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by

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The power of weather

Some empirical evidence on predicting day-ahead power prices through weather forecasts*

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April 24, 2008

Abstract

This paper examines the predictive power of weather for electricity prices in day-ahead markets in real time. We find that next-day weather forecasts improve the forecast accuracy of day-ahead electricity prices substantially, suggesting that weather forecasts can price the weather premium. Moreover, we find that the predictive power of weather forecasts for electricity prices can be further exploited by allowing for non-linear effects of the weather forecasts.

Key words: Electricity prices, forecasting, GARCH models, weather forecasts.

JEL Classification Code: C53, G15, Q40.

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1 Introduction

A decade ago, the electricity industry was strongly regulated and electricity prices reflected the short-term production costs. Hence, back then the electricity price did not reflect the temporal effects such as seasonality, weather and business activity. But this all changed when many governments worldwide started reforming their electricity industry as of the mid-1990s. Currently, the economic law of demand and supply determines the price in marketplaces where electricity can be traded in spot or forward (i.e. hour-ahead, day-ahead, month-ahead, or longer contracts).

Many studies have documented these stylized facts by examining the prices observed in day-ahead markets[1], which are by far the most liquid power wholesale markets, see Escribano, Pena, and Villaplana (2002), Lucia and Schwartz (2002) and Koopman, Ooms, and Carnero (2007). Bunn and Karakatsani (2003) provide a thorough review of the stochastic price models presented in these studies and classify these into three groups: random walk models, basic mean-reversion models, and extended mean-reversion models that incorporate time-varying parameters (to control for seasonality and volatility patterns). They conclude that the idiosyncratic price structure has not been accurately described. Furthermore, the results reported in these studies are often obtained from in-sample tests; hence they do not resolve the issue of the out-of-sample predictive value of power models.

Only a few studies have recognized the need for modelling weather directly, but these mainly addressed the weather effect on electricity sales (see, for example, the special issue of Journal of Econometrics 1979). Moral-Carcedo and Vicns-Otero (2005) also study temperature effects on the variability of daily electricity demand in Spain, and document empirical evidence of a non-linear relationship between variations in temperature and the demand response. More attention to the relationship between prices and weather is, however, given in very recent studies. Knittel and Roberts (2005) compare price models that incorporate seasonal and temperature variables with models that do not include these variables on hour-ahead electricity prices obtained from the California market, and provide preliminary evidence that the first-mentioned models significantly outperform in terms of forecasting accuracy. Kosater (2006) develops a similar exercise on the European Energy Exchange (the German market), but he extends the set of weather variables to wind velocity, to proxy for windmill producers,

[1]On these markets, hourly prices are quoted for delivery of electricity at certain hours on the next day.

and uses non-linear models in the class of Markov regime-switching models. He finds that the significance of the weather-price relationship for forecasting is confined to certain hours. Huisman (2007), on contrary, focuses on how temperature influences the probability of a spike and he shows that the difference between the actual and expected temperature significantly influences this probability.

In this study we focus on the predictive power of weather variables for electricity prices in real time. As agents submit their bids and offers for delivery of electricity in all hours of the next day, weather conditions on the delivery day cannot be exactly known at the time when electricity prices are quoted. Therefore, we introduce weather forecasts, which are available in real time when prices are traded, in stochastic price models to forecast day-ahead prices in two bidding areas of the Nordic Power Exchange, Oslo and Eastern Denmark. We include a set of weather variables (temperature, precipitation and wind speed) to approximate the fact that both electricity demand and supply are subject to weather conditions and we implement specific models for different bidding areas due to the heterogeneity in weather conditions and production plants.

We find that an ARMA model extended with power transformations of next-day weather forecasts yields the best forecasting results for predicting day-ahead prices. This model outperforms in terms of forecast accuracy ARMA models extended with realized weather when prices are traded but not delivered, or extended with only deterministic trends. The improvement is substantial, always higher than 5%, and statistically significant for applications to different markets and different series (24 hour daily average prices or peak hour prices). In particular, we show that weather forecasts, even if subject to forecast errors, have substantial predictive power to anticipate price jumps. Furthermore, we show that the relation between prices and weather forecasts is non-linear, and a model that incorporates weather forecasts must be carefully specified depending on data of interest.

We think that our results have two important implications. First, agents who set bid and ask electricity prices can partially price the short-term future weather effect or premium, documented in the aforementioned studies, by using weather forecasts. When demand does not meet supply, electricity prices increases dramatically. Therefore, a model that has properties to anticipate spikes can help to cover the risk of (physical and financial) market participants who have to close their positions at that day. Second, future research is motivated on the non-linear effects of weather forecasts on electricity prices.

The remainder of the paper is structured as follows. Section 2 introduces the day-ahead power markets and presents the data. Section 3 describes the forecasting models. Section 4 discusses the empirical results. Section 5 concludes.

2 Data

On January 1, 1991, the Norwegian government started a deregulation process for its electricity industry that resulted in the establishment of the first national power market for short-term delivery of power (real-time and day-ahead[2]) in the world, the Nordic Power Exchange (NPX). Two years later, in 1993, the range of products was extended to include financial derivative contracts that have longer maturity horizons. A few years later, Sweden joined the NPX (1996), soon followed by Finland (1998), Western-Denmark (1999) and Eastern-Denmark (2000). Since 2003 all customers of Scandinavian electricity markets may trade freely in the market. The NPX, now also named Nord Pool ASA, is considered to be the most liquid wholesale market worldwide. Nord Pool ASA consists of a day-ahead market (Elspot), a financial market (Elbas), and a clearing service. In the remainder, we mainly focus on the Elspot market. For more details on Nord Pool ASA we refer to NordPool (2004).

The Nord Pool market is largely dependent on electricity that is generated by renewable sources. In particular, hydro-plants, which use water stored in reservoirs or lakes, are dominant in Norway and partly Sweden; wind plants, which use wind to produce electricity, are dominant in Denmark. We again refer to NordPool (2004) for more details.

Electricity prices are affected by regional and temporal influences due to the transportation and transmission limits of electricity. This statement is particularly important in the Nord Pool market. For instance, when a power plant stops in the eastern part of Sweden this only affects the power supply in the surrounding region. Hence, this will not affect the power supply in the western part of Sweden and the rest of the market. Similarly, rainfall in the southern part of Norway will potentially affect the regional demand and/or supply curve, but not the bidding curves in other regions. Nord Pool faces the problem by splitting the market into several bidding and price areas. Therefore, we take into account the Nord Pool bidding area prices separately, rather than examining the Elspot system price (which is a weighted average of the bidding prices in all Nord Pool bidding areas). We examine two out of the eleven bidding areas in Nord Pool, i.e. the Oslo area and Eastern Denmark area. It is interesting to note that these areas are the most densely populated areas in Scandinavia.

[2]We recall from section 1 that day-ahead means that prices are quoted on day t for delivery of electricity at certain hours on the day $t+1$.

2.1 Electricity prices

The dataset used in this study consists of day-ahead prices in EUR/MWh for Oslo and Eastern Denmark from the period December 24, 2003 to March 14, 2006[3]. Nord Pool provides bidding area prices both in the local currency and in EUR. We choose EUR to compare directly the two area prices. Daily prices are computed as the arithmetic mean of the available 24 hourly price series on the physical market of each country. In our analysis we also use peak prices, which are defined as the average price of hourly prices from 8 am to 8 pm.

As in Wilkinson and Winsen (2002) and Lucia and Schwartz (2002), we start from a statistical analysis of the data we have[4]. Figure 1 plots the time series, the log transformations and the first differences of log transformation of the daily day-ahead electricity prices; Table 1 gives some important descriptive statistics. A first casual look discloses an erratic behavior of the prices. The series follow a small positive increasing trend with several spikes. Interestingly, prices in Oslo have more negative spikes than positive spikes. In Oslo, and in general Southern-Norway, hydro-power plants are considered producers of "cheap storable" electricity and for them it is convenient to export electricity to other areas where it is more expensive to produce electricity, as thermal markets (meaning electricity produced from gas, coal and/or nuclear fuel plants). Then the Oslo area imports at higher electricity prices to satisfy its demand. However, electricity in thermal markets is also often offered at discount prices to avoid costs for ramping up and down later (Bunn and Karakatsani, 2003), for example during night hours, and the problem of bottlenecks (cable constraints) can occur. This implies that Oslo producers offer their "cheap" electricity to the Oslo market, decreasing the prices. The price level observed for Eastern Denmark is substantially higher. Prices are highly non-normally distributed; their volatility is very high such as the kurtosis; their skewness is positive. The wind-power drivers of the Danish market can help to explain it. Oslo has a more regular distribution, but a Jarque-Bera test rejects the null hypothesis of normality for each of the six series. The series are characterized by weekly patterns. From Table 1 we can observe that prices are lower during the weekend than on working days. Moreover, as in Misiorek, Trueck, and Weron (2006) we find evidence of higher prices on Monday. Yearly patterns, well documented in other studies, are more difficult to detect probably due to the fact that the series are not very long. Electricity prices are very persistent and possibly close to non-stationary.

[3]Electricity prices may be available for a longer sample, but weather forecasts are available to us only for this sample.

[4]We briefly discuss some stylized facts; we refer for a more detailed analysis, for example, to Lucia and Schwartz (2002) and Pilipovic (1997).

Table 1 shows that the sample autocorrelations are high up to 14-day lags. The Dickey Fuller test on the series does not reject the null hypothesis of non-stationarity at any level of significance for Oslo prices and 1% level of significance for Eastern Denmark prices. This result should prompt us to model the first difference prices. However, the empirical evidence provided in the literature to forecast electricity prices is in favour of price levels. For example, Lucia and Schwartz (2002) find that models based on levels and log levels provide more accurate results than models based on first differences and log first differences in forecasting Nord Pool electricity prices. And Weron and Misiorek (2005) find that in terms of out-of-sample statistics, ARMA models (based on log level) do better than ARIMA models (based on first difference of log prices) in forecasting electricity prices. Moreover, the Dickey Fuller test does not account for non-linear trends which may exist but not known to us. Therefore, we consider both hypotheses. From Figure 1, we can observe another stylized fact: volatility clustering. Dramatic spikes tend to occur in clusters, mainly as a result of consecutively exceeding the system capacity.

In our application we use log prices (and the first difference of them) and not the level. The log transformation reduces the spike behavior of the prices and makes moments of the distribution of electricity prices more similar to standard distributions, in particular for Eastern Denmark.

2.2 Weather forecasts

Our decision to focus on precise bidding areas of Nord Pool is motivated by the nature of weather variables. Weather observations and relative forecasts refer to a square area around the measurement station. Hence it is impossible to have single observations that cover the entire country of the markets under consideration. The combination of different stations could be applied, but as data from minor cities are scarce, the weather forecast errors may arise, thereby introducing further noise in the forecasting process. The areas that we study are, on the contrary, small and homogenous in terms of weather. Therefore, we use weather observations and forecasts for Oslo and Copenhagen. The weather around Oslo should well approximate the weather in the area itself, the most populated zone of this bidding area, and to the south of Oslo along the seacoast where most of the electricity for south-east Norway is produced. The weather in the area of Copenhagen may be a proxy for the weather of the city of Copenhagen, again the most populated zone of this bidding area, and of Zealand, the main island in Eastern Denmark.

Daily average temperatures in degrees Celsius, total precipitation in mm, and wind power in m/s are applied. Weather observations on day t and weather forecasts of the same day made at time $t-1$ are obtained from the EHAMFORE index, which is provided by Meteorlogix (www.meteorlogix.com)[5]. We assume that market operators use the weather forecasts provided by Meteorlogix in their decisions. We think that this assumption is quite realistic considering the market share of Meteorlogix in providing real-time information services in the agricultural, energy, and commodity trading markets, and Bloomberg in providing data to operators.

Figures 2-3 plot the series of observed and forecasted temperature, precipitation and wind in Oslo, and temperature and wind in Copenhagen[6]. Temperatures are highly persistent, have highly seasonal patterns, and forecasts are quite precise. The correlation between temperature observations and their forecasts made the day before is higher than 0.9 for both areas. The level of wind is particularly high in Eastern Denmark, and forecasts are less accurate. The correlation between observations and forecasts is around 0.5 for both areas. We also notice that wind forecasts have a quite stable pattern in the initial months of 2004, because the Meteorologix (such as other meteorological institutes) applies a different scaling forecasting model in those months. We decide to keep these forecasts to extend the sample period as much as we can. Moreover, it is logical to assume that market operators had received this information in real time and used it to take their decisions. Observed precipitation and forecasted precipitation in the Oslo area are quite different. First, forecasting precisely precipitation is quite difficult; and second, observations are often zero, but models always forecast positive (eventually small) numbers.

Some graphical relations between the forecasted weather variables and electricity prices may be identified. For example, high precipitation in Oslo at the end of May 2004 or in October 2004 corresponds to low prices; few days of very low temperatures in Oslo in February 2005 correspond to high prices; strong wind in Eastern Denmark at the end of 2004 and beginning of 2006 is associated with low prices. Using real weather does not change the conclusion: a graphical analysis is not satisfactory because the relation between weather variables and electricity prices is possibly highly non-linear as we will discuss in section 4.1.

Several studies, see e.g. Koopman, Ooms, and Carnero (2007) and Deng (2004), argue that the water reservoir is the key variable to plan production, even more than the amount of precipitation. Even if we agree with this view, we emphasize that in this paper we work with local prices, and local water reservoirs are in most cases not

[5]Data from the EHAMFORE index are available in Bloomberg. Data on realized (or observed) precipitation on day t in Oslo from Meteorlogix are partially integrated with values of several different stations around Oslo from the Meteorological Institute (www.met.no) to fill in missing points.

[6]The graph of precipitation variables is not reported as those variables are never chosen in the model selection procedure.

observable. This is particularly true when the number of electricity producers is high, as for example in the Oslo area. And we do not yet have a model to construct regional water reservoirs. Therefore, we opt to apply total precipitation as a proxy for water reservoirs.

3 Forecasting models

Knittel and Roberts (2005) show that traditional time series approaches such as ARMA and ARIMA models provide more accurate results in forecasting electricity prices than their continuous counterparts. Starting from these findings we construct several models that may cope with the stylized facts of electricity prices.

3.1 AR(I)MA

The first model is a traditional time series approach to model electricity prices, the autoregressive moving average (ARMA) model (Hamilton (1994)). The ARMA(p, q) model implies that the current value of the investigated process (say, the log price) P_t is expressed linearly in terms of its past p values (autoregressive part) and in terms of the q previous values of the process ϵ_t (moving average part):

$$\phi(L)P_t = \theta(L)\epsilon_t \tag{1}$$

where $\phi(L)$ and $\theta(L)$ are the autoregressive and moving average polynomials in the lag operator L respectively, defined as:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_p L^p \tag{2}$$

$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - ... - \theta_q L^q \tag{3}$$

and where ϵ_t is an independent and identically distributed (iid) noise process with zero mean and finite variance σ. The motivation of an ARMA process follows from the correlogram. Table 1 shows high correlation between the current price and the previous days' prices.

The ARMA modelling approaches assume that the time series under study is (weakly) stationary. If it is not, a transformation of the series to stationarity is necessary, such as first differentiating. The resulting model is known as the autoregressive integrated moving-average model (ARIMA). We define the ARIMA model as:

$$\phi(L)p_t = \theta(L)\epsilon_t \tag{4}$$

where $p_t = (P_t - P_{t-1})$.

3.2 AR(I)MAX

ARMA models apply information related to the past of the process and do not use information contained in other pertinent time series. However, as the data analysis shows, electricity prices are generally governed by various fundamental factors, such as seasonality and load profiles. The ARMAX(p, q) can be written as:

$$\phi(L)(P_t - X_t) = \theta(L)\epsilon_t \tag{5}$$

where $X_t = \sum_{i=1}^{k} \psi_i x_{i,t}$, where $x_t = (x_1, x_2, ...x_k)'$ is the $(k \times 1)$ vector of explanatory variables at time t, and where $\psi = (\psi_1, \psi_2, ..., \psi_k)'$ is a $(k \times 1)$ vector of coefficients. Following the analysis in the previous section, we use two explanatory variables: a dummy with values 0 on working days and 1 on holidays, a dummy with values 1 on Monday and 0 elsewhere. First difference log prices can be used and the ARIMAX model can be given by:

$$\phi(L)(p_t - X_t) = \theta(L)\epsilon_t \tag{6}$$

In the empirical application, the ARIMAX model will be our benchmark.

3.3 AR(I)MAXW

Adverse weather conditions may change the demand for electricity, and may also affect the production. Low levels of precipitation and/ or wind speed may cause a reduction on the supply of energy, in particular in electricity markets which depend on renewable producer plants, such as Norway and Denmark. Furthermore, producer plants may study future weather conditions to estimate demand and plan their supply optimally.

Forecasts of the average daily temperature in degrees Celsius, precipitation in mm and wind speed in m/s are applied as further explanatory variables in models (5) and (6). The ARMAXW and ARIMAXW models are respectively:

$$\phi(L)(P_t - X_t - W_t) = \theta(L)\epsilon_t \tag{7}$$

and

$$\phi(L)(p_t - X_t - W_t) = \theta(L)\epsilon_t \tag{8}$$

where $W_t = \sum_{j=1}^{l} \varphi_j w_{j,t}$, $w_t = (w_{1,t}, w_{2,t}, ..., w_{l,t})'$ is the $(l \times 1)$ vector of weather forecast variables at time t, and $\varphi = (\varphi_1, \varphi_2, ..., \varphi_l)'$ is a $(l \times 1)$ vector of coefficients. This model includes deterministic components that account for genuine regularities in the behavior of electricity prices and stochastic components that come from weather shocks.

Knittel and Roberts (2005) apply a similar model for forecasting California electricity prices, where the set of weather variables consists of the level, the square and the cubic of realized temperature. As in Knittel and Roberts (2005), we allow non-linearity in the relation between prices and weather variables by including the level, the square and the cubic of the temperature forecasts, and the level and the square of the precipitation and wind forecasts. Precipitation and wind forecasts are always positive and therefore we do not consider it useful to include their cubic transformation. Compared to Knittel and Roberts (2005) we add wind speed since wind may play a role both in the demand for electricity in such markets where electricity is used for heating - people associate colder temperature with stronger wind - and in the supply of wind power plants. We also introduce an explanatory variable to model another dimension of weather, i.d. precipitation, allowing us to approximate the supply in hydro dominated plants.

Considering that temperature is so persistent, we specify a further ARIMAXW model using realized values (at time $t-1$ to account for the fact that prices on day t are traded on the previous day). Weather observations do not have forecasting errors and this may help to improve electricity price forecasts even if weather refers to the previous day[7].

3.4 ARIMAX-GARCH

AR(I)MA models assume homoscedasticity, i.e. constant variance and covariance functions, but the preliminary data analysis has disclosed that electricity prices exhibit volatility clustering. We extend previous models by assuming a time-varying conditional variance of the noise term. The heteroskedasticity is modelled by a generalized autoregressive conditional heteroskedastic GARCH(r, s) model (Bollerslev (1986)). Relaxing the assumption of homoscedasticity may change the parameter estimates of AR(I)MA, and consequently the out-of-sample forecast of the investigated process.

The model is:

$$\phi(L)(p_t - X_t) = \theta(L)\epsilon_t \tag{9}$$

$$\epsilon_t = \nu_t h_t^{1/2} \qquad with\ \ h_t = \alpha_0 + \sum_{i=1}^{s} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{r} \beta_j h_{t-j} \tag{10}$$

where ϵ_t is an independent and identically distributed (iid) noise process with zero mean and conditional time-varying variance h_t, and the coefficients have to satisfy $\alpha_i \geq 0$ for $1 \leq i \leq s$, $\beta_j \geq 0$ for $1 \leq j \leq r$, and $\alpha_0 > 0$ to ensure that the conditional variance is strictly positive.

[7]We also apply realized weather in an ARMAXW model but the results are worse than for the ARIMAXW, and therefore reported.

3.5 ARIMAXW-GARCH

Following the same reasoning for model (9)-(10), the ARIMAX model can be extended by assuming a noise process with a time-varying conditional variance, that is:

$$\phi(L)(p_t - X_t - W_t) = \theta(L)\epsilon_t \tag{11}$$

$$\epsilon_t = \nu_t h_t^{1/2} \quad \text{with } h_t = \alpha_0 + \sum_{i=1}^{s} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{r} \beta_j h_{t-j} \tag{12}$$

3.6 ARIMAXW-GARCHW

Koopman, Ooms, and Carnero (2007) find that seasonal factors and other fixed effects in the variance equation are also important to estimate electricity prices. We follow these suggestions and assume the conditional variance of the noise term in ARIMAXW model to be time-varying and modelled with a GARCH expression. The model is specified as:

$$\phi(L)(p_t - X_t - W_t) = \theta(L)\epsilon_t \tag{13}$$

$$\epsilon_t = \nu_t h_t^{1/2} \quad \text{with } h_t = \alpha_0 + \sum_{i=1}^{s} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{r} \beta_j h_{t-j} + \sum_{f=1}^{k+l} \varrho_f z_{f,t} \tag{14}$$

where $z_t = [x_t', w_t']'$, and where $\varrho = (\varrho_1, \varrho_2, ..., \varrho_{k+l})'$ is a $((k+l) \times 1)$ vector of coefficients. Since Koopman, Ooms, and Carnero (2007) assume autoregressive fractionally integrated moving average noises, we do consider integration of order one to simplify the estimation. And Koopman, Ooms, and Carnero (2007) include water reservoir, which is excluded in this study for the aforementioned reasons. These choices may reduce the predictive power of the ARIMAX-GARCHW model, but it is also true that the econometric skills of agents trading in electricity markets and forced to take decisions in a short time are often not so sophisticated and therefore our assumptions can better approximate the models applied by market participants.

4 Empirical Results

We apply the models described in section 3 to our dataset, and assess which model performs best in terms of forecasting accuracy. Before the out-of-sample forecast exercise, we estimate the set of models using the complete sample to have an ex-post predictability idea.

We describe some assumptions. We apply a non-linear ordinary least square (NLS) estimator (Davidson and MacKinnon (1993)) for AR(I)MA-type models and the quasi maximum likelihood (QML) estimator (Davidson and MacKinnon (1993) and Greene (1993)) for GARCH family models.

We restrict our AR(I)MA-type models to be AR(I)MA(7,(1,)0). Autocorrelation analysis and in-sample criteria would suggest more complex AR(I)MA forms. In particular, lags 14, 21, 28 and 56 still have high correlations for both the ARMA and ARIMA class of models, suggesting longer weekly and monthly price behaviors. However, the risk of over-parametrization and the evidence presented in previous studies, for example Lucia and Schwartz (2002), show that an ARMA(7,0) specification provides optimal forecasts on daily day-ahead electricity prices. Hence, this induces us to restrict the models to the aforementioned specification. Following the same reasoning we choose a GARCH(1,1) specification for this group of models.

The inclusion of the weather variables follows from statistical evidence. We allow different transformations of the weather forecast variables on the two markets to incorporate the fact that the weather may affect only the supply of electricity, which is different in the two markets. We minimize the Akaike information criteria to specify the model.

4.1 In-sample analysis

The in-sample analysis is based on the overall sample, from December 24, 2003 to March 14, 2006. Table 2 reports estimation results. As general evidence, we notice that ARIMA models select more lags than ARMA models. We now move to specific models and we start to focus on the ARIMAX model which is considered to be a very accurate forecasting model. The coefficient estimate of the variable $D_{hol,t}$, which is a dummy variable with value 1 if day t is not a working day or 0 if day t is a working day, is statistically significant and negative. The coefficient estimate of the variable $D_{Monday,t}$, which is a dummy variable with value 1 if day t is Monday and 0 elsewhere, is, on the contrary, statistically significant and positive. These results confirm evidence in Table 1 and tell us some important information on how agents quote prices. Prices are set lower during weekends (or not a working day) when electricity utilization is lower, but when the market is back to standard working conditions, agents seem initially to overreact and then adjust their positions.

Even if the fit is quite high, residuals of the ARIMAX model are not normally distributed. We think that weather variables can explain part of them. Figure 4 shows that the errors of the ARIMAX model have a non-linear relation with the daily average temperature and the total precipitation, but have a linear-like relation with the wind speed. Therefore, in the ARIMAXW for temperature forecasts we use the level, the square and the cubic; for precipitation and wind forecasts we use the level and the square. The selection criterium results in the following specific set of weather variables:

$$W_t = a_1 Temp_t + a_2 Temp_t^2 + a_3 Temp_t^3 + b_1 Prec_t + b_2 Prec_t^2 + \gamma Wind_t,$$

where $Temp_t$, $Prec_t$ and $Wind_t$ are the forecasts of daily average temperature, total precipitation and wind speed, respectively, on day t. The square of the wind is then excluded in the selection procedure. Figure 4 indicates a direct linear relation between prices and wind speed and the empirical findings are consistent with the graphical analysis.

The interpretation of estimated coefficients for the weather variables is not often straightforward due to non-linear relations. For example, the temperature forecasts affect the day-ahead electricity price via the following function:

$$f(Temp_t) = a_1 Temp_t + a_2 Temp_t^2 + a_3 Temp_t^3$$

Taking the first order derivative, we get

$$\frac{\mathrm{d}f(Temp_t)}{\mathrm{d}Temp_t} = a_1 + 2a_2 Temp_t + 3a_3 Temp_t^2.$$

By substituting in the previous equation a_1, a_2 and a_3 with their empirical estimates, and solving $\frac{\mathrm{d}f(Temp_t)}{\mathrm{d}Temp_t} = 0$, we find the roots $\simeq [4.5, 19]$. We interpret this to mean that when the temperature is lower than 4.5, it is negatively influenced, i.e. the lower the forecasted temperature, the higher the electricity price. When the temperature forecast is above 19, it is positively influenced, i.e. the higher the forecasted temperature, the higher the electricity price. When the temperature is in the interval [4.5,19], there is no relation. Intuitively, this reflects the fact that when the temperature forecast is relatively higher or lower than the switching points, 4.5 and 19, the consumption of electricity will rise. Meanwhile the difficulty of producing electricity also increases when it is extremely hot or cold. Following similar reasoning, we find that precipitation influences prices negatively such that higher precipitation leads to lower prices. This is consistent with the hydropower nature of Oslo electricity markets. The coefficient of the wind speed is not statically different from zero, but excluding it does not minimize the selection criteria. The estimate is negative and we do not have strong economic explanations for it. We conclude by noting that the Akaike criterium is the highest when weather variables are introduced, supporting this strategy.

4.2 Out-of-sample analysis

We forecast Oslo log electricity prices from January 1, 2005 to March 14, 2006. We repeat the selection procedure in section 4.1 over the initial in-sample period, from

December 24, 2003 to December 31, 2004. The reduced specific form in this short sample of all models remains the same as in full sample analysis. This indicates that relations do not seem to be sample dependent. In forecasting when new values are available we re-estimate models to produce a new forecast, but we do not re-specify it. An expanding window is used, which means that to forecast the price of one day, all the previous data are included.

We compare forecasts from different models using the Root Mean Square Prediction Error (RMSPE), defined as

$$RMSPE = \sqrt{\frac{1}{n}\Sigma_{s=1}^{n}(P_{T+s} - \hat{P}_{T+s})^2}$$

where P_{T+s} is the log price at time $T+s$, $\hat{P}_{T+s}$ is the forecasted log price at time $T+s$, and $n = 438$ is the number of days being forecast. Results are given in Table 3. The key evidence is that weather forecasts improve electricity forecasts. The ARIMAXW model provides the most accurate forecasts. The improvement with respect to the ARIMAX model is 6% and it is statistically significant[8]. Figure 5 can help to interpret the result. Figure 5 shows the 60-day average RMSPE for the ARIMAX model and the ARIMAXW model. From the graph, we find that, when the error of the former model is at a relatively lower level, the errors of the two models are similar, but when there is a higher error due to possible jumps, the latter model often predicts better. Price jumps are mainly due to problems of inelasticity of demand, and of non-storability of electricity with consequent shortages in the supply. These problems often arise when weather conditions are adverse and weather forecasts have a natural role in signalling ex-ante them.

The statistics of ARMAXW are also better than those of the ARIMAX model, but lower than the ARIMAXW. This confirms that weather variables have predictive power, but ignoring the evidence of non-stationarity of the price series associated with the strongly non-linearity of the relation between prices and weather variables reduces predictive accuracy. And, indeed, all the ARIMA models we use outperform the ARMA counterparts. Adding GARCH specification to approximate evidence of volatility clustering does not provide more accurate results. In particular, the ARMAXW-GARCHW proposed by Koopman, Ooms, and Carnero (2007) does not outperform the benchmark model. As we discuss in section 3.6, our ARMAXW-GARCHW model is, however, simpler than the estimated model of Koopman, Ooms, and Carnero (2007) and the set of variables is different.

[8] We compare the predictive accuracy of different models by using the t-type statistics proposed by McCracken (2007).

Weather variables are very persistent and forecasting them, in particular precipitation and wind speed, is very difficult. Therefore, we decide to test the robustness of previous results with respect to the assumption of using real-time weather conditions, i.d. using the weather of today to predict the price of tomorrow. We specify and estimate an ARIMA model with power transformations of realized weather (level, square and cubic of temperature, level and square of wind speed) and two dummy variables for describing Monday and non-working days. We call this model ARIMAXRW. Results are very similar to the ARIMAX model, but the ARIMAXW outperforms it.

We test the robustness to electricity peak hour prices. Peak hour prices are defined as the average of the hourly prices from 8 am to 8 pm. As a matter of fact prices are more likely to be volatile in that specific frame. The Akaike selection criterium often specifies models as for daily prices[9]. We could anticipate this considering the role of peak hours in determining daily prices. Forecasting results are reported in Table 3. The ARIMAXW is clearly the best model, which seems to confirm our conjecture that weather forecasts help to anticipate sharp movements in prices.

We implement our analysis in a different Nord Pool bidding area, Eastern Denmark. We re-estimate and re-specify all the models. We find that the variable precipitation is not significant, which can be explained by the fact that Denmark does not rely on hydropower. We develop a forecasting exercise similar to the Oslo study. Again the ARIMAXW model provides the best forecasts. The improvement is higher than 10%, and it is statistically significant at the 1% level. Figure 5 shows that also for the Eastern Denmark example weather forecasts help to partially anticipate price jumps. Furthermore, from Table 3 we can observe that using realized weather observations reduces forecast accuracy and results for the ARIMAXW model are robust to peak hour prices.

5 Conclusion

In this paper we study whether weather variables have predictive power for electricity prices in real time. We collect forecasts of several weather variables for two bidding areas of Nord Pool, Oslo and Eastern Denmark, and we use them to predict the respective prices. Our empirical results suggest that weather forecasts play a central role in forecasting day-ahead prices. Weather forecasts give relevant information to partially anticipate spikes in the prices, providing more accurate forecasts compared to several alternative approaches. Results are robust to using real-time observed weather and to peak hour price applications. We find that the relation between electricity prices and

[9]Estimation results using peak prices are available upon request.

weather forecasts is highly non-linear and depends on the price drivers behind each bidding area.

There are several topics for further research. First, the set of weather forecasts might include other weather-related variables, such as water reservoir levels. Observations of these variables are not available to us, but results support the construction of specific models to compute forecasts of them. Second, considering the strong non-linear relation of prices and weather forecasts, weather forecasts might be included in other non-linear models, such as Markov regime-switching models, jump models or time-varying models. Finally, models based on weather forecasts might be used in predicting movements of the forward price curve in power financial markets. The reported evidence that weather has predictive power for the underlying day-ahead price process could imply that this price factor might be reflected in the price of derivative instruments for day-ahead electricity contracts as well.

References

Bollerslev, T., 1986, Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31, 307–327.

Bunn, D.W., and N. Karakatsani, 2003, Forecasting electricity prices, Discussion paper London Business School.

Davidson, R., and J.G. MacKinnon, 1993, *Estimation and Inference in Econometrics* (Oxford University Press).

Deng, D., 2004, Modelling and investigating the relationship between electricity prices and water reservoir content at Nord Pool power exchange, Discussion paper Gothenburg University.

Escribano, A., J. Pena, and P. Villaplana, 2002, Modeling electricity prices: International evidence, Discussion paper Universidad Carlos III de Madrid.

Greene, W.H., 1993, *Econometric Analysis, 4th. ed* (Prentice Hall).

Hamilton, J.D, 1994, *Time Series Analysis* (Princeton University Press).

Huisman, R., 2007, The influence of temperature on spike probability in day-ahead power markets, Discussion paper Erasmus University.

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

Koopman, S.J., M. Ooms, and M.A. Carnero, 2007, Periodic seasonal reg-ARFIMA-GARCH models for daily electricity spot prices, *Journal of American Statistical Association.*

Kosater, P., 2006, On the impact of weather on German hourly power prices, Discussion paper University of Cologne.

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

McCracken, M.W., 2007, Asymptotics for out-of-sample tests of Granger causality, *Journal of Econometrics* 140, 719–752.

Misiorek, A., S. Trueck, and R. Weron, 2006, Point and interval forecasting of spot electricity prices: Linear vs. non-linear time series models, *Studies in Nonlinear Dynamics & Econometrics* 10.

Moral-Carcedo, J., and J. Vicns-Otero, 2005, Modelling the non-linear response of Spanish electricity demand to temperature variations, *Energy Economics* 27, 477–494.

NordPool, 2004, The Nordic power market: Electricity power exchange across national borders, Discussion paper Nord Pool.

Pilipovic, D., 1997, *Energy Risk* (McGraw-Hill).

Weron, R., and A. Misiorek, 2005, Forecasting spot electricity prices with time series models, *Proceedings of the European Electricity Market EEM-05 Conference* pp. 133–141.

Wilkinson, L., and J. Winsen, 2002, What can we learn from a statistical analysis of electricity prices in New South Wales, *The Electricity Journal* 15, 60–69.

Table 1: Descriptive statistics

	Oslo			Eastern Denmark		
	Level	Log	Diff	Level	Log	Diff
Mean	30.43	3.403	0.001	32.85	3.446	0.001
St dev	4.965	0.154	0.055	12.74	0.280	0.185
Max	52.45	3.960	0.461	29.69	5.463	1.737
Min	17.16	2.843	-0.252	235.7	2.127	-0.902
Skewness	1.319	0.513	0.963	6.295	1.293	1.310
Kurtosis	6.278	4.768	12.86	79.13	8.181	17.21
Working days	30.90	3.420	0.011	34.81	3.5004	0.0318
No working days	29.35	3.366	-0.023	28.40	3.3232	-0.069
Mondays	31.04	3.424	0.070	36.68	3.525	0.224
ρ_1	0.938	0.928	-0.126	0.651	0.778	-0.191
ρ_7	0.824	0.78	0.346	0.493	0.671	0.298
ρ_{14}	0.678	0.677	0.351	0.405	0.555	0.273
DF	-0.535	-1.678	-7.134***	-3.311**	-2.691**	-15.18***

Note: The table reports descriptive statistics on level (Level) and logarithm (Log) of electricity prices, and of logarithm first difference (Diff) in Oslo and Eastern Denmark. Lines Mondays, working days and no working days give the sample average prices on Mondays, working days and no working days (weekends and holidays) respectively. Lines ρ_1, ρ_7 and ρ_{14} give the 1^{st}, 7^{th} and 14^{th} sample autocorrelation. The last line refers to the Augmeted Dickey-Fuller test; one, two or three asterisks denote significance relative to the asymptotic null hypothesis respectively at 10%, 5% and 1% levels.

Table 2: In-sample estimation: Oslo

Models	ARMA	ARMAX	ARMAXW	ARIMA	ARIMAX	ARIMAXW
c	3.914	3.387	3.593	0.001	-0.004	0.004
	[1.963]	[0.035]	[0.250]	[0.001]	[0.002]	[0.004]
ϕ_1	0.711	0.779	0.699	-0.254	-0.215	-0.240
	[0.023]		[0.036]	[0.034]	[0.035]	[0.035]
ϕ_2			0.088	-0.237	-0.189	-0.208
			[0.037]	[0.035]	[0.036]	[0.036]
ϕ_3	-	-	-	-0.208	-0.162	-0.183
				[0.036]	[0.036]	[0.036]
ϕ_4	-	-	-	-0.240	-0.189	-0.208
				[0.036]	[0.036]	[0.036]
ϕ_5	-	-	-	-0.191	-0.124	-0.144
				[0.036]	[0.036]	[0.036]
ϕ_6	0.142	[0.023]	0.128	-0.076	-	-
	[0.034]	0.172	[0.037]	[0.034]		
ϕ_7	0.144		0.075	0.240	0.052	0.049
	[0.035]		[0.036]	[0.035]	[0.035]	[0.035]
d_h	-	-0.040	-0.043	-	-0.020	-0.021
		[0.004]	[0.004]		[0.004]	[0.004]
d_m	-	0.019	0.015	-	0.074	0.073
		[0.004]	[0.004]		[0.006]	[0.006]
a_1	-	-	-0.005	-	-	-0.0035
			[0.001]			[0.0002]
a_2	-	-	0.0001	-	-	4.66E-05
			[5.60E-05]			[2.48E-05]
a_3	-	-		-	-	-1.32E-06
						[1.52E-06]
b_1	-	-		-	-	-0.024
						[0.007]
b_2	-	-		-	-	0.007
						[0.004]
γ	-	-	-0.004	-	-	-7.6700E-004
			[0.001]			[4.96E-04]
Adj. R-squared	0.893	0.839	0.918	0.214	0.353	0.377
AIC	-3.123	-3.319	-3.381	-3.172	-3.366	-3.396

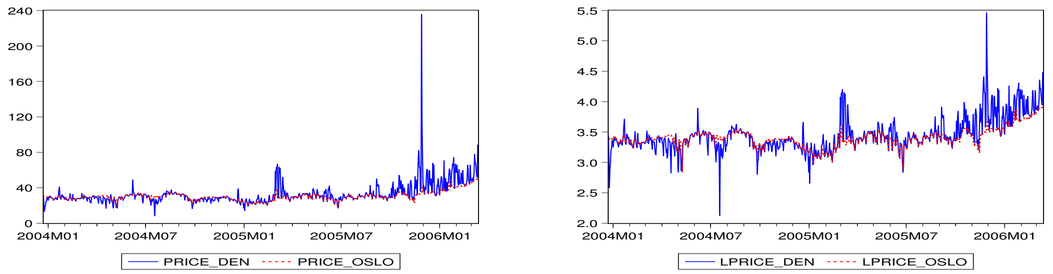
Note: The table reports the coefficient estimates (and their standard errors between square brackets), and selection criteria tests of the models on Oslo log prices and first difference log prices for models in section 3.

Table 3: Out-of-sample forecasting results: RMSPE

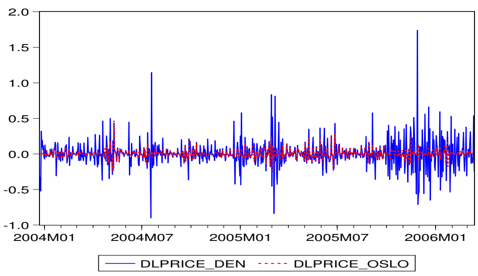
	Oslo		Eastern Denmark	
	24h	Peak	24h	Peak
ARIMAX	0.048	0.059	0.170	0.176
ARMA	1.151	1.136	1.099	1.276
ARMAX	1.031	1.018	1.006	1.125
ARMAXW	0.990	0.974**	0.984*	1.101
ARIMA	1.118	1.126	1.101	1.123
ARIMAXW	**0.942****	**0.907****	**0.905****	**0.899****
ARIMAXRW	0.988	0.999	0.998	1.002
ARIMAX-GARCH	1.029	1.009	1.028	0.984
ARIMAXW-GARCH	1.010	0.996	1.035	1.019
ARIMAXW-GARCHW	1.008	1.002	1.027	1.013

Note: The table reports forecasting statistics of the alternative models in Oslo and Eastern Denmark electricity markets using daily average prices (24h) or peak hour (8am-8pm), (Peak) prices. The first line in the table reports the value of RMSPE for the ARIMAX model while all the other lines report statistics relative to the ARIMAX model. Asterisks indicate results of the forecast accuracy comparison t-type statistics as in McCracken (2007) of the given models against those of the ARIMAX model. The null hypothesis is that the two forecasts have the same mean square error. Critical values are reported in table 1 in McCracken (2007). In our case $\pi \simeq 1.2$ and $k_2 = 6$. One asterisk denotes significance relative to the asymptotic null hypothesis at 5%, two asterisks denote significance relative to the asymptotic null hypothesis at 1%.

Figure 1: Prices



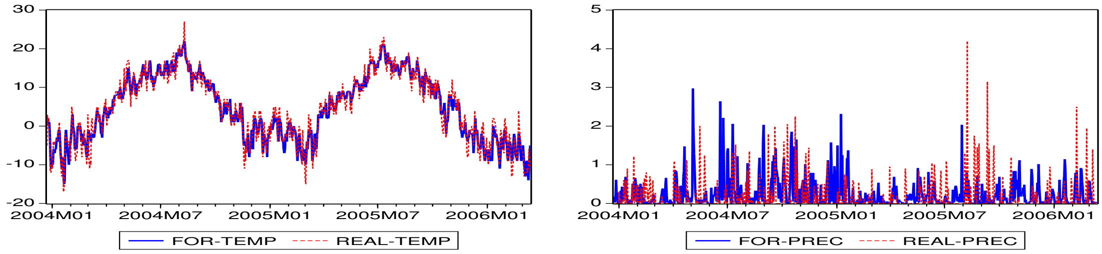
(a)



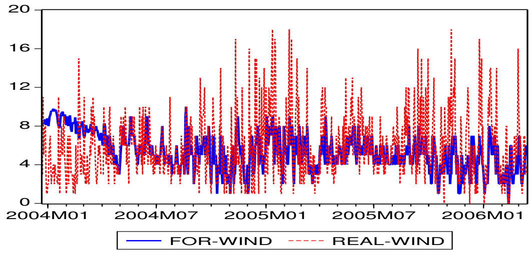
(b)

Note: The graphs in this figure present in Panel a) prices (in the left panel) and log prices (in the right panel) of daily electricity prices in Oslo, Eastern Denmark and the Netherlands; in Panel b) histograms of daily electricity prices in Oslo (in the left panel) and Eastern Denmark (in the right panel) markets; and in Panel c) histograms of daily electricity prices in the Netherlands market.

Figure 2: Weather variables: Oslo



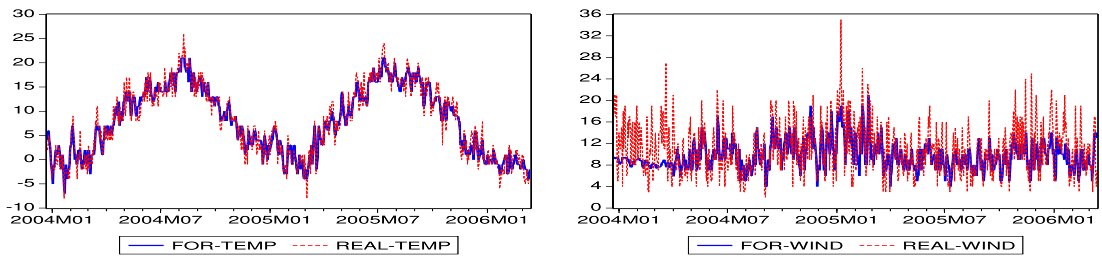
(a)



(b)

Note: The graphs present in Panel a) realized (REAL-) and forecasted (FOR-) daily average temperature (in the left panel), and total precipitation (in the right panel); in Panel b) realized (REAL-) and forecasts (FOR-) on wind speed in the Oslo area.

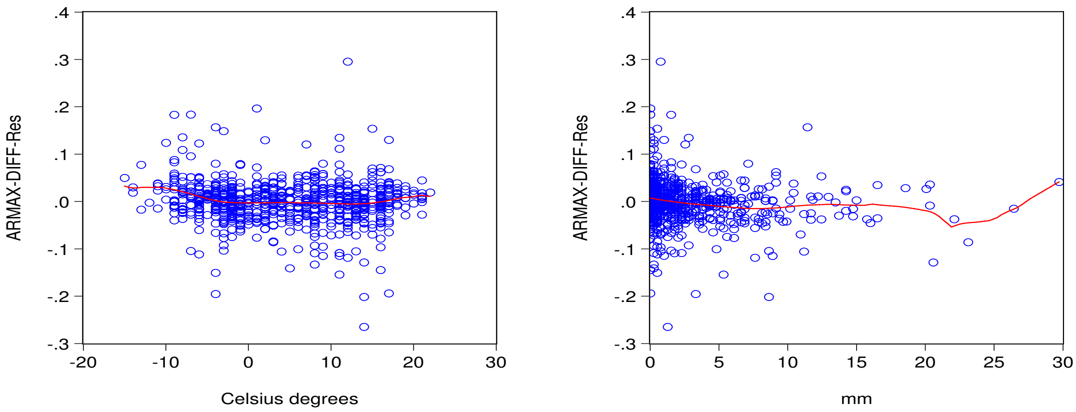
Figure 3: Weather variables: Eastern Denmark



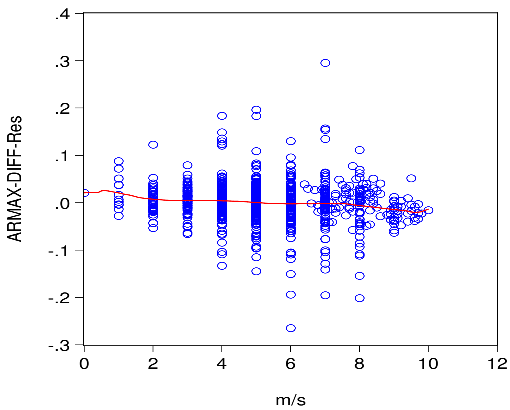
(a)

Note: The graphs in figures 2 and 3 present realized (REAL-) and forecasted (FOR-) daily average temperature (in the left panel) and realized (REAL-) and forecasted (REAL-) wind speed in the Copenhagen area.

Figure 4: Scatter plot: Oslo



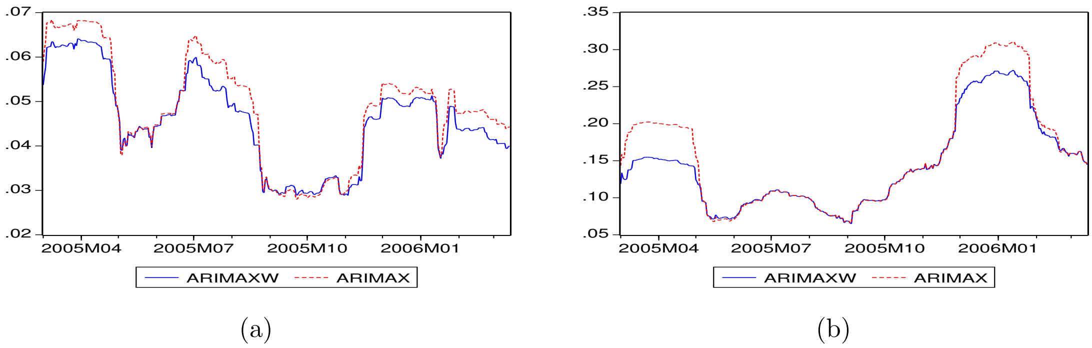
(a)



(b)

Note: The graphs in this figure present in Panel a) the scatter plot of the errors of ARIMAX model against the forecasts of the daily average temperature (in the left panel), and total precipitation (in the right panel); in Panel b) the scatter plot of the errors of ARIMAX model against the forecasts of the wind speed in Oslo.

Figure 5: 60-day average RMSPE



Note: The graphs in this figure present in Panel a) the 60-day moving average RMSPE given the ARIMAX and ARIMAXW models in forecasting Oslo log electricity prices; in Panel b) the 60-day moving average RMSPE given the ARIMAX and ARIMAXW models in forecasting Eastern Denmark log electricity prices.

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