Norwegian University of Life Sciences
School of Economics and Business

Philosophiae Doctor (PhD)
Thesis 2022:41

Three Essays on Electricity Prices

Tre essay om elektrisitetspriser

Erik Smith-Meyer

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Summary

The thesis explores how the Nord Pool power market prices forward-looking information. Specifically, the thesis investigates the efficiency, or the biasedness, of the derivatives side of the power market, how temperature is priced by the market, and how to account for uncertainty in future information. The thesis consists of an introductory chapter which comprises the context and background for the three studies, including a summary. Using data on current and future-looking information from futures prices, the thesis brings new evidence on how the efficiency of the futures market at Nord Pool has developed. Furthermore, the thesis investigates relationship between the relationship between temperature and power prices and the price forecasting information implied in weather forecasts.

The first essay, co-authored with Ole Gjølberg, investigates whether the Nordic power futures market is efficient. Several studies have found electricity futures prices to be overshooting subsequent spot prices. This could be a result of long hedging pressure, or it could come about because of an immature and inefficient market. Considering seasonality and structural breaks, we test the forecasting performance of Nordic power futures. The paper's main conclusion is that the forecasting of power futures has experienced a structural break around 2008. After this period, power futures have provided unbiased forecasts of electricity spot prices. Prior to 2008, a persistent futures forecasting error appeared to be too large to be explained by a risk premium only. Our suggestion is that the opening of the Nor-Ned cable between Norway and the Netherlands played a central role in making the market more efficient.

The second essay analyses the effect of temperature on electricity spot prices. It proposes a new econometric model which accounts for seasonality in this effect. Using data on prices and realized temperatures on Nord Pool and the five Norwegian price zones the study shows that the temperature effect on price varies across season, price area and price quantile. This suggests that pricing models based on constant coefficients for temperature may be misleading, "averaging out" seasonal effects. Consequently, one must carefully take

this into account when modelling the electricity price process, as has been done in the third essay.

The third essay is an empirical study which investigate how the information content in weather forecasts affects prices. As there is more uncertainty in longer term forecasts than shorter term forecasts, a method for adjusting the models according to this uncertainty is proposed. The study shows that by utilizing the forward-looking information available in temperature forecasts, improvements in the accuracy of daily forecasts up to nine days ahead can be achieved. Also, because of the horizon dependent uncertainty of temperature forecasts, one should not use the same estimated coefficients for all time horizons. Rather, a separate set of coefficients should be estimated depending on the forecasting horizon, thereby mixing incremental and direct forecasts.

The thesis provides new insight into the effect of future looking information on the electricity spot prices. The findings indicate that futures on the Nord Pool spot price has been unbiased estimates of the future spot price since 2008. Furthermore, the effect of temperature on price were investigated and were found to be seasonally dependent, different across Norwegian price zones, and different across price quantiles. Also, the information from temperature forecasts is beneficial to use in price forecasts for up to 9 days ahead, but the uncertainty in temperature forecasts has to be accounted for.

Sammendrag

Avhandlingen utforsker hvordan kraftmarkedet Nord Pool priser fremtidsrettet informasjon. Nærmere bestemt undersøker avhandlingen markedseffisiensen, eller forventningsskjevheten, til derivatsiden av kraftmarkedet, hvordan foventet temperatur prises av markedet, og hvordan man skal ta hensyn til usikkerheten til fremtidig informasjon. Avhandlingen består av et innledende kapittel som inneholder konteksten og bakgrunnen for de tre studiene, inkludert en oppsummering. Ved hjelp av markedsdata og fremtidsrettet informasjon fra terminpriser gir avhandlingen nye bevis på hvordan effisiensen i futuresmarkedet på Nord Pool har utviklet seg. Videre undersøker avhandlingen sammenhengen mellom temperatur og kraftpriser og hvordan temperaturprognoser er priset inn i kraftprisene.

Det første essayet, som ble skrevet sammen med Ole Gjølberg, undersøker om det nordiske fremtidsmarkedet for kraft er effisient. Flere studier har funnet at terminprisene for elektrisitet i gjennomsnitt er høyere enn påfølgende spotpriser. Dette kan være et resultat av at det er flere kjøpere som ønsker å sikre posisjonene sine eller det kan komme av et umodent og ineffektivt marked. Etter å ha tatt høyde for sesongvariasjon og strukturelle endringer tester vi prognoseresultatene for fremtidskontrakter på det nordiske markedet. Essayets hovedkonklusjon er at fremtidskontraktenes evne til å forutsi fremtidige kraftpriser har hatt et strukturelt brudd rundt 2008. Etter denne perioden har fremtidskontraktene gitt forventningsrette prognoser for spotprisene på elektrisitet. Fremtidskontraktenes forventningsskjevhet som ble observert før 2008 var for stor til å kunne forklares av risikopremie alene. Vårt forslag er at åpningen av Nor-Ned-kabelen mellom Norge og Nederland spilte en sentral rolle i å gjøre markedet mer effisient.

Det andre essayet analyserer effekten av temperatur på spotprisene på elektrisitet. Her presenteres en ny økonometrisk modell som justerer for sesongmessighet i denne effekten. Ved hjelp av prisdata og realiserte temperaturer på Nord Pool og de fem norske prissonene viser studien at temperatureffekten på pris varierer over sesong, prisområde og priskvantil.

Dette antyder at prismodeller basert på konstante koeffisienter for temperatur kan være villedende og utjevne denne sesongbaserte effekten. Følgelig må man ta hensyn til dette når man modellerer strømprisprosessen, slik det er gjort i det tredje essayet.

Det tredje essayet er en empirisk studie som undersøker hvordan informasjonsinnholdet i værmeldingene påvirker spotprisene. Siden det er mer usikkerhet i langsiktige prognoser enn kortsiktige prognoser, foreslås det en metode for å justere modellene i henhold til denne usikkerheten. Studien viser at ved å bruke den fremtidsrettede informasjonen som er tilgjengelig i temperaturprognoser, kan forbedringer i nøyaktigheten av daglige prisprognoser opptil ni dager fremover oppnås. På grunn av den horisontavhengige usikkerheten i temperaturprognosene bør man heller ikke bruke de samme estimerte koeffisientene for alle tidshorisonter. Snarere bør et eget sett med koeffisienter estimeres avhengig av prognosehorisonten, og dermed blande trinnvise og direkte prognoser.

Avhandlingen gir ny innsikt i effekten av fremtidsrettet informasjon om spotprisene på elektrisitet. Funnene tyder på at futures for spotprisen på Nord Pool har vært forventningsrette anslag over den fremtidige spotprisen siden 2008. Videre ble effekten av temperatur på pris undersøkt og funnet å være sesongavhengig, forskjellig på tvers av norske prissoner og forskjellig på tvers av priskvantiler. Informasjonen fra temperaturprognosene er også gunstig å bruke i prisprognoser i inntil 9 dager fremover, men usikkerheten i temperaturprognosene må tas høyde for.

Power markets and pricing

As a backdrop for my econometric studies of price relationships in the Nordic power market, I will start out by presenting some issues and facts related to electricity as a commodity and challenges in power markets. This is to put the subsequent econometric analyses in a broader context and to provide some basic insights into issues for readers not familiar with electricity markets. In the first section, I will dwell on what makes electricity different from other energy commodities. Then in the next section I will present some challenges that the liberalization of electricity markets are confronted with, Thereafter, I will briefly outline the roles of the two power exchanges serving the Nordic market, i.e., Nord Pool (physical electricity) and NASDAQ Nordic (power derivatives). This is followed by some reflections on the pricing of power futures within the established theory for commodity futures before I briefly discuss some topics on temperature and power prices. A summary of the three empirical studies concludes.

Electricity – a different commodity

The transformation of electricity power markets into commodity markets, with a bidding process for suppliers and consumers, paved the way for introducing financial instruments and models for risk management and forecasting. Commodity finance delves into the pricing and transfer of risk. The main goal of this thesis is to contribute to the understanding of the pricing of risk and improving price forecasting, especially by including temperature information and temperature forecasts.

As pointed out by several analysts (e.g., Biggar and Hesamzadeh, 2014) the electricity market is different from most other commodity markets given by the idiosyncratic nature of electricity itself. The very nature of electricity requires that production and consumption take place simultaneously. Electricity is a “flow commodity”, as the electric energy “flows” in the direction of the least resistance through power lines, as expressed by Ohm's law. These power lines have limited capacity, a so-called thermal limit, where no more electricity can flow without inducing damage to the line itself. There is also an efficiency loss when electricity is transported over great distances.

These transmission constraints often cause regional markets to form with large and variable price differentials between markets due to bottle necks in the grid. While other energy commodities like oil and natural gas also display geographical price differences for physically identical goods due to transportation costs, these differences are typically smaller, and less variable compared to those found in power markets.

Electricity's limited possibility for storing is another characteristic not shared with other energy carriers like oil and gas. This contributes to geographical price differences and, more importantly, a very much higher price volatility compared to almost all other commodities. Electric power can be stored directly in batteries, but this is an expensive option. *Potential* electric power can be stored as water in hydro power plants, as nuclear rods in nuclear power plants, and as coal and natural gas for fossil-fuel based power plants. The mode for extracting electric power from these sources are then the available installed production capacity, which again is limited.

Most modes of production have a certain flexibility when it comes to production planning. Renewable sources less so. Wind power is a growing source of electricity generation, and the challenge of production planning caused by unexpected wind "supply" often cause production to deviate substantially from what was planned or expected. In a power system heavily dependent upon wind, this can in itself cause large price variations. Combining this with limited transmission capacity, days with affluent wind supplies can cause prices to fall to very low level. Sometimes below zero!

Price variations due to demand shifts also depend on where on the supply curve the equilibrium between supply and demand occurs. The so-called merit order curve implies that supply is very flat (elastic) up to a certain point where it becomes highly inelastic. At this part of the curve, even relatively small demand shifts may cause significant price changes.

Liberalized electricity markets

Historically, the power market was organized in several quite disjoint markets, where one company had vertical control over generation, long distance transmission, and finer grid distribution. These markets were tightly regulated monopolies, where prices were regulated to reduce economic deadweight loss. In addition to vertical integration, long-term contracts, which reduce the ability of the company to set prices, are also common in markets with a monopoly provider. This reduces the price sensitivity even further of the demand to changes in supply. A consequence of the highly inelastic demand in markets with long-term contracts, were that companies had to install excess capacity to be able to secure supply, even at peak demand. Another negative consequence of monopoly power was the lack of incentives for investment in long distance transmission lines between markets. This further exacerbated the need for local capacity at peak demand.

One solution to the problems inherit in monopoly markets is market liberalization, where generation, transmission, and distribution are allocated based on economic bidding, and not based on an engineering viewpoint. There are still natural monopolies in these markets, notably the market for transmission, which need to be regulated.

For a liberalized market to function, several issues must be sorted out. It is not possible in electricity markets to separate the market for generation and consumption of power from the market for transportation of power. The problem of balancing generation and consumption, taking into the transmission constraints, is a constrained optimization problem performed by a central body which is the market operator. For each hour the next day, every seller submits their supply function, which is an offer function stating the volume they are willing to produce at specified prices. For the same hours, every purchaser submits their demand function, which is a bid function that states the volume they are willing to buy at specified prices. In economic theory, all economic actors are assumed to be maximisers of an objective function, often assumed to be the profit function. The market operator then does the calculations to find the prices which balance the market, given the transmission constraints. One price per price zone is set. These price zones are assumed to be free of transmission congestion, such that one price balances the market. When the balancing prices has been set, the market operator informs the individual sellers and buyers at which rate they can generate and consume electricity, for each hour the next day, at the market price.

In the absence of market power, a liberalized market solves the problem of efficiently allocating a given rate of consumption of electricity among customers with different needs and preferences. The customer buys electricity until the marginal utility of one unit of electricity equals the market price. The producer sells electricity until the marginal cost of producing one unit of electricity is equal to the market price. This mechanism, in a well-functioning market, yields the welfare-maximizing price.

The shift from monopoly markets to liberalized electricity markets indicated a shift from secure long-term contracts to short term price uncertainty for both sellers and buyers of electricity. To enable the market actors to manage and price this risk, a power derivatives market is usually created. Here, contracts for delivery of power from one day to several years ahead are traded.

Nord Pool and NASDAQ Nordic

The fundament for the liberalization of the Nordic power market was laid by the "New Energy Act" in Norway in 1991. The market itself was established in 1993, which makes it the world's oldest electricity wholesale market. It quickly became a success story of market liberalization. During the next 20 years, this market expanded to include not only Norway, but also Sweden, Denmark, Finland, and the Baltic states, for a total population of 33 million.

Countries either adhere to a single price zone, or they are split into multiple. The price within each zone is assumed to be uniform, which means there is no congestion. As such, area prices are calculated based on supply and demand, given the transmission constraints to and from the other price zones. In addition, a theoretical price is calculated, assuming no transmission constraints. This is then called the system price, which is important for power derivatives.

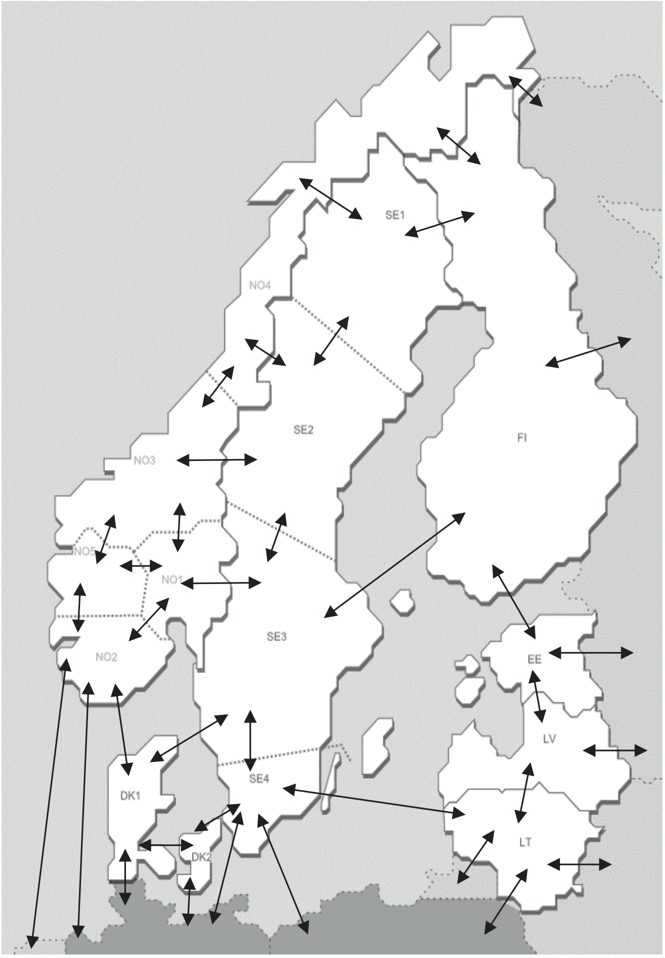

Figure 1. Overview of the Nordic power market. Several countries are split into price zones. Interconnections between price zones are shown by arrows.

At Nord Pool, sellers and buyers submit their bids for all hours the next day no later than noon at the day before delivery. This Elspot market is the day-ahead market. Bidders cannot always foresee the supply and demand every hour the next day. In case of deviations, Nord Pool also runs an intra-day market called Elbas, which ensures balance in the grid at any time by rapidly removing or adding power to the grid.

The modes of production differ among the countries in the Nord Pool pricing area, with a total generation of 409 TWh (see Table 1). Norway and Northern Sweden has mainly hydro power, which can be exported to other areas in years with normal and above normal precipitation. The wind power in Denmark and Sweden will only be available when the wind is blowing, so customers must rely on other sources when it is not. Thermal power from fossil and nuclear fuels can be produced regardless of the amount of wind and precipitation and is a source of baseload energy. In sum, these sources of electric power are complements, and they enable the countries to support each other in different market situations.

Country	Norway	Sweden	Finland	Denmark	Estonia	Latvia	Lithuania
Production (TWh)	132	165	67	29	7	6	3
Per capita (MWh)	24	16	12	5	5	3	1
Production mode (TWh)							
Nuclear	0	64	23	0	0	0	0
Fossil fuels	2	2	12	5	5	3	1
Hydro	124	64	12	0	0	2	0
Solar	0	0	0	1	0	0	0
Wind	6	20	6	16	1	0	2
Biomass and waste	0	14	14	7	1	1	1

Table 1. Production of electricity for year 2019. (Halsanæs et al. 2021)

Power futures

Financial contracts are used for risk management activities, like hedging and speculation, with the futures contract being the most common. These contracts are currently traded on NASDAQ Nordic Commodities, with horizons from one day to ten years (although often with low liquidity as far as the longest maturities are concerned). The contracts are daily, weekly, monthly, quarterly, and yearly with financial settlement and with the system price as the reference price. The physical limitations on the interconnections between the price zones and the limited ability to store power results in large price, swings compared to other commodity markets. In order to be able to manage risk related to the difference between the system price and the regional price, NASDAQ also provide so-called EPADs (formerly known as contracts for differences, CfD), making it possible to buy/sell contracts written on e.g., the difference between the price in the Oslo area and the price for the whole system (which would have prevailed with on bottlenecks in the transmission grid). These contracts have a payoff equal to the difference between the futures price in a price zone and the system price. By combining a futures contract and an EPAD , a market actor can hedge the future power price in a price zone (Spodniak et al. (2015).

There are two popular views of commodity futures prices. One is to explain the difference between futures prices and corresponding spot prices in terms of interest, insurance, warehousing cost, and convenience yield of storing a commodity, the so-called the theory of storage. The theory dates back to classic contributions to commodity futures pricing in seminal works by Kaldor (1939), Working (1948), Brennan (1958), and Telser (1958). The other view splits a futures price into two parts - a spot price expectation and a risk premium. This is described by Cootner (1960), Dusak (1973), Breeden (1980), and Hazuka (1984).

The two theories are perspectives on the same economic spot-futures process, but due to the problem of storing electricity, the expectation theory is most relevant in our context. The expectation theory can either use the futures price to forecast the future spot price, or it can use the current basis to forecast the future spot price change. See Eydeland and Geman (1999).

Bias in futures prices, with respect to realized or expected spot prices, is also known as the risk premium. If there is no hedging pressure, then long and short hedgers cancel each other out, and the futures price can be thought of as an unbiased estimate of the future spot price. However, if there is more demand for either long or short hedging than the other, then there will be a hedging pressure which must be absorbed by other market actors, i.e., speculators. The payment, or return, from taking on this risk is the risk premium. This payment must be seen in the context of the risk taken on. If the risk premium is of such size to be the source of abnormal profits, then the market may be considered immature.

With the possibility to lock in a price in the future, there is also a need to understand the pricing of these futures contracts and to make more accurate forecasts of the future power price. As demand for power is dependent on, among other things, the temperature, this thesis uses temperature information to better understand this future price. Temperature forecasts provide market actors with a potentially useful glimpse of the future physical state of the market. This motivates more research on the intersection of power prices and temperature.

Summary of the three essays

This dissertation consists of three independent essays. They all shed light on important topics within electricity price risk management. Whereas the first essay investigates the relationship between spot and futures prices, a theme well known from analysis of financial markets, the two other essays try to shed more light on the importance of temperature in relation to price forecasts. These three papers provide useful and incremental knowledge concerning electricity price forecasting.

The first essay, "The Nordic Futures Market for Power: Finally Mature and Efficient?", deals with the risk premium at Nord Pool. After the creation of a power derivatives market at Nord Pool in 1995, evidence of bias between futures prices and corresponding spot prices has been found by several studies. Gjølberg and Johnsen (2001) found indications of non-rational pricing behaviour where all available information did not seem to be included in the futures price. The futures price was an upwards biased predictor of the spot price level and spot price change. The size of the forecast errors was in such a magnitude that they could not be interpreted as risk premiums alone. The inclusion of public information like seasonality, spot price levels and spot price changes could improve the forecast considerably, indicating an inefficient market. Studies of other markets, like Bessembinder and Lemmon (2002) which considered the U.S. markets, found the same pattern of the risk premium. These markets, along with Nord Pool, were developed during the 1990's. Later studies considering Nord Pool, like Botterud et al. (2002, 2010) found the bias to be about 5 % over a four- to six-week horizon. Lucia and Torró (2008) reported a somewhat smaller risk premium for the Nordic market in 1998–2007, averaging some 3–4 % over four-week horizons. All these studies use simple econometric models to estimate the risk premium. However, Weron and Zator (2014) point out that there are certain pitfalls related to the simultaneity problem, correlated measurement errors, and the possible presence of seasonality which are associated with these models. In our study, we try to correct for these pitfalls by including extra explanatory variables, in addition to the basis. Given the commission of the NorNed cable between Norway and Netherlands, we check for a structural break in the risk premium. We also do a simulation in which we short the short-term futures to take advantage of a persistently non-zero risk premium.

Our conclusion is that up until 2008, Nord Pool futures were biased forecasts of corresponding spot prices, whereas after 2008, this was not the case. We do indeed find that there was a significant break in the level of the risk premium. This break may come about because of a change in hedging pressure, or the change may be due to the market getting more efficient. We hypothesise that the physical change to the market infrastructure by the commission of the NorNed cable in the spring of 2008 may have induced this break in risk premium.

The first essay used the basis to model the risk premium. Another important strain of research uses models of expected prices to estimate the risk premium, as in Lucia and Torro (2008). The last two essays contribute to this last strain of research by improving how temperature information can improve on price forecasts.

In the Nordic region, electrical appliances are an important heating technology for residential and commercial buildings. As the temperature drops, more electricity is used for heating which shifts the demand side of the market to form a new price equilibrium, as shown by Cancelo, Espasa and Grafe (2008), and Bessec and Fouquau (2008). The second essay, "Temperature and Prices in the Nordic Power Market" tries to shed light on how changes in temperature are statistically connected to changes in the price of electricity. It looks at both the temperature effect on price, and relative importance of temperature as an explanatory variable of the electricity price across several dimensions. The common way to model the effect of temperature on prices is to include one or more temperature variables which have a linear effect on price (Weron and Misiorek (2008), Huurman et al. (2012)).

One of the main contributions of the essay is to account for seasonality in the temperature effect on price. Using daily observations from all days of the in-sample years 2010-2018, disregarding the time of year, I find that changes in temperature explain about 6 % of price changes. However, when differentiating seasonal effects, I find that temperature explains between close to 0 % in August and September to over 19 % in December, as measured by incremental change in R^2. The model with time-varying temperature effect on price is used to forecast price data for 2019 on all Norwegian price zones and on the system price. The results indicate that to allow for separate coefficients by month for the temperature effect yields lower forecast errors than to use the traditional constant coefficient. Also, the temperature effect differs between the Norwegian price zones. Quantile regression of Koenker and Basset (1978), is often used for either value-at-risk estimation, or for interval forecasting. We find that the temperature effect on price varies substantially across the price distribution, in general being negative, but sometimes positive. This suggests non-linearity, which then may be modelled with the fitted quantile regression. In general, changes in prices below 19 EUR/MWh are not related to temperature changes, and prices above 19 EUR/MWh are negatively related to temperature changes.

The process of forecasting is a constant battle to unveil future information, often in the form of statistical relationships. One such piece of future information come in the form of temperature forecasts. Temperature influences both the production, in the long run, and especially the demand, in the short run, for electricity, thereby affecting the price process. As shown by Smith-Meyer (2022), the Nord Pool system price is positively affected by negative changes in temperature, shifting demand upwards for lower temperatures. This would consequently put an upward pressure on the price. The idea to use temperature forecasts for electricity price forecasting is not a new one. Huurman et al. (2012) used one-day forecasts to help predict the day-ahead power price. Other studies, like Weron and Misiorek (2008) used realized next-day temperatures to predict the power price and found that the temperature is as good a predictor as load.

Temperature forecasts have gotten increasingly accurate over the years, and according to Lorenz (1963), the possible useful horizon for weather forecasts is up to two weeks. Accordingly, in the third essay, "Electricity Price Forecasting and Weather Forecast", we address the question whether forward-looking information from temperature forecasts can improve on daily electricity price forecasts up to nine days ahead. An initial study makes clear that the uncertainty in the temperature forecast increase with forecast horizon. An auto regressive model with several exogenous variables, among them the temperature forecast, is used to forecast the spot price at the Norwegian price zone NO1 (Oslo). This AR model, with and without regularization, is compared to univariate models without temperature and without other exogenous variables. The analysis shows that to use information from the temperature forecast yield more precise spot price forecasts for all horizons, up to nine days ahead. Another novel result in the paper is that in order to account for the increased temperature forecast uncertainty for longer horizon forecasts, one model should be estimated per forecast step, thereby combining incremental and direct forecasting. The paper also highlights the importance of regularization, where using LASSO regularization reduced forecast errors more than Ridge and Elastic Net regularization.

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The Nordic Futures Market for Power: Finally Mature and Efficient?

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Abstract

A number of studies have found nearby futures prices in the Nordic power market to be biased forecasts, overshooting subsequent spot prices. This could be due to a persistent risk premium in a market dominated by long hedgers. However, in several studies the size of the bias has been taken as evidence of the market being immature and inefficient. In this paper, we present the results from an updated study of the forecasting performance of Nordic power futures. Using observations from October 2003 through January 2015, we estimate the standard models as well as a set of models in which we allow for seasonal variations and possible shifts in the risk premium given structural changes in the market. Furthermore, we report the results from simulated investments in which we persistently short nearby futures and maintain this position through expiration. We find that after 2008 Nordic short-term power futures have turned unbiased and more precise forecasts. Consequently, we conclude that the Nordic futures market for power has matured and now appears to be at least weak form efficient. We suggest that the physical integration of the Nordic and the Dutch markets through the opening of the NorNed cable in 2008 may have been a factor contributing to this development.

KEYWORDS. Nordic power prices. Futures bias. Market efficiency.

1 Introduction

In this article, we study the forecasting performance of nearby Nordic power futures in order to see whether the futures bias reported in a number of previous studies still prevails and if so, whether this means that the market is inefficient. The paper is organised as follows. First, we present some basic facts regarding the Nordic power market. We then survey the literature on the performance of power futures. Next, we specify a set of econometric models similar to those used in previous studies on power futures performance. However, we expand the standard models by allowing for differences in the risk premium and forecasting performance depending on whether the market is in contango or in backwardation. We also test out a set of models in which we include seasonal explanatory variables. After presenting the results from estimating these models, we simulate a simple investment strategy to reveal whether the bias is something more than a risk premium, i.e., whether the Nordic market is inefficient in the way that there are abnormal profit opportunities.

2 Nordic power market basics

As of 2015, the Nordic physical power market includes Norway, Sweden, Denmark, Finland, Estonia, Latvia, and Lithuania. Spot market trading is organized at Nord Pool Spot where roughly 300 TWh or 70 per cent of consumption in the Nordic market is traded in the hourly day-ahead-market. The trade in power derivatives, introduced by Nord Pool in 1995, now takes place at NASDAQ OMX. During recent years, a wide range of financial contracts written on both base and peak load power with maturities ranging from one day to ten years have been traded at the exchange.[2] In addition, there are contracts written on price differences in different regions, so called EPADS (Electricity Price Area Differentials, previously known as Contracts for Difference, CfDs).

Given the special physical characteristics of electricity, contracts are settled on a cash basis. So-called DS (deferred settlement) futures (previously known as forwards) cover the longer maturities (years, quarters, and months). Year contracts are cascaded (split) into quarters, while quarters are cascaded into months. For these contracts there is no settlement during the trading period prior to expiry date. Mark-to-market is accumulated on a daily basis throughout the trading period but not realized until the delivery period. Settlement of shorter horizon futures (days and weeks contracts) involves both a daily mark-to-market settlement and a final spot price reference cash settlement after expiry date.

In this paper, we analyse the forecasting performance of nearby futures, i.e., DS Month futures with four weeks left to expiry. Disregarding technicalities related to mark-to-market settlements; contracts held through expiration are settled against the average spot price during the delivery period. For the Month contract this amounts to the average Nordic system price during the 672 to 744 hours following expiration (number of hours depending on which month).

[2] Details on Nordic power derivatives can be found at http://www.nasdaqomx.com/commodities/markets/power/nordic-power

There is a substantial trade in power derivatives in the Nordic market. After the start-up in the mid-1990s, traded volumes grew rapidly reaching a top in 2002 of more than 3,000 TWh of which some 1,000 TWh were traded at the exchange, while some 2,000 TWh were OTC cleared. The collapses of Enron and TXU Europe triggered an exodus of most US power companies, causing a drastic reduction in trade in 2003. Still, there is a substantial trade in power contracts at NASDAQ OMX. In 2011, traded volume related to Nordic power was some 1,028 TWh accumulated over roughly 130,000 transactions. However, while total volume is large, liquidity varies substantially across the different contract maturities, some contracts being quite illiquid. In general, contracts with long horizons (Quarter and Year contracts) make up the by far largest part of traded volumes. The share of short-term contracts (Month, Week, and Day contracts) is less than 10 per cent of total trade.

During the 12-year period 2003-15, the nominal power price in the Nordic market has averaged some 40 Euro/MWh (Figure 1). However, the fluctuation around this level has been substantial as shown in Figure 2. Spot price changes (measured as log returns) 2003-15 had a *monthly* standard deviation of 27%. This represents a volatility significantly higher than that found in other commodity markets. The volatility was particularly high between September 2011 and October 2012.

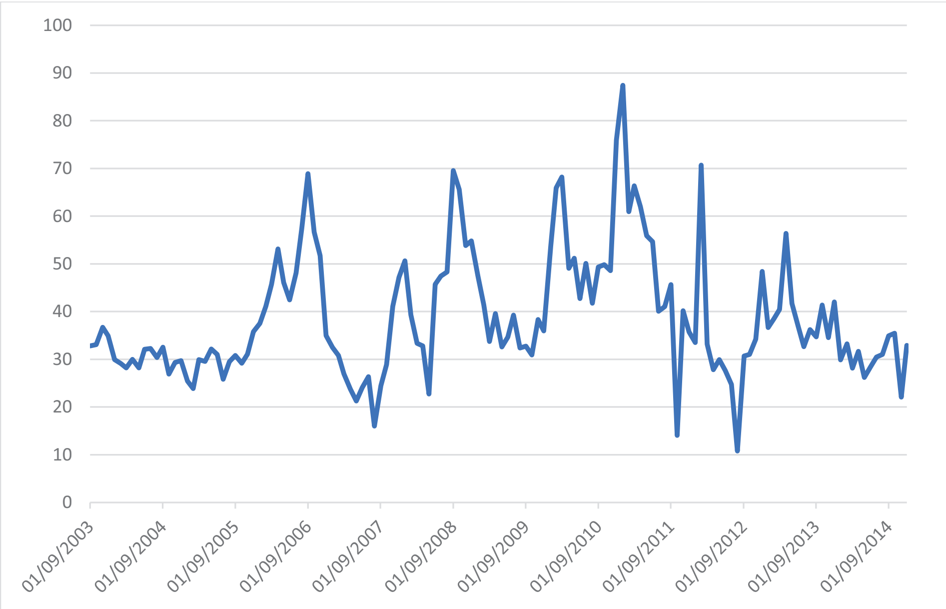

FIGURE 1

Monthly Nord Pool System Price (Euro/MWh), September 2003–January 2015

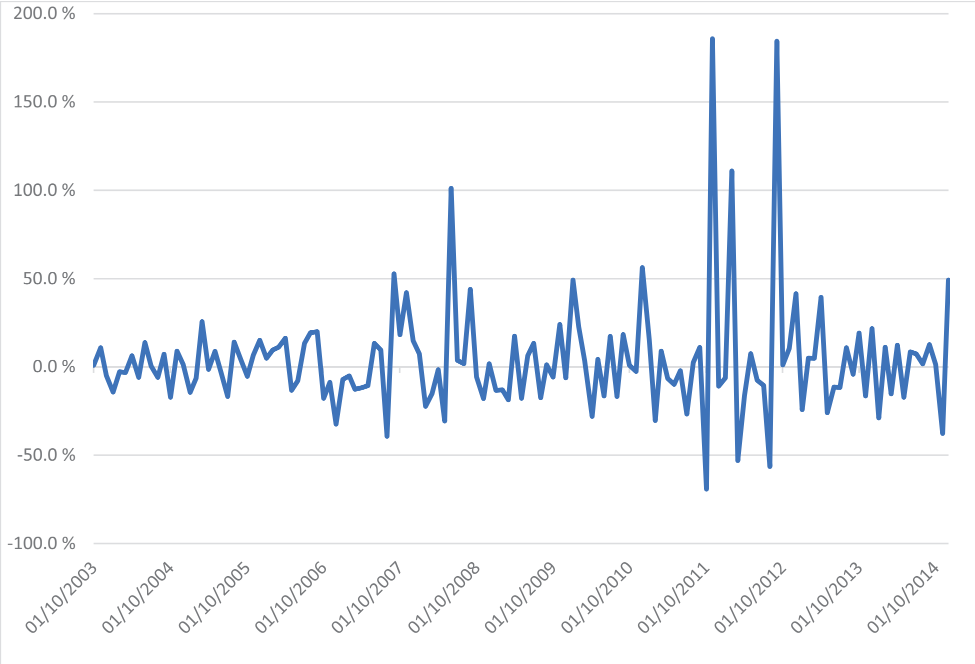

FIGURE 2

Monthly per centage change in Nord Pool System Price, September 2003–January 2015

3 Literature on power futures

Using standard notation, the observed futures price at time t for a contract with maturity at T can be written as

$$F_{t,T} = E[S_T|\Omega_t] + \pi_t^T$$

where $E[S_T|\Omega_t]$ is the spot price expected to prevail at time T given the information set available at t while π_t^T is the risk premium over the period till the expiration of the contract. In a balanced market, i.e. in a market where long and short hedging demands are equal, the futures price is theoretically an unbiased estimator of the spot price. If there is a persistent net long or net short hedging demand, the futures price will deviate from the expected spot price positively or negatively and therefore appear to be "biased" in statistical terms.

Several studies have reported evidence of a statistical bias in electricity futures markets in the way that the difference between the futures price and the subsequent spot price has turned out as significantly different from zero. In an early study, Gjølberg and Johnsen [2001] concluded that the futures price at Nord Pool periodically had been outside its (theoretical) arbitrage limits and that the futures price and the basis were biased and poor predictors of subsequent spot price levels and changes, respectively. Forecast errors were following a systematic pattern and the futures price did not seem to incorporate available information, indicating non-rational pricing behavior. Bessembinder and Lemmon [2002] found a risk premium in the US power markets, varying in size and direction depending on season. Botterud et al [2002] and [2010], found that the nearby futures prices in the Nordic market tended to overshoot the subsequent spot price. In their more recent study covering the period 1996-2006, they found the bias to be in the range of 4.6 to 5.1 per cent over 4 to 6-week horizons. For longer maturities (i.e., Season and Year contracts), Christensen et al. [2007] found a significant negative risk premium which they related to abuse of market power. Disregarding the issue of market power, the fact that the risk premium over longer horizons has an opposite sign of those over shorter horizons may simply be due to different hedge demand (short vs. long) across horizons. Shawky et al [2003] analysed the California-Oregon border market. They found a risk premium in the range of 4 per cent per month. Although very high compared to other commodity markets, they suggested that this large premium was due to the unique physical features of electricity as a commodity. Alternatively, they suggested that the finding might be caused by "limited industry-outsider participation", or in other words non-competitive markets. Lucia and Torro [2008] reported a somewhat smaller risk premium for the Nordic market 1998-2007, averaging some 3-4 per cent over four-week horizons. Furio and Meneu [2010] studied the Spanish power market and reported a one-month risk premium of some 2.8 per cent for the period 2003-04 and 2006-08. Diko et al. [2006] likewise found a substantial and significant positive risk premium in the German, Dutch and French markets. Redl et al. [2009] found that the Nordic one-month futures 2003-08 had overshot the subsequent spot price by 8 per cent on average and by 9 per cent and 13 per cent in the German EEX base load and peak load markets, respectively. The authors concluded that market inefficiencies cannot be ruled out. Based on observations from the Nordic market covering the period 1995-2008 Gjølberg and Brattested [2011] found forecast errors over 4-6-week horizons averaging 7.5-9.3 per cent. They concluded that a bias this size could not be explained by a risk premium alone, suggesting that the market is inefficient.

These studies have all in common that they use simple statistical models to estimate the forecasting performance of futures prices. As pointed out in a recent study by Weron and Zator [2014], there are a number of potential pitfalls when applying such models related to the simultaneity problem, correlated measurement errors and the possible presence of seasonality. While the present study starts out with the standard approach, we expand the model to include explanatory variables that may correct for such factors. In the end, however, the issue of market efficiency boils down to whether or not any observed price regularity can be utilized in ways that generate abnormal profits. In the futures markets as in the kitchen, “the proof of the pudding is in the eating” (Pasour, 1980). Consequently, after having run a set of standard econometric models on a data sample covering observations from October 2003 to January 2015, we simulate a simple investment game based on the assumption that the Nordic short-term futures are persistently overshooting subsequent spot (system) prices.

4 Methodological approach

There are two standard popular models for analysing the forecasting performance of forward or futures prices. The first one estimates the spot price level as a function of the previous futures price level

$$ln\, S_T = \alpha + \beta\, ln\, F_t^T + \epsilon_t \tag{1}$$

In the second, the spot price change is modelled as a function of the previous futures-spot difference (“the basis”),

$$(lnS_T - lnS_t) = \alpha + \beta_1(lnF_t^T - lnS_t) + \epsilon_T \tag{2}$$

Assuming that the futures price at time t for delivery at time T (F_t^T) is an unbiased forecast of the spot price at T, the estimated β in (1) should not differ significantly from unity, while the constant may be taken as an estimate of the risk premium, the rest being unsystematic error with zero mean and constant variance. Similarly, the slope parameter in a regression of the relative change in the spot price from t to T on the relative basis in t (i.e. the relative difference between the futures and the spot price) as in (2) should not differ significantly from unity.

However, the risk premium – and consequently the forecasting performance of the futures price - may depend on the shape of the forward curve, specifically whether the market is in backwardation or in contango, i.e. whether the current futures price is below or above the current spot price. The net hedge demand may shift from short to long when the market is expected to turn. We allow for this by including a term-structure dummy $BACK_t = 1$ whenever $(F_t^T - S_t) < 0$ and 0 otherwise both as a shift in the constant or the risk premium (δ_1) as well as a change in the slope (δ_2) allowing for a change in the bias if the market is in backwardation.

$$(\ln S_T - \ln S_t) = \alpha + \beta\,(\ln F_t^T - \ln S_t) + \delta_1\, BACK_t + \delta_2\,[BACK_t \times (\ln F_t^T - \ln S_t)] + \epsilon_t \tag{3}$$

Botterud et al (2010) found seasonality in the risk premium. Likewise, Flethen et al (2011) found significant monthly patterns at Nord Pool using data from 2003 to 2009. Fanone et al (2013) used monthly dummies to de-seasonalize their EPEX data from 2007 to 2010 before investigating German intra-day electricity pricing. Geman and Roncoroni (2006) used trigonometric functions to model seasonality in three US power markets finding clear seasonal patterns in spot prices, as did Benth et al (2012). Several studies have found seasonality in factors relevant to investors in power markets. A fundamental example is seasonality in temperature, which affects both demand and production. Spot price seasonality was documented by Weron (2008) and Botterud et al (2010), albeit at a decreasing rate from mid-1990's to mid-2000's. Using data for the same period, seasonality in futures prices were found by Torro (2009) who also found a significant seasonality in the futures-spot spread (i.e. the basis). Lucia and Schwarz (2002) found a seasonal pattern in power prices to be crucial in explaining the shape of the futures/forward curve as estimated by a sinusoidal function. Lucia and Torro (2008) found a seasonal pattern in the risk premium. Weron and Zator (2014) found that part of this seasonality in the case of Nord Pool could be explained by seasonal variations in reservoir levels.

In order to capture possible seasonal effects on the forecasting performance of Nordic power futures, we have augmented models 2 and 3 with monthly dummy variables and with trigonometric functions as in

$$ln\, S_T = \alpha + \beta\, ln\, F_t^T + \Sigma_{i=1}^{11} MD_i + \epsilon_t \quad (4)$$

where $\Sigma_{i=1}^{11} MD_i$ is a vector of monthly dummies for the first 11 months of the year, and

$$ln\, S_T = \alpha + \beta\, ln\, F_t^T + \beta_s \sin(2\pi t) + \beta_c \cos(2\pi t) + \epsilon_t \quad (5)$$

Similarly, model (3) has been expanded with seasonality dummies and a trigonometric function,

$$\ln S_T - \ln S_t = \alpha + \beta\, (\ln F_t^T - \ln S_t) + \delta_1\, BACK_t + \delta_2\, [BACK_t \times (\ln F_t^T - \ln S_t)] + \Sigma_{i=1}^{11} MD_i + \epsilon_t \quad (6)$$

and

$$\ln S_T - \ln S_t = \alpha + \beta\, (\ln F_t^T - \ln S_t) + \delta_1\, BACK_t + \delta_2\, [BACK_t \times (\ln F_t^T - \ln S_t)] + \beta_s \sin(2\pi t) + \beta_c \cos(2\pi t) + \epsilon_t \quad (7)$$

The results from estimating these models are summarized in the next section.

5 Econometric results

The futures prices used in this study are closing prices for DS Month futures September 2003 – January 2015. Specifically, we record on the 1st business day of each month the closing price for the Month contract that expires the last trading day of this month and hence is settled against the average spot price of the subsequent month. The spot price observed at t is consequently the average Nordic system price for the day we observe the futures price, while the price against which we evaluate the futures forecasting performance is the average Nordic system price through the "delivery month". Considering the futures price as a forecast, this implies a forecasting horizon of roughly 1,5 months.

Table 1 reports the results from estimating the standard model (1). Tests for non-stationarity (not reported) concluded that both spot and futures prices are stationary in logs. Furthermore, residual tests clearly revealed the presence of autocorrelation as well as heteroscedasticity. Consequently, robust standard errors (Newey-West) were calculated. For the full period as for the three sub-periods, the beta is numerically below unity. However, the robust standard errors are so large that one cannot conclude that the betas are significantly below unity. (Using non-robust standard errors would have changed this conclusion). The results in table 1 furthermore indicate that the slope parameter has been numerically approaching 1 towards the most recent years (after 2008). The explained variance, however, remains relatively low (0.60) throughout the period.

Period	α	β	Adj R^2
2003 Oct - 2015 Jan	0,47 (0,31)	0,86 (0.09)	0,61
2003 Oct - 2008 Jul	0,66 (0,43)	0,80 (0,12)	0,62
2008 Aug - 2015 Jan	0,26 (0,42)	0,92 (0,12)	0,60

TABLE 1. ESTIMATION RESULTS MODEL (1). ROBUST STANDARD ERRORS (HECSE) IN PARENTHESES.

These results are supported by the estimations of model 2, reported in table 2. The estimated slope parameter is not significantly different from unity, and its numerical value is very close to one for the most recent period, during which a relatively large part of the system price *changes* are explained by the previous month's basis. As regards the constant term, which may be interpreted as a risk premium (or a systematic forecast error), it is significant for the full sample October 2003 – January 2015. However, it is no longer significant after 2008. Thus, something appears to have happened after 2008.

Period	α	β	Adj R^2
2003 Oct - 2015 Jan	-0,05 (0,02)	0,92 (0,09)	0,42
2003 Oct - 2008 Jul	-0,06 (0,03)	0,74 (0,27)	0,20
2008 Aug - 2015 Jan	-0,04 (0,03)	1,01 (0,07)	0,55

TABLE 2. ESTIMATION RESULTS MODEL (2). ROBUST STANDARD ERRORS (HECSE) IN PARENTHESES.

Table 3 reports the results from estimating model 3, in which we include a shift and an interaction dummy for those months that the market has been in backwardation. The estimated risk premium and the slope parameter remain very much the same as for model (2). Prior to 2008, the constant is significant, after 2008 it is not, the slope remains not significantly different from unity.

Period	α	β	δ_1	δ_2	Adj R^2
2003 Oct - 2015 Jan	-0,07 (0,04)	0,96 (0,12)	0,06 (0,05)	0,00 (0,01)	0,42
2003 Oct - 2008 Jul	-0,12 (0,07)	1,07 (0,41)	0,06 (0,08)	-0,01 (0,02)	0,20
2008 Aug - 2015 Jan	-0,03 (0,06)	0,94 (0,10)	0,02 (0,06)	0,01 (0,01)	0,55

TABLE 3. ESTIMATION RESULTS MODEL (3). ROBUST STANDARD ERRORS (HECSE) IN PARENTHESES.

Including calendar dummies as well as other ways of taking seasonalities into account as in models (4) – (7) do not change the conclusions above. As can be seen from table 4, reporting the result from estimating on the basis of the full sample, the slope is very close to unity while the seasonal variables are generally insignificant in terms of forecasting spot price changes. In other words, the futures price already incorporates seasonal information, which is to be expected in a market populated by rational and informed agents.

	Dummies		Trig functions		Dummies		Trig functions		Dummies		Trig functions	
	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
α	0,34	(0,26)	0,40	(0,27)	-0,12	(0,08)	**-0,05**	(0,02)	-0,12	(0,08)	-0,06	(0,04)
β	**0,88**	(0.08)	**0,87**	(0,08)	**0,97**	(0,11)	**1,00**	(0,10)	**0,97**	(0,12)	**1,00**	(0,12)
δ_1									0,04	(0,05)	0,03	(0,04)
δ_2									0,00	(0,01)	0,00	(0,01)
D_{Jan}	0,00	(0,05)			0,00	(0,06)			0,00	(0,06)		
D_{Feb}	0,08	(0,08)			0,09	(0,10)			0,08	(0,10)		
D_{Mar}	0,08	(0,09)			0,09	(0,09)			0,08	(0,10)		
D_{Apr}	0,13	(0,08)			0,14	(0,10)			0,12	(0,10)		
D_{May}	0,05	(0,08)			0,08	(0,09)			0,06	(0,09)		
D_{Jun}	0,09	(0,08)			0,12	(0,09)			0,11	(0,09)		
D_{Jul}	0,02	(0,09)			0,05	(0,10)			0,02	(0,10)		
D_{Aug}	0,05	(0,09)			0,07	(0,10)			0,06	(0,10)		
D_{Sep}	0,06	(0,09)			0,08	(0,08)			0,08	(0,08)		
D_{Oct}	0,03	(0,08)			0,03	(0,07)			0,02	(0,08)		
D_{Nov}	0,05	(0,07)			0,07	(0,07)			0,06	(0,07)		

β_s			0,02	(0,03)			0,02	(0,03)			0,02	(0,03)
β_c			0,02	(0,03)			-0,04	(0,03)			-0,03	(0,03)
Adj R^2	0,59		0,61		0,40		0,42		0,39		0,42	

TABLE 4. ESTIMATION RESULTS MODEL (4) – (7). ROBUST STANDARD ERRORS (HECSE) IN PARENTHESES.

Thus, the econometric results are easily summarized. While there for a long time was a significant risk premium (or forecast error), this seems to have vanished during recent years. More accurately, it seems that after 2008-09, the futures price and the basis now appears to be unbiased forecasts of the subsequent spot price and spot price change, respectively. In addition to being unbiased, the futures price and the basis after 2008 have become more precise forecasts.

6 Profits from simulated investments

While unbiased futures prices may suggest that the market is efficient, unbiasedness obviously is not proof of efficiency, just as statistical bias may prevail even in an efficient market. Statistical regularities must be of a magnitude and strength that outweigh transaction costs and risk.

In order to see whether biased futures prices can be utilized in order to make profits beyond a risk premium, we follow a uniform mechanical trading strategy of merely shorting nearby power futures. We hold the short position through the expiration date, after which the contract is settled against the average spot price (the system price) during the delivery period. We take a monthly position in the nearby month contract. This contract is quite liquid with an average volume of some 1,200 contracts traded a day. The investment (for simplicity assumed to be 1 MWh) is repeated during 136 months. Each month generates a loss or a profit. Thus, each investment is an independent bet and the proceeds from each investment are set aside in a separate account. Consequently, we can take a substantial loss in a given month without eroding our capital base. When calculating the outcomes of our investments, we disregard capital costs on base collateral as well as broker fees. We assume that we sell futures at closing price at the day of the investment. As bid–ask spreads are typically quite small this assumption has little effect on the calculated results.

During the period October 2003 – January 2015, the mean settlement turned out to be lower than the previous month's futures price in 85 of the 136 months, generating a positive result for 62.5% of the trades. There are, however, periods with a far lower success frequency, and there are variations in the magnitude of profits or losses. Figure 3 visualizes the results month by month, while Table 5 summarizes the mean profits (in Euros per MWh) for the full sample and the two sub- periods 2003-08 and 2008-15.

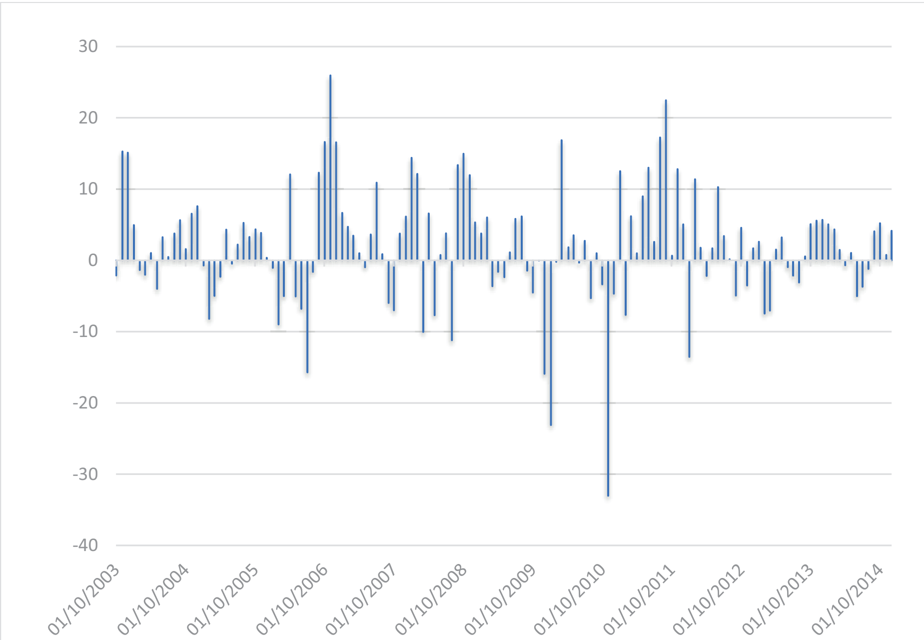

FIGURE 3. MONTHLY PROFITS IN EUROS

Period	Mean profit (Euros)	Skewness	Kurtosis	Mean profit (per cent)	Skewness	Kurtosis
Oct 03-Jan 15	1.90 (2.75)	-0.44	2.89	3.5 (2.34)	-0.62	1.52
Oct 03-Jul 08	2.53 (2.54)	0.46	0.78	5.3 (2.18)	-0.22	-0.18
Aug 08-Jan 15	1.57 (1.65)	-0.97	4.17	2.6 (1.24)	-0.95	2.85

TABLE 5. PROFITS IN EUROS AND PER CENT FROM TRADING STRATEGY

The returns from shorting a month contract every month 2003-15 were on the average 3.5 per cent (monthly) or 1.90 Euro/MWh. While the variation as measured by standard deviation is large, the mean is significantly greater than zero at the 0.01 level. There are also fat tails and left-skewed distributions, and there have been months with substantial losses. While the simple trading strategy generated substantial profits up till mid-2008, the mean profit during the most recent seven years (2008-15) is not significantly different from zero. As can be seen from figure 4, the trading strategy generated losses for almost two years 2009-10. Even if the losses turned into profits 2011, the strong upward trend seems to have been broken around 2008/09. Thus, pursuing a strategy based on the assumption that futures overshoot subsequent spot prices, no longer seems to generate profit. In other words, some sort of a structural break seems to have occurred around 2009.

FIGURE 4. CUMULATIVE GAINS SEPTEMBER 2003 – JANUARY 2015 FROM MONTHLY SHORTING 1 MWH

The hypothesis of a structural break 2008-09 is supported by running a set of Chow tests on the futures-spot spread (the basis). The tests clearly indicate a break point during the Fall of

2008. This is visualized in figure 5 showing a strong change in the term structure towards the end of 2008, sending the basis from a long period of backwardation into contango. A number of factors may explain this development. However, one event stands out as the factor that would contribute to making the market more efficient, namely the opening of the NorNed in the spring of 2008. This 580-kilometre long HVDC link with a voltage of some 450 kV and capacity of 700MW or some 6 TWh per year contributed to the integration of the Nord Pool area with Holland and the continent. This integration of areas with different production technologies as well as different risk exposures most likely shifted net hedge demand, as reflected in figure 5. Furthermore, a larger and more heterogeneous market generally tends to make the derivative market more efficient.

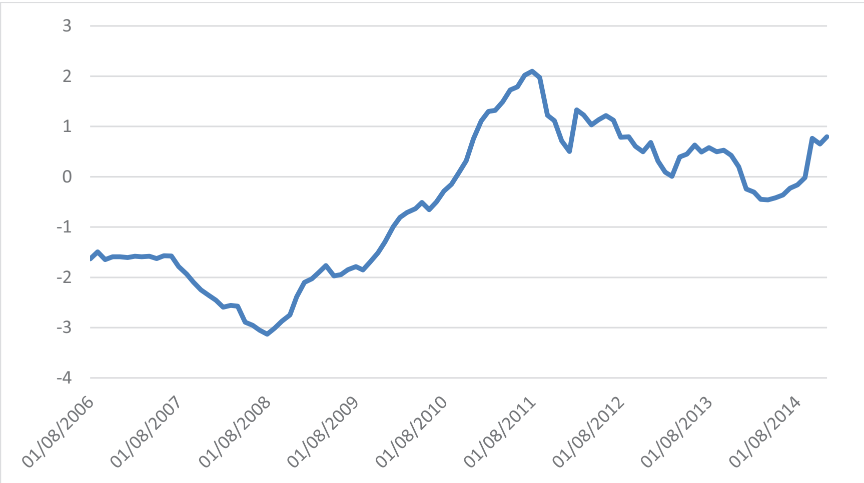

FIGURE 5. BASIS CALCULATED AS 3 YEARS ROLLING AVERAGE FOR MONTHLY CONTRACTS.

7 Conclusion

Nord Pool futures prices were for a long time, biased forecasts of subsequent spot prices. After 2008 this no longer seems to be the case. Both the futures price (over one-month horizons) and the basis have increasingly become unbiased and more precise forecasts of the subsequent system price and system price change, respectively. While biased futures prices simply may reflect a risk premium, previous studies have suggested that the size of the bias in the Nordic futures market has been too large to be defined as a risk premium only. The fact that the bias has disappeared during recent years may reflect changes in the risk premium. Alternatively, the change may be due to the market getting more efficient. The econometric results and the results from a simple trading simulation presented in this study support the latter explanation. The observed development may be interpreted as the market having become more mature and efficient after 2008. There may be several reasons for this. One may be the opening up of the NorNed cable in the spring of 2008, physically integrating the Nordic and the Dutch markets and thus including buyers and sellers with different risk exposures.

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Temperature and Prices in the Nordic Power Market

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Abstract

Several authors have found temperature to be an important determinant of power prices. Even so, most of the research that incorporate temperature when modelling electricity prices assume a single, constant coefficient to explain price variations over seasons, across regional markets, and price quantiles. Most research account for seasonality by adjusting the intercept, keeping the slopes constant. This article focuses on the daily spot price characteristics on the Nordic day-ahead market for electricity and at the five Norwegian price zones, with an emphasis on temperature as an explanatory factor. A new model, which takes into account seasonality in the coefficients is proposed. Using daily observations from all days of the in-sample years 2010-2018, disregarding the time of year, I find that changes in temperature explain about 6 % of price changes. However, when differentiating seasonal effects, I find that temperature explains between close to 0 % in August and September to over 19 % in December, as measured by incremental change in R^2. I also find that the temperature effect differs across the Norwegian price zones, NO4 being less sensitive to temperature. Furthermore, the temperature effect is more than twice as strong in the highest than in the lowest price decile. This suggests that pricing models based on constant coefficients for temperature may be misleading, "averaging out" seasonal effects. An R^2 of more than 0.9 implies that most of the variation in price changes is explained by a parsimonious AR model, which would be easy to implement by producers and large consumers. A forecasting exercise shows that using a time varying temperature effect on price for day-ahead spot price forecasting is still a challenging exercise.

1. Introduction

This article analyzes how temperature changes affect the spot prices at Nord Pool, both the Nordic System Price and the Norwegian area prices. Market actors like producers and consumers focus on the price of electricity, and especially what the system price and the area prices will be in the future. As temperature is regarded as an important price driver, it is of interest to analyze the relationship between changes in temperature and prices. This article will therefore present estimates on temperature effects on prices.

The contribution of this paper is to propose a new model for day-ahead electricity price forecasting, where seasonality in coefficients is allowed. I estimate an autoregressive model with exogenous variables, including temperature, to assess the effect of temperature changes on electricity spot price changes. The model quantifies the effects of temperature on prices across seasons, price zones and quantiles at Nord Pool. A forecasting exercise is performed to show the value of including this information in the bidding process. Previous literature (Huurman et al (2012) and Weron and Misiorek (2008)) has mainly focused on the system price and only two price zones (Oslo and Eastern Denmark). Furthermore, they assume a fixed coefficient for the entire year. Several factors might influence the temperature elasticity on price. My model will assume the effect of temperature on price is relatively high where there is a large population compared to the production capacity. Also, the model assumes that the effect differs across seasons, with the strongest effect occurring during the coldest months of the year, as electricity to a great extent is used for heating in the Nordic Countries, and where the price equilibrium is far to the right on the merit order curve.

This paper presents estimates of an auto regressive model with exogenous variables, including temperature, to assess the effect of temperature changes on electricity spot price changes. Previous studies have adjusted the intercept and not the slopes on explanatory variables to account for seasonality. A forecasting exercise is performed to demonstrate the value of including this information in the bidding process.

Results from my analysis offer insight into the price formation process at Nord Pool and the Norwegian price zones. Especially, how much of the variation in prices can statistically be explained by variation in temperature? Also, how does the effect of temperature on price develop during the year, adjusted for seasonality in the effect from the other exogenous variables? Answers to these questions will enable sellers and buyers to understand how temperature information is valued in the market. Given new temperature information, they can adjust their bids according to estimated effects from temperature to prices. Assuming that a bidder receives private information on temperature deviations from expected levels, they may possibly try to trade on this using information about the relationship between temperature forecast and realized prices.

The remainder of this paper is organized as follows: Section 2 surveys the literature most closely related to the temperature effect on prices. In section 3, I describe the Nordic power market structure and discuss the data employed in this study. Section 4 presents econometric models for modelling power prices with emphasis on how temperature may affect the price. Section 5 discusses the econometric results, while concluding remarks are given in section 6.

2. Literature

As a consequence of the liberalization of the electricity markets starting in the 1990's, several approaches have been put forth to model electricity prices. Notable examples are parameter rich fundamental models as presented by Johnsen (2001) and Vahviläinen and Pyykkönen (2005), reduced-form continuous-time models as presented by Geman and Roncoroni (2006) and Cartea and Figuera (2005), and regime switching models as used by Huisman and Mahieu (2001), and Paraschiv et al. (2015). Reduced-form models are extensively used for derivatives valuation and risk analytics. For electricity price forecasts, these models do not provide an advantage over statistical time-series models, like the auto-regressive family of models according to Weron (2014).

This paper is not the first to investigate the effect that temperature has on electricity demand or prices. There are several possible approaches, and this paper uses a statistical method in the form of an autoregressive time series model. There are several reasons why such a model is suitable for modeling electricity prices. It can capture the weekly seasonality which is often found in electricity markets. It is also a model which can be augmented with exogenous factors, in this case temperature. Additionally, the AR model has shown itself to be a robust framework which is used both in forecasting and modeling of the electricity price process, see Weron (2014) for an extensive overview. The use of a univariate framework is also motivated by the fact that univariate AR models compare well with multivariate models in forecasting day-ahead electricity prices, according to Ziel and Weron (2018).

Auto-regressive (AR) models facilitate the inclusion of exogenous variables. Temperature is a major determinant of electricity load, which in turn is a determinant of price, as shown by Cancelo, Espasa and Grafe (2008) and Bessec and Fouquau (2008). Earlier papers have estimated temperature's effect on load, but not price, e.g., Pardo et al. (2002), Valor et al (2001), and Gaillard et al (2016). Auffhammer, Baylis, and Hausman (2017) model the impact of temperature on average load and peak load, and they find that climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. In their model, demand is a piecewise linear function of temperature to capture temperatures effect on demand along the temperature scale, daily and monthly dummies to capture seasonality, and a polynomial term to capture intra-day patterns.

Other studies have investigated the link between price and temperature. Knittel and Roberts (2005) use a data set from the Californian market to find that all temperature variables investigated explain a significant portion of the variation in electricity prices. Their models, which include temperature variables with constant coefficients during the year, outperform models which do not include these variables when forecasting hourly day-ahead prices. They use an ARMAX model with the temperature, squared temperature, and cubed temperature as explanatory variables. Huisman (2008) uses a Markov switching model augmented with realized temperature. He finds that, in the Dutch power market, higher temperatures in summer increase the probability of price spikes. Also, deviations from average temperature help explain the price level. Weron and Misiorek (2008) use a number of autoregressive models to forecast day-ahead electricity prices. These models are defined with and without load forecast or realized temperature, and with and without normally distributed or semi-parametric error terms. They find that models including information from realized temperature or load forecast make more accurate predictions, as measured by root mean squared error, than pure autoregressive price models, and that there is only a marginal difference between information from realized temperature, and load forecast. In addition, Huurman et al (2012) found that an ARIMA model extended with power transformations of next-day weather forecasts yield better point forecasting results in terms of root mean square prediction error for predicting day-ahead prices at Nord Pool's Oslo and Eastern Denmark price zones. Using weather forecasts instead of realized temperature only marginally lowered the forecast errors. Bigerna (2016) generated temperature forecasts which were used to explain power prices in six Italian price zones. Including temperature forecasts reduced root mean squared percentage forecast error for day-ahead price forecasts.

At Nord Pool, the electricity prices for the price zones are set at the day before delivery as sellers and buyers of electricity has to submit their price/volume bids before noon on the day before delivery. These bids are then aggregated into supply and demand functions where the resulting hourly prices and loads is given by their intersection. Due to transmission constraints, the prices might differ between the price zones. As temperature has been found to have an effect on price, the price reflect the previous day expected temperature conditions for the day of delivery.

If weather systems across adjacent price zones are correlated, leading to correlated shocks to temperature, then the electricity price in different price zones might have similar error structures. If this is the case, then the estimation of the electricity price for the price zones may involve non-zero covariances between the error terms in nearby price zones. If the error terms are correlated, then the seemingly unrelated regressions approach of Zellner (1962) is appropriate. In this framework, the coefficients are equal to those estimated by OLS but with the seemingly unrelated regression one can test for differences in coefficient values across models while taking into account for correlated errors. Different from my study, Huisman et al. (2007) used seemingly unrelated regression to get information on the correlated error structures between hourly power prices on the Central European power market.

AR models can also be used to estimate the distribution of the dependent variable via quantile regression. It has been used in several papers investigating the electricity markets. Quantile regression (QR) of Koenker and Bassett (1978), is a regression technique where one can estimate a given quantile of the dependent variable conditioned on the independent variables. It enables us to estimate possibly skewed distributions relative to the dependent variable, giving information about the drivers behind different quantiles of the price distribution.

3. Data

This article analyzes daily spot prices in five regional markets as well as the system price March 15th, 2010 - December 31st, 2019. Data prior to March 15th, 2010, were not considered, as there have been several geographical changes to the Nord Pool area and the Norwegian price zones prior to this date. The geographical location of the price zones can be seen in Figure 1.

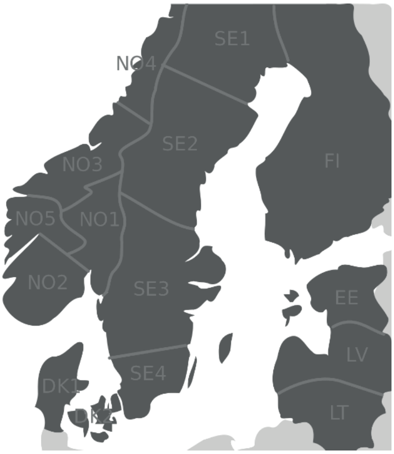

Figure 1. Geographical location of price zones at Nord Pool.

Both spot price and temperature data are daily averages. The data set was split into a training set and a test set, with a cutoff on December 31st, 2018, leaving 2019 for the test set. I analyze the data from the price zones NO1 (East), NO2 (South), NO3 (Central), NO4 (North), and NO5 (West), as well as the system price. Over this time period, the system price has averaged at 35.4 EUR/MWh. However, Figure 2 shows that there has been significant price variation with substantial volatility in the log-returns. The high standard deviation of the daily log-price changes of 3.8 %, equivalent to a yearly standard deviation of 72 %, is higher than in most commodity markets. This represents risks which is important to model for market participants. The evolution of the system price and the differences between the area prices and the system price can be found in Figure 3. As shown in the figure, the area prices almost always differ from the system price.

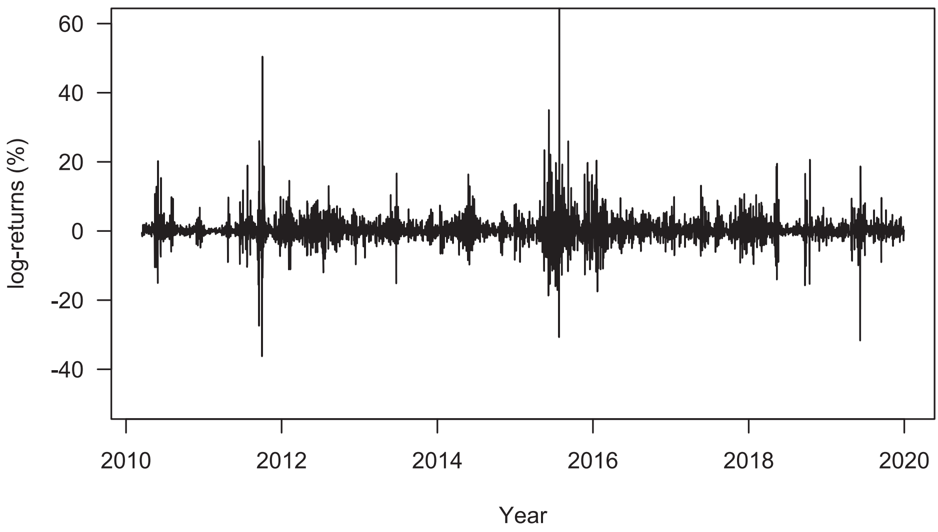

Figure 2. Daily percent price changes, Nord Pool system price 2010-2019.

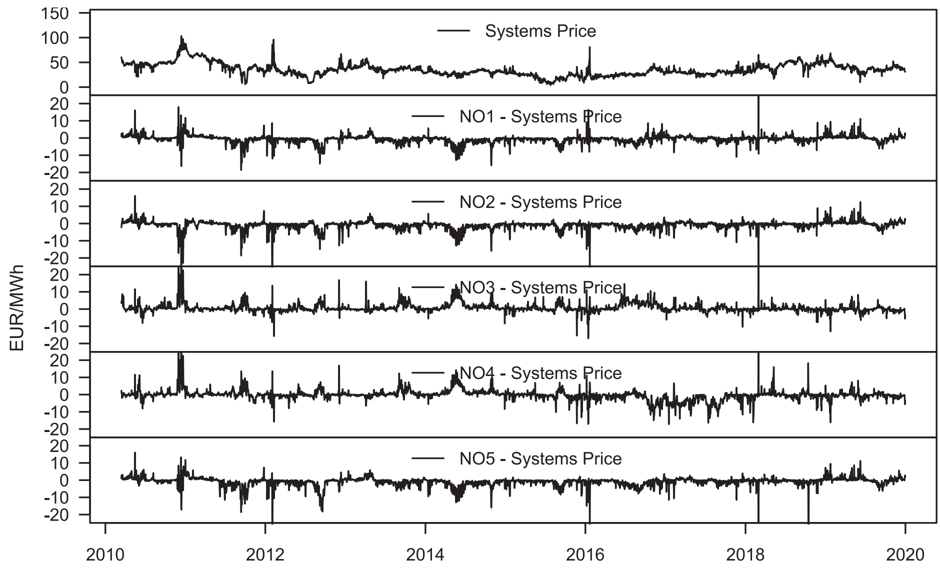

Figure 3. **System price (EUR/MWh) and differences between area price and system price, 2010-2019.**

Another issue with the data regards the estimation of daily temperature. The overall daily average temperature for Nord Pool has been proxied by a population weighted average of temperatures in Oslo, Stockholm, Helsinki, and Copenhagen, to construct a population adjusted temperature index, which we call the Nord Pool temperature. Ideally, one weather station per city is used and the data has been provided by the Norwegian Meteorological Institute[4], Swedish Meteorological and Hydrological Institute[5], and Danish Meteorological Institute[6]. For each price zone, a population weighted average of the temperature for the three largest cities is taken as a proxy for the relevant temperature in the price zone. This introduces measurement error in the calculations, but on the other side, one must keep in mind that the fourth largest city in either price zone is small. For zone NO5 (East), Bergen is the only major city and is thus assigned a weight of 100 %[7].

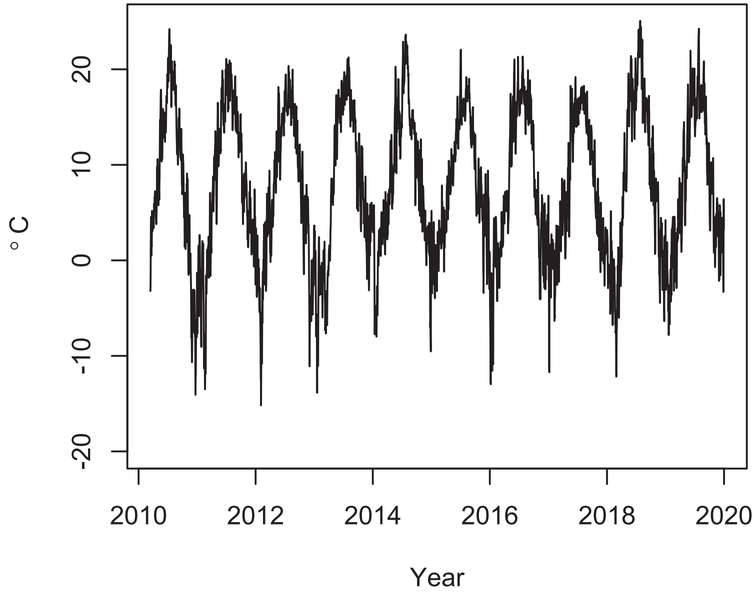

Figure 4. Temperature index for the Nord Pool area, population weighted

The Nord Pool temperature over the period from 2010 to 2019 can be seen in Figure 4, which shows the substantial variation of daily temperatures over the course of a season. If the

4 http://met.no/English/

5 https://www.smhi.se/en/about-smhi

6 https://www.dmi.dk/

7 The populations used in calculations are (in 1000's): Nord Pool (Copenhagen – 1,308, Stockholm 1,539 - , Oslo – 925, Helsinki 1,268), NO1 (Oslo - 925, Drammen -110, Fredrikstad - 106), NO2 (Kristiansand - 58, Stavanger - 203, Skien - 90), NO3 (Trondheim - 169, Ålesund - 49, Molde - 20), NO4 (Tromsø - 32, Bodø - 38, Harstad – 20'), NO5 (Bergen -247). NO5 only use observations from one city as the next largest city in this zone is Voss with population 6'.

relative change of temperature on price varies with the season, then this could be accounted for in an econometric model.

Temperature forecasts are getting increasingly more accurate, Haiden et al. (2018). In practice, market actors in the power market place their bids to sell or purchase electricity before noon on the day prior to delivery. While bidding, they could thus have information about the forecast for the next day, which means 12 to 36 hours ahead. On this basis, the realized temperature at day t may be treated as a relevant day-ahead forecast which is known at the time of bidding, day t-1, (Bigerna (2018), Weron and Misiorek (2008)). This assumed temperature forecast is then used in the day-ahead spot price modeling.

Descriptive statistics for the Nord Pool area and five Norwegian price zones for spot price and temperature is presented in Table 1.

Table 1. Descriptive statistics for Nord Pool and Norwegian price zones. Daily observations prices and population weighted temperatures, 2010-2019.

Variable	Zone	Mean	Median	Min	Max	SD
Spot (EUR/MWh)	Nord Pool	35.4	33.7	3.9	103.3	12.7
	NO1 (East)	34.7	32.7	3.0	95.8	13.4
	NO2 (South)	34.3	32.4	3.0	95.8	12.8
	NO3 (Central)	36.1	34.4	4.1	145.5	13.1
	NO4 (North)	35.1	33.3	4.1	145.5	13.3
	NO5 (West)	34.3	32.4	2.6	95.8	13.4
Temperature (°C)	Nord Pool	8.1	7.6	-15.0	25.2	7.7
	NO1 (East)	7.6	7.4	-14.6	25.8	7.7
	NO2 (South)	7.6	7.6	-13.0	23.4	5.7
	NO3 (Central)	6.2	5.4	-17.0	24.4	6.4
	NO4 (North)	5.1	4.6	-13.7	24.3	6.2
	NO5 (West)	8.5	8.3	-9.0	26.3	5.6

Obviously, there are differences both in prices and temperatures between the price zones. However, the differences are not large, apart from the spot price has spiked higher for the area prices in NO3 (Central) and NO4 (North), than for the system price. As seen from the table, the variation in temperature is lower for NO2 (South), and NO5 (West) because of the more stable coastal climate due to the proximity to the ocean of the cities in these zones. On the other hand, NO1 (East) has a more continental climate with greater variation in temperature between cold and warm seasons. Figure 5 shows the monthly average temperature for zones NO1 (East) and NO4 (North), compared to the Nord Pool temperature. As expected, the temperature in NO4 (North) is lower than the temperature in NO1 (East) during the entire year, except during wintertime when the ocean warms the coastal areas in NO4 (North). These differences might translate into seasonality of temperature on price.

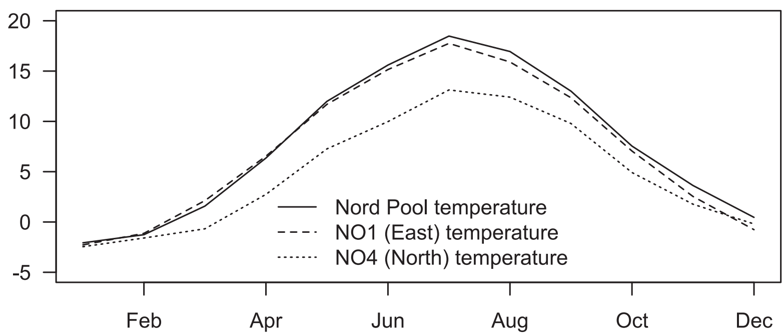

Figure 5. Mean monthly temperatures (°C) for zones NO1 (East) and NO4 (North) compared to Nord Pool (a weighted mean of temperatures for Oslo, Stockholm, and Copenhagen).

4. Method

I transform both temperatures and prices to logarithms to stabilize volatility and thus treat all coefficients as elasticities. During the period in question, electricity prices have been uniformly positive in the Norwegian market and a logarithmic transformation is straightforward. However, in the Nordic market, it is natural for negative temperatures to occur during wintertime. A solution to this problem is to measure temperature as degrees Kelvin, and not as degrees Celsius. An advantage of the Kelvin scale is that it has equal increments to the Celsius scale and is thus easy to interpret for practitioners as zero degrees Celsius equals 273.15 degrees Kelvin. Also, various specifications of the ADF and Phillips-Perron tests are used to check for stationarity in the logarithm of the time series. The results clearly indicate that the time series are stationary, and no differencing is needed.

Several studies, among them Kristiansen (2012), have shown that an auto regressive model could be considered due to short term seasonality in spot prices. Based on Bayesian information criteria (BIC), seven lags would suffice to describe my data, following Huurman et al (2012). Lags two through six are set to zero, as there is no theoretical reason to expect them to be otherwise significant. They also contribute to multicollinearity as measured by variance inflation factors. Empirically, these lagged values of the spot price have a small, but significant, effect on the spot price. These effects do not translate into a different effect of changes in temperature on changes in spot price, and as such they are not needed in the equation for my purposes. A dummy variable is added to account for the fact that more electricity is used during workdays than during holidays, as in Weron and Misiorek (2008). However, my model differs from Weron and Misiorek (2008) in that I do not include a minimum hourly price from the day before. What is new in my model is the interactions where I take into account that the effect of temperature and other variables on price can change during the season. The reduced form model investigated is thus:

$$\ln(S_t) = \beta_0 + \sum_{i=2}^{12} D_i + \beta_1 \ln(S_{t-1}) + \sum_{i=2}^{12} DS1_i + \beta_2 \ln(S_{t-7}) + \sum_{i=2}^{12} DS7_i + \beta_3 \ln(T_t) + \sum_{i=2}^{12} DT_i + \beta_4 WD_t + \sum_{i=2}^{12} DW_i + \epsilon_t \quad (1)$$

where $\beta_0$is the intercept, $ln(S_{t-1})$ and $ln(S_{t-7})$are the 1-day and 7-day AR lags of the spot price, $ln(T_t)$is the logarithm of temperature and $WD_t$is a dummy variable which equals one if the day is a working day and zero otherwise. Dummy variables are included to be able to test for seasonal differences in the effect of temperature on prices, adjusted for seasonality in the other coefficients, including the intercept, with January as the base case. D_i captures the seasonality in the slope, whereas the interaction terms $DS1_i$, $DS7_i$, DT_i, and DW_i capture the seasonality in the slopes. The model defined in (1) is estimated in-sample on the system price, and on the different area prices before it is used on out-of-sample data to create day-ahead forecasts. The hypothesis I am set to test is the one of no difference in forecast error metrics between a model which is estimated with a constant slope on temperature and one which is estimated with time varying slope on temperature. The error metrics considered in this study is RMSE (Root mean squared error) and MAPE (Mean absolute percentage error), as used in Huurman et al (2012), Weron and Misiorek (2008), and Ziel and Weron (2018). RMSE has the benefit of sharing units with the original series, in this case EUR/MWh which makes interpretation of the average size of the error intuitive. MAPE has the benefit of giving an average relative error but might be misleading in the presence of close to zero prices, Weron

(2014), and Sing and Mohanty (2015). In my data set, no prices were close to zero, as seen in Table 1.

To investigate the effect of temperature change along the distribution of the spot price, I use the following quantile regression model:

$$Q^q\left(\ln(S_t)\right) = \beta_0^q + \beta_1^q \ln(S_{t-1}) + \beta_2^q \ln(S_{t-7}) + \beta_3^q \ln(T_t) + \beta_4^q WD_t + \epsilon_t \qquad (2)$$

where $q \in (0,1)$ are the quantiles for which the parameters of the equation are estimated. If the 0.5 quantile were to be estimated, I would minimize the absolute residuals:

$$\underset{\beta_0,\beta_1,\beta_2,\beta_3,\beta_4}{\arg\min} \sum_{t=1}^{T} \left| \ln(S_t) - \widehat{\ln S_t} \right| \qquad (3)$$

where $\widehat{\ln(S_t)} = \ln\left[\hat{\beta}_0^q + \hat{\beta}_1^q \ln(S_{t-1}) + \hat{\beta}_2^q \ln(S_{t-7}) + \hat{\beta}_3^q \ln(T_t) + \hat{\beta}_4^q WD_t\right]$ is the estimated value. This can also be expressed as follows:

$$\underset{\beta_0,\beta_1,\beta_2,\beta_3,\beta_4}{\arg\min} \sum_{t=1}^{T} \left[0.5 - \mathbf{1}_{S_t - \widehat{S_t} < 0}\right] \times \left[\ln(S_t) - \widehat{\ln S_t}\right] \qquad (4)$$

which implies that sign is changed to positive for negative residuals. In addition, the residuals have weight according to their modulus. For other quantiles, I minimize the following expression for specific values of q:

$$\underset{\beta_0,\beta_1,\beta_2,\beta_3,\beta_4}{\arg\min} \sum_{t=1}^{T} \left[q - \mathbf{1}_{S_t - \widehat{S_t} < 0}\right] \times \left[\ln(S_t) - \widehat{\ln S_t}\right] \qquad (5)$$

Here, the residuals are weighted according to the sign of $\ln(S_t) - \widehat{\ln S_t}$, i.e., negative residuals will have a weight of 1-q, whereas positive residuals will have a weight of q. This provides the coefficients for the q^{th} quantile regression.

There are more factors that have been found by other studies to have an influence on the spot price. This includes reservoir levels, which are the water levels in the reservoirs of hydro power plants, and variables concerning higher moments of the spot price. In my setup, these were found to be insignificant, and the related results are not reported.

5. Results

To estimate how much of the changes in the spot price is caused by temperature variation, all subsets of equation (1) where one variable at the time is added, and the incremental increase in R^2 is recorded, according to Lindeman, Merenda and Gold (1980). Among all $4!$ combinations, the average marginal increase in R^2 from inclusion of the variable was recorded and shows that temperature has a relative importance of explaining about 6 % of the variation in the spot price. The spot price one and seven days ago explain 52 % and 42 %, respectively. One can also take note of the low importance of working days, which explain 1 %. However, all variables, including the working day variable, are statistically significant, in the base case.

Second, I investigate if parameter values, and importance, on temperature differ during the year for the individual months. A table of coefficients from the model estimated on the system price can be found in Appendix 1. The base case is January, and all dummies are deviations from this base case. From the table it is apparent that there is seasonal variation in the temperature effect on price, even if seasonality in the other variables and the intercept has been taken account for.

The results for the temperature effect on price for all months and all price zones can be found in Table 2. There is a clear pattern regarding the seasonal temperature sensitivity. During wintertime, the value is negative for all zones. This implies that a negative temperature change is connected with a positive price change. For example, the temperature sensitivity of the system price is -3.21 in January. For the Nord Pool area, the temperature index is hovering around -1 degrees Celsius, which is around 272 degrees Kelvin, during this month. If the temperature index drops by 1 %, or from -1 to -4 degrees Celsius, it would on average lead to a 3.14 % increase in the power price. However, in summertime this relationship breaks down and one cannot say that temperature has an effect on the electricity price. A surprising observation is the relatively high sensitivity during May. Apart from a possible spurious relationship, one factor which outweighs the warmer weather during this month is the fact that reservoir levels are usually at its lowest in April and May. On average, the reservoir levels during this month are at 30 % in Norway and at just above 20 % in Sweden. This means that several reservoirs cannot be utilized as they would fall below the minimum regulated level, implying less supply side flexibility. Colder weather in May would also affect the inflow, as the temperatures can easily drop below zero in the mountains where most of the water is stored as snow, adversely affecting supply. This is especially true for run-of-water power plants which do not have reservoirs, thereby putting an upward pressure on the price. On the other hand, warmer weather would increase supply from the same power plants due to snow melting, thus lowering the price. Due to the insignificant effect of temperature on price during summer months, only data consisting of the months from October to May will be considered in the following analysis.

Table 2. Monthly coefficient values for logarithm of temperature and across price zones, March 2010 - December 2018.

Zone		jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec	Average
	β_3	**-2.49**	**-3.26**	**-1.52**	**-1.86**	**-1.38**	-0.35	0.62	**-1.30**	-1.31	**-2.46**	**-2.33**	**-4.09**	**-1.81**
Nord Pool	p-value	**0.00**	**0.00**	**0.01**	**0.00**	**0.01**	0.68	0.38	**0.01**	0.07	**0.00**	**0.00**	**0.00**	
	T explains	7.7%	18.7%	9.9%	0.5%	1.0%	3.5%	10.3%	0.0%	0.1%	5.7%	10.7%	19.9%	
	β_3	**-3.58**	**-2.61**	-2.29	**-1.65**	-0.90	0.45	1.43	-0.34	-1.51	**-3.20**	**-1.76**	**-2.76**	**-1.56**
NO1	p-value	**0.00**	**0.00**	0.06	**0.00**	0.06	0.47	0.06	0.49	0.10	**0.00**	**0.00**	**0.00**	
	T explains	8.8%	11.8%	10.8%	0.4%	0.8%	1.2%	8.9%	0.1%	0.1%	6.5%	9.3%	15.8%	
	β_3	**-2.88**	**-3.03**	**-2.00**	**-1.96**	**-1.45**	-0.07	-0.45	-0.12	-1.93	**-3.51**	**-1.85**	**-2.85**	**-1.84**
NO2	p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	0.91	0.21	0.73	0.08	**0.00**	**0.00**	**0.00**	
	T explains	6.9%	9.7%	8.2%	0.5%	1.6%	0.0%	0.2%	1.0%	1.1%	5.9%	10.6%	14.9%	
	β_3	**-1.18**	**-2.11**	**-2.03**	**-1.89**	**-1.62**	-0.76	0.06	-0.05	-0.18	**-2.61**	**-1.90**	**-1.89**	**-1.35**
NO3	p-value	**0.03**	**0.00**	**0.03**	**0.00**	**0.00**	0.13	0.82	0.90	0.79	**0.01**	**0.00**	**0.00**	
	T explains	2.3%	7.0%	9.5%	0.4%	0.6%	0.0%	1.0%	4.3%	2.8%	5.5%	10.6%	11.2%	
	β_3	**-1.79**	**-2.39**	-0.48	**-1.69**	**-1.44**	-0.73	0.68	0.27	-0.10	**-1.26**	**-1.32**	**-2.12**	**-1.03**
NO4	p-value	**0.04**	**0.01**	0.35	**0.00**	**0.00**	0.23	0.20	0.61	0.88	**0.03**	**0.00**	**0.00**	
	T explains	1.9%	5.0%	5.8%	0.2%	0.5%	0.2%	1.5%	0.2%	0.0%	1.4%	2.0%	5.1%	
	β_3	**-2.20**	**-3.06**	**-1.77**	**-1.58**	-0.87	0.17	0.37	-0.45	-1.28	**-1.96**	**-1.45**	**-2.82**	**-1.41**
NO5	p-value	**0.00**	**0.00**	**0.00**	**0.00**	0.07	0.80	0.53	0.33	0.35	**0.01**	**0.00**	**0.00**	
	T explains	2.7%	5.0%	7.6%	0.2%	0.8%	0.1%	3.7%	0.2%	0.1%	1.9%	6.9%	11.4%	

Third, the model is estimated for Nord Pool and the five price zones in Norway on in-sample data for months October to May. For all regressions, autocorrelation is a problem as measured by the Ljung-Box Q test, and H_0 of homoscedastic residuals are rejected by Breusch Pagan test. This problem is circumvented by using HAC standard errors. However, the models were specified as seemingly unrelated regression models, which allow for non-zero correlation of errors among models. Results from the estimation can be found in Table 3. The most important detail to notice is that the coefficient for the temperature effect on price is negative, which indicates that an increase in temperature is accompanied by a decrease in spot price.

Table 3. Results from seemingly unrelated regressions. March 2010 - February 2018. Bold font indicates statistical significance at 5 % level.

Zone		Const	$\ln(S_{t-1})$	$\ln(S_{t-7})$	$\ln(T_t)$	WD	R^2-adj	Temp. explains	N
Nord Pool	β	**6.72**	**0.79**	**0.15**	**-1.17**	**0.07**	0.91	5.6%	2109
	p-value	0.00	0.00	0.00	0.00	0.00			
NO1	β	**5.21**	**0.82**	0.12	**-0.90**	**0.06**	0.92	5.9%	2109
	p-value	0.00	0.00	0.00	0.00	0.00			
NO2	β	**6.72**	**0.85**	0.10	**-1.17**	**0.05**	0.93	5.8%	2109
	p-value	0.00	0.00	0.00	0.00	0.00			
NO3	β	**5.78**	**0.81**	**0.13**	**-1.00**	**0.07**	0.91	4.1%	2109
	p-value	0.00	0.00	0.00	0.00	0.00			
NO4	β	**4.14**	**0.85**	**0.12**	**-0.72**	**0.06**	0.93	1.6%	2109
	p-value	0.00	0.00	0.00	0.00	0.00			
NO5	β	**6.03**	**0.89**	0.06	**-1.05**	**0.06**	0.93	4.1%	2109
	p-value	0.00	0.00	0.10	0.00	0.00			

For Nord Pool, the temperature coefficient is -1.17, which means that if temperature moves by 1 %, then on average the spot price moves by 1.17 % in the opposite direction during wintertime. If mean values are used, then a 1 degree drop in temperature would increase the spot price by almost 0.20 Euros per MWh. One can see that there is substantial variation between the different zones. Prices in NO4 (North) are least affected by changes in temperature with a coefficient of negative 0.72. This means that a 1 % decrease (increase) in temperature is accompanied by a 0.72 % increase (decrease) in the spot price. The coefficient for Nord Pool is the highest with a value of negative 1.17, so the temperature effect is over 50% as large as in NO4. To test whether or not the sensitivities fitted on area prices are statistically different compared to the temperature effect found on the system price, I can use an F-test, taking into account the correlation structure among errors in different models. It turns out that the difference between the temperature effect at Nord Pool and at NO4 is statistically different with a p-value of 0.016 None of the other differences were significant. Statistically, this will motivate the use of separate sets of coefficients per price zone if one were to model the price/temperature dynamics in NO4. The correlation structure of errors among the model estimations can be found in Table 4. For all correlation pairs, H_0 of no correlation were rejected.

Table 4. Correlation structure of errors.

	sys	no1	no2	no3	no4	no5
sys	1.00	0.85	0.82	0.87	0.80	0.68
no1	0.85	1.00	0.88	0.71	0.64	0.75
no2	0.82	0.88	1.00	0.64	0.55	0.80
no3	0.87	0.71	0.64	1.00	0.88	0.51
no4	0.80	0.64	0.55	0.88	1.00	0.47
no5	0.68	0.75	0.80	0.51	0.47	1.00

The question is now whether or not the time varying temperature effects on price translates into a more tangible difference. If the observed temperature is treated as a one-day forecast as done in Weron and Misiorek (2008) and Bigerna (2018), the model can be used to create a forecast of the five area spot price series. The "Naïve" forecast assumes that the price at time t is equal to that of time $t-1$. What I call the "Constant effect" forecast is made with coefficients estimated from the in-sample system price and temperature. Here, the temperature coefficient is held constant, not varying among the months. The "Time varying effect" forecast is made with coefficients estimated from the in-sample system price and temperature but with different coefficient sets by month.

As can be seen from Tables 5 and 6, for all price zones, RMSE and MAPE for the "Time varying effect" model is higher than that from using a model assuming a constant temperature effect on price, indicating that there might be overfitting when using the full model specification.

Table 5. RMSE from day-ahead forecast of area prices by use of the naïve model, a model estimated with a constant temperature effect and a model estimated with time-varying temperature effect. Based on out-of-sample data from 2019

	Naive	Constant effect	Time varying effect
Nord Pool	4.09	3.67	3.85
NO1	4.88	4.47	4.42
NO2	3.69	3.38	3.41
NO3	4.29	3.91	4.02
NO4	3.85	3.55	3.48
NO5	3.80	3.59	3.65

Table 6. MAPE from day-ahead forecast of area prices by use of the naïve model, a model estimated with a constant temperature effect and a model estimated with time-varying temperature effect. Based on out-of-sample data from 2019. Numbers in percentage points.

	Naive	Constant effect	Time varying effect
Nord Pool	7.03	6.57	6.87
NO1	6.31	6.16	6.20
NO2	5.97	5.72	5.78
NO3	6.14	5.94	6.39
NO4	5.05	4.83	4.78
NO5	6.27	6.21	6.27

Fourth, an electricity producer or consumer armed with a temperature forecast would be interested in knowing the effect of a temperature change on the electricity price during the colder months of the year, given the electricity price level. If the consumer or producer has information about the next-day temperature before noon, what should the bid be? To measure this effect, one can use quantile regression to get the effect of the independent variables on the dependent variable, given the level of the dependent variable. A quantile regression version of equation (1) is estimated, and the results can be found in Table 5.

As R^2 has no meaning for quantile regression, the relative importance of temperature on price has not been calculated. The sensitivity of temperature changes on price changes are mostly negative for all price zones, but it varies substantially across the price distribution. As can be seen from Table 7, the effect of temperature changes on the system price can be relevant for price forecasts, given that the price level is at or above the first quantile. Coefficients on the other variables in the regression equation also exhibit variation across the quantiles. This means that anyone trying to forecast electricity prices at Nord Pool for the months from October to May could consider the negative effect of temperature changes on price changes for all but the lowest price levels.

Table 7. Coefficient values for logarithm of temperature per quantile and per price zone from March 2010 to February 2018. Bold font indicates statistical significance at 5 % level.

		Quantiles								
		Q0.1	Q0.2	Q0.3	Q0.4	Q0.5	Q0.6	Q0.7	Q0.8	Q0.9
Systems Price Given Quantile		23.2	26.4	28.9	31.0	33.5	36.6	40.2	46.3	53.5
Nord Pool	β_3	**-0.39**	**-0.76**	**-0.80**	**-0.86**	**-0.90**	**-0.86**	**-0.74**	**-0.93**	**-1.10**
	p-value	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NO1	β_3	-0.19	**-0.42**	**-0.44**	**-0.50**	**-0.49**	**-0.54**	**-0.57**	**-0.62**	**-0.88**
	p-value	0.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NO2	β_3	**-0.76**	**-0.78**	**-0.69**	**-0.71**	**-0.68**	**-0.68**	**-0.77**	**-0.85**	**-1.13**
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NO3	β_3	**-0.93**	**-0.86**	**-0.75**	**-0.72**	**-0.66**	**-0.61**	**-0.57**	**-0.68**	**-0.85**
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NO4	β_3	-0.45	**-0.37**	**-0.31**	**-0.30**	**-0.35**	**-0.41**	**-0.45**	**-0.61**	**-0.91**
	p-value	0.07	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NO5	β_3	**-0.68**	**-0.66**	**-0.69**	**-0.66**	**-0.68**	**-0.65**	**-0.68**	**-0.78**	**-0.93**
	p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 6 provides a more detailed picture of the evolution of the coefficient on logarithm of temperature at Nord Pool for quantiles in the interval [0.02,0.98]. The corresponding OLS estimate using all observations is marked with a red line, with 95 % confidence intervals marked with dashed lines. What is clear from the graph, is that for almost all quantiles the quantile regression estimate is different from the OLS estimate. For all but the largest price quantiles, the OLS estimate overestimates the negative effect temperature changes has on price changes. It is important to notice the large confidence interval bands for high and low quantiles, which is a coefficient uncertainty often seen in quantile regression.

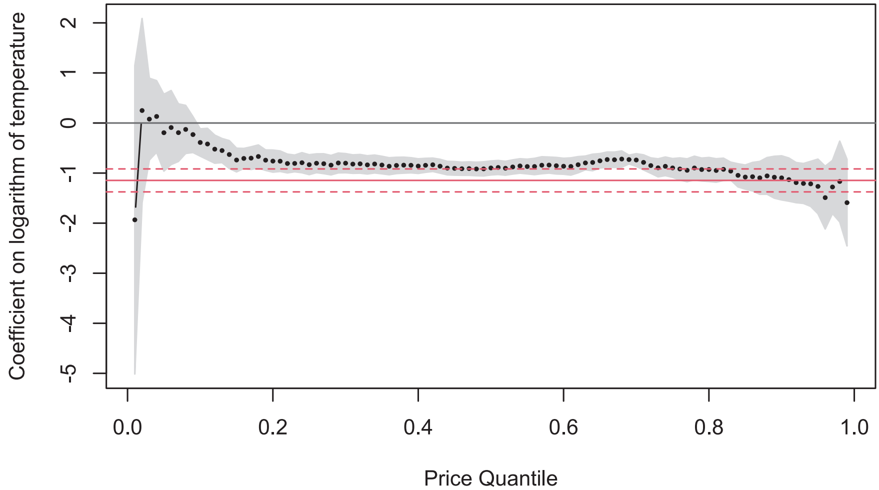

Figure 6. Coefficient values for the logarithm of temperature for Nord Pool system price. Gray area indicates 95 % confidence interval around quantile regression coefficient estimate. Red line indicates OLS regression estimate with dashed lines indicating the corresponding 95 % confidence interval.

6. Concluding remarks

This article examines the time-varying relationship between temperature and spot price at Nord Pool and the five price zones of the Norwegian power market. The market price for electricity in Northern Europe is affected by temperature, especially by cold temperatures, which causes a need for residential and commercial heating. Most previous studies have treated the effect of temperature changes on power prices as a constant across price zones, seasons, and price quantiles (Weron and Misiorek (2008), Huurman (2012)). I question this assumption. By estimating time varying effects from temperature on power prices I test the validity of the standard assumption. The main results of this paper are summarized in the following.

A seasonal pattern between relative changes in temperature and in spot prices was found for both the Nord Pool market and all five price zones in Norway, with this relationship being negative for the months from October to May, controlled for seasonality in the intercept and the other slopes. Specifically, if mean values are used for the Nord Pool system price for these months, then a 1 degree drop in temperature would increase the spot price by almost 0.20 Euros per MWh, on average. This implies that a lower temperature is linked to a higher price.

During summertime, this relationship breaks down and even reverses for Nord Pool, Eastern Norway, and Southern Norway. A surprising observation is the relatively high sensitivity during May. Spurious correlation is always a possibility, but one factor which outweighs the warmer weather during this month is the fact that reservoir levels are usually at its lowest in April and May. This means that some reservoirs cannot be utilized as they would fall below the minimum regulated level, thereby putting an upwards pressure on prices during periods of low temperature. A large variation in the sensitivity between price and temperature across different price zones and months implies that it would be advantageous to account for these in spot price modelling.

The relative importance of temperature in explaining the variation in electricity prices, in my framework, ranges from 1.6 % in price zone NO4 (North), to 5.9 % in NO1 (East), with the relative importance at 5.6 % for the Nord Pool system price overall. The temperature effect of temperature on prices also changes due to season, even if controlled for seasonality in the other coefficients in our model. Also, the temperature effect on prices varies substantially across the price distribution, in general being negative, but sometimes positive. This suggests non-linearity, where changes in prices below 19 EUR/MWh are not related to temperature changes, and prices above 19 EUR/MWh are negatively related to temperature changes.

The challenges of utilizing time-varying temperature effects on electricity prices is demonstrated through a day-ahead forecasting exercise. To use a time-varying model would not reduce RMSE or MAPE. However, one might use regularization to deal with dimensionality.

Appendix 1

Table 8. Model summary for the estimation of model (1) based on in-sample data for Nord Pool system price. "D" identifies dummy variables where January is base case. Bold font indicates significance on the 5% significance level.

	Coeff	p-val		Coeff	p-val		Coeff	p-val		Coeff	p-val		Coeff	p-val
Intercept	**18.71**	0.00	s1	**0.73**	0.00	s7	**0.16**	0.00	T	**-3.27**	0.00	DW	**0.08**	0.00
Dfeb	3.88	0.44	DS1feb	-0.03	0.54	DS7feb	0.04	0.35	DTfeb	-0.70	0.43	DWDfeb	0.00	0.90
Dmar	-7.81	0.12	DS1mar	-0.11	0.15	DS7mar	**0.18**	0.01	DTmar	1.35	0.13	DWDmar	-0.04	0.07
Dapr	-7.39	0.13	DS1apr	-0.01	0.89	DS7apr	0.08	0.16	DTapr	1.28	0.14	DWDapr	-0.03	0.10
Dmay	**-10.05**	0.02	DS1may	**-0.13**	0.01	DS7may	**0.21**	0.00	DTmay	**1.74**	0.02	DWDmay	0.03	0.16
Djun	**-18.83**	0.00	DS1jun	**-0.10**	0.03	DS7jun	**0.19**	0.00	DTjun	**3.30**	0.00	DWDjun	-0.01	0.50
Djul	**-22.43**	0.00	DS1jul	**0.10**	0.03	DS7jul	0.03	0.51	DTjul	**3.91**	0.00	DWDjul	-0.02	0.28
Daug	-11.85	0.05	DS1aug	0.09	0.09	DS7aug	-0.03	0.52	DTaug	2.09	0.05	DWDaug	-0.01	0.69
Dsep	**-14.16**	0.01	DS1sep	0.09	0.06	DS7sep	-0.01	0.76	DTsep	**2.48**	0.01	DWDsep	-0.03	0.17
Doct	0.49	0.92	DS1oct	**0.15**	0.00	DS7oct	**-0.13**	0.00	DToct	-0.09	0.92	DWDoct	0.00	0.89
Dnov	-2.60	0.56	DS1nov	-0.07	0.25	DS7nov	0.11	0.07	DTnov	0.45	0.57	DWDnov	-0.03	0.12
Ddec	8.21	0.07	DS1dec	-0.03	0.55	DS7dec	0.04	0.35	DTdec	-1.47	0.06	DWDdec	-0.02	0.32

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Weather Forecasts and Electricity Price Forecasting

By

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Abstract

This paper investigates whether using forward-looking information from the weather service can improve short-term price forecasts of Nordic and Norwegian power prices. A dataset from Nord Pool spanning five years (2010-2015) is used to test the 1 to 9-day forecasting performance of auto regressive models with temperature forecasts as one of the exogenous variables. The results indicate that including forward looking information from the weather service in the model brings significant forecast improvements for all forecast horizons considered. Also, including other exogenous variables which may have an effect on the electricity price provides more accurate forecasts. Furthermore, the results indicate that regularization techniques should be used to reduce dimensionality. Also, since longer horizon temperature forecasts exhibit larger uncertainty, price forecasts should be made by a model which mixes direct and incremental forecasts.

1. Introduction

As a result of the liberalization of the electricity markets with large price fluctuations and consequently a greater need for risk management, electricity price forecasting has become more important during the last two decades.

In a previous article I have studied the relationship between temperature and power prices over different seasons and market regions. In this paper, I will analyze to what extent weather forecasts can improve upon price forecasts from models that do not include information on future weather conditions. Furthermore, I present results from including uncertainty about future weather forecasts in the forecasting model. In that way this article adds to the existing power price forecasting literature.

In the event of changes in power demand, some generators, like hydro power plants with water reservoirs, are quite flexible whereas nuclear and coal fired power plants are among the least flexible. Due to multi-level seasonality and temperature changes, peaks are formed in the demand for electricity. This increased demand pushes up the bidding price for electricity as more expensive sources of power must step in to join the relatively inexpensive baseload power supply. As a result, the supply curve becomes steeper for high demand levels because technologies with higher marginal cost are introduced. This is referred to as the merit order curve. As regards the demand curve, it is generally steep (low price elasticity). As a consequence, shifts in demand cause large price changes when the price equilibrium occurs in the inelastic part of the supply curve. Conversely, shifts in demand result in marginal price changes when equilibrium occurs at the flat part of the supply curve. Short term shifts in demand are often caused by colder weather, as electricity is an important energy source of residential heating in the Nordic market.

As a consequence of steep supply and demand curves, electricity prices usually exhibit higher volatility than other energy products, which implies a significant price risk for market actors, both on the buy and sell side. Other characteristics include seasonality on both a yearly, weekly, and daily level, with price spikes and the possibility of negative prices. Derivatives contracts on electricity prices makes it possible to transfer risk across time periods and across market actors.

A market actor can place bids in the day-ahead spot market or in the several days-ahead futures market. If a market actor can estimate how temperature information is priced by the market, she can place bids which contain more information than those of market actors which do not yet have this information.

Introducing an econometric model for the hourly time series of electricity prices of the European Power Exchange, Ziel, Steinert and Husmann (2015) forecast electricity prices up to a four-week horizon. They used a VAR model with hourly price, load, and renewable production and compare it with several multi- and univariate benchmarks. Their multivariate model without regularization has the same forecast performance as measured by MAE as the univariate model but if the multivariate model is regularized, then the multivariate model provides more accurate forecasts. Steinert and Ziel (2019) incorporate forward-looking information from futures contracts to make electricity price forecasts up to four weeks ahead. Including forward-looking information improved on the forecast performance as measured by a lower MAE compared with several benchmark models, even if futures prices were not quoted during weekends and holidays. Weron and Misiorek (2008) forecast day-ahead spot electricity prices at Nord Pool, including information from realized temperature as an exogenous factor and found that models with temperature information provides lower forecast errors than models without such information. Huurman et al (2012) use one day temperature forecasts to improve on the day-ahead price forecasting on Nord Pool (Oslo and Eastern Denmark price zones). By applying univariate AR models, they find that weather forecasts can price the weather premium on electricity prices.

In this study I will follow up on these studies by including temperature forecasts up to 9 days ahead. As temperature forecasts are made every six hours, every day, it provides a stream of forward looking information. This contrasts with the futures markets, which do not quote prices during week-ends and holidays. More knowledge about the future and how the market reacts to future information can enable market actors to post more accurate bids.

This paper addresses the question whether forward-looking information from temperature forecasts can improve on daily electricity price forecasts up to nine days ahead. I will also examine the value of adding additional exogenous variables and regularization, and compare three different regularization methods, namely Ridge regression, LASSO regression and Elastic Net regression. In addition, two different methodologies of multi-period forecasting are compared. In this respect, I bring several innovations to the electricity forecasting literature.

The article proceeds as follows. The next section presents the data and descriptive statistics. Section 4 describes the method and models I will use to answer my research questions. In-sample analysis is presented in section 5. Section 6 gives a detailed view of the out-of-sample results, and section 7 concludes.

2. Literature

Research on electricity price forecasting has taken different approaches to price modeling, see Weron (2014) for an overview. To this end, the auto regressive (AR) family of time series models has been shown to produce particularly robust forecasts as exemplified by Raviv et al (2015), who forecast day-ahead prices with vector autoregressive (VAR) models. They use lags of hourly electricity prices and dummy variables for weekly and yearly seasonality as the only exogenous variables, where the VAR structure consists of the 24 hourly time series of electricity prices. In their setup, multivariate models have better predictive ability than univariate models, as measured as a reduction of root mean squared error (RMSE). However, Ziel, Steinert and Husmann (2015) show that if exogenous information from variables which may affect the price of electricity are included, AR models which model daily data tend to have better predictive ability for short horizons of less than 12 days than the corresponding hourly VAR model considered in the study. If the VAR model were regularized, it provided forecasts with lower MAE than the un-regularized univariate model. However, they did not regularize the coefficient estimates in the univariate model for comparison.

Within electricity price forecasting, usually the one day-ahead price has been the focus of attention. There are some studies which apply a longer forecast horizon. Maciejowska & Weron (2013) forecast prices for short-term (one through seven days) and medium-term (30 and 60 days). Autoregressive models augmented with exogenous variables (ARX) are used for all hours of the day to make forecasts of hourly prices, which then are aggregated to forecasts of daily prices. Maciejowska and Weron (2016) use autoregressive models to forecast the UK electricity price for up to 45 days. They find that models including hourly price information are well suited for short-term forecasting, whereas models including daily price information are well suited for medium-term forecasting. Interestingly, the inclusion of CO2 emissions allowances did not improve on the forecast accuracy.

A number of studies have utilized the potential information in futures prices. As shown in Smith-Meyer & Gjølberg (2016), electricity price futures contracts on Nord Pool/Nasdaq have provided unbiased estimates of the spot price one month later. Paraschiv et al (2015) also forecast electricity prices, for one-week and one-month horizons. Their results indicate more accurate forecasts for their regime-switching model, with forward-looking information from futures contracts, than the benchmark time-series model without such forward-looking information. Steinert & Ziel (2019) use a VAR model augmented with futures prices to forecast prices at EPEX Spot for up to four weeks, which shows promising results compared to benchmark ARX and VARX models without this forward looking information. The problem with futures prices is the discontinuous information flow they provide as prices are often not provided during weekends or holidays, creating an information gap. Daily futures are often traded at larger volumes for shorter maturities, whereas the volume for longer maturities drops off exponentially. The longer maturity contracts thus yield less accurate and weaker price signals than shorter maturity contracts.

Another source of forward-looking information can come from the weather. Temperature influences both the production and especially the demand for electricity, thereby affecting the price process. As shown by Smith-Meyer (2022), the Nord Pool system price is positively affected by negative changes in temperature, indicating that demand for electricity increases with lower temperatures. This effect is most pronounced for all seasons, other than the summer months between April and September. Knittel and Roberts (2005) find that price models which include seasonal and temperature variables significantly outperform models which do not include these variables, in terms of forecasting hourly day-ahead electricity prices obtained from the California market. Huurman et al (2012) found that an ARIMA model extended with power transformations of next-day weather forecasts yields better point forecasting results, in terms of RMSE for predicting day-ahead prices at Nord Pool. Temperature forecasts are created every day for up to two weeks ahead, thereby providing a valuable source of continuous forward-looking information for short-term electricity price forecasting. Weron and Misiorek (2008) found that the inclusion of realized temperature in their ARX model rendered the inclusion of load insignificant for a study with Nord Pool data.

The number of parameters to be estimated in an AR model increases with the number of explanatory variables and with the number of lags. As such, the problem of overfitting must be considered. As a means to lessen the probability of overfitting, and to make the forecasting model robust, regularization has been considered by several studies on the power markets. Among those, Ziel & Weron (2018) use VAR models with hourly prices and seasonal dummies to estimate day-ahead power prices. Their models are regularized with the LASSO procedure, and they find that multivariate and regularized models estimate day-ahead prices more accurately than univariate models.

3. Data

As visualized in Figure 1, Nord Pool is divided into price zones which sometimes encompass whole countries. In this paper I study the forecasting information in weather forecasts regarding future power prices. As found in Smith-Meyer (2022), temperature affect the electricity spot price for the months from and including October, to and including May. These months are thus of interest for this study, and data for the other months are disregarded, apart from in the descriptive statistics. I model electricity prices at zone NO1 which is situated around Oslo. The data spans the period from March 15th, 2010, to May 11th, 2015, with the first out-of-sample data point being on May 13th, 2014, in order to test the models for a whole season.

Figure 1. **Nord Pool bidding area with price zones.**

Realized temperatures and temperature forecasts are collected for the city of Oslo, which is the largest city in price zone NO1. The one through nine-day temperature forecast is made by European Centre for Medium-Range Weather Forecasts (ECMWF) and the data were acquired through Norwegian Meteorological Institute. One important feature of temperature forecasts is the increasing uncertainty of the forecast as the forecast horizon increases, as can be seen in Table 1, with uncertainty measured by the standard deviation of forecast errors. A total of six instances of temperature forecasts are missing, all non-adjacent. Missing forecasts made at time t for h days ahead have been filled with the forecast made at t-1 for h+1 days ahead. This is not possible for the 9-day forecast, which have been filled with the 9-day forecast of the previous day. Removing the rows with missing temperature forecasts did not alter the end-result.

Days ahead	1	2	3	4	5	6	7	8	9
Sandard Deviation	1.45	1.59	1.76	2.04	2.25	2.63	3.10	3.55	3.75

Table 1. **Standard deviation of temperature (Centigrade) forecast errors (daily averages).**

To test the forecast performance of models without temperature and other exogenous variables, I need to include in my models several variables which are expected to influence the electricity price.

Nuclear power production in Sweden is included in the model, as price zone NO1 is connected to the Swedish SE3 price zone by a power line with a capacity of over 2GW in either direction. This enables nuclear power from Sweden to affect the market in Eastern Norway. There are currently three nuclear power plants in Sweden, with a total of eight reactors which are between 45 and 30 years old. Two currently decommissioned reactors at Oskarshamn were still active during the years 2010 to 2015, from which I have data. Total production capacity for this period was 8,2 GW, but as can be seen from Figure 2, the actual production usually varies between 50 and 100 % of capacity. Theoretical production is therefore just above 200 GWh per day, which is only achieved for some periods of the year, which is mainly during wintertime. There are several reasons why the production varies. Scheduled and unscheduled maintenance take up a sizeable portion of the year. Another reason is that not all reactors are of the same size and efficiency. The two now decommissioned reactors at Oskarshamn were among the smaller reactors and were only profitable when prices seemed to be high enough over time, for instance during wintertime, placing themselves on the right-hand side of the merit order curve. Data for nuclear production were acquired from www.svk.se

	Mean	Median	Min	Max	SD
Spot price (EUR/MWh)	37.1	34.4	3.0	95.8	14.4
Nuclear (GWh/day)	166.2	169.6	78.5	219.7	33.3
Coal (EUR/Tonne)	57.4	55.3	38.1	83.9	11.7
Natural Gas (EUR/100 therms)	67.0	68.7	32.0	89.2	11.3
Wind Denmark (GWh/day)	29.7	24.5	0.7	103.7	21.5
Wind Sweden (GWh/day)	23.0	18.4	0.3	100.7	17.6
Reservoir (%)	60.2	65.3	18.1	92.0	20.0
Temperature (°C)	7.1	7.0	-16.1	25.8	8.1

Table 2. Descriptive statistics, daily observations, price zone NO1

The coal prices which are used in this study are the Rotterdam coal futures, continuous contract #1, which is the front month contract. For natural gas, the prices for UK natural gas front month continuous contract have been used. As I do not model the currency risk in this study, the prices of coal and natural gas have been transformed to Euros. When no prices have been quoted because of weekends and holidays, the last known price has been used.

As 95 % of electricity production in Norway comes from hydropower, reservoir levels might have an influence on the electricity price. If water is scarce, the price usually increases because power plants cannot produce electricity without getting close to the minimum required water level. If this level is breached, the power plant is fined. The reservoir level is published by www.nve.no every Wednesday at 13:00. Total reservoir capacity in Norway is enough to produce 86 TWh, which is most of the yearly consumption. Melting of snow usually fills the reservoirs during early summers when demand is lower, and the reservoirs are depleted during wintertime when demand is highest, and precipitation falls as snow. Reservoir levels have been used in other studies like Kristiansen (2014) and Botterud et al (2010).

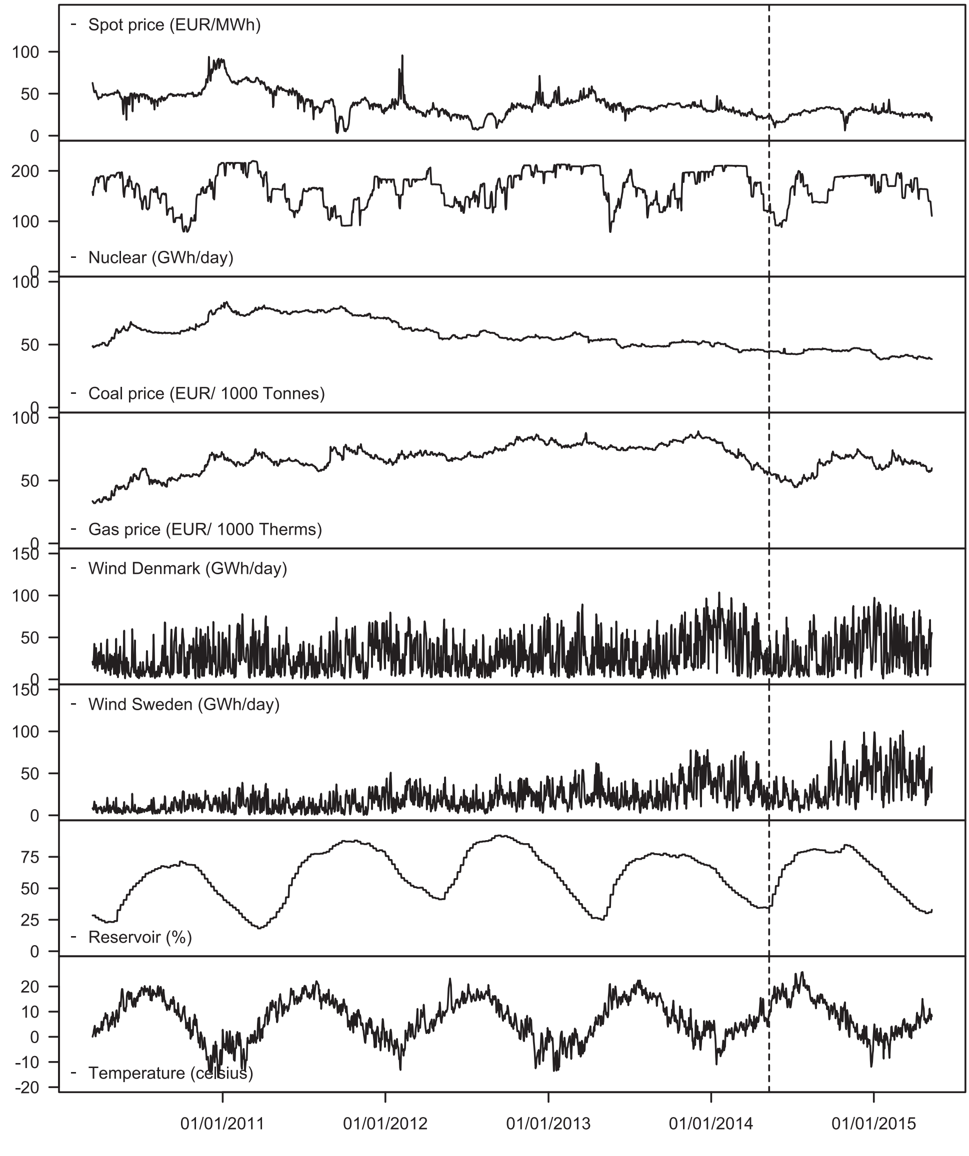

Figure 2. Time series used in AR models as measured in levels. Dotted vertical line indicates border between in-sample data and out-of-sample data. For the analysis, data is logarithmically transformed, and only data for months from and including October to and including May are used.

During the last two decades, wind power capacity has been built, first in Denmark and later in Sweden. During 2015, the two countries produced 14 TWh and 16 TWh from this power source, respectively. As the marginal cost of wind power is close to zero, this production places itself on the left of the merit order curve thereby lowering prices. The production is measured in GWh per day. As can be seen from Figure 1, the wind production is highly volatile, often dropping close to zero.

4. Method

The models which are used to test the different hypotheses in this paper is reduced-form AR models with exogenous variables. AR models on daily prices have been used by Weron and Misiorek (2008), Kristiansen (2012), and Nowotarski and Weron (2016), whereas VAR models on hourly prices have been used by Raviv et al (2015), Huisman et al (2007) and He et al (2015). The model I propose is

$$s_t = \beta_0 + \sum_{i=1}^{n} \beta s_i \cdot s_{t-i} + \sum_{i=1}^{n} \beta n_i \cdot n_{t-i} + \sum_{i=1}^{n} \beta c_i \cdot c_{t-i} + \sum_{i=1}^{n} \beta g_i \cdot g_{t-i} + \sum_{i=1}^{n} \beta wd_i \cdot wd_{t-i} + \sum_{i=1}^{n} \beta ws_i \cdot ws_{t-i} + \sum_{i=1}^{n} \beta rn_i \cdot rn_{t-i} + \beta nt \cdot nt_t + \beta tf_h \cdot tf_{t,h} + \epsilon_t$$

where the spot price (s) is explained by n lags of the spot price, nuclear production (n), coal price (c), natural gas price (g), wind power in Sweden (ws), wind power in Denmark (wd), in addition to the reservoir level in Norway (rn). I also include the normal temperature for Oslo (nt) and the temperature forecast made at time $t-h$ for time t, $(tf_{\mathrm{t,h}})$. The normal temperature deals with seasonality and seasonal dummies were rendered insignificant by the inclusion of the normal temperature, which provides for a more parsimonious model. The temperature forecast which is used in the model is made by subtracting the deterministic normal temperature (seasonal component) from the original temperature forecast. This will then model the stochastic part of the temperature process. Nuclear power and wind generation is expected to have a negative effect on the spot price as increased generation will shift the supply curve to the right. Increased coal and gas prices increases the cost of generation from coal and gas fired power plants and are thought to have a positive correlation with the spot price. Also, when the reservoir levels are lower, the water value is higher and hydro power plants with reservoirs will submit their bids at a higher price.

The data, except temperatures, are transformed logarithmically to model any exponential non-linearities in the data. Logarithms also ensure the model returns positive forecasted production and prices. Negative prices have not been observed in this market as they have in other markets with larger prevalence of wind and solar power.

The number of lags considered in the model were chosen based on in-sample analysis of final prediction error (FPE) criteria, which theoretically minimizes the mean squared error, see Lütkepohl (2006) and Akaike (1969, 1971). This information criteria yields the same result as the more known Akaike information criteria (AIC) for large samples, see Akaike (1974). Based on these criteria, an AR structure with eight lags, $n = 8$, minimizes the theoretical one-step mean squared forecast error.

In order to generate forecasts for the spot price for more than one period ahead, an AR structure with eight lags is used to create forecasts for nuclear production, wind production, coal and gas prices, and reservoir levels.

Most forecasting of time series is iterative, see Pesaran et al (2011), meaning that first the one-period forecast is made, and the coefficient set from this estimation is used to make the multi-period forecasts. Another way to forecast is to make a direct forecast, where one model per forecasting horizon is estimated and used, without iteration. When the model includes forward-looking information, like a temperature estimate or a spot price estimate from a futures price, the iterative process might disregard the uncertainty of longer-period estimates. There might be less uncertainty around the coefficients making a forecast from t to t+1, than from t+8 to t+9. My framework enables us to test whether one set of coefficients should be used for all forecast horizons, or one set of coefficients per forecast horizon should be used.

Coefficients are estimated based on the in-sample data up until time t. Out-of-sample forecasts are then made for a one day to a nine-day horizon. The in-sample data is then augmented with the next day to reflect the additional information a forecaster would have at time $t + 1$ before making the next one to nine-day forecasts.

Ordinary least squares seek to minimize the sum of squared residuals:

$$\|\hat{y} - y\|_2^2 = \left\|X\hat{\beta} - y\right\|_2^2$$

where $\|\cdot\|_2$ is the Euclidan norm, X is the matrix of independent variable values, $\hat{\beta}$ is the coefficient vector, and y is a vector containing values of the dependent variable. The OLS estimator returns unbiased coefficient estimates under certain assumptions. However, the uncertainty of the coefficients is $Var(\hat{\beta}) = \sigma^2(X'X)^{-1}$, where the unknown error variance can be estimated as $\hat{\sigma}^2 = \frac{e'e}{n-m}$, where e is the residual vector, n is the number of observations, and m is the number of coefficients to be estimated. This variance is often high under multicollinearity or when there are many predictor variables. Sometimes it can be beneficial to reduce this variance at the cost of an increased bias. This is the idea behind regularization, and some of the more known methods include Ridge regression, LASSO regression, and Elastic Net regression.

Ridge regression, which was put forth by Hoerl and Kennard (1970), improves prediction error by shrinking large regression coefficients in order to reduce overfitting. It does so by penalizing the sum of squares by adding the sum of square coefficients and is often called L_2 regularization:

$$\left\|X\hat{\beta} - y\right\|_2^2 + \lambda\left\|\hat{\beta}\right\|_2^2$$

β is chosen to minimize this sum for a set of different values of $\lambda \in [0, \infty\rangle$. If λ is set to zero, then there is no shrinkage of the parameters, and the OLS coefficient vector is returned. As λ increases, the coefficients are pulled towards, but not entirely to zero. The randomly shuffled in-sample data is split into ten sections where iteratively, nine sections are used to estimate the parameters, and the last section is used to compute the sum of forecast errors. This means that each sample is given the opportunity to be used in the hold out set one time and used to train the model nine times. The ten sets of forecast errors are then averaged, and the λ which minimizes this sum is kept being used for forecasting out-of-sample. This leave-ten-out procedure is used by all regularization methods considered in this paper.

The LASSO estimation of Tibshirani (1996), which among others has been used by Ziel (2016), differs from ridge regression in penalizing the sum of squared residuals by the sum of absolute coefficients values. It is often called L_1 regularization:

$$\left\|X\hat{\beta} - y\right\|_2^2 + \lambda\left\|\hat{\beta}\right\|_1$$

In LASSO regression, less important coefficients are often set to zero, which is why LASSO regression often is used in covariate selection. As in Ridge regression, the λ which minimizes the penalized sum of squares is kept and used for forecasting.

The last regularization method considered in this paper is the Elastic Net regression. This is a linear combination of the L_1 and L_2 regularizations:

$$\left\|X\hat{\beta} - y\right\|_2^2 + \lambda\left[\alpha\left\|\hat{\beta}\right\|_1 + (1-\alpha)\left\|\hat{\beta}\right\|_2^2\right]$$

where $\alpha \in [0,1]$. Now there are two hyperparameters to be estimated, λ and α.

To answer my research questions, several models and their modes of estimation will be considered. The naïve approach, where the forecast for all future time periods is equal to the last known value is a popular benchmark. The only model without temperature information is a univariate autoregressive model (AR no temperature). Forecasts from this model will be compared to those form a univariate autoregressive model with temperature forecast (ARX). To facilitate a comparison between the forecast performance of models with and without regularization, an autoregressive model with all explanatory variables is estimated (ARX FULL). This model is also estimated using regularization (ARX RIDGE, ARX LASSO, and ARX ELASTIC NET). The forecasts from abovementioned models are estimated using one separate set of coefficients per forecast horizon. To find the value of the use of separate sets of coefficients, forecasts from restricted models are made. These restricted models, which use only the one-step-ahead set of coefficients are identified with a "C" term (ARX C, ARX C, ARX RIDGE C, ARX LASSO C, and ARX ELASTIC NET C).

5. In-sample results

One of the questions to be answered in this paper is whether one set of coefficients should be used across all forecast iterations from forecast day one to forecast day nine. To this end, one must look at how the coefficients differ between the horizons. The coefficients from the ARX model are presented in Table 3. The specification is a such

$$s_t = \beta_0 + \sum_{i=1}^{8} \beta s_i \cdot s_{t-i} + \beta nt \cdot nt_t + \beta tf_h \cdot tf_{t,h} + \epsilon_t$$

One can see that the importance of temperature forecast is shrinking towards zero as older forecasts are used. This coincides with the greater uncertainty of longer horizon temperature forecasts, indicating that to use the coefficient set from one-period forecasts could overstate the importance of the temperature forecast at longer horizons. For example, a one unit change in temperature forecast is related to a 0.46% change in the spot price in the opposite direction according to the one-day forecast model whereas according to the nine-day forecast model this relationship is only 0.22%.

Horizon	Intercept	βs_1	βs_2	βs_3	βs_4	βs_5	βs_6	βs_7	βs_8	βnt	βtf	R^2
1	0.19	0.87	0.00	-0.01	-0.04	0.10	0.05	0.29	-0.31	-0.0005	-0.0046	0.9537
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
2	0.20	0.87	0.00	-0.01	-0.04	0.10	0.05	0.29	-0.31	-0.0005	-0.0047	0.9538
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
3	0.19	0.87	0.01	-0.01	-0.04	0.10	0.05	0.29	-0.31	-0.0004	-0.0044	0.9535
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
4	0.19	0.88	0.01	-0.01	-0.05	0.10	0.05	0.30	-0.32	-0.0003	-0.0043	0.9534
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
5	0.18	0.88	0.01	-0.01	-0.05	0.09	0.05	0.29	-0.31	-0.0003	-0.0044	0.9535
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
6	0.17	0.89	0.00	-0.01	-0.05	0.09	0.05	0.29	-0.31	-0.0003	-0.0037	0.9529
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
7	0.16	0.90	0.00	-0.01	-0.05	0.10	0.05	0.29	-0.31	-0.0004	-0.0032	0.9525
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
8	0.16	0.91	0.00	-0.02	-0.05	0.09	0.05	0.29	-0.32	-0.0004	-0.0027	0.9522
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	
9	0.15	0.91	0.00	-0.01	-0.06	0.09	0.05	0.29	-0.31	-0.0003	-0.0022	0.9519
	(0.05)	(0.08)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.0006)	(0.0008)	

Table 3. **Coefficients per temperature forecast horizon for the ARX model. Estimated from in-sample data, March 15th, 2010, to May 12th, 2014, for months Jan-May and Oct-Dec. Numbers in parenthesis are standard errors.**

In the "ARX FULL" model with all explanatory variables, eight endogenous variables with eight lags and two exogenous variables implies 67 coefficient estimates per regression, for each of the nine horizons. Table 4 shows the coefficient for temperature forecast in the equation for the spot price. Even in this multivariate framework, the importance of temperature forecast is shrinking towards zero when older temperature forecasts are used. This indicates that also in the multivariate case, a separate set of coefficients per forecast step could be used to reduce forecast errors. Also, there are no significant autocorrelated lags in the residuals of the multivariate equation for the spot price.

Horizon	1	2	3	4	5	6	7	8	9
Coefficient on temperature forecast	-0.0048	-0.0049	-0.0045	-0.0045	-0.0045	-0.0037	-0.0032	-0.0026	-0.0025

Table 4. Coefficients for the impact of temperature forecast on the spot price in the VARX model. Estimated from in-sample data.

As can be seen from figure 3, the weekly seasonality is captured by the lag structure in both the univariate and the multivariate models. If only seven lags had been used, it would have been necessary to include a weekly dummy to capture the short-term seasonality like in Nowotarski and Weron (2016) and Weron and Misiorek (2008). The ACF and PACF functions of the other variables resemble those corresponding to the spot price.

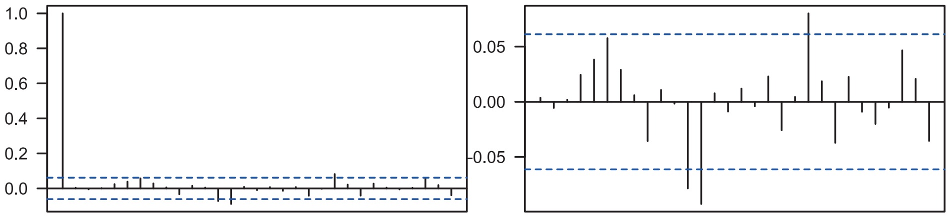

Figure 3. Autocorrelation function (ACF) to the left and Partial autocorrelation function (PACF) to the right for spot price in-sample residuals from ARX model with 8 lags.

There are some ARCH effects in the residuals, with the ACF coefficient for lag one of squared residuals equalling 0.4. This is not accounted for in this study, as an initial analysis indicated that the conclusions to my three hypotheses would not change.

One important characteristic of an AR process is its ability to generate stable forecasts. In our case, several variables have to be forecasted to make a forecast more than one day ahead. This stability of the system can be investigated by looking at the characteristic polynomial of the coefficient matrixes in the corresponding VAR model. To test this, I include all variables in the VAR model, the temperature variables are exogenous, and estimate the coefficients but with all non-diagonal coefficients set to zero. This will yield the same coefficient set as in the AR models above, but it is easier to find the characteristic polynomial of the system.

VARX							
Intercept	0.02	Normal temperature		-0.0003		Temperature forecast	-0.0048
	Spot	Nuclear	Coal	Gas	Wind DK	Wind SE	Reservoir
t-1	0.86	-0.14	0.13	-0.21	0.01	0.00	-0.04
t-2	0.00	0.23	-0.18	0.29	0.00	0.00	-0.10
t-3	0.02	-0.21	0.01	0.30	0.00	0.00	0.12
t-4	-0.08	0.17	0.56	-0.59	-0.01	0.01	0.07
t-5	0.11	-0.18	-0.13	0.49	0.00	0.00	0.07
t-6	0.07	0.22	-0.50	-0.33	0.01	-0.01	-0.38
t-7	0.29	-0.06	-0.39	0.52	0.00	0.02	0.33
t-8	-0.34	-0.03	0.59	-0.47	0.00	-0.02	-0.07

VARX RIDGE							
Intercept	0.02	Normal temperature		-0.0010		Temperature forecast	-0.0080
	Spot	Nuclear	Coal	Gas	Wind DK	Wind SE	Reservoir
t-1	0.41	-0.02	0.02	-0.01	0.00	0.00	-0.01
t-2	0.00	0.02	0.02	0.01	0.00	0.00	0.08
t-3	0.03	0.03	0.00	0.00	0.00	0.05	0.00
t-4	0.00	0.00	0.01	0.00	0.06	0.00	0.01
t-5	0.00	0.00	0.00	0.08	0.02	0.00	-0.02
t-6	0.00	-0.01	0.07	0.01	0.00	-0.02	0.00
t-7	0.00	-0.06	-0.01	0.01	-0.03	0.00	-0.01
t-8	0.00	-0.01	0.00	0.00	0.00	0.00	0.00

VARX LASSO							
Intercept	-0.05	Normal temperature		0.0000		Temperature forecast	-0.0051
	Spot	Nuclear	Coal	Gas	Wind DK	Wind SE	Reservoir
t-1	0.84	0.00	0.00	0.00	0.01	0.00	-0.01
t-2	0.00	0.02	0.00	0.00	0.00	0.00	0.00
t-3	0.06	0.00	0.00	0.00	0.00	0.00	0.00
t-4	0.00	0.00	0.00	0.00	0.05	0.00	0.00
t-5	0.00	0.00	0.00	0.07	0.00	0.00	0.00
t-6	0.00	0.00	0.22	0.00	0.00	0.00	0.00
t-7	0.00	-0.25	0.00	0.00	-0.01	0.00	-0.01
t-8	0.00	-0.01	0.00	0.00	0.00	0.00	0.00

Table 4. Coefficient values for the electricity spot price of VARX, VARX RIDGE and VARX LASSO. Estimated from in-sample data.

In my case, all the roots of the characteristic polynomial of the VAR setup have modulus greater than one, which implies that the system of AR models describe a stable process which will create stationary forecasts with time invariant means, variances, and covariance structure.

Regularization works by reducing the variance of the forecasts, but at a cost of higher bias. It achieves this goal by adjusting the coefficients in the model, selecting the optimal coefficients which are penalized by the size of the coefficients. The in-sample estimated coefficients of the one-step ahead ARX FULL model estimated by OLS, Ridge and LASSO regression can be found in Table 4. From the table, one can see that the coefficients from the three estimation methods differ, sometimes substantially. As expected, the LASSO estimation sometimes sets coefficients to zero, selecting a more parsimonious model.

6. Out-of-sample results and discussion

As the number of lags in the model were chosen based on FPE and AIC which minimizes the mean squared error, root mean squared error (RMSE) is chosen to assess the forecasts. RMSE also has the benefit of representing the uncertainty in units of the underlying variable. Using MAE or MAPE did not change the conclusion. The results for all investigated models per horizon are found in Table 5. MSE and RMSE yield the same answers as the square root is a strictly monotonic function.

Models \ Horizon	1	2	3	4	5	6	7	8	9
Naive	2.63	3.70	4.28	4.55	4.82	5.03	5.23	5.68	6.02
ARX no temperature	2.52	3.51	4.04	4.39	4.71	5.06	5.40	5.80	6.11
ARX	2.39	3.29	3.76	4.12	4.40	4.75	5.07	5.46	5.78
ARX C	2.39	3.29	3.77	4.13	4.43	4.79	5.10	5.50	5.84
ARX FULL	2.25	2.33	2.48	2.66	2.72	2.70	2.64	2.82	2.97
ARX FULL C	2.25	2.32	2.47	2.63	2.68	2.69	2.68	2.92	3.09
ARX RIDGE	2.23	2.30	2.41	2.51	2.51	2.53	2.53	2.65	2.69
ARX RIDGE C	2.23	2.30	2.40	2.49	2.49	2.54	2.57	2.76	2.82
ARX LASSO	2.07	2.10	2.23	2.37	2.45	2.48	2.43	2.53	2.64
ARX LASSO C	2.07	2.10	2.22	2.34	2.41	2.46	2.45	2.62	2.77
ARX ELASTIC NET	2.06	2.11	2.24	2.38	2.46	2.49	2.45	2.56	2.68
ARX ELASTIC NET C	2.06	2.11	2.24	2.38	2.45	2.50	2.48	2.65	2.80

Table 5. Root mean squared error (RMSE) per model and forecast horizon for the period from 2014-05-21 to 2015-05-11.

The results enable us to make several comparisons. The AR model without temperature creates forecasts with smaller forecast errors than the Naïve approach, but only up to 5 days ahead. After this horizon, the Naïve approach provides more accurate forecasts.

The model "ARX no temperature" is an autoregressive model with spot price as the dependent variable and its corresponding lags as independent variables. The ARX model contains, additionally, the normal temperature and a de-normalized temperature forecast as exogenous variables. The value of including temperature in the model can be seen from the more precise forecast made by the ARX model, as measured by a lower RMSE for all forecast horizons considered. This indicates that the temperature forecast contains relevant information for electricity price forecasting even up to 9 days into the future.

One can see that the ARX model which uses one set of coefficients per horizon, considering the increasing uncertainty of the temperature forecast for longer horizons, returns slightly more accurate forecasts for day three until day nine. The ARX CONST model, which uses the set of coefficients which optimizes the one-day forecast, performs just as well for the first two iterations.

For the full model, the benefit of making one set of coefficients per horizon show itself from the sixth iteration onwards, reflecting the development in the coefficient on the temperature forecast as seen in table 4. Consequently, if the forecast horizon is short, then one set of coefficients seem to suffice.

What is the benefit of including so many variables? If I compare the ARX model with the multivariate ARX FULL model, what first catches the eye is the relatively large RMSE for forecasts made by the ARX model for longer horizons. Even at shorter horizons, the ARX FULL model produce more accurate forecasts, suggesting the included variables do contain some relevant statistical information which can be used to forecast the electricity spot price.

One solution to improve the forecasting performance of the multivariate model could be to use regularization. Compared to the OLS ARX FULL model, the ARX RIDGE model produce forecasts which have slightly lower RMSE than the non-regularized model. However, the benefit of regularization is evident if I look at the ARX LASSO model. Ridge regularization is characterized by the inclusion of all coefficients whereas LASSO regularization often sets some coefficient values to zero. The benefit can be seen already from the one-day ahead forecast, as the forecast from the VARX LASSO model exhibit lower RMSE than the forecasts from all the other models considered in this study, even the linear combination of Ridge and LASSO in the ARX ELASTIC NET model.

7. Conclusion

As a result of the peculiarities of electricity prices and the opportunity to transfer risk, electricity price forecasting has increased in importance during the last two decades. Information from futures is sometimes non-existent, often not continuously available, and often thinly traded. Hence, temperature forecasts may provide a useful source of forward-looking information for electricity price forecasting.

Some studies have used information from temperature forecasts to improve on day-ahead price forecasts. Other studies have forecasted power prices for horizons of more than one day, but without using information from the weather. This study use a dataset from Nord Pool spanning five years (2010-2015) to test the one to nine-day forecasting performance of auto regressive models with exogenous variables, herein the temperature forecast.

In this study, inclusion of information from temperature forecasts reduce the forecast errors, as measured by RMSE, compared to models which do not include this information. The first contribution of the paper is to show that this result holds for all horizons up to and including 9 days, which is the longest horizon considered in this study. Furthermore, I find that it is beneficial to consider that uncertainty is an increasing function of the temperature forecasts' horizon. The second contribution is to show how to account for this increased uncertainty by proposing a forecasting method which mixes direct and incremental forecasts. In this framework, one function is estimated for each forecasting horizon like in direct forecasting, but the forecasting itself is iterative. In this way, the uncertainty in the temperature forecasts are accounted for by the 9 differing coefficient sets. Additionally, I show that for AR models it is beneficial to include several exogenous variables which contain information which is beneficial when forecasting power prices. Lastly, I show that there is a reduction in the forecasting errors, as measured by RMSE, if regularization is applied on the coefficient sets.

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