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Modelling Price Spikes in Electricity Markets – the Impact of Load, Weather and Capacity

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Abstract

We examine the impact of explanatory variables such as load, weather and capacity constraints on the occurrence and magnitude of price spikes in regional Australian electricity markets. We apply the so-called Heckman correction, a two-stage estimation procedure that allows us to investigate the impact of the considered variables on extreme price observations only, while correcting for a selection bias due to non-random sampling in the analysis. The framework is applied to four regional electricity markets in Australia and it is found that for these markets, load, relative air temperature and reserve margins are significant variables for the occurrence of price spikes, while electricity loads and relative air temperature are significant variables to impact on the magnitude of a price spike. The Heckman selection model is also found to outperform standard OLS regression models with respect to forecasting the magnitude of electricity price spikes.

Keywords*: Electricity Markets, Price Spikes, Selection Bias, Inverse Mills Ratio, Heckman selection model.*[1]

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1. Introduction

In recent decades, many countries have transformed the electricity power sector from monopolistic, government controlled systems into deregulated, competitive markets. Like other commodities, electricity is now traded under competitive rules using spot and derivative contracts (Harris, 2006). Electricity prices are far more volatile than other commodity prices, as pointed out by e.g. Eydeland and Wolyniec (2012), Huisman (2009) or Weron (2006). The volatility of electricity, measured by daily standard deviation of returns, can be as high as 50 percent, while the maximum volatilities of stocks are usually lower than 4 percent (Weron 2000). Therefore, the risk of extreme outcomes in electricity spot markets is of significant concern to market participants.

Electricity prices often exhibit unique behaviour compared to other commodity markets. Typical features include mean-reversion, seasonality, extreme volatility and so-called price spikes (Bierbrauer et al., 2007; Higgs and Worthington, 2008; Huisman et al., 2007; Janczura and Weron, 2010; Kanamura and Ohashi, 2008; Lucia and Schwartz, 2002). The latter usually describe abrupt, short-lived and generally unanticipated extreme changes in the spot price and can be considered as one of the most pronounced features of electricity spot markets. Despite their rarity, spikes account for a large part of the total variation of changes in the spot price and are therefore an important component of the risk faced by market participants. Spikes are also a key reason for designing derivatives contracts such as futures and options that have been introduced to allow electricity buyers and sellers to hedge against extreme price movements in the spot market (Anderson, 2007; Shawky et al., 2003). For example, in Australia, next to yearly and quarterly futures contracts, also option contracts or so-called '$300 cap products' are traded in the ASX Australian Electricity Futures and Options Market. For these contracts, the payoff is determined based on both the frequency and magnitude of observed half-hourly price spikes during a calendar quarter. To evaluate these instruments accurately and to facilitate price spike risk management, it is necessary to understand the impacts of different factors on the occurrence and magnitude of price spikes.

From a modelling perspective, price spikes are one of the most serious reasons for including discontinuous components in econometric models of electricity price dynamics. The literature suggests a variety of approaches how to achieve this, including, for example, autoregressive time-series models with thresholds (Misiorek et al., 2006), mean reverting jump-diffusion models (Cartea and Figueroa 2005, Clewlow and Strickland, 2000; Geman and Roncoroni, 2006, Knittel and Roberts, 2005) or Markov-switching models incorporating spikes by proposing different price regimes (Becker et al., 2007; Bierbrauer et al., 2007; de Jong, 2006; Huisman and Mahieu, 2003; Kanamura and Ohashi, 2008; Kosater, 2008; Weron et al., 2004).

Factors explaining the large variation of electricity prices in general, and the occurrence of price spikes in particular, have also been analysed in a number of studies, see, for example, Escribano et al. (2002), Huisman (2008), Kanamura and Ohashi (2007, 2008), Knittel and Roberts (2005), Kosater (2008), Mount et al. (2006).

Escribano et al., (2002) and Knittel and Roberts (2005) suggest a jump-diffusion model with time-varying intensity parameter, where the intensity of the jump process is modelled as being dependent on deterministic seasonal and diurnal factors. Kanamura and Ohashi (2007) provide a structural model for electricity prices taking into account the nonlinear relationship between supply and demand in the market and spot electricity prices. In particular they focus on modelling the relationship between demand and occurring price spikes by formulating the supply function as a hockey-stick shaped curve and by incorporating the demand seasonality explicitly. Mount et al. (2006) confirm the hockey stick shape of the electricity supply curve and argue that supply is elastic when demand is lower than a certain threshold, but when demand exceeds this threshold, supply is virtually infinitely inelastic, what leads to price spikes. Due to the different phases of price behaviour for electricity prices, the authors suggest to use a regime-switching model with two different states where the price process itself as well as the transition probabilities between the regimes are dependent on explanatory variables such as demand and the reserve margin. Kanamura and Ohashi (2008) follow a similar approach and employ a regime-switching model with a non-spike and a spike regime. Transition probabilities are then dependent on the relationship between demand levels and the threshold of supply capacity, changes in demand as well a trend caused by the deviation of temporary demand fluctuation from its long-term mean. Huisman (2008) introduces a temperature dependent regime-switching model, where either price levels or both price levels and the probability for a transition to the spike regime are dependent on the temperature deviation from its mean level. Kosater (2008) particularly focuses on the impact of weather on the price behaviour in different regimes while Cartea et al. (2009) relate the occurrence and magnitude of price spikes to forward looking capacity constraints.

Generally, the literature agrees that electricity spot prices behave quite differently in the spike regime compared to the normal regime, see e.g. Huisman (2009) and Janczura and Weron (2010). Also, studies by, e.g., Cartea et al. (2009), Kanamura and Ohashi (2007, 2008), Mount et al. (2006), seem to provide evidence that also the relationship between determinants of electricity spot prices and the price itself is quite different when prices are extreme than under a normal regime. Therefore, when modelling the relationship between explanatory variables such as load, weather or capacity constraints and the magnitude of price spikes, a model that focuses on spike observations only and not the entire sample of spot electricity prices may be more appropriate. This idea motivated us to conduct this study.

The contribution of this paper is twofold. First, this is one of the few studies to concentrate in particular on explaining and modelling the magnitude of price spikes in electricity spot markets. Many models that have been suggested in the literature for the behaviour of spot electricity prices feature components that have been designed to include price spikes, such as e.g. a jump-diffusion component or a separate regime for price spikes. However, often the suggested models do not include additional explanatory variables besides the price process itself (Bierbrauer et al., 2007; de Jong, 2006; Huisman and Mahieu, 2003) or the relationship between exogenous variables and electricity prices is modelled using the entire sample (Kanamura and Ohashi, 2007; Kosater, 2008; Mount et al., 2006). Given the changing nature in the relationship between exogenous variables and electricity prices, it may well be that a model that attaches all weight to spike observations and zero weight to non-spike observations may perform better in modelling and forecasting the spikes. In a similar line of thought, Christensen et al. (2009, 2012) suggest that the intensity of the occurrence of price spikes is not homogenous, but is also driven by additional exogenous variables. Building on this fact, the authors suggest to focus more on forecasting extreme price events only instead of modelling the entire price trajectory. Note, however, that these authors are only concerned with modelling the occurrence of price spikes and not with modelling the actual magnitude of the extreme prices what is the focus of our study. Clearly, market participants will not only be interested in the occurrence of a price spike, but would also like to obtain an estimate for the size or magnitude of the extreme observation.

Second, to our best knowledge, in this paper we provide the first application of the Heckman selection model to electricity markets in order to determine appropriate models for the occurrence and magnitude of price spikes. Following Hill et al. (2008), the application of this technique can be used to appropriately estimate the relationship between exogenous and a dependent variable for a non-random subset of the observations. For our application of modelling electricity price spikes this means that we are able to estimate the relationship between the considered explanatory variables and the subsample of observed electricity prices spikes only while controlling for potential selection bias. Note that a similar approach has been applied to modelling losses from operational risk in a recent paper by Dahen and Dione (2010). However, to our best knowledge this study presents the first application of the technique to electricity spot markets.

The remainder of the paper is organized as follows In Section 2 we present a brief overview of regional Australian electricity markets, focusing on market price caps and products available to hedge the risk of occurring price spikes. Section 3 describes the theoretical basis for the inclusion of the considered explanatory variables. Section 4 reviews the Heckman selection method and illustrates how it can be applied to model the magnitude of electricity price spikes. Section 5 reports the estimation results for the Heckman selection model, different OLS models and evaluates their performance. Finally, in Section 6 we conclude and discuss future work.

2. The Australian National Electricity Market

Since the late 1990s the Australian electricity market has experienced significant changes. At that point in time, to promote energy efficiency and reduce the costs of electricity production, the Australian government commenced a significant structural reform. Key objectives of this reform were the separation of transmission from electricity generation, the merge of twenty-five electricity distributors into a smaller number of distributors, and the functional separation of electricity distribution from the retail supply of electricity. Also retail competition was introduced through the reform such that state's electricity purchases could be made through a competitive retail market and customers were now free to choose their retail supplier.

As a wholesale market, the National Electricity Market (NEM) in Australia began operating in December 1998. It is now an interconnected grid comprising several regional networks which provide supply of electricity to retailers and end-users. The NEM includes the states of Queensland (QLD), New South Wales (NSW), Victoria (VIC) and South Australia (SA), while Tasmania (TAS) is connected to VIC via an undersea inter-connector. The link between electricity producers and electricity consumers is established through a pool which is used to aggregate the output from all generators in order to meet the forecasted demand. The pool is managed by the Australian Energy Market Operator (AEMO). Unlike many other markets, the Australian spot electricity market is not a day-ahead market but electricity is traded in a constrained real-time spot market where prices are set each 5 minutes by AEMO. Therefore, generators are able to submit their offers every five minutes. This information is used to select generators to produce electricity in the most cost-efficient way.

The final price is determined in half-hour intervals for each of the regions as an average over the 5-minute spot prices for each trading interval. AEMO determines the half-hourly spot prices for each of the regional markets separately. Note that for Australian electricity markets until June 30, 2010 the market price cap was A$10,000/MWh. The market price cap determines the maximum possible bidding price and therefore, also the highest possible outcome for a half-hourly price. On July 1, 2010 the bid-cap was increased to A$12,500/MWh, while it was further increased to A$12,900/MWh on July 1, 2012 and to A$13,100/MWh on July 1, 2013. Price spikes play an important role in hedging decisions for NEM market participants, since Australian electricity markets can be considered as being significantly more volatile and spike-prone than other comparable markets (Higgs and Worthington, 2008). There have been several occasions in the regional markets, when the determined half-hourly price was close to or even reached the determined market price cap. Therefore, research on the determinants of the occurrence and magnitude of price spikes is of significant importance for market participants.

In recent years, also the market for electricity derivatives has developed rapidly including electricity forward, futures and option contracts being traded at the Sydney Futures Exchange (SFE). Next to the futures contracts that are priced with respect to average electricity spot prices during a delivery period, the SFE also offers a number of alternative derivative contracts. These include, for example, option contracts or so-called '$300 cap products' for a calendar quarter. For these contracts, the payoff is determined by the sum of all base load half hourly spot prices for the region in the calendar quarter greater than $300 (i.e. the severity of the spikes) and the total number of half hourly spot prices for the region in the calendar quarter greater than $300 (i.e. the frequency of the spikes). While in this study we do not price these products, our results will be of great interest in particular with respect to modeling the payoff distribution of these contracts in future work.

Note that for electricity markets derivative contracts typically do not require physical delivery of electricity but are settled financially. Therefore, market participants can participate in electricity derivatives markets and increase market liquidity without owning physical generation assets.

3. Explanatory variables

Generally, the reasons for the occurrence of a price spike can be manifold and may include the unexpected outage or shut-down of power plants, problems with the network transmission grid, extreme temperature events, unanticipated high loads, or they may be a result of the bidding behaviour of market participants, see, e.g., Eydeland and Wolyniec (2012), Harris (2006), Weron (2006). Therefore, as pointed out by Misiorek et al. (2006) the spot electricity price can be considered as the outcome of a vast number of variables including fundamentals (like loads and network constraints) but also unquantifiable psycho- and sociological factors that can cause an unexpected and irrational buyout of certain contracts leading to price spikes.

The empirical literature suggests a number of variables that may have a significant impact on the occurrence and magnitude of price spikes, see e.g. Becker et al. (2007), Cartea et al. (2009), Huisman (2008), Kosater (2008), Lu et al. (2005), Mount et al. (2006), Weron and Misiorek (2008). Generally, these variables can be grouped into three classes: (i) factors related to electricity demand and load, (ii) factors related to weather conditions, and, (iii) factors related to the capacity of the system and the reserve margin.

The load measures electricity demand and given that electricity supply is constrained in the short run, the load usually has a significant impact on wholesale electricity prices. Load patterns typically exhibit seasonality throughout the day, week and the year. The load has been determined as one of the key factors determining spot electricity prices in many studies. For example, Lu et al. (2005) suggest that electricity load is a significant variable in determining the probability of the occurrence of a price spike. Misiorek et al. (2006) conclude that day-ahead load forecasts issued by the system operator in California (CAISO) lead to more accurate day-ahead spot price forecasts than the actual load. They explain this phenomenon by the fact that the prices are an outcome of the bids, which in turn are placed with the knowledge of load forecasts but not actual future loads. Indeed, electricity suppliers generally do not know the exact system load by the time they enter their bids. Instead, they often have to rely on weather variables and/or past observations of load (Mount et al. 2006, Weron and Misiorek 2008).

Also, weather conditions will have a significant impact on electricity consumption. It can be expected that during a cold winter or a hot summer, electricity consumption will increase due to the use of heating or air-conditioning, respectively. Various weather variables can be considered, but temperature and humidity are the most commonly used load predictors. Hippert et al. (2001) report that of the 22 research publications considered in their electricity load prediction survey, 13 made use of temperature only, three made use of temperature and humidity, three utilized additional weather parameters, and three used only load parameters. Generally, with respect to temperature, electricity demand and hence spot prices depend more on the deviation from the normal temperature, rather than the temperature itself (Huisman 2008). For this reason, in our empirical analysis we will use the absolute or squared deviation of the air temperature from 18 degrees Celsius.

Finally, the reserve margin measures the relationship between the available capacity in the system and peak demand. It provides a measure for the aptitude of the market to maintain reliable operation while meeting unforeseen increases in demand (e.g. extreme weather) and unexpected outages of existing capacity. It has been found to be a significant factor in determining the occurrence of price spikes in previous studies, see e.g. Cartea et al. (2009), Lu et al. (2005), Mount et al. (2006), just to mention a few. For this reason, we also consider the reserve margin as an explanatory variable for the occurrence and magnitude of price spikes in this study.

4. Methodology

This section discusses the Heckman correction that can be applied in order to overcome a selection bias in the modeling procedure when estimating the relationship between the considered explanatory variables and the magnitude of price spikes. We will also briefly review the so-called Box-Cox transformation technique that is applied to the raw price data in order to obtain approximate normality of the variables that is required by the Heckman selection model. We also provide an overview of measures for comparing the forecast ability of the different models that are applied in this paper.

4.1. The Heckman selection model

The Heckman selection model is a statistical approach developed by Heckman (1979) to correct for selection bias. Standard econometric literatures (Hill et al., 2008; Greene, 2008; Verbeek, 2008) argue that when the majority of the observations for the dependent variable takes on a value of 0, a standard Ordinary Least Squares (OLS) regression approach is not appropriate, for a detailed proof see, e.g., Kennedy (2003). Under these circumstances an alternative approach for regression analysis is required. In this paper, the dependent variable of interest is the magnitude of observed price spikes in our sample. As argued by several authors, see e.g., Cartea et al. (2009), Kanamura and Ohashi (2007, 2008), Mount et al. (2006), the relationship between explanatory variables such as load, weather or capacity constraints and spot electricity prices may be very different for price spikes than for price observations under a normal price regime. Therefore, one of the motivations of this study is that we believe that a model that focuses on spike observations only and not the entire sample of spot electricity prices may be more appropriate to quantify this relationship for extreme observations. However, including observations of price spikes only into the analysis, is somehow critical due to the bias of pre-selecting data based on whether observations are classifies as a price spike or not. Such a systematic pre-selection violates the random sample principle and, therefore, we need to apply an econometric technique is able to correct estimates for the sample selection bias. In this paper we decide to use the Heckman correction for this task.

The Heckman (1979) selection model is essentially a two-stage procedure and the resulting model can generally be described by a system of two equations. The first equation determines the probability of the occurrence of an event, i.e. a binary choice model, while the second equation estimating the relationship between the explanatory variables and the outcome of the dependent variable. The first step, i.e. the model for the occurrence of an event is typically modeled using a probit equation and estimated using Maximum Likelihood. Then for each observation the so-called Inverse Mills Ratio (IMR) is calculated as the standard normal density function divided by the cumulative standard normal distribution function of the probit model for the occurrence of the event. Then, in a second step, the dependent variable, i.e. the size or magnitude of an event, is regressed on the explanatory variables and the IMR using standard OLS. Then a test to detect the presence of a sample selection bias can be conducted by testing whether the coefficient of the IMR is significantly different from zero (Hill et al., 2008). If the coefficient of the IMR is significantly different from zero, a selection bias is present and the Heckman correction is favorable to applying standard OLS to the selected data. Note that the full model, i.e. the selection equation (the binary choice model) and the equation (the standard OLS equation) are typically estimated jointly using maximum likelihood.

4.2 The Lognormal and Box-Cox transformation

In the Heckman selection model, it is assumed that error terms are normally distributed such that large deviations of the dependent variable from normality would possibly provide spurious results. Spot electricity prices, however, usually exhibit positive skewness and excess kurtosis, indicating that the empirical distribution is far more heavy-tailed than the normal distribution. Therefore, often a transformation of the observed spot prices is conducted before the estimation of an econometric model, see e.g. Bierbrauer et al. (2007), Huisman (2009), Weron and Misiorek (2008). The most popular transformation in the econometric literature for electricity markets is to use the logarithm of the actually observed prices in order to dampen the extreme volatility, skewness and excess kurtosis. In our empirical analysis, we therefore also consider log-transformed spot electricity prices for estimation of the model instead of the originally observed prices.

An alternative and more general technique for the transformation of heavy-tailed price data is to apply the Box-Cox (1964) transformation in order to obtain approximate normality of the considered variables (Davidson and MacKinnon, 1993). The Box-Cox transformation of a variable *y* is defined as

$$y(\lambda) = \begin{cases} \frac{y^{\lambda} - 1}{\lambda} & (\lambda \neq 0) \\ \log y & (\lambda = 0) \end{cases} \tag{1}$$

where y denotes the original observation, is the so-called transformation parameter and y(λ) denotes the transformed variable. Clearly, this technique offers a more flexible way of transforming data, depending on the choice of the parameter λ. Note that for the special case when λ is chosen to be zero, the Box-Cox transformation becomes the logarithmic transformation. To estimate the optimal value for λ that generates transformed observations being as close as possible to a normal distribution, maximum likelihood estimation is used, see, e.g., Davidson and MacKinnon (1993) for further details. Due to the popularity of the log-transformation in the literature on modeling electricity spot prices, in our empirical analysis we will provide the results for models based on the logarithm transformation as well as the Box-Cox transformation with $\lambda \neq 0$.

4.3. Measures to compare forecast accuracy

In our empirical analysis we will compare the performance of different models with respect to their ability to appropriately model the magnitude of a spike. In particular, we will compare the results for the estimated Heckman correction-based model in comparison to standard OLS regression approaches. Clearly, there has been a variety of measures suggested in the literature in order to compare the performance of econometric models. Given that we are mainly interested in the ability of the models to appropriately quantify or forecast price spikes, we will focus on the following three measures: the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE) as well as Log likelihood of the estimated models. Note that we decided to rather use the MAE instead of the Mean Squared Error (MSE), since the latter is usually much more dominated by a few large outliers. Since price spikes can be of quite extreme magnitude and for the considered time period take on values up to $10,000, it is likely that a comparison of models based on the MSE would be dominated by the few really extreme observations only. The MAE is defined as

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|y_t - f_t\right|, \tag{2}$$

where T denotes the number of observations, y_t the transformed spot price (either using the natural log or Box-Cox transformation), and f_t is the model forecast for the transformed price. In a similar manner the MAPE is defined as

$$MAPE = \frac{100}{T}\sum_{t=1}^{T}\left|\frac{y_t - f_t}{y_t}\right|. \tag{3}$$

Clearly, the MAPE focuses more on the relative forecast error and will, therefore, give less weight to extreme spike observations that are also expected to coincide with large model forecast errors.

5. Empirical Results

5.1. Data and Models

We consider data on price spikes for four Australian regional markets, namely NSW, QLD, SA and VIC. Note that these are the states with the highest electricity demand in Australia (Higgs, 2009), while SFE offers a variety of derivatives contracts, including futures as well as $300 cap options in those states only. Electricity spot prices and system loads at the half-hourly frequency are obtained from AEMO. We use data from the period April 1, 2002 to June 30, 2010, the time period where the market price cap had been set to A$10,000/MWh (AEMO, 2012). As mentioned previously, from July 1, 2010 onwards the cap was increased to A$12,500/MWh, while it was further increased to A$12,900/MWh on July 1, 2012 and to A$13,100/MWh on July 1, 2013 such that data on price spikes from later periods may exhibit different properties due to the revised market price caps. We therefore decided to exclude all price observations from July 1, 2010 onwards from the conducted analysis.

Half-hourly weather data are obtained from the Bureau of Meteorology (BOM) and includes relative air temperature, wet bulb temperature, dew point temperature, relative humidity and mean sea level pressure (BOM, 2012). We decided to use observations on weather that are measured at airport weather stations in Sydney for NSW, Brisbane for QLD, Adelaide for SA and Melbourne for VIC. Data on the capacity in the system is obtained from AEMO. Based on the information provided on the capacity and load in the market, we define the reserve margin as $r = [capacity / load] - 1$. Clearly, with this specification values of r close to zero indicate that there is only little reserve capacity available. On the other hand, larger values of r illustrate more reserve capacity in the market. Note, however, that we have data on the so-called supply capacity only which reflects the installed capacity for each market, rather than the actual operational capacity.

To illustrate the extremely spiky behaviour in the Australian NEM, consider Figure 1. The figure provides a plot of half-hourly electricity prices in QLD for the considered time period April 1, 2002 – June 30, 2010 and illustrates that half-hourly electricity prices exhibit extreme variation and a high number of spikes. We also observe that for the QLD market, half-hourly prices reach the bid-cap of 10,000 A$/MWh in a few cases. There are also occasions on which prices are negative. This situation occurs when the cost of turning off electricity generators is high and producers are willing to put negative bids into the system to ensure that they can dispatch the generated electricity.

Table 1 provides detailed descriptive statistics for half-hourly electricity prices in the four states, both for the entire sample as well as for the pre-selected sample that only contains price spikes. Note that in this study we classify all price observation greater than A$300/MWh as price spikes. Recall that in Australia, option contracts or so-called A$300

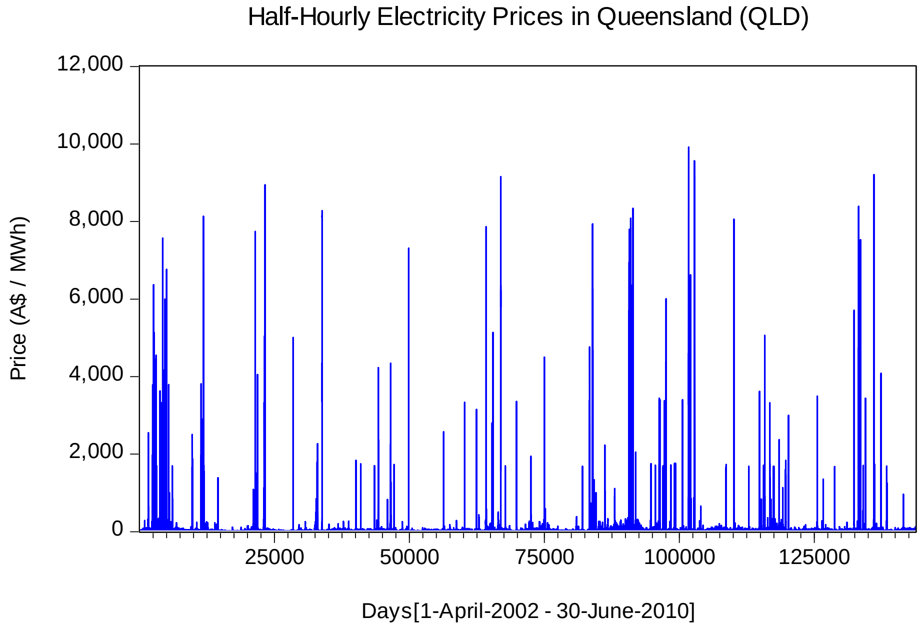

Figure 1: Half-hourly electricity price (A$/MWh) for the QLD market during the considered time period April 1, 2002 – June 30, 2010.

cap options are traded in the ASX Australian Electricity derivatives market. The payoff for these products is determined based on both the frequency and magnitude of observed half-hourly prices in excess of A$300/MWh during a calendar quarter. Therefore, given these products available in the market, we believe that the most natural definition of a spike is an observation greater than A$300/MWh.

State	Obs	Mean	Std Dev	Min	Max	Skewness	Kurtosis
All Prices							
NSW	144,624	41.16	229.96	-264.31	10,000.00	29.71	1,005.33
QLD	144,624	37.33	198.85	-675.46	9,920.99	30.30	1,076.61
SA	144,624	46.29	296.32	-1,000.00	9,999.92	29.37	924.00
VIC	144,624	36.84	170.21	-496.71	10,000.00	41.71	2,043.70
Price Spikes (Prices > A$ 300 / MWh) Only							
NSW	743	2037.29	2488.34	300.03	10000.00	1.65	4.74
QLD	590	2176.19	2228.11	300.04	9920.99	1.52	4.56
SA	549	3252.93	3556.68	300.82	9999.92	1.04	2.45
VIC	408	2057.05	2448.91	300.13	10000.00	1.94	6.02

Table 1: Descriptive statistics of half-hourly electricity prices for NSW, QLD, SA, VIC for the period April 1, 2002 – June 30, 2010. The upper panel contains descriptive statistics for the entire sample, while the lower panel provides descriptive statistics for the pre-selected sample of spikes, i.e. price observations greater than A$300/MWh.

For the entire sample we find that the average price is around $35-45/MWh, while the maximum half-hourly price during the sample period is $10,000/MWh or very close to $10,000/MWh for each of the four markets. The standard deviation can be as high as $296/MWh for SA, but is greater than four times the average spot price for each of the markets. As it is typical for spot electricity prices, data is heavily skewed to the right and exhibits excess kurtosis. For the selected sample of price spikes only, we find that with 408 observations VIC exhibits the lowest number of spikes during the sample period, while in NSW for the same period 743 spikes can be observed. The average magnitude of a spike ranges from A$2,037 in NSW up to A$3,253 in SA. As mentioned before, in each state here are spikes that reach the A$10,000 market price cap during the considered sample period.

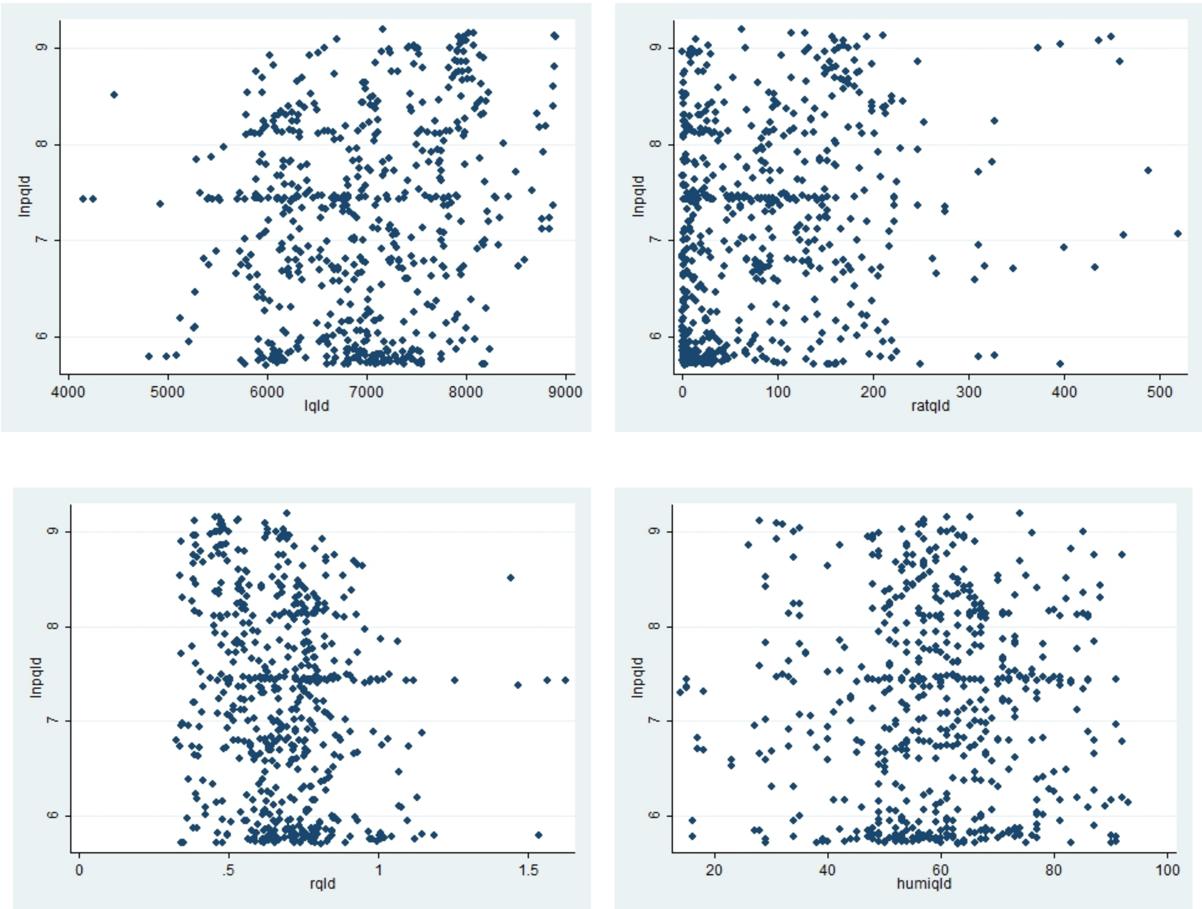

Figure 2: Scatter plot for the relationship between the log transformation of observed price spikes (dependent variable) and the explanatory variables market load (upper left panel), relative air temperature (upper right panel), reserve margin (lower left panel, humidity (lower right panel) for QLD market.

Figure 2 shows the relationship between the log transformed price spikes in the QLD market (i.e. the plot contains only price observations greater than A$300/MWh) and the explanatory variables market load, relative air temperature, reserve margin and humidity for this market. From a first glance, the plots do not indicate a strong relationship between the explanatory variables and the observed magnitude of price spikes in the QLD market.

We now specify the following model for a more detailed analysis of the relationship between the considered explanatory variables and observed spot electricity prices. For our analysis, the Heckman selection model can be specified by a system containing the two equations (4) and (5). Equation (4) denotes the probit model, i.e. the first stage of the Heckman selection procedure. The probit model is concerned with the determinants of the occurrence of a price spike and, therefore, is estimated using all observations on price data available:

$$DPS_t = \gamma_0 + \gamma_1 L_t + \gamma_2 r_t + \gamma_3 rat_t + \gamma_4 webt_t + \lambda_5 dwpt_t + \gamma_6 humi_t + \gamma_7 selp_t + \varepsilon \quad (4)$$

$$DPS \begin{cases} 1 & when\, a\ price\, spike\, occurs \\ 0 & \end{cases}$$

Hereby, *DPS* a dummy variable for the occurrence of a price spike, *L* is the market load and *r* is the reserve margin that is defined as *r = [capacity / load] – 1*. Further, *rat* denotes the relative air temperature that is based on the deviation of the temperature from 18 degrees Celcius, i.e. *rat = [air temperature – 18]*$^{\wedge 2}$, *webt* denotes the wet bulb temperature measured using a standard mercury-in-glass thermometer, *dwpt* is the dew point temperature, i.e. a measure of the moisture content of the air and the temperature to which air must be cooled in order for dew to form. Finally, *humi* denotes the air humidity and *selp* is the sea level pressure that is affected by changing weather conditions.

Then equation (5) denotes the second stage of the estimation procedure, and, i.e. the model for the magnitude of the occurred price spikes:

$$LNP_t = \beta_0 + \beta_1 L_t + \beta_2 rat_t + \beta_3 r_t + \beta_4 IMR_t + \nu \quad (5)$$

Hereby, *LNP* denotes the log transformation (alternatively, the Box-Cox transform) of the observed electricity price spikes, *L* is the market load, *rat* the relative air temperature (as defined earlier), *r = [capacity / load] – 1* is the reserve margin and IMR denotes the so-called Inverse-Mills-Ratio that is specified as

$$IMR = \frac{\phi(\gamma_0 + \gamma_1 L \ + \gamma_2 r + \gamma_3 rat \ + \gamma_4 webt + \lambda_5 dwpt + \gamma_6 humi \ + \gamma_7 selp)}{\Phi(\gamma_0 + \gamma_1 L \ + \gamma_2 r + \gamma_3 rat \ + \gamma_4 webt + \lambda_5 dwpt + \gamma_6 humi \ + \gamma_7 selp)} \tag{6}$$

and can be calculated for each observation based on equation (5). Table 2 shows the number of observations for each market for the original sample and the censored sample that only contains observations of price spikes greater than A$300/MWh. Obviously, for all markets, the sample size for the probit model is quite large, since all price observations greater than 0 are included, while the sample size for the second step in the Heckman selection model, equation (5), is much smaller but is still reasonable to provide reliable estimation results. Note that we excluded negative and zero prices from the analysis, since both the logarithmic and the Box Cox transformation can only be applied to positive numbers.

State	**NSW**	**QLD**	**SA**	**VIC**
Observations (No Missing Data)	141,358	143,853	142,666	140,505
Censored Observations	140,645	143,267	142,128	140,108
Uncensored Observations	713	586	538	397

Table 2: Sample sizes (number of observations) details for each state

5.2. Estimation results

5.2.1. Heckman selection model with log transformation

Table 3 reports the estimation results of the Heckman selection model with log-transformed data for the spot electricity prices. We find that for the estimated probit model the variables load, relative air temperature and reserve margin are significant. As expected, load and relative air temperature have a positive impact on the probability of occurrence of a price spike while the reserve margin has a negative impact, i.e. the closer the system is to full capacity (reserve margin *r* close to zero), the higher is the probability of a price spike.

Region	NSW			QLD			SA			VIC		
Variable	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**
Dependent Variable: LNP												
Cons	1.0252	0.50		4.8838	5.13	***)	-3.3654	-1.26		5.0556	2.95	***)
L	0.0004	3.10	***)	0.0002	2.58	***)	0.0029	4.33	***)	0.0002	1.46	
rat	0.0026	2.99	***)	0.0015	2.50	**)	0.0025	3.22	***)	0.0007	1.26	
r	0.4989	1.22		-0.6766	-1.54		0.3381	0.44		2.7471	4.01	***)
IMR	0.3958	1.53		0.3838	2.98	***)	1.5296	2.10	**)	-0.1988	-0.61	
Dependent Variable: DPS												
Cons	14.2095	4.78	***)	38.9371	10.28	***)	2.8418	0.80	***)	-7.7089	-2.29	**)
L	0.0006	26.24	***)	0.0003	7.41	***)	0.0012	10.32	***)	0.0005	12.82	***)
r	-1.3859	-10.33	***)	-1.4679	-10.17	***)	-0.9129	-7.48	***)	-1.7051	-9.42	***)
rat	0.0033	10.14	***)	0.0031	8.88	***)	0.0012	4.07	***)	0.0031	10.46	***)
webt	0.0615	3.12	***)	-0.1481	-5.70	***)	-0.0133	-0.85		-0.0301	-1.63	
dwpt	-0.0545	-3.22	***)	0.0569	2.45	**)	-0.0070	-0.63		0.0529	3.47	***)
humi	0.0122	4.51	***)	-0.0031	-0.89		0.0028	1.13		0.0016	0.55	
selp	-0.0231	-8.05	***)	-0.0397	-11.11	***)	-0.0065	-1.89	*)	0.0019	0.59	
Adj-R2	0.05			0.06			0.14			0.08		

Table 3: Estimation results for Heckman selection method for the log transformation of spot electricity prices. The upper reports results for equation (5) referring to the model for the magnitude of the observed price spikes, while the lower panel provides results for the probit model for the occurrence of a spike specified in equation (4).

In the equation for the magnitude of price spikes, the *IMR* is significant for the QLD and SA market, while it is almost significant at the 10 percent level for NSW. The Heckman correction for sample selection bias is therefore important when examining factors affecting the magnitude of price spikes in electricity spot markets. Also, the variables load *L* and relative temperature *rat* are significant and have the expected positive sign in all markets except for VIC. Note, however, that the reserve margin *r* is only significant in VIC and yields a coefficient with a positive sign for three of the regional markets. This is counterintuitive, since it suggests that price spikes are of greater magnitude with more reserve capacity in the system. These results may be due to the low quality of data on supply capacity which reflects only the installed capacity, rather than the actual operational capacity.

In general, the estimated models do not have a very high explanatory power and yield adjusted R^2 coefficients of determination between 0.05 for NSW and 0.14 for SA. This is not surprising since by definition, price spikes are rather unexpected events and can be considered as the outcome of a vast number of variables including fundamentals (like loads and network constraints) but also unquantifiable psycho and sociological factors that can cause an unexpected and irrational buyout of certain contracts (Misiorek et al., 2006). Therefore, for example, an R-squared of 14 percent as it is obtained for the SA market can be considered quite high, since it explains a significant fraction of the variation in the magnitude of the spikes.

State	Λ
NSW	-0.6608
QLD	-0.5643
SA	-0.2189
VIC	-0.2405

Table 4: Optimal Box-Cox parameter estimates for each state based on Maximum-Likelihood estimation (Davidson and MacKinnon, 1993)

Region	**NSW**			**QLD**			**SA**			**VIC**		
Variable	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**
Dependent Variable: BCP												
Cons	1.4317	70.42	***)	1.6943	92.68	***)	1.3069	2.32	**)	3.0458	9.85	***)
L	0.0000	3.22	***)	0.0000	2.09	**)	0.0006	4.26	***)	0.0000	1.28	
rat	0.0000	3.08	***)	0.0000	3.00	***)	0.0006	3.53	***)	0.0001	1.23	
r	0.0067	1.65	*)	-0.0172	-2.03	**)	-0.0407	-0.25		0.4687	3.79	***)
IMR	0.0044	1.72	*)	0.0098	3.95	***)	0.3916	2.53	**)	-0.0316	-0.54	
Dependent Variable: DPS												
Cons	14.2095	4.78	***)	38.9371	10.28	***)	2.8418	0.80		-7.7089	-2.29	**)
L	0.0006	26.24	***)	0.0003	7.41	***)	0.0012	10.32	***)	0.0005	12.82	***)
r	-1.3859	-10.33	***)	-1.4679	-10.17	***)	-0.9129	-7.48	***)	-1.7051	-9.42	***)
rat	0.0033	10.14	***)	0.0031	8.88	***)	0.0012	4.07	***)	0.0031	10.46	***)
webt	0.0615	3.12	***)	-0.1481	-5.70	***)	-0.0133	-0.85		-0.0301	-1.63	
dwpt	-0.0545	-3.22	***)	0.0569	2.45	**)	-0.0070	-0.63		0.0529	3.47	***)
humi	0.0122	4.51	***)	-0.0031	-0.89		0.0028	1.13		0.0016	0.55	
selp	-0.0231	0.00	***)	-0.0397	-11.11	***)	-0.0065	-1.89	*)	0.0019	0.59	
Adj-R2		0.06			0.06			0.11			0.07	

Table 5: Estimation results for Heckman selection method for the Box-Cox transformation of spot electricity prices. The upper reports results for equation (5) referring to the model for the magnitude of the observed price spikes, while the lower panel provides results for the probit model for the occurrence of a spike specified in equation (4).

5.2.2. Heckman selection model with Box-Cox transformation

Table 4 reports the estimation of the Box-Cox transformation parameter λ, based on Davidson and MacKinnon (1993), for each of the considered states, while Table 5 presents the estimation results for the Heckman selection model after applying the Box-Cox transformation. We obtain results very similar to when the log transformation had been used for the observed spot electricity prices. Note that in the estimated model, the two variables load *L*, relative air temperature *rat* are significant for all markets and show the expected sign. Also the reserve margin *r* is significant for three of the four markets and yields the expected negative coefficient for QLD and SA, while the coefficient is positive and significant for VIC. Also results for the explanatory power of the model are very similar to those obtained for the log transformation. Interestingly, the explanatory power of the model with the Box-Cox transformation is slightly lower than when the log transformation is applied.

Region	**NSW**			**QLD**			**SA**			**VIC**		
Variable	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**
Dependent Variable: LNP, All Prices												
Cons	1.3997	107.74	***)	0.9257	36.47	***)	1.6226	89.14	***)	0.6716	49.19	***)
L	0.0002	183.77	***)	0.0004	121.33	***)	0.0012	154.19	***)	0.0005	238.43	***)
rat	0.0016	53.96	***)	-0.0001	-4.09	***)	0.0002	7.47	***)	0.0004	20.88	***)
r	-0.1278	-26.37	***)	0.1253	15.57	***)	-0.0525	-12.94	***)	-0.0920	-18.04	***)
Adj-R2	0.44			0.28			0.48			0.49		
Region	**NSW**			**QLD**			**SA**			**VIC**		
Variable	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**
Dependent Variable: BCP, All Prices												
Cons	1.1393	988.33	***)	1.1416	338.17	***)	1.7190	212.00	***)	1.1080	189.88	***)
L	0.0000	215.73	***)	0.0001	136.07	***)	0.0005	143.08	***)	0.0002	246.87	***)
rat	0.0001	21.15	***)	-0.0001	-20.84	***)	-0.0001	-10.98	***)	0.0000	4.80	***)
r	-0.0154	-35.72	***)	0.0095	8.91	***)	-0.0596	-33.00	***)	-0.0462	-21.21	***)
Adj-R2	0.50			0.34			0.48			0.50		

Table 6: Estimation results using OLS for the entire sample of electricity spot prices from April 1, 2002 to June 30, 2010. Note that the results on the explanatory power of the model cannot be compared to Table 3 and 5, since the estimation refers to a much larger data set that contains mainly price observations from a 'normal' price regime.

5.2.3. OLS model estimated with all electricity prices

Table 6 reports the estimation results for a standard OLS regression model when all transformed electricity prices are regressed on the explanatory variables (load, reserve margin, relative air temperature). Results are presented both for the log transformation (upper panel) as well as for the Box-Cox transformation (lower panel). The results indicate that all three explanatory variables are significant for each of the considered markets and for both transformations. The coefficient for load always has the expected sign while relative air temperature yields a negative sign for QLD when the log transformation is used and for QLD and SA when the Box-Cox transformation is employed. Surprisingly, also the coefficient for the reserve margin is positive for QLD for both types of transformation. The explanatory power of the models measured by the adjusted R-square is quite high, indicating that the considered variables provide significant explanatory power for the level of spot electricity prices. However, since all price observations are considered in this model, results for the coefficient of determination are not really comparable to the Heckman selection model that is applied to observed price spikes in excess of A$300/MWh only.

Region	**NSW**			**QLD**			**SA**			**VIC**		
Variable	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**
Dependent Variable: LNP, Price Spikes only (Prices > A$ 300 / MWh)												
Cons	4.0378	7.91	***)	6.2360	7.43	***)	1.9256	2.57	**)	4.0665	7.35	***)
L	0.0002	5.16	***)	0.0001	1.58		0.0016	6.79	***)	0.0003	4.10	***)
rat	0.0014	4.12	***)	0.0014	2.37	**)	0.0013	3.04	***)	0.0010	2.67	***)
r	0.9574	3.44	***)	-0.2017	-0.49		1.7630	5.52	***)	2.4064	6.06	***)
Adj-R2	0.07			0.05			0.17			0.12		
Region	**NSW**			**QLD**			**SA**			**VIC**		
Variable	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**	**Coef**	**t-Stat**	**Sign**
Dependent Variable: BCP, Price Spikes only (Prices > A$ 300 / MWh)												
Cons	1.4654	287.26	***)	1.7288	107.47	***)	2.6651	17.57	***)	2.8885	28.91	***)
L	0.0000	5.01	***)	0.0000	0.67		0.0003	5.77	***)	0.0000	3.59	***)
rat	0.0000	3.91	***)	0.0000	2.85	***)	0.0003	3.19	***)	0.0002	2.53	**)
r	0.0119	4.29	***)	-0.0051	-0.64		0.3223	4.99	***)	0.4145	5.78	***)
Adj-R2	0.07			0.04			0.14			0.11		

Table 7: Estimation results using OLS for the sub-sample of price spikes, i.e. prices greater than A$300/MWh only.

5.2.4. Standard OLS results for price spike sub-sample

Table 7 presents the estimation results of for the transformed price spikes on the considered explanatory variables ignoring the selection bias. Results are quite similar to those for the Heckman selection procedure with significant and positive coefficients for the variables load L and relative air temperature rat for most of the regional markets. Interestingly, load is not significant for the QLD market anymore. However, reserve margin *r* is significant for three of the four markets (NSW, SA, VIC) but in each case yields a counterintuitive positive sign. As indicated by the results for the Heckman selection model where the IMR was significant for several of the considered markets, estimation results of a simple OLS model are not reliable because they are biased. However, results on adjusted R^2 are very similar to the results we obtain for the Heckman selection model.

5.3. Comparing the forecasting ability of the models

In the following, we compare the forecasting ability of the three estimated models (Heckman selection model, OLS model using all prices, OLS model using price spikes only) for the observed price spikes in the sample. Hereby, as pointed out in Section 4.3, we focus on the following three performance measures: MAE, MAPE and log likelihood of the estimated models. Results for all three models and performance criteria are shown in Table 8. We find that for each of the considered measures and markets, the Heckman selection model yields the best performance. This is true both for the logarithmic and the Box-Cox transformation of the price data. For all markets, the estimated OLS model that uses price spikes only performs second best, while the OLS model using all prices performs significantly worse.

The poor performance of the standard OLS model that is estimated using all prices can be explained by the fact that the model is calibrated using mainly non-spike observations and only gives a small weight to actual price spikes. It also points towards the non-linear relationship between wholesale prices and the considered explanatory variables as it has been suggested e.g. by Kanamura and Ohashi (2008), Mount et al. (2006) or Weron (2006). These studies also suggest that the relationship between load or demand and electricity wholesale prices can be characterized by a hockey stick shape. Overall, the weaker performance of a standard OLS model for quantifying the magnitude of price spikes is not very surprising.

More interestingly, the estimated Heckman selection model also outperforms an OLS model that is estimated using price spikes only. This indicates that a correction for the selection bias in the estimation as well as the inclusion of the Inverse Mills Ratio into the model plays an important role and should be further examined in future studies.

Natural Log Transformation for Price			
METHOD	**1) OLS - All Prices**	**2) OLS - Price Spikes**	**3) Heckman Selection**
NSW			
MAE	2.75	0.94	0.94
MAPE	38.20	13.57	13.54
Log Likelihood	-1,784.76	-1,067.90	-1,067.05
QLD			
MAE	3.57	0.87	0.86
MAPE	48.81	12.39	12.26
Log Likelihood	-1,600.50	-833.97	-829.90
SA			
MAE	2.81	0.95	0.94
MAPE	36.80	13.43	13.28
Log Likelihood	-1,362.85	-820.71	-814.70
VIC			
MAE	2.75	0.84	0.84
MAPE	37.92	12.03	12.08
Log Likelihood	-993.98	-557.55	-557.21

Box Cox Transformation for Price			
METHOD	**1) OLS - All Prices**	**2) OLS - Price Spikes**	**3) Heckman Selection**
NSW			
MAE	0.08	0.01	0.01
MAPE	5.25	0.65	0.65
Log Likelihood	764.57	2,217.11	2,217.85
QLD			
MAE	0.21	0.02	0.02
MAPE	11.96	0.96	0.95
Log Likelihood	77.47	1,483.25	1,490.47
SA			
MAE	0.76	0.19	0.19
MAPE	20.64	5.40	5.33
Log Likelihood	-651.99	38.92	46.39
VIC			
MAE	0.69	0.15	0.15
MAPE	20.31	4.54	4.54
Log Likelihood	-443.89	121.95	122.29

Table 8: MAE, MAPE and log likelihood of the estimated models for the OLS using the entire sample, OLS applied to price spikes only and the Heckman selection model. Note that results are reported for log transformation and Box-Cox transformation of the original prices.

6. Summary and Conclusions

In this paper, we propose the Heckman selection model framework to examine factors driving the frequency and magnitude of price spikes. Using this framework, estimation results are not influenced by low (or normal) electricity prices while the selection bias due to non-random sampling is overcome. The literature suggests that electricity spot prices behave quite differently in the spike regime compared to the normal regime, see e.g. Huisman (2009) and Janczura and Weron (2010). Studies by, e.g., Cartea et al. (2009), Kanamura and Ohashi (2007, 2008), Mount et al. (2006), seem to provide further evidence that also the relationship between determinants of electricity spot prices and the price itself is quite different when prices are extreme than under a normal regime. Therefore, when modelling the relationship between explanatory variables such as load, weather or capacity constraints and the magnitude of price spikes, a model that focuses on spike observations only and not the entire sample of spot electricity prices may be more appropriate.

The Heckman procedure is applied to four regional electricity markets in Australia and it is found that for each of these markets, load, relative air temperature and reserve margins are significant variables for the occurrence of price spikes, while load and relative air temperature are have a significant impact on the magnitude of a price spike. It is also found that the Inverse Mills Ratio is significant for several of the considered markets, what indicates that estimation results of a standard OLS model to pre-selected data of price spikes will generally lead to biased results. The performance of the Heckman selection model for the quantification of price spikes is also compared with the performance of an OLS model using all prices and an OLS model using price spikes only. We find for all of the considered measures that the Heckman selection model performs best in each of the considered markets. Our results encourage further application of the Heckman selection model to electricity markets.

Bibliography

AEMO 2012, '*AEMO Submission to the Review of the Reliability and Emergency Reserve Trader (RERT) Issues Paper*', AEMO.

Anderson, EJ, Hu, X & Winchester, D 2007, 'Forward Contracts in Electricity Markets: The Australian Experience', *Energy Policy*, vol. 65, pp. 329 – 344.

Australia Government Bureau of Meteorology (BOM), http://www.bom.gov.au/climate/glossary/, viewed 26 June 2012.

Becker, R, Hurn, S & Pavlov, V 2007, 'Modelling Spikes in Electricity Prices', *The Economic Record*, vol. 35, pp. 371 - 382.

Bierbrauer, M, Menn, C, Rachev, ST & Trück, S 2007, 'Spot and Derivative Pricing in the EEX Power Market', *The Journal of Banking & Finance*, no. 31, pp. 3462 – 3485.

Box, GEP & Cox, DR 1964, 'An Analysis of Transformations', *Journal of the Royal Statistical Society Series B (Methodological)*, vol. 26 no. 2, pp. 211 – 252.

Brooks, C 2008, *Introductory Econometric for Finance 2nd Edition*, Cambridge University Press, Cambridge.

Cartea, A, Figueroa, EG, & Geman,HS 2000, 'Modelling Electricity Prices with Forward Looking Capacity Constraints', *Applied Mathematical Finance*, vol. 16 no. 2, pp. 103 – 122.

Cartea, A & Figueroa, MG 2005, 'Pricing in Electricity Markets: A Mean Reverting Jump Diffusion Model with Seasonality', *Applied Mathematical Finance*, vol. 12 no. 4, pp. 313 – 335.

Christensen, TM, Hurn, AS & Lindsay, KA 2009, 'It Never Rains but It Pours: Modelling the Persistence of Spikes in Electricity Prices', *Energy Journal*, vol. 30 no. 1, pp. 25 – 48.

Christensen, TM, Hurn, AS & Lindsay, KA 2012, 'Forecasting Spikes in Electricity Prices', *International Journal of Forecasting*, vol. 28 no. 2, pp. 400 – 411.

Clewlow, L & Strickland, C 2000, *Energy Derivatives – Pricing and Risk Management*, Lacima Publications, London UK.

Dahen, H & Dione, G 2010, 'Scaling Models for the Severity and Frequency of External Operational Loss Data', *The Journal of Banking & Finance*, no. 34, pp. 1484 – 1496.

Davidson, R & MacKinnon, JG 1993, *Estimation and Inference in Econometrics*, Oxford University Press, Cambridge.

De Jong, C 2006, 'The Nature of Power Spikes: A Regime-Switching Approach', *Studies in Nonlinear Dynamics and Econometrics*, vol. 10, no. 3, pp. 1 – 26.

Escribano, A, Pena, JI & Villaplana, P 2002, 'Modelling Electricity Prices: International Evidence', *Working Paper 02-27*, Universidad Carlos III de Madrid.

Eydeland, A & Wolyniec, K 2012, *Energy and Power Risk Management 2nd Edition*, Wiley, Hoboken NJ.

Frontier Economic Report 2010, '*Implications for the National Electricity Market from Increases to the Market Price Cap and/or Cumulative Price Threshold*', Frontier Economics Pty. Ltd., Australia.

Geman, H & Roncoroni, A 2006, 'Understanding the Fine Structure of Electricity Prices', *Journal of Busines*, vol. 79, no. 3, pp. 1225 – 1261.

Greene, WH 2008, *Econometric Analysis 6th Edition*, Pearson Prentice Hall, USA.

Heckman, J 1979, 'Selection Bias as a Specification Error', *Econometrica*, vol. 47 no. 1, pp. 153 - 161.

Harris, C 2006, *Electricity Markets: Pricing, Structures and Economics*, Wiley, Chichester.

Higgs, H 2009, 'Modeling Price and Volatility Inter-Relationship in the Australia Wholesale Spot Electricity Markets', *Energy Economics*, no. 31, pp. 748 – 756.

Higgs, H & Worthington, A 2008, 'Stochastic Prices Modeling of High Volatility, Mean Reverting, Spike-Prone Commodities: The Australia Wholesale Spot Electricity Market', *Energy Economics*, no. 30, pp. 3172 – 3185.

Hill, RC, Griffiths, WE & Lim, GC 2008, *Principles of Econometrics 3rd Edition*, John Wiley & Sons Inc., New Jersey USA.

Hippert, HS, Pedreira, CE & Souza, RC 2001, 'Neural Networks for Short Term Load Forecasting: A Review and Evaluation', *IEEE Transactions on Power Systems*, vol. 16 no. 1, pp. 44 - 55.

Huisman, R & Mahieu, R 2003, 'Regime Jumps in Electricity Prices', *Energy Economics*, no. 25, pp. 425 – 434.
Huisman, R, Huurman, C & Mahieu, R 2007, 'Hourly Electricity Prices in Day-Ahead Markets', *Energy Economics*, no. 29, pp. 240 – 248.
Huisman, R, 2008, 'The Influence of Temperature on Spike Probability in Day-Ahead Power Prices', *Energy Economics*, no. 30, pp. 2697 – 2704.
Huisman, R, 2009, *An Introduction to Models for the Energy Markets*. Risk Books.
Janczura, J, & Weron, R 2010, 'An Empirical Comparison of Alternate Regime-Switching Models for Electricity Spot Prices', *Energy Economics*, no. 32, pp. 1059 – 1073.
Kanamura, T & Ohashi, K 2007, 'A Structural Model for Electricity Prices with Spikes Measurement of Spike Risk and Optimal Policies for Hydropower Plant Operation', *Energy Economics*, no. 29, pp. 1010 – 1032.
Kanamura, T & Ohashi, K 2008, 'On Transition Probabilities of Regime Switching in Electricity Prices', *Energy Economics*, no. 30, pp. 1158 – 1172.
Kennedy, P 2003, *A Guide to Econometrics 5th Edition*, Pearson Prentice Hall, USA.
Knittel, CR & Roberts, MR 2005, 'An Empirical Examination of Restructured Electricity Prices', *Energy Economics*, no. 27, pp. 791 – 817.
Kosaster, P 2008, 'On the Impact of Weather on German Hourly Power Prices', *Energy Economics*, no. 30, pp. 2697 – 2704.
Lucia, JJ & Schwartz, ES 2002, 'Electricity Prices and Power Derivatives: Evidence from the Nordic Power Exchange', *Review of Derivatives Research*, no. 5, pp. 5 – 50.
Lu, X, Dong, ZY & Li, X, 2005, 'Electricity Market Price Spike Forecast with Data Mining Techniques', *Electric Power Systems Research*, no. 73, pp. 19 – 29.
Misiorek, A, Trück, S & Weron, R 2006, 'Point and Interval Forecasting of Spot Electricity Prices: Linear vs Non-Linear Time Series Models', *Studies in Nonlinear Dynamics & Econometrics*, vol. 10 no. 3, Article 2.
Mount, TD, Ning, Y & Cai, X 2006, 'Predicting Price Spikes in Electricity Markets Using a Regime-Switching Model with Time-Varying Parameteres', *Energy Economics*, no. 28, pp. 62 – 80.
Shawky, AH, Marathe, A & Barrett, CL 2003, 'A First Look at the Empirical Relation between Spot and Futures Electricity Prices in the Unites States', *The Journal of Futures Markets*, vol. 23 no. 10, pp. 931 – 955.
Verbeek, M., 2008. A Guide to Modern Econometrics 3rd edition. John Wiley & Sons Ltd., West Sussex England.
Vuong, QH 1989, 'Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses', *Econometrica*, vol. 57 no. 2, pp. 307 - 333.
Weron, R 2000. 'Energy Price Risk Management', *Physica A*, no. 285, pp. 127 - 134.
Weron, R, Bierbrauer, M & Trück, S 2004. 'Modelling Electricity Prices: Jump Diffusion and Regime Switching', *Physica A*, no. 336, pp. 39 - 48.
Weron, R 2006, *Modeling and Forecasting Loads And Prices In Deregulated Electricity Markets,* John Wiley & Sons Inc., New Jersey USA.
Weron, R & Misiorek, A 2008. 'Forecasting Spot Electricity Prices: A Comparison of Parametric and Semiparametric Time Series Models', *International Journal of Forecasting*, no. 24, pp. 744 - 763.