meals, watching television and so forth.

The results for spikes in the model show that all 377 observed spikes contribute significant effect in demand change in all regions, consistent with expectations and with the existing price literature.

6.5 Conclusion

The deregulation of the electricity supply chain and its reorganisation into wholesale markets offers a rich opportunity for researchers. The physical nature of electricity and the mode of organisation of its various markets give rise to price characteristics and behaviours that are not widely found in more traditional financial markets. It is widely held that in wholesale pool markets for electricity, like Australia's NEM, demand for electricity is a primary driver of spot price. The motivation for undertaking the research presented in this chapter is to investigate the extent to which the seasonal factors and outlier effects that are found to be significant in half-hourly price and returns as shown in Chapter Five are present in the demand and demand changes series. Findings suggest that of the seasonal effects considered, intra-day effects are more significant and persistent than day of the week, monthly or yearly effects, but with some variation between regions. The variation between regions is broadly consistent with findings in the literature on price behaviour (see Worthington, Kay-Spratley and Higgs, 2003). Extreme positive spikes in demand change represent less than 0.05% of observations across all NEM regions under study, yet results show that extreme spikes are statistically significant, similar to findings in the literature pertaining to returns on spot price [e.g. Higgs and Worthington (2005) and Thomas *et al.,* (2006)]. The notion that demand drives price is accepted as fact in electricity markets, and a preliminary comparison between the occurrences of spikes in returns on price versus spikes in demand change suggests that demand-side spikes may not be consistent with price shocks. A further stage of development of this research, presented in Chapter Eight, will be to investigate the extent to which the seasonal and outlier effects documented in this study transmit to the spot price.

Chapter 7: GARCH Modelling of High-Frequency Volatility in Australia’s National Electricity Market

7.1 Introduction

The deregulation and restructuring of the Australian electricity industry and the development of the National Electricity Market (NEM) has moved Australia’s electricity industry a long way towards the broad aims of greater competition and lower wholesale electricity prices. That said, greater competition and lower general prices have come at the cost of higher price volatility. The non-storable nature of electricity, difficulties in forecasting and managing demand, a poorly maintained transmission and distribution infrastructure, and the potential for market power and information asymmetry, among others, can provide a load-matching problem for market operators[34]. These conditions create clear seasonal patterns in wholesale electricity prices by time of day, weekday, month and to a lesser extent yearly patterns (see *inter alia* Lucia and Schwartz, 2002; and Chapters five and six). Intra-day patterns are the predominant form of seasonality and they are frequently accompanied by short-run spikes that are a significant and challenging feature of price behaviour [see Wolak (1997), Goto and Karolyi (2004), Higgs and Worthington (2005)].

[34] In the Australian summers of 2005/6 and 2006/7, persistent high temperatures have resulted in “load shedding” becoming a recurrent feature of electricity supply, particularly in southern Victoria and southeast Queensland. The system operator, NEMMCO, may from time to time direct electricity providers to disrupt supply in order to maintain system balance (see section 3.1).On January 16, 2007, VIC1 prices reached the $10,000 VoLL level for two hours after bushfires disrupted the interconnector between NSW and VIC. On the afternoon of that day, Victoria's demand peaked at 9100 megawatts, 4.2 per cent above the previous high observed on February 2006. (R Myer, “Power Meltdown Could Savage Snowy Hydro” http://www.theage.com.au/articles/2007/01/17/1168709832134.html, accessed 18/1/07).

High volatility has been a feature of price behaviour in the NEM since its establishment in 1998. When prices are highly volatile, it creates uncertainty about generators' revenues[35] and retailers' and distributors' costs. Further, high price volatility can make capacity planning and investment decisions difficult for generators and for owners and operators of the distribution grid. System operators and industry regulators also need to understand volatility to ensure that markets are designed and operated in a way that limits market power and promotes confidence and safety for market participants. Finally, information about volatility informs measures of risk that are critically important to managers of energy commodity portfolios. Valuing derivatives and hedge contracts meaningfully and accurately requires meaningful and accurate measures and forecasts of price volatility over the life of an instrument[36].

In addition to generally high levels of volatility relative to the pre-NEM period and in comparison with more conventional financial markets (see Bunn and Karakatsani, 2003), volatility clustering has been identified as a characteristic of electricity markets (Lucia and Schwartz, 2002). Autoregressive conditional heteroskedasticity (ARCH) models allow volatility shocks to cluster in time and may offer some insight into the volatility observed in electricity markets. To date, a relatively small number of ARCH-based studies have been undertaken in electricity markets. Lucia and Schwartz (2002) report volatility clustering in the form of GARCH effects and seasonality in both the deterministic component of prices and in jump (spike)

[35] Taxpayer-owned Snowy Hydro faced possible large losses from the failure of the NSW-to-Victoria interconnector on Tuesday 16/1/07. VIC1 prices soared dramatically, sitting on $9000 a megawatt-hour for most of the afternoon and then hit the $10,000 mark for two hours after bushfires disrupted the cross-border transmission line. The average power price in normal times is about $30 a MWh. Snowy, a peak-power provider, has hedge contracts with Victorian power retailers and can usually deliver up to 1900 MW to Victoria via the interconnector. Being unable to deliver power via the interconnector, it had to meet its hedge contract obligations by buying wildly expensive power on the spot market and selling it to the retailers at their contract price. (ibid)

[36] Ibid.

intensity. Escribano *et al.* (2002) show volatility to be time-varying with evidence of heteroskedasticity in conditional variance for daily spot prices in Argentina, New Zealand, Nordpool (Norway and Sweden) and Spain. Knittel and Roberts (2001) apply a range of models of asset prices to hourly prices in the California market, including an EGARCH specification.

Of particular interest in the Australian context is the ARCH-based study of Worthington, Kay-Spratley Higgs (2005). This paper examines electricity prices and price volatility among the five Australian electricity markets in the NEM by applying a multivariate generalised autoregressive conditional heteroskedasticity (MGARCH) model to identify the source and magnitude of spillovers, in a sample of half-hourly spot prices for the period December 1998 to June 2001. The authors find a large number of significant own volatility and cross-volatility effects in all five markets, indicating the presence of strong ARCH and GARCH effects. It should be noted that for the purposes of their analysis a series of daily arithmetic means is drawn from the trading interval data (following Lucia and Schwartz, 2002). The authors recognise that this treatment will entail the loss of at least some 'news' impounded in more frequent trading interval data, but correctly note that "…daily averages play an important role in electricity markets, particularly in the case of financial contracts…"[37].

Higgs and Worthington (2005) presents an investigation of the intra-day price volatility process in Australian electricity markets by employing five different ARCH processes: GARCH (generalised ARCH), Risk Metrics (normal integrated GARCH),

[37] For example, the electricity futures contracts traded via the Sydney Futures Exchange (SFE) are settled against the arithmetic mean of half hourly spot prices in a given month.

normal APARCH (asymmetric power ARCH), Student APARCH and skewed Student APARCH (following Ding, Granger, and Engle, 1993; and Giot and Laurent, 2003a, 2003b). The authors include the documented systematic features – intra-day and monthly patterns (calendar effects), intra-day innovation and volatility spillovers (ARCH and GARCH effects) and market activity (demand and information asymmetry effects), with a view to providing a characterisation of the volatility process. The data employed consists of half-hourly electricity price relatives and demand volumes from 1 January 2002 to 1 June 2003 for NSW1, QLD1, SA1 and VIC1[38]. The natural log of the price for each half-hourly interval is used to produce a time series of price relatives for analysis. In their analysis, the inclusion of news arrival is proxied by the contemporaneous volume of demand, time-of-day, day-of-week and month-of-year effects as exogenous explanatory variables. The authors find that on the basis of the log-likelihood, Akaike Information (AIC) and Schwartz Criteria (SC), the skewed Student APARCH form is the best model for all four markets under consideration. Their results also indicate significant innovation (ARCH effects) and volatility (GARCH effects) in the conditional standard deviation equation, even with market and calendar effects included. They further observe significant asymmetric news responses in intra-day price volatility.

The previous Australian research typically confines its analysis to one regional market in the NEM over a relatively short time horizon (less than two years). This study considers a much larger data sample that is broader in scope than the previous papers – covering a six-year sample of higher-frequency half-hourly data, across five regions in the NEM, as compared to 1-2 year samples using daily average data from one or

[38] The SNOWY1 region is not included in the Higgs and Worthington (2005) study.

two regions only. I believe the use of a very-much-larger data set better characterises the volatility process by examining the market over a wider range of conditions and a broader market base. The treatment of seasonal effects and outliers is precise and specific and differs markedly from the generalised functional forms applied in the earlier studies; and this study finds that preferred ARCH model specifications and conditional error distributions differ when using high-frequency data. Further, the work presented in this chapter establishes a basis for the application of GARCH-based event study methodologies applied in the further research presented as Chapter Eight.

Half-hourly trading-interval prices for the period from the commencement of the NEM in December 1998 to March 2005 are used and five NEM regions (NSW1, QLD1, SA1, SNOWY1 and VIC1) are included. The GARCH variants considered include the "basic" GARCH specification (Bollerslev, 1986), the Threshold GARCH (TARCH) model of Glosten, Jaganathan and Runkle (1993), Nelson's (1991) Exponential GARCH (EGARCH) and the Power ARCH (PARCH) model proposed by Ding *et al.* (1993). The approach used in this study differs further from the previous Australian ARCH-based studies in that discrete half-hourly returns are used rather than log-based price relatives, to allow for the presence of negative prices, which were identified in Chapter Five as a significant feature of the data. This study is further distinguished from previous work in that seasonal effects and individual spikes are treated by pre-whitening the data by removing seasonalities and outlier effects in an OLS framework *before* fitting the various GARCH models to the data. The reasons for doing so are twofold: firstly, after accounting for spikes and seasonalities, significant residual ARCH effects are observed in the whitened returns data (see section 7.3). I am interested in developing better understanding of underlying volatility process in the returns series *without* the noise contributed by seasonalities and outliers; and secondly, a model specified with a conditional mean and variance process that includes a very large number of variables (up to 260 to account for seasonal and outlier effects and serial correlation) *and* over a very large sample size (>110,000 returns observations in each region), is too unwieldy for available computing capabilities and as such a two-stage procedure is called for. The rest of the chapter is organised as follows: Data and preliminary statistical analysis is provided in section 7.2. Models and econometric methodology and main estimation results are presented in sections 7.3 and 7.4. Section 7.5 summarises findings and suggests further related research.

7.2 Data

This study employs half-hour discrete returns for each of the five NEM regions that have been pre-whitened of seasonal and outlier effects following the process outlined in Chapter Five. The base returns data are discrete half-hourly returns as defined by equation 5.1[39], and the filtered data used in this study are derived by capturing the residuals from the model defined by equation 7.1.

[39] The base returns series used in this study are half-hourly discrete returns as used in chapter five ie.:

$$RP_t = \frac{(P_t - P_{t-1})}{|P_{t-1}|}. \tag{5.1}$$

Where RP_t represents the half-hourly discrete proportionate change in price ("return") at time t, P_t is half-hourly price at time t and $|P_{t-1}|$ is the absolute value of the previous half-hourly price, at time $t-1$. The denominator is specified as the absolute value to allow for the presence of negative prices.

$$RP_{R,t} = \alpha_0 + \sum_{j=1}^{6} \beta_{2,j} DAY_j + \sum_{k=1,\neq 9}^{12} \beta_{3,k} MTH_k + \sum_{l=1999,\neq 2001}^{2006} \beta_{4,l} YR_l$$
$$+ \sum_{m=1,\neq 23}^{48} \beta_{5,m} HH_m + \sum_{o=1}^{N_{R,S}} \beta_{6,o} SPIKE_{R,o} + \sum_{p=1}^{N_{R,N}} \beta_{7,p} NEG_{R,p} + \varepsilon_t \qquad (7.1)$$

Where:

$RP_{R,t}$ represents the discrete return for region R at time t;

DAY_j represents the dummy variable for each day of the week (j=1 for Monday, 2 for Tuesday,…,6 for Saturday). MTH_k represents the dummy variable for each month (k=1 for January, 2 for February,…,12 for December).

YR_l represents the dummy variable for each year included in the sample period (l=1999,…,2006).

HH_m represents the dummy variable for each half-hourly trading interval (m=1 for 00:00hrs, 2 for 00:30hrs…,48 for 23:30hrs)

$SPIKE_{R,S}$ represents a set of $N_{R,S}$ dummy variables, one for each extreme spike as previously defined, with $N_{R,S}$ representing the number of extreme returns observed in region R for the period of the study (see Table 5.2);

$NEG_{R,N}$ represents the dummy variable for the return associated with an occurrence of a negative price (p=1,…,$N_{R,N}$), with $N_{R,N}$ representing the number of occurrences of a negative price for region R during for the period of the study.

This model represents a relatively simple but highly effective method for controlling for seasonalities and the effects of individual spikes[40]. The data used in this study are

[40] The model specification represented by equation 7.1 differs from equation 5.2 in that it does not include lagged dependent variables to control for serial correlation in the returns series. The rationale for this difference is explained in section 7.3

the residuals represented by the error term, ε_t in the model. Descriptive statistics for the filtered returns series are shown in Table 7.1. Augmented Dickey-Fuller (ADF) statistics and results of ARCH-LM tests for each region's filtered returns series are also included in Table 7.1.

The standard deviation is generally high relative to the mean and takes on a range of values across the regions, indicating a high degree of variability in the filtered returns and considerable variation between the 5 regions. The highest mean returns are found in QLD1, SA1 and SNOWY1 and these regions exhibit the largest standard deviations. Consistent with the findings of the earlier studies and with the returns series as discussed in Chapter Five, Augmented Dickey-Fuller (ADF) statistics reject the hypothesis of a Unit Root at the 1% level of significance for all five regions.

Table 7.1: Descriptive Statistics for Filtered Half-Hourly Returns ε_t.
(by Region, December 1998 to March 2005).

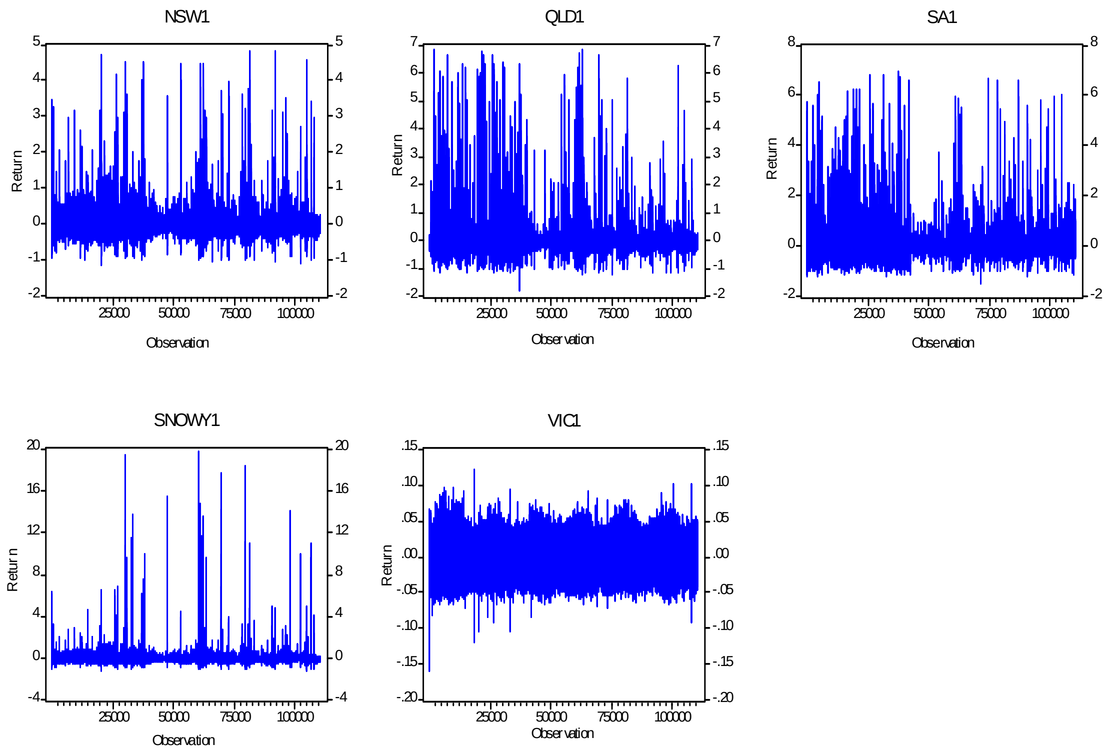
ε_t	NSW1	QLD1	SA1	SNOWY1	VIC1
Mean	$-2.44\text{x}10^{-17}$	$1.29\text{x}10^{-16}$	$1.57\text{x}10^{-17}$	$1.48\text{x}10^{-17}$	$2.72\text{x}10^{-17}$
Median	-0.006	-0.014	-0.019	-0.008	-0.007
Maximum	4.82	6.86	7.00	19.82	4.39
Minimum	-1.13	-1.81	-1.46	-1.21	-1.30
Std. Dev.	0.18	0.30	0.29	0.28	0.19
Skewness	6.52	8.92	7.97	29.87	4.81
Kurtosis	121.53	139.03	122.96	1459.27	72.50
JB stat	$6.56\text{x}10^{7}$	$8.68\text{x}10^{7}$	$6.76\text{x}10^{7}$	$9.80\text{x}10^{9}$	$2.27\text{x}10^{7}$
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF Stat	-38.34	-32.22	-34.27	-36.10	-40.02
ARCH-LM Test					
F-Stat	95.06	57.06	49.53	44.89	62.12
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	110718	110718	110718	110718	110718

The critical values of significance for skewness and kurtosis at the 0.05 level are 0.0305 and 0.0610, respectively. JB is the Jarque-Bera statistic. The critical value for the ADF statistic at the 0.01 level is -3.43

The distributions of filtered returns for all 5 regions demonstrate positive skewness and extremely high kurtosis. This fat-tailed character persists despite the removal of extreme spikes in the raw returns data and is consistent with the findings of Huisman and Huurman (2003), Higgs and Worthington (2005) and Wolak (2000).

The *p*-values for the Jarque-Bera (JB) statistics presented in Table 7.1 reject the null hypothesis of a normal distribution at the 1% level of significance for all five regions. It follows that these half-hourly returns are not well approximated by the normal distribution, implying that it may be appropriate to fit ARCH-type volatility models. The p-values for F-statistics in the ARCH-LM test results confirm the presence of ARCH effects in all five regions. Figure 7.1 suggests that volatility clustering is a feature of the data and the high positive skewness values suggest that there is a significant asymmetric response to positive shocks. It appears that VIC1 exhibits a different pattern of returns to the other regions, evidenced by smaller kurtosis and skewness.

Figure 7.1: Filtered Discrete Returns by Region, for the period 7/12/1998 to 31/3/2005



7.3 Methodology

The descriptive statistics presented in the previous section indicate that it may be appropriate to use ARCH models to describe the volatility process in returns to electricity prices in the NEM. This assertion is consistent with the findings of the earlier Australian studies and studies of foreign electricity markets that find temporal variation in electricity price volatility, with evidence of heteroskedasticity in conditional variance [see Bunn and Karakatsani, (2003) and Escribano *et al.,* (2002)].

Since Bollerslev (1986) proposed the Generalised ARCH (GARCH) model, there have been numerous developments in the ARCH literature to refine the mean and variance equations in order to better capture temporal variations in financial market volatility[41]. An important innovation has been development of ARCH model specifications to describe the asymmetry present in financial data, where the current conditional volatility estimate for an asset is often dependent on the size and sign of past observations. For stock markets, this phenomenon was initially attributed to leverage effects (see *inter alia* Black 1976, Christie 1982 and Nelson 1991). The presence of asymmetry in other financial markets such as foreign exchange markets required a different explanation. Bekaert and Wu (2000) suggest that volatility feedback mechanisms are a more likely explanation. Several ARCH models capture this characteristic, including Nelson's (1991) Exponential GARCH (EGARCH) and the Threshold ARCH and Threshold GARCH specifications that were introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993). In their examination of electricity price relatives, Higgs and Worthington (2005) argue that there is evidence of significant asymmetric effects in the volatility process.

A fat-tailed or leptokurtic distribution of prices and returns is a well-documented characteristic of electricity markets (see inter alia. Huismann and Huurman, 2003, Worthington, Kay-Spratley and Higgs, 2005 and Higgs and Worthington, 2005). Further innovations have been made to ARCH models to accommodate this characteristic in asset prices in conventional financial markets. Typically, this modification to the standard class of model involves replacing the standard normal density with some other assumed distribution such as a *t*-density (see Engle and Bollerslev 1986), the GED density (see Nelson 1991) and the autoregressive conditional density of Hansen (1994).

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41 Developments in ARCH modelling and its application are surveyed in Bollerslev, Chou and Kroner (1992), Bera and Higgins (1993), Ding, Granger, and Engle (1993), Diebold and Lopez (1995), Pagan (1996), Giot and Laurent (2003a, 2003b), and Mitchell and McKenzie (2003, 2006).

A further modification to the standard class of the ARCH model focuses on the specification of the power term that is used to transform the data to emphasize periods of volatility and relative tranquility. The standard class of ARCH model uses a squared power term, which may stem from the normality assumption traditionally invoked when describing the data. The presence of leptokurtosis suggests that this assumption may be invalid in which case the potential superiority of a squared transformation is lost and other power terms may be more appropriate (Mitchell & McKenzie, 2006). For example, Taylor (1986) and Schwert (1989) argued in favour of the standard deviation GARCH model, where a power term of unity is specified. Ding *et al.* (1993) introduced a new class of power-ARCH (PARCH) model in which the power parameter is estimated rather than imposed, thereby allowing an infinite number of transformations of the data.

Higgs and Worthington (2005) find support for the Student-APARCH model in favour of other ARCH specifications. The Asymmetric Power-ARCH (APARCH) model proposed by Ding, Granger and Engle (1993) extends the PARCH model to capture the asymmetric volatility response to negative and positive shocks. The Student-APARCH model is a further extension designed to account for the acute leptokurtosis in Australian electricity markets (see Bauwens and Giot, 2001, and Giot and Laurent, 2003a and 2003b).

ARCH models by and large are purely adaptive models and provide no clear theoretical basis for favouring one model specification over another[42]. As such they

[42] For a discussion of the atheoretic nature of ARCH models see Diebold and Lopez (1995), Goodhart and O'Hara (1997) and Ackert and Racine (1997).

are regarded more as descriptive tools than representative of the actual data generating process. There are a wide variety of features found in the financial markets data and a very large number of models have been proposed to describe these features (Mitchell and McKenzie, 2005, 2006). Further, there are a growing number of univariate and multivariate extensions to the basic ARCH model, as such it would not be feasible to include all of the different specifications in this analysis. With this in mind and given that the purpose of this study is to examine the relative efficacy of univariate ARCH models in describing the filtered data, I have chosen to limit the scope of this study to the more basic forms of ARCH model that may reflect established characteristics of electricity prices, these being the TARCH, EGARCH and PARCH specifications as discussed above. The basic GARCH specification is included for comparison, to determine if a relatively simple model describes the data adequately, despite the documented characteristics of the data.

7.3.1 Model Specification

The Mean Equation

The basic GARCH (1,1) specification of Bollerslev (1986), gives the mean equation as follows:

$$Y_t = X_t^{'}\theta + \varepsilon_t \qquad (7.2)$$

As such the mean equation (7.2) is a function of exogenous variables with an error term. For the purposes of this study the mean equation is modified to include appropriate AR and MA terms to control for serial autocorrelation in the data:

$$Y_t = X_t^{'}\theta + \sum_{i=1}^{p}\alpha_i Y_{t-i} + \sum_{i=1}^{q}\beta_i \varepsilon_{t-i} \qquad (7.3)$$

where E_t is a dummy variable assigned the value of one on event days (or at event time) and zero otherwise. γ represents the event coefficient, which is interpreted as the average abnormal return on the event day; and p and q are chosen to capture significant spikes in the autocorrelation function.

GARCH Model Specification

The GARCH (1,1) conditional variance equation is given by equation 7.4:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (7.4)$$

In which ω is a constant term, the ARCH term, ε_{t-1}^2, is given as the first lag of the squared residual from the mean equation and represents news about the volatility from the previous period, and the GARCH term, σ_{t-1}^2, represents last period's forecast variance. The specification of this model is consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by further large changes. In conventional financial markets, this specification is taken to suggest that an agent or trader predicts this period's variance as a function of a long term average (the constant), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly large, then the trader will increase the estimate of the variance for the next period.

Threshold ARCH (TARCH)

It is often observed in financial markets research that a downward price movement in the market will generate a higher volatility response than an equivalent upward movement. This is described as asymmetric news impact. The TARCH specification proposed by Glosten, Jaganathan, and Runkle (1993) and Zakoian (1994) is used to test for this asymmetric news impact. The occurrence of extremely short-lived spikes followed by periods of relative calm is a well-established feature of electricity price behaviour. Evidence in support of the existence of volatility spikes is found by Wolak (1997) and Goto and Karolyi (2004). Higgs and Worthington (2005) find that price spikes, early-morning, late-afternoon and early evening hours are associated with high volatility and that negative price spikes, and other times of the day, week and year are associated with relatively lower volatility.

The GJR TARCH specification for the conditional variance is:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta\sigma_{t-1}^2 \qquad (7.5)$$

The basic GARCH model of equation 7.4 is extended to include a threshold term $\gamma\varepsilon_{t-1}^2 d_{t-1}$. In this model, $d_t = 1$ if $\varepsilon_t < 0$, and 0 otherwise. In this model, an upward spike (ε_t<0) has an impact of α and a downward or negative spike (ε_t>0) has an impact of $\alpha+\gamma$. If $\gamma > 0$, a negative spike increases volatility and a leverage effect is present. If $\gamma \neq 0$, the impact of news on the series' returns is asymmetric.

The asymmetric volatility response identified by Higgs and Worthington (2005) indicates that volatility tends rise in response to 'good news' for traders (proxied by positive price spikes – see Chapter Five) and fall in response to 'bad news' (negative spikes)', which is a form of perverse asymmetry that is counter to the effects generally observed in conventional financial markets.

Exponential GARCH

Nelson's (1991) Exponential GARCH (EGARCH) model is formulated to capture news in the form of leverage effects. In the EGARCH model the specification for the conditional covariance is given by:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad (7.6)$$

The left-hand side is the *log* of the conditional variance, implying that any leverage effects are exponential and that forecasts of conditional variance are guaranteed to be non-negative. In interpreting the model, the presence of leverage effects is indicated by $\gamma_k<0$, and the impact is asymmetric if $\gamma_k \neq 0$. While the basic GARCH model (equation 7.4) requires the restrictions in estimation that $\sigma_t^2>0$, for t = 1…T , the EGARCH model allows unrestricted estimation of the variance, i.e. $-\infty < \log(\sigma_i^2) < \infty$, *implying* that $\sigma_t^2>0$, and so the assumption that $\sigma_t^2>0$, for t = 1…T is automatically satisfied.

Power ARCH

The power-ARCH (PARCH) specification proposed by Ding *et al.* (1993) generalises the transformation of the error term in the models. The PARCH specification is given by equation 7.7:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} \alpha\left(\left|\varepsilon_{t-1}\right| - \gamma_i \varepsilon_{t-i}\right)^{\delta} \qquad (7.7)$$

The power parameter, δ, is estimated rather than imposed, and an optional threshold parameter, γ, may be included to capture asymmetry. The Bollerslev (1986) model sets δ=2, γ=0, and the Taylor (1986) model sets δ=1and γ,=0. Empirical estimates indicate the power term is sample dependent and values of near unity are common in the case of stock data (see Ding *et al.* 1993), while for foreign exchange data the power term varies between unity and two (see McKenzie and Mitchell, 2002). When fitting a PARCH model to electricity price data, the choice of power parameter is not obvious. Higgs and Worthington (2005) find some variation between regions in the estimated power term of a model for electricity prices.

7.3.2 Model Estimation Procedure

Preliminary attempts to estimate the four GARCH specifications to order (1,1) with a mean equation inclusive of the very large number of seasonal and outlier control variables identified in Chapter Five created convergence problems that meant the model could not be reliably estimated[43]. In view of this constraint a decision was taken to undertake a two-stage estimation process by firstly pre-filtering the data by controlling for seasonalities and outliers in the returns series using OLS estimation in equation 7.1, capturing the residuals (ε_t) from the model (referred to herein as the "filtered returns"), then simultaneously estimate the mean and conditional variance equation over the filtered returns, incorporating appropriate AR and MA terms in the

[43] Initial attempts using EVIEWS and SPSS statistical software packages to fit GARCH(1,1), TARCH(1,1), EGARCH(1,1) and PARCH(1,1) models to each region's discrete returns series, while controlling carefully for seasonal an outlier effects and serial correlation required that the mean equation be specified to include as many as 260 dummy variables (47 intra-day, six weekday, 11 monthly, six for year and up to 190 spikes, depending on region – see chapter five), over a sample size of 110,718 observations for each region. Almost all attempts to fit basic GARCH(1,1) processes to such large models failed to converge after 1000-1500 iterations.

mean equation to control for serial correlation. In view of the very large sample size, and according to Engle (1982), this two-stage approach should not result in loss of asymptotic efficiency in model estimation.

ARCH specification also requires that an assumption be made about the conditional distribution of the error term. There are three assumptions commonly employed when working with ARCH models: normal (Gaussian) distribution, t-distribution, and Nelson's (1991) Generalized Error Distribution (GED). Preliminary analysis of the full data set found that the Generalised Error Distribution (GED) was the most appropriate for model estimation[44].

Given a distributional assumption, ARCH models are typically estimated by the method of maximum likelihood. For the GED, the contribution to the log-likelihood for observation *t* is:

$$l_t = -\frac{1}{2}\log\left(\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right) - \frac{1}{2}\log\sigma_t^2 - \left(\frac{\Gamma(3/r)(y_t - X_t'\beta)^2}{\sigma_t^2\Gamma(1/r)}\right)^{r/2} \qquad (7.8)$$

Where the tail parameter $r > 0$. The GED is a normal distribution if $r = 2$ and leptokurtic if $r < 2$.

[44] In preliminary analysis, GARCH(1,1), TARCH(1,1), EGARCH(1,1) and PARCH(1,1) models were estimated over full data samples for all five regions, assuming normal (Gaussian), student-*t*, constrained student-t (with degrees of freedom set at 2 and 4) and GED. In all five regions, the distributions of standard errors were found to be significantly non-normal and significantly asymmetric and as such neither the assumption of a normal distribution nor a student-*t* distribution for the standard errors was supported. Note also that Nelson's (1991) EGARCH specification as represented by equation 7.5 assumes that the standard errors ε_t follow a Generalised Error Distribution.

7.4 Empirical Results.

For clarity, the empirical results are presented in Tables 7.2 to 7.6, where the tables present the results for the five regions in alphabetical order. Each table presents the estimated coefficients, standard errors and *p*-values for the conditional mean and variance equations for the four different GARCH processes under examination along with the estimated GED parameter (*r*), Akaike Information (AIC) and Schwartz Bayes Criteria (SBC), Durbin-Watson (DW) statistic and F-Statistic and p-value showing the results of ARCH-LM tests.

The uppermost section of each table describes the ARMA structure required to account for serial correlation for each region. There is some variation between regions, with NSW1 demonstrating significant AR effects the 1% level at lags 1,5,7 and 8; QLD1 demonstrating significant AR effects at lags 1, 47 and 48 and significant MA effect at lag 48; SA1 showing significant AR effects at lags 1, 47 and 48. Interestingly SNOWY1 exhibits the same type of AR structure as QLD1 with significant AR effects at lags 1, 47 and 48 and similar magnitude of coefficients across all four GARCH specifications, while VIC1 demonstrates significant AR effects at lags 1, 5, 7, 47 and 48. Durbin-Watson statistics for all model specifications in all regions are close to 2, indicating a lack of significant residual serial correlation after model estimation.

Table 7.2: Estimated Coefficients for Conditional Mean Returns and Variance Equations (NSW1)

	GARCH(1,1)		TARCH(1,1)		EGARCH(1,1)		PARCH(1,1)	
	Coeff.	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**
Mean Equation								
ω	-0.006	0.000	-0.006	0.000	-0.006	0.000	-0.005	0.000
AR(1)	0.048	0.000	0.048	0.000	0.048	0.000	0.047	0.000
AR(5)	-0.025	0.000	-0.025	0.000	-0.024	0.000	-0.023	0.000
AR(7)	-0.030	0.000	-0.030	0.000	-0.029	0.000	-0.029	0.000
AR(48)	0.402	0.000	0.402	0.000	0.402	0.000	0.405	0.000
Variance Equation								
ω	0.003	0.000	0.003	0.000	-1.265	0.000	0.019	0.000
α	0.474	0.000	0.497	0.000	0.553	0.000	0.379	0.000
β	0.482	0.000	0.481	0.000	0.793	0.000	0.575	0.000
γ			-0.046	0.001	-0.002	0.616	-0.086	0.000
δ							1.065	0.000
r	0.875	0.000	0.875	0.000	0.873	0.000	0.876	0.000
AIC	-1.665		-1.665		-1.663		-1.671	
SBC	-1.664		-1.664		-1.662		-1.670	
DW-Stat	2.054		2.055		2.054		2.054	
ARCH-LM Test								
F-Stat	0.119	0.731	0.144	0.704	0.055	0.815	0.055	0.815
#Obs	110670		110670		110670		110670	

This table provides the estimated coefficients and p-values for the mean and conditional standard deviation equations for the NSW1 regional electricity pool in the NEM. ω is the constant in the conditional mean equation, $\alpha$is the ARCH coefficient, γ is the leverage effect, $\delta$is the power of the conditional standard deviation process, AIC and SBC are Akaike Information and Schwartz-Bayes Criteria respectively. DW stat is the Durbin-Watson Statistic. ARCH-LM tests were specified with 48 lags, representing one full trading day.

The results from fitting the various GARCH specifications vary somewhat from region to region. For NSW1 (see Table 7.2), the ARCH parameter (α), GARCH parameter (β), and parameter for the asymmetric volatility response (γ) (where applicable) in the GARCH, TARCH and PARCH specifications sum to less than one, and EGARCH imposes no constraints on the parameter estimates, indicating in NSW1 all four models result in stable ARCH processes and are viable models. The ARCH parameter (α), and GARCH parameter (β) are positive and significant in all four models, indicating the presence of ARCH and GARCH effects in the filtered returns. The estimated GED parameter (*r*) is in the order of 0.88, falling between 0 and 2, indicating that the distribution of standard errors is leptokurtic[45], which is consistent with the fat-tailed character observed in Australian electricity prices and returns.

The parameter for the asymmetric volatility response (γ) is negative and significant in the TARCH and PARCH models indicating an asymmetric response for positive returns in the conditional variance equation. This result is broadly consistent with the skewness values shown in Table 7.1 and suggested by Figure 7.1 and reflects the condition that volatility tends rise in response to positive spikes and fall in response to 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)[46]. Ranking by Akaike Information (AIC) and Schwartz Bayesian Criteria (SBC) favours the PARCH model over the other three specifications. F-Statistics resulting from the ARCH-LM test are significant for all four models, indicating that heteroskedasticity has largely been accounted for by all four model specifications, with the p-value for the PARCH model's *F*-Statistic indicating that this model may be accounting for a greater proportion of heteroskedasticity than the other models. Finally, the power coefficient (δ) of the standard deviation process in the PARCH model is significantly different from one, indicating it is more relevant to model the conditional standard deviation of electricity markets in a non-linear form.

[45] See Nelson (1991).
[46] See *inter alia* Thomas and Brooks, 2001.

Results for QLD1 differ markedly from those found for NSW1 (see Table 7.3).

Table 7.3: Estimated Coefficients for Conditional Mean Returns and Variance Equations (QLD1)

	GARCH(1,1)		TARCH(1,1)		EGARCH(1,1)		PARCH(1,1)	
	Coeff.	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**
Mean Equation								
ω	-0.020	0.000	-0.022	0.000	-0.025	0.000	-0.021	0.000
AR(1)	0.017	0.000	0.016	0.000	0.015	0.000	0.016	0.000
AR(47)	0.014	0.000	0.014	0.000	0.014	0.000	0.014	0.000
AR(48)	0.934	0.000	0.937	0.000	0.941	0.000	0.937	0.000
MA(48)	-0.841	0.000	-0.846	0.000	-0.853	0.000	-0.845	0.000
Variance Equation								
ω	0.003	0.000	0.003	0.000	-1.209	0.000	0.013	0.000
α	0.899	0.000	0.798	0.000	0.696	0.000	0.658	0.000
β	0.390	0.000	0.391	0.000	0.806	0.000	0.479	0.000
γ			0.196	0.000	-0.183	0.000	0.043	0.000
δ							1.248	0.000
r	0.741	0.000	0.741	0.000	0.723	0.000	0.741	0.000
AIC	-1.510		-1.510		-1.481		-1.514	
SBC	-1.509		-1.509		-1.480		-1.513	
DW-Stat	2.183		2.182		2.178		2.181	
ARCH-LM Test								
F-Stat	0.182	0.669	0.172	0.678	0.129	0.720	0.094	0.760
#Obs	110670		110670		110670		110670	

This table provides the estimated coefficients and *p*-values for the mean and conditional standard deviation equations for the QLD1 regional electricity pool in the NEM. ω is the constant in the conditional mean equation, α is the ARCH coefficient, γ is the leverage effect, δ is the power of the conditional standard deviation process, AIC and SBC are Akaike Information and Schwartz-Bayes Criteria respectively. DW stat is the Durbin-Watson Statistic. ARCH-LM tests were specified with 48 lags, representing one full trading day.

The sum of the α, β and γ values is markedly greater than 1 in the GARCH and TARCH models (summing to 1.29 and 1.19, respectively) suggesting an explosive ARCH process. The α and β values for the PARCH specifications sum to 1.09, less marked than the other two specifications but still indicating a potentially unstable model, leaving the EGARCH which imposes no constraints on the parameter estimates as the only viable model, despite the AIC and SBC estimates slightly favouring the PARCH specification. In the EGARCH model, the α and β estimates are significant and positive, indicating the presence of ARCH and GARCH effects in the filtered returns.

While the *F*-Statistics resulting from the ARCH-LM test are not significant for all four models, indicating that heteroskedasticity has been accounted for by all four model specifications, the *p*-values for the test statistic suggest that the PARCH model may be taking better account of the ARCH effects. Like NSW1, the estimated GED parameter (r) is in the order of 0.88, falling between 0 and 2, indicating that the distribution of standard errors is leptokurtic; and the parameter for the asymmetric volatility response (γ) is negative and significant, indicating an asymmetric response for positive returns in the conditional variance equation.

SA1 yields results that are more consistent with the QLD1 than NSW1 (see Table 7.4). Again, F-Statistics resulting from the ARCH-LM test are all significant, indicating that heteroskedasticity has largely been accounted for by all four model specifications. The sum of the ARCH parameter (α), and GARCH parameter (β), in the GARCH model is greater than 1 (1.09). For the TARCH model, the α and β values sum to 0.93 but the addition of the γ parameter results in a value of 1.28.

Table 7.4: Estimated Coefficients for Conditional Mean Returns and Variance Equations (SA1)

	GARCH(1,1)		TARCH(1,1)		EGARCH(1,1)		PARCH(1,1)	
	Coeff.	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**
Mean Equation								
ω	-0.017	0.000	-0.017	0.000	-0.018	0.000	-0.017	0.000
AR(1)	0.058	0.000	0.055	0.000	0.053	0.000	0.051	0.000
AR(47)	0.067	0.000	0.069	0.000	0.071	0.000	0.067	0.000
AR(48)	0.239	0.000	0.242	0.000	0.242	0.000	0.243	0.000
Variance Equation								
ω	0.005	0.000	0.005	0.000	-0.919	0.000	0.028	0.000
α	0.625	0.000	0.451	0.000	0.544	0.000	0.423	0.000
β	0.464	0.000	0.480	0.000	0.836	0.000	0.602	0.000
γ			0.347	0.000	-0.160	0.000	0.075	0.000
δ							0.964	0.000
r	0.698	0.000	0.702	0.000	0.698	0.000	0.704	0.000
AIC	-1.098		-1.101		-1.095		-1.108	
SBC	-1.097		-1.100		-1.094		-1.107	
DW-Stat	2.186		2.180		2.177		2.174	
ARCH-LM Test								
F-Stat	0.416	0.661	0.540	0.462	0.278	0.598	0.115	0.735
#Obs	110670		110670		110670		110670	

This table provides the estimated coefficients and *p*-values for the mean and conditional standard deviation equations for the SA1 regional electricity pool in the NEM. ω is the constant in the conditional mean equation, α is the ARCH coefficient, γ is the leverage effect, δ is the power of the conditional standard deviation process, AIC and SBC are Akaike Information and Schwartz-Bayes Criteria respectively. DW stat is the Durbin-Watson Statistic. ARCH-LM tests were specified with 48 lags, representing one full trading day.

The estimated GED parameter (r) is in the order of 0.7 for both models, indicating that the distribution of standard errors is leptokurtic. The parameter for the asymmetric volatility response (γ) is negative and significant in both the EGARCH and PARCH models, indicating an asymmetric response for positive returns in the conditional variance equation, consistent with NSW1 and SA1. Finally, ranking by Akaike Information (AIC) and Schwartz Bayesian Criteria (SBC) favours the PARCH model over the EGARCH specification. The *p*-values for the ARCH-LM test statistic suggest that the PARCH model may be taking better account of the ARCH effects than the EGARCH model. The power coefficient (δ) of the standard deviation process in the PARCH model is significantly different from one, indicating that the conditional standard deviation of electricity markets should not be modelled in a linear framework.

Results for the conditional variance equation for SNOWY1 are shown in Table 7.5:

Table 7.5: Estimated Coefficients for Conditional Mean Returns and Variance Equations (SNOWY1)

	GARCH(1,1)		TARCH(1,1)		EGARCH(1,1)		PARCH(1,1)	
	Coeff.	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**
Mean Equation								
C	-0.014	0.000	-0.015	0.000	-0.017	0.000	-0.013	0.000
AR(1)	0.007	0.000	0.007	0.000	0.007	0.000	0.006	0.000
AR(47)	0.008	0.000	0.009	0.000	0.012	0.000	0.008	0.000
AR(48)	0.949	0.000	0.950	0.000	0.948	0.000	0.952	0.000
MA(48)	-0.828	0.000	-0.831	0.000	-0.826	0.000	-0.833	0.000
Variance Equation								
$\boldsymbol{\omega}$	0.003	0.000	0.003	0.000	-1.504	0.000	0.020	0.000
$\boldsymbol{\alpha}$	0.575	0.000	0.527	0.000	0.581	0.000	0.428	0.000
$\boldsymbol{\beta}$	0.431	0.000	0.431	0.000	0.738	0.000	0.546	0.002
$\boldsymbol{\gamma}$			0.099	0.000	-0.111	0.000	0.022	0.000
$\boldsymbol{\delta}$							1.061	0.000
r	0.806	0.000	0.807	0.000	0.804	0.000	0.805	0.000
AIC	-1.717		-1.717		-1.704		-1.723	
SBC	-1.716		-1.716		-1.703		-1.722	
DW-Stat	1.975		1.975		1.975		1.974	
ARCH-LM Test								
F-Stat	0.002	0.989	0.001	0.986	0.001	0.989	0.018	0.894
#Obs	110670		110670		110670		110670	

This table provides the estimated coefficients and p-values for the mean and conditional standard deviation equations for the SNOWY1 regional electricity pool in the NEM. ω is the constant in the conditional mean equation, α is the ARCH coefficient, γ is the leverage effect, δ is the power of the conditional standard deviation process, AIC and SBC are Akaike Information and Schwartz-Bayes Criteria respectively. DW stat is the Durbin-Watson Statistic. ARCH-LM tests were specified with 48 lags, representing one full trading day.

Like QLD1 and SA1, results for SNOWY1 eliminate the GARCH and TARCH specifications on the basis of the α, β and γ values adding to values greater than 1 (≈1.06 for both models). This notwithstanding, F-Statistics resulting from the ARCH-

LM test are all significant, indicating that heteroskedasticity has largely been accounted for by all four model specifications.

Of the remaining EGARCH and PARCH models, the AIC and SBC estimates favour the PARCH model. Interestingly, the *p*-values for the ARCH-LM test statistic are markedly larger for SNOWY1 than the other regions and although the AIC/SBC ranking favours the PARCH model, the *p*-value suggests that the EGARCH model might have better overcome the problem of heteroskedasticity in the returns series.

The ARCH parameter (α), and GARCH parameter (β) in the viable EGARCH and PARCH models are positive and significant, indicating that the filtered returns exhibit ARCH and GARCH effects. Consistent with the previous three regions, the estimated GED parameter (r) is between 0 and 2 for both models, indicating that the distribution of standard errors is leptokurtic, the parameter for the asymmetric volatility response (γ) is negative and significant in both the EGARCH and PARCH models, and the power coefficient (δ) of the standard deviation process in the PARCH model is significantly different from unity.

In VIC1 (Table 7.6), the estimated GARCH, EGARCH and PARCH models are stable, and the TARCH model is the only one rejected on the basis of instability (α, β and γ sum to 1.05).

Table 7.6: Estimated Coefficients for Conditional Mean Returns and Variance Equations (VIC1)

	GARCH(1,1)		TARCH(1,1)		EGARCH(1,1)		PARCH(1,1)	
	Coeff.	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**
Mean Equation								
ω	-0.005	0.000	-0.006	0.000	-0.007	0.000	-0.006	0.000
AR(1)	0.053	0.000	0.051	0.000	0.050	0.000	0.051	0.000
AR(5)	-0.026	0.000	-0.026	0.000	-0.024	0.000	-0.023	0.000
AR(7)	-0.022	0.000	-0.023	0.000	-0.021	0.000	-0.021	0.000
AR(47)	0.073	0.000	0.075	0.000	0.076	0.000	0.074	0.000
AR(48)	0.330	0.000	0.330	0.000	0.330	0.000	0.330	0.000
Variance Equation								
ω	0.004	0.000	0.004	0.000	-1.320	0.000	0.029	0.000
α	0.513	0.000	0.417	0.000	0.591	0.000	0.391	0.000
β	0.448	0.000	0.457	0.000	0.772	0.000	0.554	0.000
γ			0.179	0.000	-0.081	0.000	0.031	0.002
δ							0.962	0.000
r	0.841	0.000	0.807	0.000	0.843	0.000	0.844	0.000
AIC	-1.456		-1.457		-1.458		-1.464	
SBC	-1.455		-1.456		-1.457		-1.463	
DW-Stat	2.109		2.106		2.104		2.106	
ARCH-LM Test								
F-Stat	0.921	0.337	0.553	0.457	0.248	0.618	0.029	0.865
#Obs	110670		110670		110670		110670	

This table provides the estimated coefficients and *p*-values for the mean and conditional standard deviation equations for the VIC1 regional electricity pool in the NEM. ω is the constant in the conditional mean equation, α is the ARCH coefficient, γ is the leverage effect, δ is the power of the conditional standard deviation process, AIC and SBC are Akaike Information and Schwartz-Bayes Criteria respectively. DW stat is the Durbin-Watson Statistic. ARCH-LM tests were specified with 48 lags, representing one full trading day.

As in the other 4 regions, ranking by Akaike Information and Schwarz-Bayes Criteria favours the PARCH model over the remaining viable models and like NSW1, QLD1 and SA1, the p-values for the ARCH-LM test statistic suggest that the PARCH model might better address heteroskedasticity in the data. The ARCH parameter (α), and GARCH parameter (β) in the EGARCH and PARCH models are positive and significant, consistent with the other regions. The leptokurtic character of the distribution of the standard is supported by the GED parameter (r) estimate of 0.84. The parameter for the asymmetric volatility response (γ) is negative and significant in both the EGARCH and PARCH models, and like the other regions the power coefficient (δ) of the standard deviation process in the PARCH model indicates that a non-linear conditional standard deviation equation is appropriate.

In summary, ranking by AIC and SBC favours the Power-ARCH (PARCH) specification in all five regions, although it should be noted that in QLD1 the sum of the ARCH, GARCH and Threshold (asymmetric volatility response) parameters sum to a value slightly greater than unity which signals an unstable model, in which case the choice of model defaults to the EGARCH specification. Model instability rejects the GARCH model in QLD1, SA1 and SNOWY1; and the TARCH model is rejected on the basis of instability in all but NSW1. In the generally-favoured PARCH model, strong ARCH effects, and strong lagged volatility or GARCH effects are evident.

In all five regions the PARCH models indicate that the estimated asymmetric coefficients (γ_1) are significant and negative for all four regional markets indicating that positive shocks are associated with higher volatility than negative shocks. This outcome is consistent with the findings of Higgs and Worthington (2005), but is contrary to what is generally observed in equity markets. Interestingly, in an examination of the Nordpool spot price, Solibakke (2002: 28) found "…insignificant asymmetric volatility coefficient for all specifications… suggesting equal reaction patterns to positive and negative shocks" while in their application of a Threshold ARCH model to North American regional markets, Hadsell, Marathe and Shawky (2004) estimated that the asymmetric effect was also significant and *negative* thus capturing a strong market response to 'negative' news in US electricity prices.

In all five regions, the estimated GED parameter (r) associated with all models lies between 0 and 2, consistent with the generally-observed leptokurtic character of distributions relating to electricity prices. Finally, in all five regions, the estimated power coefficients (δ) of the standard deviation process in the PARCH model were 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.

7.5 Conclusion

The study presented in this chapter investigates the efficacy of four different GARCH model specifications in describing the underlying intra-day volatility processes in returns on electricity prices in five regional pools (designated NSW1, QLD1, SA1, SNOWY1 and VIC1) in Australia's National Electricity Market (NEM). Four GARCH specifications, Generalised ARCH (GARCH), Threshold ARCH (TARCH), Exponential GARCH (EGARCH) and Power-ARCH (PARCH) models are applied to half-hourly returns on electricity prices for the period 7 December 1998 (commencement of the NEM) to 31 March 2005. Unlike previous GARCH-based studies on electricity prices, which seek to incorporate seasonal factors and outlier (price spike) effects in their models of the conditional mean equation, the very large data set used and the desire to investigate the underlying volatility process in the absence of these structural effects required that the returns data be deseasonalised and stripped of extreme spike effects prior to estimating the conditional mean and conditional variance equation in the GARCH estimation process.

The results show that significant ARCH and GARCH effects are present in the data and that Power ARCH specification with a Generalised Error Distribution applied to the standard errors generally describes the volatility process better than the other three GARCH models. The asymmetric volatility response captured by the PARCH model generally indicates that volatility tends rise in response to ‘good news’ for traders (proxied by positive price spikes – see Chapter Five) and fall in response to ‘bad news’ (negative spikes), which is counter to the effects generally observed in conventional financial markets but consistent with the findings of previous Australian GARCH-based studies. Finally, the estimated GED parameter (r) for each region confirms the fat-tailed properties that are generally observed in electricity market data in Australia and overseas.

A possible extension to this work might be in an investigation of the application of other ARCH specifications to the data, possibly including higher-order GARCH specifications. Remembering that most ARCH/GARCH specifications and estimation procedures have been developed for more “conventional” financial markets and it may be that a further extension to the GARCH family is warranted, or that a different distributional assumption about the standard errors in the model is required. A further extension is possibly suggested by the recent work of Mitchell and McKenzie (2005, 2006) in the field of GARCH model selection criteria. This study and the previous Australian studies use the scheme of ranking models by Akaike Information (AIC) and Schwartz Bayesian Criteria (SBC). This approached may be well-established in practice but it has its detractors (see *inter alia* Pagan and Schwert, 1990) and it may be that there are more appropriate model selection criteria for electricity markets.

Chapter 8: The Effect of Extreme Spikes in Demand on Electricity Prices - An Event Study Approach.

8.1 Introduction

The non-storable nature of electricity is well-documented feature of the commodity that ensures that markets clear instantly through an adjustment of prices. In the absence of storage there is no capacity to use inventory to smooth short-run shocks to supply or demand, with the result that spot prices for electricity display excessive volatility compared to other traded commodities and financial assets (Bunn and Karakatsani, 2003). Much of this volatility can be attributed to relatively infrequent but extremely large spikes in price, which may be caused by a range of factors including unexpected peaks in demand, unplanned generation unit outages, transmission network failure, generator pool price re-bidding, unexpected weather variation and physical constraints on transmission between regions.

An understanding of the spike process is of interest to generators, retailers and end-users for valuation of real and financial assets and for risk management. The Australian Government's white paper "Securing Australia's Energy Future" (2004) recognises the significant economic impact of price spikes:

> "These peaks…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".

A better understanding of price spikes is vitally important for electricity generators, particularly peak-load producers, whose business is entirely dependent on the occurrence of high prices and extreme price spikes (Blanco and Soronow, 2001).

Large industrial and commercial users are also interested in spikes because of the economic impact of load shedding during peak periods[47], while distributors and retailers can benefit from improved forecasting of volatility and price spikes to aid in hedging their purchase price risk.

In Chapters 5 and 6, individual spikes in demand and price in the NSW1, QLD1, SA1, SNOWY1 and VIC1 regions in the NEM are identified over a six-year period and shown to be a significant feature of both price and demand. As stated, unexpected peaks in demand are considered by many to be among the possible causes of price spikes. This study is motivated by two questions. Firstly, does a spike in demand result in a contemporaneous spike in price? If not, is there a significant price response to a demand spike? The first question is investigated in the following section.

8.1.1 Spike Coincidence

Consistent with the earlier analysis in Chapters five and six, this study defines a spike in half-hourly price change (hereafter referred to as "returns") or in demand change as any observed half-hourly percentage change that is more than four standard deviations greater than the mean half-hourly change[48]. Table 8.1 collates the occurrences of spikes as defined, by region and shows that there are 377 spikes in demand change

[47] The National Electricity Code sets a maximum spot price of $10,000 per megawatt hour as the maximum price at which generators can bid into the market. When this maximum market price is reached, NEMMCO directs network service providers to interrupt customer supply to maintain physical balance and stability in the system. This process if supply interruption is referred to as "load shedding". For example, on January 16, 2007, VIC1 prices reached the $10,000 VoLL level for two hours after bushfires disrupted the interconnector between NSW and VIC. A series of rolling cuts to supply throughout various areas of the Victoria occurred during that afternoon.

[48] While conventional practice is to apply a filter for outliers at three standard deviations from the mean, an initial survey of the data indicated that there is a very high incidence of high prices and returns around and above the threshold at three standard deviations to justify applying a filter for outliers at four standard deviations in order to capture "true" outliers.

observed across all regions during the sample period. VIC1 shows the highest incidence of demand spikes with 113 (30%) of the 377 observed, followed by SNOWY1 with 109 (29%), NSW1 with 94 (25%) observed spikes during the sample period. There are 566 extreme spikes in returns observed across all regions during the same sample period. QLD1 has the highest incidence of extreme price spikes by state (with 190 occurrences (34% of the total sample of spikes), followed by SA1 with 162 (29%), both have a markedly higher incidence than VIC1 with 98 (17%), NSW1 with 90 (16%) and SNOWY1 with 26 occurrences (5%).

Table 8.1: Summary of Occurrences of Extreme Spikes
(by Region, December 1998 to March 2005).

	NSW1	QLD1	SA1	SNOWY1	VIC1	Total
Spike CD_t	94	26	35	109	114	**377**
Spike RP_t	90	190	162	26	98	**566**

Spike CD_t *and Spike* RP_t *represent the number of spikes as defined in demand change and returns respectively.*

With the possible exception of NSW1, there is a marked disparity between the incidence of spikes in demand and prices, suggesting that they are not necessarily contemporaneous. In order to investigate the extent to which spikes in demand change and spikes in returns coincide, a dummy variable series was generated for each of the demand change and returns series incorporating all observed spikes as defined, resulting in a vector for each series in which "1" represents the occurrence of a spike as defined and "0"otherwise. A "coincidence vector" was created by multiplying the two spike vectors together:

$$\begin{bmatrix} SC_1 \\ . \\ . \\ . \\ SC_N \end{bmatrix} = \begin{bmatrix} SpikeCD_1 \\ . \\ . \\ . \\ SpikeCD_N \end{bmatrix} \otimes \begin{bmatrix} SpikeRP_1 \\ . \\ . \\ . \\ SpikeRP_N \end{bmatrix} \tag{8.1}$$

Where:

$SpikeCD_i$=1 for the occurrence of a spike in half-hourly demand change as previously defined and 0 otherwise;

$SpikeRP_i$=1 for the occurrence of a spike in half-hourly return as previously defined and 0 otherwise;

And SC_i =1 where a spike in half-hourly demand change and a spike in half-hourly return occur at the same trading interval.

Table 8.2 shows the occurrence of spikes in both demand change and returns along with the coincidence of spikes. The results are somewhat surprising and show that a spike in demand change as currently defined does not result in a contemporaneous extreme spike in returns.

Table 8.2: Extreme Spike Coincidence
(by Region, December 1998 to March 2005).

	NSW1	QLD1	SA1	SNOWY1	VIC1	Total
Spike CD_t	94	26	35	109	114	**377**
Spike RP_t	90	190	162	26	98	**566**
SC_t	0	1	1	0	2	**4**

Spike CD_t *and Spike* RP_t *represent the number of spikes as defined in demand change and returns respectively.* SC_t *represents the count of coinciding spikes.*

In markets such as the NEM pools that are designed to clear instantly, we would expect to see a higher rate of coincidence between extreme spikes in demand and price spikes. This result may suggest that other factors, perhaps supply-side outages, may be more significant drivers of price spikes than unexpected shocks to demand.

Despite the apparent lack of coincidence between extreme values in price and demand, it is of interest to see whether there is evidence of a significant response in price as a result of a demand shock. This chapter seeks to extend the work on spike analysis in Chapters 5 and 6 by employing an event-study approach to examine the extent to which extreme spikes in demand trigger a response in price. To date no other study in the electricity literature has used an event-study approach to answer this question. A 'traditional' event study approach based on average abnormal returns around a spike event and a GARCH-based event study approach (following McKenzie, Thomsen and Dixon, 2004) have been used and results show that despite the almost negligible coincidence of demand and price spikes there is evidence of a significant price response to demand spikes in NSW1, QLD1 and VIC1, but not in SA1 or SNOWY1.

The rest of the chapter is organised as follows: Section 8.2 presents a discussion of event study methods. Data and preliminary statistical analysis is provided in section 8.3. Models and main estimation results are presented in sections 8.4 and section 8.5 summarises findings and suggests further related research.

8.2 Event Study Methods

Traditional event studies in the equity markets start with the hypothesis that if a particular event materially affects the value of a firm (or portfolio), the change in value will be reflected in the company's stock showing an abnormal return. Typically, abnormal returns, AR_{it}, are obtained as the difference between observed returns R_{it} of firm i at event week t and the expected return, $E(R_{it})$, based on an appropriate benchmark:

$$AR_{it} = R_{it} - E(R_{it}) \tag{8.2}$$

By averaging the abnormal returns in common event time, average abnormal returns are obtained, where N is the number of firms in the sample (t=0 corresponds to period 0 in event time):

$$\overline{AR_{it}} = \frac{1}{N}\sum_{i-1}^{N} AR_{it} \tag{8.3}$$

The null hypothesis is that abnormal returns are not significantly different from zero, and the standard test statistic is a t-statistic as defined by equation 8.4:

$$t = \overline{AR_{i,t}} \Big/ \sigma(AR_{it})\frac{1}{\sqrt{N}} = \sqrt{N}\left(\overline{AR_{i,t}} \Big/ \sigma(AR_{it})\right) \tag{8.4}$$

in which $\sigma(AR_{it})$ is the standard deviation of the cross-sectional sample abnormal returns. The test statistic t is approximately normally distributed as N becomes large (Thomas, 1997). In the context of daily stock returns, the statistical properties of event study methods have been examined extensively. Brown and Warner (1985) found that statistical tests based upon standard event study methods are well specified and generally robust to features of daily price change data such as non-normality.

Event study methods developed in the study of equity markets have been adapted and successfully applied to studies of market-related events in commodity futures markets (McKenzie, Thomsen & Dixon, 2004). The objective of these studies has generally been to test market efficiency in terms of the extent to which commodity futures prices in the United States markets react to a variety of market-related events, including the release of United States Department of Agriculture (USDA) reports on various agricultural commodities. Milonas (1987) examines the effect of USDA crop announcements; Schroeder, Blair and Mintert (1990) examine the effect of USDA inventory reports on cattle and hog futures; and Patterson and Brorsen (1993) consider the impact of USDA export sales reports. In the context of meat futures prices, Robenstein and Thurman (1996) and Lusk and Schroeder (2002) examined the response of red meat futures prices to adverse health reports. McKenzie & Thomsen (2001) examine the effect on futures prices of meat recalls due to *E.coli* contamination.

McKenzie *et al.* (2004) discusses two event study approaches that are widely used as standards for measuring the reaction of commodity prices to market-related events. The first is described by the authors as a constant mean return (CMR) model that measures abnormal returns as prediction errors from some benchmark model of normal returns. Examples that have used a CMR model include Milonas (1987), Schroeder, Blair, and Mintert (1990), Mann and Dowen (1997), and McKenzie and Thomsen (2001). A second approach involves regression methods with abnormal returns being estimated as coefficients of dummy variables that correspond to events. Studies employing an Ordinary Least Squares regression framework include Robenstein and Thurman (1996) and Lusk and Schroeder (2002). Patterson and Brorsen (1993) extend the OLS approach using a GARCH framework. Recognising that the variance of futures prices changes through time, GARCH models are used in evaluating the price movements in grain futures in response to USDA grain export sales reports.

The CMR model, OLS regression and GARCH approaches are all aimed at measuring the same phenomenon - the average abnormal return on an event day. Test statistics in each approach relate to the same null hypothesis: that the average abnormal return on an event day is zero. With the CMR model, the researcher compares the return (percentage price change) on the event date with some meaningful benchmark normal return or expected return[49].

In regression-based approaches to event studies, the average effect of an event is parameterised within a regression model of the form:

$$R_t = \theta^{'} X_t + \beta E_t + \varepsilon_t \qquad (8.5)$$

Where the vector X_t includes a constant term and non-event related variables that may effect the return. E_t is a dummy variable assigned the value of one on event days (or at event time) and zero otherwise. β represents the event coefficient, interpreted as the average abnormal return on the event day. Binder (1998) observes that the regression approach is "easier" than the CMR model approach because it estimates the benchmark model and the abnormal returns in one step and the appropriate statistical tests can be done directly in standard regression software packages. As noted by McKenzie *et al.* (2004), another issue relates to parameter constancy. In the CMR model, the normal return is estimated from a portion of the data set close in time to the event. In contrast, futures event studies following the regression approach use all available data over a given study period to estimate abnormal returns. Although the use of all available data would seem to be preferable, the authors note that any structural breaks in the data series could lead to spurious inferences with respect to event-induced price responses[50]. If the normal return is not constant over the sample, the CMR model potentially yields a more precise estimate of the average abnormal return than would an OLS regression. Within the regression model in equation (8.4),

[49] Care should be taken in selecting a meaningful benchmark return, as there may be a range of exogenous or market-wide factors operating on a price. To correctly measure the impact of a particular event we need to control for "unrelated" factors (Serra, 2002). In the case of electricity prices (and returns), significant seasonal and outlier effects are present and it would be desirable to control for them.

[50] There are no structural breaks in the data series used for this study.

the parameter constancy issue can be addressed if the non-event related explanatory variables explain changes in the conditional mean over the study period. That said, this is not necessarily an advantage of the regression approach, as the CMR model as described here can be modified easily to incorporate non-event related variables. The market model is such a modification that has been used widely in stock market event studies (see Brown & Warner, 1985).

GARCH-type model extensions to the regression approach can accommodate distributional problems that are often a feature of returns data. When the data-generating process is better represented by models allowing for time variation in the conditional second moment and the distribution of returns is leptokurtic, GARCH-type model parameter estimates may be more efficient than their OLS counterparts (see Greene, 2000; McKenzie *et al.*, 2004), A recent example of a GARCH-type event study using commodity futures prices is presented in Park (2000) in a study of the effect of limit-lock days on daily corn, oats, soybeans, and wheat futures price changes.

Prior to McKenzie *et al.* (2004), no studies had examined whether GARCH-type models improve the size or power of test statistics within an event study framework. The regression model of Equation 8.5 can be easily extended to include GARCH effects. Under a standard GARCH specification the conditional mean and conditional volatility of returns are modelled as:

$$R_t = \theta' x_t + \varepsilon_t \qquad (8.6)$$

where the mean equation (8.6) is a function of exogenous variables with an error term. In McKenzie *et al.* (2004), the mean equation is modified to include the event dummy E_t as previously defined:

$$R_t = \theta' x_t + \beta E_t + \varepsilon_t , \qquad (8.7)$$

In which the event coefficient, β, is interpreted as the average abnormal return on the event day.

The conditional variance equation is unmodified from the standard GARCH specification and is given by:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (8.8)$$

In which ω is a constant term, the ARCH term, ε_{t-1}^2, is the first lag of the squared residual from the mean equation and represents news about the volatility from the previous period, and the GARCH term, σ_{t-1}^2, represents last period's forecast variance.

Although GARCH models with conditionally normal errors are able to partially account for kurtosis, they generally fail to sufficiently capture the kurtosis evident in the distribution of asset returns (Wang *et al*., 2001). Baillie and Myers (1991) advocate using a GARCH model with a Student's *t*-distribution (GARCH-T) when modelling commodity futures returns when they are found to exhibit excess kurtosis. The Student's *t*-distribution, originally suggested by Bollerslev (1987) models thicker tails than the normal distribution.

McKenzie *et al.* (2004) compare the statistical performance of a CMR approach with OLS and GARCH event study methods using agricultural futures data and find that all three forms are well specified under their null hypotheses of zero abnormal returns. The authors find that all three approaches yield broadly similar results and test statistics from OLS and GARCH specifications perform similarly in terms of their size but GARCH specifications are generally more powerful. They believe that this statistical advantage is explained by the ability of GARCH specifications to account for the distributional characteristics of futures price changes such as excess kurtosis and volatility clustering (ARCH effects). McKenzie *et al.* (2004) also suggest that regression and GARCH models have an advantage over CMR specifications in the presence of event clustering[51], because the abnormal return is parameterised within the estimation model and clustering is therefore not an issue.

It is now well established that like futures prices and returns, electricity prices and price changes (herein referred to as "returns") also demonstrate excess kurtosis (see Huismann and Huurman, 2003; Worthington, Kay-Spratley and Higgs, 2005; Higgs and Worthington, 2005; and Thomas *et al.*, 2006). The presence of ARCH effects in the electricity data is established in the Australian literature (see Worthington, Kay-Spratley and Higgs, 2005; and Higgs and Worthington, 2005) and in Chapter Seven of this thesis. Specifically, results in Chapter Seven show that while significant GARCH effects are found in electricity returns, there is some variation between regions and that a Power-ARCH (1,1) specification is favoured in the interconnected NSW1,

[51] McKenzie *et al.*. (2004) note that the meaning of the term "event clustering" as it is used in this context is different from its usage in the event study literature in equity markets. In studies of stock price behaviour, "event clustering" typically refers to an event that affects several firms in the same calendar period. Here the term is used to refer to cases where multiple events occur within a short time of one another.

SNOWY1 and VIC1 regions, while an EGARCH(1,1) specification better describes the volatility processes in QLD1 and SA1. In view of the McKenzie *et al.* (2004) findings which show that in the presence of these effects a GARCH-based event study approach offers advantages over other techniques, it would seem a useful exercise to apply a GARCH-based event study method to returns in electricity prices. With that in mind, section 8.4 develops appropriate GARCH-based specifications based on the analysis conducted in Chapter Seven, along with a standard CMR-style event study approach for comparison.

8.3 Data

8.3.1 Price Data

Consistent with the analysis conducted for Chapter Five, the raw price data used to derive the returns series employed by this study are half-hourly pool price observations sourced directly from NEMMCO for the period from 7th December 1998 to 31st March, 2005. Descriptive statistics and preliminary analysis of the price series is presented in detail in section Chapter Four, section 4.2. The sample size is 110,719 observations for each of the NSW1, QLD1, SA1, SNOWY1 and VIC1 regional pools in the NEM.

8.3.2 Returns Data

In the context of commodity futures contracts, Black (1976) notes that because futures contracts require no initial investment, futures positions cannot be said to yield rates of return as they are generally understood, i.e. as a result of change in value of the holder's initial investment over time. Because there is no ability to hold a unit of electricity and there is no "initial investment" in the commodity as such, spot electricity also does not yield a rate of return in the traditional sense. In light of this characteristic and for reasons of consistency with previous event studies, the "returns" are percentage price changes over a half-hourly trading interval. In general, attempts to model or forecast prices in financial markets should be based on successive variations in price and not on the prices themselves (see*, inter alia*, de Bodt, Rynkiewicz & Cottrell, 2001).

Because the spot prices in the NEM are determined at discrete half-hourly intervals, the market should not be viewed as a continuous market in the way of most conventional financial markets[52], therefore a discrete returns specification is preferred over log returns. Consistent with the previous empirical chapters in this thesis, the returns used in this study are half-hourly discrete returns, ie:

$$RP_t = \frac{(P_t - P_{t-1})}{|P_{t-1}|}. \tag{8.9}$$

Where RP_t represents the half-hourly discrete proportionate change in price ("return") at time t, P_t is half-hourly price at time t and $|P_{t-1}|$ is the absolute value of the previous half-hourly price, i.e. at time t-1. The denominator is specified as the absolute value to allow for the presence of negative prices[53].

[52] A log returns specification will dampen the extreme spike effects I am attempting to capture, and is not defined in the presence of negative prices, the effects of which are also examined. See section 4.2.2 for a discussion of negative spot prices.
[53] Discussed in chapters four and five.

Descriptive statistics for the half-hourly returns series are shown in Table 5.1 (see Chapter Five, section 5.3.2), in which the mean, standard deviation, minimum, maximum, range, skewness, kurtosis and Augmented Dickey-Fuller statistics are reported for each region's returns series. Mean half-hourly returns vary widely between regions, from 2.72% for VIC1 to 9.55% for SNOWY1. The standard deviation of returns is generally high, is widely dispersed across the regions and is consistent with the pattern of means, ranging from 111% for VIC1 to an extremely high 1700% for SNOWY1. The highest maximum return of 454,250% is observed in SNOWY1 and lowest in VIC1 of 14,243%. SNOWY1 also exhibits a markedly wider range of returns than the other regions. The distributions of returns for QLD1, SA1 and SNOWY1 demonstrate positive skewness with NSW1 and VIC1 demonstrating a relatively low degree of negative skewness. Distributions of returns in all regions demonstrate extremely high kurtosis. Jarque-Bera (JB) statistics reject the null hypothesis of normal distribution at the 1% level of significance for all five regions. Augmented Dickey-Fuller (ADF) statistics clearly reject the hypothesis of a Unit Root at the 1% level of significance for all five regions, again consistent with the findings of the earlier studies.

8.3.3 Demand Data

The basic demand data that the spike series used in this study are extracted from are half-hourly observations of total demand (as described in section 4.2.1), sourced directly from NEMMCO for the period from 2:00am on December 7, 1998, to

11:30pm on March 31, 2005. The sample size is 110,719 observations for each of the five NEM under study (NSW1, QLD1, SA1, SNOWY1 and VIC1)[54].

8.3.4 Changes in Demand

The half-hourly pool price and its associated returns exhibit strong seasonal effects and spike effects as a result of the occurrence of price spikes, as shown in Chapter Five. Similar seasonal and spike effects are found in half-hourly changes in demand for electricity (see Chapter Six). As indicated in section 8.1, demand shocks are believed to be one of the potential causes of price spikes and I am interested in investigating the extent to which a spike in demand change triggers a response in price change (referred to here as "returns").

As with spot price, NEMMCO's total demand is reported at half-hourly intervals in discrete time and for consistency with the approach taken with price, the demand change series used in this study were generated as half-hourly discrete changes rather than log changes, according to equation 8.10:

$$CD_t = \frac{(D_t - D_{t-1})}{D_{t-1}}. \qquad (8.10)$$

Where CD_t is discrete percentage change in demand at time t, D_t is half-hourly demand at time t and D_{t-1} is the previous half-hourly total demand, i.e. at time $t-1$. The results of tests for the presence of a unit root show that the demand and demand changes series are stationary. Given that this study is concerned only with the incidence of spikes in demand change (CD_t), summary statistics for the demand

[54] Descriptive statistics and preliminary analysis of the demand series is presented in chapter four, section 4.2.1.

change series (CD_t) are not reported here. Descriptive statistics and preliminary analysis of the demand series is presented in Chapter Six, section 6.3.2.

8.4 Methodology

8.4.1 GARCH Model Specification

As discussed in section 8.2, McKenzie *et al.* (2004) establish that when the distribution of returns is highly leptokurtic and significant volatility clustering is present in the data, a GARCH-based event study approach provides advantages over other techniques. Results in Chapter Seven show that there are significant GARCH effects found in electricity returns as defined but that there is some variation between regions. Based on ranking by Schwarz-Bayes and Akaike Information Criteria (see McKenzie and Mitchell, 2002), PARCH (1,1) specification is favoured in all regions but model parameters indicate that the PARCH(1,1) model may be unstable in QLD1 and SA1[55] . For these reasons, the PARCH(1,1) specification is used in this study for NSW1, SNOWY1 and VIC1 regions, and the EGARCH(1,1) specification is used for QLD1 and SA1 as it better describes the volatility processes in those two regions.

In view of the McKenzie *et al.* (2004) findings and the results in Chapter Seven, a GARCH-based event study specification is developed, with variation in the specification of the conditional variance equation according to the previously-determined 'best-fit' for each region. In Chapter Seven, the mean equation is modified

[55] See chapter seven, section 7.4.

to include appropriate AR and MA terms to control for autocorrelation in the data according to:

$$Y_t = X_t^{'}\theta + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \qquad (8.11)$$

where p and q are chosen to capture significant spikes in the autocorrelation function.

Following McKenzie *et al.* (2004), the mean equation is further modified to include an event dummy E_t:

$$Y_t = X_t^{'}\theta + \phi E_t + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \qquad (8.12)$$

where $E_t = 1$ on event days and 0 otherwise and the event coefficient ϕ is interpreted as the average abnormal return on the event day.

Consistent with the results in Chapter Seven, a PARCH (1,1) specification is used for NSW1, SNOWY1 and VIC1 and an EGARCH specification is used for QLD1 and SA1[56].

Power ARCH

The power-ARCH (PARCH) specification proposed by Ding *et al.* (1993) generalises the transformation of the error term in the models. The PARCH specification is given by equation 8.13:

[56] In preliminary analysis PARCH (1,1) and EGARCH (1,1) models were run for all five regions with appropriate AR and MA terms and the event dummy E_t included in the specification of the mean equation. In QLD1 and SA1, coefficients for the event dummy were not materially different between the EGARCH (1,1) and PARCH (1,1) models but in the PARCH(1,1) models for each of these two regions the coefficients for the ARCH (α), GARCH (β) and power (γ) parameters summed to a value greater than unity, indicating a potentially unstable model. For this reason the preferred PARCH(1,1) specification is applied to NSW1, SNOWY1and VIC1 and the EGARCH(1,1) specification is applied to QLD1 and SA1.

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum_{i=1}^{p} \alpha\left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^{\delta} \tag{8.13}$$

The power parameter, δ, is estimated rather than imposed, and an optional threshold parameter, γ, may be included to capture asymmetry. The Bollerslev (1986) model sets δ=2, γ=0, and the Taylor (1986) model sets δ=1and γ,=0. Empirical estimates indicate the power term is sample-dependent and values of near unity are common in the case of stock data (see Ding *et al.* 1993), while for foreign exchange data the power term varies between unity and two (see McKenzie and Mitchell 2002). When fitting a PARCH model to electricity data, the choice of power parameter is not obvious. Higgs and Worthington (2005) find variation between regions in the estimated power term of a model for electricity prices.

Exponential GARCH

Nelson's (1991) Exponential GARCH (EGARCH) model is formulated to capture news in the form of leverage effects. In the EGARCH model the specification for the conditional covariance is given by:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \tag{8.14}$$

The left-hand side is the *log* of the conditional variance, implying that any leverage effects are exponential and that forecasts of conditional variance are guaranteed to be non-negative. In interpreting the model, the presence of leverage effects is indicated by γ_k<0, and the impact is asymmetric if $\gamma_k \neq 0$. While the basic GARCH model (see equation 7.4) requires the restrictions in estimation that σ_t^2>0, for t = 1…T , the

EGARCH model allows unrestricted estimation of the variance, -∞ < log(σ_i^2) < ∞, *implying* that σ_t^2>0, and so the assumption that σ_t^2>0, for t = 1…T is automatically satisfied.

8.4.1.1 GARCH Model Estimation Procedure

As discussed in Chapter Seven, attempts to restrict GARCH specifications to order (1,1) with a mean equation inclusive of the very large number of seasonal and outlier control variables identified in Chapter Five created convergence problems that meant the models could not be estimated reliably[57]. In view of this constraint, a decision was taken to undertake a two-stage estimation process by firstly pre-filtering the data to control for seasonalities and outliers in the returns series using OLS estimation[58]. The residuals (ε_t) from the OLS model are then captured (referred to herein as the "filtered returns"). The mean and conditional variance equation are then estimated over the filtered returns, incorporating appropriate AR and MA terms in the mean equation to control for serial correlation. According to Engle (1982), this two-stage approach should not result in loss of asymptotic efficiency in model estimation for large sample sizes. For the purposes of this event study analysis, the mean equation is modified to include an event dummy as defined in equation 8.12.

The OLS model used to generate the filtered returns for this study is shown in Chapter Seven, equation 7.1 and shown again here.

[57] Initial attempts using EVIEWS and SPSS statistical software packages to fit GARCH(1,1), TARCH(1,1), EGARCH(1,1) and PARCH(1,1) models to each region's discrete returns series, while controlling carefully for seasonal an outlier effects and serial correlation required that the mean equation be specified to include as many as 260 dummy variables (47 intra-day, six weekday, 11 monthly, six for year and up to 190 spikes, depending on region – see chapter five), over a sample size of 110,718 observations for each region. Almost all attempts to fit basic GARCH(1,1) processes to such large models failed to converge after 1000 iterations.
[58] See equation chapter seven, equation 7.1.

$$RP_{R,t} = \alpha_0 + \sum_{j=1}^{6} \beta_{2,j} DAY_j + \sum_{k=1,\neq 9}^{12} \beta_{3,k} MTH_k + \sum_{l=1999,\neq 2001}^{2006} \beta_{4,l} YR_l + \sum_{m=1,\neq 23}^{48} \beta_{5,m} HH_m + \sum_{o=1}^{N_{R,S}} \beta_{6,o} SPIKE_{R,o} + \sum_{p=1}^{N_{R,N}} \beta_{7,p} NEG_{R,p} + \varepsilon_t \quad (8.15)$$

Where:

$RP_{R,t}$ represents the discrete return for region R at time t;

DAY_j represents the dummy variable for each day of the week (j=1 for Monday, 2 for Tuesday,…,6 for Saturday). MTH_k represents the dummy variable for each month (k=1 for January, 2 for February,…,12 for December).

YR_l represents the dummy variable for each year included in the sample period (l=1999,…,2006).

HH_m represents the dummy variable for each half-hourly trading interval (m= 1 for 00:00hrs, 2 for 00:30hrs…,48 for 23:30hrs)

$SPIKE_{R,S}$ represents a set of $N_{R,S}$ dummy variables, one for each extreme spike in returns as previously defined, with $N_{R,S}$ representing the number of extreme returns observed in region R for the period of the study (see Chapter Five, Table 5.2);

$NEG_{R,N}$ represents the dummy variable for the return associated with an occurrence of a negative price (p=1,…,$N_{R,N}$), with $N_{R,N}$ representing the number of occurrences of a negative price for region R during for the period of the study.

The data used in this part of the study are the residuals represented by the error term, ε_t in the model. Descriptive statistics for the filtered returns series are shown in Table 8.3. Augmented Dickey-Fuller (ADF) statistics and results of ARCH-LM tests for each region's filtered returns series are also included in Table 8.3. The mean values for the sample are very small yet the standard deviation is generally high relative to the mean and takes on a range of values across the regions, indicating a high degree of variability in the filtered returns and considerable variation between the 5 regions. Although close to zero, the highest mean returns are found in QLD1, SA1 and SNOWY1 and these regions exhibit the largest standard deviations.

Table 8.3: Descriptive Statistics for Filtered Half-Hourly Returns ε_t.

(by Region, December 1998 to March 2005).

ε_t	**NSW1**	**QLD1**	**SA1**	**SNOWY1**	**VIC1**
Mean	-2.44×10^{-17}	1.29×10^{-16}	1.57×10^{-17}	1.48×10^{-17}	2.72×10^{-17}
Median	-0.006	-0.014	-0.019	-0.008	-0.007
Maximum	4.82	6.86	7.00	19.82	4.39
Minimum	-1.13	-1.81	-1.46	-1.21	-1.30
Std. Dev.	0.18	0.30	0.29	0.28	0.19
Skewness	6.52	8.92	7.97	29.87	4.81
Kurtosis	121.53	139.03	122.96	1459.27	72.50
JB stat	6.56×10^{7}	8.68×10^{7}	6.76×10^{7}	9.80×10^{9}	2.27×10^{7}
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF Stat	-38.34	-32.22	-34.27	-36.10	-40.02
ARCH-LM Test					
F-Stat	95.06	57.06	49.53	44.89	62.12
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	110718	110718	110718	110718	110718

The critical values of significance for skewness and kurtosis at the .05 level are 0.0305 and 0.0610, respectively. JB – Jarque-Bera. The critical value for the Augmented Dickey-Fuller ststistic at the 0.01 level is -3.43

Consistent with the findings of the earlier studies and with the returns series as discussed in Chapter Five, Augmented Dickey-Fuller (ADF) statistics reject the hypothesis of a Unit Root at the 1% level of significance for all five regions.

The distributions of filtered returns for all 5 regions demonstrate positive skewness and extremely high kurtosis. This fat-tailed character persists despite the removal of extreme spikes in the raw returns data and is consistent with the findings of Huisman and Huurman (2002), Higgs and Worthington (2005) and Wolak (2000). The p-values for *F*-statistics in the ARCH-LM tests suggest that heteroskedasticity effects are present and highly significant. As discussed in Section 7.3.2, preliminary analysis of the full data set found that Nelson's (1991) Generalised Error Distribution (GED) was the most appropriate for model estimation.

8.4.2 Standard Event Study Methodology

For the purposes of comparison with the GARCH approach described in the previous section a traditional event study approach is also included. Traditional event study methods in equity markets are generally based on the premise that if a particular event, for example a company announcement, materially affects the value of a firm, any change in value will be reflected in the company's stock showing an abnormal return at some time interval shortly after the event. The basic event study approach is described in section 8.2. (see equations 8.2 to 8.4). For the purpose of analysing the response of electricity returns to demand spikes, the standard approach is adapted by identifying demand spikes within each NEM region and selecting a sample of half-hourly returns either side of the spike event.

Abnormal returns are generated as:

$$AR_{st} = R_{st} - E(R_{st}) \qquad (8.17)$$

Where R_{st} is the half hourly return as defined by equation 8.8 observed at trading interval t around spike s. Mean half-hourly returns are generally very small, and given that this analytical approach is included for comparison with the GARCH approach which does not include mean-adjusted returns, the expected half-hourly return $E(R_{st})$ in equation 8.13 is set to zero so that $AR_{st} = R_{st}$. The selection of "normal period" around the event time can be somewhat arbitrary. The spot market in the NEM is designed to adjust instantly to demand and supply variation through an adjustment of prices, so a sample space of 12 half hourly trading intervals either side of the demand spike event is selected as a reasonable window, long enough to so as not to be biased by very short-term price movements, yet short enough so as not to be influenced by price-sensitive market information other than the spike in question.

The demand spikes within each region are then arranged in common event time and the cross-sectional average abnormal returns are obtained as

$$\overline{R_{s,t}} = \frac{1}{N}\sum_{s-1}^{N} R_{s,t} \tag{8.18}$$

where N is the number of spikes in the region's cross-sectional sample and t=0 corresponds to trading interval 0 in event time, when the demand spike occurs.

The null hypothesis is that abnormal returns are equal to zero, and the standard test statistic is:

$$t = \overline{R_{s,t}} \Big/ \sigma(R_{st})\frac{1}{\sqrt{N}} = \sqrt{N}\left(\overline{R_{s,t}} \Big/ \sigma(R_{st}) \right) \tag{8.19}$$

In which $\sigma(R_{st})$ is the standard deviation of the cross-sectional sample of abnormal returns as defined.

If there is event clustering in the sample data, the abnormal return measure may be biased (see Brown & Warner, 1985, McKenzie *et al.*, 2004). A number of spikes in demand change are observed to occur at consecutive half-hourly trading intervals in four of the five regions. In order to control for possible cross-sectional dependence as a result of these consecutive spikes, any spikes occurring within 12 hours of each other (24 trading intervals) within a region were dropped from that region's sample. This action reduces the number of demand spike events tested in NSW1 from 94 to 89, in QLD1 from 23 to 15, in SA1 from 30 to 17 and in VIC1 from 109 to 106. Consecutive spikes as described are not observed in the SNOWY1 sample.

8.5 Empirical Results

Results for the GARCH-based event study approach for the five regions are shown in Table 8.4. Table 8.4 presents and the estimated coefficients, standard errors and *p*-values for the conditional mean and variance equations for the preferred GARCH specifications for each region along with the estimated GED parameter (*r*), Akaike Information (AIC) and Schwartz Bayesian Criteria (SBC), Durbin-Watson (DW) statistic and F-Statistic and p-value showing the results of ARCH-LM tests.

The uppermost section of the table describes the ARMA structure required to account for serial correlation for each region. There is some variation between regions, with NSW1 demonstrating significant AR effects the 1% level at lags 1,5,7 and 8; QLD1 demonstrating significant AR effects at lags 1, 47 and 48 and significant MA effect at lag 48; SA1 showing significant AR effects at lags 1, 47 and 48. SNOWY1 exhibits the same type of AR structure as QLD1 with significant AR effects at lags 1, 47 and 48 and similar magnitude of coefficients. VIC1 demonstrates significant AR effects at lags 1, 5, 7, 47 and 48.

Table 8.4: Estimated Coefficients for Conditional Mean Returns and Variance Equations for All Regions

	NSW1 PARCH(1,1)		QLD1 EGARCH(1,1)		SA1 EGARCH(1,1)		SNOWY1 PARCH1,1)		VIC1 PARCH(1,1)	
	Coeff.	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**	**Coeff.**	**P-val**
Mean Equation										
ω_m	-0.005	0.000	-0.026	0.000	-0.018	0.000	-0.013	0.000	-0.006	0.000
ϕ	**0.087**	**0.000**	**0.038**	**0.000**	**0.003**	**0.694**	**0.003**	**0.523**	**0.041**	**0.000**
AR(1)	0.047	0.000	0.016	0.000	0.054	0.000	0.006	0.000	0.051	0.000
AR(5)	-0.023	0.000							-0.023	0.000
AR(7)	-0.029	0.000							-0.021	0.000
AR(47)			0.016	0.000	0.072	0.000	0.008	0.000	0.074	0.000
AR(48)	0.405	0.000	0.937	0.000	0.241	0.000	0.952	0.000	0.330	0.000
MA(48)			-0.845	0.000			-0.834	0.000		
Variance Equation										
ω_v	0.019	0.000	-1.210	0.000	-0.923	0.000	0.020	0.000	0.029	0.000
α	0.379	0.000	0.699	0.000	0.546	0.000	0.428	0.000	0.390	0.000
β	0.576	0.000	0.806	0.000	0.835	0.000	0.547	0.000	0.554	0.000
γ	-0.086	0.000	-0.185	0.000	-0.161	0.000	0.021	0.003	0.031	0.001
δ	1.065	0.000	-1.210	0.000	-0.923	0.000	1.061	0.000	0.961	0.000
r (GED)	0.876	0.000	0.721	0.000	0.700	0.000	0.805	0.000	0.844	0.000
AIC	-1.671		-1.481		-1.095		-1.723		-1.464	
SBC	-1.670		-1.480		-1.094		-1.722		-1.463	
DW	2.054		2.181		2.178		1.974		2.106	
ARCH-LM Test										
F-Stat	0.096	1.000	0.296	0.999	0.735	0.820	0.007	1.000	0.316	0.999
#Obs	110670		110670		110670		110670		110670	

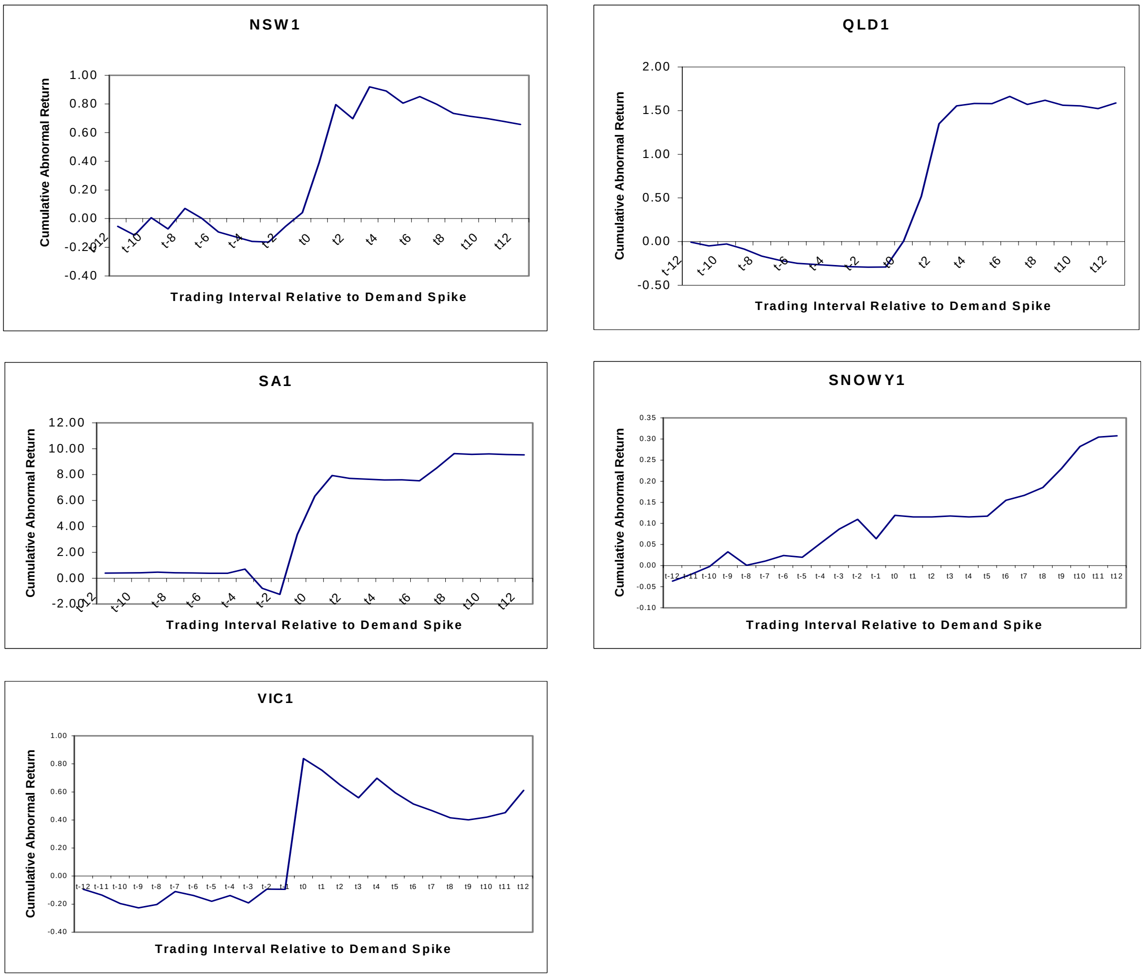
This table provides the estimated coefficients and *p*-values for the mean and conditional variance equations for the NSW1, QLD1, SA1, SNOWY1 and VIC1 regional electricity pools in the NEM. ω_m is the constant term in the mean equation, ϕ is the event parameter, ω_v is the constant term in the conditional variance equation, α is the ARCH coefficient, γ is the leverage effect, δ is the power of the conditional standard deviation process. r is the GED parameter and AIC and SBC are Akaike Information and Schwartz-Bayes Criteria respectively. DW is the Durbin-Watson Statistic.

Durbin-Watson statistics for all model specifications in all regions are close to 2, indicating a lack of significant residual serial correlation after model estimation. The GED parameter (r) falls between 0 and 2, suggesting that the distribution of standard errors is leptokurtic in all regions. The *p*-values for the *F*-Statistic in the ARCH-LM tests indicate that ARCH effects have largely been accounted for by the models.

Interestingly the coefficients for the event study parameter (ϕ) show there is some regional variation in the price response to demand spikes. Despite the lack of temporal coincidence between spikes in returns and demand change suggested by Table 8.2, there is a significant and positive response indicated in NSW1, SNOWY1 and VIC1, although it is worth noting that the coefficients in these three regions are small. By contrast QLD1 and SA1 do not appear to demonstrate a significant response.

Results for the standard event study approach are shown in Table 8.6 and are supported by Figure 8.1, which shows cumulative average abnormal returns around event time for each region.

Figure 8.1: Cumulative Average Abnormal Returns by Region



Parametric test results shown in Table 8.6 are broadly consistent with the results of the GARCH–based method. Significant and positive responses are evident in NSW1 and VIC1 at event time (t_0), with the response in SNOWY1 positive but borderline significant. Results for QLD1 and SA1 are also consistent with the GARCH results, with a positive but not significant response indicated at event time (t_0). These results also show that while the price response is positive at event time, a variety of significant positive and negative responses at trading intervals around the event time for all 5 regions, with no clear common pattern between regions.

Table 8.5: Results for Standard Event Study Approach by Region, for the Horizon t=-12 to +12

	NSW1		**QLD1**		**SA1**		**SNOWY1**		**VIC1**	
t	$\overline{R}_{st}$	***t-stat***	$\overline{R}_{st}$	***t-stat***	$\overline{R}_{st}$	***t-stat***	$\overline{R}_{st}$	***t-stat***	$\overline{R}_{st}$	***t-stat***
t_{-12}	-0.05	-5.38	-0.01	-0.17	0.40	2.10	-0.04	-2.23	-0.09	-5.40
t_{-11}	-0.06	-6.92	-0.04	-1.42	0.01	0.09	0.02	0.88	-0.04	-3.12
t_{-10}	0.12	6.27	0.02	0.63	0.01	0.11	0.02	0.86	-0.06	-3.97
t_{-9}	-0.08	-6.12	-0.06	-3.24	0.05	0.65	0.04	1.50	-0.03	-3.58
t_{-8}	0.14	0.72	-0.08	-4.39	-0.04	-1.19	-0.03	-2.01	0.02	2.08
t_{-7}	-0.07	-7.67	-0.05	-2.29	-0.02	-0.32	0.01	0.57	0.09	1.50
t_{-6}	-0.10	-9.49	-0.03	-1.81	-0.03	-0.57	0.01	0.67	-0.03	-2.97
t_{-5}	-0.03	-0.80	-0.01	-0.51	0.00	0.02	0.00	-0.20	-0.04	-4.21
t_{-4}	-0.03	-3.33	-0.01	-1.36	0.33	1.12	0.03	1.17	0.04	5.37
t_{-3}	-0.01	-0.39	-0.01	-0.88	-1.50	-0.77	0.03	0.48	-0.05	-5.24
t_{-2}	0.11	7.38	-0.01	-0.28	-0.46	-0.70	0.02	0.85	0.10	5.31
t_{-1}	0.10	5.51	0.00	0.06	4.63	1.46	-0.05	-2.32	0.00	-0.04
t_0	**0.35**	**12.92**	**0.29**	**2.77**	**2.97**	**1.06**	**0.06**	**1.97**	**0.93**	**2.54**
t_1	0.40	3.37	0.51	1.44	1.59	1.01	0.00	-0.18	-0.08	-3.40
t_2	-0.10	-4.85	0.83	1.45	-0.23	-2.38	0.00	0.00	-0.11	-6.43
t_3	0.22	8.29	0.21	1.74	-0.06	-0.86	0.00	0.13	-0.09	-7.82
t_4	-0.03	-2.26	0.03	0.27	-0.07	-1.40	0.00	-0.15	0.14	9.06
t_5	-0.09	-8.46	0.00	-0.01	0.01	0.22	0.00	0.09	-0.10	-8.43
t_6	0.05	2.96	0.08	1.24	-0.06	-1.49	0.04	1.72	-0.08	-5.71
t_7	-0.05	-6.55	-0.09	-2.23	0.98	0.88	0.01	0.69	-0.05	-2.82
t_8	-0.06	-6.15	0.05	0.88	1.11	1.01	0.02	1.06	-0.05	-5.75
t_9	-0.02	-2.01	-0.06	-0.98	-0.06	-0.89	0.05	2.23	-0.01	-1.86
t_{10}	-0.01	-1.40	-0.01	-0.14	0.05	0.89	0.05	2.61	0.02	1.18
t_{11}	-0.02	-2.17	-0.03	-1.28	-0.06	-0.78	0.02	1.28	0.03	1.05
t_{12}	-0.02	-2.26	0.06	0.59	-0.03	-0.44	0.00	0.18	0.16	6.17

There is a difference in magnitude of event response in these results compared to the GARCH-based results, which is most likely attributable to the fact that the GARCH model is correcting for a range of seasonal and outlier effects in the price series that are not accounted for by the standard approach. The standard approach is based on the raw returns data described by equation 8.8 whereas the data used in the GARCH approach are the filtered returns generated as the residuals from equation 8.11. It is unclear then the extent to which these responses at times other than t=0 other may be influenced by intra-day seasonal factors.

8.6 Conclusion

Extreme spikes are a significant feature of electricity prices, particularly in Australia's National Electricity Market (NEM) and are attributable to the non-storable nature of electricity and aspects of market operation that are designed to ensure that the market clears instantly through an adjustment of prices, as demand and supply fluctuate. Better understanding of the dynamics of spot prices, particularly the spike process, is of interest to generators, retailers and end-users for valuation of real and financial assets and for risk management.

In Chapters 5 and 6, individual spikes in demand and price in the in the NSW1, QLD1, SA1, SNOWY1 and VIC1 regions in the NEM are identified over a six year period and established to be a significant feature of both price and demand progression. This study extends the work on spike significance in Chapters 5 and 6 by seeking the answers to two questions - does a spike in demand result in a contemporaneous spike in price? If not, is there a significant price response to a demand spike?

The answer to the first question appears to be somewhat surprising in that there is a marked absence of exact temporal coincidence between extreme spikes in half-hourly demand change and extreme spikes in half-hourly price change across the five NEM regions considered. In view if this result, an event-study approach is employed to examine the extent to extreme spikes in demand trigger a response in price. To date no other study in the electricity literature has used an event-study approach to answer this question. A 'traditional' event study approach and a GARCH-based event study approach (following McKenzie, Thomsen and Dixon, 2004) are used and results show that despite the almost negligible coincidence of demand and price spikes across the NEM there is evidence of a significant positive price response to a demand spikes in NSW1, QLD1 and VIC1, but not in SA1 or SNOWY1. It should also be noted that although statistically significant the size of the response is quite small. All that said, it may be that the findings of this study are dependent on the spike definition used and the use of returns on price and demand, however preliminary analyses have suggested that a more liberal definition of a spike may result in problems for GARCH model estimation and that the study of price levels yields similar results to returns[59]. In markets like the NEM pools that are designed to clear instantly, one would intuitively expect to see a higher rate of coincidence between extreme spikes in demand and price. These findings suggest that one or more of the other causal factors may make a greater contribution to the occurrence of a price spike. Other factors, perhaps supply-side disruption in the form of generator outages or transmission failure, may be more significant drivers of price spikes than unexpected shocks to demand. The events of the afternoon of January 16, 2007, may provide a clue. On that day extreme high temperatures in Victoria and New South Wales resulted in unusually high demand for

[59] See chapters 4 and 5.

electricity, but the transmission interconnector between the two states was disrupted by intense bushfires, with the result that peak-load power generated by the Snowy Hydroelectric Scheme could not be delivered to the grid in Victoria. Victorian prices hovered in the high $9,000 range for most of the afternoon and reached the $10,000 market cap level for two hours, resulting in load shedding and widespread cuts to power supply throughout the state. This suggests that a useful extension to this work would be to collate event data relating to supply disruptions and compare their occurrence with price spikes to determine the extent to which supply-side shocks are transmitted to price.

Chapter 9: Conclusion

9.1 Overview

Chapter One advances the argument that the deregulation and restructuring of the electricity supply sector in many jurisdictions, while intended to increase competition among suppliers and choice for end users has resulted in idiosyncratic price behaviour characterised by strong intra-day, weekly and monthly seasonal patterns and extreme price spikes that contribute to excess volatility in the market. This excess volatility brings with it new risk management challenges and associated costs. Reform of the electricity supply industry, in countries or regions where it has taken place, has usually involved the disaggregation of vertically-integrated, state-owned monopolies that control the whole electricity value chain, from fuel extraction through generation, transmission and distribution to retail sales. In general, sector restructuring has involved splitting off the generation and distribution/retail business with some degree of privatisation or corporatisation, while the transmission infrastructure (the 'poles and wires') has generally remained in state hands.

Under regulated regimes prices were generally fixed (or were periodically adjusted for inflation), based on the supplier's short-run marginal cost of production and delivery plus some reasonable return to the state as owner. In the new market setting, generators compete to sell into an electricity market pool and the distributors purchase electricity from the pool at prices determined by the interaction of demand and supply on an hourly or half-hourly basis. Unlike other traded energy commodities like oil and gas, electricity is not storable. As such inventory cannot be use to 'smooth out' shocks to demand or supply, which gives rise to the extremely high volatility observed in these new, deregulated markets. Further, demand tends to be highly inelastic to price, and when compared with financial markets (stock, bonds) or with other commodities the behaviour of electricity prices is regarded as quite complex and volatile (see Escribano *et al.*, 2002; Bunn and Karakatsani, 2003). A unique feature of electricity prices in some jurisdictions is the occurrence of negative prices, which arise as a result of the price bidding practices of generators[60]. The deregulation has introduced new elements of price uncertainty to both the production and consumption sides of the sector and tools for financial risk management in the form of futures contracts, options and swaps are being developed by and for the industry.

In the Australian context, the 'Hillmer reforms' of the early 1990s led to the disaggregation of the vertically integrated government-owned electricity authorities into separate generation, transmission, distribution and retail sales sectors in each State. The goal of the reform process was to increase competition in the industry and provide greater choice for end-use electricity consumers. As in other countries that have undertaken programmes of restructuring and deregulating their electricity supply industries, the restructuring and deregulation of electricity markets in Australia has brought about fundamental changes in the behaviour of wholesale spot prices. Australian wholesale electricity prices demonstrate high volatility, strong mean-reversion (prices tend to fluctuate around a long-term equilibrium, usually reflecting generators' short-run marginal costs), and abrupt and unanticipated price jumps or spikes that are generally associated with shocks to price-inelastic demand and supply (Higgs & Worthington, 2006). Indeed it has been shown that electricity prices in the

[60] See chapter four, section 4.2.2 for discussion.

Australian market display volatility and spike behaviour far in excess of other, similar electricity markets, largely as a result of local market design and regulation (Booth, 2004).

Excess volatility and the resultant uncertainty about prices increases the risk of trading in the spot market and increases consumer prices as participants pay for various risk management measures used to mitigate the consequences of being caught when prices spike to high levels. The characterisation and understanding of the behaviour of electricity prices is therefore an important and necessary research objective and will help to better inform a range of electricity market considerations, not least among which are valuation of real assets in the sector and financial claims on the commodity, new investment decisions on the part of suppliers and distributors, and management of price risk, not only by suppliers but by large commercial and industrial users for whom electricity is a basic input to their business.

9.2 Summary and Findings

The focus of this thesis is on modelling the structural characteristics of electricity prices in the Australian National Electricity Market. Seasonalities including time-of-day, day-of-week, monthly and yearly effects and large price spikes are a well-documented feature of electricity markets and several studies examine their effect in aggregate using various functional forms (e.g. Kaminski, 1997; Clewlow and Strickland, 2000a; de Jong and Huismann, 2002; and Goto and Karolyi, 2004). The literature on electricity price modelling frequently identifies the presence of extreme price jumps with rapid reversion to the mean as a cause of extreme volatility in electricity prices [Bunn (2004), Alvaro, Peña, and Villaplana (2002), Hadsell, Marathe and Shawky (2004)]. Modelling electricity prices in the Australian and overseas markets is a difficult process and this provides a strong incentive for further research into the Australian electricity price market. Various models developed in the study of financial time-series data have been applied to electricity time series but there is much work yet to be done to fully account for the main components of price structure. Knittel and Roberts (2001) and Goto and Karolyi (2004) highlight the need to explore this structure and include it in price specifications.

The previous research on spike behaviour generally attempts to capture spike effects using some generalised functional form [See Clewlow and Strickland, 2000a and (2000b), Higgs and Worthington (2003, 2005), Bunn (2004), Alvaro, Peña, and Villaplana (2002), Hadsell, Marathe and Shawky (2004) and Goto and Karolyi (2004)]. Most of these studies use daily price data, which is inadequate, given that spikes tend to be very short lived and multiple spikes may occur on a trading day. This thesis extends the earlier research by examining intra-day prices and identifying and capturing *individual* spikes and modelling their effects, along with seasonal factors. The existing literature also uses data sampled over a one or two year horizon and the Australian studies tend to concentrate on only one or two regions in the NEM. By using half-hourly data, sampled over a longer period (six years) from five NEM regions, this study better establishes the extent to which these extreme within-day price spikes and negative prices are a regular feature of the data. As such it is potentially significant for producers, regulators and researchers.

Briefly, the four empirical chapters in the thesis addresses the following research questions: (1) are individual extreme spikes significant in half-hourly prices, to what extent are seasonal factors significant, and is there regional variation within the NEM? (Chapter Five); (2) to what extent are any structural characteristics identified in the prices series evident in half-hourly demand (Chapter Six); (3) having accounted for seasonalities and outlier effects in price, can the underlying volatility processes be described using established empirical models? (Chapter Seven); and (4), given that demand variation is generally accepted to be a driver of price variation, do the extreme values observed in demand and price coincide and to what extent does a demand shock result in a response in price? (Chapter Eight). Chapters five and six employ a relatively straightforward OLS regression approach to modelling the effects of seasonal factors and extreme price spikes. Chapter Seven tests the efficacy of a range of common GARCH model specifications under several different assumptions about the distribution of the conditional error term. Chapter Eight brings together the spike analysis conducted in Chapters five and six with the GARCH analysis in Chapter Seven, in a GARCH-based event study framework to investigate the effect of spikes in demand on price.

The thesis is organised as follows. Chapter Two introduces the domain of relevant literature, including recent research on price formation in electricity markets given the special nature of electricity as a traded commodity and special aspects of market design that it requires. The literature on stochastic modelling of electricity prices is presented, particularly the various adaptations of techniques from the "conventional" financial markets and their strengths and limitations when applied to modelling electricity prices. The next section of the chapter discusses the literature emphasising structural modelling, especially the complex mix of seasonalities and outlier effects observed in electricity prices. The emerging field of non-parametric modelling for price forecasting is briefly introduced, and the emerging body of Australian literature is presented and discussed. Chapter Three provides an overview of the institutional characteristics of electricity markets. First, it provides background to the recent deregulation and restructuring of the Australian electricity supply industry. Second, it provides an overview of the important historical and operational aspects of Australia's National Electricity Market (NEM), including a worked example demonstrating the method of deriving the half-hourly spot price. Fourth, it provides an overview of the significant markets in other countries that have undertaken similar restructures of their electricity supply industry.

Chapter Four describes the data collection and collation procedures and sources of the electricity price and demand data used in this thesis. The summary descriptive statistics for each data set are also presented. This chapter also includes discussion of the process of determination of half-hourly demand values and a discussion of the phenomenon of negative spot prices, which are impossible in financial markets but are a sporadic yet significant feature of prices in the NEM.

Chapter Five investigates seasonalities and spike effects in Australian electricity prices in considerable detail and over a longer sample period than the existing literature. Over the six-year period of the study, time-of-day effects are found to be significant in half-hourly prices and are broadly consistent across all five regions of the NEM, with positive returns generally occurring at times of peak population activity in the morning and early evening and negative returns observed at most other times. There is also evidence of a transient, early evening spike effect in returns arising in 2002 and 2003 and dissipating over subsequent years. Day-of-week effects generally appear stronger for Monday and Friday than for other days of the week. Monthly effects show some consistency between NSW1, SNOWY1 and VIC1 in late autumn to early winter and in early summer. Extreme spikes, although representing less than 0.1% of observations in any region, are found to have highly statistically significant positive effect on returns. The occurrence of negative prices, although relatively rare and unique to electricity markets are found to have a significant negative effect on returns. These findings reinforce the assertions of previous researchers that seasonal and price spike effects should be incorporated into stochastic models of electricity price behaviour.

The purpose of the research presented in Chapter Six is to investigate the extent to which the seasonal factors and outlier effects that are found to be significant in half-hourly price and returns as shown in Chapter Five are present in demand for electricity. Of the seasonal effects considered, intra-day effects are more significant and persistent than day of the week, monthly or yearly effects, but with some variation between regions. The variation between regions is broadly consistent with findings in the literature on price behaviour (see Worthington, Kay-Spratley and Higgs, 2005), suggesting that for the purposes of analysis it is appropriate to treat the different regions in the NEM as separate markets. Extreme positive spikes represent less that 0.05% of demand observations across all NEM regions under study, yet results show that extreme demand spikes are statistically significant, similar to research findings pertaining to spot price, for example Higgs and Worthington (2005) and Thomas *et al.* (2006).

The study presented in Chapter Seven investigates the efficacy of four different GARCH model specifications in describing the underlying intra-day volatility processes in returns on electricity prices in five regional pools (designated NSW1, QLD1, SA1, SNOWY1 and VIC1) in Australia's National Electricity Market (NEM). four GARCH specifications, Generalised ARCH (GARCH), Threshold ARCH (TARCH), Exponential GARCH (EGARCH) and Power-ARCH (PARCH) models are applied to half-hourly returns on electricity prices for the period 7 December 1998 (commencement of the NEM) to 31 March 2005. Unlike previous GARCH-based studies on electricity prices, which seek to incorporate seasonal factors and generalised outlier effects in their models of the conditional mean equation, the very large data set used and the desire to investigate the underlying volatility process in the absence of these structural effects required that the returns data be pre-whitened prior to estimating the conditional mean and conditional variance equation in the GARCH estimation process. The results show that significant ARCH and GARCH effects are present in the data and that Power ARCH specification with a Generalised Error Distribution applied to the standard errors generally describes the volatility process better than the other three GARCH models, although in the QLD1 and SA1 regions the PARCH model is potentially unstable, so the choice of model reverts to the EGARCH(1,1) which does not impose the same parameter restrictions. Interestingly, the asymmetric volatility response captured by the PARCH model generally indicates that volatility tends rise in response to positive price spikes (see Chapter Five) and fall in response to negative spikes, which is counter to the effects generally observed in conventional financial markets but consistent with the findings of previous Australian GARCH-based studies in electricity.

The final empirical chapter, Chapter Eight, extends the work on spike significance presented in Chapters five and six by seeking the answers to two questions - does a spike in demand result in a contemporaneous spike in price? If not, is there a significant price response to a demand spike? The answer to the first question appears to be somewhat surprising in that there is a marked absence of exact temporal coincidence between extreme spikes in half-hourly demand change and extreme spikes in half-hourly price change across the five NEM regions considered. In view if this finding, an event-study approach is employed to examine the extent to which extreme spikes in demand trigger a response in price. To date no other study in the electricity literature has used an event-study approach to answer this question. A 'traditional' event study approach and a GARCH-based event study approach (following McKenzie, Thomsen and Dixon, 2004) are used and results show that despite the almost negligible coincidence of demand and price spikes across the NEM there is evidence of a significant positive price response to a demand spikes in NSW1, QLD1 and VIC1, but not in SA1 or SNOWY1. It should also be noted that although statistically significant the magnitude of the response is relatively small, and it may be that other causal factors, perhaps unexpected supply disruptions, make a greater contribution to spike evolution.

9.3 Directions for Future Research

The work undertaken for this thesis reinforces the view that the behaviour of electricity markets is highly idiosyncratic when compared to other more "conventional" financial markets. Although many of the characteristics of electricity prices can be replicated to some extent with existing stochastic models and a structural approach to modelling is warranted, there are several modelling issues that are worthy of further exploration. These include: the factors driving the behaviour of spot prices, for example economic fundamentals including demand-side behaviour, fuel costs; regulatory constraints, market design effects, the effects of forward contracting and option sales by generators, perceived risks, trading inefficiencies and strategic use of market power and short-run anomalies like generation plant outage or transmission grid failure. The magnitude, relative importance and intra-day variation of these economic fundamentals and their influence on prices, especially the behaviour of demand and any strategic trading behaviour on the part of generators may be worthy of further exploration, as would the changing nature and dynamics of structural effects as markets evolve and mature.

Much of the work on empirical price modelling attempts to adapt familiar models from financial assets to the characteristics of electricity. Knittel and Roberts (2001) find that the forecasting performance of standard financial models is relatively poor in the presence of seasonal effects and extreme behaviour and without adjustment for these effects. A further possibility for research is the distributional characteristics of electricity prices. It may be that the findings of Knittel and Roberts (2001) to some extent result from the fact that most "standard" financial models require some assumption about the distributional characteristics of prices and returns and these assumptions may not hold in electricity markets. Further investigation of these effects may also be of significance for financial institutions wishing to trade in the electricity markets or to develop risk products for market participants.

Although the imperfections of electricity market offer a rich structure for modellers, and most of the economic, technical and behavioural influences could be captured by a mixture of econometric and stochastic specifications, the political, environmental and social sensitivity of the electricity sector is becoming increasingly important. Even though markets have been deregulated in many jurisdictions, the threat of regulatory interference is ever present (see Bower, 2004). High prices only have to persist for a few months before price caps emerge, as indeed they have in Britain, Spain, and Australia. In more recent times the social, industrial and environmental impacts of the electricity industry have become a point of discussion among politicians and the wider community. Carbon emissions trading schemes exist in other parts of the world and for Australia, some form of national regulatory impost for carbon dioxide emissions is not far away, either in the form of "carbon taxes" or a required emissions trading scheme (various disjoint forms of voluntary and compulsory scheme already operate in Australia). There is much work to be done in the meantime on understanding electricity prices but it would seem prudent in the longer run to consider how these additional factors might be incorporated into model specifications.

A further possibility for research is the effect of market power and supplier bid behaviour. Robinson and Baniak (2002) argue that in the UK setting, generators with market power have the incentive to create volatility in the spot market in order to benefit from higher risk premiums in the contract market. Criticisms along these lines have recently been made regarding the operations of Snowy Hydro as a peak producer in the local market. Similarly, changes in purchasing or contracting behavior by large purchasers of electricity may also have an influence on price volatility; an aspect of volatility development that has had little treatment in the Australian setting. Smith (2003), argues that the US spot electricity markets lost much of their volatility as large consumers, like California, moved out of electricity purchases in the spot market to long-term contracts and a similar effect was observed in England and Wales when the spot market was changed from a compulsory market (like Australia) to a non-compulsory, residual settlement market. Wolak (1997) and Goto and Karolyi (2004) in their comparative studies of markets note that volatility characteristics appear to be closely related to the institutional structure of markets, with extreme price spikes more prevalent in markets with compulsory participation, as is the case in Australia's NEM. It may be possible to proxy changes in the competitive environment to provide empirical evidence whether competition increases or decreases price volatility and it is feasible that changes in regulatory regimes could be more directly included as exogenous factors in a study of electricity price and volatility. Better understanding of the effects of changes to market operation and regulation may provide useful insight for future regulation and market management in Australia.

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