What is an Electricity Price Spike and What is Not? A Review of Spike Identification Techniques

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What is an Electricity Price Spike and What is Not? A Review of Spike Identification Techniques

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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, high volatility and the occurrence of jumps and spikes. We examine the effects on model estimation for different treatment of extreme observations on determining the number of outliers and the estimation the seasonal pattern after replacement of the outliers. Our findings point out the substantial impact the treatment of extreme observations may have on these issues and therefore, also on the pricing of electricity derivatives like futures and forward contracts.

Key words: Power Markets, Price Spikes, Robust Estimation, Seasonality, Spot Price Modeling
1 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; Kirsch 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 (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...
prices we will then compare the remaining seasonal patterns.

2 Price Spikes and Jumps

One of the most pronounced features of electricity markets are the abrupt and generally unanticipated extreme changes in the spot prices known as jumps or spikes. Within a very short period of time, the system price can increase substantially and then drop back to the previous level. These temporary price escalations account for a large part of the total variation of changes in spot prices and firms that are not prepared to manage the risk arising from price spikes can see their earnings for the whole year evaporate in a few hours. This section deals with stylized facts of such extreme events and gives some explanation on what actually causes price spikes and jumps.

2.1 Occurrence of Spikes

The literature points out, that electricity prices are far more volatile than any other commodity normally, see e.g. Ethier and Mount (1998); Mugele et al. (2005); Pilipovic (1997); Simonsen (2005); Weron (2000). Measuring volatility by the daily standard deviation of returns, electricity exhibits extreme volatility up to 50% while in general even very volatile stocks do not exceed 4%. Figure exemplarily shows the spot price and log spot price of the Phelix Base (day) index from January 1, 2006 to December 31, 2006 including several price spikes in the time series. Often in the literature such rapid price changes are called interchangeably spikes or jumps. Note however, that the latter term is in fact incorrect as the prices do not stay at the new level, but rather tend to rapidly return to the normal regime.

The spike intensity is also non-homogeneous in time. Generally, the spikes are especially notorious during on-peak hours, i.e. around 9h and 18h on business days, and during high consumption periods: winter in Scandinavia, summer in mid-western U.S., etc. As the time horizon increases and the data are aggregated the spikes are less and less apparent. For weekly or monthly averages, the effects of price spikes are usually neutralized in the data. It is not uncommon that prices from one day to the next or even within just a few hours can increase tenfold. The ‘spiky’ nature of spot prices is the effect of non-storability of electricity. Electricity to be delivered at a specific hour cannot be substituted for electricity available shortly after or before. As currently there is no efficient technology for storing vast amounts of power, it has to be consumed at the same time as it is produced. Hence, extreme load fluctuations - caused by severe weather conditions often in combination with generation outages or
transmission failures - can lead to price spikes. The spikes are normally quite short-lived, and as soon as the weather phenomenon or outage is over, prices fall back to a normal level, see e.g. Kaminski (1999); Weron et al. (2004b).

Despite their rarity, price spikes are the very motive for designing insurance protection against electricity price movements. This is one of the most serious reasons for including discontinuous components in realistic models of electricity price dynamics. Failing to do so, will greatly underestimate, say, the option premium, and thus increase the risk for the writer of the option. For instance in the U.S., where the size of the spikes can be much more severe, there are examples of power companies having to file for bankruptcy after having underestimated the risks related to price spikes. A textbook example is the bankruptcy of the Power Company of America (PCA), a well established power-trading company.

2.2 Causes for the Price Spikes

The main reason for spikes in electricity spot prices is the bidding strategies used by the market players. Since electricity is an essential commodity for many market participants, it is quite important to secure a sufficient and continuous supply of power at any time. Hence, some of the agents may be willing to pay almost any price to secure this supply. As a consequence, on a regular basis, bids are placed at the maximum allowed level for the amount of electric power anticipated by the market players to be needed for that particular hour, see e.g. Simonsen (2005). It is important to recall that in
auction markets the spot price is what a buyer has to pay for each unit of power independent of what he or she did bid initially as long as their bid was above (or equal to) the spot price. Hence, with this type of strategy, the worst case scenario is that a buyer has to stick with the high prices for a maximum of 24 hours. After this period, he or she is free to try to get power cheaper from alternative sources. With this type of bidding strategies, there will always be some buyers that are willing to pay a considerable amount in order to cover their need of electricity. And since the suppliers are aware of these strategies they place their bids accordingly, to maximize their profits.

2.3 Identification of 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). Hereby, a wavelet transform that is robust to outliers is suggested to preprocess the spot prices.

Note that in some approaches like regime-switching models or time-series approaches with a jump-diffusion component it may not be necessary to define the spikes in advance since the model specification and calibration algorithm does not require such a definition.

Obviously, the different techniques may lead to quite different definitions or
results of price jumps in spikes in electricity spot prices. As pointed out in the previous section, so far no empirical study has been conducted to examine the effects the different identification methods for spikes may have on the determination of the seasonal pattern or parameter estimates for the stochastic processes.

3 Data and Models

3.1 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 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.

3.2 Using Fixed Price Thresholds

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 (FT) 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 overestimated. Hence, the fixed threshold method was also applied to the detrended series. The results for this method (FTD) 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.
3.3 Recursive Filter (RF)

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:

\[
\hat{m}_t = \text{median}(x_{t-3}, ..., x_t, ..., x_{t+3}), \quad t = 4, ..., 2188. \tag{1}
\]

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

\[
\hat{s}_k = w_k - \frac{1}{7} \sum_{i=1}^{7} w_i, \tag{2}
\]

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
Fig. 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).

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 3.4.

3.4 Percentage Thresholds (PT)

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: $\hat{m}_{2,t} = \text{median}(y_{t-15}, ..., y_{t+15}), t = 16, ..., 2176$. 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 3.4.
3.5 Recursive Model Estimation (RM)

Another method for detection of extreme observation can be based on the goodness-of-fit of the seasonal pattern to the data. Hereby, in each step the number of outliers is reduced based on the marginal reduction of the mean-squared-error (MSE) of fitting a seasonal pattern to the new series. In each step the observations above the determined new threshold are replaced by the threshold and then a new seasonal pattern is estimated. In each recursive step the next threshold was chosen to be the mean of the three highest prices below the threshold. The procedure stops when the reduction in the MSE of the fitted seasonal pattern was less than 1%.

3.6 Wavelet Decomposition

Yet another outlier detection approach utilizes wavelets, more specifically, low-pass 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 support – 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,

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

(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 $j = J - 1, J - 2, \ldots$, 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 (WA $S_3$) and
Fig. 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.

$S_5$ approximations (WA $S_5$) as well as the results for outlier detection for the two approximation techniques are displayed in Figure 4.

4 Empirical 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 parameter estimates of the seasonal pattern and stochastic models.

4.1 Number of Spikes

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 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
<table>
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<th>Method</th>
<th>#spikes</th>
<th>FT</th>
<th>FTD</th>
<th>RF</th>
<th>RM</th>
<th>PT</th>
<th>S3</th>
<th>S5</th>
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</thead>
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<tr>
<td>FT</td>
<td>50</td>
<td>-</td>
<td>19/19</td>
<td>18/37</td>
<td>18/18</td>
<td>21/22</td>
<td>11/12</td>
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<td>19/50</td>
<td>-</td>
<td>17/37</td>
<td>17/18</td>
<td>17/22</td>
<td>11/12</td>
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<td>18/50</td>
<td>17/19</td>
<td>-</td>
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<td>16/22</td>
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<td>-</td>
<td>18/22</td>
<td>11/12</td>
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<tr>
<td>PT</td>
<td>22</td>
<td>21/50</td>
<td>17/19</td>
<td>16/37</td>
<td>18/18</td>
<td>-</td>
<td>11/12</td>
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<tr>
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<td>11/50</td>
<td>11/19</td>
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<td>17/19</td>
<td>15/37</td>
<td>17/18</td>
<td>19/22</td>
<td>11/12</td>
<td>-</td>
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</tbody>
</table>

Table 2  
Number of detected spikes for each method and conditional probability that an observations that has been classified as outliers by another technique is also classified as outlier. For example 17/19 in the row 'RF', column 'FTD' indicates that 17 out of the 19 observations being classified as outliers by method 'FTD' have also been identified by method 'RF'.

A relatively high number of detected outliers has been replaced.

In a second step we compare the actual observations that were classified as outliers by the different methods. Table 2 reports the number of detected spikes for each method and the fraction of these observations that are also classified as outliers by the other techniques. The results confirm the significant differences between the techniques as it comes to identification of electricity price spikes. While there is obviously a certain number of extreme spikes that are identified by all techniques, for smaller price jumps or spikes none of the techniques delivers identical results.

### 4.2 Seasonal Patterns

In a next step, 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:

$$f(t) = \alpha + \beta \cdot t + d \cdot D_{day} + m \cdot D_{mon}.$$  (4)
<table>
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<th>Parameter</th>
<th>Original</th>
<th>FT</th>
<th>FTD</th>
<th>RF</th>
<th>RM</th>
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<td>Aug</td>
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<td>-3.25</td>
<td>-6.05</td>
<td>-6.46</td>
<td>-5.66</td>
<td>-5.50</td>
<td>-5.81</td>
<td>-4.89</td>
</tr>
<tr>
<td>Nov</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dec</td>
<td></td>
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<td></td>
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</tr>
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</table>

Table 3
Parameter estimates after applying a stepwise estimation procedure for the seasonal pattern depending on the different outlier detection techniques. Only the remaining significant parameters at the 5% level are reported here.

Hereby, \( \alpha, \beta \) are constant parameters and \( d \) and \( m \) denote the corresponding parameter vectors for the daily \((day = 1, \ldots, 7)\) and monthly \((mon = 1, \ldots, 12)\) dummy variables \( D_{day}, D_{month} \). The function \( f(t) \) was calibrated via numerical optimization using a non-linear least squares regression in Matlab. We followed a stepwise procedure such that in each recursion all variables with non-significant coefficients at the 5% level were eliminated until all coefficients were significant. Estimation results for the remaining significant parameters for each of the pre-processing technique can be found in Table 2.

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 ($\beta = 0.0136$) if the outliers are detected by a fixed threshold technique without detrending. The other methods yield estimates for the trend parameter between $\beta = 0.0150$ 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 considered to be 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 Friday is 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 some 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, we find substantial differences in terms of the number of significant parameters as well as the estimated seasonal pattern depending on the chosen technique for outlier detection.

4.3 Forecasting Results

To further illustrate the effects of the different preprocessing techniques on the seasonal pattern and possible price forecasts, 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
Table 4
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.

<table>
<thead>
<tr>
<th>Method</th>
<th>Original</th>
<th>Fixed</th>
<th>Fixed Detr</th>
<th>Filter</th>
<th>Percent</th>
<th>Wave $S_3$</th>
<th>Wave $S_5$</th>
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</thead>
<tbody>
<tr>
<td>Jan</td>
<td>54.52</td>
<td>49.01</td>
<td>52.48</td>
<td>52.97</td>
<td>52.32</td>
<td>53.54</td>
<td>52.20</td>
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<tr>
<td>Feb</td>
<td>55.08</td>
<td>49.53</td>
<td>53.05</td>
<td>53.58</td>
<td>52.91</td>
<td>54.17</td>
<td>52.79</td>
</tr>
<tr>
<td>Mar</td>
<td>55.51</td>
<td>49.94</td>
<td>53.52</td>
<td>54.08</td>
<td>53.36</td>
<td>54.68</td>
<td>53.25</td>
</tr>
<tr>
<td>Apr</td>
<td>49.13</td>
<td>46.54</td>
<td>48.19</td>
<td>48.46</td>
<td>48.04</td>
<td>48.84</td>
<td>48.17</td>
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<tr>
<td>May</td>
<td>46.39</td>
<td>43.77</td>
<td>45.50</td>
<td>45.72</td>
<td>45.27</td>
<td>46.14</td>
<td>45.40</td>
</tr>
<tr>
<td>Jun</td>
<td>51.03</td>
<td>47.93</td>
<td>50.17</td>
<td>50.20</td>
<td>49.70</td>
<td>50.85</td>
<td>50.05</td>
</tr>
<tr>
<td>Jul</td>
<td>57.38</td>
<td>51.44</td>
<td>52.94</td>
<td>52.08</td>
<td>52.16</td>
<td>56.37</td>
<td>54.95</td>
</tr>
<tr>
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<td>50.40</td>
<td>50.48</td>
<td>50.13</td>
<td>50.87</td>
<td>50.26</td>
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<tr>
<td>Sep</td>
<td>53.56</td>
<td>51.89</td>
<td>52.68</td>
<td>52.95</td>
<td>52.48</td>
<td>53.33</td>
<td>52.61</td>
</tr>
<tr>
<td>Oct</td>
<td>53.63</td>
<td>50.87</td>
<td>52.59</td>
<td>52.85</td>
<td>52.42</td>
<td>53.30</td>
<td>52.55</td>
</tr>
<tr>
<td>Nov</td>
<td>59.59</td>
<td>53.45</td>
<td>54.47</td>
<td>54.69</td>
<td>55.09</td>
<td>58.70</td>
<td>57.14</td>
</tr>
<tr>
<td>Dec</td>
<td>57.69</td>
<td>51.80</td>
<td>53.09</td>
<td>52.30</td>
<td>55.55</td>
<td>56.89</td>
<td>55.45</td>
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<tr>
<td>MAD</td>
<td>4.16</td>
<td>2.14</td>
<td>2.03</td>
<td>2.11</td>
<td>0.59</td>
<td>1.66</td>
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</tr>
</tbody>
</table>

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 a 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. These results also have substantial impact on the pricing of electricity forward and futures contracts or risk management of such contracts, since they will be dependent on the forecasted price level.

5 Conclusion

In this paper we investigated the effects of outlier treatment on the estimation of the seasonal component and stochastic models in electricity markets. Since electricity spot prices usually exhibit several price jumps and spikes, an important issue is the estimation of a component to deal with trends and seasonality in the data. Unfortunately, in regression analysis, often classical estimation routines like OLS are very sensitive to extreme observations and outliers. 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. Overall, the choice of the technique for outlier detection has to be considered as an important decision 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. This will also have a significant impact on the pricing of derivatives like forward and futures contracts in the market. Further investigation of the issue including an extensive forecasting study as well as the application of the different techniques to the pricing of forward contracts should provide further inside insight of the issue.

References


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


