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Lars Ivar Hagfors

Essays on electricity price modelling

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Abstract

This doctoral thesis consists of 6 separate research essays. The essays all use various econometric modelling techniques to examine different aspects of the move towards cleaner energy in Europe, from an economic point of view. In doing this, this thesis makes contributions in two different fields. First, within the field of electricity price modelling. Every essay that is included in this thesis involves some form of electricity price modelling. Most notable is the use of quantile regression models. Here we develop a method where we look at the variations of the coefficients themselves across different quantiles and time periods in order to identify the main fundamental drivers behind extreme prices. Other modelling techniques are also applied, where appropriate. Second, within the field of real options, where we extend the literature by developing a real options model to choose between two different locations for a transmission asset, as well as a real options model to determine the economic value of investing in a large scale battery storage. These are applications in technologies that tie directly into the role of dampening the negative market effects caused by intermittent renewable energy.

In the first essay we develop a model using quantile regressions to examine the effect of various price drivers on the price distribution in the UK electricity market. Using this method, we are able to show how the sensitivity towards different fundamental factors change across quantiles and time of day. We also demonstrate how this framework can be used to perform a scenario analysis, by introducing shocks to one fundamental variable at a time, ceteris paribus, we can model how the price could be expected to react.

In the second essay we take the method we developed in the first paper and apply it to the German electricity market. We specifically focus the analysis on the renewable energy sources, wind power and photovoltaic, in order to learn how the

market reacts to the introduction of the new renewable energy sources. We find some evidence that negative prices can be atrributed to the introduction of wind power.

In the third essay we look more closely at the positive and negative price spikes found in the German electricity market. We develop models to predict the probability of extreme price occurrences in the German day-ahead electricity market, primarily in order to determine the effect the different fundamental variables have on this probability. The main findings are that positive spikes are most closely related to high demand, low supply and high prices the previous day. Negative spikes, on the other hand, are related to low demand and high wind power production levels.

The fourth essay aims to model the EPEX and Nord Pool electricity markets using our quantile regression framework, in order to contrast and compare the effects of the various price drivers between the two markets. This is motivated by the plans to construct the NordLink cable, connecting the two markets. Our main findings indicates that the two markets behave very differently. This supports the hypothesis that connecting the two markets could both be economically viable and also be beneficial in order to reduce the spikes and volatility in the German market due to the differences in characteristics.

The fifth essay develops a real options model to evaluate two mutually exclusive transmission cable projects. The two alternatives being considered are a cable connecting Norway and the UK and a cable connecting Norway and Germany. This builds on the conclusions from essays 1-4, which together leads to a hypothesis that such a transmission cable is beneficial.

In the sixth essay we develop a real options model to evaluate the profitability of investing in a large scale battery bank. Having demonstrated the high volatility in the EPEX in previous essays, this technology would be one way of mitigating that problem while also potentially making a trading profit by buying low and selling high. While our numbers specifically relate to a particular battery technology, the same framework could also easily be applied to pump storage or similar projects.

Contents

1. Introduction

The EU 2020 climate and energy package, enacted in legislation in 2009, sets three key targets for a cleaner and greener energy production in the European Union by 2020.

1. A 20% cut in greenhouse gas emissions
2. 20% of EU energy production to come from renewable energy sources
3. A 20% improvement in energy efficiency

Each country within the EU has taken on binding annual targets, gradually ramping up, so that the targets should be met by 2020.

In order to reach these climate goals set for 2020 and beyond, the European electricity markets have been rapidly transforming over the recent years, moving from a mainly fossil-based production towards a cleaner energy-mix including technologies such as wind, solar and hydro. Differences in climate, topology, available natural resources and policy have led to different changes in the production mix in different markets during the introduction of the new renewable technologies. Some markets, such as the Nord Pool, has a large portion of their supply covered by hydropower, an energy source that is easy to control and highly predictable. Other markets, such as the German EPEX, rely heavily on intermittent energy sources such as wind and photovoltaic. These energy sources are not controllable. Electric power is only being produced when and where the wind is blowing or the sun is shining. This may or may not occur at the same time as the demand for electricity is present. Because of these differences, one must assume that the challenges facing the different markets regarding factors such as volatility, supply-security, environmental concerns are different.

The purpose of this thesis is to investigate the consequences of the move towards cleaner energy in Europe. In case we identify any negative consequences, we also wish to look for possible solutions that can help mitigate these negative side effects. We will be investigating this phenomenon primarily through the lens of econometric modelling. By creating statistical models for the price formation process in several European electricity markets, we can isolate and investigate the specific effect the renewable energy sources has on important variables such as electricity price and price volatility. This will help us identify and quantify certain negative externalities caused by transitioning to a renewable energy production. Where significant problems are identified, we can also use econometric models to estimate the economic viability of technology/infrastructure-based solutions that could potentially help limit the negative effects. This leads to two main research questions:

1. By modelling the electricity price formation in several European energy markets, particularly by analyzing the fundamental factors and their role in the price formation, can we identify some of the important challenges introduced into these markets following the recent transition to renewable energy?
2. Can we identify economically viable solutions that can help dampen the negative impact of the introduction of renewable energy, possibly by looking at how different markets can complement each other?

In doing this, this thesis makes contributions in two different fields. First, within the field of electricity price modelling. Every essay that is included in this thesis involves some form of electricity price modelling. Most notable is the use of quantile regression models. Here we develop a method where we look at the variations of the coefficients themselves across different quantiles and time periods in order to identify the main fundamental drivers behind extreme prices. Other modelling techniques are also applied, where appropriate. Second, within the field of real options, where we extend the literature by developing a real options model to choose between two different locations for a transmission asset, as well as a real options model to determine the economic value of investing in a large scale battery storage. These are applications in technologies that tie directly into the role of dampening the negative market effects caused by intermittent renewable energy.

1.1 Electricity price modelling

1.1.1 Litterature Review

The literature regarding modeling of electricity prices in various markets is extensive. Much of the efforts of earlier work revolves around forecasting the future price of electricity. Bunn and Karakatsani (2003) gives an overview of several methods used for forecasting electricity prices. Nogales et al. (2002) develop a dynamic regression model and a transfer function model for accurate price forecasts in the Spanish and the Californian electricity market. Torro (2007) further develops time series modeling with an ARIMAX model to model weekly futures prices at the Nord Pool market. Karakatsani and Bunn (2008a) critique Nogales et al. (2002), among others, for limiting forecasting models to autoregressive effects and few explanatory variables. They argue that such models are not appropriate for modeling complicated markets. To achieve good day-ahead forecasting performance for electricity spot prices in the British market, they apply a time-varying parameter regression model and a regime-switching model, including several explainatory variables. They conclude that the best predictive performance is obtained from models involving market fundamentals, non-linearity, and time-varying coefficients.

Chen (2009) complements the research of Karakatsani and Bunn (2008a) by studying the non-linear relationship between electricity prices and their fundamental drivers in the British market. Acknowledging the limitations of regime-switching models, Chen (2009) develops a structural finite mixture regression (SFMR) model. Its forecasting performance outperforms regime-switching models and linear regression models. The results also demonstrate that prices in different trading periods within a day are driven by different fundamental factors. Chen and Bunn (2010) confirm these results using a logistic smooth transition regression (LSTR) model for the British market.

Different modelling techniques have been applied in order to capture and model the distribution of extreme price behaviour. Bunn et al. (2016) use a multifactor, dynamic, quantile regression formulation and show how the price elasticities of the fundamentals vary extensively across quantiles. However, the elastisities of gas, coal and carbon prices exhibit no specific pattern across quantiles hence they hardly have any influence on the peak price distribution. Thomas et al. (2011) develop an autoregressive (AR) model to capture the effects of individual spikes while controlling for seasonality in spot price returns in the Australian electricity market. They conclude that incorporation of supply and demand information is necessary to adequately capture negative prices. Christensen et al. (2012) extend the research on AR models by looking at the prediction of spikes using an autoregressive conditional hazard (ACH) model on the Australian electricity market. As a benchmark, the logit model is used, yielding similar results. Focusing on the short-term forecasts of spike occurrences, Eichler et al. (2014) develop variations of the dynamic binary response model, e.g. with regime-switching mechanisms, proposed by Kauppi and Saikkonen (2008). The models have a superior fit on the Australian market data and they suggest to replace the logistic function by an asymmetric link function leading to significant improvements. Eichler et al.

(2014) also extend the ACH model used in Christensen et al. (2012) by incorporating past price information with that improving the performance of the model. Karakatsani and Bunn (2010) apply various statistical models to investigate the relationship between fundamental drivers and electricity price volatility in the UK market, which is a different piece of the puzzle for understanding extreme price behaviour.

In the litterature, the focus has shifted from forecasting prices based on the entire price distribution to isolating normal range prices from the price spikes. Byström (2005) and Paraschiv et al. (2016) investigate the performance of Extreme Value Theory (EVT) on accurately modeling and forecasting the extreme tails of electricity price distributions. Both studies conclude that EVT is a powerful tool for this purpose. Lu et al. (2005), Zhao et al. (2007b) and Zhao et al. (2007a) model normal and extreme prices separately to achieve more complete and robust models and more accurate forecasts. Zhao et al. (2007b) use a method based on data mining by applying two algorithms to the data - support vector machine and probability classifier - to predict the spike occurrence. The results are highly accurate and provide improved risk management practices related to extreme price prediction, but provide limited economic insights. Higgs and Worthington (2008) study the Australian spot electricity market, which exhibits frequent price spikes, and employ three models to capture these effects; a stochastic, a mean-reverting and a regime-switching part. The regime-switching model outperforms the other two because the allowance of price spikes is better. A shortcoming of the model is the unrealistic assumption of constant transition probabilities. Mount et al. (2006) solves this issue by adjusting the regime-switching model by modeling the transition probabilities as a function of the load and/or the implicit reserve margin. By modeling the volatile behaviour of the electricity prices in the Pennsylvania-New Jersey-Maryland (PJM) Power Pool, they provide accurate spike predictions. However, the model is dependent on precise reserve margin measurements, which are not easily obtained.

Regime switching models are frequently used to model spike behaviour (Arvesen et al. (2013), deJong and Huisman (2002), Keles et al. (2011), Weron et al. (2004),Weron (2009), Weron and Misiorek (2005)). They allow the spot price to switch between a base regime and higher/lower jump regimes. Paraschiv et al. (2015) propose a regime-switching approach to simulate price paths and forecasts on the EPEX. They extend the approach from Kovacevic and Paraschiv (2014) to include serial dependencies and transition probability for spike clustering. Christensen et al. (2009) perform a Poisson AR framework to identify spikes defined as threshold exceedances. Keles et al. (2011) consider positive price spikes and negative prices at the EPEX by implementing a regime-switching model. All of the above-mentioned models focus mainly on positive spikes in markets dominated by conventional energy sources. Consequently, the models are not including the impact of renewable energy production. Literature including the impact of renewable energy sources on spikes and negative prices is limited. This particularly applies to negative prices, which have become increasingly more common in latter years (Paraschiv et al. (2014), Schneider (2011) and Keles et al. (2011)).

Huisman et al. (2013) investigate the effect of renewable energy sources on electricity prices indirectly by studying hydro power in the Nord Pool market. They argue that theoretical and simulation studies show declining electricity prices when introducing sustainable energy supply, but empirical studies supporting this result are scarce. Paraschiv et al. (2014) investigate directly the influence of renewable energy sources on the German electricity market. By analyzing the impact of wind and photovoltaic on day-ahead spot prices at the EPEX, they conclude that the introduction of renewable energy sources increase the extreme price behaviour and influence the fuel mix for electricity production.

1.1.2 Quantile regression

In an economy heavily reliant on electricity, and where the market structure is becoming increasingly complex, considerable time and energy is devoted towards understanding the electricity price formation. Electricity prices are characterized by complicated non-linear relationships to fundamental variables (Chen and Bunn (2010)), and the relationships are challenging to model. Bunn et al. (2016) introduced quantile regression for modelling the electricity price. Whilst they demonstrated the value of quantile models for Value-at-Risk forecasting, compared to the benchmarks of GARCH and CAViAR methods, that study was a methodological comparison and did not address in detail the distinctly different intraday characteristics hour by hour of the price risk distribution. Yet it is well known that price formation (and hence risk) varies systematically throughout the day with different models generally being specified for peak, off-peak and mid-peak hours to reflect the dynamics of load following and the various technologies setting the marginal prices. With this in mind, it is an open question how the determinants of risk vary on an intraday basis.

There is also a different strand of literature using quantile regressions to forecast electricity prices, represented by works such as Nowotarski and Weron (2015) and Maciejowska et al. (2016). Their approach differs from that of Bunn et al. in that it uses quantile regression combine several point forecasting methods in order to model a distribution over the individual point forecasts, creating a sort of ensemble model. This is shown to produce more robust and accurate price forecasts, but it is not designed to accurately model the underlying price distribution.

For several agents in the energy market, such as consumers, suppliers, traders and regulators, modelling the tails of price distributions is often more important than formulating central expectations. Due to the sparseness of data in the tails and the extreme sensitivity of the results to misspecification in the functional form of the distribution, modelling can be difficult. Thus, robust parametric methods for specifying predictive distributions (e.g. Guermat and Harris (2002b;a)), regime switching models (eg. Dias and Ramos (2014), Arvesen et al. (2013)) as well as semi-parametric formulations for estimating specific quantiles (e.g. Engle and Manganelli (2004), Gerlach et al. (2011)), have characterized recent research.

Linear quantile regression was introduced by Koenker and Bassett Jr (1978), and later described by Hao and Naiman (2007) and others. It offers a semi-parametric formulation of the predictive distribution so that the quantiles of the distribution can be estimated with distinct regressions. This makes it possible to estimate different coefficient values for the fundamental factors at different quantile levels. As electricity prices are likely to have different sensitivities to fundamental variables across the price distribution, due to the non-linear properties of the merit order curve, quantile regression is well suited for modelling the electricity prices. Many different models have been developed to capture different price formation processes for normal and extreme events. Karakatsani and Bunn (2008b) applied a Markov regime-switching model, while Chen and Bunn (2010) used a smooth transition logistic regression model.

With quantile regression we are able to model the quantiles directly, without any assumptions about the distribution of the residuals. Electricity prices are characterized by high volatility, skewness, volatility clustering and large spikes. This highly non-normal behavior of electricity prices makes a semi-parametric technique, such as quantile regression, even more appealing. We are also able to investigate the relationship between the dependent and independent variables across the entire distribution, and thus build up a more complete picture of how fundamental factors affect the electricity price in various price ranges.

From a risk perspective we want to be able to estimate the tail dependencies accurately and quantile regression works well for this purpose. Quantile regression is closely related to value at risk in estimating the price at extreme quantiles. For traders and risk managers it is thus a useful tool for assessing price risk and developing hedging strategies.

The quantile regression model is semi parametric, thus we do not make any assumptions neither about the distribution of our data, nor about the residuals. Due to the highly non-normal behavior of the electricity price, as well as time-varying volatility, this is an advantage for our research. Significance testing of quantile regression is still very much in the exploratory stage, and no single approach has yet gained widespread support. For further discussion, see Volgushev et al. (2013).

1.2 Summary of essays

1.2.1 Summary of essay 1 - Modeling the UK electricity price distributions using quantile regression:

In this paper we develop fundamental quantile regression models for the UK electricity price in each trading period. Intraday properties of risk, as represented by the predictive distribution rather than expected values, have previously not been fully analyzed. The sample covers half hourly data from 2005 to 2012. From our analysis we are able to show how the sensitivity towards different fundamental factors changes across quantiles and time of day. In the UK the supply of electricity is to a large extent generated from coal and gas plants, thus the price of gas and coal, as well as the carbon emission price, are included as fundamental factors in our model. We also include the electricity price lagged by one day, as well as demand and margin forecasts. We find that the sensitivities vary across the price distribution. Our findings also suggest that the sensitivity to fundamental factors exhibit intraday variation. We find that the sensitivity to gas relative to coal is higher in high quantiles and lower in low quantiles, as well as some indications of market power being exercised during peak hours. We have demonstrated a scenario analysis based on the quantile regression models, showing how changes in the values of the fundamentals influence the electricity price distribution.

Within the context of the dissertation, this paper serves as a methodological development rather than an attempt to answer the research questions of the thesis directly. The method we develop in this paper is something we use in several subsequent papers in order to show the volatility effects of intermittent renewables in the German electricity market.

The main contribution of this paper is developing a framework where we use quantile regressions to examine the electricity intraday sensitivities of the electricity price to a number of price drivers across the whole price distribution.

1.2.2 Summary of essay 2 - Using quantile regression to analyze the effect of renewables on EEX price formation:

This paper develops fundamental quantile regression models for the German electricity market. The main focus of this work is to analyze the impact of renewable energies, wind and photovoltaic, on the formation of day-ahead electricity prices for all trading periods in the EEX. We find that the renewable energy sources overall has a mild price dampening effect, and that the negative prices often attributed to wind power is a rare event that mainly occurs during night-time periods of unusually low price and demand.

This is a short conference paper in which we apply the methodology developed in essay 1 to examine the renewable production in the German market, leading up to the increased focus on this market in the remaining parts of the dissertation.

The main contribution of this paper is providing more insight into how the introduction of new renewable energies is altering the behaviour of the price distribution and increases the volatility.

1.2.3 Summary of essay 3 - Prediction of extreme price occurrences in the German day-ahead electricity market:

Understanding the mechanisms that drive extreme negative and positive prices in day-ahead electricity prices is crucial for managing risk and market design. In this paper, we consider the problem of understanding how fundamental drivers impact the probability of extreme price occurrences in the German day-ahead electricity market. We develop models using fundamental variables to predict the probability of extreme prices. The dynamics of negative prices and positive price spikes differ greatly. Positive spikes are related to high demand, low supply, and high prices the previous days, and mainly occur during the morning and afternoon peak hours. Negative prices occur mainly during the night, and are closely related to low demand combined with high wind production levels. Furthermore, we do a closer analysis of how renewable energy sources, hereby photovoltaic and wind power, impact the probability of negative prices and positive spikes. The models confirm that extremely high and negative prices have different drivers, and that wind power is particularly important in relation to negative price occurrences. The models capture the main drivers of both positive and negative extreme price occurrences, and perform well with respect to accurately forecasting the probability with high levels of confidence. Our results suggest that probability models are well suited to aid in risk management for market participants in day-ahead electricity markets.

In the context of the thesis, this paper demonstrates how the German energy market is experiencing large positive and negative spikes that are related to the introduction of renewable energy sources. The intermittent nature of wind- and solar-based electricity generation makes it hard to match the supply and demand. The production mix relies on a significant base load production coming from inflexible coal power plants. There is not enough flexibility in the system to ramp the production up or down in order to counteract the fluctuations from the renewables. This leads to a fairly frequent worst case scenario of having to send power directly to the ground, resulting in negative prices, or a shortage leading to a positive spike.

The first contribution of this paper is estimating logit models for forecasting the probability of an extreme price as a function of selected fundamental variables. This analysis reveals which fundamental variables drive the probability of extreme price occurrences and quantifies the impact on the probability of observing extreme prices.

The second contribution of this paper is therefore a further exploration of how forecasts of photovoltaic and wind power production affect the probability of extreme prices.

1.2.4 Summary of essay 4 - A Comparative Analysis of Price Drivers of Day-Ahead Electricity Prices in EPEX and Nord Pool:

In this paper we analyze the fundamental drivers behind electricity spot prices in Nord Pool and the German European Power Exchange (EPEX), and compare the price formation dynamics in these two markets. The comparison is motivated by the NordLink cable, which will connect Germany and Norway in 2020. It will exploit the differences in market characteristics, and is expected to reduce the price spread and improve utilization of renewable energy sources. Our paper increases the understanding of the market mechanisms, which is required by market participants in order to adapt to the future changes.

Separate quantile regression models are estimated for each trading period to capture varying intraday properties of the electricity prices. We examine the price formation dynamics across the entire distribution, and how it differs between Nord Pool and EPEX.

The results show that the fundamental variables impact the two markets differently and non-linearly throughout the trading day. Autoregressive effects are most influential in Nord Pool, together with demand and supply in the highest quantile. Overall, most variables have a low price impact; this is likely due to the large amount of flexible and stable hydro power which cancels out fluctuations in other parameters. EPEX has a higher number of important price drivers across the price distribution. Demand is the primary price determinant, while fossil fuel prices, autoregressive effects, and wind power production also notably impact the price formation. The energy mix characteristics are the likely reason for these differences, as EPEX is much more inflexible due to large-scale thermal production and intermittent renewable energy.

In the greater context of the dissertation, this paper demonstrates empirically that the two markets we analyze behave very differently. This leads us to a hypothesis that connecting the two markets could potentially be beneficial in order to reduce the volatility and spikes in the German market.

This paper contributes to the research on fundamental electricity drivers in both Nord Pool and EPEX, and provides a detailed analysis and comparison of the intraday price dynamics across the entire spot price distribution in these two markets.

1.2.5 Summary of essay 5 - Investment in Mutually Exclusive Transmission Projects under Policy Uncertainty:

In this paper we evaluate mutually exclusive transmission projects under policy and economic uncertainty. The alternatives being considered are transmission investment projects between Norway and Germany, and Norway and the UK. We apply a real option valuation framework allowing the investor to choose the optimal time and location of the investment, and also how different conditions affect the decision to invest in either of these two projects. The analysis shows that the value of the option does not necessarily increase with volatility.

Within the context of the thesis, this paper demonstrates a framework for calculating the value of a transmission cable between the Nord Pool market and UK or EPEX. This ties into essays 1-4 which together led to a hypothesis that such a transmission asset would be beneficial also for the market stability and counteracting the increased volatility in EPEX.

The main contribution of this paper is twofold. First, we apply real option analysis to consider which geographical locations to connect via an underwater transmission cable. Second, our paper is one of the few to apply real option valuation to transmission assets.

1.2.6 Summary of essay 6 - Investment in Electric Energy Storage Under Uncertainty: A Real Options Approach:

In this paper we develop a real options approach to evaluate the profitability of investing in a battery bank. The approach determines the optimal investment timing under conditions of uncertain future revenues and investment cost. It includes time arbitrage of the spot price and profits by providing ancillary services. Current studies of battery banks are limited, because they do not consider the uncertainty and the possibility of operating in both markets at the same time. We confirm previous research in the sense that when a battery bank participates in the spot market alone, the revenues are not sufficient to cover the initial investment cost. However, under the condition that the battery bank also can receive revenues from the balancing market, both the net present value (NPV) and the real options value are positive. The real options value is higher than the NPV, confirming the value of flexible investment timing when both revenues and investment cost are uncertain.

In the context of the dissertation, a large scale battery storage facility would be able to counteract some of the issues we have detected in the EPEX market in our fundamental models. The main problem there is that the intermittent nature of wind in particular, and to some extent solar, makes it so that the supply of electricity is often too high in periods of low demand and vice versa. Large scale electricity storage would be able to capture the excess production in low demand periods and deliver it to the market when the demand is higher rather than letting electricity go to waste or having to sell it at very low prices. Furthermore, assuming the existence of a transmission cable, as described in essay 4, the same framework can be applied to a pump storage project.

The main contribution of this paper is a quantification of the value of investing in a battery bank in a real options context.In addition, we use a state of the art MRS for the spot price that captures the characteristics of the prices. We are also the first to propose a MRS for the balancing price. Further, the approach for optimal hourly dispatch of the battery bank includes participation in both the spot and balancing market. Finally, the model takes into account the uncertainty of the investment cost and the revenues by applying the real options framework.

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2. Essay 1 - Modeling the UK electricity price distributions using quantile regression

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Modeling the UK electricity price distributions using quantile regression

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ABSTRACT

In this paper we develop fundamental quantile regression models for the UK electricity price in each trading period. Intraday properties of price risk, as represented by the predictive distribution rather than expected values, have previously not been fully analyzed. The sample covers half hourly data from 2005 to 2012. From our analysis we are able to show how the sensitivity towards different fundamental factors changes across quantiles and time of day. In the UK the supply of electricity is to a large extent generated from coal and gas plants, thus the price of gas and coal, as well as the carbon emission price, are included as fundamental factors in our model. We also include the electricity price lagged by one day, as well as demand and margin forecasts. We find that the sensitivities vary across the price distribution. Our findings also suggest that the sensitivity to fundamental factors exhibit intraday variation. We find that the sensitivity to gas relative to coal is higher in high quantiles and lower in low quantiles, as well as some indications of market power being exercised during peak hours. We have demonstrated a scenario analysis based on the quantile regression models, showing how changes in the values of the fundamentals influence the electricity price distribution.

1. Introduction and literature review

In an economy heavily reliant on electricity, and where the market structure is becoming increasingly complex, considerable time and energy is devoted towards understanding the electricity price formation. Electricity prices are characterized by complicated non-linear relationships to fundamental variables [4], and the relationships are challenging to model. Bunn et al. [3] introduced quantile regression for modeling the electricity price. Whilst they demonstrated the value of quantile models for Value-at-Risk forecasting, compared to the benchmarks of GARCH and CAViAR methods, that study was a methodological comparison and did not address in detail the distinctly different intraday characteristics hour by hour of the price risk distribution. Specifically, in that study, only a single time series of prices at period 38 (GMT 18:30–19:00) was analyzed. Yet it is well known that price formation (and hence risk) varies systematically throughout the day with different models generally being specified for peak, off-peak and mid-peak hours to reflect the dynamics of load following and the various technologies setting the marginal prices. With this in mind, it is an open question how the determinants of risk vary on an intraday basis. In this study we address that question through the application of multifactor, quantile regression on all 48 half hourly prices from the GB market, across the range of quantiles from 1% to 99%, estimated over the period 2005–2012. This represents a more complete analysis of the intraday price risks and their separate drivers than has so far been undertaken.

For several agents in the energy market, such as consumers, suppliers, traders and regulators, modeling the tails of price distributions is often more important than formulating central expectations. Due to the sparseness of data in the tails and the extreme sensitivity of the results to misspecification in the functional form of the distribution, modeling can be difficult. Thus, robust parametric methods for specifying predictive distributions (e.g. Refs. [8,9]), regime switching models (eg. Refs. [2,5]) as well as semi-parametric formulations for estimating specific quantiles (e.g. Refs. [6,7]), have characterized recent research.

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Quantile regression, introduced by Koenker and Bassett [14]; offers a semi-parametric formulation of the predictive distribution so that the quantiles of the distribution can be estimated with distinct regressions. This makes it possible to estimate different coefficient values for the fundamental factors at different quantile levels. As electricity prices are likely to have different sensitivities to fundamental variables across the price distribution, due to the non-linear properties of the merit order curve, quantile regression is well suited for modeling the electricity prices. Many different models have been developed to capture different price formation processes for normal and extreme events. Karakatsani and Bunn [11] applied a Markov regime-switching model, while Chen and Bunn [4] used a smooth transition logistic regression model.

With quantile regression we are able to model the quantiles directly, without any assumptions about the distribution of the residuals. Electricity prices are characterized by high volatility, skewness, volatility clustering and large spikes. This highly non-normal behavior of electricity prices makes a semi-parametric technique, such as quantile regression, even more appealing.

By looking at each pre-defined trading period as an individual market, we are able to reveal intraday variation in the price sensitivity towards fundamental factors, as well as varying sensitivities across the price distribution. We model the electricity price as a function of the fundamental factors, resulting in a simple and parsimonious model. The explanatory variables are the price of the main input factors in production, gas and coal, the carbon emission price, the lagged price as well as forecasts of demand and reserve margin. By running separate models for each year, we find that the sensitivities to the fundamental factors are stable over time, implying that our model withstands time-varying structural changes.

Further, we demonstrate a scenario analysis that market participants can use as an example to plan for a range of scenarios concerning the distribution of the price given different input ranges for the fundamental variables. We can create a conditional distribution of the electricity price by changing each fundamental factor, ranging from its minimum to maximum value of our data set. This enables us to detect the main risk drivers at different parts of the day as well as at different parts of the price distribution. This information can be utilized by all market participants in order to reduce risk and make better trading and bidding strategies.

This paper has the following structure: Section 2 presents the background of the GB electricity market and Section 3 describes the data set we use for our analysis. Section 4 contains a description of the models we apply and the results are reported in Section 5. In Section 6 you find our scenario analysis. In Section 7 we present our conclusion.

2. Electricity market fundamentals

2.1. The GB electricity market

Since April 2005, under the BETTA (British Electricity Trading and Transmission Arrangements), the electricity systems of England, Wales and Scotland have been integrated. The transmission system is also linked to continental Europe through interconnectors to France and the Netherlands. Six major retail suppliers, British Gas, SSE, Npower, Scottish Power, E.On and EDF, cover most of the integrated generation market. However, different suppliers operate at different times of the day, thus implying a less competitive environment especially at times of scarcity. When reserve margin is low, the competition will decrease and generators with market power may create market prices substantially above short-term marginal costs.

Electricity is a flow commodity and is sold and consumed continuously and instantaneously. Traded products are therefore defined and sold in the form of metered contracts for the constant delivery of a certain amount of power over a specific period of time. In GB the specified time period is half an hour, giving 48 periods each day. Period 1 corresponds to GMT 00:00–00:30, period 2 corresponds to GMT 00:30–01:00 and so on, ending with period 48, corresponding to GMT 23:30–24:00. The APX (formerly UKPX) is the spot market where power contracts are traded. Members submit their bids electronically up to two days ahead of delivery, and the market is cleared.

In the short run consumers are inelastic [12] and prices are thus a function of demand, competition and costs. The electricity supply curve is a merit order curve, where each plant's spot on the curve represents the cost and capacity of the plant. The difference between costs is mainly due to technology and fuels used in production. The plants with the lowest marginal costs, enter at the lowest level of the curve. These are renewables and nuclear plants. Coal fired plants follow, and together they cover base load, operating most of the time. At the right end of the curve, natural gas enters through CCGT plants, which are fired up to cover peaks in demand. CCGT plants are mostly powered using natural gas, but they can also be fueled using coal and biomass, making them very flexible.

2.2. Electricity price formation

We model the electricity price as a function of the fundamental variables influencing the price.[1,2] Naturally, the electricity price will to a large extent depend on the price of the main fuels used in production. In 2012 the electricity in Britain was generated from coal (39%), gas (28%), nuclear (19%), renewables (11%) and other sources (3%) [16]. Gas and coal are the two largest fuel sources and are thus considered fundamental factors in our model. We have chosen not to include renewables. The share was only 4% in 2005, and even though it increased towards the end of our data set, ending at 11% in 2012 [16], the share was still not sufficiently high for it to have a large impact on prices in the whole timespan we are studying.[3] Coal is the fuel that emits the most carbon, hence the carbon emission price acts as an add-on to the coal price. For period 38 (GMT 18:30–19:00), Bunn et al. [3] found that the carbon emission price did not significantly affect the electricity price. This might, however, be different for other periods when coal comprises a larger share of the fuels used in production. Further, we believe it is still important to include the carbon emission price in the model, because it is intended to affect the dynamics between coal and gas based electricity generation.

The market clearing price is set at the level where demand equals supply, thus demand has a crucial role in the price formation process and should be a part of our model. Further, we include the reserve margin forecast, as it reflects the level of scarcity in the market. With inelastic demand the level of scarcity will be crucial

[1] The explanatory variables used in this kind of model needs to be specifically adapted to the market under investigation, as well as the period of the day that is being modeled. If the input mix changes dramatically over time one should also allow for time varying coefficients [17].

[2] The model is built on observable variables for some fundamentals that might influence the price formation. We acknowledge that there can be certain unobservable factors that we are unable to include in the model, and therefore we are not able to fully explain the whole price formation.

[3] The share of renewables, particularly wind, has increased significantly after 2012 in the UK. There is therefore a need to investigate specifically how the wind production influences the energy price formation, similar to [10] who investigates the influence on renewables on the price formation in the german energy market.

for determining the price. We include the demand forecast and reserve margin forecast made by the system operator. These forecasts are available the previous day and may be used by market participants when submitting their bids. We expect the lagged price, fuel prices and demand to have a positive effect on the electricity price, whereas the margin level is expected to have a negative effect. The sensitivity of the electricity price to each fundamental variable, both across time and across quantiles, is elaborated in the sections below.

2.2.1. Lagged price

High prices have a tendency to be followed with high prices [3]. Also, as prices approach marginal cost, we expect them to stabilize at a certain level depending on the degree of market power in the market. Market power can allow producers to keep prices high enough to make a profit, but at the same time keep them sufficiently low to prevent other producers, with technologies higher on the merit order curve, to enter. Market power opens up possibilities for repeated gaming [18], such as signaling between the producers to keep prices above what can be explained by marginal costs. This can be seen as a form of behavioral adaption and is reflected in a high sensitivity to yesterday's price. Because high prices are associated with situations with a strong degree of market power, we expect to see sensitivity to lagged price increasing with higher quantiles as well.

2.2.2. Gas price

We expect the sensitivity to changes in the gas price to be higher in high demand periods, because gas is the main fuel used to cover peak load (demand in excess of base load). Also, we expect electricity prices to be more sensitive to changes in all fuel prices during periods with high demand. This being because higher demand gives producers greater capability to exercise market power, and thus allow changes in fuel prices to be more directly reflected in electricity prices. Sensitivity to the gas price should increase with quantiles.

2.2.3. Coal price

Unlike gas, coal is mainly used to cover base load, and thus the use of coal is relatively constant for the entire 24-h. However, as for gas, we expect electricity prices to be more sensitive to changes in all fuel prices during periods with high demand. This also means that sensitivity to the coal price is not expected to increase across quantiles in the same way as gas price sensitivity.

Because coal comprises a larger share in base load production than gas, the electricity price should be more sensitive to changes in coal price than gas price at low quantiles and in periods when demand is low. Likewise, prices should be more sensitive to changes in gas price than coal price for high quantiles and in periods when demand is high, since gas plants are fired up to cover demand in excess of base load. We note that this to some extent is determined by the relative price levels.

2.2.4. Carbon emission price

Because coal emits more carbon than gas when utilized in power production, the carbon emission fee will have a higher incremental effect on the coal price compared to the gas price. The intention is that in times when the coal price lies below the gas price, the carbon emissions cost will rise to prevent substitution from gas to coal. Therefore, we expect the variation in sensitivities to carbon emission prices across periods and quantiles to follow the same trend as sensitivity to the coal price. However, in our data the carbon emissions price is very low, mainly due to too many issued quotas, and thus it is unclear how it actually effects the electricity price.

2.2.5. Demand forecast

We expect demand to have the largest effect on electricity prices during the day and early evening, when the demand is higher and the margin levels are lower. Hence, prices should also be more sensitive to demand at higher quantiles. As the supply function is convex, we expect this sensitivity to increase non-linearly with higher quantiles. High prices are likely to coincide with low margin levels, making the price very sensitive to changes in demand. Also, an increase in demand above normal levels implies firing up additional plants higher on the merit order curve, thus pushing prices up.

2.2.6. Reserve margin forecast

A reduction in reserve margin will push prices upwards. We expect prices to be more sensitive to margin levels in high demand periods and for the higher quantiles for each period. These situations are likely to represent times of scarcity. Since demand is inelastic and producers have more capacity to exercise market power at times of scarcity, changes in margin is expected to cause large price changes.

3. Data

3.1. Variable description

Our data set spans from 22.04.2005 until 28.06.2012. Two events make 2005 a natural starting point for our analysis. Firstly, Scotland was included in the British wholesale electricity market April 1, 2005. Secondly, the EU Emission Trading Scheme was established on January 1, 2005, allowing carbon emission trading to commence at the beginning of 2005. For electricity prices we have data for the same period, although there are some observations missing. For these periods we have interpolated linearly by taking the average of the price the previous and next day, within the same period. For fuel prices we have daily prices, weekends not included. By the same principle as for electricity prices we have interpolated using the prices quoted for Friday and Monday (Table 1).

Gas, coal and carbon emission prices are all lagged by one day in the model. Demand forecasts and margin forecasts are both made the previous day. This means that all variables used in the analysis are known to the market before the power exchange closes for the trading period concerned. This is done to ensure exogeneity of the explanatory variables.

3.1.1. Power price

UKPX (now APX) is the day-ahead and on-the-day power exchange, allowing high frequency trading up to an hour before real time. Every day consists of 48 periods of 30 min each. Prices are quoted in £/MWh and represents the volume weighted prices for each period as cleared on the exchange in the preceding 48 h.

3.1.2. Demand forecast

This forecast is made available the previous day by the System Operator for each half-hourly trading period. It reflects available

Table 1
Data granularity of the explanatory variables in our model.

Variable	Half-hourly	Daily
Power prices	X	
Gas prices		X
Coal prices		X
Carbon emission prices		X
Demand forecasts	X	
Reserve margin forecasts	X	

Table 2
We have chosen 6 periods; 10, 14, 19, 25, 35 and 43, each representing a certain time period of the day, that we will focus on in our analysis.

Time of day	Period	Time period	Representative period
Night	47–12	23.00–06.00	10 (04.30–05.00)
Early morning	13–15	06.00–07.30	14 (06.30–07.00)
Late morning	16–22	07.30–11.00	19 (09.00–09.30)
Afternoon	23–31	11.00–15.30	25 (12.00–12.30)
Early evening	32–38	15.30–19.00	35 (17.00–17.30)
Late evening	39–46	19.00–23.00	43 (21.00–21.30)

market information and avoids the endogeneity issues concerning simultaneity, which might be a problem when using actual demand, since it is released the day before. The basis of which the demand forecast is calculated, however, is not known to us. This means that other endogeneity issues such as omitted variables and measurement errors might still be a problem. However, because demand is such an important price driver, we still choose to include it in our model.

3.1.3. Reserve margin forecast

The System Operator makes forecasts of the available reserve margin for each half-hourly trading period. This is defined as the difference between the sum of the maximum available output capacities, as initially nominated by each generator prior to each trading period, and the demand forecast described above.

3.1.4. Gas price

We use the daily UK natural gas spot price from the NBP (National Balance Point). The price is quoted in £/MMBtu (MM British Thermal Unit).

3.1.5. Coal price

We use the daily HWWI world index coal price. The price is quoted in \$/ton. We have translated it into £/ton, taking into account the \$/£rate.

3.1.6. Carbon emission price

We use the EEX-EU carbon emissions allowance daily spot price. The price is quoted in €/ton. We have translated it into £/ton, taking into account the €/£rate.

3.2. Organization of data

In order to give an overview of the differences across periods in our analysis we chose to divide the 48 periods into six groups each describing a certain time of the day. This allows us to capture similar features such as sensitivities to the different exogenous variables and price characteristics for a specific time of the day, thus providing relevant information to different market participants. A representative period for each group has been chosen to present a comparison of differences throughout the day. These are outlined in Table 2 below.

We further define period 10 as the anti-peak, period 25 as the day-peak and period 35 as the super-peak for each day. From Table 3 we see that of all the periods, period 35 has the highest average price of the day and exhibits the highest volatility, skewness and kurtosis in our data set. Period 10 has the lowest average price, and exhibits the lowest volatility, skewness and kurtosis.

3.3. The data series

Figs. 1–4 shows the evolution of the power prices, the spot prices of gas, coal and carbon emission, as well as the day ahead demand and reserve margin forecasts. Due to the large data set we

Table 3
Descriptive Statistics of the power price for period 10, 14, 19, 25, 35 and 43.

Period	Mean	Median	Maximum	Minimum	Volatility	Skewness	Kurtosis
10	29.51	29.10	57.62	6.38	9.64	0.18	2.31
14	34.74	33.50	139.36	5.27	12.42	1.11	6.55
19	47.22	43.71	206.14	13.79	21.49	2.16	10.95
25	54.20	48.38	409.66	15.89	28.43	3.38	23.90
35	61.94	51.78	553.30	13.22	42.08	3.93	28.98
43	43.97	41.91	208.46	15.98	17.94	2.38	13.92

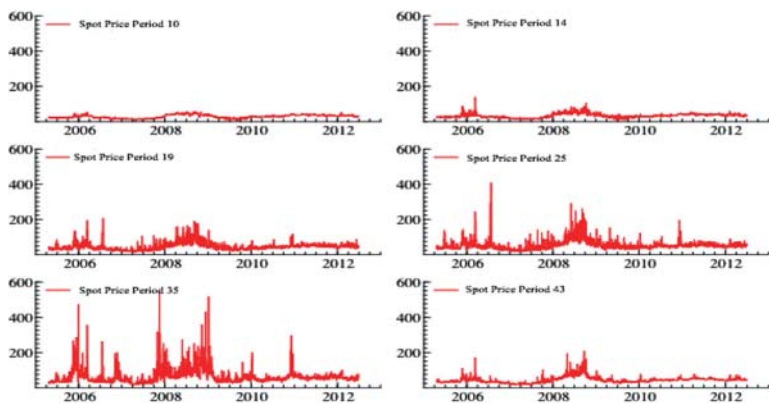

Fig. 1. The actual series of the power price for period 10, 14, 19, 25, 35 and 43 respectively. The data spans from 22.04.2005 to 28.06.2012.

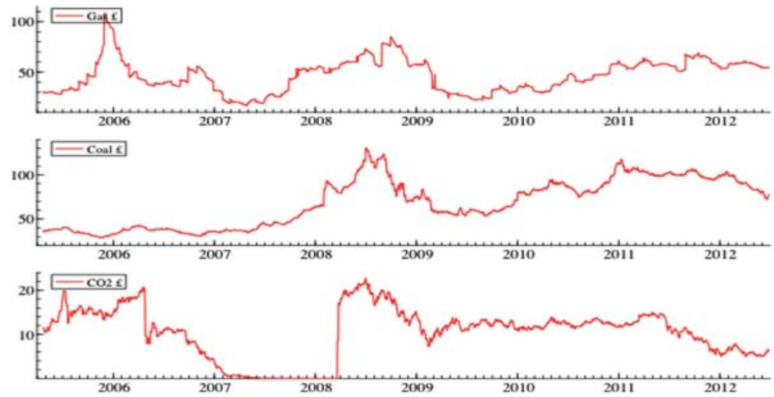

Fig. 2. The actual series of the daily UK natural gas spot price from the NBP (National Balance Point) (quoted in £/MMBtu), the daily HWWI world index coal price (translated into £/ton) and the EEX-EU carbon emissions allowance daily spot price (translated into £/ton), respectively. The data spans from 22.04.2005 to 28.06.2012.

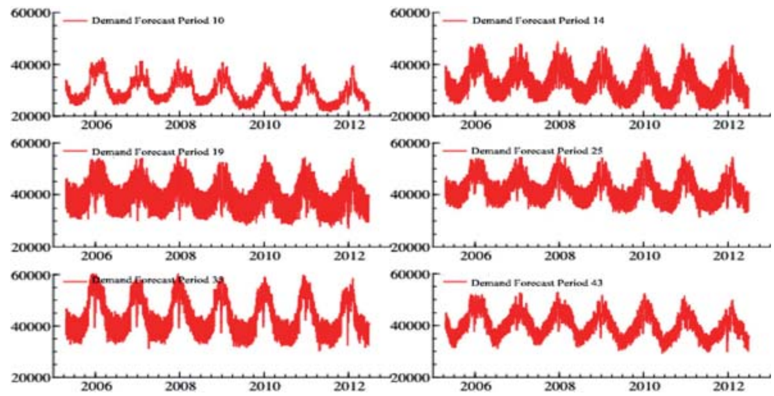

Fig. 3. The actual series of the UK national demand forecast from the system operator for period 10, 14, 19, 25, 35 and 43 respectively (quoted in MW). The data spans from 22.04.2005 to 28.06.2012.

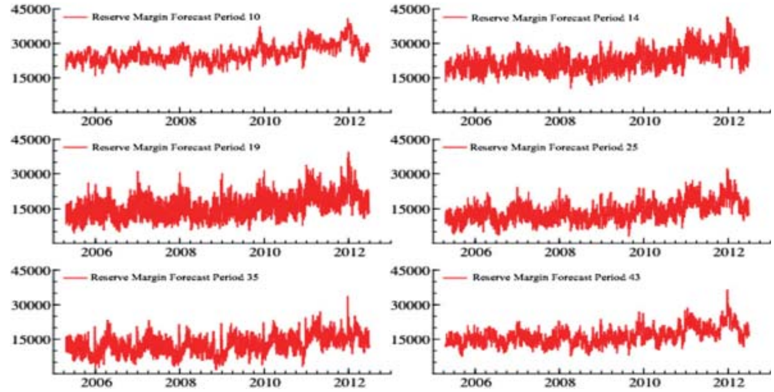

Fig. 4. The actual series of the UK national forecast of reserve margin from the system operator for period 10, 14, 19, 25, 35 and 43 respectively (quoted in MW). The data spans from 22.04.2005 to 28.06.2012.

Table 4
Test statistics from the Jarque Bera normality test, Breuch–Godfrey LM test, White's Heteroscedasticity test and ARCH LM test.

Period	Jarque Bera test	Breuch–Godfrey test	White's test	ARCH LM test
10	7659.96***	44.45***	523.75***	169.63***
14	13955.5***	284.06***	331.18***	145.39***
19	1365.8***	125.69***	311.5***	57.96***
25	517.69***	31.8***	431.75***	107.04***
35	1278.07***	46.55***	402.16***	61.02***
43	3451.77***	55.39***	63.72***	63.72***

*** Indicates that we reject the respective null hypothesis at the 1% level.

have chosen only to show the data series of the representative periods for electricity prices, demand and margin forecasts. The price series reveal typical spot electricity features such as spikes, mean reversion, seasonality and high, time varying volatility. Fig. 1 also shows clear signs that the price dynamics vary between the different time periods.

3.4. Descriptive statistics

In Table 3 we present a summary of descriptive statistics for the representative periods, confirming what we observed in Fig. 1, that is a high standard deviation and substantial skewness and kurtosis. A more extensive analysis of the descriptive statistics for all 48 periods has also been performed. All skew coefficients are positive. This effect is anticipated for electricity markets at that time and reveals that extreme price outliers occur on the upside of the average. Extreme prices are also common in electricity markets. We also see that there is high correlation between the period's mean price and the standard deviation, skewness and kurtosis levels. We detect severe serial correlation in the data. However, it drops substantially from lag 1 to 2. For some periods we detect prominent autocorrelation in lag 7.

As a benchmark we ran OLS regressions and performed various residual tests, revealing that the residuals are non-normal, heteroscedastic, serial correlated and have ARCH-effects. Results for our representative periods are summarized in Table 4. We also performed an ADF test for stationarity in the series. The results are reported in Tables 5 and 6. Electricity price and margin forecasts appear stationary, so does the demand forecast for the most part. We cannot, however, reject the unit root null hypothesis for gas, coal and carbon emission prices.

4. Models

4.1. Linear quantile regression

Linear quantile regression was introduced by Koenker and Bassett [14]; and seeks to compute a set of regression functions, each corresponding to a different quantile of the conditional distribution of the price. The difference between quantile regression and OLS is that while OLS estimates the regression coefficients so that the regression line run through the average of the data set, quantile regression lines will pass through different quantiles of the distributions. For lower quantiles the majority of the data set will lie above the quantile regression line. For higher quantiles the majority of the data set will lie below the quantile regression line [1]. The advantage of quantile regression is that we are able to investigate the relationship between the dependent and independent variables across the entire distribution, and thus build up a more complete picture of how fundamental factors affect the electricity price in various price ranges.

From a risk perspective we want to be able to estimate the tail dependencies accurately and quantile regression works well for this purpose. Quantile regression is closely related to value at risk in estimating the price at extreme quantiles. For traders and risk managers it is thus a useful tool for assessing price risk and developing hedging strategies.

The quantile regression model is semi parametric, thus we do not make any assumptions about the distribution of our data or about the residuals. Due to the highly non-normal behavior of the electricity price, as well as time-varying volatility, this is an advantage for our research. Significance testing of quantile regression is still very much in the exploratory stage, and no single approach has yet gained widespread support. For further discussion, see Ref. [19].

We let q ε (0,1) be quantile 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95%, 99%. Our linear quantile regression model will then be given by:

$$Q_q(\ln P_{i,t}) = \alpha_i^q + \beta_{i,1}^q \ln P_{i,t-1} + \beta_{i,2}^q \ln GAS_{t-1} + \beta_{i,3}^q \ln COAL_{t-1} + \beta_{i,4}^q \ln CO2_{t-1} + \beta_{i,5}^q \ln DF_{i,t} + \beta_{i,6}^q \ln MF_{i,t}$$

where $i = 1,\ldots,48$.

Further we let $\boldsymbol{X}_{i,t}$ be the 6-dimensional vector, representing the six independent variables in Section 3.1. We can then rewrite the model as:

$$Q_q(\ln P_{i,t}|\boldsymbol{X}_{i,t}) = \alpha_i^q + \boldsymbol{X}_{i,t}\boldsymbol{\beta}_i^q$$

We find the q quantile regression coefficients for period i, $\widehat{\alpha}_i^q$ and $\widehat{\boldsymbol{\beta}}_i^q$, as the solution to the following minimization problem:

$$\min_{\alpha_i^q,\boldsymbol{\beta}_i^q} \sum_{t=1}^{T} \left(q - 1_{\ln P_{i,t} \le \alpha_i^q + \boldsymbol{X}_{i,t}\boldsymbol{\beta}_i^q}\right)\left(\ln P_{i,t} - \left(\alpha_i^q + \boldsymbol{X}_{i,t}\boldsymbol{\beta}_i^q\right)\right)$$

$$\text{Where } 1_{\ln P_{i,t} \le \alpha_i^q + \boldsymbol{X}_{i,t}\boldsymbol{\beta}_i^q} = \begin{cases} 1 & \text{if } \ln P_{i,t} \le \alpha_i^q + \boldsymbol{X}_{i,t}\boldsymbol{\beta}_i^q \\ 0 & \text{otherwise} \end{cases}$$

Table 6
ADF test of the daily UK natural gas spot price, the daily HWWI world index coal price (translated into £/ton) and the EEX-EU carbon emissions allowance daily spot price (translated into £/ton). The data spans from 22.04.2005 to 28.06.2012. We have chosen 5 lags in the ADF test.

	Gas price	Coal price	Carbon emission price
t-ADF	−2.284	−1.367	−2.24

*, ** and *** Indicates that we reject the null hypothesis and find stationarity at the 10%, 5% and 1% level respectively.

Table 5
ADF test for stationarity in the power Price, the UK national demand forecast and the UK national margin forecast, for period 10, 14, 19, 25, 35 and 43. The data spans from 22.04.2005 to 28.06.2012. We have chosen 5 lags in the ADF test.

	10	14	19	25	35	43
Price, t-ADF	−3.446***	−4.217***	−6.855***	−8.558***	−8.858***	−4.983***
Demand, t-ADF	−2.665*	−4.197***	−7.227***	−5.149***	−3.270**	−2.804*
Margin, t-ADF	−6.234***	−5.758***	−7.458***	−5.892***	−6.241***	−5.644***

*, ** and *** Indicates that we reject the null hypothesis and find stationarity at the 10%, 5% and 1% level respectively.

We run the quantile regression in EViews, obtaining 432 models (48 × 9). The associated standard errors are obtained using the Huber Sandwich method. This method is robust when the residuals are heteroscedastic [13]. The use of natural logarithms implies that our coefficients will be interpreted as elasticities, i.e. how sensitive the electricity price is towards a change in the fundamental factors, measured in relative terms.

5. Quantile regression results

In Table 7 we present the comprehensive quantile regression results. We show the quantile regression results for the six representative periods, with its associated pseudo R-squared [15].

In general, coefficients are significant, and we find that lagged price, fuel prices and demand forecast have a positive effect on electricity prices, while margin forecast has a negative effect. At night, when market activity is low, lagged price is by far the variable in our model that affect prices most. As activity increases during the day, demand, margin and fuel prices affect the electricity price with increased strength, while the lagged price affects electricity prices less. Carbon emission prices have little or no effect on electricity prices.

We use Pseudo R-square to measure the goodness-of-fit of the model for each associated period and quantile. In general the Pseudo R-square is quite stable over the whole 24 h, and at a level ranging from 0.42 to 0.76. We note that the pseudo R-squares are slightly higher for off-peak than peak periods. This suggests that

Table 7
Quantile regression results for period 10, 14, 19, 25, 35 and 43. Numbers in italic represent coefficients that are insignificant at a 5% level assuming a t-distribution. R-squared is a [15] goodness-of-fit measure (pseudo R-squared).

	1%	5%	10%	25%	50%	75%	90%	95%	99%
Period 10									
const	−5.278	−3.333	−2.261	−0.771	*0.198*	*0.375*	1.009	*0.874*	*−0.456*
lprice	0.981	0.836	0.861	0.840	0.798	0.724	0.599	0.479	0.307
gasprice	*0.037*	0.076	0.066	0.080	0.092	0.125	0.190	0.243	0.321
coalprice	0.174	0.159	0.102	0.089	0.097	0.109	0.140	0.169	0.209
carbon	−0.015	*−0.001*	*0.002*	*0.001*	0.003	*0.005*	0.003	0.005	0.011
demand	0.316	0.278	0.187	0.100	0.055	0.079	0.105	0.175	0.403
margin	*0.094*	*−0.009*	*0.001*	−0.044	−0.083	−0.113	−0.192	−0.238	−0.319
R-squared	0.611	0.682	0.718	0.749	0.752	0.716	0.659	0.627	0.571
Period 14									
const	−5.788	−1.636	*−0.572*	0.729	1.246	1.039	1.704	*1.799*	4.141
lprice	0.281	0.346	0.440	0.508	0.545	0.497	0.404	0.348	0.220
gasprice	0.322	0.278	0.239	0.222	0.215	0.259	0.288	0.333	0.450
coalprice	0.401	0.339	0.267	0.228	0.198	0.205	0.233	0.246	0.229
carbon	0.012	0.015	0.019	0.018	0.017	0.014	0.012	0.012	0.016
demand	0.654	0.348	0.262	0.172	0.142	0.201	0.241	0.300	0.291
margin	−0.175	−0.239	−0.239	−0.269	−0.281	−0.317	−0.408	−0.476	−0.682
R-squared	0.580	0.637	0.671	0.684	0.677	0.641	0.611	0.596	0.565
Period 19									
const	1.513	1.520	1.325	*0.722*	1.197	1.634	2.819	3.821	*5.110*
lprice	0.181	0.216	0.226	0.303	0.350	0.406	0.414	0.403	0.399
gasprice	0.329	0.334	0.360	0.354	0.365	0.378	0.374	0.382	0.486
coalprice	0.436	0.405	0.360	0.321	0.268	0.237	0.242	0.212	0.156
carbon	0.020	0.022	0.027	0.021	0.014	0.009	*0.004*	*0.003*	*−0.023*
demand	0.092	0.110	0.145	0.205	0.204	0.230	0.244	0.217	*0.217*
margin	−0.295	−0.310	−0.319	−0.325	−0.361	−0.436	−0.565	−0.617	−0.743
R-squared	0.596	0.616	0.608	0.583	0.549	0.528	0.545	0.542	0.505
Period 25									
const	2.738	4.386	4.480	4.773	4.408	5.504	5.664	5.240	4.822
lprice	0.210	0.214	0.252	0.305	0.422	0.464	0.451	0.506	0.506
gasprice	0.270	0.292	0.311	0.330	0.314	0.324	0.311	0.258	0.152
coalprice	0.397	0.403	0.353	0.289	0.221	0.201	0.214	0.181	0.265
carbon	0.030	0.028	0.025	0.017	0.008	*0.001*	*0.002*	*−0.002*	*−0.007*
demand	*−0.023*	−0.147	−0.149	−0.143	*−0.090*	*−0.078*	*0.060*	*0.159*	0.291
margin	−0.269	−0.308	−0.310	−0.336	−0.353	−0.476	−0.627	−0.669	−0.746
R-squared	0.538	0.518	0.494	0.449	0.421	0.431	0.470	0.489	0.530
Period 35									
const	−1.795	−2.174	−2.038	−1.611	*0.276*	1.776	2.846	4.122	*2.781*
lprice	0.216	0.268	0.288	0.372	0.467	0.528	0.492	0.455	0.471
gasprice	0.346	0.318	0.336	0.329	0.306	0.281	0.324	0.318	0.201
coalprice	0.349	0.301	0.270	0.224	0.189	0.162	0.159	0.166	*0.176*
carbon	0.023	0.028	0.021	0.009	*0.003*	*−0.006*	−0.016	*−0.011*	*0.006*
demand	0.385	0.391	0.400	0.373	0.270	0.227	0.292	0.286	0.565
margin	−0.253	−0.202	−0.220	−0.236	−0.321	−0.420	−0.590	−0.695	−0.810
R-squared	0.624	0.597	0.577	0.569	0.556	0.560	0.573	0.577	0.561
Period 43									
const	*1.450*	1.514	2.184	1.806	1.606	2.118	2.861	4.241	9.207
lprice	0.364	0.449	0.490	0.597	0.684	0.762	0.795	0.827	1.006
gasprice	0.247	0.194	0.204	0.168	0.155	0.129	0.116	0.130	*0.082*
coalprice	0.340	0.297	0.257	0.195	0.131	0.078	0.059	*0.017*	*−0.031*
carbon	0.029	0.024	0.021	0.013	0.005	*0.000*	*−0.002*	*−0.005*	*−0.007*
demand	*−0.047*	*−0.019*	−0.051	*−0.008*	*0.014*	*0.000*	*0.002*	*−0.041*	−0.286
margin	−0.128	−0.148	−0.182	−0.182	−0.178	−0.205	−0.276	−0.362	−0.616
R-squared	0.660	0.692	0.695	0.682	0.665	0.637	0.633	0.620	0.589

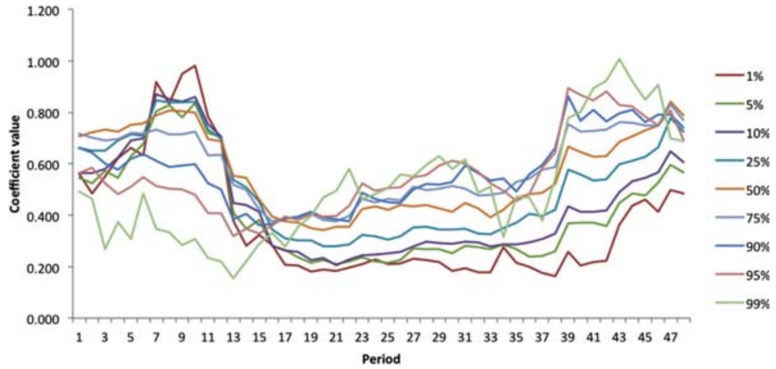

Fig. 5. The graphs show the development in the lagged price coefficient value associated with each quantile, across all 48 periods, found from quantile regression.

during times of scarcity, electricity spot prices are not completely determined by fundamental factors, but partly influenced by the exertion of market power by producers.

5.1. Lagged price

For the trading periods from the late morning until midnight (period 16–48), sensitivity is generally increasing with higher quantiles, as we expected. However, for the periods with the lowest activity, during the second half of the night (period 7–12), sensitivities are instead decreasing with higher quantiles. For the first half of the night and the early morning (period 1–6 and 13–15), sensitivities are larger for the middle quantiles. These are all periods with moderate demand. For the periods with the least demand, in the second half of the night, the lowest quantiles probably represent prices very close to marginal cost and behavioral adaption might thus explain why these prices are similar to the ones observed on the previous day. During the night, demand is neither high nor low, and under such circumstances it seems reasonable that the middle quantiles, representing "normal" prices, will be consistent with the corresponding prices the day before (Fig. 5).

5.2. Gas price

For nearly all periods, sensitivity is higher for periods with high demand than for periods with low demand. The highest sensitivities are found during the day and early evening, while the lowest sensitivities are found during the night and late evening. This is according to expectations.

During the night, early morning and first half of the late morning (period 1–19), sensitivities are generally increasing with higher quantiles. From period 12 to 13, when we approach daytime, the coefficient makes a positive jump, larger for the lowest quantiles. This underlines the fact that prices are much more sensitive to changes in gas price when demand is high. In the second half of the late morning, afternoon and early evening (period 20 to 38), coefficients are more equal across quantiles (except the 95% and 99% quantile), with most coefficients within the 0.25–0.35 range. Towards the end of this period, the coefficients start to decrease with higher quantiles, a trend that continues for the rest of the day (Fig. 6).

5.3. Coal price

As expected, sensitivity is higher for periods with high demand than for periods with low demand. The highest sensitivities are found during the day and evening, while the lowest sensitivities are found during the night. However, we can see that the variation is smaller than for gas. This is according to expectations, because coal mainly is used for base load production.

In the late morning, afternoon, early evening and late evening (period 15–46) the coefficient is higher for low quantiles than high

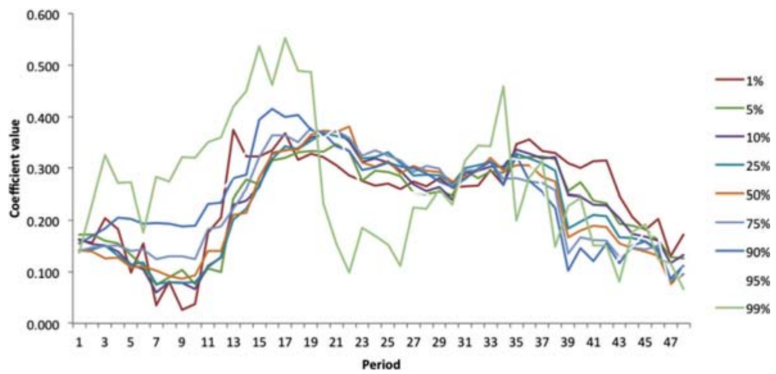

Fig. 6. The graphs show the development in the gas price coefficient value associated with each quantile, across all 48 periods, found from quantile regression.

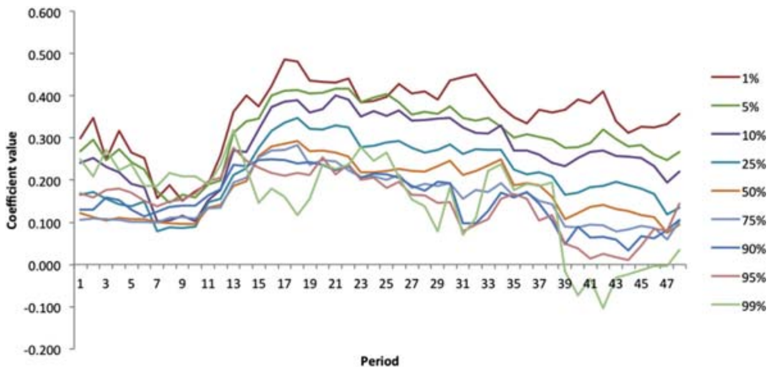

Fig. 7. The graphs show the development in the coal price coefficient value associated with each quantile, across all 48 periods, found from quantile regression.

quantiles. During several evening periods, the coefficients are so small that they even are insignificant for the 95% and 99% quantiles. At night, sensitivities are generally highest for the extreme quantiles. The reason for the increased sensitivity at high quantiles might be that during nighttime few gas plants are operating and thus coal plants will cover peaks in demand caused by e.g. extreme weather. High prices during the night will therefore be very sensitive to changes in the coal price (Fig. 7).

5.4. Carbon emission price

As suspected, the carbon emission price has little effect on electricity prices. The coefficient is generally close to zero and often insignificant. It is worth noticing that the carbon price was equal to zero for quite some time in our data set.

The carbon emissions price does, however, tend to follow the sensitivity pattern of coal. It is generally increasing with higher quantiles during the night, and decreasing with higher quantiles during the day and evening. During the night the coefficient is mainly insignificant for low quantiles, while during the day and night it is often insignificant for high quantiles (Fig. 8).

5.5. Demand forecast

Looking at the results for the night, early morning and late morning (period 45–22) as well as the early evening (period 31–38) we observe that sensitivities for the middle quantiles generally are higher when the period's demand level is higher. For the extreme quantiles there is greater variation (Fig. 9).

In the late morning (period 15–22), the sensitivity is slightly increasing with quantiles. In the night and early morning (period 45–14) as well as tge early evening (period 31–38) sensitivities are generally highest for the extreme quantiles. The difference across quantiles is clearly largest during the night.

We also notice some slightly negative coefficients around the beginning of the afternoon and the beginning of the late evening (periods 23 and 39). This is when the demand is dropping and marginal technologies may be reluctant to be called off. Hence their offers become more competitive. With higher demand and more expensive plant being called, this effect is likely to be more pronounced.

5.6. Reserve margin forecast

Margin levels affect the price according to expectations, with sensitivity increasing in periods with higher demand and with higher quantiles. During the periods of night with the lowest demand levels (period 7–12), the coefficient gets so low that margin forecast has an insignificant effect on prices for the 1%–10% quantiles. During peak hour periods, the effects from reserve margin get higher (in absolute terms) with higher quantiles (Fig. 10).

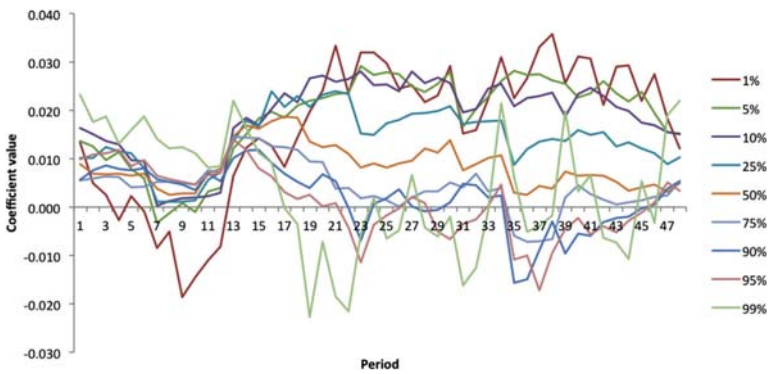

Fig. 8. The graphs show the development in the carbon emission price coefficient value associated with each quantile, across all 48 periods, found from quantile regression.

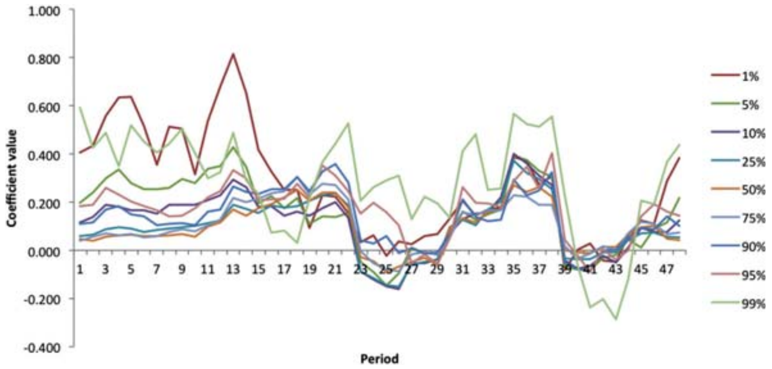

Fig. 9. The graphs show the development in the demand forecast coefficient value associated with each quantile, across all 48 periods, found from quantile regression.

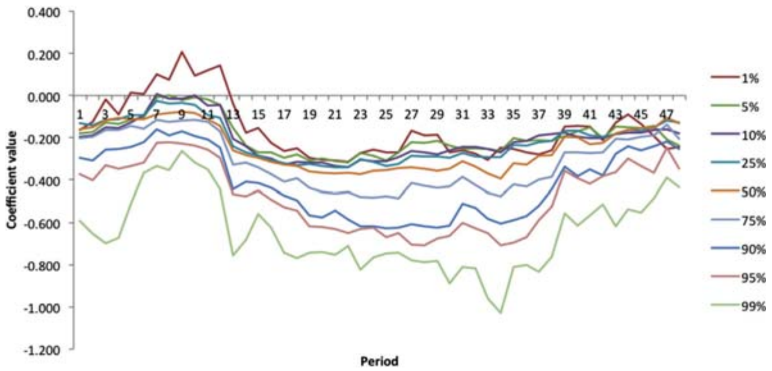

Fig. 10. The graphs show the development in the reserve margin forecast coefficient value associated with each quantile, across all 48 periods, found from quantile regression.

5.7. A comparison of sensitivities to the prices of gas and coal

Looking at Fig. 11 we clearly see that the coal coefficient generally is larger than the gas coefficient at low quantiles, whilst the opposite is the case at high quantiles. This is according to expectations.

The coal price affects the electricity price more for the 5% quantile as compared to the median, while the gas price has more effect for the 95% quantile as compared to the median. This indicates that producers are generally more vulnerable to coal price volatility, while consumers are more exposed to gas price volatility. Not surprisingly, electricity price is more sensitive to demand and margin forecasts at the 95% quantile than at the 5% quantile.

6. Scenario analysis based on the quantile regression model

In this section we present an example that demonstrates how the models can be used to perform a scenario analysis, showing the effect of changes in the fundamental variables on the electricity price distribution. Starting with a base scenario, we can introduce shocks to one or more fundamental variable and obtain the resulting price distribution.

Our base scenario was formed by applying the values of the fundamental variables from the last day of our data set, 28.06.2012, to the associated quantile regression models for period 10, 14, 19, 25, 35 and 43. The actual values on this date are reported in Table 8. By looking at ranges of values for the fundamentals, we are able to construct scenarios of distributions for the electricity price. In our example we investigate the effect of shocks of varying magnitude to the reserve margin forecast. In a similar way, we can also analyze the effects on the price distribution from changing other fundamental variables, individually or jointly. Hence we can directly investigate how a change in one or more of the independent variables affect the different value at risk estimates for the different time periods.

6.1. Scenario analysis example – reserve margin forecast

We applied a set of margin forecasts ranging from 1500 MW to 40925 MW, which is equal to the minimum and maximum margin forecasts in our data set. The results can be seen in Fig. 12. For all periods and parts of the distribution, a decrease in reserve margin will lead to an increase in the electricity price. However, the effect on the electricity price is rapidly decreasing with higher levels of reserve margins. As soon as the reserve margin reaches a threshold level the effect converges for all quantiles and approach zero. Once there is enough supply in the market to cover the demand, having an excess of production capacity in reserve has little or no effect on the market price. On the other hand, if margin levels fall below the threshold, prices will respond to this by increasing exponentially as the margin levels drop further. Changes in margin below the threshold affect the electricity prices more than any other fundamental variable. This implies that both producers and buyers

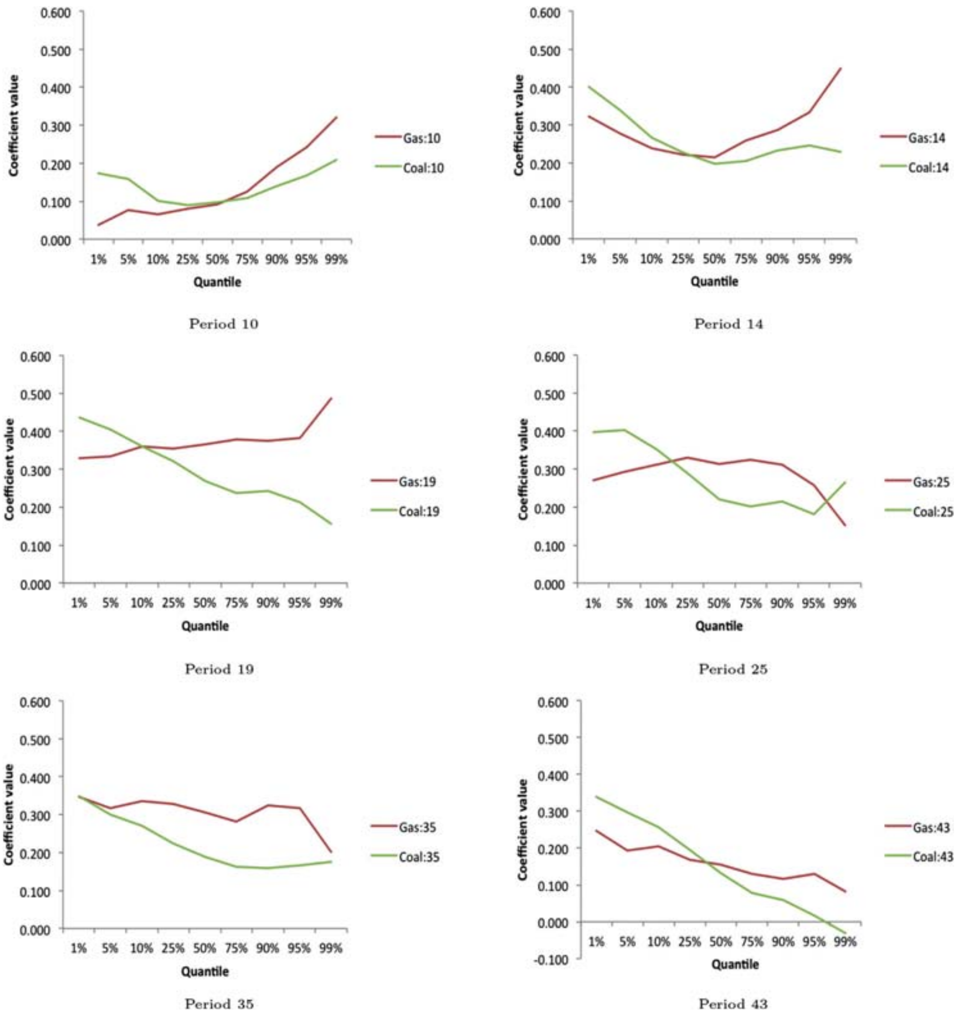

Fig. 11. The graphs show the development in the gas price coefficient value relative to the coal price coefficient value across quantiles for period 10, 14, 19, 25, 35 and 43, found from quantile regression.

Table 8
Base scenario. Actual value of each fundamental variable on 28.06.2012.

Period	Gas (−1)	Coal (−1)	Carbon emission (−1)	Price (−1)	Demand forecast	Margin forecast
Period 10	54.363	77.197	6.318	30.100	25161.000	26442.000
Period 14	54.363	77.197	6.318	32.570	30296.000	22005.000
Period 19	54.363	77.197	6.318	41.100	39454.000	13392.000
Period 25	54.363	77.197	6.318	48.250	41094.000	12068.000
Period 35	54.363	77.197	6.318	55.200	40874.000	11812.000
Period 43	54.363	77.197	6.318	48.260	34956.000	18260.000

should monitor the threshold level carefully, and take into account whether margin levels are expected to fall below or rise above it when placing their bids. The threshold level is different for each period and quantile. During nighttime (period 10 and 43) the effect is small and almost equal to zero for levels of reserve margin above 1500 MW. During daytime the effect on the price of changes in reserve margin is larger. For low margin levels the conditional price distribution has a long right tail. The thresholds levels are higher during day than night, and increasing with higher quantiles during daytime. Market participants should pay close attention when margin levels drop below 20000 MW. Above this level effects on the price will be minor. With the extreme impacts of forecasted scarcity on the electricity price, producers will have incentives to under-report the production capacity of their plants. This underlines the importance of strong regulation and surveillance of the reporting procedures.

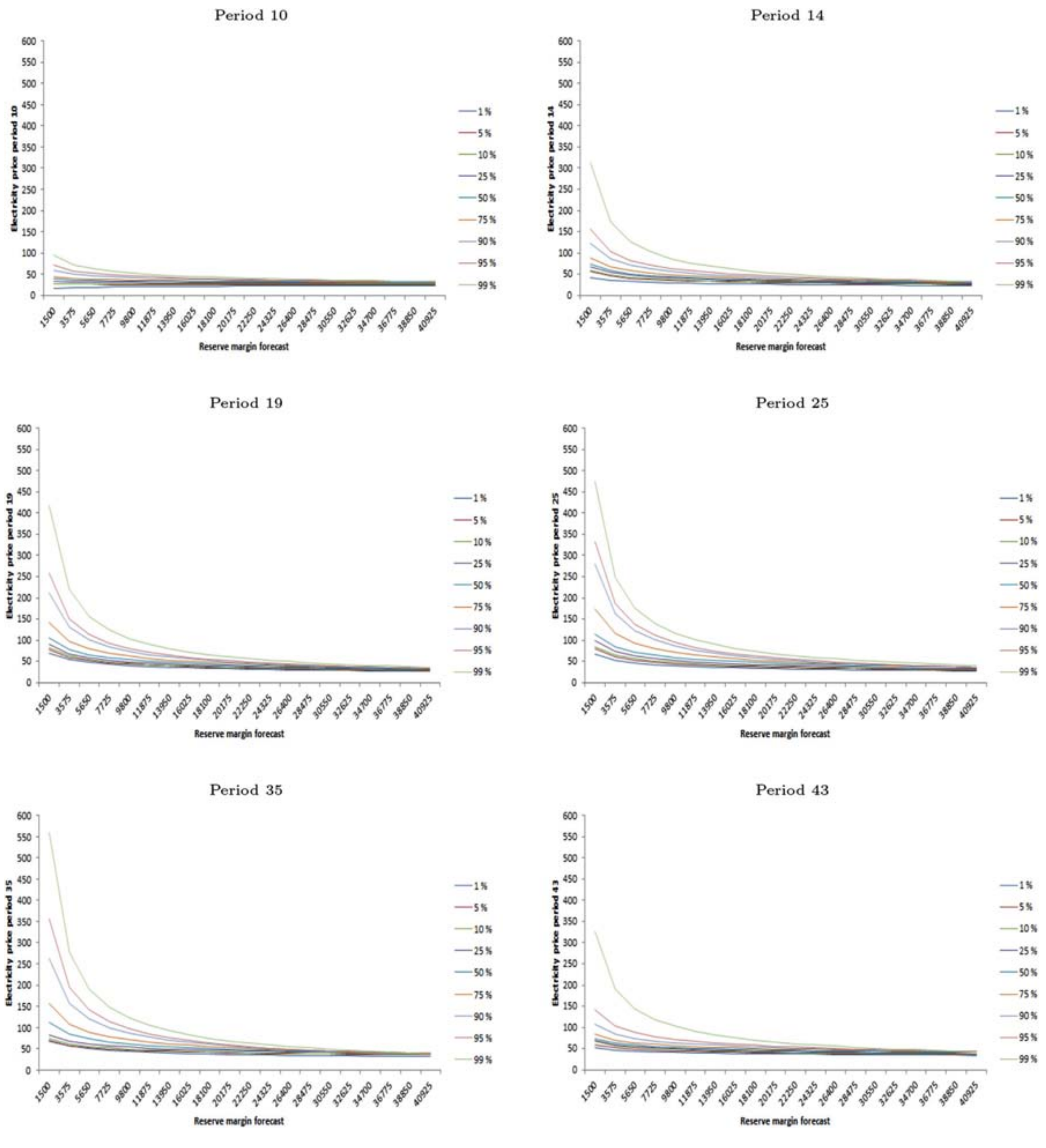

Fig. 12. Scenario analysis of the power electricity price for period 10, 14, 19, 25, 35 and 43, when the reserve margin forecast varies from 1500 MW to 40925 MW. The base scenario is calculated by applying data from the last day of the data set, 28.06.2012, to the different quantile regression models. The reserve margin forecast on 28.06.2012 was 26442 MW, 22005 MW, 13392 MW, 12068 MW, 11812 MW and 18260 MW for period 10, 14, 19, 25, 35 and 43, respectively.

7. Conclusions

Using quantile regression, we have characterized the non-linear effects of fundamental factors on the wholesale electricity price for each delivery period in the UK electricity market. The complex market dynamics were confirmed as we found that the sensitivity to the different factors vary substantially both across the day and across the price distribution. We have paid special attention to the tails, both in our regression analysis and in the scenario analysis.

We demonstrated how lagged prices, prices of gas, coal and carbon, and forecasts of demand and reserve margin influence the price distribution in each of the 48 periods in rather intuitive ways.

In general, we find positive elasticities for the underlying fuel commodities. It was revealed how the sensitivity to gas relative to coal is increasing with the demand level throughout the day. We found, that for our data set, carbon emission prices generally had no significant effect on electricity prices. The sensitivity to changes in demand is generally positive, but the way its impact on prices develops over quantiles varies with the time of day. The elasticity of reserve margin is negative, with increased impact on higher quantiles and in periods with high demand. We confirm the positive sensitivity to lagged price and how it is decreasing with the demand level. We found that the model explained more of the variation in electricity prices, as measured by the adjusted R-squared, in off-peak than in peak periods. This is likely because periods with low margin allow producers to exercise market power more effectively, pushing prices above what is explained by the fundamental variables included in our model.

By performing an example scenario analysis, we have demonstrated how scenario analysis can be used to illustrate the actual magnitude changes in the fundamental variables have on the electricity price distribution. The effect of previous prices, as captured by the lagged price, represents the main risk factor for producers, in terms of large price drops. Additionally, producers face risk if the price of the fuel used in production increases, and they cannot recover the extra cost through a sufficient increase in the electricity price. The main risk drivers for buyers and consumers are a high lagged price and low levels of reserve margin. In general, the main risk is carried by the consumer side.

We believe that our findings have important implications for market participants in both the spot and financial electricity market. Our paper provides a deeper understanding of the price formation process and reveals insight on the main risk drivers. Based on this market participants can fine tune their bids and reduce their exposure to risk. An advantage of quantile regression is that it is easy to apply compared to alternatives such as regime switching models or CaViaR based models. This gives it a widespread appeal, and increase the probability that it will be implemented by market participants.

The next natural step is to do forecasts based on this model and test its forecasting ability. Further research can extend the quantile regression analysis to include more explanatory variables. Our model can then serve as a point of reference. Renewables have over the time span of our data set become a much more influential fuel source, and will have a natural place in future electricity market modelling, when the share of electricity produced from renewables has stabilized at a sufficient level. For some periods the model might benefit from including lag 7 of the endogenous variable in order to capture weekday effects. Also, a proxy for market power could be included for the peak periods. By comparing the goodness-of-fit and forecasting performance to our model, one can evaluate whether these modifications are successful.

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3. Essay 2 - Using quantile regression to analyze the effectof renewables on EEX price formation

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Using quantile regression to analyze the effect of renewables on EEX price formation

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Abstract. This paper develops fundamental quantile regression models for the German electricity market. The main focus of this work is to analyze the impact of renewable energies, wind and photovoltaic, on the formation of day-ahead electricity prices for all trading periods in the EEX. We find that the renewable energy sources overall has a mild price dampening effect, and that the negative prices often attributed to wind power is a rare event that mainly occurs during nighttime periods of unusually low price and demand.

1 Introduction and literature review

Price dynamics for electricity markets has become increasingly complex as deregulation, market integration, and changes in input mix have taken place in different regions around the world. Electricity markets are characterized by mean reversion, seasonality, time varying volatility, jumps, positive skewness, high kurtosis and a complex relation to fundaments as the supply curve is convex and highly non-linear while the demand curve is almost in-elastic. Another complicating factor is that the input mix for power production might change over time (e.g. using more renewables), hence changing the dynamics for a given market over time. Considerable efforts have been performed from practitioners and academics trying to understand the price formation in different markets.

For consumers, suppliers, risk managers, traders and regulators concerned with market surveillance, modeling and forecasting the tails of the power price distributions is crucial when assessing risk. Risk in this context is usually measured by Value at Risk (VaR) or Expected Tail Loss (ETL) using information of the return/price distribution. At the same time, one is also interested in finding out how the different risk factors (supply and demand variables) influence different parts of the price distribution. The aim of this paper is to establish a model that enables us to perform such analysis.

In this paper, we analyze the impact of renewable energies, wind and photovoltaic, on the formation of day-ahead electricity prices for different hours for the German (EEX) market using quantile regression. More specifically, we quantify the non-linear relationship between the renewables (and other supply/demand variables) on prices at different hours. E.g. we can study how wind production influences the 5% price quantiles at hour 3. The effect of a given variable will vary whether prices are high or low and whether we look at off-peak versus on-peak hours. According to our knowledge, no such study has been performed yet for the German market.

Our study is based on selected references investigating empirically how supply and demand variables influence the electricity price formation in different markets. In the Nord Pool market, references [1] and [2] study how Nord Pool market prices relates to water reservoir levels (in Nord Pool, hydro power is the dominant supply source). The estimation technique is non-linear regression capturing the shape of the convex supply curve. They argue that the marginal cost of hydro production varies depending on reservoir levels that determine hydro production capacity. The results show that higher reservoir levels, more hydro capacity, lead to significant lower power prices. They conclude that an increase in low marginal costs renewable power supply reduces the power prices and in the paper they demonstrate the numerical effects.

For the UK market, early studies by reference [3] applied a Markov regime-switching model, while reference [4] used a smooth transition logistic regression model investigating how fundamentals influence different periods of the day. Both studies give valuable insight into how sensitivities vary over time and parts of the day. Reference [5] introduced quantile regression for modeling the UK electricity price. By analyzing the period 38, they demonstrate how gas, coal, carbon prices, forecasts of demand and supply influence the electricity prices in a non-linear way. They also demonstrated how the model could be used for Value-at-Risk forecasting, where this fundamental quantile regression model performed used as good as complex GARCH and CAViaR methods, although their approach was simpler to implement. Reference [5] does not address the distinctly different intraday characteristics

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hour by hour of the price risk distribution though. Yet it is well known that price formation (and hence risk) varies systematically throughout the day with different models generally being specified for peak, off-peak and mid-peak hours to reflect the dynamics of load following and the various technologies setting the marginal prices. With this in mind, reference [6] investigates all 48 half hourly prices from the UK market, across the range of quantiles from 1% to 99%, estimated over the period 2005–2012. This paper also demonstrates the usage of scenario analysis where one can investigate how a change in one of the independent variables (e.g. forecast of demand) influences a specific period price quantile.

Regarding fundamental price models for the German market, [7] is a central reference. They find that the sensitivities of day-ahead electricity spot prices to the fundamental variables coal, gas, oil, and renewable energies, vary over time using a state space framework. They observe a continuous price adaption process of electricity prices to market fundamentals. Overall, the results show the importance of linking electricity spot prices to their fundamentals and suggest that purely stochastic models can be a too simplistic assumption. Since the input mix in Germany has changed over the last years, the paper also highlights the importance of a model allowing for time-varying sensitivities to fundamentals. They also show how the increase in the infeed from renewable energies, wind and PV, led to a partial decrease in electricity day-ahead prices in Germany. This effect is noticeable for afternoon, evening and night hours in case of wind, and for noon peak hours, in case of PV. Furthermore, the inclusion of renewable energies improves considerably the explanatory power of the model. Additionally, renewable energies substitute the use in production of traditional fuels situated to the right of the merit order curve. In particular, the sensitivity of electricity prices to gas decreases over time. This fact becomes more visible for peak hours, due to the increase in the PV infeed.

Our paper is a combination of the quantile regression approach described in [5] and [6] applied on the dataset given in [7]. Since the German market has a different input mix than the UK market, we cannot simply transfer results from one study to another. Our aim is to investigate non-linear relationship between fundamentals (particular wind and solar production) and prices and detect how the price distribution (hence risk) is influenced by the various drivers in the German market.

The paper is organized as follows. In Section 2, we offer a brief overview of the data and descriptive statistics. Section 3 describes the quantile regression models applied, and Section 4 discusses the preliminary results from these models. Finally, in Section Section 5 we conclude.

2 Data

The data used to estimate our model spans from January 1, 2010 to May 31, 2014 and consists of hourly data for most of the EEX specific market data and fundamentals and daily data for the main fuel sources. A brief overview of the variables used in the model is presented in Table 1. We refer to [7] for a more detailed description and discussion of the relevance of each variable.

3 Model

The model used for our analysis is a quantile regression model [8,9]. This method allows us to investigate the relationship between the dependent and independent variables across the entire distribution, and provides us with a tool to get a better picture of how the fundamental factors affect the price in different quantiles.

The model is specified using levels, not natural logarithms. It is specifically set up this way to show how the relative impact of the fundamental factors in the model change across time and quantiles, with a particular interest for the lower extreme prices which some times reach negative numbers.

Letting $q \in (0,1)$ represent the different quantiles, 1%, 5%, 10%, 25%, 50%, 75%, 90%, 95% 99%, our linear quantile regression model will then be given by:

$$\begin{aligned} Q_q(P_{i,t}) = {} & \alpha_i^q + \beta_{i,1}^q\, P_{i,t-1} + \beta_{i,2}^q\, AVG\_SPOT \\ & + \beta_{i,3}^q\, SPOT\_VOL + \beta_{i,4}^q\, COAL_{t-1} + \beta_{i,5}^q\, OIL_{t-1} \\ & + \beta_{i,6}^q\, EUA_{t-1} + \beta_{i,7}^q\, EX\_WIND_t + \beta_{i,8}^q\, EX\_PV_t \\ & + \beta_{i,9}^q\, Z_i\, EX\_PPA_t + \beta_{i,10}^q\, EX\_DEMAND_t \\ & + \beta_{i,11}^q\, DEMAND_t, \end{aligned}$$

where
$i = 1, \ldots, 24$ represents the 24 time periods throughout the day.
$Z_i = 1$ for hours $7, \ldots, 21$ and 0 for the remaining hours.

We let $X_{i,t}$ be the 11-dimensional vector of independent variables. We can then rewrite the model as:

$$Q_q(P_{i,t}|X_{i,t}) = \alpha_i^q + \beta_i^q X_{i,t}.$$

We find the q quantile regression coefficients for period i, $\overline{\alpha}_i q$ and $\overline{\beta}_i q$, as the solution to the following minimization problem:

$$\min_{\alpha_i^q, \beta_i^q} \sum_{t=1}^{T} (Q - 1_{P_{i,t} \le \alpha_i^q + X_{i,t}\beta_i^q})(P_{i,t} - (\alpha_i^q + X_{i,t}\beta_i^q)),$$

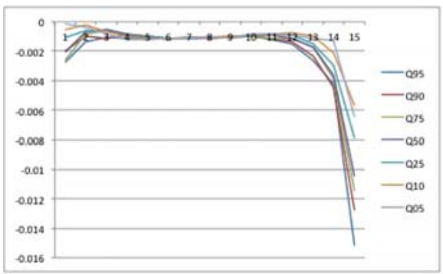
where

$$1_{P_{i,t} \le \alpha_i^q + X_{i,t}\beta_i^q} = \begin{cases} 1 & \text{if } P_{i,t} \le \alpha_i^q + X_{i,t}\beta_i^q \\ 0 & \text{otherwise} \end{cases}.$$

The quantile regressions are estimated using STATA, using the sqreg command. A total of 216 (9×24) models have been estimated. This method estimates all the quantiles for any given hour simultaneously, generating a variance–covariance matrix that allows for meaningful comparisons of coefficients across quantiles. Standard errors are obtained via bootstrapping.

Table 1. Brief overview of the data used in for the model. Refer to [7] for a full description.

Variable, units	Description	Data source
Lagged spot price, EUR/MWh	Market clearing price for the same hour of the last relevant delivery day	European Energy Exchange: http://www.eex.com
Average lagged spot price, EUR/MWh	Average market clearing price across all 24 h of the last relevant delivery day	European Energy Exchange: http://www.eex.com
Spot price volatility, EUR/MWh	Standard deviation of market clearing prices for the same hour on the last five relevant delivery days	European Energy Exchange: http://www.eex.com
Coal price, EUR/12 000 t	Latest available price (daily auctioned) of the front-month Amsterdam–Rotterdam–Antwerp (ARA) futures contract before the electricity price auction takes place	Bloomberg, Ticker: GTHDAHD Index
Oil price, EUR/bbl	Last price of the active ICE Brent Crude futures contract on the day before the electricity auction takes place	Bloomberg, Ticker: COA Comdty
Price for EUA, EUR 0.01/EUA 1000 t CO_2	Latest available price of the EEX Carbon Index (Carbix), daily auctioned at 10:30 am	European Energy Exchange: http://www.eex.com
Expected wind and PV infeed, MWh	Sum of expected infeed of wind electricity into the grid, published by German transmission system operators in the late afternoon following the electricity price auction	Transmission system operators: http://www.50Hertz.com, http://www.amprion.de, http://www.transnetbw.de, http://www.tennestto.de
Expected power plant availability, MWh	Ex ante expected power plant availability for electricity production (voluntary publication) on the delivery day (daily granularity), published daily at 10:00 am.	European Energy Exchange and transmission system operators: ftp://infoproducts.eex.com
Expected demand, MWh	Demand forecast for the relevant hour on the delivery day as modeled in [X]	Own data, German Weather Service: http://www.dwd.de
Lagged demand, MWh	Sum of total vertical system load and actual wind infeed for the same hour on the last relevant delivery day	Transmission system operators: http://www.50Hertz.com, http://www.amprion.de, http://www.transnetbw.de, http://www.tennestto.de



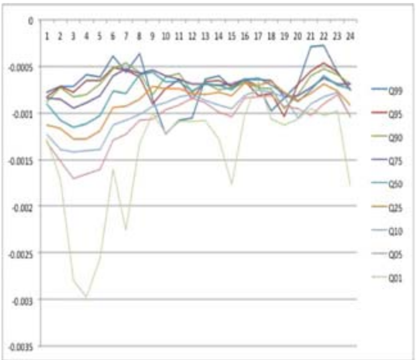
Hour	Q95	Q90	Q75	Q50	Q25	Q10	Q05
6	0	0	0	0	0,01	0,458	0,864
7	0	0	0	0	0,008	0,511	0,249
8	0,001	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0
18	0	0	0	0	0	0,001	0,004
19	0	0	0	0	0	0	0,011
20	0	0	0	0	0	0	0

Fig. 1. Graphical representation of the coefficients for PV infeed for various quantiles, as well as the *P*-values for these coefficients.

4 Results

4.1 PV infeed

As shown in Figure 1, the coefficients for PV are found to be significant in the model for all but one extreme quantile. Overall, we observe that PV lowers the electricity market price. This is in line with the literature [7]. We observe a higher marginal effect of PV on the prices in higher quantiles. In the evening peak there is also, in absolute value, a higher marginal effect by PV on the market prices. Here we observe, to a larger extent, that the marginal effect in absolute terms increases with quantiles. Overall, PV reduces the chance of extreme spikes at EEX.



Hour	Q99	Q95	Q90	Q75	Q50	Q25	Q10	Q05	Q01
0	0	0	0	0	0	0	0	0	0,001
1	0	0	0	0	0	0	0	0	0,345
2	0	0	0	0	0	0	0	0	0,239
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0,018
5	0	0	0	0	0	0	0	0	0,008
6	0	0	0	0	0	0	0	0	0,136
7	0,31	0	0	0	0	0	0	0	0
8	0,015	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0
12	0,004	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0,017
14	0	0	0	0	0	0	0	0	0,022
15	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0,002
17	0,012	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0
19	0,015	0,001	0	0	0	0	0	0	0
20	0,264	0	0	0	0	0	0	0	0
21	0,143	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0,011

Fig. 2. Graphical representation of the coefficients for wind infeed for various quantiles, as well as the *P*-values for these coefficients.

4.2 Wind infeed

As shown in Figure 2, the coefficients for wind infeed is found to be significant in the model for all but a few cases of extreme quantiles in certain hours. According to historical price data from the EEX, negative prices occur mainly during the night hours. According to the literature, this is to a large extent caused by high wind infeed. This occurs because a large excess of electricity is produced night, when the demand is very low. For very low quantiles, often corresponding to where the negative price spikes are found, the marginal effect of wind is more powerful. Overall, we observe that wind decreases the electricity prices. During the night hours in particular, we observe that the marginal effects decrease in absolute values with the quantiles.

5 Conclusions

Using quantile regression, we have characterized the non-linear effects of fundamental factors on the wholesale electricity price for each delivery period in the EEX. We confirm the complex market dynamics by demonstrating that the different factors vary substantially both across the trading periods and across the price distribution.

Even though this is just a preliminary study, we find clear indications that the renewable energy sources have a price dampening effect on the EEX. However, the negative spikes often attributed to wind production seems to be a rare event happening in low demand periods and not something that affects a large trading volume.

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4. Essay 3 - Prediction of extreme price occurrences in the German day-ahead electricity market

Lars Ivar Hagfors, Hilde Hørthe Kamperud, Florentina Paraschiv, Marcel Prokopczuk, Alma Sator, Sjur Westgaard

Quantitative Finance 16.12 (2016): 1929-1948.

5. Essay 4 - A Comparative Analysis of Price Drivers of Day-Ahead Electricity Prices in EPEX and Nord Pool

Lars Ivar Hagfors, Hilde Hørthe Kamperud, Alma Sator, Sjur Westgaard

Working paper, under review.

A Comparative Analysis of Price Drivers of Day-Ahead Electricity Prices in EPEX and Nord Pool

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Abstract

In this paper we analyze the fundamental drivers behind electricity spot prices in Nord Pool and the German European Power Exchange (EPEX), and compare the price formation dynamics in these two markets. The comparison is motivated by the NordLink cable which will connect Germany and Norway in 2020. It will exploit the differences in market characteristics, and is expected to reduce the price spread and improve utilization of renewable energy sources. Our paper increases the understanding of the market mechanisms, which is required by market participants in order to adapt to the future changes.

Separate quantile regression models are estimated for each trading period to capture varying intraday properties of the electricity prices. We examine the price formation dynamics across the entire distribution, and how it differs between Nord Pool and EPEX. The results show that the fundamental variables impact the two markets differently and non-linearly throughout the trading day. Autoregressive effects are most influential in Nord Pool, together with demand and supply in the highest quantile. Overall, most variables have a low price impact; this is likely due to the large amount of flexible and stable hydro power which cancels out fluctuations in other parameters. EPEX has a higher number of important price drivers across the price distribution. Demand is the primary price determinant, while fossil fuel prices, autoregressive effects, and wind power production also notably impact the price formation. The energy mix characteristics are the likely reason for these differences, as EPEX is much more inflexible due to large-scale thermal production and intermittent renewable energy.

1 Introduction

The two day-ahead electricity markets, Nord Pool and EPEX, are to be connected for the first time in 2020 when the NordLink cable between Norway and Germany starts operating. In this context it is important to compare the day-ahead electricity price formation between the Nord Pool spot market and the German spot market, EPEX, in order to better understand how future price formation might change. The Nordic power production is strongly dominated by hydro power, a highly flexible and predictable energy source. Germany's power production is dominated by large-scale inflexible thermal energy, such as nuclear and coal, with a fairly large and swiftly growing share of intermittent wind and photovoltaic power.

Connecting two markets with complimentary characteristics is expected to be beneficial for market participants on both sides. For instance, when EPEX wind production is very high, the excess energy can be exported to Nord Pool to cover demand, hence storing hydro power for later use (Mauritzen (2013)). Oppositely, when wind production is low in Germany, Nordic hydro producers can increase production and export to EPEX, preventing prices from spiking, as has been observed in the recent past. Overall, the interconnection is expected to reduce the price spread between the two markets. A thorough understanding of the present market situation and how it will be impacted by the changes is important for many market participants, as the interconnection is likely to impact the price dynamics.

The objective of our analysis is to study how different exogenous variables, e.g., demand, wind power, and fuel prices, impact the price formation. The price dynamics is compared based on fundamental variables in order to understand the similarities and the differences between the two markets. We analyze the spot price distribution in both EPEX and Nord Pool using linear quantile regressions. Linear quantile regression is sufficiently powerful to facilitate a comparative study, as our purpose is not to forecast prices or examine which model provides the best results methodologically, but to compare the dynamics. Furthermore, it allows us to model each quantile of the distribution separately, providing insight into the dynamics of the price formation across the whole distribution. Each trading period is modeled separately to assess how the impact varies throughout the trading day. Low, intermediate, and high quantiles of the price distributions are modeled to capture the non-linear impact of each fundamental variable.

In order to meet the European climate and environmental targets, large increases in renewable energy and improved interconnections are needed. Germany plans to eliminate all nuclear power production by 2022, and thus requires large increases in new energy capacity. These changes are slowly modifying the fundamental structure of the market. Our analysis is therefore relevant for assessing and comparing the market dynamics of EPEX and Nord Pool. According to Statnett, the main grid operator in Norway, the NordLink cable is found to be profitable and to have positive impacts on security of supply and intermittency issues caused by renewable energy (Statnett (2013)). Both markets have been analyzed separately (Hagfors et al. (2016b), Paraschiv et al. (2014), Huisman et al. (2013) and Huisman et al. (2015)), but a comparative analysis of the price drivers as presented here does not, according to our knowledge, exist in literature.

Our results clearly show that the price formation dynamics in EPEX and Nord Pool are different, and that the fundamental variables have highly non-linear effects in various quantiles and times of day. With its less flexible energy mix, EPEX has a high number of relevant price drivers. The most influential factors are the balance between production and consumption, followed by fuel prices and autoregressive effects. Wind and volatility mainly impact the tails of the price distribution. The price formation dynamics in Nord Pool are dominated by autoregressive effects, while other factors tend to be influential only in the tails. The sensitivities of fossil fuel prices and wind power production are lower than in EPEX, which makes sense considering the differences in energy mix. The flexible hydro production balances fluctuations in other factors, thus limiting the price impact when prices are in the normal range.

The remainder of this paper is structured as follows. In Section 2 an overview of existing literature on use of fundamental models on electricity prices and previous market comparisons is presented. Next, Section 3 presents market descriptions of the German EPEX market and Nord Pool, a comparison of energy mixes, and a discussion on expected future changes. Section 4 discusses choice of data and its statistical properties, and includes an analysis of correlations between EPEX and Nord Pool. Linear quantile regression and modeling choices are presented in Section 5. The impact of each fundamental variable is analyzed and compared in Section 6; the price drivers are examined throughout the entire trading day and price distribution. Finally, the conclusion of the comparative analysis is presented in Section 7, as well as recommendations for further work.

2 Literature Review

Our paper can be placed in the context of two main research areas: (i) fundamental modeling of electricity prices, and (ii) interactions and comparisons between different electricity markets. Understanding the electricity price formation and modelling it with high accuracy has been a popular topic in the literature for years. Identifying the drivers behind electricity prices and their individual impact is required to be able to understand the relationship between fundamental variables, such as demand and supply, and consequently prices.

The literature regarding fundamental modeling of electricity prices in various markets is extensive. Nogales et al. (2002) develop a dynamic regression model and a transfer function model for accurate price forecasts in the Spanish and the Californian electricity market. Torro (2007) further develops time series modeling with an ARIMAX model to model weekly futures prices at the Nord Pool market. Karakatsani and Bunn (2008) critique Nogales et al. (2002), among others, for limiting forecasting models to autoregressive effects and few explanatory variables. They argue that such models are not appropriate for modeling complicated markets. To achieve good day-ahead forecasting performance for electricity spot prices in the British market, they apply a time-varying parameter regression model and a regime-switching model, including several explainatory variables. They conclude that the best predictive performance is obtained from models involving market fundamentals, non-linearity, and time-varying coefficients.

Chen (2009) complements the research of Karakatsani and Bunn (2008) by studying the non-linear relationship between electricity prices and their fundamental drivers in the British market. Acknowledging the limitations of regime-switching models, Chen (2009) develops a structural finite mixture regression (SFMR) model. Its forecasting performance outperforms regime-switching models and linear regression models. The results also demonstrate that prices in different trading periods within a day are driven by different fundamental factors. Chen and Bunn (2010) confirm these results using a logistic smooth transition regression (LSTR) model for the British market.

Intraday properties of fundamental spot price drivers are also investigated by Bunn et al. (2016) and Hagfors et al. (2016a). They apply fundamental quantile regression models to model electricity prices in the British market. They show that the sensitivities to fundamental factors varies across quantiles and the time of the day as well as across the price distribution.

Literature covering quantile regression models for Nord Pool is scarce. Lundby and Uppheim (2011) use quantile regressions for Value at Risk (VaR) forecasting of the spot price in Nord Pool. Weron et al. (2004) apply a mean reverting jump diffusion model to capture the main characteristics of the spot price. Vehviläinen and Pyykkönen (2005) model the impact on the spot price, by presenting a model suited for mid-term analysis using a combination of three models of consumption, generation and marginal water value.

Huisman et al. (2013) and Huisman et al. (2015) investigate how the increase of low marginal cost renewable energy supply impacts the electricity prices in Nord Pool. Both papers conclude that higher reservoir levels lead to lower electricity prices and Huisman et al. (2015) show how the impact of supply and demand factors on the prices differ as reservoir levels changes. Paraschiv et al. (2014) continue the examination of renewable energy sources (wind and photovoltaic) on electricity prices by studying the EPEX day-ahead prices in Germany. Using a state space model, they find that renewable energy increases extreme price fluctuations, and that the price sensitivity differs for each variable in each trading period. These results are confirmed and is extended by Hagfors et al. (2016b). Hagfors et al. (2016b) run quantile regression models to investigate the influence of fundamental drivers, especially the impact of wind and photovoltaic power, on the EPEX day-ahead electricity price distribution.

Nicolosi and Fürsch (2009) study the consequences for the conventional generation capacity mix in Germany, considering the growing share of renewable energy. They find that more intermittent energy increases the volatility of the residual demand. The higher residual demand volatility in turn increases the volatility of the electricity price. Ketterer (2014) also examines the impact of wind on German electricity prices. His results show that the price level is reduced due to wind power generation, while the volatility increases.

Some literature comparing the design, bidding process, or transmission management of electricity markets also exists (Imran and Kockar (2014), Ela et al. (2014), and de Menezes and Houllier (2016)). However, literature comparing fundamental electricity drivers of different electricity markets as comprehensively as this paper does not, to our knowledge, exist. Thus, this paper contributes to the research on fundamental electricity drivers in both Nord Pool and EPEX, and provides a detailed analysis and comparison of the intraday price dynamics across the entire spot price distribution.

3 Market Description and Analysis

3.1 Electricity Markets

EPEX and Nord Pool are similar in the sense that both are transparent, liberalized and competitive electricity spot markets, and have an increasing share of renewable energy sources. The introduction of near zero marginal cost renewable power, in the form of wind and photovoltaic power, has changed the merit order curve, which is a ranking of available energy sources based on ascending price per MWh. When producing, renewable energy substitutes the traditional base load technologies, which results in lower power prices, as cheaper plants become the price setters. This has been observed in Germany in later years; prices have even become negative when high levels of wind power generation coincide with low demand (Paraschiv et al. (2014)).

Renewable energy poses a challenge to power markets, as the intermittency strongly impacts traditional producers and increases the need for flexible capacity to ensure security of supply (Kilic and Baute (2014) and Forrest and MacGill (2013)). An example of an energy source fulfilling these requirements are hydro reservoirs, such as those found in Norway and Sweden.

3.1.1 EPEX

The expansion of renewable production has been strongly incentivized by the German government. This has resulted in wind and photovoltaic power production increasing rapidly, reaching 19.2% of total power production in 2015, as seen in Table 1. The most significant regulatory change to achieve this was the Renewable Energy Act (EEG) from 2000, which guaranteed producers of renewable energy a minimum compensation per produced kWh. The latest significant regulatory change, the Equalization Mechanism Ordinance (AusglMechV), significantly changed the market mechanisms of trading renewable energy. It obliged TSOs to sell EEG-electricity on the day-ahead market, starting 1st of January 2010.

The overall target of the EEG is to achieve 35% renewable energy production in 2035, and 80% in 2050 (Gullberg et al. (2014)). In addition, the German government has decided that nuclear energy is to be phased out by 2022, while transitioning to a low-carbon energy system. Consequently, continued encouragement to develop renewable energy is necessary to cover the German energy demand. Average spot prices have been reduced due to the increased renewable capacity (Hagfors et al. (2016b), Schneider and Schneider (2010), and Paraschiv et al. (2014)), but Fanone et al. (2013) argue that the feed-in tariffs exceed the reduction in power prices, causing a negative net effect for consumers.

3.1.2 Nord Pool

Nord Pool Spot AS is one of the the largest power exchange in Europe, and has a large share of hydro production, as shown in Table 1. Wind power production has steadily increased in recent years, and has reached a share of 8.9% in 2015. Increased renewable energy production in Norway and Sweden is facilitated through a joint market for tradable green electricity certificates introduced in 2012. The aim is to ensure 26.4 TWh of new renewable production by 2020. Producers of clean, renewable energy are issued tradeable certificates. Conventional producers are required to buy these in proportion to their electricity sales. In this way an additional income for renewable producers is ensured. The price of certificates is not fixed, but determined in the open market.

3.2 Energy Mix Comparison

Table 1: Energy mix (2015). Source: EPEX (Energiebilanzen (2015)), Nord Pool (Data provided by ENTSO-E (2015)). Total renewables includes hydro, wind, PV, biomass, and incineration.

	Fossil	Nuclear	Wind	PV	Hydro	Other	Total renewables
EPEX	51.8%	14.1%	13.3%	5.9%	3.0%	11.8%	29.9%
Nord Pool	10.5%	18.4%	8.9%	0.2%	55.9 %	6.1%	70.8%

Nord Pool and EPEX are fundamentally different markets; Nord Pool is largely based on stable and flexible hydro production, while Germany relies heavily on less flexible thermal energy and intermittent renewable energy. The different market structures are also highlighted by the share of total renewable energy; Nord Pool has 70.8%, versus 29.9% found in EPEX. These differences in energy mixes are likely to have a large impact on the price formation and intraday price patterns.

The share of hydro power production varies according to water inflow each year, but constitutes approximately 56% of power production in Nord Pool (Statnett (2013)). As a consequence, the share of fossil and nuclear power in the Nord Pool energy mix is only 28.9%, drastically lower than the 65.9% found in EPEX. The higher share of large-scale thermal energy in Germany partially explains the higher number of negative price occurrences. The costs of shutting down/reducing thermal power production exceed the losses of operating at low/negative prices which typically occur with high levels of low-cost renewable production. According to Keles et al. (2011), utilities are willing to accept -€120/MWh or lower to get rid of excess electricity produced, as energy storage is not a viable option with current technologies. Hydro power producers in Nord Pool can more easily adjust the production to handle variability in the power in-feed from renewable energy sources, preventing the prices from fluctuating excessively. The variable cost of hydro production is the opportunity cost of producing today versus delaying production, when the price expectation may be higher or lower. Increasing production is thus only beneficial to hydro producers if the price today exceeds the expected benefit at a later time.

Intermittency caused by renewable energy can be absorbed by hydro reservoirs, as discussed by Mauritzen (2013), Green and Vasilakos (2010), and Gullberg et al. (2014). The reservoirs can be utilized as storage by using renewable energy when it is very cheap to pump water back into the reservoirs, allowing for future use when it is scarce. Hydro reservoirs can also function as storage by producing less when cheap renewable energy is available. Li (2015) shows that the growth of wind power in Nord Pool has lowered the spot price volatility, because of the interaction with hydro resources and strong transmission lines. In contrast, Ketterer (2014) shows that the increase in wind power production has increased price volatility in EPEX. Conclusively, recent developments in Nord Pool and Germany have impacted the volatility of day-ahead prices differently. The phasing out of stable nuclear power plants in Germany is likely to further increase the price volatility, as the share of intermittent renewable energy increases.

Clearly, flexibility is valuable in systems with a large share of intermittent renewable energy. However, sufficient transfer capacity between the areas with large intermittent production and hydro-rich areas is necessary to alleviate the adverse impacts from intermittency.

3.3 Future Developments

The energy mix is expected to change further in near future in both markets. Germany is transitioning towards less large-scale nuclear and carbon-emitting coal energy, while expanding renewable energy production. The Nordic countries are also focused on increasing the amount of wind energy, thus moving towards an even lower-carbon system.

To accommodate the ambitious goals set by Germany, it is necessary to develop more renewable energy plants while handling the variability issues arising. Security of supply is ensured by having sufficient flexible reserves, which can be addressed through different measures. As discussed by Gullberg et al. (2014) and Jacobsen and Zvingilaite (2010), there are several options to achieve this; installing more peak load plant capacity, enhance energy storage, or improve interconnections between areas. Strong interconnections promote more stable prices and an increasingly competitive market that further limits opportunities to exercise market power when supply is scarce (Li (2015)).

The NordLink cable is expected to facilitate better use of resources on both sides, as improved transmission reduces adverse effects of renewable energy production (Jacobsen and Zvingilaite (2010)). Security of supply will be improved, while utilization of renewable energy production is enhanced as predictability improves. Market participants will benefit from importing/exporting by exploiting the price spread between Nord Pool and EPEX. In dry years, the interconnection is likely to improve the handling of energy shortages and lead to lower consumer prices in Nord Pool. For EPEX, an interconnection improves load balancing and reduces volatility thus lower extreme price occurrences, as well as expanding the power trading market. However, to fully utilize the benefits, the transmission grid between north and south Germany must be strengthened. The transmission capacity of 1400 MW is unlikely to equalize the prices in Nord Pool and EPEX; Statnett (2013) claims there will be congestions and relatively large price differences most of the time.

4 Data Analysis

4.1 Choice of Data

4.1.1 Choice of Price Data

We analyse hourly day-ahead spot prices in the German EPEX and in Nord Pool between 4$^{\text{th}}$ of January 2010 and 31$^{\text{st}}$ of May 2014. Significant regulatory changes were effective in Germany from early 2010, as discussed in Section 3.1.1. The regulatory changes altered the market mechanisms and reduced the volatility of electricity prices as a consequence, as shown by Ketterer (2014). As discussed in Section 3.2, the energy mix has changed in recent years, primarily in the form of more wind and photovoltaic power, and an ongoing reduction of nuclear power in Germany. We therefore consider data pre-2010 not to be representative for the current state of these day-ahead electricity markets for comparative purposes.

Electricity prices differ considerably from those of other assets because they are seasonal, exhibit volatility clustering and mean-reversion, as well as occasional observations of extremely high/low prices. Unlike most other asset prices, electricity day-ahead prices are often stationary, as confirmed by the results of an augmented Dickey Fuller (ADF) test with 7 lags. Based on test statistics of -36.27 for EPEX and -16.17 for NordPool, both price series are stationary at 1% significance level. The Ljung-Box Q-statistics with 7 lags included confirm the expectation of auto-correlation in the day-ahead spot prices. Each trading period has its own unique set of fundamental price drivers, as confirmed by Chen and Bunn (2010). Hence each trading period is treated as a separate time series in the modeling, yielding 1609 data points for every period. This is done to capture the different intraday characteristics exhibited by electricity prices, and to facilitate a comparison of price drivers in two fundamentally different markets throughout the trading day.

4.1.2 Choice of Fundamental Variables

The fundamental variables chosen to model the spot price in EPEX are given in Table 4, and variables used to model the Nord Pool spot price are given in Table 5. Fuel and CO_2 prices are equal in both markets, as these commodities are traded on common Northern European markets. The first and seventh lag of the spot prices are used to capture recent trends and weekly patterns commonly observed in power markets; typically, electricity prices tend to be lower during weekends. Volatility is considered a relevant variable to explain the price formation, as it is well known that electricity prices exhibit volatility clustering and correspondingly erratic behavior. Volatility is, for both markets, computed from an exponentially weighted moving average on the residuals of a seven-lag OLS-regression. The parameter lambda is set to 0.94, a value we consider resonable to smoothly capture recent market movements. The demand forecast for EPEX is modeled according to the approach described in Paraschiv et al. (2014). Each trading period is modeled separately while accounting for time of year and weekday, so that the demand variable captures the intraday seasonality pattern of electricity prices. Demand data used in Nord Pool is based on realized load, not forecasts. This is mainly related to data availability, as demand forecast data for Nord Pool was unavailable

Table 2: Descriptive statistics of realized and forecasted demand in Nord Pool. Due to data availability we use values for 2013-14. Source: Nord Pool

	Mean	Std. Error	Median	Excess Kurtosis	Skew	Range	Min	Max
Demand	45803	68.38	44750	-0.56	0.34	44498	27275	71773
Forecast	45964	68.55	44952	-0.60	0.33	44322	27766	72088

until November 2011. Based on results presented in Table 2, the characteristics of forecasted and realized demand are nearly identical in years 2013/14; the descriptive statistics are very similar, and the correlation is 0.996. Only excess kurtosis somewhat differs, as it is slightly less for the forecast, implying its distribution is a bit more havy-tailed than the realized demand. The correlations with the spot price in this period are nearly equal; 0.419 with realized demand, and 0.414 with forecasted demand. We therefore choose to treat realized demand as interchangeable with forecasted demand for the Nord Pool market for the purpose of this analysis. Forecasts for wind, photovoltaic and power plant availability (PPA) are available for Germany, while similar data is not available for the entire sample period for Nord Pool. Note that the PPA forecast is based on voluntary submission by producers and is therefore not complete; however, a large majority of relevant companies report their forecasts and the data is thus a good approximation for the entire market (Paraschiv et al. (2014)). In Nord Pool, we choose to use realized total production as the supply variable, due to data availability. As seen in Table 3, the descriptive statistics of forecasted and realized supply are very similar, and the correlation between the series is 0.994. For wind we use true wind production, as forecasts are unavailable for the modeled time period. Given a high correlation of 0.969 between forecasted and realized wind production, we find this approximation to be reasonable. Electricity certificate prices and hydro reservoir levels are only included in the models used for the Nord Pool spot price, as these variables are only found in this market.

Table 3: Descriptive statistics of realized and forecasted supply in Nord Pool. Due to data availability we use values for 2013-14. Source: Nord Pool

	Mean	Std. Error	Median	Excess Kurtosis	Skew	Range	Min	Max
Production	45849	73.45	44584	-0.49	0.36	49973	24120	74093
Forecast	45064	73.10	43842	-0.47	0.38	46169	25170	71339

Table 4: Overview of the variables chosen for modeling the EPEX spot price.

Variable, units	Description	Data source	Resolution
Lagged spot price, €/MWh	Market clearing price for the same hour of the last relevant delivery day – lag 1 and lag 7 have been used	European Power Exchange (EEX)	Hourly
Expected demand, MWh	Demand forecast for the relevant hour on the delivery day as modelled in Paraschiv et al. (2014)	Own data, German Weather Service	Hourly
Expected wind power infeed, MWh	Expected infeed published by German transmission system operators following the electricity price auction	Transmission system operators http://www.50hertz.com/de/, http://amprion.de/ https://www.transnetbw.com/en, http://www.tennet.eu/nl/home.html	Hourly
Expected photovoltaic infeed, MWh	Expected infeed published by German transmission system operators following the electricity price auction	Transmission system operators http://www.50hertz.com/de/, http://amprion.de/ https://www.transnetbw.com/en, http://www.tennet.eu/nl/home.html	Hourly
Expected power plant availability, MWh	Ex ante expected power plant availability for electricity production (voluntary publication) on the delivery day, published daily at 10:00 am	European Power Exchange and transmission system operators: ftp://infoproducts.eex.com	Daily
Coal price, €/12,000 t	Latest available price (daily auctioned) of the front-month Amsterdam-Rotterdam-Antwerp (ARA) futures contract before the electricity auction takes place	European Power Exchange	Daily
Gas price, €/MWh	Last price of the NCG day-ahead natural gas future on the day before the electricity price auction takes place	Bloomberg, Ticker: GTHDAHD Index	Daily
Oil price, €/bbl	Last price of the active ICE BrentCrude futures contracton the day before the electricity price auction takes place	Bloomberg, Ticker: COA Comdty	Daily
Price for EUA, € 0.01/EUA 1000 t CO_2	Latest available price of the EEX Carbon Index (Carbix), daily auctioned at 10:30 am	European Power Exchange (EEX)	Daily
Spot price volatility	Volatility at each data point based on an EWMA model	European Power Exchange(EEX)	Hourly

Table 5: Overview of the variables chosen for modeling the Nord Pool spot price.

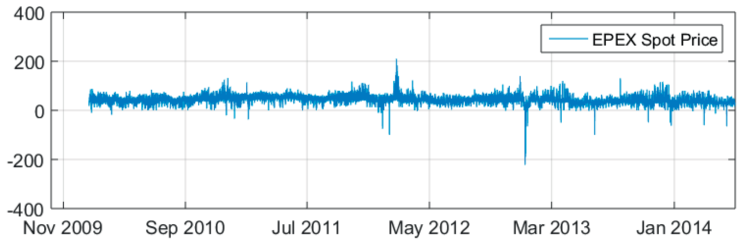
Variable, units	Description	Data source	Resolution
Lagged spot price	Market clearing price for the same hour of the previous delivery day - lag 1 and lag 7 have been used	Montel/Nord Pool	Hourly
Consumption, MWh	Realized consumption for the relevant hour on the relevant day	Montel/Nord Pool	Hourly
Water reservoir level, TWh	Weekly reservoir levels in Nord Pool in TWh, includes Norway, Sweden and Finland. Daily data obtained by linearly interpolating between weekly data points	Nord Pool	Weekly
Wind power production, MWh	Realized wind power production for the relevant hour on the relevant day	Energinet.dk	Hourly
Supply, MWh	Realized production for the relevant hour on the relevant day	Montel/Nord Pool	Hourly
Coal price, €/12,000 t	Latest available price (daily auctioned) of the front-month Amsterdam-Rotterdam-Antwerp (ARA) futures contracts before the electricity auction takes place	European Power Exchange (EEX)	Daily
Gas price, €/MWh	Last price of the NCG day-ahead natural gas spot price on the day before the electricity price auction takes place	European Power Exchange (EEX)	Daily
Oil price, €/bbl	Last price of the active ICE BrentCrude futures contract on the day before the electricity price auction takes place	Bloomberg, Ticker: COA Comdty	Daily
Price for EUA, € 0.01/EUA 1000 t CO_2	Latest available price of the EEX Carbon Index (Carbix), daily auctioned at 10:30 am	European Power Exchange (EEX)	Daily
El-certificate price, €/ certificate	Swedish electricity certificate average price (volume-weighed), converted from SEK/certificate to €/certificate	Macrobond	Daily
Spot price volatility	Volatility at each data point based on an EWMA model	European Power Exchange (EEX)	Hourly

4.2 Descriptive Statistics of Prices

The descriptive statistics of the spot prices are presented in Table 6. We first note that Nord Pool has the highest maximum price of €300.03/MWh compared with €210/MWh in EPEX, but that the German prices have a larger price range due to negative prices - implying thicker tails. Although the Nord Pool price range is shifted to the right, the mean price is €1.90 lower than in EPEX, implying that very high prices in Nord Pool are less frequent. The median in EPEX slightly exceeds the mean, also indicating there is a higher chance of observing prices in the upper tail. This is somewhat contradicted by the negative skewness of -1.02, as it implies a higher probability of observing prices in the lower end of the distribution. Statistically, the Nord Pool spot price mainly differs from the EPEX price in that the skewness is positive, and that the mean exceeds the median. The implication is that the probability of observing prices in the upper part of the distribution is higher in Nord Pool. Further, it implies that EPEX prices are more likely to be extremely high or low, which is supported by a higher mean and thicker left tail. The high positive excess kurtosis, large standard deviation and high Jarque-Bera test-statistic confirm that the price distributions are highly non-normal and thick-tailed in both markets. Further, we note that both price series clearly exhibit occasional spikes and volatility clustering, as seen in Figure 1.

Table 6: Descriptive statistics of EPEX and Nord Pool spot prices.

	Mean	Median	Maximum	Mininimum	Std. Dev.	Skew	Ex. Kurtosis	Jarque-Bera
EPEX	42.94	43.07	210.00	-221.99	15.52	-1.02	16.44	441492
Nord Pool	41.04	38.61	300.03	1.38	15.85	1.72	12.91	287786



(a) Overview of EPEX spot price over time.

(b) Overview of Nord Pool spot price over time.

Figure 1: Plots of both price series over time.

Table 7: Descriptive statistics of fundamental variables in EPEX.

	Demand	PPA	Wind	PV	Coal	Gas	Oil	CO_2	Vol
Mean	54850	55146	5297	2514	71.23	23.21	74.17	9.35	8.63
Median	54852	55535	3894	93	70.69	24.00	75.73	7.76	7.33
Maximum	79884	64169	26256	24525	99.02	39.50	83.78	16.84	134.53
Minimum	29201	40016	229	0	51.49	11.15	61.03	2.48	1.78
Standard Dev.	10082	4894	4432	4280	11.6	4.1	4.8	4.3	5.8
Skew	-0.05	-0.27	1.52	2.04	0.24	-0.63	-0.72	0.28	6.23
Excess Kurtosis	-1.04	-0.77	2.30	3.75	-1.08	0.88	-0.35	-1.48	82.04
Jarque-Bera	1776	1426	23299	49469	2220	3804	3537	4008	11031893

Table 8: Descriptive statistics of fundamental variables in Nord Pool.

	Demand	Supply	Wind	Reservoir	Coal	Gas	Oil	CO_2	El.cert	Vol
Mean	45468	45264	1171	69.97	71.23	23.21	74.17	9.35	23.40	3.76
Median	44282	44191	915	73.84	70.69	24.00	75.73	7.76	23.37	2.56
Maximum	71773	74093	4494	109.61	99.02	39.50	83.78	16.84	42.85	79.48
Minimum	22245	23011	1	19.94	51.49	11.15	61.03	2.48	1.19	0.28
Standard Dev.	9400	9636	951	25.10	11.59	4.13	4.78	4.33	4.06	4.32
Skew	0.34	0.30	0.89	-0.26	0.24	-0.63	-0.72	0.28	0.25	5.80
Excess Kurtosis	-0.63	-0.51	-0.02	-1.10	0.88	-0.35	-1.08	-1.48	1.24	57.30
Jarque-Bera	1371	990	5045	2364	2220	3804	3537	4008	2854	5473298

The characteristics of estimated volatility of both price series are presented in Tables 7 and 8. The average volatility in EPEX is €8.63/MWh, more than twice as high as in Nord Pool (€3.76/MWh), and likely to increase even further as discussed in Section 3.2. This strengthens the implication that the tails of the EPEX prices are thicker compared with Nord Pool.

The correlations between day-ahead price and its own lags are shown in Table 9 for both markets. The correlations in Nord Pool are much higher, but the weekday-effect (lag 7) is stronger in EPEX relative to the other correlations. The correlation with the seventh lag exceeds the correlation with the other lagged prices, except the first lag. The high correlations in Nord Pool are supported by the lower volatility, as it indicates that prices are likely to be similar on a day-to-day basis. Further, high correlation is supported by the lower price range in Nord Pool.

From the price plots in Figure 1, we note that the Nord Pool price is always positive, unlike in Germany where there are negative price observations. As seen from Table 10, most negative prices occur during night, and the minimum and average negative prices during night are much more extreme than those observed during day, when average demand is higher. Further, from Figure 3 we note that negative EPEX prices tend to occur when wind power production is at its highest - Paraschiv et al. (2014) and Hagfors et al. (2016b) show this happens mainly during night.

4.3 Descriptive Statistics of Fundamental Variables

Descriptive statistics of all variables are presented in Tables 7 (EPEX) and 8 (Nord Pool). We first note that demand in EPEX varies notably more than PPA, as the range and standard deviation is less for the latter. In

Table 9: Auto-correlation between prices in EPEX and Nord Pool.

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
EPEX Spot Price	0.69	0.52	0.48	0.46	0.47	0.58	0.68
Nord Pool Spot Price	0.92	0.86	0.83	0.82	0.81	0.83	0.84

Table 10: Overview of characteristics of negative prices in German EPEX.

Trading period	Number of Negative Prices	Average Negative Price	Minimum Price
1	7	-35.5	-149.9
2	16	-30.5	-200.0
3	20	-34.8	-222.0
4	20	-38.8	-221.9
5	13	-46.6	-199.9
6	13	-38.7	-199.0
7	22	-30.4	-199.9
8	13	-22.2	-156.9
9	5	-1.4	-6.0
10	2	-1.4	-2.8
11	3	-1.9	-5.7
12	2	-4.2	-8.3
13	4	-2.7	-9.9
14	5	-19.8	-59.5
15	10	-24.6	-100.0
16	11	-17.6	-100.0
17	6	-15.3	-46.9
24	5	-30.4	-91.0

Nord Pool, demand and supply have quite similar statistical properties. The range is slightly shifted towards higher values for supply, indicating excess supply is more likely than very high demand. Demand and supply parameters are slightly positively skewed in Nord Pool, indicating higher levels are slightly more likely to occur - the opposite is true for EPEX. The more volatile EPEX demand/supply relationship supports the higher volatility of German electricity spot prices as previously discussed. Excess kurtosis is negative in both markets; the distributions are quite flat with relatively thin tails, meaning these variables mostly are stable.

The correlation between demand and supply is very high (0.97) in Nord Pool. A plausible explanation for this is the low elasticity of demand - and thus required supply. The supply side in Nord Pool is dominated by flexible hydro power, so that supply is able to adjust to demand; hence, high demand is followed by higher supply levels. Correlation between demand and PPA in Germany is much lower at 0.34, indicating that high demand levels are less likely to coincide with high levels of supply. One possible explanation is that intermittent renewable energy strongly affects the balance between supply and demand by either increasing or decreasing supply relative to demand.

It is also very interesting to look at the relationship between the standard deviation of demand and PPA/supply in EPEX/Nord Pool; for Nord Pool, the standard deviation is approximately the same for demand and supply. In EPEX, however, demand varies much more than PPA, even though the mean values are similar. This may be due to the extensive share of large scale thermal energy in EPEX. Large-scale thermal plants are unable to vary the output swiftly due to physical and financial constraints, resulting in very low volatility of supply relative to demand. The relatively high correlation of 0.66 between demand and spot prices in EPEX confirms that high prices are more likely when demand is high, and oppositely for low demand. This correlation is lower in Nord Pool at 0.45, which may be explained by fewer situations where scarcity pricing is necessary due to available and relatively low cost supply in cases of high demand.

Wind is negatively correlated with the spot prices in both markets, with a correlation of -0.33 with EPEX and -0.14 with NP. This is as anticipated, as wind is expected to lower day-ahead prices. The correlation is more negative in EPEX, which corresponds well with the higher share of wind in EPEX (Table 1). The correlations between CO_2 and gas, and oil are all quite high (CO_2 and gas: -0.64, CO_2 and oil: -0.67, oil and gas: 0.71) - not surprising, as these commodities are closely linked. CO_2 has a relatively high, positive correlation with coal (0.56), while the correlation with gas is negative. The high correlations strongly imply that multicollinearity is present, a phenomenon which adversely affects the modeling; this issue is further discussed in Chapters 5 and 6.

Overall, the correlations indicate that the markets behave quite similarly in some aspects; demand, coal, and environmental costs are positively correlated with the spot price, as expected.

4.4 Correlation of Variables Across Markets

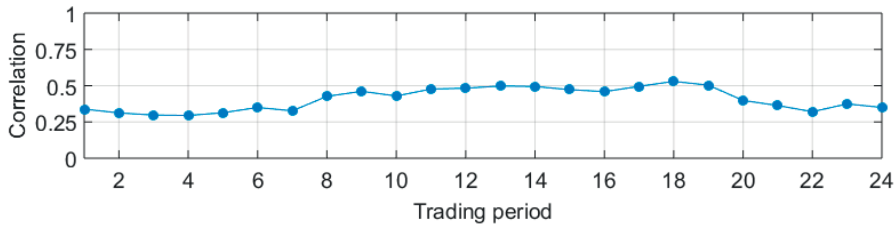
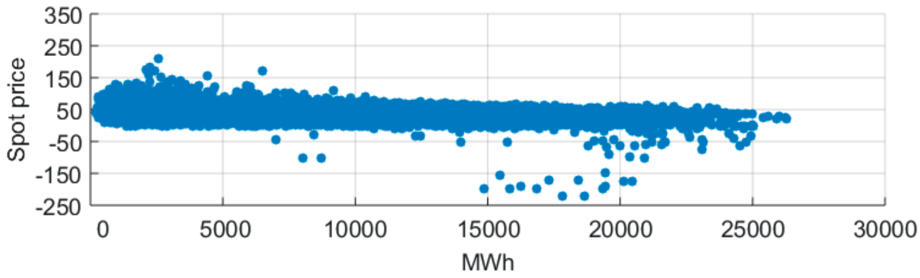


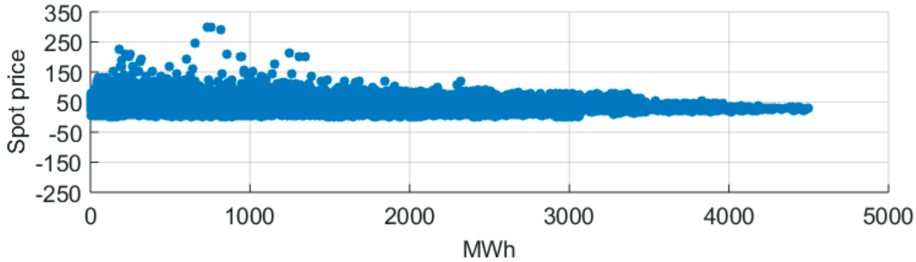
Figure 2: Correlations between hourly spot prices in EPEX and Nord Pool.

The correlations between hourly spot prices in EPEX and Nord Pool are shown in Figure 2. Considering how the spot prices and fundamental variables compare is relevant for understanding the market dynamics. We first note that the spot price correlation varies between 0.30 to 0.53, with the highest correlations in peak load periods. Thus, prices are more similar across the markets when demand is at its highest. During night, in off-peak periods, the correlations are lower. Generally, the correlations are not very high, implying the interconnection will be operated at full transfer capacity a large share of the time due to the price spread (Statnett (2013)). The weak correlation of 0.27 between the volatility series suggests that volatile periods are unlikely to coincide, and that extreme prices are unlikely to occur simultaneously, hence increasing the stabilization benefits of connecting the markets.

Interestingly, demand (0.67), supply (0.67), and wind power (0.65) exhibit much stronger correlations across markets than the spot prices and volatilities. This implies similar consumption and production patterns that result in different price impacts due to the different market structures and production technologies (Table 1). However, as noted, the price correlations are at their highest when peak demand typically



(a) EPEX.



(b) Nord Pool.

Figure 3: Scatter plots of wind power production versus spot price.

occurs and peak load plants are more likely to be required in both markets. EPEX has a large share of thermal power, which is harder to adjust according to fluctuations in the load. Nord Pool production is easily adjusted to match demand, as discussed in the previous section. This is in line with the higher price volatility in EPEX, and the less flexible production.

5 Methodology

5.1 Linear Quantile Regression

We will employ different quantile regression models for Nord Pool and EPEX due to different fundamental variables. For Nord Pool the regression model is given by:

$$\begin{aligned} Q_q(\ln P_{i,t}) = {} & \alpha_i^q + \beta_{i,1}^q \ln P_{i,t-1} + \beta_{i,2}^q \ln P_{i,t-7} + \beta_{i,3}^q \ln DEMAND_{i,t} + \beta_{i,4}^q \ln SUPPLY_{i,t} \\ & + \beta_{i,5}^q \ln WIND_{i,t} + \beta_{i,6}^q \ln RES.LEVELS_t + \beta_{i,7}^q \ln GAS_{t-1} + \beta_{i,8}^q \ln OIL_{t-1} \\ & + \beta_{i,9}^q \ln COAL_{t-1} + \beta_{i,10}^q \ln CO_{2\,t-1} + \beta_{i,11}^q \ln EL.CERT_{t-1} + \beta_{i,12}^q \ln VOLATILITY_{i,t} \end{aligned}$$

while the regression model for EPEX will be:

$$\begin{aligned}
Q_q(\ln P_{i,t}) = \alpha_i^q &+ \beta_{i,1}^q \ln P_{i,t-1} + \beta_{i,2}^q \ln P_{i,t-7} + \beta_{i,3}^q \ln EX.DEMAND_{i,t} + \beta_{i,4}^q \ln EX.WIND_{i,t} \\
&+ \beta_{i,5}^q \ln EX.PV_{i,t} + \beta_{i,6}^q \ln EX.PPA_t + \beta_{i,7}^q \ln COAL_{t-1} + \beta_{i,8}^q \ln GAS_{t-1} + \beta_{i,9}^q \ln OIL_{t-1} \\
&+ \beta_{i,10}^q \ln CO_{2\,t-1} + \beta_{i,11}^q \ln VOLATILITY_{i,t}
\end{aligned}$$

where $q \in [0,1]$ is the 5%, 25%, 50%, 75% and 95% quantile. The log spot price of each day, $\ln P_{i,t}$, is the dependent variable on $\mathbf{X}_{i,t}$, which is the vector of explanatory variables, where i represents the 24 time periods throughout the day, and t represents the trading day. The constant for each quantile q is represented by α_i^q and the regression coefficients are represented by $\boldsymbol{\beta}_i^q$. α_i^q and $\boldsymbol{\beta}_i^q$ are found by the following optimization

$$\min_{\alpha_i^q, \boldsymbol{\beta}_i^q} \sum_{t=1}^{T} (q - \mathbf{1}_{\ln P_{i,t} \leq \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q})(\ln P_{i,t} - (\alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q)),$$

where

$$\mathbf{1}_{\ln P_{i,t} \leq \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q} = \begin{cases} 1, & \text{if } \ln P_{i,t} \leq \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q, \\ 0, & \text{otherwise.} \end{cases}$$

Thus the models can be rewritten as:

$$Q_q(\ln P_{i,t}|\mathbf{X}_{i,t}) = \alpha_i^q + \mathbf{X}_{i,t}\boldsymbol{\beta}_i^q,$$

with the respective vector of explanatory variables for each market. [1]

5.2 Transformation of Negative Prices

Use of logarithmic price series has the benefit of yielding coefficients that can be interpreted as elasticities. This facilitates comparison across factors and markets. For the German EPEX prices, this is not straightforward, as there are negative price observations for most of the trading periods (Table 10). To account for negative prices and facilitate a logarithmic transformation, an option is to truncate the negative prices by setting them to a low positive value. This is corresponding to the approach taken by Forrest and MacGill (2013) when modeling the Australian NEM. The benefit of this approach is that the price series become more or less directly comparable, and trading periods with no negative prices are not affected, i.e., trading period 18-23. However, estimating lower quantiles in trading periods with a higher number of negative price occurrences is problematic. The results will be highly distorted if very low prices are treated as outliers. Some trading periods have up to 20 negative prices, approximately 1.5% of total observations (Table 10). Particularly the trading periods in the middle of the night have very low average negative prices; truncating these hours may cause a substantial loss of information. Thus, another option to handle negative prices is to shift all the prices, such that all values become positive and can be logarithmically transformed. This approach

[1] The *sqreg* function in STATA has been used to estimate the quantile regression models. This estimates all the quantiles for a given hour simultaneously, and standard errors are obtained by bootstrapping

achieves less distortion in lower quantiles, but complicates the interpretation of the estimated coefficients as they cannot be interpreted as elasticities.

To minimize the adverse effects, we choose to use both methods according to which quantiles are being modeled. Upper quantiles for EPEX will not be noticeably impacted by truncating the lowest prices to a low positive value. Lower quantiles, on the other hand, will be distorted as a large amount of the data points would be artificially removed. Therefore, it is more reasonable to shift this data. With this reasoning, quantiles up to and including 25% are modeled using shifted EPEX prices. €223.37/MWh is added to each data point, ensuring the lowest EPEX price equals the lowest Nord Pool spot price of €1.38/MWh (Table 6). Quantiles above 25% are modeled using truncated data, minimizing the adverse effects. The data is truncated such that prices below €1/MWh are set to €1/MWh. The Nord Pool prices have not been altered, as there are no negative prices in the series.

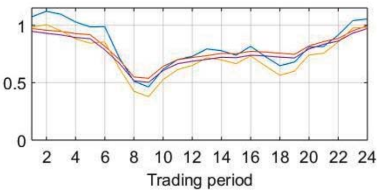
5.3 Transformation of Coefficient Estimates from Shifted Data

Directly interpreting the coefficients as elasticities from the lower quantile regressions in EPEX is not possible, nor are the estimates comparable with the higher quantiles. Therefore, to achieve comparable quantile curves, elasticity estimates for EPEX for quantiles 5% and 25% are backed out from the shifted coefficient estimates. First, the average value of each input variable is calculated for each trading period. A spot price estimate is computed from these average values and the coefficients estimated from shifted data, before incrementing a specific variable by +1% and calculating a new price estimate. The percentage change for the price estimates is taken as the elasticity of that specific variable; all variables and both quantile 5% and 25% in EPEX are handled in this manner.

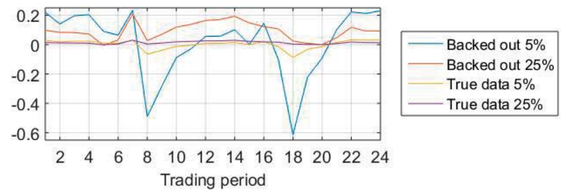
To ensure that the backed out approach yields adequate results, the approach was applied on the Nord Pool price data for comparison. A selection of the results is shown in Figure 4. It is assumed that these results are transferable to the EPEX data set, and that it behaves similarly. The degree of similarity is high, particularly when the significances are high, such as for the first lag (Figure 4a). The backed out elasticities tend to deviate primarily when the significances are low, such as for supply shown in Figure 4b. The backed out elasticities tend to be shifted on the y-axis relative to the true estimates. Further, we note that the quantile curves obtained from true data are slightly smoother, especially for the 5% quantile. Based on these results, we argue that backed out EPEX elasticities based on average values of input data provides an adequate foundation for a comparative analysis.

5.4 Transformation of Explanatory Variables

To facilitate a comparison of the coefficient estimates of explanatory variables, the input variables must be on logarithmic form. All factors other than EPEX spot prices and photovoltaic forecasts are always larger than zero and logarithmically transformable. The photovoltaic forecasts series naturally include a large number of zero forecasts, thus we chose to set all values below 1 MWh to the value of 1, achieving a minimum logarithmic value of zero. There were 988 data points with forecasted production above 0 and below



(a) Lag 1.



(b) Supply.

Figure 4: Backed out and true coefficient estimates of lag 1, lag 7, and supply in Nord Pool.

1 MWh. It is reasonable to assume that solar in-feed below 1 MWh is practically zero production. All other variables were positive and directly transformed to logarithmic values for both markets. To obtain daily hydro reservoir estimates from weekly data, linear interpolation was used, assuming that the hydro usage is approximately linear within a single week.

5.5 Multicollinearity

As noted in Section 4.3, the correlations between gas, oil, and CO_2 prices are very high - all are above 0.64. These variables are highly linearly correlated, and should not be simultaneously included in the modeling to ensure the results are properly interpretable. To account for this, we remove the correlated variables when estimating the impact of each variable. For instance, when estimating the quantile curves of gas price in EPEX and Nord Pool, regressions excluding oil and CO_2 prices are estimated to capture the impact of the gas price. Further, the correlation between coal and CO_2 is quite high at 0.56. Testing indicated that the model results were less robust when both were included simultaneously; thus, quantile curves for coal are modeled excluding CO_2, and vice versa when estimating CO_2 curves.

When modelling all the other variables, all variables are used in the regressions. This is not detrimental to the analysis, as it focuses on how the estimated coefficients - and thus the impact on price formation - varies throughout the trading day. In these cases the values of the linearly correlated variables do not matter.

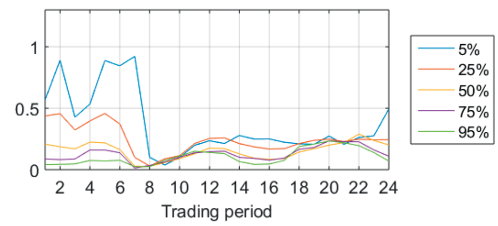
6 Results and Discussion

6.1 Quantile Regression Results

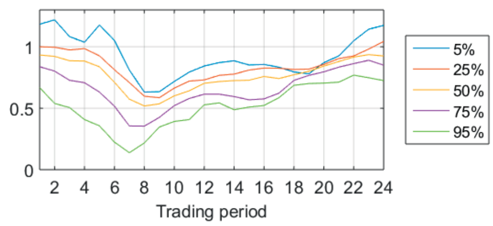
The results for each fundamental variable will be separately discussed and compared in the following sections. Photovoltaic forecasts, hydro reservoir levels, and prices of green electricity certificates are only present in one of the markets, and cannot be compared across markets. They are included in the models for their respective markets for robustness, but will not be analyzed and discussed in detail. To examine the drivers throughout the entire price distribution, results for quantiles 5%, 25%, 50%, 75%, and 95% are presented. The models used to estimate coefficients for analysing the linearly correlated prices of oil, gas, CO_2 and coal differ from the other models, as discussed in Section 5.5. When analyzing the results, consideration of the significance of each variable is necessary, thus the p-values from the regression results are presented and evaluated. Note that a lack of significance indicates that a particular fundamental factor is not found statistically relevant for the price formation in a given trading period and quantile.

As discussed in Section 5.2, the 5% and 25% quantile regressions for EPEX are estimated on shifted price data. The elasticities for these two quantiles have been backed out from the regression results, using the approach described in Section 5.3. This is done to achieve comparable elasticities for all estimated quantiles. The Nord Pool elasticities are all estimated on unaltered data.

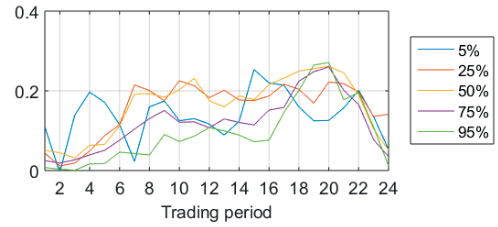
6.2 Lagged Prices



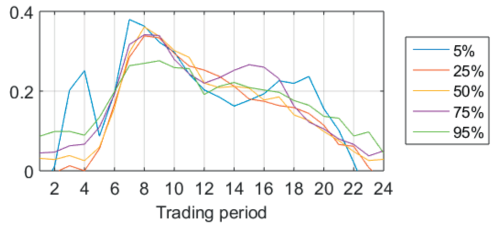
(a) Lag 1, EPEX.



(b) Lag 1, Nord Pool.



(c) Lag 7, EPEX.



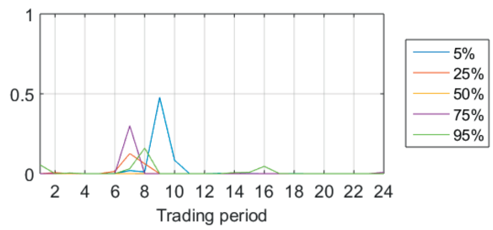
(d) Lag 7, Nord Pool.

Figure 5: Coefficient estimates of lag 1 and lag 7 throughout the trading day.

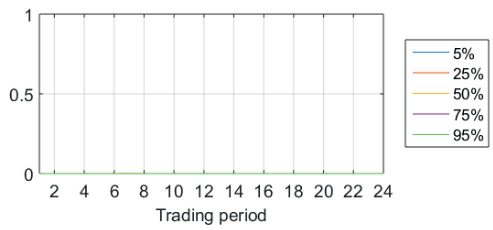
The coefficient estimates of the first and seventh lagged prices are presented in Figure 5. The significances of both lags are shown in Figure 6; lag 1 is practically always significant, with few exceptions in EPEX. The estimated coefficients for lag 1 tend to be highest during night, and lowest in the late morning for both markets and all quantiles. In contrast, the elasticities of the seventh lag are low during night compared to day, particularly in Nord Pool. The results imply that yesterday's price is a more important price driver in trading periods with predictable low average demand relative to higher-demand trading periods.

The coefficient magnitudes of lag 1 are mostly larger than those of lag 7 in Nord Pool. The highest lag 1 coefficient is 1.22% in trading period 2, compared with 0.38% for lag 7 in trading period 7, both in quantile 5% in Nord Pool. This corresponds with the discussion in 4.2, where the auto-correlation between spot price and lag 1 (0.92) is found to be noticeably higher than the correlation between spot price and lag 7 (0.84). Further, we note from 5a and 5b that the coefficient magnitudes of lag 1 decrease with higher quantiles, implying that other factors drive very high prices in both markets. In EPEX, this is particularly evident in the early morning. The seventh lag tends to be most influential when people and industry are more active, thus capturing the difference between a working day and a weekend.

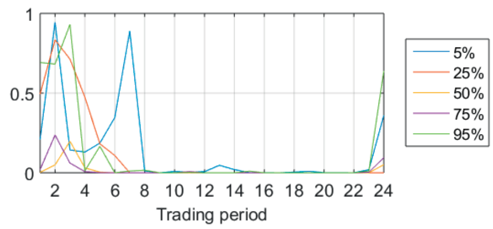
Lag 1 and lag 7 in EPEX have relatively similar impacts on the spot price throughout the trading day, with some exceptions during night when the impact of the first lag is higher. This is as expected, since the correlations with the spot price for both variables are almost equal (Table 9). Therefore, the day-ahead and the weekday-effect have approximately the same influence in EPEX. Oppositely, the lag 1 magnitudes are larger than those of lag 7 in Nord Pool, thus the day-ahead effect is more pronounced relative to the weekday effect. These results show that the weekly consumption patterns are relatively more important to the price formation in EPEX than in Nord Pool. The higher volatility exhibited by the EPEX spot prices, as discussed in Section 4.2, likely explains the lesser importance of price lags as price drivers. Nord Pool prices are generally much more stable, and it is thus reasonable that the price of the next trading day are more similar to recent prices.



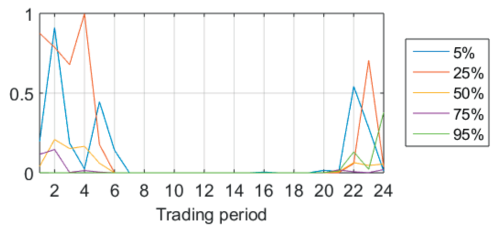
(a) Lag 1, EPEX.



(b) Lag 1, Nord Pool.



(c) Lag 7, EPEX.



(d) Lag 7, Nord Pool.

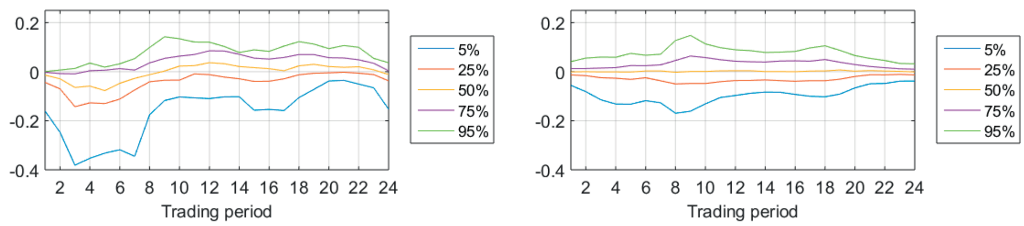
Figure 6: Significance of lag 1 and lag 7 coefficients throughout the trading day.

6.3 Price Volatility

From the discussion in 4.2 we know that the price range and price volatility in EPEX is much higher than in Nord Pool, suggesting the tails of the price distribution in EPEX are thicker. From the significances shown in Figure 8 we observe that volatility in Nord Pool is significant in all quantiles except 50%. In EPEX, the 25% and 50% quantiles are the least significant quantiles. The tails are highly significant throughout the trading day, except quantile 95% during night. This confirms that volatility is a more important driver in the tails of the price distributions. Considering that electricity prices exhibit volatility clustering, it is not unanticipated that high volatility further increases high prices or reduces already low prices.

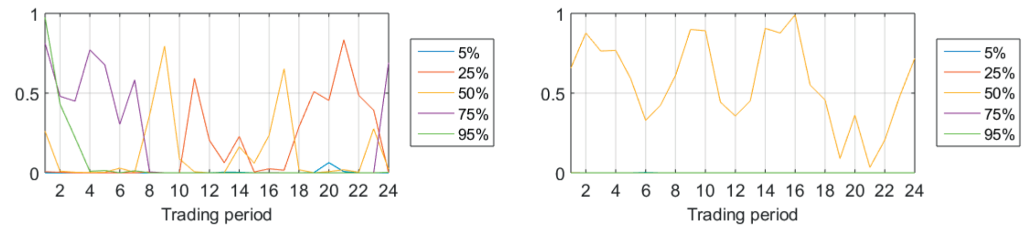
The coefficients for both markets are shown in Figure 7. In general, the quantile curves are quite similarly shaped in each market, with similar positive magnitudes in the two highest quantiles. These volatility curves closely follow the average daily demand, with small peaks around noon and early evening, and the magnitudes are lowest during night. This implies that price volatility is closely related to demand when prices are high. The elasticities are at their highest in the 95% quantile in trading period 9 in both markets; 0.14% in EPEX, and 0.15% in Nord Pool. Although significant, price volatility is not the primary price driver behind high prices, as the elasticities are low.

The price impact of volatility is negative in the low quantiles for both markets, where the magnitudes of the lowest quantile are noticeably larger in EPEX than in Nord Pool. This suggests that the price reducing impact is at its strongest when unpredictable wind production leads to negative prices in EPEX. The 50% quantile also has significant negative coefficients in EPEX during night, implying that when prices are on expected levels and average demand is low, higher volatility tends to decrease spot prices. The negative price impact of volatility in Nord Pool is quite similar throughout the trading day, but slightly stronger during day. The effect in the 5% quantile is notably lower than the 25% quantile, confirming that volatility is most influential in the tails in both markets.



(a) EPEX. (b) Nord Pool.

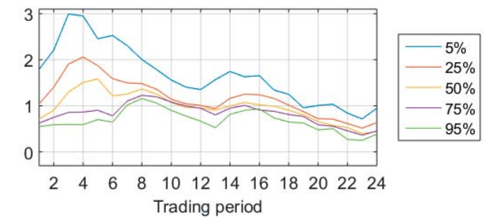
Figure 7: Coefficient estimates of price volatility throughout the trading day.



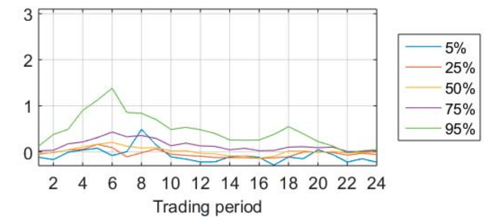
(a) EPEX. (b) Nord Pool.

Figure 8: Significance of price volatility coefficients throughout the trading day.

6.4 Demand

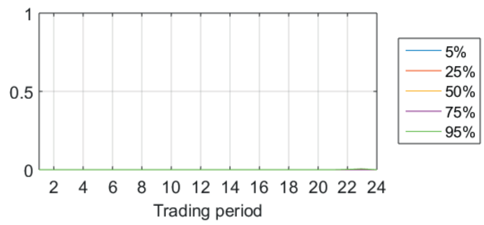


(a) EPEX.

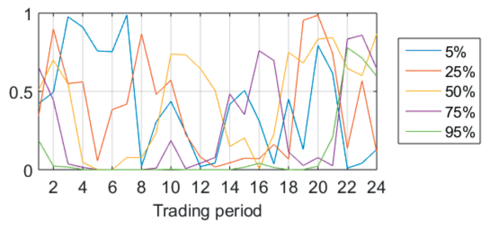


(b) Nord Pool.

Figure 9: Coefficient estimates of demand throughout the trading day.



(a) EPEX.



(b) Nord Pool.

Figure 10: Significance of demand coefficients throughout the trading day.

The coefficient estimates of demand are shown in Figure 9, and significances are depicted in Figure 10. We initially note that demand is always influential in EPEX. The significances vary greatly in Nord Pool, and are only notably high for the 95% quantile. These results are supported by the correlations between spot prices and demand discussed in Section 4.4; the correlation in EPEX of 0.66 by far exceeds that of 0.45 in Nord Pool. Further, Nord Pool is a less volatile market; the large amount of hydro provides flexibility in the power system, as discussed in Section 3.2. Therefore, fluctuations in demand are only influential in parts of the spot price distribution.

The upper quantile volatility coefficient curves follow the average demand curves. Thus, the dynamics behind the highest prices are closely related to both average demand levels and price volatility in both markets. As expected from the significances and correlations, the magnitudes of demand coefficients in EPEX, shown in Figure 9a, exceed those of Nord Pool, confirming demand is a more important price driver for all quantiles in EPEX. The influence of demand is at its highest during very early morning and late afternoon in both markets, but the Nord Pool elasticities tend to peak 2-3 trading periods after those in EPEX.

A major difference between the two markets is that the coefficient magnitudes decrease with higher quantiles in EPEX, while they increase with higher quantiles in Nord Pool. The 5% quantile coefficients in

EPEX are notably higher than the other quantiles, with a peak value of 2.99% in trading period 3. The highest Nord Pool elasticity is 1.38%, found during trading period 6 in the 95% quantile. The demand elasticities for both markets are at their highest when average demand is low. Changes in demand are most influential in off-peak periods. This may be due to market participants not anticipating changes in lower-demand trading periods, so that unexpected changes induce higher price impact than otherwise expected.

The importance of demand in higher quantiles in Nord Pool can be explained by several factors. The flexibility provided by the hydro reservoirs enables demand fluctuations to be covered without utilizing more expensive peak-load plants. However, when demand is very high, more expensive peak load plants will be switched on and become price setters, thus increasing the spot price. Although Nord Pool is a highly competitive market with many producers, situations with power scarcity may allow producers with available capacity to exercise market power and set prices above the marginal cost, further increasing prices in the highest quantiles.

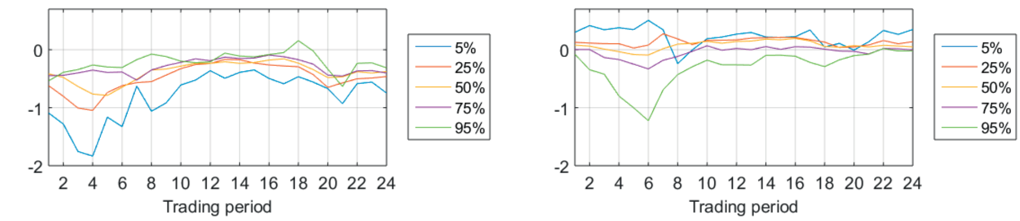
6.5 Supply Parameters

6.5.1 PPA/Supply

The estimated coefficients for the supply parameter in EPEX and Nord Pool are presented in Figure 11, and the significances are found in Figure 12. Note that the variables used to represent supply in EPEX and Nord Pool are differently defined, as discussed in Section 4.1.2. The supply parameter is more significant in EPEX than in Nord Pool, likely due to the differences in energy mixes discussed in Section 3.2, as most German producers have limited ability to adjust the production if desired.

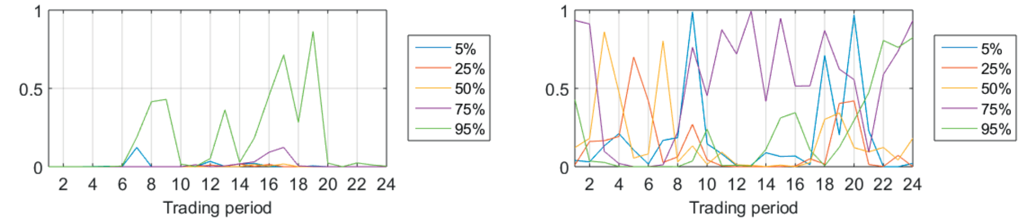
As expected, PPA coefficients are negative, confirming that increasing supply reduces the spot price. The coefficients magnitudes in EPEX decrease with higher quantiles, hence PPA is most influential when prices are either in the low or expected range. PPA tends to be most influential in off-peak periods, and the lowest elasticity of -1.83% is found in quantile 5% in trading period 4. Inflexible large scale thermal load is typically used to cover most of the demand in these trading periods, and a relatively strong price-reducing impact is anticipated as production cannot be swiftly and cost-efficiently adjusted following load fluctuations. The lesser importance of PPA in upper quantiles indicates that increasing expected supply levels are unable to entirely prevent spot prices from reaching very high levels, as these prices are likely to have other primary determinants.

Nearly all elasticities in Nord Pool are negative, with few exceptions for the three lowest quantiles. There are some positive and significant estimates in the 5% quantile, particularly during night and early morning. The coefficients are mostly insignificant for all quantiles, except the 95% quantile during the first half of the day and 5% during night/noon. This implies that supply in Nord Pool is most influential in the tails of the price distribution. The highest negative elasticity of -1.12% is found for the 95% quantile in trading period 6. Supply is generally found to have a price-dampening effect in Nord Pool for upper quantiles, particularly for off-peak periods. Unlike EPEX, the supply elasticities become more negative with higher quantiles, strongly implying that supply is more price-dampening for higher prices. This may be due to the flexibility offered by hydro reservoirs, as production can be swiftly ramped up when spot prices and profits are higher - consequently increasing the market supply and lowering the spot price.



(a) EPEX. (b) Nord Pool.

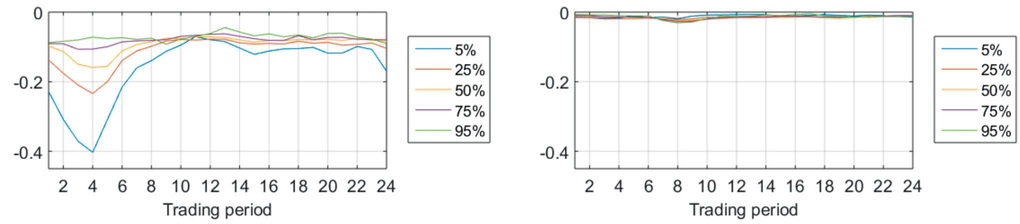
Figure 11: Coefficient estimates of PPA/supply throughout the trading day.



(a) EPEX. (b) Nord Pool.

Figure 12: Significance of PPA/supply coefficients throughout the trading day.

6.5.2 Wind Power Production

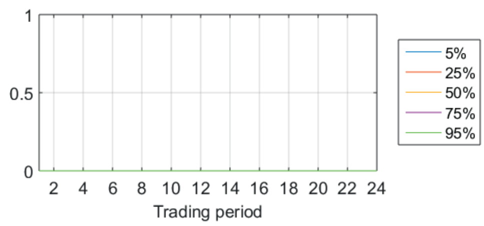


(a) EPEX. (b) Nord Pool.

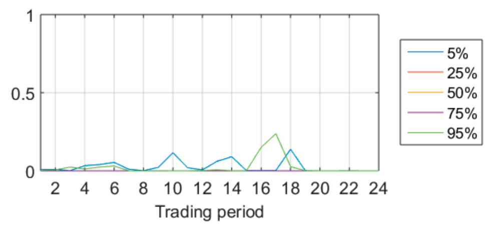
Figure 13: Coefficient estimates of wind power production throughout the trading day.

The coefficients for wind power production for all quantiles are shown in Figure 13. Unsurprisingly, the estimated coefficients are all negative. Consequently wind production reduces electricity spot prices, as the introduction of low marginal cost wind power substitutes more expensive power plants. The magnitudes of the coefficients are noticeably higher in EPEX than Nord Pool, which is reasonable considering the larger share of wind power in EPEX than in Nord Pool; 13.3% compared with 8.9% (Table 1). This is further supported by the more negative correlation between wind power and spot price in EPEX, as discussed in Section 4.3.

As seen from the significance plots in Figure 14, wind is practically always significant in both markets. Exceptions are some trading periods in the 5% and 95% quantiles in Nord Pool. However, the elasticities in Nord Pool are very low for all quantiles, hence wind is not a dominant price driver. In EPEX, the influence of wind is at its highest during night and early morning, when the average demand is at its lowest and wind likely constitutes a large share of the production. The elasticities decrease in magnitude towards higher quantiles, confirming that wind is most influential in the lower tail. This is further supported by Figure 3, from which it is clear that low spot prices tend to occur when wind power production is high. Overall, wind is an important electricity price driver in EPEX, and is particularly important in the formation of low spot prices.



(a) EPEX.



(b) Nord Pool.

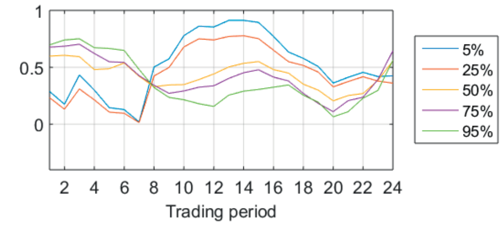
Figure 14: Significance of wind power production coefficients throughout the trading day.

6.6 Fuel Prices

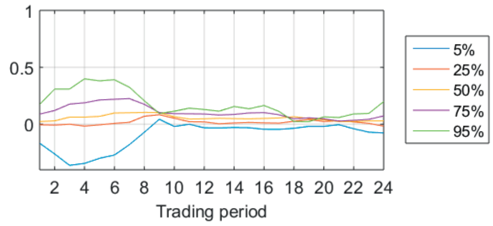
The results for the different fuel parameters are presented here. Note that each model for coal, oil and gas is estimated excluding the highly correlated variables, to isolate the impact of each respective fundamental variable.

6.6.1 Coal

As depicted in Figure 16, coal prices are highly significant in EPEX, and less significant in the lower tail in Nord Pool. From Figure 15, we note that the estimated coefficients are positive when significant in both markets, confirming that higher coal prices increase the electricity prices. An exception is found in the 5% quantile in Nord Pool, where the elasticities during night are negative and significant. The coal price coefficients in EPEX are noticeably higher than those in Nord Pool, indicating coal price is a more important driver behind electricity prices in Germany. This is according to expectations due to the higher share of coal in the German power system, as discussed in Section 3.2.

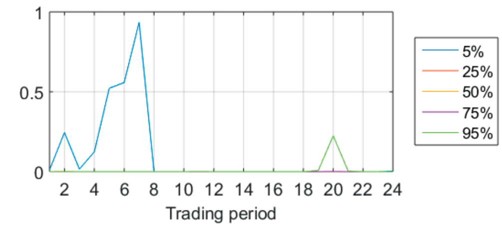


(a) EPEX.

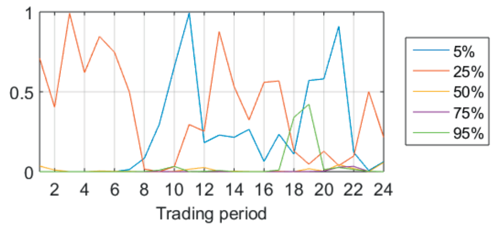


(b) Nord Pool.

Figure 15: Coefficient estimates of coal prices throughout the trading day.



(a) EPEX.



(b) Nord Pool.

Figure 16: Significance of coal price coefficients throughout the trading day.

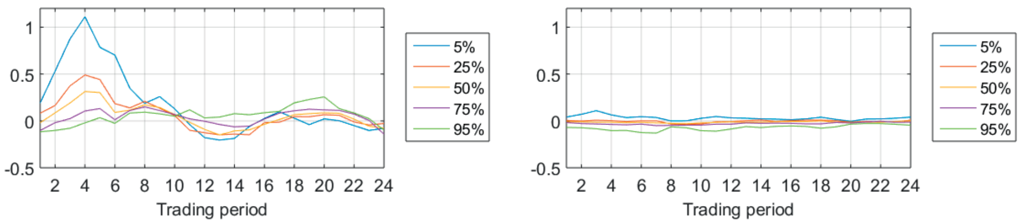
In EPEX, the coal price is most influential in the upper quantiles during night, as it is often the price setter in these trading periods. During day the dynamics are different in EPEX; the lower tail coefficients are most influential. High demand levels cannot be covered by base load alone, yielding coal less relevant in the highest quantiles during day. Base load covers a larger share of demand when electricity prices are close to or below expected levels, as the results indicate. Thus, coal is an important determinant behind lower prices in trading periods when demand is at medium to high levels.

The two lowest quantile curves in EPEX are quite similar magnitude-wise, and peak during day; note that the 5% quantile is mostly insignificant during night and early morning. This strongly indicates that spot prices in the lowest quantiles are driven by other factors - such as wind power. In Nord Pool, the lower quantiles are mostly insignificant, implying that coal is not an important driver behind low prices. An exception is the 5% quantile during night, when coefficient values are negative. This is unanticipated, but may be due to higher coal prices shifting production towards lower marginal-cost technologies, such as large-scale nuclear or hydro production. The upper quantiles are more significant, and have positive coefficients which increase with higher quantiles. Like in EPEX, the coal price coefficient magnitudes for Nord Pool are at their highest during night in the 95% quantile. At those times when hydro is less able to meet demand, for instance during dry years, coal price becomes more important and leads to higher nightly spot prices.

6.6.2 Gas

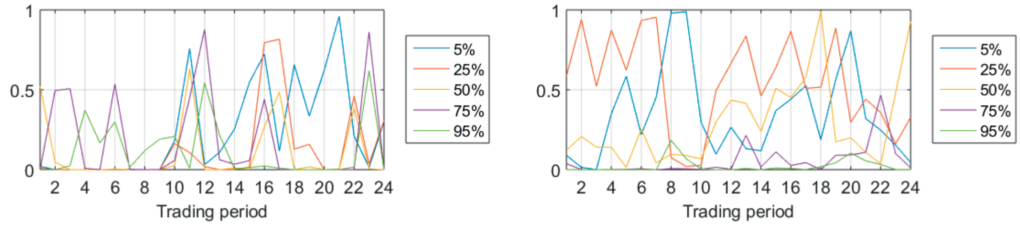
The gas price coefficients for all trading periods and quantiles are presented in Figure 17, with significances shown in Figure 18. The significances vary throughout the trading day and tend to increase with higher quantiles, particularly in Nord Pool. Gas is slightly more significant in EPEX, which is reasonable considering the larger share of thermal energy and lack of flexible hydro to cover peak load.

The upper quantiles are the most significant in Nord Pool, however, the coefficient magnitudes are negligible, hence gas is not an important price driver in Nord Pool. In EPEX, the impact of gas price varies across different quantiles. The 5% and 25% quantiles are significant during night, with high positive magnitudes for the 5% quantile. The 5% quantile elasticity peaks at 1.11% in trading period 4. The high coefficient values for low quantiles during night are unexpected, as gas is not commonly used to cover load during off-peak hours when prices are low. The explanation may be that a sudden drop in low marginal cost wind power production necessitates the use of gas, thus increasing the price.



(a) EPEX. (b) Nord Pool.

Figure 17: Coefficient estimates of gas price throughout the trading day.



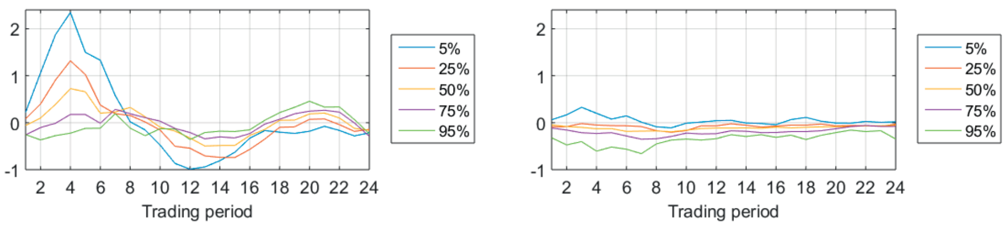
(a) EPEX. (b) Nord Pool.

Figure 18: Significance of gas price coefficients throughout the trading day.

Interestingly, the coefficients become negative and significant for the three lowest quantiles in EPEX in the middle of the day, simultaneously as photovoltaic average production levels peak. The negative coefficients are possibly due to substitution; low marginal cost photovoltaic power replaces more expensive peak load plants, and spot prices are lowered. Oppositely, the 95% quantile has significant and positive coefficients in these trading periods. This is likely due to gas covering demand when low marginal cost photovoltaic production is lacking, thus increasing the upper tail prices. Gas price coefficients are positive and significant for quantiles 75% and 95% in the early evening when demand is at its highest, as anticipated. Large scale thermal plants and renewable energy sources are unable to cover peak demand, and gas power plants are used, consequently increasing the prices. This effect increases with higher quantiles, as the 95% quantile estimates are well above those of the 75% quantile.

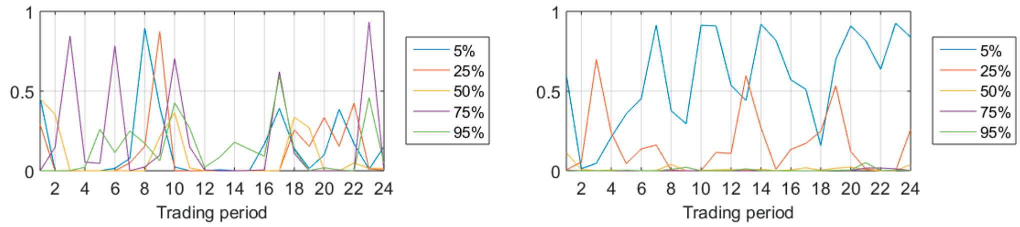
6.6.3 Oil

The coefficient estimates for the oil price are given in Figure 19, with corresponding significances given in Figure 20. In Nord Pool, quantile 5% is insignificant throughout the trading day, closely followed by the 25% quantile. The insignificance illustrates that when prices are already low, oil does not affect the price formation, which is expected as oil-fueled plants are used mainly to cover peak demand. The significance of the remaining quantiles in Nord Pool is unexpected as the share of oil in this market is negligible. The significances in EPEX vary greatly, but are highest for all quantiles in the middle of the day and in the evening for the two highest quantiles.



(a) EPEX. (b) Nord Pool.

Figure 19: Coefficient estimates of oil price throughout the trading day.



(a) EPEX. (b) Nord Pool.

Figure 20: Significance of oil price coefficients throughout the trading day.

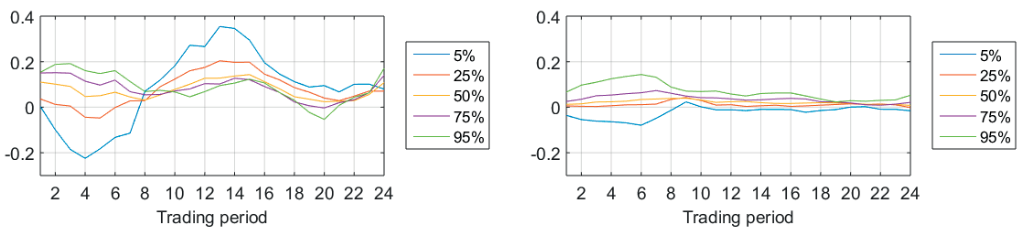
In Nord Pool, the quantile estimates are negative and particularly low during morning for the 95% quantile; the elasticity is -0.66% in trading period 7. The negative coefficient estimates decrease towards zero for lower quantiles. The negative coefficients are unexpected, as for the gas price discussed previously. A possible explanation is that high electricity prices during night motivate hydro producers to ramp up production to cover demand, thus lowering the highest prices and reducing the need for fossil fueled peak load plants. Overall, the sensitivities to oil price are very low, thus oil is not an important price driver in Nord Pool.

The highest elasticities in EPEX are found in quantiles 5% and 95%. Similar to the gas price, the 5% quantile has a strong positive impact during night; this may be due to a sudden lack of wind power necessitating the use of peak load plants to meet demand. According to Paraschiv et al. (2014), oil is rarely used for power production in Germany and is primarily related to coal transportation. This may explain the positive price impact in off-peak periods, when coal dominates the power production. In the afternoon, all quantiles but 95% are significant and negative. As for gas, this is likely related to cheaper low marginal cost photovoltaic power substituting the peak load plants. The results found in the peak periods are according to expectations; the two highest quantiles have a notably positive elasticities, as oil is more likely to be the price setter.

6.7 CO2 Emission Cost

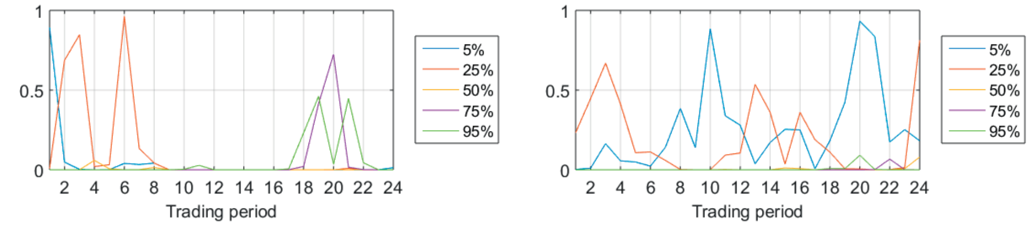
When assessing the sensitivities to the cost of CO_2 presented in Figure 21, it is important to note that this cost is primarily related to coal, as it emits the largest amounts of CO_2. Hence, it is as expected that the estimated quantile curves for CO_2 are similarly shaped to those of coal. This is also true for the significance curves shown in Figure 22. Note that the CO_2 quantiles have the opposite shape compared to gas/oil curves, as expensive carbon allowances shift some production from coal to gas/oil which emit less CO_2.

The lower quantile CO_2 elasticities are highest during day in EPEX, as for the coal price. During night, the highest quantile curve has the largest positive coefficients, while the lowest quantile is most negative. Further note that the magnitudes of CO_2 elasticities are less than those of coal. This implies that the cost of carbon amplifies the price impact of coal throughout the price distribution. Keep in mind that the 5% quantile elasticities in EPEX are backed out as described in Section 5.3, thus the high magnitudes may be exaggerated. Considering that a 1% increment in the CO_2-price is less in absolute value than a similar change in the coal price, we conclude the sensitivity to carbon emission costs is low in EPEX.



(a) EPEX. (b) Nord Pool.

Figure 21: Coefficient estimates of CO_2 price throughout the trading day.



(a) EPEX.

(b) Nord Pool.

Figure 22: Significance of CO_2 price coefficients throughout the trading day.

Low coefficient values in Nord Pool are as anticipated, considering the low share of fossil fuels. However, as seen in Figure 22b, the coefficients are mostly significant except quantiles 5% and 25%. From Figure 21b we conclude there is a small positive sensitivity to emission costs. The CO_2 price is most influential in the 95% quantile, with coefficients nearly as high as those in EPEX during night. The implication is that fossil fuels are used primarily when prices are high for each trading period. This is further confirmed by the low significance of the lower quantile curves. Carbon emission costs are not a main price driver in Nord Pool, but rather accentuate the impact of fossil fuels, particularly coal. The cost of CO_2 is notably more influential in EPEX due to the considerably larger share of thermal energy.

7 Conclusion

In this paper we analyze the electricity spot price distribution in EPEX and Nord Pool using quantile regressions. We analyze and compare how different fundamental variables non-linearly influence the different price quantiles throughout the trading day in each market. This is motivated by the upcoming market integration due to the NordLink cable, which will connect Norway and Germany in 2020. The impact from each variable varies throughout the trading day and across the price distribution. Clearly, electricity markets are complex as the relations between fundamental variables and day-ahead prices are highly non-linear across several dimensions.

Autoregressive effects are the most important price drivers in Nord Pool; the first lagged price is the most influential variable and is thus the best price predictor. The seventh lag has notably lower coefficients, but is also a highly influential variable in Nord Pool. The first lag is most influential in off-peak periods and lower tail, while the seventh lag is most relevant in trading periods with higher demand. In EPEX, lagged prices are less important relative to other variables, but the impact of the first lag slightly exceeds that of the seventh lag. The intraday price dynamics are similar to Nord Pool: the first lag is most influential during off-peak, while the seventh lag is more relevant when demand is higher. The volatility of the prices explains the differences in relevance of autoregressive effects. Nord Pool day-ahead prices are much more stable, and it is reasonable that lagged prices are better price determinants. The price impact of the volatility variable is very similar in both markets: it is highly significant in both tails and tends to make prices deviate further from the expected value.

Demand has a particularly large impact in EPEX, as the elasticities are high for all quantiles. Supply in EPEX - expressed through voluntarily reported power plant availability - has a price lowering influence for the entire price distribution. Both the demand and supply parameters in EPEX tend to have lower absolute elasticities with increasing quantiles, implying that the highest prices are driven by other factors. The dynamics are completely opposite in Nord Pool; both demand and supply are only influential in the highest quantile, implying that prices in the normal range are barely influenced by these variables. The differences in impact from changes in demand and supply are related to the energy sources used; the flexibility provided by hydro in Nord Pool smoothly balances load fluctuations. The results support this, as hydro reservoir levels were found to be primarily influential in the tails of the prices.

The lower and upper tails in EPEX have quite different dynamics; some variables are relevant in only one tail, while others influence both tails. In addition to demand and supply strongly impacting the lower tail, wind power production has a notably strong influence - particularly during night when negative prices are known to occur. The fossil fuel prices are important in both tails, but with very different impacts. Coal is most important during day for lower quantiles, while it is most relevant for upper quantiles during night. Gas and oil are similar to each other; the quantile plots have positive peaks during night and early evening, and a slight negative dip in the middle of the day. These dips are unexpected, but are plausibly explained by low cost photovoltaic power substituting the fossil fuels, resulting in lower prices. Both gas and oil are used to cover peak load, hence the positive impact on prices in the highest quantiles in peak demand periods is according to expectations. The irrelevance of both oil and gas in Nord Pool is as anticipated, as the share of fossil fuels is quite low. Coal has a small significant impact, and exhibits similar dynamics as in EPEX during night; the elasticities are positive and increasing with higher quantiles. This is likely due to coal covering the base load and becoming the price setter for the highest prices in off-peak periods. As CO_2 quantile curves closely follow those of coal, the impact is quite similar in both EPEX and Nord Pool. In addition to emphasizing the price impact of coal, an increase in cost of CO_2 also encourages shifting to fuel sources emitting less carbon.

Overall, the analysis of the impact of fundamental variables confirms that the price formation dynamics differ greatly in these two markets. Nord Pool spot prices are primarily driven by autoregressive effects, while other variables, such as demand, are influential only in some quantiles. It appears that much of the potential price impact from fundamental variables is balanced by the large hydro reservoirs. EPEX has a higher number of relevant price drivers compared to Nord Pool. This is likely explained by the structure of the German power market, which consists of large scale thermal power in combination with unpredictable renewable energy sources, resulting in a much less flexible system. Consequently, changes in the balance between production and consumption, or fuel prices, have stronger impacts on the electricity price formation.

A thorough understanding of dynamics in these two markets is important for market participants. Producers benefit from the insights given by this analysis, as it supports investment planning in these markets, and assists in developing hedging strategies. Further, it is valuable for TSOs, as it improves future grid operation and development, as well as investors considering entering or expanding their presence in these markets. Connecting two markets is most beneficial if there are differences in prices and price dynamics, which is clearly the case for Nord Pool and EPEX, as shown in our analysis. Market participants in both EPEX and Nord Pool will mutually benefit and increase trading profits. Further, intermittency issues in Germany are offset and security of supply is enhanced.

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6. Essay 5 - Investment in Mutually Exclusive Transmission Projects under Policy Uncertainty

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Investment in mutually exclusive transmission projects under policy uncertainty

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A B S T R A C T

In this paper we evaluate mutually exclusive transmission projects under policy and economic uncertainty. The alternatives being considered are transmission investment projects between Norway and Germany, and Norway and the UK. We apply a real option valuation framework allowing the investor to choose the optimal time and location of the investment, and also how different conditions affect the decision to invest in either of these two projects. The analysis shows that the value of the option does not necessarily increase with volatility.

1. Introduction

The European Union (EU) has committed to a binding goal for all member states of fifteen percent cross-border transmission capacity by the end of 2030. In this paper we aim to analyse the profitability and optimal investment timing of additional transmission capacity between countries when uncertainty is taken into account. This is done using real option valuation with the option to invest in one of two mutually exclusive projects; either building an interconnector from Norway to Germany or from Norway to the United Kingdom (UK).

The main contribution of this paper is twofold. First, we apply real option analysis to consider which country to connect to. In the real options literature there are several papers considering mutually exclusive investment projects (Childs et al., 1996; Dixit, 1993; Décamps et al., 2006), but they do not consider the option of choosing between different locations. Second, our paper is one of the few to apply real option valuation to transmission assets. We draw inspiration from the paper of Fleten et al. (2011), who analyse the option to invest in an interconnector, where the aim is to choose the optimal capacity of the cable. In this paper we focus on the application of real options when choosing between mutually exclusive projects under policy and economic uncertainty.

The two policy schemes we focus on are the EU emission trading system (ETS) and capacity markets. We find that capacity markets have no impact regarding project choice, but it does influence the option value. A reform to the EU ETS, necessarily increasing CO_2 emission prices, can increase the option value, leading to an increased spread between the Norwegian and German/UK electricity prices. The differences in production mix between the German and the UK market also makes a tightened EU ETS have a different effect on the two markets. The effects of the policy schemes are included in the model through the revenues from the two cables. We model the revenues as uncertain and fluctuating over time.

We further investigate the benefits of looking at the option to invest in one of the two locations. Other papers have developed models for choosing the optimal entering strategy into a new market. Gilroy and Lukas (2006) considered the option of choosing between two different market entry strategies. They emphasise the value of considering the option to invest as mutually exclusive

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choice between different locations. By doing so, the value of the option increases and it helps practitioners obtain an optimal investment strategy.

The valuation methodology builds on Rubinstein (1994), and takes into account the yearly revenue streams for two potential projects, ramping restrictions and capacity markets. One important finding is the effect of uncertainty on the option value. The result shows that the option value does not necessarily increase when the volatility increases, unlike what we commonly find in real option valuations.

The rest of this paper is organised as follows: In Section 2 we present characteristics and trends in the electricity market, together with a brief description of the Norwegian, German and the UK electricity market. Section 3 discusses the main policy related uncertainties in the electricity market and how these uncertainties might affect the electricity price. Section 4 introduces and explains the two factor real option model. Section 5 presents the data set and describes the main findings. In Section 6 we perform a sensitivity analysis of the real option model and conclude in Section 7.

2. The electricity market

In the Norwegian production system hydropower produces over 98% of the total generated electricity. Only a small fraction of the system is thermal generation emitting CO_2. Norway utilizes a market based support scheme established to promote new electricity production based on renewable energy sources, the Norwegian–Swedish electricity certificate market. The increased portion of new renewable generation is expected to increase the surplus in the Nordic system. The electricity price in Norway is low compared to other countries in Europe, as hydropower is the price setter in most hours.

In the United Kingdom, 36% of the total generated electricity was generated from coal, 28% from natural gas, 21% from nuclear and 17% from renewables in 2013 (Department of Energy and Climate Change, 2015). The government is also investing in a new nuclear power plant, Hinkley Point C, to secure supply as most of UKs existing nuclear stations are due to close before 2023. A capacity market will be introduced in December 2014 to create incentive to invest in new generation. The UK chose to introduce a price floor of 18 £/tCO_2 for all market participants to give an incentive to invest in low-carbon power generation.[1]

In Germany, 48% of the total generation was generated from coal, 28% from renewables, 17% from nuclear and 6% from natural gas in 2013. Germany actually has a target of consuming 80% of its total electricity consumption from renewables by 2050. To this end, Germany has introduced a feed-in-tariff aimed to accelerate investments in renewable energy by providing a fee above the retail electricity price. This is a part of the Energiewende in Germany, the transition of the power sector from nuclear and coal to renewables.

The financial crisis has stalled investments in new generation capacity and reduced demand for electricity. This in combination with increased deployment of wind and solar generation, the evolution in the costs of gas and coal, and the low carbon price have resulted in reduced wholesale electricity prices in Germany (European Commission, 2015).

3. Policy uncertainty

The European Union introduced the EU2050 target to make the transition to a competitive low-carbon society by 2050. As a consequence of the framework, the energy markets have experienced extensive changes during the last decades, creating an uncertain environment for investors. This paper focuses on what we consider the two main sources of policy uncertainty in EU during the next 45 years; the future of the EU ETS and the possible introduction of capacity remuneration mechanisms. The EU ETS was implemented to reach the 2050 target of 80% emission reduction compared to 1990 levels (European Council, 2014). Today it is not incentivising much emission reductions due to the low carbon price. If it fails to increase the incentive to invest in green technology, it is expected that it will be reformed or replaced with another type of scheme. In addition, several countries have either implemented capacity markets or are considering it because they are concerned for their security of supply.

3.1. EU emission trading system

The EU ETS was started in 2005 and is the largest cap-and-trade scheme in the world. An absolute quantity limit (or cap) on CO_2 emissions is placed on 12000 emitting facilities located in the EU. This constitutes 45% of the total carbon emissions in the EU. These facilities must measure and report their CO_2 emissions and subsequently surrender an allowance for every ton of CO_2 they emit during annual compliance periods.

The carbon price fell from almost 30 €/tCO_2 in mid-2008 to less than 5 €/tCO_2 in mid-2013 as there was a surplus of 2 billion allowances in 2013. The surplus has primarily been built up as a reaction to the financial crisis. It led to a reduction of industrial production, emissions, and thus the demand for allowances. The supply of allowances for 2008–2020, which is based on a much better outlook for the economy, is fixed. This has led to a low carbon price, which weakens the incentive for emission-saving investments.[2]

The short-run effect of an increase in CO_2-prices in EU ETS is an increased electricity price. However, long term effects depend on investment reactions, which in turn is highly dependent on governmental policies. The future

[1] *Carbon price floor: reform and other technical amendments* published by the British government https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/293849/TIIN_6002_7047_carbon_price_floor_and_other_technical_amendments.pdf.

[2] The web page of European Commission on EU ETS http://ec.europa.eu/clima/policies/ets/reform/index_en.htm

energy mix is uncertain, and thus the impact on spreads are uncertain.

For the valuation of an interconnector it is interesting how the EU ETS will influence the revenues through the electricity price spread between the two countries. The Norwegian system is dominated by hydropower, while both the UK and the German system are dominated by thermal generation. This implies that the carbon price will have a greater effect on the prices in the UK and Germany. There are hours where the Danish coal-plants are the price setters in the Norwegian market. However, hydropower is the price setter in most hours, due to existing bottlenecks in the grid. In these hours, the spread between the electricity prices will increase with a higher carbon price since there is no carbon emission from hydropower.

3.2. Capacity remuneration mechanisms

In energy-only markets the producers of electricity are paid based on the MWh delivered to the consumers. The question is whether some kind of capacity market should be implemented in addition to the energy-only market to contribute to the security of supply. It is designed to give incentives for investment in new generation, ensuring that existing generation does not get shut down and to increase the demand-side response, making demand more price elastic. Several EU-members have already implemented different types of capacity mechanisms, including Greece, Ireland, Italy, Portugal, Spain, Sweden and the UK.

The capacity market in the UK has committed to let interconnectors participate in its auctions from 2015 on.[3] For the cable revenues this means that the new interconnectors can bid into the auctions and receive revenues from this market. Thus there is less policy uncertainty here.

A report published by the German Advisory Council on the Environment (SRU) highlights a strategic reserve as a better option than a capacity market to secure supply, due to a smaller intervention in the market.[4] However, the Council does not rule out capacity market as a necessity to ensure security of supply in the medium term. In October 2014, The Ministry of Economic Affairs and Energy in Germany published its Green Paper on the future development of the German electricity market. The paper considers two approaches for the long-term development of the electricity market: an optimised energy-only market or capacity market alongside the energy-only market.[5]

It is uncertain how the electricity price will be affected by the capacity market. The general price level can decrease if the capacity market creates an incentive in the energy-only market to invest in capacity with lower marginal cost than the current price setter in off-peak hours. The resulting change in the wholesale price is dependent on the steepness of the merit order curve and how much new capacity is added in. More capacity in the market also reduces the market power of incumbents since the companies can to a smaller extent profit from price spikes by withholding capacity (Cramton and Ockenfels, 2012). Capacity markets can also be designed to only pay a fixed capacity payment to peak plants. The incentives for investments in base load and mid merit capacity can be reduced, resulting in lower peak prices and higher mid-merit prices.

According to Cramton and Ockenfels (2012), by getting costs recovered in two markets, the generation companies reduce their risk premium in the spot market. Therefore, a capacity market can lower the electricity price in the spot market by reducing the risk premium. The Department of Energy and Climate Change (DECC) has performed an assessment of the capacity market in the UK, which confirms that the general level of the wholesale price decreases. At the same time, it is difficult to predict the effect a capacity market has on the electricity price, due to the lack of empirical data.

The congestion rent (interconnector revenue) is equal to the hour-by-hour price difference between the two markets. We consider an asymmetric capacity market, i.e. a capacity market is only implemented in one market. We will refer to the market that introduces the capacity market, as market A, and the other market, as market B. In this paper Germany and the UK are market A since UK is implementing a capacity market and Germany is considering it due to the constrained capacity situation in the two markets. Norway is market B because it is not considering implementing a capacity market. We will therefore assume that the capacity situation is more constrained in market A, implying higher peak load prices.

A capacity market can lead to lower peak prices in market A. If the peak prices are still higher in market A than in market B, A will continue to import from B in peak hours, so there will not be an immediate impact on traded volumes between the two markets. The effect on the congestion rent is dependent on how much the peak prices in market B decrease with peak prices in market A. We believe the peak prices will be reduced further in A than in B. This is dependent on the correlation between the two markets. It is not likely that the peak prices are reduced with the same amount, because this requires perfect correlation. This suggests reduced congestion rent. If the capacity market lowers the peak price in market A to the level where some peak prices in B are at the same level as in A, the capacity of the cable is not fully utilised and the trade volume is altered. As a consequence the congestion revenue will be reduced. At the same time, the interconnector will also get revenues in the capacity market, which compensates for the reduction in the congestion revenue.

Another result of introducing a capacity market in market A, could be that the overall market price decreases. If the market price is sufficiently lowered it will change the

[3] *State aid: Commission authorises UK Capacity Market electricity generation scheme*, press release by European Commission July 2014 http://europa.eu/rapid/press-release_IP-14-865_en.htm

[4] *Shaping the Electricity Market of the Future – Key Recommendations* published by German Advisory Council on the Environment in November 2013 http://www.umweltrat.de/SharedDocs/Downloads/EN/02_Special_Reports/2012_2016/2013_11_Special_Report_Electricity_Market_KfE.pdf?__blob=publicationFile.

[5] *Ein Strommarkt für die Energiewende* published by Ministry of Economic Affairs and Energy in October 2013 http://www.bmwi.de/BMWi/Redaktion/PDF/G/gruenbuch-gesamt,property=pdf,bereich=bmwi2012,sprache=de,rwb=true.pdf.

trade patterns so that market B imports more than before, shifting the overall market price downwards. An analysis published by the European Commission suggests that the congestion rent is reduced in peak hours and increased in low load hours.[6] Therefore it is difficult to determine in advance the total effect on the revenue.

4. Modelling the investment option

To model the investment decision a real options model has been developed. The characteristics of the investment decision will be explained in Section 4.1. The technical consideration is stated in Section 4.2 and the historical data used for the sensitivity analysis is introduced in Section 4.3. All these subsections are used to provide a better understanding of the modelling which follows in Section 4.4. Finally, the numerical implementation is explained in Section 4.5.

4.1. Characteristics of the investment decision

In the following paragraphs we will go through the main assumptions to provide a better understanding of the model in Section 4.4

Assumption 1. The market is perfectly competitive. This means that all market participants are price takers, that they do not have the market power to change the prices. This is a common assumption when considering investments in the electricity market (Fabbri et al., 2005; Yucekaya, 2013).

Assumption 2. The two investment projects are mutually exclusive; the decision to make one investment prevents making the other investment. We make this assumption based on technical limitations in the Norwegian electricity market. Statnett estimates that the maximum load in Norway could be as high as 25 000 MW and the production capacity is 28 000 MW.[7] In 2020, the total exchange capacity of the interconnectors in Norway will be equal to 5400 MW with the two already planned cables being built. These values indicate that there will be situations in the future when there will not be enough capacity to meet demand and at the same time export maximum capacity on the cables. These situations will decrease the profitability of the cables, by reducing the number of hours the cable can export maximum capacity. By introducing one more interconnector the situation will be even more strained and the number of hours with reduced capacity will increase. We therefore conclude that there is enough capacity in the Norwegian system to build one more cable, but that it will not be profitable to build two more cables.

Assumption 3. A new cable will at the earliest be built in 2020. Therefore, we set $t=0$ equal to year 2020. One of the reasons for this is that to own and/or run an interconnector in Norway, Statnett must obtain a license from the Norwegian Ministry for Petroleum and Energy (OED). The process of applying for a license usually takes several years. This highlights the importance of looking ahead when considering investments in new interconnectors.

Assumption 4. The option has a lifespan of 10 years, following Schwartz (1997, p. 969). After 10 years, the option is worthless. One justification is that competing projects that would destroy our option will take a long time to develop. A cable from a different country in the Nordpool-area, such as Sweden, would reduce the option value greatly, due to a decreased spread between prices in the Nordic area and continental Europe.

4.2. Technical considerations

Statnett is the only company in Norway which holds a license to own transmission assets which can be used for import and export of electrical energy (Energiloven 4–2). Reliable cost parameters for their projects have been made available to us. The costs used in this analysis are given in Table 1. All the values is quoted in million Norwegian NOK. Except for two parameters discussed in the following paragraph, these are identical to the numbers provided to us by Statnett, inflated to 2020 numbers assuming an annual discount rate of 4%.

We have chosen to change the two parameters “congestion rate from other interconnectors” and “net cost of domestic grid reinforcement”. The reason is rooted in two assumptions: (1) the investment is taking place in 2020 or later and (2) the investment is made after two new interconnectors are installed. In this investment decision, we are looking at the case where the two cables are assumed to be operating. With the two new cables installed, the total capacity on the interconnectors are doubled compared to the current situation. Therefore, we conclude that the losses in congestion revenues are doubled from Statnett's estimate. The investment and total annual costs are presented in Table 2. Figures have been converted from NOK to EUR using an exchange rate (EUR / NOK) of 8.

The second change from Statnett's estimate is a decrease of the net cost of domestic grid reinforcements. Statnett is planning to invest 20–30 billion NOK in the transmission grid, independent of new interconnectors, the next decade.[8] Most of these reinforcements are expected to be in place before 2020. Therefore, we assume that there is less need for domestic grid reinforcements for the next cable.

The technical parameters for the cable are assumed to be identical for both cables. We use a capacity of 1400 MW, an availability of 99% and a lifetime of 40 years. We chose to use the same capacity, availability and lifetime of the cable as Statnett employed in the studies for the NordLink and NSN cable. We assume that capacity, lifetime and availability are constant.

[6] *Capacity mechanisms in individual markets within the IEM* published by the European Commission in February 2013 http://ec.europa.eu/energy/gas_electricity/consultations/doc/20130207_generation_adequacy_study.pdf

[7] *Estimated maximum production in Norway 2012* published by Statnett in 2011.

[8] *Investment plan in Norwegian transmission grid* published by Statnett in 2014.

Table 1
Cost parameters for transmission capacity.

Type of cost	Germany	UK
Annual costs		
Congestion revenues from other interconnectors	−447	−477
Maintenance costs	−26	−33
Transit costs	−11	−39
System operating cost	−164	−164
Transmissions losses in the domestic grid	−132	−79
Investments costs		
Investment cost in cable and station	−8422	−9146
Net cost of domestic grid reinforcements	−2369	−829

Table 2
Technical parameters for transmission capacity.

Cost	Germany (Mill. EUR)	UK (Mill. EUR)
Investment cost	1348	1247
Total annual cost	1930	1953

Ramping is defined as the change in power flow from one time unit to the next. A continuous ramping project has been installed on the new interconnector to Denmark, Skagerak 4, to improve the frequency quality on the intra hour imbalance. With continuous ramping, the power flow can change with a rate of 1000 MW/h. If this project is proven successful, Statnett will implement continuous ramping on all their new interconnectors including NSN and Nordlink (Statnett, 2013). We assume that continuous ramping will be introduced before 2020, and therefore the ramping is set to 1000 MW/h.

4.3. Market data

The market data is hourly historical spot prices from 2003 to 2013 from Norway (Nordpool spot), Germany (EPEX) and the UK (APX). The parameters; start revenues, correlation, drift rate and volatility are based on this data. For the Norwegian spot price the area price in the south Norway (NO2) region is chosen as the interconnectors which we consider will be connected to this region.

The spot prices of electricity change from hour to hour due to change in demand. Fig. 1 shows the spot prices of electricity in the three countries in an average week in February 2013. The figure illustrates that the Norwegian spot price on average is the lowest, and does not have the same spikes in average price as the two other annual spot prices. One can see that the price spread between Norway and the two other countries are high during the day and small at night.

Our findings from the historical data confirm that the Norwegian electricity prices tend to be less volatile then the two others prices. The Norwegian price also experiences less price spikes than the other two. One of the reasons for this is that the Norwegian generation assets can easily and without cost be regulated up and down to meet demand (see Section 2). The revenues from an interconnector are based on the price spread between two connected markets. Even though a country might have larger electricity prices than another market, it does not necessarily make it more profitable than the other market. The important parameters are how many hours the prices are different (i.e. the spread option is different from zero) and the absolute price difference between prices in these hours. The historical interconnector revenues are based on market data of the different spot prices, considering ramping and availability. Since 2010, the price spread between the UK and Norway has grown, making it more profitable to invest in the interconnector to UK. Before 2009, the German interconnector was equally profitable.

4.4. A model for valuing the two factor investment option

A transmission line gives the owner the right to transport electricity from one point to another. The value of such a line is the same as the value of the option on the spread between end point prices. Let P_a and P_b be the price of a unit of power at the endpoints, a and b, of the transmission line. Let K_i be the maximum capacity the line can transport at a given time and $K_{i_{RES}}$ denote the capacity allocation in the reserve market. The hourly revenue of the transmission line is therefore given by:

$$R_i = |P_b - P_a|(K_{i_t} - K_{i_{RES}}) + P_{reserve}(K_{i_{RES}}), \quad \text{where } K_i \ge K_{i_{RES}}$$

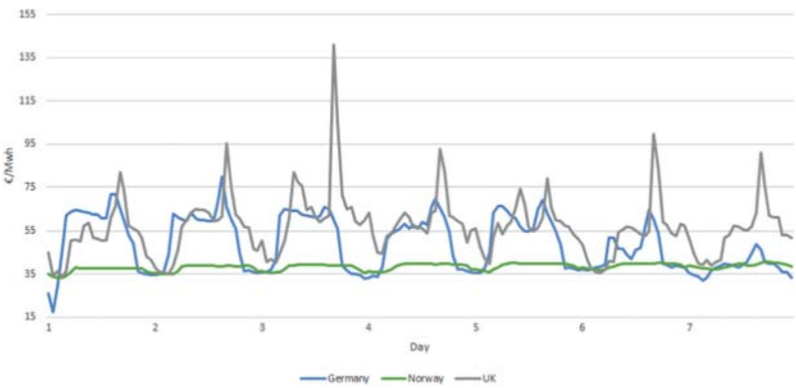


Fig. 1. The historical spot price in the three countries in an average week in February 2013.

The capacity, K_i, that can be transported on the line can change form hour to hour due to ramping restrictions. K_i is determined by the present state of the electricity price and the maximum capacity of the cable (K_{max}):

$$K_{i_t} = \begin{cases} \text{Min}(K_{max} & \text{for } P_a > P_b \\ \quad \text{or } K_{i_{t-1}} + 1000) & \\ \text{Max}\big(\text{Min}(0, K_{i_{t-1}} + 1000) & \text{for } P_a = P_b \text{ and } K_{i_{t-i}} > 0 \\ \quad , \text{Max}(0, K_{i_{t-1}} - 1000)\big) & \\ \text{Min}\big(\text{Min}(0, K_{i_{t-1}} + 1000) & \text{for } P_a = P_b \text{ and } K_{i_{t-i}} < 0 \\ \quad , \text{Max}(0, K_{i_{t-1}} - 1000)\big) & \\ \text{Max}(-K_{max} \text{ or } K_{i_{t-1}} & \text{for } P_a < P_b \\ \quad - 1000) & \\ 0 & \text{for elsewhere} \end{cases} \tag{1}$$

The transmission revenues, R_1 and R_2, are given in annual revenues. We calculate them by summing up the hourly revenues (R_i):

$$R_{annual} = \sum_{i=1}^{\text{Hours in a year}} R_i$$

The two potential cable investments have different expected payoffs. The reason for this can partly be explained by different endpoint prices and capacity market design/existence. We will therefore get two different annual revenues, where R_1 is defined as the revenue of the first cable and R_2 the revenue of the second cable.

For computational tractability, the payoff between the price difference in the Norwegian and German (UK) market, i.e R_1 (R_2) is modelled as a geometric Brownian motion. Our argument for this is two-fold. First, revenues will be non-negative. Second, we are trying to capture the long-term dynamics of the present value of the revenues, so the relevant empirical basis is limited to, e.g. ten observations of annual revenues. In this case, a simple model is preferable. For this paper we assume that the two revenue streams follow two distinct GBM processes:

$$dR_1 = \alpha_1 R_1 dt + \sigma_1 R_1 dz_1, \tag{2}$$

$$dR_2 = \alpha_2 R_2 dt + \sigma_2 R_2 dz_2, \tag{3}$$

where α_1 and α_2 are the instantaneous drift rates, σ_1 and σ_2 are the volatility rates, and dz_1 and dz_2 are the increments of two correlated Wiener processes. All of the parameters are assumed to be known and constant. We impose the following relationship $\delta = \mu - \alpha$, where $\delta > 0$. Further we assume that uncertainty exists, so $\sigma > 0$ and that the investor are risk neutral $\mu = r$. The dependence between the two uncertain variables is described by the instantaneous covariance term, given by:

$$\text{Cov}(dR_1, dR_2) = \rho\sigma_1\sigma_2 R_1 R_2 dt, \quad \text{where } \rho \le 1.$$

We want to find an expression for the option value of the investment decision. Let $F(R_1, R_2)$ be the option value of the best of two mutually exclusive underlying assets. In this case this is two cables. We further assume that the transmission investment can be totally spanned and replicated by other traded assets in the market. Therefore, we obtain the following PDE using a contingent claim analysis:

$$\frac{\partial F}{\partial t} + \frac{1}{2}\sigma_1^2 R_1^2 \frac{\partial^2 F}{\partial^2 R_1} + \frac{1}{2}\sigma_2^2 R_2^2 \frac{\partial^2 F}{\partial^2 R_2} + \rho\sigma_1\sigma_2 R_1 R_2 \frac{\partial^2 F}{\partial R_1 \partial R_2} + \alpha_1 R_1 \frac{\partial F}{\partial R_1} + \alpha_2 R_2 \frac{\partial F}{\partial R_2} - rF = 0 \tag{4}$$

We set out to determine the boundary between investing in one of the two projects and waiting. The following conditions have to apply:

When both asset values are zero, the value of the option to invest is zero.

$$F(0, 0) = 0 \tag{5}$$

When one of the asset values are zero, the value of F is reduced to an American call option, C, on a single underlying asset.

$$F(R_1, 0) = F(R_1) \tag{6}$$

$$F(0, R_2) = F(R_2) \tag{7}$$

Due to the correlation, the variables R_1 and R_2 are not independent. When finding an optimal investment strategy we have to consider the two start revenues in relation to each other. We define $R_1^*(R_2)$ to be the exercise boundary of the first cable as a function of the second cable. Likewise, $R_2^*(R_1)$ is the exercise boundary of the second cable as a function of revenues of the first cable.

It is financially obvious that an option on two assets will always be more valuable than an option on just one of the assets (Dixit and Pindyck, 1994). Therefore $F(R_1, R_2) \ge F(R_1)$ and $F(R1, R_2) \ge F(R_2)$ have to hold. Let C_1 and C_2 be the sum of the initial investment cost of the cable plus the present value of operation and maintenance costs. The costs are assumed to be irreversible. In addition to the hourly spot price revenues, owning a transmission line can entail the owner to additional revenues from a capacity market. We let CM denote the annual revenue for participating in a capacity market given a capacity price (R_k). The following conditions have to apply:

$$F\big(R_1^*(R_2), R_2\big) = R_1^* + CM(R_K) - C_1, \quad \text{for } R_1 > R_2. \tag{8a}$$

$$F\big(R_1, R_2^*(R_1)\big) = R_2^* + CM(R_K) - C_2, \quad \text{for } R_1 < R_2. \tag{8b}$$

4.5. Numerical implementation

Due to the complexity of the PDE in Section 4.4.[9] we must solve the equations numerically. Several researchers have developed numerical techniques for pricing multi-assets options, including Landskroner and Raviv (2008), Boyle et al. (1989) and Broadie and Detemple (1997). Rubinstein (1994) values options with two underlying assets by approximating continuous bivariate normal density functions as a discrete bivariate binomial density. This approach is called “binomial pyramids”.

The pyramid is expanding each time step with 2^{i+1}

[9] The analytical approach of guessing a solution does not work in our case, since we lack an initial guess which can solve the PDE on general form.

distinct nodes and the total number of nodes in a tree is equal to $(1 + N)^2$ at the last time step. Where N is the total number of time steps and i, is referring to a specific time step. The two underlying assets are assumed to have a risk-neutral joint lognormal distribution. The riskless interest rate is used as the discount rate and both underlying assets are expected to appreciate at the same riskless rate.

Rubinstein's (1994) multiplicative bivariate binomial model defines the possible states for the two assets. The first asset return is assumed to be either u or d, with equal probability. The second asset return is dependent on the first assets step and can be in one of for states; A, B, C or D. The time steps are based on the log transformed size of the underlying asset. In our model we are using log transformed revenues $(Y_i = \log(R_i))$ to calculate the time step. The risk neutral approach to option pricing gives us the return on the first asset, u and d, to be defined by:

$$u = e^{\mu_1 h + \sigma_1 \sqrt{h}} \quad \text{and} \quad d = e^{\mu_1 h + \sigma_1 \sqrt{h}}, \quad \text{where } h \equiv t/n. \tag{9}$$

Here $\mu_i = (r - \delta_i) - \frac{1}{2}\sigma_i^2$, where μ_i is the logarithmic mean of the underlying assets. The lifetime of the option $[0, T]$ is divided into n equal time intervals of length h. The risk free rate is r and δ_i continuous dividend yield of the underlying asset.

When we invest in an asset we do not only get the revenues from that year, but all the revenues over the lifetime of the asset. We therefore need to calculate the expected present value of the revenue stream at each node. If $R_i(t)$ is the revenue at a specific time with start value R_i, the expected present value of the revenues, from time t to the lifetime of the cable, T_2, can be calculated knowing that the underlying asset follows a geometric Brownian motion:

$$E[R_i(t)] = R_i\left(\frac{1 - e^{-(r-\alpha)T_2}}{r - \alpha}\right), \quad \text{for } t \in [0, T] \tag{10}$$

The n time intervals are denoted by i, where $i = 0, 1, \ldots, n$. The underlying revenue of asset 1 at each node is set equal to $R_1 u^j d^{i-j}$, where $j = 0, 1, \ldots, i$ is the number of up movements of underlying asset 1. For our cable, the revenues therefore are:

$$R_{1total}(i, j) = R_1 u^j d^{i-j}\left(\frac{1 - e^{-(r-\alpha_1)T}}{r - \alpha_1}\right) \tag{11}$$

If the return of the first asset is u, the return of the second asset is A or B with equal probability, depending on the correlation, ρ, between the two assets. Then if the return of the first asset is d, the return of the second asset is C or D. If the first move is (u,A) the second move can be (u,A), (u,B), (d,C) or (d,D). Multiplying these two moves together, the total return over the first two moves is either (u^2, A^2), (u^2, AB), (ud,AC), or (ud,AD), with equal probability $\frac{1}{4} \times \frac{1}{4} = \frac{1}{16}$. The mathematical formulation for the four possible steps are defined by:

$$A = e^{\mu_2 h + \sigma_2 \sqrt{h}[\rho + \sqrt{1-\rho^2}]} B = e^{\mu_2 h + \sigma_2 \sqrt{h}[\rho - \sqrt{1-\rho^2}]} C = e^{\mu_2 h - \sigma_2 \sqrt{h}[\rho - \sqrt{1-\rho^2}]} D = e^{\mu_2 h - \sigma_2 \sqrt{h}[\rho + \sqrt{1-\rho^2}]} \tag{12}$$

These definitions of (u,d) and (A, B, C, D) can be used to construct the appropriate size of the moves in a square binomial pyramid. To build the lattice for each state variable recombine the condition $AD=BC$ is imposed (Landskroner and Raviv, 2008). Starting at the end of the pyramid, the value of the option can be estimated at each node. Working backwards through the pyramid, 4 nodes are discounted into 1 at each move, using the same probability for each node.

For any node (i, j, k) the lattice evolves to four nodes, $(i + 1, R_1 u, R_2 A)$, $(i + 1, R_1 u, R_2 B)$, $(i + 1, R_1 d, R_2 C)$ and $(i + 1, R_1 d, R_2 D)$. Where $R_2 A$, $R_2 B$, $R_2 C$ and $R_2 D$ are the values of the underlying asset 2 in the different nodes. The value of asset 2 in each node, at any time period i and with j up moves of asset 1, is set equal to:

$$R_2(i, j, k) = R_2 e^{\mu_2 ih + \sigma_2 \sqrt{h}\left[\rho(2j-i) + \sqrt{1-\rho^2} \times (2k-i)\right]}, \quad \text{where } k = 0, 1, \ldots, i \tag{13}$$

where R_2 is the start value of asset 2, μ_2 is the logarithmic means of the underlying assets 2 and ρ is the correlation between the two assets. The total value of the revenue stream for asset 2 with a lifespan of T_2 years is:

$$R_{2total}(i, j, k) = R_2 e^{\mu_2 ih + \sigma_2 \sqrt{h}\left[\rho(2j-i) + \sqrt{1-\rho^2} \times (2k-i)\right]}\left(\frac{1 - e^{-(r-\alpha_2)T_2}}{r - \alpha_2}\right) \tag{14}$$

The assets can potentially participate in capacity markets. Therefore, there is a possibility of receiving a revenue stream for participation in such a market. We define CM_i to be the total revenues received by participating in a capacity market. cm_i is the yearly revenues received from the government for participating in a capacity market. CM_i is defined by the sum of all capacity revenues received over the lifetime of the cable:

$$CM_i = \sum_{i=1}^{years} cm_i \tag{15}$$

The intrinsic value is the maximum value of the two assets minus the costs. For our call option, the intrinsic value of best of asset R_1 and R_2 is given by:

$$F(R_1, R_2) = \text{Max}\Big(0, \text{Max}(R_{1_{total}} + CM_1 - C_1, R_{2_{total}} + CM_2 - C_2)\Big) \tag{16}$$

where $R_{1_{total}}$ and $R_{2_{total}}$ total are the total revenue received by the cable investment over the lifetime of the investment. CM_1 and CM_2 is the revenues from participating in capacity markets, and C_1 and C_2 the total investment and maintenance cost of the investment. When the values of the two assets are given at any node, the value of the option at each node can be calculated by starting at maturity where the value is known with certainty and working backwards by discounting four nodes into one node at each move. The value of the investment at maturity, $i=T$, is:

$$F_{T,j,k} = Max\Big(0, Max\Big(R_{1totalT,j,k} + CM_1 - C_1, R_{2totalT,j,k} + CM_2 - C_2\Big)\Big) \tag{17}$$

At maturity there is no possibility of waiting, which means that the option value at maturity is equal to the maximum of zero and the intrinsic value. The value can never be lower than zero due to the fixed boundary conditions.

The value of the option is given by $F(0)$, which is the value of the option in year 0. It is found by working backwards through the pyramid and finding the option value at every node. This is done by taking the maximum of the intrinsic value and the value of waiting. If the option has a positive value in year 0, the project has a potential for making a profit. The option value at every node is:

$$F_{i,j,k} = \mathrm{Max}\Big(0.25e^{-rh}(F_{i+1,j,k} + F_{i+1,j,k+1} + F_{i+1,j+1,k} + F_{i+1,j+1,k+1}), \mathrm{Max}\Big(R_{1totali,j,k}+CM_1 - C_1, R_{2totali,j,k} + CM_2 - C_2\Big)\Big) \quad (18)$$

The first argument in the outer bracket is the value of waiting while the second argument is the value of investing. By using this equation we find the value of the option.

5. Application

5.1. Estimation of parameters

The parameters are estimated based on historical market data, technical reports published by Statnett and other public sources of information. The method and assumptions applied to estimate the parameters are given in the following paragraphs.

The annual revenues are a function of the difference in the electricity prices between the interconnected regions and the technical parameters of the cable. The intraday characteristics of the electricity price are captured by modelling the electricity price with a time resolution of one hour. The difference in the electricity prices between the interconnected regions were found by using the Phelix price from the European Power Exchange (EPEX) SPOT, the UKPX price on the Amsterdam Power Exchange (APX) and NO2 (south norway) price from Nordpool. We have used data from 2003 to 2013 to calculate the correlation between the two revenue streams, ρ, and discounted the 2013 revenues with the risk adjusted rate to get the revenues for the two cables in 2020 (year 0), R_1 and R_2, respectively. The risk adjusted rate is chosen based on NOU 2012:16 (Norway's public reports). NOU 2012:16 recommends to use a risk adjusted rate of 4% for an economic analysis of a public investment with a lifetime of 40 years.[10]

The participants in a capacity market are committed to deliver energy when needed or they will face penalties. This fear of not being able to meet their obligations affects the amount of capacity the interconnector owner bid in the auction. The price difference between the two regions that are interconnected determines the direction of the power flow. This means that Statnett cannot guarantee the capacity they bid in the auction, if the price in the UK is higher than the price in Norway at that time. We therefore assume Statnett will bid only 900 MW of the cables capacity in the auctions to reduce the risk of facing penalties. The total revenue from the capacity market in UK, CM_2, is calculated based on a capacity price of £30 kW/year.

The expected growth rate (α) for the cable revenues has a positive value. They were calculated based on the following inflation values: UK 2.56 percent, Germany 1.51 percent, Norway 2.13 percent.[11] The growth rate (α) is set to be half the inflation. Borovkova et al. (2012) argued that the assumption that a commodity, in our case the cable revenues, will experience a positive growth forever is unrealistic. If the growth rate is set higher than inflation it means that the revenues will grow to an infinite size over infinite time. The Ragnar Frisch Centre for Economic Research found that the electricity price difference between Norway and Germany will increase to approximately 10 €/MWh in 2030, which implies a positive growth rate of the cable revenues.[12] We therefore choose to set the expected growth rates between zero and the inflation rate in the two countries. This is consistent with Fleten et al. (2011) which also chose a positive growth rate on the cable revenues between Germany and Norway.

The volatility parameters of the revenue processes have been set based on (i) analysis of the time series of hypothetical revenues 2003–2013, and (ii) on a qualitative judgement of the relevant uncertainties that affect future price spreads. A GARCH analysis reveals that historical revenues have about the same level of variance. However, our discussions in Section 3 on the policy related issues concluded that revenues of the cable to Germany are exposed to higher policy related uncertainty than revenues of the cable to the UK, and therefore have higher volatility. The main reason is that the UK has implemented a capacity market and set a floor on the CO_2 price, while Germany is debating how to ensure security of supply and has not taken any measures to (unilaterally) increase the CO_2 emission price.

Based on these findings, the analysis uses the following parameters given in Table 3. The estimation of the investments costs, C_1 and C_2, are described in Section 4.2.

5.2. Results

We have evaluated the real option of investing in one of two mutually exclusive transmission projects. The value of the option to invest is 6531 million Euro. The value of the investment option with different start revenues is illustrated in Fig. 2, keeping one starting revenue fixed, we change the value of the other across a relevant range. In both Figs. 2 a and b, the value of the option increases with higher starting values. The reason for this is that the costs are held constant and revenues increases. This leads to a higher expected value and therefore a higher option value. Kay et al. (2009) observed the same result when they

[10] *Samfunnskonomiske analyser* published by the Ministry of Finance in Norway in 2012 http://www.regjeringen.no/nb/dep/fin/dok/nouer/2012/nou-2012-16/6/7.html?id=700896

[11] Source: Inflation.eu.

[12] *Simulations using the LIBEMOD model within the CELECT project* report published by Ragnar Frisch Centre for Economic Research in 2009.

Table 3
Parameter for real option valuation of the investment project.

Notation	Parameter	Value
R_1	Revenue from cable 1 in year 0	380 Mill. EUR
R_2	Revenue from cable 2 in year 0	176 Mill. EUR
CM_2	Revenue from capacity market project 1	0 Mill. EUR
CM_2	Revenue from capacity market project 2	914 Mill. EUR
C_1	Investment cost project 1	3280 Mill. EUR
C_2	Investment cost project 2	3200 Mill. EUR
r	Risk-free rate of return	4%
α_{R_1}	Drift rate of revenue 1	0.9%
α_{R_2}	Drift rate of revenue 2	1.2 %
σ_{R_1}	Volatility of revenue 1	17%
σ_{R_2}	Volatility of revenue 2	14%
ρ	Correlation between revenue 1 and 2	0.7
δ_{R_1}	Dividend of revenue 1	3.1%
δ_{R_2}	Dividend of revenue 2	2.8%
T	Lifetime of the option	10 years
T_2	Lifetime of cable	40 years
ex_1	Exchange rate (£/€)	1.1
ex_2	Exchange rate (€/NOK)	8

valued Bermudan options on multiple assets.

The option has zero value when both start revenues are close to zero (see Fig. 2b). In this case, the expected revenues from the cable investment are so small that none of the projects would ever break even. In other words, the initial investment cost would be higher than the potential gain from any of the two expected revenue streams. Before the start revenues reach the threshold value where the investment cost and the potential gain are equal, the option value is equal to zero.

Fig. 2 also illustrates that the option has a positive value when one of the start revenues is equal to zero. In the mathematical model (see Eqs. (6) and (7)), we presented the boundary condition that the value of the option can be positive even though one of the start revenues is equal to zero. As the figure here shows, this boundary condition is satisfied for both cables. The option value is also increasing, when the start revenue of the cable that has an positive option value increases.

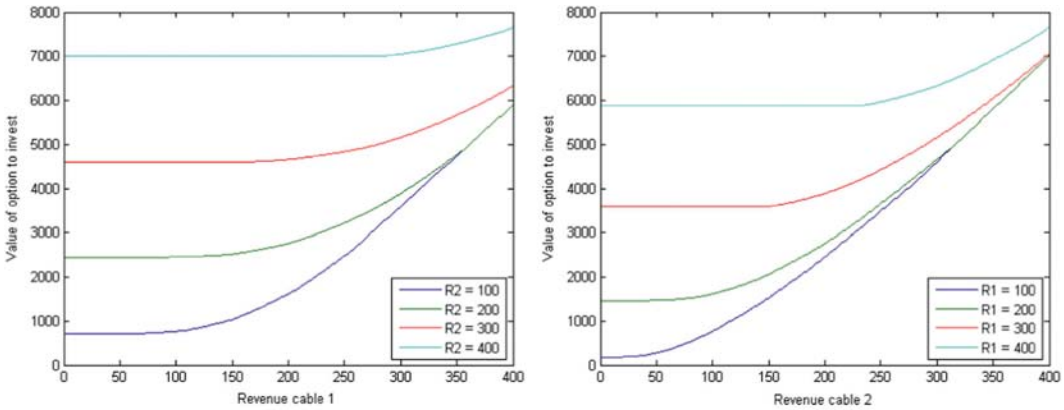
The value of our investment option is higher than both of the individual projects Statnett estimated (Statnett, 2013). In Statnett's analysis, they viewed the investment decision as a net present value of a single project. We analyse the investment decision as a real option analysis of two mutually exclusive projects. This increases the option value.

Table 4 shows that the value of the option increases with higher start revenues for project 1. It illustrates that the option to invest depends on both projects after the start revenue hits a threshold limit (Rt). Here, the threshold limit is the value of R_1 that makes it optimal to wait instead of immediately investing in project 2. From the table it is possible to see that it is between 176 and 300, because this is where the option value starts to change with R_1. This confirms the results of Geltner et al. (1996), that an option on mutually exclusive projects has a higher value compared to the situation of a net present value approach of two independent projects. The reason for this is that the investment option has flexibility of choosing which project to invest in at what time. This flexibility has a value when the start revenues has hit a threshold value (Rt).

5.2.1. The effect of time

Fig. 3a shows a two dimensional early exercise boundary for non-negative values of R_1 and R_2. The figure consists of three different regions, which indicates the optimal investment strategy between waiting and exercising the option. The blue region illustrates where it is optimal to immediately invest in the cable to Germany and the grey region is where it is optimal to immediately invest in the cable to UK. The white region is where it is optimal to wait. If we are in the waiting region we will invest the first time the revenue hits either of the investment thresholds.

Point A in Fig. 3a, which represent $R_1 = 176$ and $R_2 = 380$, is located in the grey region. The location of the point tells us that the optimal investment strategy is to



(a) R_1 = constant and R_2 changing. (b) R_2 = constant and R_1 changing.

Fig. 2. The value of the option to invest when one R is kept constant and the other is changing.

Table 4
Value of investment option for different values of R_1.

Startprice	Option value (Mill. EUR)
$R_1=0$, $R_2=380$	6531
$R_1=176$, $R_2=380$	6531
$R_1=300$, $R_2=380$	6586
$R_1=400$, $R_2=380$	7389

invest in the cable to UK in 2020. To change this optimal investment strategy, the intersection point between the two revenues has to be in another region. Point C illustrates a situation where it would be optimal to build the cable to Germany. From the figure one can see that the starting values of the revenue R_1 has to be above 350 million euro to consider building the cable to Germany. In point B the optimal investment strategy would be to wait till the revenues hit one of the two threshold boundaries.

When both R_1 and R_2 get close to zero, it is optimal to wait. The intuition behind the shape of the curve at these values can be developed as follows. When R goes to zero, the value of the option decreases. When the total value of the revenues of the projects is smaller than the investment costs, it would never be optimal to exercise the option. This is why we observe the waiting region close to origin. The waiting region increases as both revenues goes to infinity. Geltner et al. (1996) got the same shape for their exercise region. The reason behind an increased waiting region as R goes to infinity is that both projects are so in the money that both would be optimal. In such a situation it is optimal to wait, since the value of waiting is more valuable than the intrinsic value of either of the two projects. By applying financial theory, we would argue that in such a situation you can invest in either of the two projects because either way the intrinsic value is infinitely large.

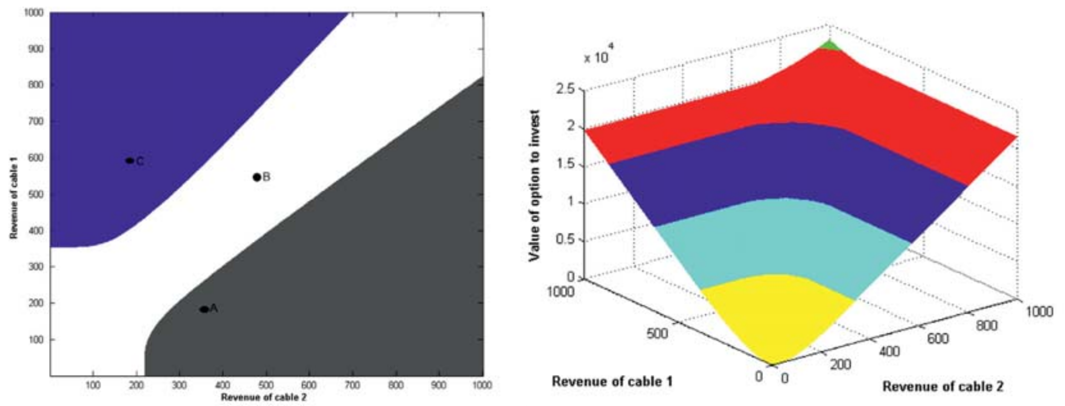
Fig. 3b shows the three dimensional exercise boundary obtained for the investment option. The region above the surface is the waiting region and the area below the surface is the immediate exercise region. The shape is consistent with what we would expect, also for larger values of revenue stream. The surface continues linearly with no additional curvature other than located around the strike price. Kay et al. (2009) obtained the same shape for their multi assets call option. For small values of yearly revenues (R), it is never be optimal to exercise the option. This is illustrated by the curved surface having a value equal to zero.

5.2.2. The effect of volatility

Dixit and Pindyck (1994) observe that the option value and investment threshold increase with volatility for a case with one asset. Geltner et al. (1996) observed the same effect when looking at a two-asset case, when increasing the volatility of one of the assets and keeping the other constant. In our case, this is true to a certain extent. This can be observed by looking at Fig. 4a and b, where the value of the option increases with volatility for intermediate values of volatility (on the x-axis) for the dashed, green and red line. The exception is for the light blue line in both graphs, that first decreases and then increases with volatility.

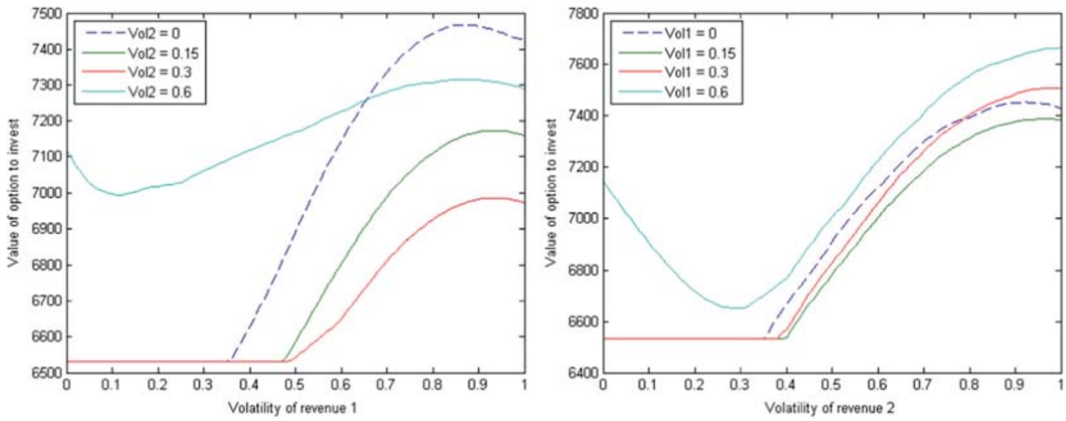
In Fig. 4a, the value of the red, green and blue lines are constant with respect to the change in σ_1 until they reach a threshold value of σ_1. The value of the option is constant because we exercise the option immediately. This means that the volatility does not affect the option value. When we reach the threshold value of σ_1, it is optimal to wait so the value of the option depends on σ_1. The light blue line is not constant as σ_1 changes, because it is optimal to wait for all values of σ_1.

Fig. 4a illustrates that the entire curve shifts downward when the σ_2 is changed from 0 to 0.15 to 0.3. It then shifts upwards when σ_2 is increased to 0.6. The same is the case for Fig. 4b, except that it starts to shift upwards sooner. This is not consistent with the characteristic feature of the Black–Scholes theory, that the sensitivity of the option price with respect to the underlying assets volatility is always positive, i.e. the option value can only increase if



(a) Exercise boundary (b) Two Assets call option Exercise boundary

Fig. 3. The exercise boundary of the option on the two cable investment projects. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)



(a) σ_2 = constant and σ_1 changing. (b) σ_1 = constant and σ_2 changing.

Fig. 4. The value of the option to invest when one σ is kept constant and the other is changing. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

the volatility increases. It is clear from the figures that the option value does not necessarily increase with volatility for basket options, both from the downward shift of the curves and from the light blue line that first decreases and then increases with the volatility. Permana et al. (2007) argued that this does not contradict the Black–Scholes theory. They reasoned that by increasing one of the volatilities it can lead to a lower variability of the spread, which ultimately drives down the option value. This refers to a spread option, but our results show that it also applies for other basket options.

By increasing both volatilities, the waiting region is extended. Geltner et al. (1996) observed the same effect, that when both volatilities increase both exercise regions are reduced. This makes sense, since a greater volatility implies a greater potential gain from waiting to see which of the projects that is most profitable.

If we keep the volatility of one of the cables constant and increase the other, the exercise regions for both cables shrink, though to a lesser extent for the cable with constant volatility. Geltner et al. (1996) noticed the same. It makes sense that the change in volatility of one cable also affects the other cable. When we increase the volatility of cable 1, it implies a greater gain from waiting to see if cable 1 become sufficiently more valuable than cable 2. This reduces the exercise region of cable 2.

5.2.3. *The effect of dividend yield*

In real option theory a high dividend rate increases the cost of waiting. The reason for this is that by choosing not to invest immediately the option holder foregoes potential revenue that it would have received by investing immediately. The size of the forgone revenue is determined by the dividend rate. The only time the investor is willing to forego revenues, is when the value of waiting is higher than the loss of revenues. The dividend therefore gives an incentive to invest earlier. It increases the cost of waiting for more information and thereby reduces the start revenues of R_1 and R_2 which makes it optimal to invest. Dixit and Pindyck (1994) also showed that a high dividend rate reduces the value of the option to invest. In Fig. 5 we keep one of the dividend rates constant and change the other, and see how this affects the value of the option.

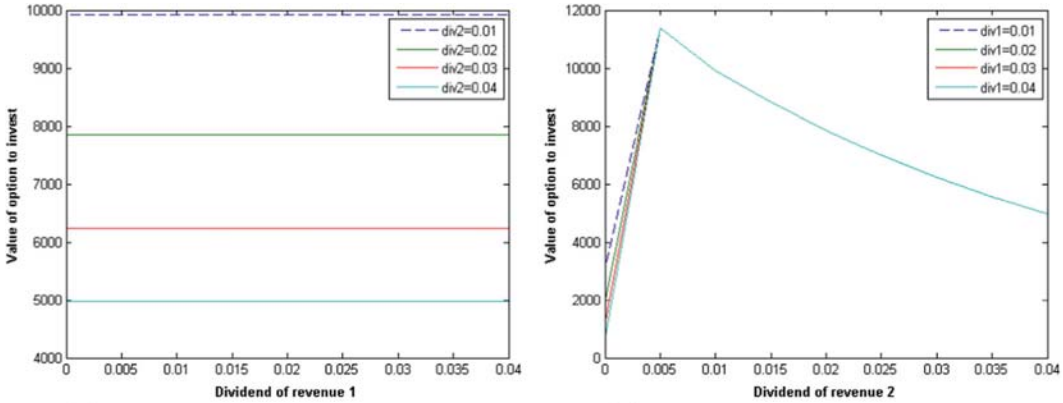
Fig. 5b shows that the value of the option to invest decreases with the dividend rate. If the dividend rate (δ) would have been zero, a call option on an investment would always be held to maturity and never exercised prematurely (Dixit and Pindyck, 1994). The reason for this is that there is no cost of keeping the option alive. This is likely the reason for the odd shape in Fig. 5b, because the dividend rate is so close to zero. This causes the option value to increase and at the same time the dividend increases in the interval ($0 < \delta_2 < 0.05$). We therefore impose a constraint that δ_1 and δ_2 has to be greater than 0.005%.

In the case where $\delta \to \infty$, the value of the option will be very small because the opportunity cost of waiting is large. In these cases, the only option is to invest now or never, and the standard net present value rule applies. The fact that the value goes to zero as the dividend increases is the reason why the curve in Fig. 5b decreased for larger values of δ_2.

Another important finding of the two asset case is illustrated in Fig. 5a. When one option is highly in the money, project 2, the dividend rate of project 1 has no effect on the option value. The value of the option does only depend on the dividend rate for project 2. This is illustrated with lower option value as the divided rates increases. The reason for this is that the optimal investment strategy is to exercise immediately in project 2, and the intrinsic value of project 2 is independent of project 1's dividend rate.

6. Sensitivity analyses

We performed a sensitivity analysis by estimating the effect the parameters have on the investment decision. In this section, the different scenarios will be explained in Section 6.1. In Section 6.2 we analyse the effect of the



(a) δ_2 = constant and δ_1 changing. (b) δ_1 = constant and δ_2 changing.

Fig. 5. The value of the option to invest when one σ is kept constant and the other is changing. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

parameters changes on the option value and optimal investment strategy.

6.1. Scenarios – The effect of parameter changes

The uncertainties in the electricity market are many and can change overnight. In this paper we have chosen to focus on long-term policy uncertainty that will affect the revenues from the cable in the long run (see Section 3). We have considered the uncertainties by taking them into account when deciding the parameters of the revenue streams (see Section 5.1). In this section we look directly at the two main policy uncertainties by creating four future scenarios, where we change the parameters. The scenarios have either low or high CO_2 price and in two of the scenarios a capacity market is implemented in Germany. We have chosen to use four scenarios: “Current Situation”, “Low Carbon Society”, “Green Growth” and “Stagnation”.

6.1.1. Scenario 1: Current Situation

The “Current Situation” scenario is based on the current market data and present policy schemes. In this scenario, we assume that Germany has not implemented a capacity market. The energy mix in Germany and the UK are different, with a large portion of gas in the UK electricity production. The gas plants are the price setter in UK, while coal determines the price in the Germany. The price of carbon emission is low and it has little effect on the settlement price in the electricity market (see Section 3.1).

In this scenario Germany has a growing portion of renewable energy in its energy mix and there are uncertainties regarding how the authorities will address the issue of security of supply. The policy uncertainties in the German market are therefore assumed to be higher than the UK market (see Section 5.1).

6.1.2. Scenario 2: Low Carbon Society

In the scenario “Low Carbon Society” a tightening of the EU ETS is causing a green shift in consumption and generation, without impacting other policy schemes. The price of carbon is increasing, resulting in increasing electricity prices, as the cost of pollution is put on consumers (see Section 3.1). As mentioned in Section 3.1, an increase in the CO_2 price will most likely result in increased spread between the revenue streams of the cables, because the price will increase more in Germany and the UK than in Norway. When the CO_2 price continues to rise this will result in a higher drift rate for both cables. We believe the increase in the drift rate will be higher for the cable to Germany based on coal being the price setter in the German market, and gas being the price setter in the UK market.

The policy uncertainties are reduced compared to scenario “Current Situation” in both countries due to the increase in the price of carbon. This gives an investor a clear signal that the EU is willing to increase cost of carbon to meet their EU2050 targets. However, there is still uncertainty regarding security of supply in Germany.

6.1.3. Scenario 3: Green Growth

In the scenario “Green Growth” the high share of renewable generation is forcing Germany to implement a capacity market to ensure security of supply and the CO_2 price is increasing. The increasing CO_2 price has a greater effect on the electricity price than the price reduction from the increased share of renewables, resulting in a net increase in electricity prices. This change is higher than the change in the Norwegian prices. The electricity prices in UK are also increasing more than the Norwegian prices due to the increasing carbon price. As in the “Low Carbon Society” scenario, the drift rate is higher for Germany than for UK (see Section 6.1.2).

In this scenario market participants know how the authorities will handle the problem associated with security of supply and global warming. Therefore, the policy uncertainty is reduced in both countries. One of the main arguments why the cable to Germany has a higher volatility than the one to UK was the possible introduction of a capacity market in Germany (see Section 5.1). Since Germany has chosen to introduce a capacity market in this scenario, the volatility in the German market decreases.

However, the volatility in Germany will still be higher than the volatility of the UK due to the uncertainty in the feed-in-tariff and how this will effect the portion of renewables in the energy mix (see Section 2).

6.1.4. Scenario 4: Stagnation

In future scenario "Stagnation", a high share of renewables has forced Germany to implement a capacity market, as in the "Green Growth" scenario (see Section 6.1.3). Implementation of the capacity market results in lower uncertainty in the market. The price of carbon emission is low, so it has small effect on the electricity price and the merit order curve. The EU ETS scheme is still struggling with the problem of efficiently reducing the cap due to a surplus of certificates. We assume that the EU has not managed to meet their EU2020 targets, and there are uncertainties on what the future carbon emission scheme will look like. Investors are therefore postponing investments in generation, which makes the electricity price uncertain.

The only change compared to the "Current Situation" scenario, is the reduction in the volatility of the cable to Germany, due to the introduction of the capacity market. However, the volatility is larger than in scenario "Green Growth", because the market participants do not know how the governments will tackle the problem of global warming.

6.2. Result of the valuation with different scenarios

The parameters for the different scenarios used in the rest of this analysis is given in Table 5. The volatilities (σ), dividend rates (δ), growth rates (α) and revenues from the capacity markets (CM) change in the different scenarios. The impact of scenarios on the investment decision are analysed in this subsection. The value of the option to invest for each scenario is given in Table 6.

From Table 6 "Low Carbon Society" and "Green Growth" are the most profitable. This is because they have higher growth rates (lower dividend rates) compared to the two others. As the dividend rate is lowered the opportunity cost of delaying investment is decreasing and therefore the option value of waiting is increasing.

The option values of the "Current Situation" and "Stagnation" scenarios are equal when using the base case starting revenues $R_1 = 176$ and $R_2 = 380$. The same is the case for "Low Carbon Society" and "Green Growth", even though the volatility are different. The reason for this is that the option value is based on the tradeoff between immediately exercising and waiting. When the optimal decision is to invest immediately, the volatility has no impact on value. The optimal investment strategy is therefore to immediately exercise the option and build the cable to UK.

The option values to invest do not change due to a capacity market in Germany i.e. the value is independent of whether Germany has a capacity market or not. The reason for this is that we consider a mutually exclusive project, where one of the projects is more in the money than the other. The additional cash flows in one project (i.e. implementation of the capacity market in Germany), in this scenario do not change the value of the option because they are not large enough to surpass or get close to the profitability of the other project. However, if we instead reduced the revenues from the capacity market in the UK, the option value would decrease.

The start revenues are an important factor determining the value of the option. Table 6 shows the value of the option to invest given various start revenues for project 1 and project 2 (R_1 and R_2). The first row of the table contains the base revenues used throughout this paper. By looking at the table, one can see that lowered start revenue results in a lower option value. When the start revenues are doubled (i.e. changed from 200 to 400 mill Euro) the option value almost triples its value. This result leads to the conclusion that there is no linear relationship between the option price and the start revenue.

In this sensitivity analysis we have chosen to model a higher CO_2 price as an increase in revenues. When the revenue increases it will cause the option value to increase. The CO_2 price and option value should therefore have a positive correlation. Further, if investors expect that the CO_2 price will increase it will create an incentive for waiting instead of immediately exercising the option. This can be illustrated by considering the scenario "Low Carbon Society" with increased yearly revenues. If R_1 and R_2 would increase to 250 and 400 mill. €/year, the optimal strategy would be to wait (see Fig. 6b).

The option values obtained by changing start revenues also shows that when the difference between the start revenues reaches a certain limit, the value of the option only depends on one of the projects. In these situations, the effect of the other project is neglectable since the value of this project is significantly less than the value of the other project. This explains why the option value does not decreases when the start revenues of R_1 goes from 176 to 0 (see Table 6).

The effect of the capacity market on the option value can be analysed by comparing the option values of the "Current Situation" when switching the start revenues of the two projects. Table 6 shows that the option value decreases, even though the start values are the same, just switched. In this situation the optimal investment strategy would be to wait (see Fig. 3a). The reason for the drop in option value is caused by the effect that the capacity market only adds an extra value to the UK investment projects. When this project gets less in the money than the German project, the option value for holding both projects decreases since the German market does not have any added revenue from a capacity market.

The timing of investment is also an important factor when determining the value of an option. From the "Current Scenario", which is the same case as we analysed in Section 5, we saw that the option value was equal to the value of immediately exercising the option. Fig. 6 shows the exercise boundaries for the four scenarios. The blue and grey colors regions illustrate where it is optimal to immediately invest in project 1 and project 2. The white region is the waiting region i.e. the region where it is optimal to delay the investment.

For all scenarios in Fig. 6, given the revenues from the cable in year 2020 (see Table 3), it will always be optimal to

Table 5
Parameters for the real options valuation with different scenarios.

Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Unit
C_1	0	0	588	588	Mill. EUR
α_{R_1}	0.9	2.5	2.5	0.9	%
α_{R_2}	1.2	1.5	1.5	1.2	%
σ_{R_1}	30	25	20	23	%
σ_{R_2}	20	15	15	20	%
δ_1	3.1	1.5	1.5	3.1	%
δ_2	2.8	2.5	2.5	2.8	%

Table 6
Value of investment option with different start revenues (million €).

Start revenues	Current Sit. (Mill.)	Low Carbon Soc. (Mill.)	Green Growth (Mill.)	Stagnation (Mill.)
$R_1 = 176$, $R_2 = 380$	6531	6996	6996	6531
$R_1 = 0$, $R_2 = 380$	6531	6996	6996	6531
$R_1 = 380$, $R_2 = 176$	5478	8210	8718	6019
$R_1 = 200$, $R_2 = 200$	2798	3801	3821	2728
$R_1 = 400$, $R_2 = 400$	7694	9779	9700	7507

invest in the cable to UK in year 2020. It is never optimal to wait for more information, because the dividends forgone by waiting are higher than what we gain from waiting. However, the start revenue for UK is based on revenues from 2013. This year, the revenues were high compared to the rest of the years in the data set. The reason for this was a high gas price and that the inflow to the Norwegian hydro system was large, which resulted in an increased spread between the electricity prices in the two countries. If the confidence interval for the start revenues is set to 80%, it would not be optimal to immediately exercise in all scenarios, i.e. for scenario "Current Situation" and "Low Carbon Society" it would now be optimal to wait.

From "Current Situation" to "Low Carbon Society", the drift rate increases while the volatility decreases. A decrease in volatility makes it less valuable to wait, so one would expect that the waiting region decreased (Tan and Vetzal, 1995). The opposite is expected when the drift rate increases, because it is possible to gain more from waiting with the higher expected growth rate and with the decreased cost of waiting you are also more willing to wait (Geltner et al., 1996). From Fig. 6a and b, we observe that the waiting region increases. However, one can observe that the blue exercise region increases and the grey decreases. One can observe that the significantly higher change in drift rate for cable 1 compared to cable 2 decreases the exercise region more for cable 2 than cable 1. This shows that an increase in drift rate of one asset has a bigger impact on the waiting region of the other asset than its own waiting region. In other words, we are now more willing to wait and see if the revenue of cable 1 increases compared to those of cable 2.

The parameters of "Green Growth" differs from those in the "Low Carbon Society" scenario, only by lower volatility and the launch of a capacity market in Germany (see Sections 6.1.2 and 6.1.3). From Fig. 6b and c, we observe that the waiting region has shrunk, and that both exercise regions have increased. Though, the blue region has increased more than the grey. This was anticipated due to the decrease in uncertainty of cable 1, that will affect both regions, but to a greater extent the blue region (see Section 5.2.2). The intuition behind this is that the investment decision is less risky, and it would give an incentive to invest in one of the two projects earlier compared to a case with higher volatility. Also, the added revenue from the capacity market will make us more willing to invest in cable 1.

The effect of changing volatility (σ) can also be illustrated by comparing the "Current Situation" scenario with "Stagnation". From "Current Situation" to "Stagnation" (see Fig. 6a and d) the only difference is the decreased volatility of cable 2 and the introduction of a capacity market in market 1 (see Sections 6.1.1 and 6.1.4). What can be observed is that the waiting region is significantly reduced and that the first possible start value for exercise is reduced for both cables, though, significantly more for cable 1. Fig. 6d also shows that the decrease in volatility has a larger impact on the exercise region than that of the capacity market. The financial implication of these findings are that market participants will experience less uncertainty and can gain only a small value of waiting for more information. This causes the waiting region to decrease, making it more attractive for investors to invest early (see Section 5.2.2).

We have also tried to remove the capacity market in the UK by setting $CM_2 = 0$, and it is still optimal to build the cable to UK in 2020. By including the capacity market in the UK, the option to invest in cable 2 only gets further in the money. This also results in increased start revenue for the interconnector to Germany, causing the waiting region to increase. What this result implies is that the effect of a capacity market on the investment decision depends on the difference in value between the two mutually exclusive projects. We have also seen that if one project is more profitable than the other, (i.e. it would never be optimal to invest in the other) an introduction of a capacity market in the less profitable market has little impact on the option value. This is the same result as in Table 6. From this we conclude that a capacity market alone will have no impact on which cable the investor chooses to invest in, given that the value gained from participating in this market is small compared to the total value received by the annual revenue streams. The capacity market will only affect how valuable it is to invest in

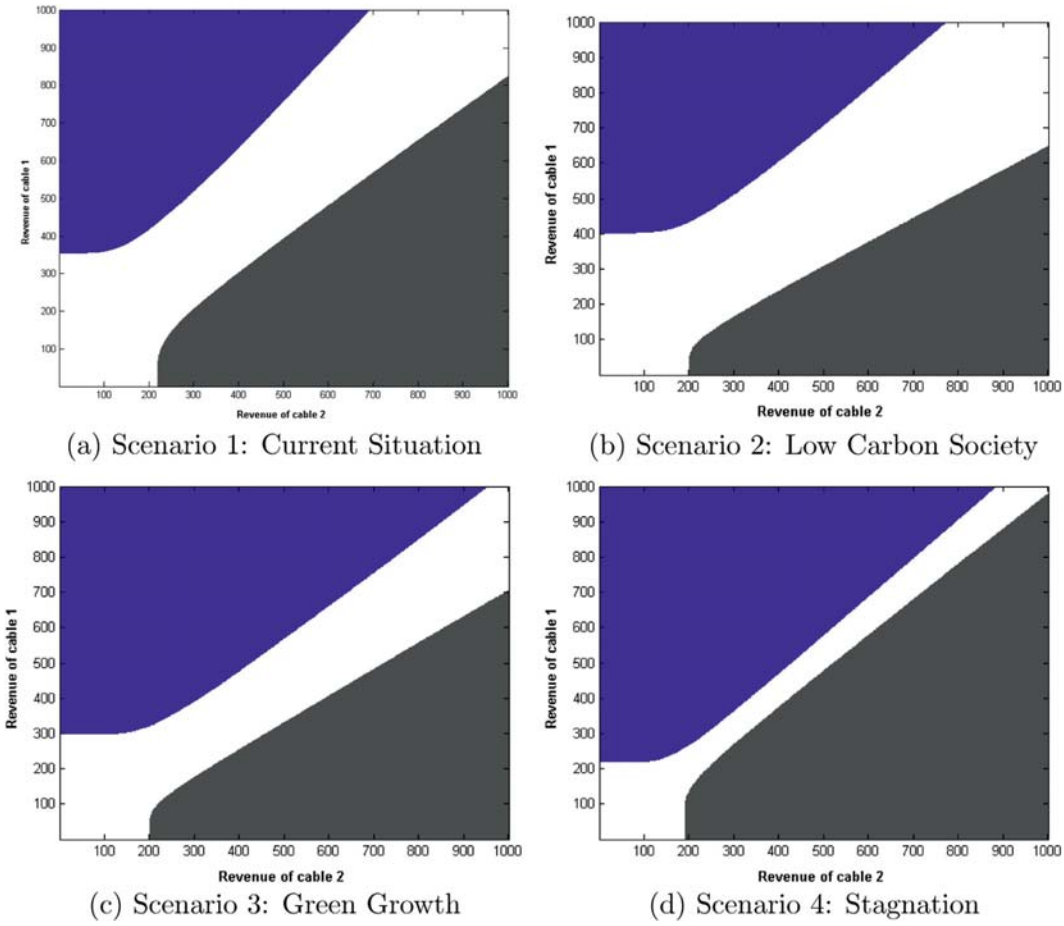


Fig. 6. Exercise boundaries for the scenarios. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

the chosen cable.

7. Conclusion

This paper analyses the option to invest in one to two mutually exclusive interconnectors, by using real option valuation. The investment alternatives under consideration are an interconnector from Norway to either Germany or the UK. The real option approach considers both the timing and location of the investment. The timing of the investment is extensively covered in the literature. However, the flexibility of choosing between different locations as mutually exclusive projects has not been considered in any papers of our knowledge. When considering location we argue the importance of looking at the differences in the policy schemes between the two locations. In this paper we consider the risk from the EU ETS and a possible introduction of capacity markets.

This paper contributes to the real option literature by considering investments in mutually exclusive transmission assets. To this day, there are few research papers considering investments in electrical transmission assets. One of the explanations is that transmission companies have for a long time been considered a monopoly. With the changing market structure transmission companies pay more attention to their costs and ROI. Transmission investments are generally characterised by high initial sunk cost and uncertain revenue streams. Therefore, considering the investment as a real option can add value by creating flexibility to postpone investment.

The result of our analysis is that it is optimal to immediately exercise the option to build the cable to UK. The interconnector project to UK dominates the alternative of investing to Germany in all future scenarios considered in this paper. We conclude that holding the option to invest in mutually exclusive projects only has a value when the difference between project values is small. If one of the projects are considerably more in the money than the other, the parameters of the other project has no major impact determining the option value. In such situations, the option value can be modelled as a call option.

Our model gives an important finding regarding the effect of volatility on the option value. The finding indicates that the option value does not necessarily increase when the volatility increases. This has already been shown in the literature, but not for the type of option considered in this paper. The result therefore contributes to a deeper understanding of the relationship between volatility and the value of a basket option.

An additional finding is how the growth rate affects the exercise boundary. The results show that if one of the growth rates is kept constant and the other is changed, the exercise regions of both cables are affected, though to a higher extent for the cable with the constant growth rate. To our knowledge, this has not been discovered in other articles and is an important contribution to the real option literature.

The effects of several uncertainties, including political uncertainties, on the investment decision are two fold. An increase in the CO_2 price, due to EU ETS, will result in an increased spread between the electricity prices. This will increase the value of the option, but also postpone investment, because the investors face higher uncertainty. Our results also conclude that a capacity market alone will have no impact on which interconnector we choose to invest in.

We find that for the given estimate of the cable start revenues, the optimal value is equal to the intrinsic value of the cable to UK. In other words, the value of the option is equal to the net present value. We would argue that the value of using a real option approach is that it confirms that the option to invest in the cable to UK in 2020 is the optimal investment strategy. A general net present value approach would only conclude that the investment is profitable, not at what time to invest. The value of the real option approach is also evident when the uncertainty increases and results in a recommendation to postpone investment beyond the net present value break-even price because of price uncertainty. We would argue that even though our result does not contradict a net present value approach, a real option analysis has value when considering an analysis of two mutually exclusive projects.

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7. Essay 6 - Investment in Electric Energy Storage Under Uncertainty: A Real Options Approach

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