Outlier Treatment and Robust Approaches for Modeling Electricity Spot Prices

Trueck, Stefan and Weron, Rafal and Wolff, Rodney

Hugo Steinhaus Center, Wroclaw University of Technology

August 2007

Outlier Treatment and Robust Approaches for Modeling Electricity Spot Prices*

Trück, Stefan
Macquarie University, Department of Economics
Sydney, 2109 NSW, Australia
E-mail: strueck@efs.mq.edu.au

Weron, Rafał
Wrocław University of Technology, Hugo Steinhaus Center
Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland
E-mail: rafal.weron@pwr.wroc.pl

Wolff, Rodney
Queensland University of Technology, School of Economics and Finance
GPO Box 2434, Brisbane QLD 4001, Australia
E-mail: r.wolff@qut.edu.au

Abstract. *We investigate the effects of outlier treatment on the estimation of the seasonal component and stochastic models in electricity markets. Typically, electricity spot prices exhibit features like seasonality, mean-reverting behavior, extreme volatility and the occurrence of jumps and spikes. Hence, an important issue in the estimation of stochastic models for electricity spot prices is the estimation of a component to deal with trends and seasonality in the data. Unfortunately, in regression analysis, classical estimation routines like OLS are very sensitive to extreme observations and outliers. Improved robustness of the model can be achieved by (a) cleaning the data with some reasonable procedure for outlier rejection, and then (b) using classical estimation and testing procedures on the remainder of the data. We examine the effects on model estimation for different treatment of extreme observations in particular on determining the number of outliers and descriptive statistics of the remaining series after replacement of the outliers. Our findings point out the substantial impact the treatment of extreme observations may have on these issues.*

Introduction

In the last two decades the power sectors worldwide have undergone a transition from monopolistic, government controlled systems into deregulated, competitive markets (Bunn, 2004; Harris, 2006; Kaminski, 2004; Kirschen and Strbac, 2004; Weron, 2006). The amount of risk borne by market participants has increased substantially, partially due to the fact that electricity is a very unique commodity. Firstly, it cannot be stored economically and requires immediate delivery, while end-user demand shows high variability and strong weather and business cycle dependence. Secondly, effects like power plant outages or transmission grid (un)reliability add complexity and randomness. Consequently, electricity spot prices exhibit very high volatility and abrupt, short-lived and generally unanticipated extreme price changes known as spikes (or jumps). The latter are, perhaps, the most distinct feature of deregulated power markets, and will be investigated in this paper.

Apart from the aforementioned spikes, the two other most prominent characteristics of spot electricity prices include seasonality (at the annual, weekly and daily time horizons) and mean-reversion. The first crucial step in defining a model for electricity price dynamics consists of finding an appropriate description of the seasonal pattern. There are different suggestions for dealing with this task: Bhanot

*Paper presented at the 56th Session of the International Statistical Institute, Invited Paper Meeting IPM71 'Statistics of risk aversion', Lisbon, Aug. 22-29, 2007.

(2000), Knittel and Roberts (2005) and Lucia and Schwartz (2002) use piecewise constant functions; Cartea and Figueroa (2005), Pilipovic (1997) and Weron et al. (2004a) model the seasonal pattern by sinusoidal functions; while Stevenson (2001) and Weron (2006) utilize a wavelet decomposition.

A critical issue in estimation of the seasonal pattern is that it might be substantially affected by the price spikes. While it is clear that price spikes should be captured by an adequate stochastic model, like jump-diffusion (Clewlow and Strickland, 2000; Geman and Roncoroni, 2006; Weron, 2007) or a regime-switching model (Bierbrauer et al., 2004; De Jong, 2006; Huisman and Mahieu, 2003), the literature does not agree on whether these observations have to be included or excluded in the estimation of the seasonal pattern. Even worse: despite the fact that price spikes are among the most pronounced features of electricity markets and account for a large part of the total variation of changes in spot prices, there is no commonly accepted definition of a price spike (Weron, 2006). A variety of methods for identification has been suggested, however, so far there has been no thorough empirical study on the effects of alternative treatment of the price spikes on parameter estimates for the seasonal pattern or the stochastic component of the spot price. It is exactly our goal to examine the consequences of the treatment of such extreme events in the estimation procedures. To identify the spikes we will consider a variety of different approaches. After such 'cleaning' of the observed spot prices we will then compare the remaining seasonal patterns.

Price Spikes

The identification of spikes is a very important issue as it bears on the estimation of the deterministic and stochastic components for models of electricity spot price dynamics. However, in the literature the definition of a spike so far has been a rather subjective matter. Obviously, price spikes are defined as prices that surpass a specified threshold for a brief period of time. But it is difficult to gain any consensus on what that threshold or time interval should be.

Some authors use fixed price thresholds to identify the spikes (Lapuerta and Moselle, 2001). Other references suggest the use of fixed log-price change thresholds, e.g., log-price increments or returns exceeding 30% (Bierbrauer et al., 2004), or variable log-price change thresholds, e.g., log-price increments or returns exceeding three standard deviations of all price changes (Cartea and Figueroa, 2005; Clewlow and Strickland, 2000; Weron et al., 2004b). Borovkova and Permana (2004) considered as jumps those price moves that were outside 90% prediction intervals, implied by the normal distribution with the mean and variance given by the 60-days moving average and 60-days moving variance of the price moves. Yet another approach was used by Geman and Roncoroni (2006) who filtered raw price data using different thresholds and selected the one leading to the best calibrated model in view of its ability to match the kurtosis of observed daily price variations. Finally, the use of wavelet decomposition to filter out the spikes has been suggested (Stevenson, 2001; Weron, 2006). Obviously, different definitions and techniques may lead to quite different results and identification of price spikes.

The Data

For our empirical analysis we have chosen data from the European Energy Exchange (EEX) in Leipzig, Germany. This power market has shown a steady increase both in the number and volume of traded products since its opening in 1999. While some of the other European power exchanges suffer from low liquidity in the spot market and concentration on futures contracts, the spot market trading volume at the EEX has been increasing significantly. The spot market is a day-ahead market and the spot is an hourly contract with physical delivery on the next day. In our analysis we consider the Phelix base *day* index. The index is an equally weighted average of all 24 hourly spot prices for that

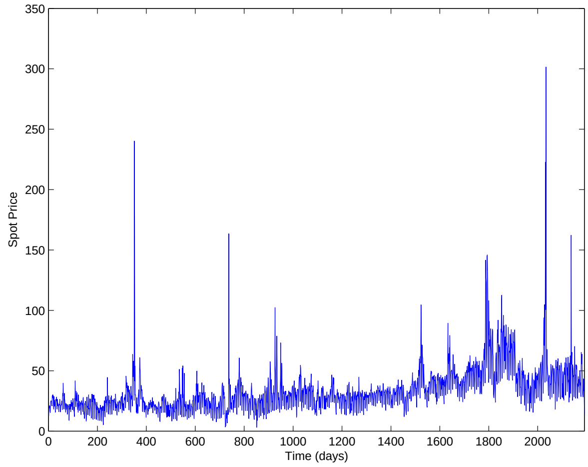

Figure 1: Spot prices of the EEX Phelix Base (day) index from January 1, 2001, to December 31, 2006, totaling 2191 observations.

particular day.

Our data comprise six years of Phelix base day prices from January 1, 2001, to December 31, 2006, totaling 2191 observations. The dynamics of the spot prices for the considered period are shown in Figure 1. Obviously, several spikes can be observed during the considered period. For example, spot prices peaked in December 2001 with a daily average of 240 EUR/MWh, in January 2003 with 163 EUR/MWh and in July and November 2006 with 301 and 162 EUR/MWh, respectively. In most cases the spikes lasted only for one or two days and prices fell back to their normal levels very quickly. There is also an obvious trend in the data such that the average price level at the end of the considered period was substantially higher than in the first two-three years.

Methods to Detect the Spikes

Probably the simplest technique to detect outliers is the use of fixed price thresholds. However, the choice of the levels themselves is non-trivial and rather arbitrary. For the present dataset, we chose to classify all prices beyond 75 EUR/MWh as extreme observations. Obviously other thresholds may be chosen depending on needs.

Nevertheless, the remaining question is how to replace the outliers. The chosen technique for replacement will also affect parameter estimates, e.g., of the seasonal pattern if the estimation is conducted using the new series. Some authors suggest to dampen prices exceeding a certain threshold with a logarithmic function or to replace the observed outliers by the thresholds themselves (Shahidehpour et al., 2002; Weron, 2006). An alternative may be to replace the extreme observations by the mean of the two neighboring prices (Weron, 2007) or by one of the neighboring prices (Geman and Roncoroni, 2006). However, this can lead to complications when there are two or more consecutive outliers. Also seasonal behavior of electricity prices may alter the prices too much. Recall, for example, that weekend prices are generally significantly lower than during the week. Hence, an alternative approach was suggested by Bierbrauer et al. (2007) where the outliers were replaced by the median of all prices having the same weekday and month as the outlier. Results for this method are displayed in the left panel of Figure 2.

As it was mentioned above, there is an obvious positive trend in the data. Hence, using fixed thresholds without detrending the time series beforehand may lead to an underestimation of spikes at the beginning of the considered period while for the later years the number of spikes may be

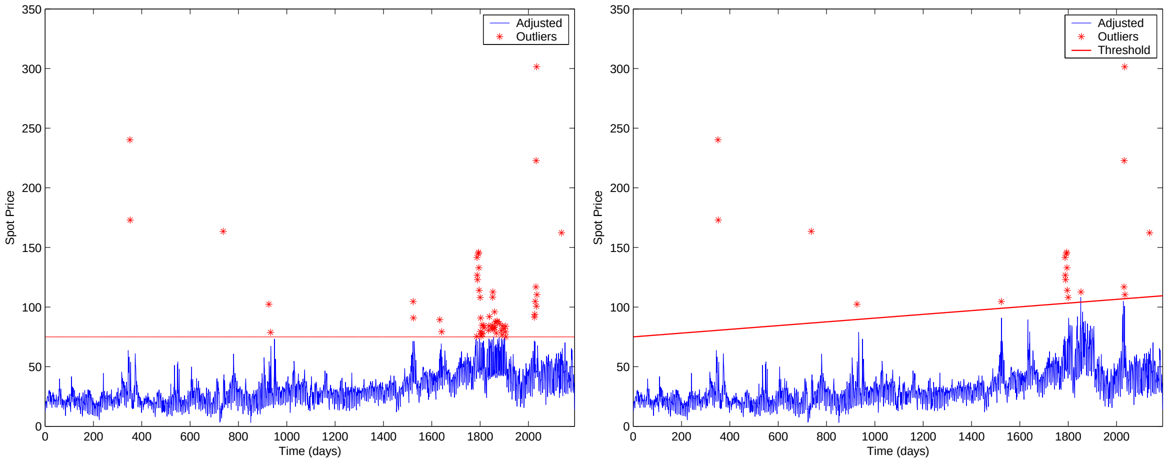

Figure 2: Time series after replacement of the spikes and original observations classified as outliers using fixed price thresholds for the original (left panel) and a detrended series (right panel).

overestimated. Hence, the fixed threshold method was also applied to the detrended series. The results for this method are displayed in the right panel of Figure 2. From a first glance one can see that clearly fewer observations are classified as outliers when the detrended series is used. For further comparison of the techniques see the next section.

Another method for detection of spikes or outliers was initially suggested in Clewlow and Strickland (2000). Hereby, a recursive filter is applied to identify price jumps in the sample distribution of daily returns. The filter consists of an iterative procedure that is repeated until no more jumps can be identified. In the first step, the sample standard deviation $\hat{s}$ of the returns is calculated before identifying returns beyond a certain range – measured in multiples of $\hat{s}$ – as extreme returns. Clewlow and Strickland (2000) suggest three standard deviations as the limit, however alternative specifications are straightforward. Returns within that limit are treated as 'normal' price returns, while the other returns are identified as outliers. After replacing the outliers, the next iteration is performed.

However, applying this technique, we have to take into account that electricity prices usually show strong weekly seasonality that may affect the number of extreme returns. A straightforward application of the recursive filter technique may lead to an overestimation of the number of extreme returns. To avoid this problem we will apply a variant of a simple moving average-based deseasonalization technique beforehand, to eliminate the weekly component. It differs from the original method (Brockwell and Davis, 1991; Weron, 2006) in that instead of using the mean it uses the median, which is more robust to outliers.

For the vector of daily prices $\{x_1, ..., x_{2191}\}$ we first estimate the trend by applying a moving average filter specially chosen to eliminate the weekly component and to dampen the noise:

$$(1) \qquad \hat{m}_t = median(x_{t-3}, .., x_t, .., x_{t+3}), \qquad t = 4, ..., 2188.$$

Next, we estimate the seasonal component. For each $k = 1, .., 7$ the average w_k of the deviations $\{(x_{k+7j} - \hat{m}_{k+7j}), 3 < k + 7j \leq 2188\}$ is computed. Since these average deviations do not necessarily sum to zero, we estimate the seasonal component s_k as

$$(2) \qquad \hat{s}_k = w_k - \frac{1}{7}\sum_{i=1}^{7} w_i,$$

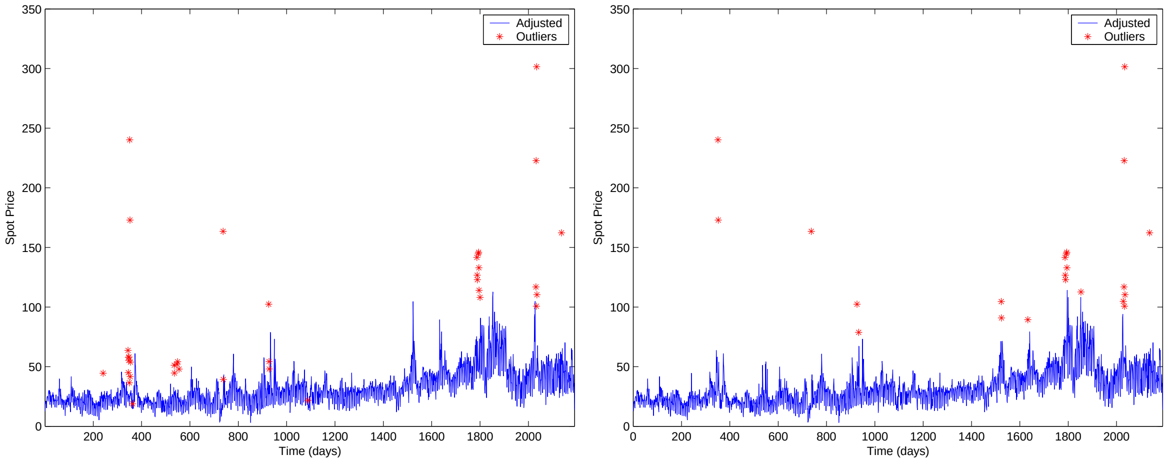

Figure 3: Time series after replacement of the spikes and original observations classified as outliers using the recursive filter technique (left panel) and percentage price thresholds for the detrended series (right panel).

where $k = 1, ..., 7$ and $\hat{s}_k = \hat{s}_{k-7}$ for $k > 7$. The deseasonalized (with respect to the 7-day period) data is then defined as $y_t = x_t - \hat{s}_t$ for $t = 1, ..., 2191$ and is used to detect and replace the outliers. Note that the deseasonalised series is not adjusted for the trend, long-term cycles or yearly seasonal components but only for the weekly seasonal pattern. However, since the recursive filter considers daily returns, long-term cycles or trends should not have any impact. Then applying the same approach as for the fixed threshold, the outliers were replaced by the median of all prices having the same weekday and month plus a linear trend component. Results for outlier detection and the remaining series are displayed in the left panel of Figure 3.

Alternatively, extreme observations may be detected using percentage thresholds. For example one may consider the largest 1% of the observations as outliers. In this case, however, it is important to consider also seasonality and trend in the data. Otherwise the identification of certain observations as outliers will be clearly dependent on the weekday or month if there is also a yearly pattern in the data. To overcome this problem, similar to the approach for the recursive filter, we first calculated the deseasonalized series y_t. However, in a second step we applied another moving average filter to take care of the lower frequency seasonality in the data: $\hat{m}_{2,t} = median(y_{t-15}, ..., y_{t+15}), t = 16, ..., 2176$. Note, that the 31 day median roughly corresponds to monthly smoothing. The difference between the deseasonalized series y_t and the moving average $m_{2,t}$ was chosen to identify the highest 1% extreme observations in terms of actual deviations from the average price level. The extreme observations were replaced by the median of all prices having the same weekday and month. After replacement of the outliers the estimated seasonal component and trend was added to the series again. Results for outlier detection and the remaining series are displayed in the right panel of Figure 3.

Yet another outlier detection approach utilizes wavelets, more specifically, lowpass filtering (Weron, 2006). The wavelet transform involves the projection of a signal onto an orthonormal set of components – the so-called wavelets. Unlike sines and cosines, individual wavelet functions are quite localized in time or (more generally) in space; simultaneously, like sines and cosines, individual wavelet functions are quite localized in frequency or (more precisely) characteristic scale (Härdle et al., 1998; Percival and Walden, 2000). Wavelets belong to families, like the Daubechies wavelet family used here. A wavelet family comes in pairs of a father (S) and mother wavelet (D). The former represents the 'lowest frequency' smooth components – those requiring wavelets with the widest sup-

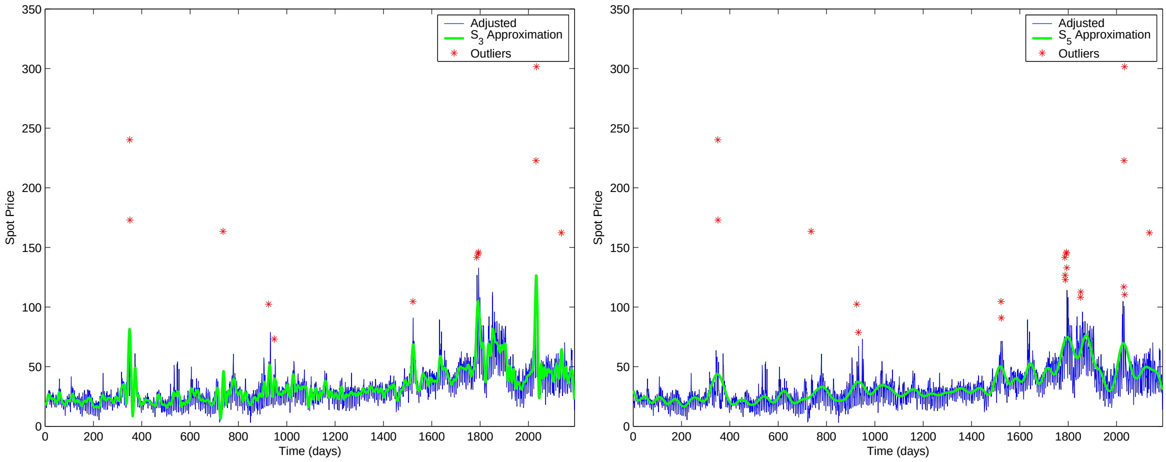

Figure 4: Time series after replacement of the spikes, S_3 (left panel) and S_5 (right panel) wavelet approximations and original observations classified as outliers using the wavelet filter technique.

port – whereas the latter captures the 'higher frequency' detail components. Any function or signal (here: the spot price series) can be built up as a sequence of projections onto one father wavelet and a sequence of mother wavelets,

$$f(t) = S_J + D_J + D_{J-1} + ... + D_1, \tag{3}$$

where 2^J is the maximum scale sustainable by the number of observations. At the coarsest scale the signal can be estimated by S_J. At a higher level of refinement the signal can be approximated by $S_{J-1} = S_J + D_J$. At each step, by adding a mother wavelet D_j of a lower scale $j = J-1, J-2, ...$, we obtain a better estimate of the original signal. This procedure is known as lowpass filtering. Here, we use the S_3 and S_5 approximations, roughly corresponding to weekly ($2^3 = 8$ days) and monthly ($2^5 = 32$ days) smoothing, respectively. Once a chosen approximation (S_3 or S_5) is subtracted from the original price series, the outliers are identified as the observations exceeding three standard deviations of the differences. We decided to replace the outliers by their wavelet approximation. A plot of the original time series and the wavelet S_3 and S_5 approximations as well as the results for outlier detection for the two approximation techniques are displayed in Figure 4.

Results

In this section we will compare the different approaches in terms of outlier detection, descriptive statistics of the remaining series and the effects of the preprocessing technique on the estimation of the seasonal pattern. In a first step we investigate the number of detected outliers, see Table 1.

The bounds for the fixed thresholds method was chosen to be 75 EUR/MWh. Obviously, depending on whether the technique is applied to the original or the detrended series there are substantial differences in the outcome. For the detrended series mostly observations in the years 2005 and 2006 were characterized as outliers, since the average price level was much higher in these years, see Figure 2. In total there are 50 observations replaced when the original series is considered. The respective number for the same threshold using a detrended time series only yields 19 outliers. Overall, considering several years of data, it seems recommendable to choose a fixed price threshold to identify price spikes only after dealing with trends or seasonalities beforehand.

For the percentage thresholds we chose to identify the highest 1% of the deseasonalized series as

Table 1: Number of detected spikes and descriptive statistics of the series after removing the spikes. Preprocessing indicates whether the trend, the annual and/or the weekly seasonal components have been removed from the original data before identifying the spikes.

Method	Preprocessing			#spikes	Max	Mean	Std	Skew	Kurt
	Trend	Year	Week						
Original	—	—	—	—	301.54	33.56	19.01	3.93	37.16
Fixed Threshold	—	—	—	50	79.49	32.01	13.43	0.83	3.52
Fixed Thres. Detrend.	✓	—	✓	19	108.25	32.64	14.90	1.24	5.08
Recursive Filter	—	—	✓	37	112.65	32.47	14.92	1.32	5.51
Percentage Thres.	✓	—	✓	22	114.06	32.70	14.99	1.24	5.13
Wavelet Approx. S_3	✓	✓	$\sim$	12	132.91	33.10	16.23	1.70	7.81
Wavelet Approx. S_5	✓	✓	—	20	114.06	32.78	15.14	1.27	5.18

outliers, yielding 22 observations. The comparative number for the recursive filter technique is higher and characterized 37 observations as outliers. It is notable that for the filter technique also a number of observations with a lower price level but high percentage returns were identified as price spikes. Examining the results for the wavelet decomposition techniques, we find that the S_3 approximation is very close to the original time series (see the left panel of Figure 4). Thus, only a small number of observations – in total 12 – is classified as outliers. The smoother S_5 approximation, on the other hand, characterizes 20 observations as outliers and yields similar results to the other techniques.

The examination of the descriptive statistics for the preprocessed series yields the following results. For all techniques, the mean of the preprocessed series is only slightly smaller than for the original observations. However, the removal of the outliers has clearly decreased the standard deviation, skewness and kurtosis of the remaining series. There is also a general tendency for the relationship between the number of replaced outliers and those statistics: the more extreme observations are replaced, the more will the standard deviation, skewness and kurtosis decrease for the preprocessed series. Hence, the preprocessed series using the wavelet S_3 approximation yields the highest values for those statistics while they are clearly the lowest for the series that was preprocessed using the simple fixed threshold technique. The results for the other four techniques (fixed threshold detrended, recursive filter, percentage threshold and wavelet S_5) yield quite similar descriptive statistics. Interestingly, the recursive filter technique yields a preprocessed series with a slightly higher skewness and kurtosis than most of the other techniques, although a relatively high number of detected outliers has been replaced.

Finally, we compare the effects of the chosen outlier detection technique on the estimated seasonal pattern. We assume that the system price of electricity S_t can be decomposed as the sum of a deterministic component f_t and a stochastic component Y_t: $S_t = f_t + Y_t, \quad t > 0$. In the following, we are not interested in specifying a model for the stochastic component Y_t, but mainly in the estimated seasonal pattern for the differently preprocessed data. To keep the results comparable, we estimated the same seasonal pattern including a constant, trend and specified dummy variables for daily and monthly effects for all preprocessed series:

$$f(t) = \alpha + \beta \cdot t + d \cdot D_{day} + m \cdot D_{mon}. \tag{4}$$

Hereby, α, β are constant parameters and d and m denote the corresponding parameter vectors for the daily ($day = 1, .., 7$) and monthly ($mon = 1, .., 12$) dummy variables D_{day}, D_{month}. The function $f(t)$ was calibrated via numerical optimization using non-linear least squares regression in Matlab. Results of the estimation in terms of parameter estimates and significance of the parameters can be found in Table 2.

Table 2: Parameter estimates for the seasonal pattern depending on the different outlier detection techniques (indicates significant parameter estimates at the 5% level).*

Parameter	Original	Fixed	Fixed Detr	Filter	Percent	Wave S_3	Wave S_5
Constant	**23.573***	**22.249**	**22.683***	**22.546***	**22.998***	**22.908***	**22.660***
Trend	**0.0158***	**0.0137***	**0.0150***	**0.0154***	**0.0151***	**0.0156***	**0.0152***
Tue	**2.388***	0.223	1.192	1.211	0.741	1.212	0.880
Wed	0.759	**1.344***	**1.725***	1.217	1.381	1.414	1.436
Thu	1.156	0.949	1.2097	1.260	1.120	0.994	0.937
Fri	**-2.372***	**-1.371***	-1.271	-0.919	**-1.854***	-1.705	**-1.750***
Sat	**-10.277***	**-8.199***	**-8.765***	**-8.580***	**-9.135***	**-9.614***	**-9.226***
Sun	**-16.818***	**-14.750***	**-15.279***	**-15.016***	**-15.687***	**-16.146***	**-15.767***
Feb	0.210	1.097	1.315	1.059	1.243	0.869	1.491
Mar	-1.129	0.128	-0.351	-0.313	-0.613	-0.666	-0.356
Apr	**-5.551***	**-2.601***	**-4.446***	**-4.764***	**-4.514***	**-4.896***	**-4.267***
May	**-8.862***	**-5.928***	**-7.791***	**-8.128***	**-7.846***	**-8.240***	**-7.609***
Jun	**-5.242***	**-2.661***	**-4.106***	**-4.677***	**-4.399***	**-4.595***	**-3.936***
Jul	-0.091	-1.430	**-2.198***	**-3.676***	**-2.888***	-1.180	-1.839
Aug	**-7.021***	**-3.708***	**-5.755***	**-6.236***	**-5.840***	**-6.505***	**-5.612***
Sep	**-4.247***	-0.898	**-2.972***	**-3.343***	**-3.061***	**-3.549***	**-2.834***
Oct	**-5.206***	**-1.829***	**-3.929***	**-4.313***	**-4.017***	**-4.512***	**-3.792***
Nov	-0.638	-0.797	**-2.901***	**-3.327***	**-2.137***	-1.228	-1.914
Dec	-1.093	-1.144	**-2.528***	**-4.078***	-1.802	-1.787	-1.459

We find that depending on the chosen technique for outlier detection, there are significant differences between parameter estimates and also in terms of which days and months are considered to be significant. For all models, the constant and trend are highly significant. Note, however, that with $\beta = 0.0158$ the parameter estimate for the trend component is the highest for the observations where no preprocessing of the outliers has been conducted followed by the wavelet technique S_3 where the trend estimate is $\beta = 0.0156$. On the other hand, the trend is estimated to be substantially lower ($\beta = 0.0137$) if the outliers are detected by a fixed threshold technique without detrending. The other methods yield estimates for the trend parameter between of $\beta = 0.0150$ and $\beta = 0.0154$.

It is also noteworthy that depending on the preprocessing of the data, often quite different dummy variables for the day or month are significant at the chosen 5% level. While for all approaches obviously Saturday and Sunday show a significant lower price level, for the original data also the dummy variables for Tuesday and Friday are significantly different from Monday, respectively Wednesday and Friday for the fixed threshold technique without detrending. On the other hand, preprocessing using the recursive filter technique or the wavelet S_3 yields only Saturday and Sunday as being significantly different from a Monday.

Similar results can be observed for the significance of dummy variables for the months. All approaches give significant parameter estimates for the months April, May, June, August and October. However, there are substantial differences for the months as well as the total number of dummy variables that yield significant estimates. While based on the simple fixed threshold preprocessing only estimates for the above mentioned months are significantly different from January, for the fixed threshold with detrending and the recursive filter approach all dummy variables for April - December are significant at the 5% level. The preprocessing using the percentage threshold technique yields significant estimates for the April - November dummy variables, while the original series and the series preprocessed with the wavelet approaches classifies April, May, June, August, September and October as significant.

Overall, there are quite substantial differences in terms of the estimated seasonal pattern de-

Table 3: Monthly price forecasts for 2007 based on the estimated seasonal pattern for the different outlier detection techniques. The last row provides the mean absolute deviation (MAD) in Euro/MWh from the forecasts for the original observations.

Method	Original	Fixed	Fixed Detr	Filter	Percent	Wave S_3	Wave S_5
Jan	54.5209	49.0125	52.4774	52.9667	52.3237	53.5435	52.2009
Feb	55.0786	49.5304	53.0487	53.5786	52.9056	54.1691	52.7876
Mar	55.5115	49.9425	53.5171	54.0819	53.3647	54.6760	53.2511
Apr	49.1317	46.5389	48.1878	48.4612	48.0433	48.8416	48.1681
May	46.3943	43.7730	45.5007	45.7155	45.2749	46.1364	45.3964
Jun	51.0264	47.9317	50.1690	50.2008	49.6956	50.8514	50.0513
Jul	57.3837	51.4427	52.9390	52.0750	52.1647	56.3713	54.9484
Aug	51.2424	48.6331	50.3961	50.4766	50.1258	50.8717	50.2593
Sep	53.5551	51.8952	52.6839	52.9507	52.4826	53.3344	52.6087
Oct	53.6332	50.8713	52.5883	52.8528	52.4226	53.2971	52.5529
Nov	59.5912	53.4480	54.4707	54.6911	55.0923	58.6951	57.1431
Dec	57.6905	51.7984	53.0882	52.2966	55.5464	56.8890	55.4473
MAD		4.16	2.14	2.03	2.11	0.59	1.66

pending on the chosen technique for outlier detection. To further illustrate the effects of the different preprocessing techniques on the seasonal pattern and possible price forecasts let us consider the following situation. Starting with a model including all possible independent variables, for each preprocessed series in a backwards stepwise regression non-significant variables are excluded from the model, remaining with a model including only significant variables. Then the estimated seasonal pattern is used to give (deterministic) price forecasts for each month in 2007. The forecast results for each of the considered methods are presented in Table 3. Note that the predicted values of the seasonal pattern should not be used as actual price forecasts, since the modeling of the stochastic component has not been considered here. However, since the system price is decomposed as the sum of the deterministic and stochastic component, significant differences in the prediction of the deterministic component will also have an substantial effect on the forecasted system price.

We find that the estimated seasonal pattern without preprocessing the data for outliers yields the highest forecasts for the deterministic part of the series for all months in 2007. On the other hand, the lowest price forecasts for each month is obtained when the simple fixed threshold technique is used for outlier detection. As the last row indicates, the average difference between these two approaches is 4.16 Euro/MWh per day. For example, the forecasted average daily price in January is almost 10% lower for the fixed threshold technique in comparison to using the original observations.The differences are smaller for the other techniques, however, the predicted price level in 2007 is still between 1.66 and 2.14 Euro/MWh lower for the outlier detection techniques fixed threshold with detrending, recursive filter, percentage threshold and wavelet S_5. Only the wavelet S_3 approximation yields similar results to the original series. Here the forecasted average price level according to the estimated seasonal pattern is only 0.59 Euro/MWh lower than for the original series. Hence, the technique that classifies the smallest number of observations as outliers also predicts the highest price level for the forthcoming months in 2007.

Overall, the choice of the technique for outlier detection has to be considered as an important choice for modeling electricity spot prices. The chosen approach will not only affect the number of observations classified as outliers, but also the estimated seasonal pattern. Hence, as a decomposition of a deterministic and a stochastic component, also parameter estimates of the stochastic model as well as price forecasts of future spot prices are affected by the treatment of extreme observations.

REFERENCES

Bhanot, K., 2000. Behavior of power prices: Implications for the valuation and hedging of financial contracts. Journal of Risk 2, 43–62.

Bierbrauer, M., Menn, C., Rachev, S., Trück, S., 2007. Spot and derivative pricing in the eex power market. Journal of Banking and Finance forthcoming.

Bierbrauer, M., Trück, S., Weron, R., 2004. Modeling electricity prices with regime switching models. Lecture Notes in Computer Science 3039, 859–867.

Borovkova, S., Permana, F., 2004. Modelling electricity prices by the potential jumpdiffusion. Proceedings of the Stochastic Finance 2004 Conference, Lisbon, Portugal.

Brockwell, P., Davis, R., 1991. Time Series: Theory and Methods. Springer-Verlag, New York.

Bunn, D. (Ed.), 2004. Modelling Prices in Competitive Electricity Markets. Wiley, Chichester.

Cartea, A., Figueroa, M., 2005. Pricing in electricity markets: A mean reverting jump diffusion model with seasonality. Applied Mathematical Finance 12(4), 313–335.

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

De Jong, C., 2006. The nature of power spikes: A regime-switch approach. Studies in Nonlinear Dynamics & Econometrics 10(3), Article 3.

Geman, H., Roncoroni, A., 2006. Understanding the fine structure of electricity prices. Journal of Business 79(3), 1225–1262.

Härdle, W., Kerkyacharian, G., Picard, D., Tsybakov, A. (Eds.), 1998. Wavelets, Approximation and Statistical Applications. Lecture Notes in Statistics 129. Springer-Verlag, New York.

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

Huisman, R., Mahieu, R., 2003. Regime jumps in electricity prices. Working paper, Rotterdam School of Management.

Kaminski, V. (Ed.), 2004. Managing Energy Price Risk: The New Challenges and Solutions, 3rd ed. Risk Books, London.

Kirschen, D., Strbac, G., 2004. Fundamentals of Power System Economics. Wiley, Chichester.

Knittel, C. R., Roberts, M. R., 2005. An empirical examination of restructured electricity prices. Energy Economics 27(5), 791–817.

Lapuerta, C., Moselle, B., 2001. Recommendations for the Dutch electricity market. The Brattle Group Report.

Lucia, J. J., Schwartz, E., 2002. Electricity prices and power derivatives: Evidence from the Nordic power exchange. Review of Derivatives Research 5, 5–50.

Percival, D., Walden, A., 2000. Wavelet Methods for Time Series Analysis. Cambridge University Press, Cambridge.

Pilipovic, D., 1997. Energy Risk: Valuing and Managing Energy Derivatives. McGraw-Hill.

Shahidehpour, M., Yamin, H., Li, Z., 2002. Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management. Wiley.

Stevenson, M., 2001. Filtering and forecasting spot electricity prices in the increasingly deregulated Australian electricity market. QFRC Research Paper 63, University of Technology, Sydney.

Weron, R., 2006. Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach. Wiley, Chichester.

Weron, R., 2007. Market price of risk implied by Asian-style electricity options and futures. Energy Economics (forthcoming), doi:10.1016/j.eneco.2007.05.004.

Weron, R., Bierbrauer, M., Trück, S., 2004a. Modeling electricity prices: Jump diffusion and regime switching. Physica A 336, 39–48.

Weron, R., Simonsen, I., Wilman, P., 2004b. Modeling highly volatile and seasonal markets: Evidence from the Nord Pool electricity market. In: Takayasu, H. (Ed.), The Application of Econophysics. Springer, pp. 182–191, proceedings of the Second Nikkei Econophysics Symposium, Tokyo.