The Influence of Temperature on Spike Probability in Day-Ahead Power Prices

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THE INFLUENCE OF TEMPERATURE ON SPIKE PROBABILITY IN DAY-AHEAD POWER PRICES

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Abstract

It is well known that day-ahead prices in power markets exhibit spikes. These spikes are sudden increases in the day-ahead price that occur because power production is not flexible enough to respond to demand and/or supply shocks in the short term. This paper focuses on how temperature influences the probability on a spike. The paper shows that the difference between the actual and expected temperature significantly influences the probability on a spike and that the impact of temperature on spike probability depends on the season.

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Introduction

Prices in day-ahead electricity markets exhibit frequent spikes. A spike is a sudden shock in the price as a result of sudden changes in demand and/or supply to which electricity producers cannot respond flexible enough. Spikes can be big in magnitude as for example in the Dutch APX market in August 2003. The heat wave was causing the temperature of water in rivers to reach such levels that the Dutch government decided to restrict the outflow of cooling water from, among others, energy producers into the rivers, thereby effectively limiting the installed production capacity. Prices in the day-ahead market spiked, reaching levels over 1,000 euro for 1MW of electricity delivered in the peak hours on August 11 and 13, whereas the average price in the peak hours was approximately 49 euro over the 20 days before August 11. This example of a supply driven cause of a multi-day price spike shows that the risk of these spikes cannot be ignored.

Spikes have an impact on the amount of market risk and credit risk that companies face. For instance, a power distribution company that purchases a part of their clients volume on the day-ahead market is confronted with a huge increase in their purchasing price of power as a results of a spike. If the company is committed to sell against fixed prices, these spikes will dramatically impact the profits and losses of the company. Not only the profitability itself is at stake (market risk), but also counter-parties and other stakeholders will observe the reduction in profitability and perceive the company as more risky (credit risk). In order to protect their positions, the counter-parties might ask for more collateral, leading to an additional cash-outflow or - at least - a reduced amount of liquid assets. Therefore, if companies purchase a part of their electricity needs on the day-ahead markets, they need to manage the market and credit risk that they face from spikes. In many cases, models that describe the behavior of day-ahead prices in power markets help to measure risk, to forecasts cash-flow sensitivity and to valuate derivative contracts on day-ahead delivery such as options, swaps and forwards.

Over the past years, models have been introduced that describe the behavior of day-ahead prices in power markets. Bunn and Karakatsani (2003) provide an excellent review of the literature. In addition to spikes, day-ahead prices are known to exhibit mean-reversion, seasonality and time-varying volatility. Focusing on spikes, these were initially modeled as a jump diffusion process. In this framework, spikes can occur at all times and are an integral part of the model itself. As a result, the mean-reversion parameter in the model reflects both the amount of mean-reversion in normal markets and the mean-reversion after a spike has occurred. Deng (1998), Ethier and Mount (1999), and Huisman and Mahieu (2003) formulate regime-switching models to capture spike behavior. Basically, they observe that spikes occur in situations where the market is not in a normal state due to a - short term - shock in supply and demand conditions. Therefore, they model spikes separately from prices under normal market conditions. The prices under normal market conditions are typically modeled as a standard mean-reverting process with seasonality factors and the prices under non-normal market conditions are drawn from a distribution with a high mean price level and a high variance. In regime switching models, a Markov process then governs the daily transition from one regime to another. The authors show that regime-switching approach is better capable of separating the mean-reversion under normal market conditions from the way how prices jump back to normal price levels after a spike has occurred.

A drawback of the models discussed above is that the probability with which a spike occurs is constant over time. That is, the probability of a spike is the same in summer and winter months, in weekdays and weekend, for all weather conditions, and for all levels of reserve capacity. This is not realistic as spikes occur as a result of shocks in demand and supply and these shocks may be caused by some event. Mount, Ning, and Cai (2006) observe this and propose a regime switching model in which the probability of spike occurrence is time-varying. More specifically, they argue and show that the probability of a spike depends on the reserve margin. The lower the reserve margin (the difference between available capacity and capacity in use), the higher the probability on a spike is as in periods with low reserve margins, there is less capacity available to compensate for shocks in supply and demand. The authors show that this specification better predicts day-ahead prices as the probability of a spike now depends on actual market conditions.

The motivation for this paper comes from the observation that Mount, Ning, Cai make in their conclusions. They state, correctly, that in order to predict day-ahead prices effectively, one needs to have access to accurate information about reserve margins. They fit their model to day-ahead PJM prices and for that market historical information on load and reserve margin was available. However, this is not the case in all markets. Furthermore, if information on reserve margins is available, it might not be easily accessible to every market participant and it might not be available on time. In this paper, the daily temperature is proposed as a variable that influences the probability on a spike as described in the example from the APX market that was discussed before. It is well known that power consumption depends on temperature (heating in winters, air-conditioning in summers) and shocks in supply or demand are related to shocks in temperature (if today is warmer than expected, consumers use more power than expected for air-conditioning and a short-term shortage might occur). Furthermore, temperature information is transparent and more widely available and may replace reserve margin as a forecasting variable for those markets where information on reserve margin is not or not accurately available. Another advantage of using temperature instead of reserve margins is that risk from changes in day-ahead prices can be hedged more effectively as weather derivatives are being traded worldwide and reserve margin derivatives do not exist directly. The goal of this paper is therefore to a) formulate a model that is in line with Mount, Ning and Cai (2006) but which depends on temperature and b) to assess how temperature affects the probability on a spike.

A temperature dependent regime-switching model

This section present a model that describes the behavior of daily average day-ahead prices. In day-ahead markets, prices are quoted for delivery in every specific hour in the next day. Many day-ahead markets do not allow for continuous trading. Before a specific closing time - usually in the morning - agents have to submit their bids and offers for delivery in each of the hours in the next day. Huisman, Huurman and Mahieu (2007) conclude therefore that hourly specific electricity prices do not follow a time series process, but behave as a panel of individual hours that coexist over time. Daily average prices can be seen as a time series and therefore the model below applies to daily average prices (base, peak and, off-peak). In the text below, *price* reflects the daily average price for day-ahead delivery.

In line with Mount, Ning, and Cai (2006), it is assumed that the electricity market can be in one out of two regimes. Regime 1 reflects a normally behaving market. Regime 2 reflects a non-normal market due to a shock in demand and/or supply that results in a spike.

Let s(t) be the natural logarithm of the day-ahead price for delivery of 1MW in day t (note that the price quote was submitted on day t-1; thus, t reflects the delivery period). Following Huisman and Mahieu (2003), the electricity price consists of a deterministic component d(t) and a stochastic component x(t). The deterministic component captures predictable elements of the price for delivery on day t. The first component of d(t) is the equilibrium or mean price level μ. The second component allows for different prices between weekends and weekdays. Let W(t) be a dummy variable that equals 1 if t is a weekend day and 0 if it is any other day. The third component allows for temperature dependency of the prices during the summer. It is assumed that especially deviations in actual temperature from expected temperature lead to price changes instead of the actual temperature level itself. Although temperature reflect the seasonality in hydropower capacity, and therefore might explain variations in prices in some markets, it is here assumed that temperature does not have an impact on the supply in normal time periods. However, the model can be easily extended for applications in such markets. Let $E_{t-1}\{\tau(t)\}$ be the expected temperature for day t based on the information available on day t-1. Let $E_{t-1}\{\Delta\tau(t)\}$ be the deviation between the actual and expected temperature. Let S(t) be a dummy variable that equals one if day t is in the summer. Summer is defined as the six month period April through September. The fourth component allows for temperature dependence in the winter. The deterministic component d(t) can be specified as follows:

(1) $d(t) = \mu_1 + \beta_1 W(t) + \beta_2 E_{t-1}\{\Delta\tau(t)\} S(t) + \beta_3 E_{t-1}\{\Delta\tau(t)\} (1-S(t))$.

The parameters β_2 and β_3 allow for different temperature dependencies in summer and winter. During the summer, electricity prices may be higher than the average prices when it is warmer due to air-conditioning usage; therefore β_2 is expected to be positive. During the winter, electricity prices may be higher than the average price when it is colder due to heating; therefore β_3 is expected to be negative.

The stochastic component x(t) is assumed to be different in both regimes. In regime 1, the normal market condition, x(t) follows a mean-reverting process:

(2) $x(t) = x(t-1) - \alpha\, x(t-1) + \sigma_1\, \varepsilon_1(t)$.

In regime 2, the spike regime, the electricity price is drawn from a distribution function with a high price level and variance:

(3) $x(t) = \mu_2 + \sigma_2\, \varepsilon_2(t)$.

Both error terms $\varepsilon_1(t)$ and $\varepsilon_2(t)$ are assumed to be IID(0,1) and mutually independent. It can be assumed that both ε's follow different distribution functions. In this paper (following Huisman and Mahieu (2003) and Mount, Ning, and Cai (2006)), both error terms are assumed to be normally distributed.

Let p(t,i,j) be the transition probability of moving from regime j on day t-1 to regime i on day t. The transition probabilities are assumed to be a function of temperature. Temperature is assumed to influence the probability on a spike in the case when the actual temperature differs from the expected temperature. As is assumed that consumption volume depends on temperature, an unexpected change in temperature might lead to an unexpected change in consumption volume. This might then lead to a spike, if power producers are not flexible enough to adjust their volumes to the new consumption level. Furthermore, the impact might differ over seasons, as in summer months unexpected higher temperature might lead to an increase in demand (air-conditioning), whereas in winter months unexpected lower prices might lead to an increase in consumption (heating). The transition probability p(t,2,1), reflecting the probability of a spike, is modeled as follows:

(4) $p(t,2,1) = \lambda_1 + \lambda_2 S(t) E_{t-1}\{\Delta\tau(t)\} + \lambda_3 (1\text{-}S(t)) E_{t-1}\{\Delta\tau(t)\}$.

The other transition probabilities are: $p(t,1,1) = 1 - p(t,2,1)$ and $p(t,2,2) = \lambda_4$ and $p(t,1,2) = 1 - p(t,2,2)$. Note that the above formulation of the transition probabilities does not restrict the probabilities to assume values between 0 and 1. In order to preserve for this, a logistic transformation is applied (following Huisman and Mahieu (2003) and Mount, Ning and Cai (2006)). That is, the value $p^*(t,2,1)$ is interpreted as the actual probability with:

(5) $p^*(t,2,1) = e^{p(t,2,1)} / (1+ e^{p(t,2,1)})$.

Data and estimation

The data consists of average prices in peak hours as they are published by the Dutch APX market between January 1st, 2003 and August 31st, 2006 (having 1339 observations). The temperature data is obtained from the KNMI and can be obtained from www.knmi.nl. The temperature reflects the average daily temperature observed in the middle of the Netherlands.

See Mount, Ning, and Cai (2006) for an excellent discussion on the estimating the parameters in a regime switching model. The parameters are estimated using Maximum Likelihood where the likelihood of the individual observations can be constructed recursively.. The observations on the temperature expectations and the daily deviations $E_{t-1}\{\Delta\tau(t)\}$, as used in equations 1 and 4, are calculated as follows. As the goal of the paper is not to research and use the best temperature model, it is chosen to model the temperature expectations as the average temperature over the last week. So, $E_{t-1}\{\Delta\tau(t)\}$ is measured as the difference between the actual temperature on day t-1 (representing the quoting day for delivery on day t) and the average temperature observed over the days t-7 through t-1. It is therefore assumed that the temperature expectation equals the average over the last week and that the observed temperature deviation from its average on day t-1 is representative for conditions on day t. Obviously, alternative models can be constructed and even actual weather forecast could be used, if historically available. It is left outside the scope of this paper.

Results

The estimates for the parameters in the above model are listed in table 1. The discussion about the parameter estimates starts with the estimates for the parameters in the deterministic component (equation 1). The mean log price level equals 3.885 (equivalent to 48,65 euro). In weekends, prices are lower as can be seen from the negative estimate for β_1. The temperature elasticities are different for the summer and the winter. For summer months, the elasticity parameter β_2 is positive and significantly different from zero. This implies that on days where the temperature is higher than what was expected, the price of power is higher. This is opposite for winter months as the β_3 parameter is negative and significantly different from zero. That is, on days where the temperature is lower than expected, the price of power is higher. These effects can be explained by the fact that when temperature changes in the short run, thereby influencing demand volume, more expensive power plants are used to generate power to meet the increased demand levels. Note that these temperature effects only affect the mean price level. The impact on spikes will be discussed later.

Table 1. Parameter estimates of the temperature regime switching model.

Parameter	Parameter	Parameter
μ_1	mean log. price level	3.885* (0.058)
β_1	weekend	-0.441* (0.093)
β_2	temperature elasticity summer	0.009* (0.005)
β_3	temperature elasticity winter	-0.007** (0.005)
α	mean reversion	0.145* (0.024)
σ_1	volatility normal regime	0.198* (0.006)
μ_2	mean spike regime	0.441* (0.093)
σ_2	volatility spike regime	0.607* (0.034)
λ_1	stationary transition probability from normal to spike regime	-3.320* (0.155)
λ_2	temperature effect on spike probability during summer	0.226* (0.088)
λ_3	temperature effect on spike probability during winter	-0.255** (0.138)
λ_4	stationary transition probability from spike to normal regime	1.538* (0.168)
LogLikelihood		-162.712

Asymptotic standard errors are presented in parenthesis.

* significant at 5% confidence level

** significant at 10% confidence level

Observations: average day-ahead prices in peak hours on the Dutch APX market from January 1st, 2003 through August 31, 2006 (1,339) observations; daily temperature observations were obtained from the KNMI.

equals 0.145 and the volatility equals 0.198. Both estimates differ significantly from zero. These results are all in line with findings from previously cited studies.

The estimates for the spike regime, reflecting the behavior of power prices under extreme market conditions, equal 0.441 for the mean and 0.607 for volatility. Both are significantly different from zero. Adding the estimate for the mean spike μ_2 to the mean price level μ_1 implies that on average the mean price level during a spike increase to 4.326 (equivalent to 75.64 euro compared to 48.65 euro in the normal regime). Furthermore, the standard deviation in the spike regime is about three times higher (0.607 compared to 0.198).

The probability with which spikes occur are time-varying an depend on temperature. The stationary transition probability parameter λ_1 equals -3.320 and is significant. This corresponds, after the logistic conversion from equation 5, with a probability of 0.035. That implies that every day a spike may occur with a probability of 3.5%. However, during the summer months, the probability of a spike might become higher on days when the temperature is higher than expected. This can be concluded from the positive and significant estimates for λ_2 (0.226). For instance, if the temperature is 1 degree Celsius higher than expected, the probability of a spike to occur increases to 4.3%. When it is 5 degrees warmer than expected, the probability equals 10,1%. Higher than expected temperature levels in the summer lead to a higher probability on a spike. This can be explained using the findings of Mount, Ning and Cai (2006) who show that in periods with low reserve capacity, the probability on spike increase. A higher than expected temperature, and therefore a higher than expected demand volume, may affect prices in two ways. In the short term, less flexible and relatively cheaper power producers slowly adjust their volumes either because they are inflexible or unwilling in cases when the expect the high temperatures to hold on only for a short period in time. In the situation in which the temperature increase is sudden, the most flexible and expensive generators have to produce to meet the extra demand leading to a spike. An alternative explanation for a spike under high temperatures is that the capacity is lowered because of reduction in cooling capacity (recall the example in the introduction) leading to a reduced reserve margin. In winter months, the opposite holds although the estimate for λ_3 is only significant on a 10% level. The sign of the estimate is negative, implying that a lower than expected temperature leads to a higher probability on a spike as reserve margin declines due to extra demand for heating. The estimate for λ_4, reflecting the transition probability from the spike regime to the normal regime, equals 1.538 and is significantly different from zero. This corresponds, after the logistic conversion, with a probability of 82.3%. That is, in about 82 of 100 spikes, the power price is back in the normal regime after one day and it stays in the spike regime in 18 cases.

Concluding remarks and discussion

This paper shows that power spikes can be predicted using temperature. It extends the findings of Mount, Ning, and Cai (2006) who show that the probability of a spike increases in periods with low reserve margins. This intuitive idea may not be applicable to all markets as information on demand, load and capacity is not transparent and available to all agents in the market in any country. In those cases, temperature can be used as a variable that replaces reserve margin under the assumption that temperature directly influences demand for electricity consumption. As temperature information is widely available, both actual values as forecasts, it provides timely information to all market participants at all times.

This paper provides a regime switching model in which the regime transition probabilities are time dependent. It is shown, that deviations from expected temperature influences the probability of a spike to occur. The impact is shown to be different over seasons. In the summer, a higher than expected temperature leads to a higher probability of a spike, whereas a lower than expected temperature leads to a higher probability of a spike in the winter.

The results of this paper can be used for many situations in which practitioners need to manage the risks of spikes. Spikes are forecastable for a certain extend and the model above make it possible to simulate spikes and to better predict and model spike occurrence. In addition, as weather derivatives are traded, the known impact of temperature on spike occurrence can be used to optimize hedging spike risk using weather derivatives.

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