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T M Christensen
A S Hurn
K A Lindsay

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T M Christensen
Department of Economics, Yale University

A S Hurn
School of Economics and Finance, Queensland University of Technology

K A Lindsay
Department of Mathematics, University of Glasgow.

Abstract

In many electricity markets, retailers purchase electricity at an unregulated spot price and sell to consumers at a heavily regulated price. Consequently the occurrence of extreme movements in the spot price represents a major source of risk to retailers and the accurate forecasting of these extreme events or price spikes is an important aspect of effective risk management. Traditional approaches to modeling electricity prices are aimed primarily at predicting the trajectory of spot prices. By contrast, this paper focuses exclusively on the prediction of spikes in electricity prices. The time series of price spikes is treated as a realization of a discrete-time point process and a nonlinear variant of the autoregressive conditional hazard (ACH) model is used to model this process. The model is estimated using half-hourly data from the Australian electricity market for the sample period 1 March 2001 to 30 June 2007. The estimated model is then used to provide one-step-ahead forecasts of the probability of an extreme event for every half hour for the forecast period, 1 July 2007 to 30 September 2007, chosen to correspond to the duration of a typical forward contract. The forecasting performance of the model is then evaluated against a benchmark that is consistent with the assumptions of commonly-used electricity pricing models.

Keywords
Electricity Prices, Price Spikes, Autoregressive Conditional Duration, Autoregressive Conditional Hazard, Electricity Futures.

JEL classification numbers
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Corresponding author
Stan Hurn
School of Economics and Finance
Queensland University of Technology
Brisbane, Qld 4001
Australia

email: `s.hurn@qut.edu.au`

1 Introduction

In the mid 1990s, the regional electricity markets of New South Wales, Queensland, Victoria, South Australia, and the Australian Capital Territory were merged to form the National Electricity Market (NEM) in Australia.[1] The NEM operates as a pooled market in which all available supply to a region is aggregated and generators are dispatched so as to satisfy demand as cost effectively as possible. If, in any given region, local demand exceeds local supply or electricity in a neighbouring region is sufficiently inexpensive to warrant transmission, then electricity is imported and exported between regions subject to the physical constraints of the transmission infrastructure. In terms of composition of the supply side, coal-fired generators and hydroelectric production have a low marginal cost of production supplying respectively 84% and 7.2% of the NEM's capacity. Gas turbines and oil-fired plants supply around 8.5% and 0.3% of the market, respectively, and only take around 20 minutes to initiate generation but have a comparatively high marginal cost of production, typically operating only during peak periods.

Wholesale trading in electricity is conducted as a spot market in which supply and demand are instantaneously matched through a centrally-coordinated dispatch process. A summary of the process for bidding, dispatch and calculation of the spot price is as follows. Prior to 12:30pm on the day before production, generators bid their own supply curve, consisting of at most ten price-quantity pairs for each half-hour of the following day, subject to a floor of -\$1,000 and a ceiling of \$10,000 per megawatt hour (MWh). Generators are free to re-bid quantities but not prices up to approximately five minutes before dispatch. Upon receipt of bids from all generators, the supply curves are aggregated and generators are dispatched in line with their bids so that demand is satisfied as inexpensively as possible.[2] The dispatch price for each five-minute interval is the bid price of the marginal generator dispatched into production. The spot price for each half-hour trading interval is then calculated as the arithmetic mean of the six five-minute interval dispatch prices observed within the half-hour, and all transactions occurring within the half-hour are settled at the spot price.[3]

Spot electricity prices are known to exhibit sudden and very large jumps to extreme levels, a phenomenon usually attributed to unexpected increases in demand, unexpected shortfalls in supply and failures of transmission infrastructure (Geman and Roncorni, 2006). The spikes reflect the fact that the central dispatch process needs to rely on the bids of the high marginal

[1]These markets were linked using large capacity transmission lines, with the exception of Queensland, which participated under the NEM market rules but was not physically connected to the NEM until February 2001.

[2]For example, suppose Generator A bids 10,000MW at -\$100/MWh and 5,000MW at \$40/MWh and Generator B bids 5,000MW at \$20/MWh. If the prevailing demand for the five minute period is 12,000MW, Generators A and B will be dispatched to supply 10,000MW and 2,000MW respectively. The dispatch price will be \$20/MWh.

[3]The NEM is therefore a continuous-trading market that is not be confused with day-ahead call markets which operate in some European markets, such as Germany, France and the Netherlands, in which prices are quoted for delivery on each hour of the following day (see, for example, Huisman *et al.*, 2007).

cost of production generators in order to satisfy demand. These extreme price events, or "price spikes", are particularly hazardous to electricity retailers who buy from the NEM at the spot price and sell to consumers at a price that is heavily regulated (Anderson *et al.*, 2006). Consequently, improving the understanding of factors contributing to the occurrence of extreme price events, as well as the accurate forecasting of these events, is crucial to effective risk management in the retail energy sector. It is this forecasting problem that is the central concern of this paper.

Traditional approaches to modeling electricity prices fall, broadly speaking, into three categories namely, traditional autoregressive time series models, nonlinear time series models with particular emphasis on Markov-Switching models and continuous-time diffusion or jump-diffusion models.[4] These models all share the common feature that they aim to characterize the trajectory of the spot price or return across time.

Taken at face value, these models appear to differ in their treatment of price spikes. Traditional autoregressive time-series models treat spikes through the use of thresholds (Misiorek *et al.*, 2006), Bernoulli and Poisson jump processes (Crespo Cuaresma *et al.*, 2004; Knittel and Roberts, 2005) and a variety of heavy tailed error processes (Contreras *et al.*, 2003; Byström, 2005; Garcia *et al.*, 2005; Swider and Weber, 2007; Panagiotelis and Smith, 2008). Markov-switching models incorporate spikes by proposing different regimes, at least one of which is consistent with a state of system stress in which a spike is more likely to occur (de Jong and Huisman, 2003; Huisman and Mahieu, 2003; Weron *et al.*, 2004; de Jong, 2006; Kosater and Mosler, 2006; Bierbrauer *et al.*, 2007; Becker *et al.*, 2007). Diffusion models of the spot price introduce spikes through the addition of a Poisson jump component with either a constant intensity parameter (Weron *et al.*, 2004; Cartea and Figueroa, 2005) or a time-varying intensity parameter (Escribano *et al.*, 2002; Knittel and Roberts, 2005) in which the intensity of the jump process is typically a linear combination of deterministic seasonal and/or diurnal factors. Within the jump diffusion approach, Chan, Gray and van Campen (2008) separate price volatility into jump and non-jump components and then explore whether volatility forecasts can be improved by explicitly incorporating the jump and non-jump components of the total variation.

All these models essentially regard price spikes as a memoryless process with intensity that is independent of its history. There is evidence, however, to suggest that the intensity of the spiking process is not homogeneous, nor is it driven by deterministic factors alone. Indeed, there appears to be a significant historical component which is important in explaining the intensity of the spiking process (Christensen *et al.*, 2009). This paper complements the existing econometric literature by focusing exclusively on forecasting extreme price events rather than

[4] Non-traditional approaches to forecasting price movements in electricity markets include artificial neural networks or other data-mining techniques (see, for example, Zhao *et al.* (2007) and Xu and Nagasaka (2009)). Another approach is to focus on forecasting value-at-risk in electricity markets (Chan and Gray, 2006) rather than providing forecasts of the actual spot price.

on the trajectory of price. The sequence of such events is treated as a realization of a discrete point process and an important characteristic of the econometric model is that it embeds the information content of previous spikes. This dependence is achieved by way of a nonlinear variant of the autoregressive conditional hazard (ACH) model originally developed by Hamilton and Jordà (2002). Although the econometric model is developed and applied in the context of a continuous-trading market, as it focuses on the forecasting of extreme events and not on modeling the trajectory of electricity prices, it lends itself to adaption for treating extreme events in day-ahead call markets as well.

The empirical work is implemented using data from four regions of the NEM. The ACH framework permits simultaneous analysis of both the historical dependence of the spike rate, as well as the influence of load and temperature factors. It is found that the occurrence of extreme price events displays significant persistence and historical dependence even after taking load and temperature factors into account. Additionally, spikes are found to be much more likely to occur when load is comparatively high, as well as during times of extremes in temperature, in accordance with the usual explanation for spikes outlined earlier. Importantly, the ACH model is found to provide superior half-hour ahead forecasts of extreme price events by comparison with forecasts made by an unconditional model that is broadly consistent with the type of memoryless electricity-pricing model often employed in the literature. It should be noted that price spikes are a generic feature of electricity markets worldwide (Escribano, *et al.*, 2002) and therefore the research reported here will be of general interest and applicability, notwithstanding the fact that this paper is set within the Australian institutional framework.

The plan of the paper is as follows. Section 2 outlines the ACH framework, its relation to ACD processes and its extension to capture nonlinearities in the duration process. Section 3 deals with data and section 4 with estimation, and a discussion of the results. In section 5, half-hour ahead forecasts of the ACH model are compared with forecasts made by a model consistent with much of the electricity-pricing literature. Section 6 concludes.

2 The Econometric Model

The econometric model outlined in this section specifies the probability of observing an event as a function of the history of a process and a set of exogenous variables. Additional factors contributing to the severity of the observed event are also analyzed. The basic framework adopted in this research is that proposed by Hamilton and Jordà (2002), modified following the work of Engle and Dufour (2000) and Fernandes and Grammig (2006).

2.1 Autoregressive Conditional Duration

Prior to the development of the actual empirical model used in this paper, its historical antecedents are reviewed briefly. Consider an orderly marked point process where events occur at random times $t_0 < t_1 < \ldots < t_n < \ldots$, with t_{i-1} representing the time at which the ith event occurred. Let $N(t)$ represent the number of events that have occurred in the interval $(t_0, t\,]$ and let $\mathcal{H}_t = \{t_0, t_1, \ldots, t_{N(t)} | N(t)\}$ represent the history of the process observed over $[t_0, t\,]$. The conditional intensity function is defined as

$$\lambda(t\,|\mathcal{H}_t) = \lim_{\Delta t \to 0^+} \frac{\text{Prob}(N(t+\Delta t) > N(t)|\mathcal{H}_t)}{\Delta t}$$

so that

$$\mathbb{E}[N(t+\Delta t) - N(t)|\mathcal{H}_t] = \lambda(t\,|\mathcal{H}_t)\Delta t + o(\Delta)\,.$$

The econometric analysis of point processes typically deals with an appropriate parametrization of λ with the aim of determining which exogenous variables, if any, drive the intensity of the process and the extent to which this intensity is influenced by its history. In the absence of memory, the process may be treated as a Poisson process with intensity dependent on exogenous variables alone. On the other hand, if the process exhibits memory, the modelling exercise becomes more interesting because it must now address the additional question of how to incorporate the history of the process (see, for example, Engle and Russell, 1998).

The autoregressive conditional duration (ACD) framework treats the conditional intensity of the process as a function of the duration between previous events. Let $u_{N(t)} = t_{N(t)} - t_{N(t)-1}$ represent the most recently observed duration between events. The conditional expectation of the next duration, *i.e.* the elapsed time from the most recent event to the next event, is

$$\psi_{N(t)+1} = \mathbb{E}(u_{N(t)+1}|\mathcal{H}_t;\theta)\,, \tag{1}$$

where θ is a vector of parameters. The ACD model of Engle and Russell (1998) is then

$$\psi_{N(t)+1} = u_{N(t)+1}\epsilon_{N(t)+1}\,,$$

in which the ϵ are i.i.d. non-negative random variables with unit mean. The conditional intensity function is given by

$$\lambda(t\,|\mathcal{H}_t) = \lambda_0\left(\frac{t - t_{N(t)}}{\psi_{N(t)+1}}\right)\frac{1}{\psi_{N(t)+1}}\,, \tag{2}$$

in which $\lambda_0(\cdot)$ is the quotient of the density function and survival function of ϵ.

A functional form for expression (1) and a distribution for the ϵ are required to fully specify the ACD model. Arguably the simplest formulation is the exponential ACD model of order (p, q) in which the ϵ are assumed to be i.i.d. exponentially-distributed random variables with unit mean and where the durations are modelled as the ARMA(p, q) process

$$\psi_{N(t)+1} = \omega + \sum_{j=1}^{p} \alpha_j u_{N(t)+1-j} + \sum_{j=1}^{q} \beta_j \psi_{N(t)+1-j} \,. \tag{3}$$

Stationarity of the duration process requires that $\omega > 0$, $\alpha_j \geq 0$ for $j = 1, \ldots, p$, $\beta_j \geq 0$ for $j = 1, \ldots, q$ and $\sum_{j=1}^{p} \alpha_j + \sum_{j=1}^{q} \beta_j < 1$. In terms of the model, the conditional expectation of the next duration is updated as events occur. In particular, when events occur in quick succession, the most recent lagged values of u are smaller, reducing the conditional expectation of the next duration. Similarly when the duration between events is comparatively large, the most recent lagged values of u are larger, increasing the conditional expectation of the next duration. Taking ϵ as exponentially-distributed means that $\lambda_0 = 1$ everywhere, so that the expression for the conditional intensity in equation (2) becomes

$$\lambda(t|\mathcal{H}_t) = \frac{1}{\psi_{N(t)+1}} \,.$$

This model has proved useful in the analysis of arrival times of stock trades (Engle and Russell, 1998; Engle, 2000) and foreign exchange trades (Engle and Russell, 1997). The basic ACD model has been extended in numerous ways (see, for example, Bauwens and Giot, 2000; Engle and Dufour, 2000; Zhang *et al.*, 2001; Bauwens and Veredas, 2004; Feng *et al.*, 2004; Engle and Russell, 2005; Fernandes and Grammig, 2006).

2.2 Autoregressive Conditional Hazard

The ACD model and its variants share the common property that they aim to model the interval between events when the underlying process is continuous in the sense that events can occur at any instant in time. There are, however, many processes in economics and finance that are fundamentally discrete, meaning that at most one event can occur within an interval of given fixed duration. In the context of the modeling problem addressed by this research, namely the incidence of price spikes in the Australian electricity market, the fixed interval of interest is half an hour and all transactions within this fixed interval are settled at the pool price for that interval. Consequently, spikes in the spot price of electricity provide one example of a situation in which there is no duration to be modeled in the sense of the ACD model.

In respect of the incidence of price spikes in the electricity market, the appropriate question is whether or not an event occurs in a given half hour. Consequently, it is necessary to think in terms of *conditional hazard*, defined by

$$h_{t+1} = \text{Prob}(N(t+1) > N(t)|\mathcal{H}_t) \,,$$

which represents the probability of an event occurring in the given interval conditioned on $\mathcal{H}_t$, the past history of events now interpreted in terms of the discrete process. Consistency between the continuous-time and discrete-time models requires the hazard of the discrete-time process to be asymptotically equivalent to the intensity of the continuous-time process as the interval length tends to zero. Hamilton and Jordà (2002) specify an autoregressive conditional hazard (ACH) model which they demonstrate is the discrete-time equivalent of the ACD model. The hazard function in this model is given by

$$h_{t+1} = \frac{1}{\psi_{N(t)+1}}\,, \tag{4}$$

where $\psi_{N(t)+1}$ is defined in equation (3).

Consistency between the discrete and continuous models is maintained for a Box-Cox transformation of the observed and expected durations. This property allows a richer parameterization of equation (3), similar to the Box-Cox ACD model introduced by Engle and Dufour (2000) which itself is a subset of the general family of ACD models proposed by Fernandes and Grammig (2006). In particular,

$$\psi^{\nu}_{N(t)+1} = \omega^* + \sum_{j=1}^{p} \alpha_j u^{\nu}_{N(t)+1-j} + \sum_{j=1}^{q} \beta_j \psi^{\nu}_{N(t)+1-j} \tag{5}$$

where $\nu > 0$. Equation (5) nests the original ACH specification ($\nu = 1$) and the ACH model in log-durations, obtained in the limit as $\nu \to 0^+$.

Equation (4) may be augmented to include the possible influence of a vector of exogenous variables, z_{t+1}, upon the conditional hazard by extending the specification of h_{t+1} to

$$h_{t+1} = \frac{1}{\Lambda(\exp(-\gamma' z_{t+1}) + \psi_{N(t)+1})}\,, \tag{6}$$

where γ is a vector of coefficients and the function Λ is chosen to ensure that h_{t+1} represents a probability. In this research, the link function proposed by Hamilton and Jordà (2002) is used, who also suggest that the constant term may be omitted from the specification of $\psi_{N(t)+1}$, in equation (3) or equivalently in equation (5), provided a constant term is included in z_{t+1} in expression (6).

To summarize, the final model for the investigation of price spikes in the four regions of the Australian electricity market comprises equations (5) and (6) with model parameters

$$\theta = (\gamma, \alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_q, \nu)\,,$$

which are to be estimated from sample data. Let X_t take the value 1 if an event occurs in the interval t and zero otherwise, then the conditional probability density function of X_t may be written as

$$\mathrm{Prob}(X_t = x_t | \mathcal{H}_{t-1}; \theta) = h_t^{x_t} (1 - h_t)^{1-x_t}\,.$$

In a sample of T intervals, the log-likelihood function is

$$\log L(\theta) = \sum_{t=1}^{T} x_t \log h_t + (1 - x_t) \log(1 - h_t)\,, \tag{7}$$

which may be maximized to obtain maximum likelihood estimates of the parameters θ.

2.3 Ordered Probit

It is often the case that associated with every event in X_t is the observed random variable Y_t, referred to as a mark, representing additional information associated with event t. In particular, one may wish to forecast the conditional distribution of the price at time t given a spike is forecast to occur. Following discussion with electricity market participants, the key issue regarding hedging price risk in the Australian electricity market is whether or not the spot electricity price is likely to exceed the strike price (A$300 per MWh) of a heavily-traded cap product. Therefore, in the context of the current forecasting problem, this mark represents a discrete measure of the amplitude of the price spike, although it should be recognized that other representations of the mark may be more appropriate in markets with different institutional structure and availability of derivatives products. The adoption of this measure of the amplitude of the price spike facilitates the use of an ordered probit model to forecast the marks.

In this application, the ACH and ordered probit components of the model share no parameters in common. The log-likelihood function for the entire problem is therefore additively separable, so that estimation of the parameters of each component may be performed separately.

3 Data

Data for the estimation period consists of a series of 111,648 half-hourly observations of the spot price and load in four Australian markets, namely New South Wales (NSW), Queensland (Qld), South Australia (SA) and Victoria (Vic). This data covers the period from 1 March 2001 to 30 June 2007. Although the National Electricity Market began operations on 12 December 1998, data prior to 1 March 2001 is discarded because all four markets were not physically connected before February 2001 and displayed significantly different characteristics pre- and post-connection. A further sample of three months (consistent with the duration of a standard electricity futures contract) spanning the period from 1 July 2007 until 30 September 2007 is reserved for evaluating the out-of-sample performance of the models and a derivatives trading strategy based on the forecasts of the spike probabilities. The data exhibit stylized properties typical of electricity prices in deregulated markets internationally (see, for example, Escribano *et al.*, 2002 and Geman and Roncorni, 2006; for the Australian market see Becker *et al.*, 2007).

Explanations for the occurrence of price spikes relate to the interaction of system demand and supply (see Barlow, 2002, and Geman and Roncorni, 2006). In short, demand for electricity is very inelastic, as the demand side is insulated from pool price fluctuations by retailers who buy electricity at the spot price and then sell the electricity to consumers at fixed rates. Electricity supplied under "normal" conditions is provided by traditional low-cost generators (coal-fired and nuclear generators). If the system becomes "stressed" due to increases in demand and/or reduction in supply, the spot price exceeds a threshold at which it becomes cost effective for generators with a higher cost of production (gas-fired and diesel generators) to compete with the low-cost generators. Prices in excess of this threshold will be thought of as "extreme price events" or "price spikes". Whilst the actual threshold used is market-specific, the argument for using a threshold to define extreme events is generic (see Mount *et al.*, 2006; Kanamura and Ōhashi, 2007).

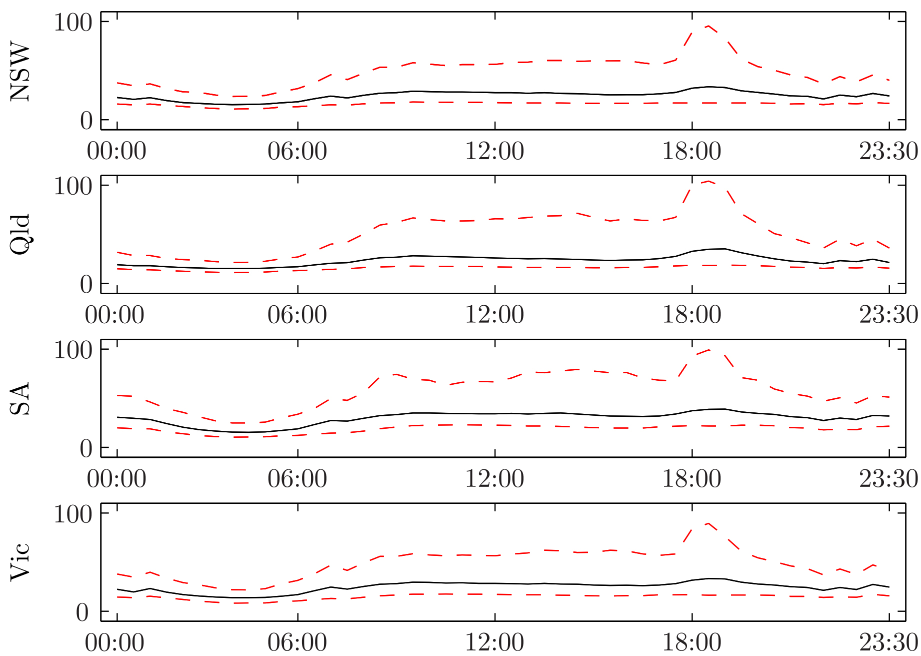

Figure 1: Plot of the median (solid line) and 10th and 90th percentile (dashed lines) spot prices by time of day.

Figure 1 shows the 10^{th}, 50^{th} and 90^{th} percentiles of the half-hourly spot electricity price for the four regions of the Australian market. It can be seen that spot prices fluctuate between \$20 and \$40 per MWh under "normal" conditions. The threshold defining an extreme price event in Australia is generally regarded as \$100/MWh which lies above the 90^{th} percentile of spot prices for each half hour of the day in all regions considered.[5] If the spot price exceeds this threshold,

[5]It is worth noting that other cutoffs were experimented with, namely a variety of percentiles of the unconditional distribution of the price series. The results were not materially affected by the threshold choice. Moreover, the threshold of \$100/MWh was deemed by market participants to be the most informative.

then a price spike is said to occur and the sequence of these spikes can be regarded as the realization of a discrete-time point process with the marks of the process representing the severity of the spikes. Two categories of price spikes are selected,[6] namely "mild" if $100 \leq P_t < 300$ and "severe" if $300 \leq P_t \leq 10,000$, where P_t is the spot price at time t. The \$300/MWh value is chosen because it is the strike price of heavily-traded cap products in the Australian market and the upper limit of \$10,000/MWh reflects the price ceiling imposed by the market regulator. The breakdown of spikes by region is shown in Table 1.

	NSW	Qld	SA	Vic
Mild	0.773	0.791	0.881	0.835
Severe	0.227	0.209	0.119	0.165
Total Events	3053	2707	5513	2753

Table 1: Proportion of extreme price events by category. "Mild" refers to prices between \$100/MWh and \$300/MWh. "Severe" refers to prices between \$300/MWh and the market cap of \$10,000/MWh.

The econometric model outlined in the preceding section may be applied to this marked point process to determine the factors driving price spikes. Note that Christensen *et al.* (2009) find that the intensity of the true process is significantly related to a historical component and that this persistence must be accounted for if the resulting econometric model is to be credible.[7] In this application, the persistence of interruptions to the supply side such as plant outages or failure of the transmission infrastructure can be regarded as stochastic events. The main assumption made here is that their effects will be primarily captured by the behaviour of the durations u and ψ that embody the memory of the point process. Of particular interest is the question of whether or not these durations are still significant in the presence of the other variables believed to determine extreme events, namely, demand-side variables like load and temperature that are included as exogenous variables, z_t, in the specification of the hazard function in equation (6).

Load directly represents contemporaneous demand because demand is inelastic and must be balanced with supply at each point in time. Recall that the regulatory framework insulates consumers from spot price fluctuations, with electricity retailers bearing the spot price risk. As a consequence, load may be regarded as exogenous. However, the series of half-hourly loads exhibit a trend in mean and volatility over the sample period and this nonstationarity must be taken into account. Therefore, the variable Load_t is constructed by de-trending the load at time t by the mean and standard deviation of the preceding years' worth of data. This has the effect of removing any trend in mean and volatility of the load while preserving obvious seasonal

[6] This choice was informed by correspondence with participants in the Australian electricity market.

[7] Christensen *et al.* (2009) provide a thorough investigation of the empirical features of electricity price spikes in the NEM.

fluctuations and abnormal load events.

Temperature variables are also expected to influence the occurrence of price spikes through their influence on demand and on transmission infrastructure. Daily temperature data were provided by the Australian Bureau of Meteorology, higher-frequency data being unavailable. To correct for the positive correlation between temperature and price in warm months, and the negative correlation between temperature and price in cool months, $\mathrm{T}_{\max,t}$ and $\mathrm{T}_{\min,t}$ represent the *daily* absolute deviations of the maximum and minimum temperatures from their average over the preceding 365 days. As a result, the variables $\mathrm{T}_{\max,t}$ and $\mathrm{T}_{\min,t}$ take the same values for all 48 half hour trading intervals on a given day. Of course, the regional markets are state-wide and substantial variations in temperature are observed within each region. To account for this as parsimoniously as possible, the temperature observations for the most populous city in each region were used following Knittel and Roberts (2005).[8]

The inclusion of the load and temperature variables in the model is potentially problematic for forecasting because a forecast of the point process at time t based on the information set at $t-1$, requires forecast values for each of the demand-side variables. However, temperature, and to a lesser extent load, effectively behave as deterministic variables and can be forecast for the next half-hour or day with a high degree of accuracy (see, for example, Ramanathan *et al.*, 1997). Consequently, the actual values of these variables at time t will be included as proxies for their forecast values.

The use of observed variables, particularly load, in the forecasting exercise introduces a potential distortion. To quantify the effect of using observed load as proxy for forecast load, a primitive forecasting scheme proposed by Weron (2006) is used as an alternative. This scheme requires that the forecast load for Saturdays, Sundays and Mondays at each point in time is simply the load recorded for the same day of the previous week; the forecast for Tuesday through Friday is given by the load of the previous day. In the NEM all participants have free access to this load data, so that this forecasting scheme is costless to implement.

4 Estimation

4.1 Estimating the ACH model

The parameters of the ACH model defined by equations (5) and (6) are estimated by maximum likelihood based on the log-likelihood function in expression (7), with standard errors computed

[8]Other methods of dealing with growth in level and variability of the load data and the changing direction of the relationship of the temperature data with price were investigated. This included removing a linear trend and linearly scaling the load data, and including the temperature data by season, rather than by absolute deviation from the preceding yearly average minimum or maximum temperature. The results were robust to the specification used.

using the typical sandwich procedure employed in quasi-maximum likelihood estimation. The variable z_t in expression (6) consisted of an intercept and the three variables described earlier, namely $\mathrm{T}_{\max,t}$, $\mathrm{T}_{\min,t}$ and Load_t.

Table 2 shows the ACH$(1,1)$ model estimated with all explanatory variables included in z_t. The coefficient of Load_t is positive and significant everywhere, indicating that a higher load reduces the denominator of expression (6), implying a higher hazard than otherwise. Abnormal maximum temperatures significantly raise the probability of extreme price events in all regions, with the exception of SA in which no effect is detected. The marginal effect of abnormal minimum temperatures only appears to raise the probability of a spike in SA (no effect is detected in the other regions). When the model was re-estimated with the observed load replaced by the load forecast (estimates using forecast loads are omitted throughout for brevity) the only material difference in the estimates was that abnormalities in maximum temperatures have no significant effect on spike occurrence in SA.

Importantly, however, the parameters embodying the memory or persistence of the spiking process, namely, the coefficients on u and ψ remain highly significant notwithstanding the inclusion of these demand-side variables. Additionally, in line with some specifications of the Poisson jump intensity popular in the literature, the model was re-estimated using both the current regressors as well as various dummy variables for diurnal, daily and seasonal factors. This typically added little to the analysis, with the vast majority of the dummy variables remaining insignificant in the presence of the load and temperature factors. Importantly the duration factors u and ψ were still highly significant in the presence of these variables.[9] Moreover, the parameter ν varies greatly across regions, from a near log specification in SA to a super-linear specification in Qld, and the linear $\nu = 1$ and logarithmic $\nu = 0$ specifications are rejected in all regions based on likelihood ratio criteria. This suggests that the original linear ACH formulation is inadequate in this context, and may need to be rethought generally unless one has prior justification for a linear ARMA duration process.

These results imply that an effective econometric model for extreme events in electricity prices must account in some way for persistence in the spiking process. This result is significant not only in the context of the current model, but also has important implications for diffusion models of spot electricity prices that attempt to incorporate jumps. When a diffusion processes is used to model the spot price, spikes are usually modeled through the addition of a Poisson jump component with either a constant intensity parameter (Weron *et al.*, 2004; Cartea and Figueroa, 2005) or a time-varying intensity parameter (Escribano *et al.*, 2002; Knittel and Roberts, 2005) in which the intensity of the jump process is typically a linear combination of seasonal, weekday and diurnal effects. A more general conclusion is that any model that drives the intensity of

[9]The results obtained by estimating these variations are omitted for the sake of brevity.

the spiking process by means of deterministic factors only and fails to capture the inherent autoregressive properties of the intensity may fail to characterize accurately the price process, precisely because they implicitly assume that the occurrence of price spikes is a memoryless process.

Variable	Parameter	NSW	Qld	SA	Vic
Constant	γ_0	-6.0563	-4.9352	-5.3748	-6.0496
		(0.1926)	(0.0328)	(0.0634)	(0.0533)
Load_t	γ_1	2.5463	2.8329	1.8809	2.5013
		(0.1337)	(0.0392)	(0.0428)	(0.0129)
$\text{T}_{\text{max},t}$	γ_2	0.1914	0.6075	-0.0210	0.3058
		(0.0225)	(0.0162)	(0.0093)	(0.0027)
$\text{T}_{\text{min},t}$	γ_3	-0.0446	-0.0538	0.0898	-0.0375
		(0.0435)	(0.0178)	(0.0096)	(0.0057)
$u_{N(t)}$	α_1	0.0310	0.0141	0.0517	0.0298
		(0.0104)	(0.0007)	(0.0001)	(0.0007)
$\psi_{N(t)}$	β_1	0.9522	0.9474	0.9481	0.9553
		(0.0021)	(0.0002)	(0.0000)	(0.0001)
	ν	0.4888	1.3425	0.0216	0.6993
		(0.1672)	(0.0313)	(0.0004)	(0.0251)
log likelihood		-7498.9	-8234.1	-8013.3	-5993.2

Table 2: ACH$(1,1)$ estimates for an unconditional hazard varying with the load, temperature and time variables. Standard errors are shown in parentheses.

One possible indicator of model consistency is whether or not the mean hazard rate evaluated using the maximum likelihood estimates of the model parameters is equal to the observed mean rate of the process. The estimated mean hazards of 0.023, 0.030, 0.027 and 0.020 for NSW, Qld, SA and Vic compare favourably with the observed mean rates of 0.022, 0.021, 0.026 and 0.017, respectively. As a robustness check of the order of the memory properties implied by the chosen values of p and q in an ACH(p,q) model, other versions of the model were estimated in which the orders of the ACH process were allowed to vary. These included limited-memory models, namely the ACH$(1,0)$ and ACH$(2,0)$ specifications, both of which were rejected in terms of model fit. Moreover, the significance of $\widehat{\alpha}_1$ in Table 2 shows that an ACH$(1,1)$ form is preferred over an ACH$(0,1)$ form. Higher-order values of q were found to provide modest, if any, improvement over the case $q = 1$.

4.2 Estimating the Probit model

As outlined earlier, only two categories of price spike are of interest in this research, namely when the price falls between \$100 and \$300 (mild) or between \$300 and the market cap of \$10,000 (severe). In the Australian market, a price of \$100 represents the level at which "peaking" generators with a high marginal cost of production find it feasible to compete with "baseload" generators. The \$300 price level is the cap for an extensively-used derivative product and \$10,000 is the regulated maximum market price. It is anticipated that the variables relating to load and temperature ought to influence not only the occurrence of extreme price events, but also the severity of the events. Therefore, the explanatory variables included in the probit analysis are the same exogenous variables as are used to vary the baseline specification of the hazard rate.

Results of the maximum likelihood estimation of the probit model are exhibited in Table 3, where standard errors are again calculated using the typical sandwich form. In accordance with results of previous studies (Mount *et al.*, 2006; Kanamura and Ōhashi, 2007), the coefficients of load are positive and significant, indicating that higher values of load are associated with more severe extreme price events. Surprisingly, unlike the ACH model of the rate at which price spikes occur, extreme maximum and minimum temperatures are found to have no significant impact on the severity of the price spikes in any region, with the exception of extremes in maximum temperatures having a negative effect upon the event severity.[10] These results are not expected, as the standard explanation for price spikes suggests that these factors should contribute positively towards spike severity.

Variable	Parameter	NSW	Qld	SA	Vic
Constant	w_0	-2.4062 (0.1145)	-1.6329 (0.0479)	-1.2518 (0.0090)	-1.6205 (0.0167)
Load_t	w_1	0.7082 (0.0829)	0.3052 (0.0383)	0.2458 (0.0127)	0.3974 (0.0106)
$\text{T}_{\max,t}$	w_2	0.0714 (0.0771)	0.0556 (0.0455)	-0.0397 (0.0115)	0.0065 (0.0105)
$\text{T}_{\min,t}$	w_3	-0.0136 (0.0865)	0.0332 (0.0539)	-0.0046 (0.0100)	-0.0181 (0.0160)
log likelihood		-1031.6	-1120.0	-936.5	-719.3

Table 3: Probit estimates for the two categories of spike using the same load and temperature variables.

5 Forecasting

To assess the forecasting performance of the ACH model, the following procedure is adopted. The parameters of the model are estimated using the sample period data (1 March 2001 to 30 June 2007). The model is then used to provide half-hourly, one-step-ahead forecasts from

[10] When the model was re-estimated with the forecast load replacing observed load, only maximum temperatures in Qld and SA were positively associated with the spike severity.

a rolling origin of the probability of a price spike for every half-hour interval in the forecast period 1 July to 30 September 2007. Rolling the forecast origin forward in order to generate the next half-hourly forecast potentially provides an extra data point for parameter estimation. For a number of reasons, however, the model parameters are not re-estimated. *First*, the spot electricity price is widely regarded as a trend stationary process. *Second*, even by the end of the forecast period the additional sample size is negligible compared to the length of the original estimation period. *Third*, the sheer size of the estimation sample, 111,648 half-hourly observations, makes estimation of the model a non-trivial exercise.

The choice of half-hour ahead forecasts is driven by the fact that the NEM operates as a continuous-trading market up to each half-hour interval. In the event of a price spike being forecast for the next half-hour interval, effective risk management requires an immediate action by retailers to mitigate the effects of the potential price spike. Retailers can reduce their reliance on the pool to meet their demand by activating the standby capacity that they may have available. Both hydro-electrical and gas-fired peaking plants can be brought from an idle state to full capacity in half an hour. If this physical response is not available, an alternative strategy is to use the futures market which trades in real time. An illustration of the use of these half-hour ahead forecasts to manage price risk using the futures market is provided in Section 5.4.

5.1 A simple benchmark

It has been established that the rate of occurrence of extreme price events depends in part upon factors relating to load and temperature effects as well as the history of the process. In particular, the hazard rate is found to depend critically upon factors measuring the recent intensity of extreme price events, namely the durations and expected durations between neighbouring events. This ability to model clustering in the spiking process means that the ACH model should produce forecasts of event probabilities that are superior to those made by models that exclude a historical component. Therefore in order to assess the forecasting performance of the preferred model, a benchmark model is required in which the variability of the hazard is attributable to exogenous variables alone.

The logit model

$$p_{t+1} = \frac{1}{1 + \exp(-\xi' z_{t+1})} \tag{8}$$

provides a straightforward basis for comparative forecast evaluation, where p_{t+1} is the one-step-ahead forecast probability of an event occurring at time $t+1$ and z_{t+1} is a vector of exogenous variables. This specification of the hazard ignores any information contained in the history of the process, yet incorporates the variables z_{t+1} in a functional form similar to that of the ACH model in expression (6). The log-likelihood is analogous to the log-likelihood function for the ACH model with the primitive forecast probability p_t replacing the conditional hazard h_t in expression (7). As argued previously for the ACH model, when forecasting events at time t conditional on information at time $t-1$, actual rather than forecast values for the temperature variables z_t are used, and both observed and primitive forecasts of load are considered separately. This ensures that both the logit and the ACH model make forecasts using the same information set, modulo the history of the process itself which is embodied only in the ACH model.

Results from the estimation of the logit model are shown in Table 4, and are roughly consistent with the ACH model. The estimated coefficients of Load_t are positive and significant in all regions. Moreover, abnormalities in maximum temperature are associated with larger probabilities of price spikes in all regions except SA. The estimated coefficients of $\mathrm{T}_{\mathrm{min},t}$ in the unconditional model are insignificant in Qld and NSW and positive and significant in SA and Vic, indicating deviations in minimum temperature from its expected value are also associated with a greater probability of price spikes in these regions. Estimates with the true load replaced by the primitive load forecast are not materially different. A standard Vuong (1989) test for non-nested models is seen to favor strongly the ACH specification.[11]

Variable	Parameter	NSW	Qld	SA	Vic
Constant	ξ_0	-5.9487 (0.0599)	-5.4145 (0.0519)	-5.3412 (0.0511)	-5.9446 (0.0616)
Load_t	ξ_1	1.7321 (0.0330)	1.1611 (0.0288)	1.4365 (0.0292)	1.4770 (0.0349)
$\mathrm{T}_{\mathrm{max},t}$	ξ_2	0.1356 (0.0078)	0.2348 (0.0093)	0.0016 (0.0072)	0.0543 (0.0069)
$\mathrm{T}_{\mathrm{min},t}$	ξ_3	-0.0066 (0.0116)	-0.0137 (0.0076)	0.0765 (0.0076)	0.0530 (0.0111)
log likelihood		-7895.8	-9191.7	-8198.7	-6510.7
Vuong stat.		68.9731	41.3181	89.6020	36.5440

Table 4: Estimates for the logit model used to produce benchmark forecasts of price spikes. The Vuong test statistic used is asymptotically $N(0,1)$ under the null that both the ACH and logit models offer equivalent descriptions of the data, and diverges to $+\infty$ in T if the ACH specification is a better description than the logit specification.

5.2 The ACH and Probit models

For an informal comparison of the ACH model against the benchmark model, Figure 2 shows the forecast half-hourly probabilities of a price spike implied by the ACH model and the benchmark model alongside the observed extreme events. It is readily illustrated that the ACH model yields substantially higher forecasts of spike probabilities during episodes of extreme price events than

[11] The conclusion of the test was robust to information criteria-based augmentations.

does the simple benchmark model. This is to be expected: the ACH model is able to adapt its conditional forecasts during episodes of stress, unlike the memoryless benchmark model. A comparison of the number of actual and predicted events over the forecast period is displayed in the upper panel of Table 5. Events are said to be forecast correctly if both the forecast probability calculated at time t for an event at time $t+1$ exceeded a threshold of 0.50 and an event actually occurred at time $t+1$. The models were said to trigger false alarms if the forecast probability exceeded 0.50 but an event did not occur at time $t+1$.

On the basis of this primitive metric, the accuracy of the ACH model in forecasting price spikes varies from a low of 0% in SA to a high of 48% in NSW. This compares very favourably with the forecasts from the benchmark model, which failed to identify accurately any price spikes in Qld, SA and Vic and only 8% in NSW. Similar forecasts of spike probabilities were made using the forecast load rather than the observed load: the ACH model correctly forecast 0% of events in SA through to 52% of events in NSW, whereas the benchmark correctly forecast no events in Qld, SA or Vic and only 5% in NSW.

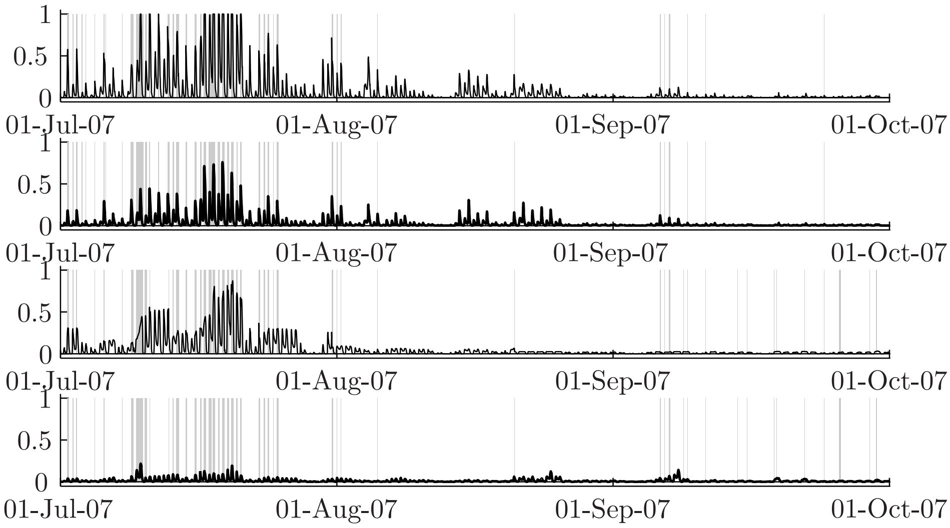

Figure 2: ACH$(1,1)$ forecast probabilities and benchmark logit forecast probabilities for the first three months following the estimation period. Extreme price events are indicated by a grey vertical bar. The top panel shows the ACH forecast probabilities for NSW, with the second panel showing the benchmark forecast probabilities for NSW. The third panel shows the ACH forecast probabilities for Qld, with the bottom panel showing the benchmark forecast probabilities for Qld. Similar results are obtained for SA and Vic.

For completeness, the lower panel of Table 5 displays the accuracy of the probit model when forecasting the intensity of the one-step-ahead events. Because, by construction, the probit component of the model is independent of the ACH component, these figures refer to all events that occurred over the forecast period, rather than just the events that were forecast correctly by the ACH model. It is immediately apparent that the probit model performs poorly in the prediction of severe events. One possible explanation for the disappointing performance of the probit component of the model is the comparatively small number of severe events in the sample, making precise estimation of the parameters of the model difficult. Alternatively, the behavior of the spikes in the forecast period may just be atypical of the pattern observed in the estimation sample.

		NSW	Qld	SA	Vic
Events		299	267	450	451
ACH	Correct	144	59	0	188
	False Alarms	34	26	0	68
Uncond.	Correct	23	0	0	0
	False Alarms	0	0	0	0
Mild	Observed	270	257	442	405
	Correct	254	257	442	405
Severe	Observed	29	10	8	16
	Correct	11	0	0	0

Table 5: The upper panel shows the total number of extreme price events, events correctly predicted and false alarms triggered for the ACH$(1,1)$ and unconditional models. The lower panel shows the number of extreme price events that were "mild" and "severe" over the forecast period, and the corresponding number categorized correctly by the probit model.

5.3 Asymmetric loss

A comparison of the benchmark and ACH models based on a variety of loss functions is now undertaken. For each model in each period of the forecast sample, the forecast probability of a price spike is compared to the actual outcome x_t, taking the value 0 if no event occurs and 1 if an event occurs, and the forecast errors are computed, namely $x_t - h_t$ in the case of the ACH model and $x_t - p_t$ for the benchmark model. Following the suggestion of Rudebusch and Williams (2009), the error norms for assessing the forecasting performance of these models are taken to be the mean absolute error (MAE), the root mean square error (RMSE) and the log-probability score error (LPSE). The log-probability score error is calculated as

$$\text{LPSE} = -\frac{1}{t_1 - t_0 + 1} \sum_{t=t_0}^{t_1} (1 - x_t) \log(1 - h_t) + x_t \log h_t \,,$$

where t_0 and t_1 denote the start and end of the forecast period, respectively, x_t takes the value 1 if an extreme event occurred at time t and 0 otherwise, and h_t (or p_t) is the forecast hazard (or benchmark probability) for time t.

It is important to remember that price spikes are particularly damaging to energy retailers who buy electricity at the unregulated spot price but sell at the heavily-regulated retail price. Consequently, failure to forecast a price spike is more detrimental to profit than forecasting a spike which does eventuate. Any forecast evaluation must therefore reflect this market reality. Following Anderson *et al.* (2006), a simple adjustment is used to reflect the asymmetric nature of the retailers' hedging problem. This adjustment requires that a higher weighting, say $(1+\kappa)$, be assigned to the absolute errors made in half hours in which extreme events occur and a lower weighting, $(1-\kappa)$, be assigned to half hours where no extreme event occurs. The asymmetric loss score is calculated as

$$\text{Asym.} = \frac{1}{t_1 - t_0 + 1} \sum_{t=t_0}^{t_1} \left(x_t(1+\kappa) + (1-x_t)(1-\kappa) \right) |x_t - h_t| \, ,$$

where h_t is replaced by p_t when assessing the efficacy of the benchmark model. In the results reported here, the value of κ is taken to be 0.5 so that the failure to predict an actual spike is penalized at three times the rate of a false alarm.[12]

	NSW	Qld	SA	Vic
	Using Actual Load			
MAE	0.0777	0.0777	0.1070	0.1060
RMSE	0.1914	0.1931	0.2999	0.2335
LPSE	0.1364	0.1318	0.3382	0.1836
Asym.	0.0734	0.0799	0.1492	0.1084
MAE	0.0743	0.0686	0.1078	0.1082
RMSE	0.2163	0.2346	0.3072	0.3026
LPSE	0.1570	0.1984	0.3640	0.3346
Asym.	0.0915	0.0923	0.1525	0.1512
	Using Forecast Load			
MAE	0.0978	0.0790	0.1087	0.1185
RMSE	0.2045	0.1958	0.2871	0.2332
LPSE	0.1523	0.1365	0.2778	0.1796
Asym.	0.0804	0.0831	0.1454	0.1146
MAE	0.0777	0.0701	0.1098	0.1086
RMSE	0.2161	0.2320	0.3045	0.3011
LPSE	0.1529	0.1889	0.3365	0.3184
Asym.	0.0936	0.0923	0.1526	0.1509

Table 6: Errors in forecast probabilities of extreme price events. Upper values in each panel are calculated from forecasts made using the ACH model, lower values in each panel are calculated from forecasts made using the benchmark model.

[12]The conclusions are insensitive to the value of κ used. The conclusions are also insensitive to using squared error in place of absolute error in the asymmetric loss function.

The results of this comparative exercise are displayed in Table 6. The ACH model forecasts with lower RMSE and LPSE than the benchmark model in all regions, and also with lower MAE in SA and VIC, when the observed load is used in forecasting spike probabilities. The most dramatic difference in forecast error between the ACH and benchmark models is recorded by the LPS measure, which Rudebusch and Williams (2009) suggest is the most appropriate for evaluating forecast probabilities. The ACH model also achieved lower errors using the asymmetric metric. Importantly, the superior forecast performance (at least in terms of these error metrics) of the ACH model over the benchmark model persists when the observed load is replaced with the primitive load forecast. This suggests that the results reported here are not merely driven by the use of actual load, a variable which may not be made public quickly enough to generate real-time, half-hour ahead forecasts.

5.4 A simple trading scheme

As noted earlier, the forecast horizon of three months used for forecast evaluation is chosen to correspond to the duration of a typical futures contract in the electricity market. Consequently, to complement the results of the forecast error comparison presented previously, the forecasts generated by the model can be used to explore the profitability of an informal trading scheme based on electricity futures contracts. The results of this exercise should be interpreted more as an illustration of the forecast performance of the ACH and benchmark models than evidence of a profitable futures trading strategy as the experiment suffers from a number of shortcomings. In particular, no intra-day futures prices are available so synthetic contracts are priced artificially. In addition, transaction costs are ignored (though conversation with market participants suggested that these are minor).

A quarterly futures contract is available in the Australian electricity market which fixes the price of electricity to the retailer for the life of the contract. Specifically, at time t during the life of the contract, the hedged price in terms of the futures contract is calculated as the time-weighted average of the following components:

(i) the mean of the actual spot electricity price for each half hour from the start of the contract to the current time t, and

(ii) the mean of the consensus of analysts' forecasts of price for each half hour for the remainder of the contract.

As no futures prices or consensus forecasts are publicly available, synthetic futures contracts are priced by taking the consensus forecast of price to be the average price for the same half hour on the same weekday in the same month for the previous five years for the relevant region.

The simple trading strategy proposed here is as follows. If at time $t-1$ the one-step-ahead probability of a price spike at time t exceeds a threshold probability of 0.5, the futures contract is entered into. The contract is closed out at time $t+k$ provided the forecast probability of a spike exceeds the threshold in each interval up to time $t+k$ but falls below threshold at time $t+k+1$. The return to this strategy is therefore the difference between the actual pool price and the hedged price specified in terms of the futures contract.

Implementing this trading scheme in the NSW market over the out-of-sample period using a threshold probability of 0.5 resulted in a return over the period of 21.47%. To compare the significance of this return to the distribution of returns generated using the benchmark model, $10,000$ samples of the length of the forecast period were drawn from the $U[0,1]$ distribution. For each sample, a spike is forecast in a given half-hour if the benchmark probability of a spike exceeds the random draw for that interval. This ensures that the distribution of simulated spikes matches that implied by the benchmark model. The trading strategy was implemented for each sample using these forecasts. The 99^{th} percentile return to this strategy was 14.53% over the same period indicating that using the futures market as a hedge based on the forecasts of the ACH model has the potential to provide significant returns. Implementing the strategy in Qld, SA and Vic gave returns of 8.02%, 0% (no trades occurred) and 24.22%, whereas the 99^{th} percentiles computed in terms of the unconditional forecasts were 6.21%, 2.80% and 5.87%, respectively. Similar results were obtained using the primitive load forecast in place of actual load. With the exception of SA, the outcome of this simple simulated trading scheme provides additional evidence of the usefulness of the ACH model in forecasting extreme events in electricity markets.

6 Conclusion

Accurate forecasting of extreme price events is of great importance for risk management in the electricity sector. The overwhelming majority of electricity-pricing models are adaptations of popular models for price or returns from the financial econometrics literature that have been augmented to capture the idiosyncratic time-series properties of electricity prices, with varying degrees of success. By contrast, this paper focuses solely on the forecasting of extreme price events, the occurrence of which is treated as a realization of a discrete-time point process. An ACH framework is used to analyze the drivers of the process and to forecast the probability of extreme price events occurring in real time. Abnormal loads were found to have a significant impact upon the probability of a price spike and on the severity of the spike, and temperature extremes were found to influence the rate at which spikes occurred, but not their severity. Importantly, stochastic factors capturing the history of the process were found to be significant in explaining the occurrence of extreme price events. Specifically, durations between price spikes were found to depend nonlinearly on previous expected and observed durations.

The ACH model is shown to provide rolling half-hour ahead forecasts of price spikes that are superior to forecasts made on the same set of exogenous information using a memoryless model. In addition, the returns generated from a simple synthetic futures trading scheme based on the one-step-ahead forecast probabilities of the ACH model provide further evidence of the strength of the model in forecasting electricity price spikes.

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