The effects of capacity constraints driven by renewable energy on the forward premium: Evidence from the Nordic power market

Author: Priscilla Tang

Student number: 355841

ERASMUS UNIVERSITEIT ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS

March 2017

Abstract

This study aims to investigate the effects of capacity constraints driven by renewable energy on the forward premium. The introduction of renewable energy sources has imposed increased uncertainty in the power market. Renewable energy sources are highly volatile and thereby difficult to predict. The uncertainty in the day-ahead power market is enhanced by the load prediction errors and failure of power plants. This uncertainty can cause sudden short-term frictions in demand and supply, referred to as capacity constraints. High capacity constraints along with the complexity of electricity as a commodity could induce large price spikes in the intraday market. It is of interest to examine whether these capacity constraints will also affect derivative pricing. Interpreting the results of the Markov regime-switching models, the models indicate that capacity constraints do not have a significant effect on the forward premium. The non-normal regime involves lower and more volatile forward premia compared to the normal regime. Generally, high capacity constraints induce a higher probability of remaining in the normal regime across all seasons or a higher probability of migrating from the non-normal regime to the normal regime in the summer. However, in the winter, the probability of migrating from the non-normal regime to the normal regime decreases under tight market conditions due to the positive skewness in the distribution of the spot price and flexible hydropower plants. The results suggest that capacity constraints are anticipated and do affect power derivative pricing.

Master thesis Financial Economics

Section Energy Finance

Supervisor: dr. LLM. M. Kiliç

Co-reader: dr. R. Huisman

JEL classification code: Q420, Q470

Keywords: renewable energy, capacity constraints, forward premium, Markov regime-switching models, one-factor model.

Table of contents

List of tables and figures

List of abbreviations

	Abbreviation	Explanation
1	CBT	Chicago Board of trade
2	CME	Chicago Mercantile Exchange
3	Comex	Commodity Exchange
4	CSCE	Coffee, Sugar and Cocoa Exchange
5	CTN	New York Cotton Exchange
6	EU	European Union
7	NYM	New York Mercantile Exchange
8	PJM	Pennsylvania, New Jersey, Maryland

1 Introduction

The environment of the energy market has changed significantly in the past years. Inevitable global warming and the plummeted oil prices have forced energy producers and speculators to widely diversify the power positions in their portfolio and thereby to invest in renewable energy. Renewable energy has become the focus of many energy companies as part of their long-term strategy to gradually transition from fossil fuels to renewable energy. Not only are energy companies increasingly interested in green energy, renewable energy has been highly prioritized by the European Union (EU). By using more renewable sources to meet energy needs, the EU lowers its dependence on imported fossil fuels and makes the energy production more sustainable. The EU has set a binding target of 20% final energy consumption from renewable sources by 2020 in the 'Renewable energy directive'. The EU already has plans to extend the target beyond 2030 to a new energy target of at least 27% of final energy consumption in the EU (European Commission, 2016). Local governments have implemented incentive and support schemes in order to realise these renewable energy targets. As the importance of renewable energy is increasing, it is interesting to analyse the impact it has on the pricing of electricity in market and more specifically in the financial market.

The pricing of electricity as a commodity is not straightforward and its price behaviour is different from other commodities. Electricity is economically non-storable or at least it is very costly to store. The inability to store electricity causes the extreme price behaviour of electricity because there is no storage capacity to act as buffer to smooth price deviations. The most prominent features of its price dynamics are the presence of seasonality, high volatility, mean reversion and spikes/jumps. The inability to store electricity means that cost-of-carry relationships between the spot price and forward price do not apply to electricity as a commodity. Instead, electricity behaves according to the expectations theory (Fama & French, 1987). The expectations theory departs from the fact that the forward price is composed of the expected spot price and the time-varying risk premium. The time-varying risk premium could be considered a compensation for risk (Longstaff & Wang, 2004). According to the expectations theory, the forward premium is equal to the change in the expected spot price plus the risk premium. Bessembinder and Lemon (2002) show that the forward premium decreases when demand variance is modest and expected demand is low. The forward premium increases when either expected demand or demand variance is high due to positive skewness in the distribution of the spot price.

One important implication of renewable energy sources is that they pose a source of uncertainty on the electricity market as the day-ahead spot prices are quoted one day prior to physical delivery of the electricity. Renewable energy sources are highly volatile and therefore hard to forecast. The uncertainty from renewable energy sources is accompanied by load prediction errors and failure of power plants. The uncertainty on the supply and demand side can cause sudden short-term frictions between demand and supply at any point in time. The short-term frictions in expected demand and supply are referred to as capacity constraints. High capacity constraints along with the complex features of electricity as commodity can induce large price spikes in the intraday power market. In a system with a well-functioning intraday market, the effects of the day-ahead capacity constraints are transferred to the intraday market, as the intraday market provides balance to the day-ahead market (Kilic & Truijillo-Baute, 2015).

However, it is not established if the effect of capacity constraints on the intraday spot prices will spill over to the financial market for electricity. It is of interest to examine whether capacity constraints will affect derivative pricing. Hence, this study aims to investigate whether capacity constraints driven by renewable energy sources at any point in time, will have impact on the forward premium the next day. The relevance of this research lies in the fact that the risk premium in electricity forward prices is considered to be some sort of risk compensation. Studying the effects of capacity constraints on the forward premium, also allows to analyse the risk compensation on the financial market due to the increased risk imposed by high capacity constraints. The results could provide insights for market participants and speculators.

This study analyses the forward premium in the Nord Pool market from 2013 to 2016. The Nord Pool market is one of the oldest spot and futures electricity markets in the world and is known for the large contribution to renewable energy generation from hydropower. As the Nord Pool is dominated by renewable energy, the respective market data serves for the purpose of this study. The one-factor model aims to model the expected spot prices at maturity based on observed ELSPOT day-ahead prices. The forward premium is constructed using one-month (M1) futures contracts acquired from NASDAQ Commodities. The forward premium is analysed by means of Markov regime-switching models. To investigate the effects of capacity constraints, the transition probabilities will be modelled as time-varying including a dummy variable for capacity constraints, distinguishing between summer and winter months.

The results indicate that the forward premium could be in two regimes, the normal regime and the non-normal regime. The normal regime is denoted by the mean of the natural logarithm of the forward premium and its mean reverting behaviour. The non-normal regime involves a mean that is lower than the mean in the normal regime. In addition, the mean in the non-normal regime is more volatile than the mean in the normal regime.

High capacity constraints induce an increase in the probability of remaining in the normal regime in both winter and summer months. High capacity constraints also induce in increase in the probability of migrating from the non-normal regime to the normal regime in the summer. This is the result of higher expected demand relatively to the available supply induced by high capacity constraints. The higher expected demand causes a positively skewed distribution of the spot prices, which will lead to higher forward premia. As result, it is likely that the forward premium will be in the normal regime, which represents the higher and less volatile forward premia. However, the probability of migrating from the non-normal regime to the normal regime decreases in the winter under tight market conditions. The probability of remaining in the non-normal regime increases in the winter under tight market conditions. This is related to the positive skewness in the distribution of the spot price in the winter and the flexibility of hydropower plants. Power producers are reluctant to adjust their output downwards such that the market can return to normal again due to higher potential power prices imposed by the positive skewness in the distribution of the spot price. Hence, the probability of remaining in the non-normal regime increases during winter months, despite the fact that the market is under tight market conditions.

It can be concluded that in general, the forward premium is at the normal and stable level instead of the lower and more volatile level. It is expected that the expected spot price should increase as result of high capacity constraints. This means that the forward premium should decrease at the maturity date. In fact, the forward premium does not decrease. This suggests that power producers have anticipated the positive skewness in the distribution of the spot price induced by high capacity constraints by increasing the forward price. Consequently, the forward premium will be higher in order to compensate for the increased revenue risk. This study shows evidence that capacity constraints do affect power derivative pricing.

This study proceeds as follows. Section 2 discusses the theoretical framework. Section 3 explains the applied methodology and section 4 describes the data thoroughly. Section 5 presents the results and section 6 concludes and discusses the results.

2 Theoretical framework

In this section outlines the dynamics in the electricity market and explains the concepts. After a short introduction into electricity markets, the characteristics of electricity as a commodity will be described. This section elaborates on forward and futures contracts and the relationship between the electricity spot price and the forward price. Based on the literature, a hypothesis will be formed about the research question. At last, an overview of existing models will be presented.

2.1 The electricity market and the role of capacity constraints

The deregulation of the power industry has led to a global trend towards the commoditization of electricity. However, electricity is not like every other commodity. As mentioned before, electricity cannot be economically stored and reliability on the transmission grid is still not perfect (Bierbrauer, Truck, & Weron, 2004). Nowadays, more electricity is generated by renewable energy sources. The Nord Pool power market is already largely developed in the field of renewable energy. The Nord Pool is the single power market for Norway, Sweden, Finland, Denmark, Estonia and Lithuania. The annual average power generation in the Nordic countries is around 420 TWh in total. Norway's power generation is dominated by hydropower while Sweden and Finland have a mixture of hydro, nuclear and thermal power (steam driven). Demark uses predominantly thermal power, however wind power is becoming more important. Estonia and Lithuania's generation is mainly driven by thermal power. In a year with normal rain and snowfall, hydropower accounts for half of the Nordic countries' power demand (Nord Pool, 2016).

Table 1: Nordic power generation by energy source (2013)

Energy source	Capacity (TWh)	%
Hydro	203	53
Nuclear	86	23
Fossil	47	12
Wind	24	6
Biomass	23	6

Besides the reduction of CO_2 emission, the use of renewable energy sources also provides economic benefits as it produces lower wholesale market clearing prices due to the low variable costs and supporting incentive schemes as feed-in tariffs or premiums provided by governments (Kilic & Truijillo-Baute, 2015). For the Nordic countries hydropower is the cheapest power source (Nord Pool, 2016). As the Nordics are largely reliant on hydropower, the level in hydro reservoirs is a measure for the level of production costs. If the level of hydro reservoirs is low, more expensive generation assets will be activated causing higher production cost. However, the use of renewable energy sources poses increased uncertainty in the electricity market as renewable energy sources are difficult to forecast and very volatile. In addition, uncertainty also arises from load prediction errors, failure of power plants and demand variability in the market. The uncertain generation of power by renewable energy sources in combination with the mechanics of the power industry and the non-storability of electricity can cause very volatile power prices.

The mechanics in the power market are different from other commodity markets. The power industry is divided in three different markets, namely the day-ahead market for physical delivery, the intraday market to balance out the day-ahead market and the financial market for forward and futures contracts.

The spot electricity market is essentially a day-ahead market in which the electricity price is quoted a day before physical delivery. Therefore, the system operator needs advanced notice to verify that the demand is feasible and lies within the transmission constraints. The spot contract is an hourly contract with physical delivery. The system price is calculated as the equilibrium price of the aggregated demand and supply for every 24 hours. The uncertainty on the supply and demand side can cause sudden short-term frictions between demand and supply in the day-ahead market. The short-term frictions between demand and supply are considered capacity constraints. Capacity constraints are defined as a ratio in which the demand prognosis is divided by the production prognosis. Capacity constraints could be considered a measure of tightness in the power market. The power market is under tight market conditions if the capacity constraints are higher than usual observed in the market. The power market is under normal market conditions, if the capacity constraints are equal to or lower than usual observed in the market.

Capacity constraints*: daily short-term frictions between demand and supply, defined as the ratio of demand over supply.* [1]

As this study investigates the effects of capacity constraints on the forward premium the next day, the capacity constraints are day-ahead. Day-ahead capacity constraints mean that the capacity constraints are recorded one day before physical delivery of the electricity.

The intraday market balances the day-ahead market when a deficit or oversupply of electricity occurs. The capacity constraints on the day-ahead market will be reflected on prices in the intraday market. The capacity constraints could induce price spikes in the intraday spot prices as prices are being balanced in real time. Intraday spot price may exhibit upward price spikes

[1] The concept of capacity constraints is further defined in section 3.2.1. Two regimes based on capacity constraints.

when demand exceeds supply significantly. Whereas intraday spot prices exhibit downward price spikes due to oversupply of electricity in the market. Sometimes, if the oversupply is substantially large, the downward pressure could induce negative prices in the intraday market.
In addition to the upward or downward price spikes, electricity also exhibits ‘normal’ price deviations. These normal price deviations are caused by seasonality during for example summer months or weekends. These normal price deviations are broadly predictable whereas spikes are unexpected. Besides these two features of electricity, there are more characteristics of electricity as a commodity. In the next section, the characteristics of electricity as a commodity will be explained.

2.2 Characteristics of electricity as a commodity

The inability to store power is a main reason why electricity exhibits extreme price dynamics. There is no storage capability to service as a buffer and smooth price deviations and spikes. The non-storability of electricity causes supply and demand to be balanced on a critical point. The special characteristics of electricity prices are captured in four stylized facts as seasonality, volatility, mean reversion and jumps or spikes. The discussion of the four stylized facts provide more understanding of the application of the models in electricity markets.

2.2.1 Seasonality

Normal price deviations are caused by the seasonality of electricity prices. Electricity prices do not follow a random walk as they fluctuate around a mean level due to the mean reverting character. The seasonality is the predicable element in the electricity prices. Seasonality in electricity prices is more profound than in other commodities during the course of a day, week and year. This arises because of the changing level of business activities or climate conditions as temperature or number of daylight hours (Bierbrauer, Menn, Rachev, & Truck, 2007). One specific demand variation relates to intra-week seasonality, in which weekdays exhibit higher demand and weekends and public holidays exhibit lower demand.

2.2.2 Volatility and mean reversion

Electricity spot prices exhibit unusually high volatility. The high volatility can be attributed to the storage capacity, transmission problems and the need for the markets to be balanced in real time. Inventories cannot be used to smooth price fluctuations, which cause temporary demand and supply imbalances difficult to correct in the short-term. However, the high volatility is not persistent, as the electricity spot prices exhibit mean reversion. When a sudden increase in demand occurs, generation assets with higher marginal costs will be activated on the supply side, which will lead to higher prices incurred on the intraday market. When demand returns to normal levels, these generation assets with relatively high marginal costs will be turned off and prices will fall (Karakatsani & Bunn, 2008).

2.2.3 Price spikes and jumps

In addition to mean reversion and strong seasonality, spot prices also exhibit infrequent large spikes or jumps. Price jumps are unpredictable discontinuities in the pricing process caused at the supply side (Bierbrauer, Menn, Rachev, & Truck, 2007). In the literature, spikes are different from jumps, as spikes are typically interpreted as the result of a sudden increase in demand related to the demand side. Capacity constraints are frictions between demand and supply that induce price spikes in the intraday market. There is no distinction between frictions due to demand factors or frictions due to supply factors. Therefore, in this study, spikes and jumps are considered the same and they will be used interchangeably.

When demand reaches the limit of available generation capacity, electricity prices will exhibit positive price spikes. Accordingly, in periods of lower demand relatively to the available generation capacity, prices will fall and negative price spikes will be exhibited. Negative prices are a result of oversupply caused by the inflexibility of the power generation assets accompanied by low demand. Price deviations and other price shocks which are not considered to be price spikes are both short-lived which means that the market is back to normal within a few days. They are both brought back at their mean level by mean reversion. However, the speed of mean reversion of non-price spikes is considerably lower than the speed at which large price spikes fade out (Cartea, Figueroa, & Geman, 2008).

2.2.4 Miscellaneous factors

The inability to store electricity is not solely responsible for the unusual pricing characteristics of power markets. The price formation of electricity is not only a result of seasonality, mean reversion, high volatility and spikes but also characteristics of the power market contribute to the pricing behaviour of electricity. These characteristics include: number of players (generators and retailers) and the composition of the generation park. In most power markets, the generation plants are owned by a small number of companies, which means that the supply is concentrated (Cartea and Villaplana, 2008). As consequence, the actions or performance of any player in the market may affect the equilibrium price. Furthermore, the marginal costs differ within a generation park as the park consists of plants which each employ a different source to produce power. Karakwatsani and Brunn (2008) examine the effects of spot price drivers in the wholesale electricity markets focussing on their intraday dynamics and transitory irregularities. They apply their model to the UK market and analyse the market with an original set of price drivers. All coefficients exhibit substantial intraday variation relating to the differing marginal costs and market design. Their research points out that the market responds to economic fundamentals, plant operating properties and strategic manipulation of capacity which is most often exercised by more flexible power plants (Karakatsani & Bunn, 2008).

2.3 Forward and futures contracts

Forward and futures contracts are widely used as a hedging instrument against unexpected price movements. A forward contract is a contract in which the buyer agrees to commit to buying the underlying commodity from the seller at some future time at a price that is fixated in advance. A forward contract is a bilateral contract between two counterparts. In essence, a futures contract is the same as a forward contract, except the fact that a futures contract is traded on an exchange, which induces a pricing difference due to the margining system imposed by exchanges (Huisman, 2009). Cash settlement takes place during the trading period for futures contracts. Cash settlement for forward contracts takes place starting at the maturity of the contract. In this study I consider futures and forward contracts as the same type of contract. The concepts forward and futures contract are used interchangeably, hence all the models apply to both forward and futures contracts.

2.4 The relationship between the spot price and forward price

The relationship between the electricity spot price and the forward price is explained by the work of Fama and French (1987), in which they consider two theories about commodity forward prices. These theories are the theory of storage and the expectations theory.

The theory of storage implies that the difference between the forward price and the spot price depends on a risk premium consisting of the interest rate of forgone interest by storing the commodity, the convenience yield on inventory and the storage costs. This theory departs from risk neutral valuation, meaning that the contract is valued considering the fact that traders can make themselves risk-free. This implies that risk and price expectations play no crucial role in the valuation of the forward contract.

The alternative theory is the expectations theory, in which the forward price is disentangled into the expected spot price and a risk premium as the noise on the expected spot price. The expectations theory states that the forward price may contain information about expected changes in the spot prices. The risk premium represents the equilibrium compensation for bearing the price and/or demand risk for the underlying commodity. Fama and French (1987) contribute to the existing literature by testing the expectations theory and the theory of storage on 21 different types of commodities. They find for some commodities that their futures price depend heavily on the interest rate, storage costs and convenience yield according to the theory of storage. As for the expectations theory, the results are mixed. They find for five out of 21 commodities that their forward price depends on the time-varying expected risk premium. On the other hand, the forward price contains information about expected spot prices for ten out of 21 commodities.

Electricity is a non-storable commodity, which means the expectations theory applies according to the definition of Fama and French (1987). This means that the forward price depends on expectations about the spot price plus a risk premium in order to compensate power producers for the risk they bear when trading at a fixed price. However, electricity is fairly a peculiar commodity and seems to behave according to a combination of the theory of storage and the expectations theory depending on the type of underlying commodity. Huisman and Kilic (2011) applied the methodology of Fama and French (1987) on electricity in which they test to what extent the forward prices for electricity reflect changes in expected spot prices and/or the risk premium. The relationship between the forward price and the spot price is defined by the formula below

$$F_{t,T} = E_t(S_T) + P_{t,T}$$

In which $E_t(S_T)$ is the expected spot price at maturity and $P_{t,T}$ is the risk premium. When subtracting the current spot price from both sides of the equation and rewriting the risk premium, the formula becomes

$$F_{t,T} - S_t = E_t(S_T) - S_t + F_{t,T} - E_t(S_T)$$

The forward premium is then equal to the change in expected spot price plus a time-varying risk premium.

Forward premium*: the change in expected spot price and the time-varying risk premium.*

It depends on the underlying commodity which element, the change in expected spot price or time-varying risk premium, is more dominant in the forward premium. Huisman and Kilic (2011) find that in markets in which electricity is primarily produced by perfectly storable underlying commodities, for example gas, the forward price contains information about both time-varying risk premia and expected spot prices. In markets where electricity is produced by imperfect or non-storable underlying commodities, the forward price only contains information about the expected spot price. The Nordic power market is dominated by hydropower produced by water. Water is imperfectly storable, but not non-storable. Therefore, it is expected that the change in expected spot price is more profound in the forward premium in the Nord Pool market.[2]

2.5 Hypothesis development

The cost-of-carry relationship that links spot prices and forward prices as a no-arbitrage condition, does not apply to electricity as it is non-storable or at least imperfectly storable. Because of this implication, the determination of the forward price and the forward premium is not straightforward. Bessembinder and Lemon (2002) adopt an equilibrium approach in pricing

[2] See the regression analysis based on Fama and French (1987) in section 5 Data.

forward contracts. The equilibrium approach relies on the assumption that prices are determined by industry participants rather than outside speculators. They argue that when expected demand is low and demand variance is modest, there is little skewness in spot prices. Consequently, power retailers feel no need to hedge themselves against unexpected price movements. This leads to a downward adjustment in the forward price. The forward power price is a downward biased predictor of the future spot price, in other words the forward premium becomes negative. In contrast, when the expected demand is high and demand variance is high, the distribution of the spot price becomes positively skewed. Short positions could incur high losses if upward spikes occur. As compensation for this risk, the forward price will be bid up, and the forward price will be an upward biased predictor of the future spot price. The results of Bessembinder and Lemon (2002) are confirmed by Longstaff and Wang (2004). They show that price peaks, due to the positive skewness in the distribution of the spot price, positively affect the forward premium. They study the properties of the electricity spot and forward prices by using a high frequency PJM dataset. The authors find that the forward premium is time-varying and is significantly affected by risk measures of price, quantity and revenue risk. They show evidence that the forward premium is essentially a compensation for risk.

Based on these findings, it is expected that high capacity constraints cause an upward pressure on the forward price, leading to higher a high forward premium. The intuition can be explained as follows. High capacity constraints prior to the maturity of the forward contract imply a significant increase of demand relatively to the supply (in other words, a significant deficit of the supply of power relatively to the expected demand) at a certain point in time. Thus, high capacity constraints induce higher expected demand and demand variance. As consequence, the distribution of the spot power prices becomes positively skewed. This means that the forward price should increase in order to compensate for the skewness in the spot price distribution. Hence, the forward premium will increase by the anticipated skewness of the spot price distribution (Bessembinder & Lemmon, 2002). Following this reasoning, the relationship between capacity constraints and the forward premium should be positive due to (higher) positive skewness in the distribution of the spot price.

Hypothesis: *high capacity constraints induce an increase in the forward premium due to increased anticipated skewness in the spot price distribution.*

It is clear that electricity is a complex commodity whose characteristics also differ across energy markets as the composition of generation parks and market players differ. Electricity deals with several factors making it hard to properly model the spot prices whilst taking into account the uncertainties. Before continuing to the methodology, several existing models will be discussed in the next section in order to define an appropriate model.

2.6 Existing models

In most of the existing literature, the authors attempt to model the power prices by using a simplified approach. These models mainly address the typical characteristics of electricity prices: seasonality, spikes, high volatility and mean reversion.

Schwartz and Smith (2000) propose a two-factor model applied to modelling oil futures prices that later has found applications for the electricity market. The authors define a two-factor model in order to model oil prices. They separate the spot price in two components, the mean reverting process in the short-term deviation and an equilibrium level. In the long run the short-term deviations are assumed to approach zero, which means that in the long-run the spot price is equal to the equilibrium level. The authors conclude that their two-factor model performs better than the one-factor models as two-factor models give better representation of real-time market.

Lucia and Schwartz (2002) extend the two-factor model of Schwartz and Smith (2000) by defining a model composed of a deterministic and a stochastic component. The deterministic seasonal component is responsible for capturing any relevant predictable component of electricity prices. The stochastic component is responsible for unpredictable short-term deviations and is assumed to follow a particular continuous time diffusion process. In their study they find a closed form solution to determine the electricity forward prices. In doing so, they use a risk-neutral or risk-adjusted valuation of the expected spot prices to the valuation date. In their study they estimate the spot price of electricity based on four models that differ in time series and in the way the deterministic component is defined. Lucia and Schwartz (2002) conclude that of all four models, the ones that are based on normal prices and not the natural logarithm of prices, perform better. In addition, a simple sinusoidal function is more adequate in capturing the seasonality embedded in forward prices.

As electricity prices are highly volatile and the existence of spikes is obvious, one needs to take this characteristic into account when modelling spot prices. Cartea and Figueroa (2005) present a mean reverting jump diffusion model for the electricity spot price and derive the corresponding forward price in closed-form. The authors suggest that mean reversion can only be properly captured by a Brownian motion and that jumps can be modelled adequately by means of a Poisson process. They take a hybrid approach in calibrating the parameters by using both historical spot market data and forward market data. The results indicate that the use of specific distributions accounting for fat tails is desired in order to deal with the complexity of the calibration of the spot prices. The authors recommend the use of Gaussian distributions for further research.

An alternative way of modelling electricity spot prices is to apply regime-switching models to deal with high volatility of power prices. These models depart from the assumption that the variable that is being modelled, can be in more than one state or regime.

Bierbrauer et. al. (2004) employ regime-switching models by specifying four different regime-switching models to forecast electricity spot prices. The four models consist of three two-regime-switching models and one three-regime-switching model. They all include a deterministic component that takes into account the seasonality and the effects of temperature and the number of daylight hours. The models differ in terms of distributions. The authors utilise Gaussian, log-normal and Pareto distributions in their models. The results point out that all the models overestimate spikes. However, the magnitude of the largest spikes in either direction is underestimated in the normal and log-normal models, but overestimated by the Pareto distribution. These results may suggest the use of more heavy-tailed distributions. All in all, they conclude that three-regime-switching models are superior to two-regime-switching models in capturing real time price spikes.

Regime-switching models can also be used in combination with jump diffusion models in which a jump component is added to the mean-reversion model. The jump is dependent on a regime-switching variable that could be in two regimes. A high regime is denoted by a higher likelihood of the occurrence of a price spike and a low regime is a regime in which the occurrence of spikes is less likely. The mean-reversion component is separated in a normal mean-reversion parameter and a jump-reversion parameter. The jump-reversion parameter is higher than the normal mean-reversion parameter such that in case a jump occurs, the model has sufficient power to revert to normal levels.

Huisman and Mahieu (2003) propose a regime-switching model with three different regimes in which they disentangle the normal mean reversion and jumps. They argue that the existence of a normal mean reverting process is not directly related to jumps and that regular jump diffusion models do not account for the fact that price spikes are rather short-lived. The idea behind their specification differs significantly from the two-state regime models. They define the three regimes as follows: i) a base regime that can contain a mean reversion component, ii) an initial jump regime and iii) a regime that describes how prices move back to the base regime after the initial jump has occurred. In contrast to the two regime switching models, the three regime switching models do not allow for two consecutive spikes to occur.

Cartea et. al (2008) model electricity spot prices with forward-looking capacity constraints using a regime jump model. The authors assume spot prices are composed of a deterministic and a stochastic component, in which the stochastic component contains a regime-switching factor. They argue for the first time that spot prices should incorporate forward-looking information that is made available to all players by the system operator. The authors assume that the deterministic component is based on the forward price of gas rather than historical power spot prices. Furthermore, they propose a measure of 'tight market conditions' based on capacity constraints. Capacity constraints define the weeks of the year in which price spikes are more likely to occur. They model the capacity constraints as an exogenous switching parameter in the stochastic component that alternates between a high and a low regime. A low regime refers to periods in which electricity prices do not exhibit large price spikes and a high regime refers to periods in which price spikes are likely to occur.

An alternative type of regime-switching models is the Markov regime-switching model with (time-varying) transition probabilities. The Markov regime-switching model consists of a deterministic and a stochastic component. The stochastic component behaves according to two regimes: mean-reverting in regime 1 and a spike in regime 2. The transition probabilities specify how the processes switch between regimes 1 and 2. The transition probabilities are specified as follows: $p_{i,j} = \Pr\{S_t = j | S_{t-1} = i\}$. This is the probability that the market was in state *i* at time *t-1* and migrates to state *j* at time *t*. For example, $p_{1,1}$ is the probability that the market was in state 1 at *t-1* and remains in state 1 at *t*. By definition, $p_{2,1} = 1 - p_{1,1}$, which is the probability of being in state 1 at *t-1* and migrating to state 2 at *t*.

Mount et. al. (2006) apply a Markov regime-switching model with time-varying transition probabilities. The mean prices in the two regimes and the transition probabilities are specified as functions of the offered reserve margin and the system load. The authors find that price spikes are most likely to occur during summer months and the probability of switching to the high regime is negatively related to the reserve margin. A high reserve margin means that it is unlikely that spikes will occur. The authors note that accurate information about reserve margin is required in order to predict price spike adequately.

Huisman (2008) includes the effect of temperature in modelling the day-ahead prices by means of a Markov regime-switching model. The author departs from the fact that information on reserve margins or load could help to forecast price spikes. Huisman (2008) uses temperature as a proxy for information on the reserve margins, as information about reserve margins lacks general availability. On the contrary, temperature information is widely available. The author includes temperature in both the time-varying transition probabilities and the deterministic component in order to capture seasonality. The results show that the probability of a spike increases significantly when temperature deviates substantially from mean temperature levels.

Kilic and Trujillo-Baute (2015) performed a study on the stabilisation of intraday power prices through more flexibility in power generation. Forecast errors will increase the need of intraday markets to adjust the excess or deficit of wind power on an hourly basis. In this study the authors question to what extent hydropower, has as a stabilizing effect on the impact of wind forecast errors on Nord Pool intraday prices. They apply a Markov regime-switching model in periods including transition probabilities dependent on reservoir levels and the wind forecast error to examine the peak and off-peak intraday power prices. Results indicate that during high reservoir levels wind power deficits are absorbed by hydropower but wind power excess is not absorbed by hydropower. This shows that hydropower is effective in controlling for volatility on the intraday market but not at all times.

Another class of spot price models concerns the equilibrium models. The equilibrium models rely on the assumptions that prices are determined by the industry participants. The spot price is the market clearing spot price at which demand meets supply. Bessembinder and Lemmon (2002) present an equilibrium model. The primary goal is to assess the equilibrium forward prices and optimal hedge positions of power firms. They assume that the forward power price will be a biased forecast of the future spot prices. Results indicate that the forward premium decreases by the anticipated variance of wholesale spot prices and increased by the anticipated positive skewness of wholesale spot prices. In addition, they document a positive bias in forward power prices for summertime delivery, while the bias in forward prices for spring and fall delivery is zero or negative.

The results of Bessembinder and Lemon (2002) are confirmed by Longstaff and Wang (2004). They examine the pricing of electricity forward contracts in the day-ahead forward market and their relation to the corresponding spot prices. The authors conduct a high-frequency analysis using hourly data and find significant risk premia in electricity forward prices, although these premia vary throughout the day. Longstaff and Wang (2004) explicitly examine whether the forward premium reflects compensation for risk-taking by regressing the forward premium on measures of price, quantity and revenue risk. Results indicate that the forward premium is significantly affected by these risk measures and that the forward premium is essentially a risk compensation in addition to the expected spot prices. Their study concludes that forward prices are less volatile than expected spot prices, and therefore provides empirical support for time-varying risk premia.

Cartea and Villaplana (2008) apply an equilibrium model in which they explain the wholesale power prices by means of two state variables: demand and capacity. By doing so, they derive the analytical expression for forward contracts and calculate the forward premium. The authors find that the volatility of demand and load is strongly seasonal and that high volatility of demand induces a higher forward premium in line with earlier research. The authors assume that the volatility of capacity and the market price of risk are constant factors. Under this assumption, the dynamics of the forward premium depend on the market, the period under study and the hedging needs of market participants.

Several models are discussed here and the most common models applied in the electricity market are: factor models, equilibrium pricing models and regime-switching models. Factor models find their application in pricing of derivatives and consist of a deterministic and a stochastic component. The deterministic component is responsible for capturing the seasonality in electricity prices and the stochastic component is responsible for the unpredictable short-term deviations. Regime-switching models assume that the variable that is being modelled, could be in more than one regime. Regime-switching models incorporate a mean reversion component for short-lived normal deviations, however they could also include a jump component. The mean reversion of this jump component is higher than the mean reversion from normal short-lived deviations. Alternatively, regime-switching models could also be modelled with transition probabilities. These type of models are known as the Markov regime-switching models. The transition probabilities indicate the probability of switching between regimes. In addition, the transition probabilities could also be modelled as time-varying. At last, equilibrium models are based on the assumption that prices are determined by market participants. The price is the equilibrium price where demand meets supply. A summary of the results in existing literature can be found in table 2.

Table 2: Summary of models in the literature

Author(s)	Data	Methodology	Results
Fama and French (1987)	CBT, CME, Comex, CSCE, CTN and NYM	Regression analysis	Mixed results, some commodities are related to a time-varying risk premium whereas others exhibit both forecasting power and time-varying expected risk premia.
Schwartz and Smith (2000)	NYM crude oil futures data & Enron futures data	Two-factor model including short-term deviations and an equilibrium level	Both datasets show more volatile spot prices than equilibrium prices, indicating short-term volatility is profound.
Lucia and Schwartz (2002)	Nord Pool market	One-factor model and two-factor model	Two-factor models are superior to one-factor models. Models based on normal prices and incorporating a sinusoidal function perform better than models based on log-prices and seasonal dummies.
Bessembinder and Lemmon (2002)	PJM and CALPEX market	Equilibrium pricing model	The forward premium decreases by the anticipated variance of wholesale spot prices and increases by the anticipated positive skewness of wholesale spot prices. Preliminary results show that the premium is highest during summer months.
Huisman and Mahieu (2003)	APX, LPX and UK market	Three regime jump model	The three regime-switching model is based on the assumption that normal mean reversion is not directly related to jumps. The model performs better than regime-switching models that simultaneously model mean reversion and spikes.
Longstaff and Wang (2004)	PJM market	Regression analysis	Results in line with Bessembinder and Lemon (2002). Forward premia are time-varying and represent risk compensation.
Bierbrauer et. al. (2004)	Nord Pool market	Two regime-switching models and a three regime-switching model	The three regime-model performs better in capturing the real time price spikes than the two regime-switching model.
Cartea and Figueroa (2005)	UK market	Jump diffusion model	The jump diffusion model performs well, and the simulated price path resembles the electricity spot prices as observed in the market.

Mount et. al. (2006)	PMJ market	Markov regime-switching model	The probability of migrating to the high regime increases when reserve margin is low. The probability of remaining in the low regime increases when reserve margin is high.
Cartea et. al. (2008)	UK market	Regime jump model	The model performs well as it is able to simulate spot prices in reasonable accordance with observed historical price paths. Forward-looking seasonality enables the model to mean revert to more realistic scenarios.
Cartea and Villaplana (2008)	UK, PJM and Nord Pool market	Equilibrium pricing model	In line with Bessembinder and Lemon (2002). Demand volatility is positively related to the forward premium. The forward premium dynamics depend on the market, hedging needs of market participants and the period.
Huisman (2008)	APX market	Markov regime-switching model	The probability of the occurrence of a price spike increases in times of extreme temperatures. The higher probability of the occurrence a price spike in the summer may also stem from consumption planning problems.
Huisman and Kilic (2011)	APX and Nord Pool market	Regression analysis	Electricity generated by perfectly storable commodities exhibit time-varying risk premia and forecasting power in the forward price whereas imperfectly storable and non-storable commodities only exhibit forecasting power in the forward price.
Kilic and Trujillo-Baute (2015)	Nord Pool market	Markov regime-switching model	Hydropower capacity is effective in controlling for volatility in the intraday market only when hydropower is used to absorb wind power deficits.

3 Methodology

The forward premium depends on two factors: the expected spot price at the maturity date and the forward price at the maturity date. The expected spot price will be modelled based on the observed spot price data on the day-ahead market by means of a one-factor model. In the one-factor model the deterministic component is disentangled from the stochastic component. Separating the deterministic component and the stochastic component allows to forecast the expected spot price more accurately. Consequently, the forward premium will be constructed by subtracting the expected spot price form the observed futures price in the market. As Markov-regime switching models outperform basic stochastic and mean reverting models (Higgs & Worthington, 2008), the effect of capacity constraints on the forward premium will be examined by applying a Markov regime-switching model. The advantage of Markov regime-switching models is that the transition probabilities can be modelled as time-varying, which allows to investigate the effect of capacity constraints over time.

In this section is organised as follows. First, model 1, the one-factor model, will be introduced. In this paragraph the stochastic component and deterministic component will be defined separately. Secondly, the Markov regime-switching models will be defined. Model 2 describes the standard Markov-regime switching model and model 3 extends by including the effect of capacity constraints.

3.1 Model 1: The one-factor model for electricity spot prices

3.1.1 The stochastic component

Following the methodology of Lucia and Schwartz (2002), the expected spot price will be modelled by applying a one-factor model. The one-factor model distinguishes between a deterministic and a stochastic component. The natural logarithm of the spot price is modelled as this allows to model non-negative prices and utilise a normal distribution. Generally, negative prices are avoided because day-ahead spot prices cannot become negative in most cases. Although negative prices can occur, they are often more likely on intraday and balancing markets.

The natural logarithm of the spot price, represented by $\ln P_t$, is modelled as the sum of two components, namely the deterministic component $f(t)$ capturing the seasonal patterns of electricity prices and a stochastic component X_t.

$$\ln P_t = f(t) + X_t \tag{1}$$

It is assumed that X_t follows a stochastic process of the form

$$dX_t = -\kappa X_t dt + \sigma dZ \tag{2}$$

X_t is the only source of uncertainty as it is the only stochastic component. X_t is defined as a state variable. X_t follows a stationary mean-reverting process with a zero long-run mean, a speed of adjustment κ, with κ > 0 and $X(0) = X_0$. dZ represents an increment to a standard Brownian motion Z_t in order to give the residuals a pure random structure.

For estimation purposes of the stochastic process, X_t is expressed in a fully discrete form

$$X_t = (1-\kappa)X_{t-1} + \sigma \tag{3}$$

Using the fact that $X_t = \ln P_t - f(t)$, equation (1) and (2) can be rewritten as follows

$$d\big(\ln P_t - f(t)\big) = \kappa(f(t) - \ln P_t)dt + \sigma dZ \tag{4}$$

An explicit solution for (2) can be obtained, which together with (1) yields:

$$\ln P_t = f(t) + X_0 e^{-\kappa t} + \sigma \int_0^t e^{\kappa(s-t)}\, dZ(s) \tag{5}$$

From this the conditional mean and variance can be derived using $X_0 = P_0 - f(0)$. $\ln P_t$ has a conditional normal distribution with conditional mean and variance given by

$$E_0(\ln P_t) = E(P_t|X_0) = f(t) + (\ln P_0 - f(0))e^{-\kappa t} \tag{6}$$

$$var_0(\ln P_t) = E(P_t|X_0) = \frac{\sigma^2}{2\kappa}(1 - e^{-2\kappa t}), \;\; \kappa > 0 \tag{7}$$

$f(t)$ is the mean value for P_t in the long run given its value at a previous moment P_0. The higher κ, the faster the convergence to the mean level as the variance and the stochastic component decreases with the time horizon. The variance has a finite limit as the horizon approaches infinity. Hence, the price P_t has a log-normal distribution with mean given by

$$E(P_t) = \exp\left(E(\ln P_t) + \frac{1}{2}var(\ln P_t)\right) \tag{8}$$

Essentially, the natural logarithm of the expected spot price is then equal to the natural logarithm of the conditional mean plus the standard deviation of the spot price. Based on the methodology of Lucia and Schwartz (2002), the closed form solution for the valuation of expected spot prices using (6), (7) and (8) becomes

$$E(P_T) = \exp\,[f(T) + (\ln P_0 - f(0))e^{-\kappa T} + \frac{\sigma^2}{4\kappa}(1 - e^{-2\kappa T})] \quad (9)$$

Ln $P_0 - f(0)$ equals the stochastic component X_0 at the time the forward contract is first entered into. According to the theory, this element together with the noise component (σ) will fade away over the course of time horizon *T. T* is the amount of days between the date when the contract is first entered into and the maturity date. The time horizon is equal to six months for M1-forward contracts as these are being traded six months prior to the maturity date.[3] The noise component (σ) and the stochastic component (X_0) will fade away by the speed of the mean reversion κ to the mean level. This mean level is denoted by the deterministic component upon the maturity date, $f(T)$. Hence, the deterministic component is an important factor in determining the spot price. In the following section the deterministic component will be discussed thoroughly.

3.1.2 The deterministic component

The deterministic component $f(t)$ is a constant function for time t including a deterministic general linear time trend. As shown in the literature (Lucia & Schwartz, 2002; Cartea and Villaplana, 2008), the volatility of weekend days and the volatility weekdays differ significantly. Therefore, the seasonality of the working and non-working days will be incorporated by including a dummy variable for weekends.

The deterministic component is modelled as accurate as possible by also taking into account the effect of temperature. According to the literature, the volatility of the spot price is consistently different between cold and warm seasons (Lucia & Schwartz, 2002; Huisman R., 2008; Bessembinder & Lemmon, 2002). Hence, it is assumed that the level of temperature influences the spot price. The effect of temperature is approximated by introducing a dummy variable for seasons. The dummy variable for seasons is defined as follows. Summer is assumed to be a season in which temperatures are high and winter is assumed to be a season in which temperatures are low. Summer months are assumed to be May to September. Winter months are assumed to be January to April and October to December. The deterministic component is then

$$f(t) = \mu_f + \beta D_t + \partial S_t \quad (10)$$

Where D_t = 1 if date is a weekend day
0 if otherwise; date is a weekday

And S_t = 1 if summer month (M=5, 6, 7, 8 & 9)
0 if winter month (M = 1, 2, 3, 4, 10, 11 & 12)

[3] Six months are assumed to be 182 days based on 365 days in a year.

Finally, the expected spot price at maturity is obtained. The forward premium at maturity can be calculated as

$$PREM_T = F_{t,T} - E(P_T) \tag{11}$$

$F_{t,T}$ is the forward price set at time t for a contract maturing at time T. $E(P_T)$ is the expected spot price at maturity.

3.2 Markov regime-switching models for forward premia

In this section, the Markov regime-switching models for the forward premium will be defined. The model alternates between two regimes: a normal and a non-normal regime. Model 2 is a standard Markov regime-switching model with constant transition probabilities. Model 3 is a Markov regime-switching model with time-varying transition probabilities. The capacity constraints are included in the time-varying transition probabilities in model 3. In addition, model 3 distinguishes between summer and winter months. In the next paragraph, the two regimes will be described and capacity constraints will be defined.

3.2.1 Two regimes based on capacity constraints

The Markov regime-switching model departs from the fact that the forward premium can be in two different states: the normal regime and the non-normal regime. The forward premium alternates between the two regimes induced by a switching parameter. The switching parameter in this study is the capacity constraints ratio.

Recall, that capacity constraints are day-ahead short-term frictions between the demand and supply of electricity. Capacity constraints are defined as a ratio in which demand is divided by supply. Capacity constraints could be considered as a measure of tightness in the power market. High capacity constraints lead to tight market conditions and low capacity constraints lead to normal market conditions.

In order to define a period in which capacity constraints are high or low, a threshold value for capacity constraints is required. If the capacity constraints at a certain point in time exceed this threshold value, the capacity constraints are high and the market could be considered tight. If the capacity constraints are equal or lower than the threshold value, the capacity constraints are low and the market could be indicated as normal.

To determine the threshold value, first the capacity constraints ratio will be constructed. The construction of the capacity constraints ratio is based on the methodology of Cartea et. al. (2008).

The capacity constraints ratio will be constructed as follows

$$\partial(t_m\ ,t_n) = \frac{D(t_m,t_n)}{P(t_m\ ,t_{n)}} \tag{12}$$

In which D is the consumption prognosis and P is the production prognosis. This ratio shows the relationship between the demand and supply forecasted on day m for day n somewhere in the future. One can calculate the forecast ratio $\partial(t_m\ ,t_{n)}$ at every point in time where $m,n\ \epsilon$ {1,2.3…,365} denote the days of the year. Hence, for example $\partial(t_{36}\ ,t_{38)}$ is the forecast ratio calculated upon day 36 for day 38 of the year. In this study the ratio will be calculated between two consecutive days. Therefore, the ratio can be written in the form $\partial(t_{n-1}\ ,t_n)$. This ratio will show forecasts made on day *n-1* for the following day *n*.

After constructing the capacity constraints ratios, a threshold value can be determined. The threshold value is equal to the average capacity constraint ratio from 1 January 2013 to 31 December 2016.[4] This threshold value indicates the average capacity constraint in the electricity market during the course of four years. Consequently, the spike regime is denoted by capacity constraints higher than the threshold value and the normal regime is represented by capacity constraints ratios equal or lower than the threshold value ∂^*.

High capacity constraints/ Tight market conditions: $\partial(t_{n-1}\ ,t_n) > \ \partial^*$ (13)

Low capacity constraints/ Normal market conditions: $\partial(t_{n-1}\ ,t_n) \leq \ \partial^*$ (14)

After defining low and high capacity constraints, the dummy variable for the capacity constraints $({I_t}^T)$ can be introduced. The dummy variable will be used in model 3, the Markov regime-switching model including time-varying transition probabilities.

${I_t}^T$	=	1	if high capacity constraint/ tight market conditions
	=	0	if low capacity constraint/ normal market conditions

3.2.2 Model 2: The two regime-switching model

This standard regime-switching model attempts to model the forward premium with constant transition probabilities. The Markov regime-switching models are based on Huisman (2008), Kilic and Trujillo-Baute (2015), Huisman and Mahieu (2003) and Mount et. al. (2006).

Let F_t be the natural logarithm of the forward premium at day *t.* Note, that t is the date that the physical delivery of electricity commences. The forward premium does not follow a random walk

[4] The Nord Pool market publishes the forecasted demand and supply from 1 January 2013 onwards.

(see figure 1), but fluctuates around a mean level. Therefore, it is assumed that the forward premium embeds a mean value, denoted by the deterministic trend. However, the forward premium is also highly volatile (see figure 1), which points out that there should also be a stochastic component incorporated in the model. The high volatility in combination with a mean value implies that the forward premium exhibits mean reversion. Therefore, it is assumed that the stochastic component should incorporate a mean reversion component. It is assumed that the forward premium consists of a deterministic component (d_t) and a stochastic component (x_t) such that

$$F_t = d_t + x_t \tag{15}$$

The deterministic component accounts for the predictable component of the forward premium and is essentially the long-term mean level of the forward premium.

$$d_t = \mu_1 \tag{16}$$

The stochastic component is modelled as a Markov regime-switching process. At any time *t*, it is assumed that the process can be in one of the two states. Let S_t be the regime in which the process is at time t ($S_t = 1{,}2$). State 1 represents a normal regime in which the stochastic component follows a mean reverting process.

$$X_t{}^1 = (1 - \alpha)X_{t-1} + \sigma_1 \in_{1,t} \quad | \, S_t = 1 \tag{17}$$

α represents the speed of mean reversion and σ_1 is the standard deviation of the error term in state 1 and is multiplied with the error term in state 1.

State 2 denotes a non-normal regime in which the likelihood of a spike occurring is higher.

$$X_t{}^2 = \mu_2 + \sigma_2 \in_{2,t} \quad | \, S_t = 2 \tag{18}$$

μ_2 is the random shock mean price in state 2, which is an increase or decrease in long-term mean price level. σ_2 represents the standard deviation of the error term in state 2 and is multiplied with the error term in state 2. The error terms $\in_{1,t}$ for regime 1 and $\in_{2,t}$ for regime 2 are assumed to be IID(0,1), mutually independent and normally distributed.

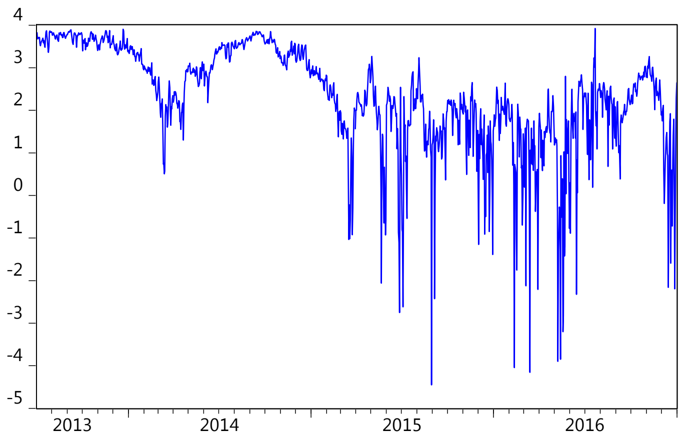
Let the element $p_{i,j}$ be the conditional probability that the process is in state *i* at time *t* given that the process was in state *j* at time *t-1,* so $p_{i,j} = \Pr\{S_t = i | S_{t-1} = j\}$. Accordingly, $p_{1,1}$ is the probability that the power market was in state 1 and remains in state 1 the following day. Hence, $p_{2,1} = 1 - p_{1,1}$ and represents the probability that power market was in state 1 at time *t-1* and has migrated to state 2 at time t. The transition probabilities are assumed to be constant over time and are defined as

$$p_{i,i} = \lambda_i \tag{19}$$

A logistic transformation is applied to restrict the probabilities to remain between 0 and 1. Furthermore, the parameters λ_1 and λ_2 are introduced such that a logistic transformation of these parameters yields the actual transition probability $p^*_{i,i}$

$$p^*_{i,i} = \frac{1}{1+e^{-\lambda_i}} \tag{20}$$

Figure 1: Natural logarithm of the forward premium



3.2.3 Model 3: The two regime-switching model with capacity constraints

Model 3 is an extension of model 2 in which the effect of capacity constraints is incurred. So far, the transition probabilities are constant. In model 3, the transition probabilities are time-varying.

Huisman (2008) showed the importance of temperature on the probability of spikes in day-ahead power prices. The author distinguishes in the Markov regime-switching model between summer and winter months. By doing so, the author could separate the effect of temperature deviations on the probability of spikes in day-ahead prices in the winter and the summer. Following this methodology, the time-varying transition probabilities in this model separate the effect of capacity constraints in summer and winter months by introducing a dummy variable for summer and winter. According to Bessembinder and Lemon (2002), the premium in forward power prices is highest during summer. Therefore, the effect of delivery during summer months is also directly modelled in the transition probabilities.

By including the capacity constraints distinguishing between summer and winter months and the effect of summer in the time-varying transition probabilities, the equation becomes

$$p_{i,i} = \lambda_i + \mathrm{K}_i^{TS} C_{t-1} I_{t-1}{}^T I_t{}^S + \mathrm{K}_i^{TW} C_{t-1} I_{t-1}{}^T I_t{}^W + \mathrm{K}_i{}^S I_t{}^S \quad (21)$$

In which $C_t = \frac{consumption_t}{production_t} - 1$ (22)

C_t denotes the short-term frictions between demand and supply as fraction of the supply. C_t and $I_t{}^T$ are lagged in order to examine the effect of capacity constraints on the forward premium the next day. $\mathrm{K}_i{}^S$ represents the effect of summer on the transition probability. The related dummy variables to indicate a summer or a winter month are defined as follows: $I_t{}^S$ is the dummy variable for summer months and takes the value 1 for the months May-September and 0 elsewhere. $I_t{}^W$ is the dummy variable for winter months and takes the value 1 for the months January-April and October-December and 0 elsewhere.

Parameter $\mathrm{K}_i{}^{TS}$ captures the influence of the short-term frictions between demand and supply under tight market conditions in the summer. Parameter $\mathrm{K}_i{}^{TW}$ captures the influence of the short-term frictions in demand and supply under tight market conditions in the winter.

As mentioned before, $I^T{}_t$ is the dummy variable that takes the value 1 if the capacity constraints are high (tight market conditions) and takes the value 0 if the capacity constraints are low (normal market conditions).[5] The transition probability at time t ($p_{i,i}$), when the market is under normal conditions, is equal to λ_i plus $\mathrm{K}_i{}^S$.

All the parameters in model 1, 2 and 3 are estimated using maximum likelihood.

[5] See section 3.2.1 Two regimes based on capacity constraints

4 Data

4.1 The Nord Pool market

The primary data is retrieved from the Nord Pool market. The Nord Pool is divided into bidding areas in which all the member have to submit orders. The system average is the equilibrium between the aggregated supply and demand curves for all bidding areas and is calculated as one price for the entire Nordic power market. The day-ahead market is referred to as the ELSPOT market where contracts are made between seller and buyer for the delivery of power the following day. The deadline for the ELSPOT market to submit bids for power is at 12.00 CET every day. The hourly prices are announced to the market at 12.42 CET or later. After this, the trades are settled. Physical delivery of electricity takes place the next day against the price quoted one day before. The financial contracts are traded through NASDAQ Commodities. The system price calculated by the Nord Pool is used as the reference price for the financial market. There is no physical delivery for financial power market contracts until the maturity date.

4.2 Data analysis

The main dataset for this study consists of the day-ahead spot prices (ELSPOT prices), the one-month (M1) futures prices, the hourly consumption prognosis and the hourly production prognosis. The futures prices are accrued from Bloomberg. The ELSPOT prices, production and consumption prognosis are accrued from the historical market database of the Nord Pool market. The ELSPOT prices are quoted on day *t-1* for day *t*. The M1-futures contracts are traded six months prior to the month of delivery. Throughout the entire month (1 month for M1 contracts) of delivery the price of electricity is fixed at the price agreed at the time the forward contract was entered into. The ELSPOT price and futures price range from 1 January 2013 to 31 December 2016.

The Nord Pool reports the consumption and production prognosis hourly and reports these according to different bidding areas. First, the hourly consumption and production prognosis are consolidated into daily prognoses by taking the 24-hour average. Secondly, the daily prognoses are transformed into one system value by taking the average of all the bidding areas. After this procedure, the hourly production and consumption prognoses are transformed into one daily system value. The daily production and consumption prognosis range from 1 January 2013 to 31 December 2016.

Figure 2: ELSPOT prices in €/MWh

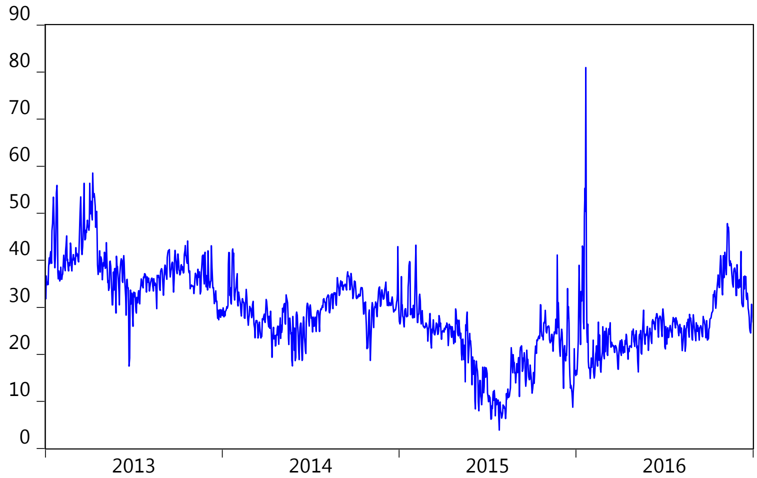


Figure 3: Daily relative changes in ELSPOT prices and capacity constraints ratio

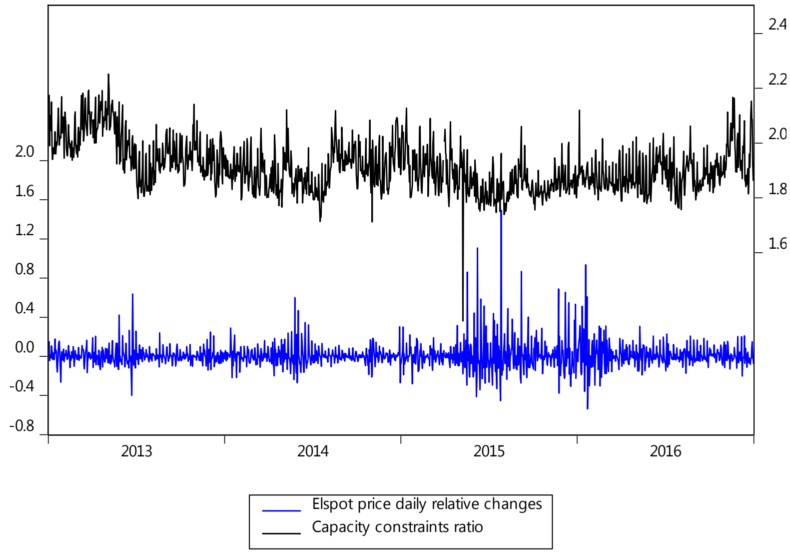
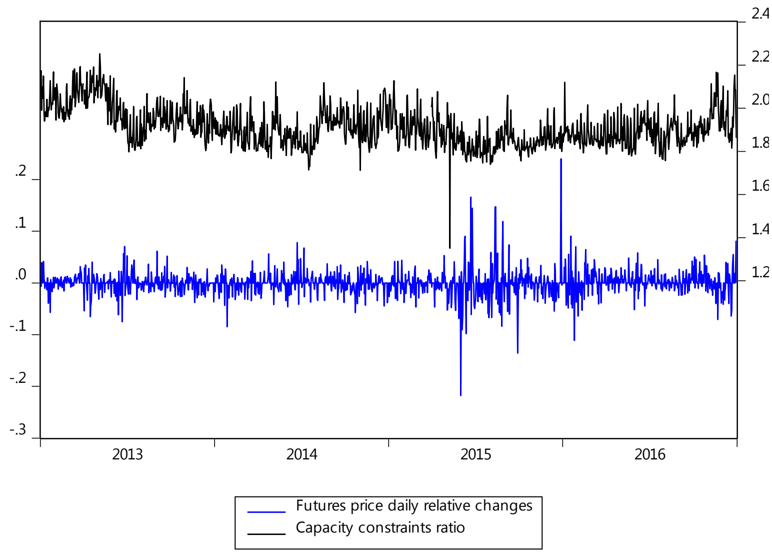


Figure 4: Daily relative changes in futures prices and capacity constraints ratio



According to the literature, electricity prices exhibit seasonality, high volatility, mean reversion and price spikes. From figure 2, it becomes clear that ELSPOT prices exhibit high volatility but the spot prices fluctuate around a mean level. This shows that the electricity prices exhibit mean reversion. In addition, the data also exhibits large peaks, confirming the last stylized fact of high price spikes. When considering the capacity constraints ratio in figure 3, it becomes clear that the mean is close to 1.90, which is the average capacity constraints ratio in the market. A capacity constraints ratio higher than approximately 1.90 indicates that the capacity constraints are high, meaning that the market is under tight conditions. A ratio lower than or equal to approximately 1.90 indicates that the capacity constraints are low, meaning that the market is under normal circumstances.

At first, it seems that the ELSPOT prices are not related to the capacity constraints ratios in figure 3. However, when taking a closer look at figure 3, it becomes clear that the effect of capacity constraints on the spot price is lagged. A large downward peak of the capacity constraints ratio is followed by a slower downward price pressure in the spot price. Similarly, a large upward peak in the capacity constraints is followed by a slower upward price pressure in the spot price. These observations are in line with the expectation that high capacity constraints induce higher spot prices due to the higher expected demand or demand variance. The higher expected demand or demand variance will cause positive skewness in the distribution of the spot price. Hence, high capacity constraints will lead to higher spot prices.

Considering figure 4, it seems that the capacity constraints ratio and the futures prices move in the same direction. From figure 4, it can be concluded that a large downward peak in the capacity constraints ratio is accompanied by a large downward peak in the futures prices. Similarly, large upward peaks in the capacity constraints ratio are accompanied by large upward peaks in the futures prices. The capacity constraints ratios are lagged one day to capture the effect on the forward premium of the next day. By lagging the capacity constraints ratios, the relationship between capacity constraints and futures prices becomes more profound.

Remarkably, the observations suggest that the spot price needs more time to adjust to the new price level after a capacity constraint has occurred. The futures price adopts faster to the new price level and thus incorporates the effect of capacity constraints faster. This is probably related to the fact that futures prices contain information about expected spot prices. It takes some time for the information embedded in the futures price, to be incorporated in the spot prices in the day-ahead market. Hence, it seems that the futures price adopts faster than the spot price to the expected price level after a capacity constraint has occurred.

Table 3: Descriptive statistics

The data ranges from 1 January 2013 to 31 December 2016. The winter months are denoted by January-April and October-December. The summer months are represented by May-September. The ELSPOT price and futures price are in €/MWh and the consumption and production prognosis are reported in MWh/day.

	Winter			Summer		
	Total	Tight	Normal	*Total*	Tight	Normal
ELSPOT price						
Mean	*30.734*	34.413	27.292	*26.353*	31.122	23.276
Min	*8.740*	14.950	8.740	*3.880*	6.300	3.880
Max	*80.99*	80.990	55.360	*43.740*	43.740	41.670
Std. dev	*8.514*	8.599	6.843	*8.482*	6.813	8.024
Skewness	*0.645*	0.651	0.309	*-0.412*	-0.822	-0.234
Kurtosis	*4.370*	4.521	3.587	*2.547*	3.626	2.469
Futures price						
Mean	*49.656*	60.927	39.182	*48.690*	60.759	40.910
Min	*13.930*	13.960	13.930	*17.054*	19.027	17.054
Max	*96.924*	96.924	93.015	*91.367*	91.367	91.367
Std. dev	*23.700*	21.877	20.296	*24.367*	23.604	21.545
Skewness	*0.096*	-0.302	0.373	*0.249*	-0.558	0.784
Kurtosis	*1.911*	2.079	2.051	*1.441*	1.719	2.162
Consumption prognosis						
Mean	*6594.120*	6734.517	6463.660	*4893.552*	4924.557	4873.550
Min	*4765.880*	4795.438	4765.880	*4023.656*	4023.656	4042.750
Max	*9400.458*	9400.458	8545.891	*6474.417*	6474.417	5734.651
Std. dev	*847.551*	945.553	722.016	*406.803*	481.447	349.570
Skewness	*0.552*	0.511	0.270	*0.444*	0.609	-0.026
Kurtosis	*3.121*	2.713	2.849	*3.685*	3.504	2.584
Production prognosis						
Mean	*3431.130*	3371.162	3486.854	*2583.482*	2484.847	2647.117
Min	*2418.822*	2418.822	2552.275	*2019.208*	2019.208	2128.519
Max	*4646.193*	4646.193	4499.453	*3130.269*	3127.372	3131.269
Std. dev	*426.214*	462.9427	381.145	*221.668*	234.647	187.350
Skewness	*0.311*	0.502	0.214	*-0.271*	0.060	-0.182
Kurtosis	*2.718*	2.779	2.668	*2.651*	2.364	2.787
N	*845*	407	438	*612*	240	372

The descriptive statistics are reported in table 3. It can be concluded that on average the forward premium (futures price – ELSPOT price) is higher during summer months (€22.337/MWh) compared winter months (€18.922/MWh). This result is in line with the results of Bessembinder and Lemon (2002) as they find higher forward premia in the summer.

Regarding the ELSPOT price, it can be concluded that the ELSPOT price is lower during summer months. The lower ELSPOT price can be explained by the expected demand, which is lower during summer month (6594.120 MWh/day in the winter and 4893.552 MWh/day in the summer). The lower demand makes sense as during summer months the utilisation of power is lower due to the number of daylight hours and temperature. However, the coefficient of variance of the spot prices (std. dev. / mean) is higher in the summer (0.277 in the winter and 0.322 in the summer), which means that the spot prices are more volatile during summer months. Moreover, the Nordic power market is largely dependent on hydropower generated by the amount of snow and precipitation. The amount of snow and precipitation determines the level of hydro reservoirs. During summer the level of hydro reservoirs is highest.[6] The level of hydro reservoirs indicates the level of marginal costs. The value of the option to store water is high when the level of hydro reservoirs is low, which leads to increased marginal costs. Similarly, the value of the option to store water is low when the level of hydro reservoirs is high causing low marginal costs. Hence, the marginal costs are low during summer months and induce lower spot prices. The lower spot prices are also indicated by the negative skewness in the distribution of the spot prices (-0.412 in the summer).

On the other hand, the futures price is higher during the winter. This can be explained by the expected demand or variance of demand. The expected demand (consumption prognosis) is substantially higher in the winter (6594.120 MWh/day) than in the summer (4893.552 MWh/day). The coefficient of variance (st. dev. / mean) for consumption prognosis is 0.129 and 0.083 for winter and summer respectively. This means that the dispersion of expected demand is higher during wintertime than during summertime. Consequently, this means that the demand variance is higher during winter months. The higher expected demand and demand variance causes the positive skewness (0.645 in the winter) in the distribution of the spot price. As result, the forward price is higher in order to compensate for this increased risk.

When considering the difference between tight and normal market conditions, it becomes clear that the forward premium is higher under tight market conditions (26.514 for winter and 29.637 for summer) compared to normal market conditions (11.89 for winter and 17.634 for summer). Migrating from normal market conditions to tight market conditions induces an increase in futures prices, more substantial than an increase in spot prices. The higher forward premium under tight market conditions can be explained by means of the expected demand and demand variance. The expected demand under tight market conditions are higher than under normal market conditions across all seasons. The expected demand is 6734.517 and 6463.660 MWh/day in the winter and 4893.552 and 4873.550 MWh/day in the summer for tight and normal markets respectively. Furthermore, the coefficient of variance of the consumption prognosis (demand variance) during winter is 0.140 and 0.111 for tight and normal markets respectively. During summer the consumption prognosis coefficient of variance is 0.098 and 0.072 for tight and normal markets respectively. The coefficients of variance are higher under tight market conditions than under normal market conditions in both seasons.

Higher expected demand and/or demand variance cause a positively skewed spot price distribution, which will lead to higher forward premia. The expected demand and demand variance are higher under tight market conditions. Based on these statistics, it is expected that high capacity constraints (i.e. tight market conditions) will lead to high forward premia.

[6] See figure 5 Nord Pool hydro reservoirs in GWh (2016).

4.2.1 The forward premium on the Nord Pool

In this section the forward premium will be examined in more detail. The methodology is based on Fama and French (1987). The forward premium consists of the change in expected spot price or the expected-to-be-realised risk premium. A regression analysis is performed to analyse which component, the change in expected spot price or the risk premium, is more dominant in the forward premium. According to the expectations theory, the forward price equals the expected spot price plus the risk premium $F_{t,T} = E_t(S_T) + P_{t,T}$. From this equation the current spot price is subtracted on both sides of the equation

$$F_{t,T} - s_t = E_t(S_T) - s_t + P_{t,T} \tag{21}$$

The risk premium could be restated by implying that the risk premium is equal to the expected-to-be realised risk premium

$$F_{t,T} - s_t = E_t(S_T) - s_t + [F_{t,T} - E_t(S_T)] \tag{22}$$

$[F_{t,T} - s_t]$ is the base, $[E_t(S_T) - s_t]$ is the expected change in spot price and $[F_{t,T} - E_t(S_T)]$ is the time-varying risk premium. To test which component is more present in the base, the following regressions are performed

$$E(S_T) - S_t = \alpha_1 + \beta_1[F_{t,T} - s_t] + \epsilon_1 \tag{23}$$

$$F_{t,T} - E(S_T) = \alpha_2 + \beta_2[F_{t,T} - s_t] + \epsilon_2 \tag{24}$$

If the theory of storage applies perfectly, β_1 should be equal to 0. Should β_1 be equal to 1 then the expectations theory applies perfectly. Note, that β_1 + β_2 = 1 based on equation (22), meaning that β_1 reflects the fraction of the forward bias that is attributable to expectations about the spot price and β_2 is the fraction of the forward bias that is attributable to the time-varying risk premia. The results are shown in table 3.

Table 4: Regression analysis Nord Pool forward premium

Reported are the results of the regression analysis of the forward premium in the Nord Pool market. β_1 is the fraction of the base that is related to the change in expected spot prices. β_2 is the fraction of the base that is related to time-varying risk premia. α_1 and α_2 are the constant terms in the regressions. The number of observations is equal to 1461.*, ** denote a test statistic is statistically significant at the 5% level of significance or 1% level of significance, respectively.

	Coefficient	Standard error	T-statistic
α_1	0.771**	(0.155)	(4.986)
β_1	0.962**	(0.006)	(170.975)
α_2	-0.771**	(0.155)	(-4.986)
β_2	0.038**	(0.006)	(6.711)

From the results it becomes clear that 3.8% of the base stems from the time-varying risk premium and 96.2% of the base stems from the change in expected spot price. According to Huisman and Kilic (2011), futures prices from markets in which electricity is mainly produced by imperfect storable or non-storable commodities, contain information about changes in the expected spot price. On the contrary, futures prices from markets in which electricity is mainly produced by perfectly storable commodities contain information about time-varying risk premia and changes in expected spot prices. The Nord Pool market shows evidence for expectations and less for time-varying risk premia. This result makes sense as the Nord Pool power market is dominated by hydropower, which is produced by the imperfectly storable commodity, water. Knowing this, it essential that the expected spot price is estimated properly as the forward price is determined by the expected spot price for the most part.

5 Results

This section presents the results of the three models applied and the respective findings. This section is organised as follows. First, the parameter estimates and findings of the one-factor model will be discussed. Secondly, the parameter estimates and the findings of the Markov regime-switching model with constant transition probabilities will be discussed. At last, the parameter estimates and findings of the Markov regime-switching model with time-varying transition probabilities including capacity constraints will be presented.

5.1 The one-factor model for electricity spot prices

Table 5: Parameter estimates for model 1

Reported are the parameter estimates for the stochastic one-factor model in which the spot price P_t comprises of a deterministic component f(t) and a stochastic component X_t:

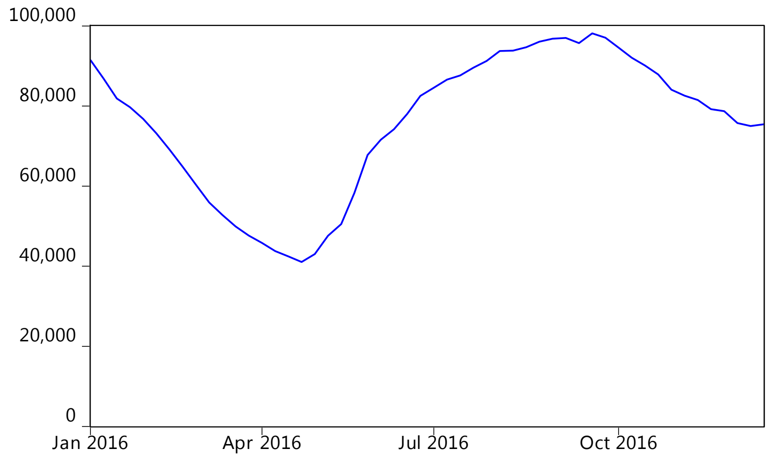
$$\ln P_t = f(t) + X_t$$

The variables for β and ∂ are dummy variables. The sample period ranges from 2 January 2013 to 31 December 2016. *, ** denote a test statistic is statistically significant at the 5% level of significance or 1% level of significance, respectively.

		Estimate	Standard error	T-statistic
Mean price	μ_f	3.434**	(0.055)	(62.180)
Weekend effect	β	-0.117**	(0.005)	(-23.516)
Mean reversion	κ	0.043**	(0.008)	(5.344)
Summer effect	∂	-0.074*	(0.035)	(-2.138)
Volatility	σ	0.100**	(0.002)	(55.00)
LogLik	-1296.64			
N	1461			

Table 5 shows the estimates of the one-factor model for expected spot prices. All the parameters are significantly different from zero. The mean log price μ_f is equal to 3.434 with a volatility of 0.100. The speed of mean reversion is 0.043 which is the speed at which price deviations from the mean level fade away. In the weekends, the mean log price is lower by 0.117. During summer months the mean log price is lower by 0.074. These results are in line with previous studies. The effect of weekend days is expected to be negative as weekend days usually exhibit lower prices than working days (Kilic & Truijillo-Baute, 2015). The effect of summer on the expected spot price is also negative. Recall that hydropower generation contributes significantly to the Nordic power generation. Hydro units are dependent on precipitation and snowfall, which varies across seasons. During summer months, the level of hydro reservoirs is highest (see figure 5). Hydropower plants are highly flexible but the price of electricity produced by hydropower plants depends on marginal costs. The marginal costs are related to the level of hydro reservoirs. The results of Huisman et. al. (2013) suggest that higher levels of hydro reservoirs induce more hydro capacity and lead to significant lower power prices. From this they conclude that an increase in the power supply of renewable energy with low marginal costs will reduce power prices significantly. Hence, the spot price is lower during summer months due to higher levels of hydro reservoirs.

Figure 5: Nord Pool hydro reservoirs in GWh (2016)



5.2 Markov regime-switching models for forward premia

Table 6: Parameter estimates for model 2

Reported are the parameter estimates of the Markov regime-switching model with constant transition probabilities for the forward premium. The transition probability can be transformed into actual transition probabilities by means of the following formula: $p^*_{i,i} = 1/(1 + e^{-\lambda_i})$. The sample period ranges from 2 July 2013 to 31 December 2016. *, ** denote a test statistic is statistically significant at the 5% level of significance or 1% level of significance, respectively.

		Estimate	Standard error	T-statistic
Mean price	μ_1	3.511**	(0.164)	(21.397)
Mean price spike	μ_2	-2.576**	(1.785)	(-14.433)
Mean reversion	α	0.020**	(0.007)	(2.644)
Probability | St= 1	λ_1	3.094**	(0.185)	(16.763)
Probability | St= 2	λ_2	2.035**	(0.205)	(9.922)
Volatility | St= 1	σ_1	0.148**	(0.005)	(32.982)
Volatility | St= 2	σ_2	1.272**	(0.050)	(25.384)
$p^*_{1,1}$	0.957			
$p^*_{2,2}$	0.884			
LogLik	330.444			
N	1277			

Reported in table 6 are the parameter estimates of the Markov regime-switching model with constant transition probabilities for the forward premium (model 2). All the parameters are significantly different form zero. The mean of the natural logarithm of the forward premium in the first state μ_1 is 3.511. In the second state the mean level will be lower by 2.576. The negative sign of μ_2 indicates that in the second state the mean level is lower than the mean level in the first state and experiences a downward spike. When considering the volatility, it is noticeable that the volatility in the second state is substantially higher (> 8 times) than the volatility in the first state. From this it could be stated that the second state is the non-normal regime, in which the forward premium is lower but more volatile than the forward premium in the normal regime. This means that in the non-normal regime, the exact magnitude of the spike is difficult to predict.

The model performs well as it distinguishes between a mean reverting regime including a mean price level (normal regime) and a highly volatile regime with lower forward premia (non-normal regime). The speed of mean reversion in the normal regime is equal to 0.020. The speed of mean reversion of expected spot prices in model 1 (0.117) is slightly lower than the speed of mean reversion of the forward premium. This means that the forward premium reverts to their normal price levels faster than expected spot prices. The mean reversion suggests that the forward price is more stable than the expected spot price since the forward premium is able to move faster to its equilibrium level then the expected spot price. This finding provides evidence for time-varying risk premia in the Nord Pool market.

The transition probabilities are assumed to be constant over time. $\lambda_1$is equal to 3.094 and λ_2 is equal to 2.035. After transforming these probabilities into actual probabilities, the transition probabilities become $\Pr\{S_t = 1|S_{t-1} = 1\}$ =0.957 and $\Pr\{S_t = 2|S_{t-1} = 2\}$= 0.884. This implies that there is a 4.33% probability that the forward premium is in the normal regime and migrates to non-normal regime the next day. Similarly, the probability that the forward premium is in the non-normal regime and moves back to the normal regime the next day is 11.56%. From these results it can be concluded that the probability of remaining in the non-normal regime is lower than the probability of remaining in the normal regime for two consecutive days.

Table 7: Parameter estimates for model 3

Reported are the parameter estimates of the Markov regime-switching model including time-varying transition probabilities dependent on capacity constraints and seasonality for the forward premium. Observations in which the capacity constraints exceed the average capacity constraints are denoted as under tight market conditions. All the other observations are denoted as under normal market conditions. The winter months are indicated by January-April and October-December whereas summer months are represented by May-September. The sample period ranges from 2 July 2013 to 31 December 2016. *, ** denote a test statistic is statistically significant at the 5% level of significance or 1% level of significance, respectively.

		Estimate	Standard error	T-statistic
Mean price	μ_1	3.505**	(0.165)	(21.248)
Mean price spike	μ_2	-2.572**	(0.179)	(-14.353)
Mean reversion	α	0.020**	(0.007)	(2.671)
Probability | St= 1	λ_1	3.212**	(0.395)	(8.126)
Probability | St= 2	λ_2	2.215**	(0.356)	(6.217)
Volatility | St= 1	σ_1	0.149**	(0.004)	(33.128)
Volatility | St= 2	σ_2	1.266**	(0.050)	(25.377)
Effect of tight market | summer | St= 1	K_1^{TS}	0.665	(0.583)	(1.140)
Effect of tight market | summer | St= 2	K_2^{TS}	-0.279	(0.624)	(-0.447)
Effect of tight market | winter | St= 1	K_1^{TW}	0.178	(0.585)	(0.305)
Effect of tight market | winter | St= 2	K_2^{TW}	0.231	(0.853)	(0.271)
Effect of summer | St= 1	K_1^{S}	-0.606	(0.508)	(-1.193)
Effect of summer | St= 2	K_2^{S}	-0.325	(0.493)	(-0.660)
LogLik	328.524			
N	1277			

Table 7 reports the estimates of the parameters of the second Markov regime-switching model with time-varying transition probabilities for the natural logarithm of the forward premium. Model 3 is an extension of model 2 by incorporating the effect of capacity constraints distinguishing between summer and winter and the effect of summer months, creating time-varying transition probabilities. All the parameters are significantly different from zero except the parameters K_1^{TS}, K_2^{TS}, K_1^{TW}, K_2^{TW}, K_1^{S} and K_2^{S}. Note that the estimates for the other parameters remain relatively unchanged reflecting the robustness of the model.

The estimates of K_1^{S} and K_2^{S} are -0.606 and -0.325 respectively. The probability of remaining in the normal regime is lower than the probability of remaining in the non-normal regime as result of the summer effect. Thereby, the probability of remaining in the non-normal regime is higher than the probability of remaining in the normal regime as result of the summer effect. The difference between the estimates of the parameters is significant at the 1% and 5% level of significance (t-statistic = -14.185), which means that the probability of remaining in the non-normal regime is significantly higher than the probability of remaining in the normal regime as result of the summer effect. This finding implies that generally, the forward premium is lower and more volatile in the summer.

The behaviour of the forward premium in the summer is related to the anticipated skewness in the distribution of the spot price. Higher expected demand and/or demand variance induce positive skewness in the distribution of the spot price. The forward premium will increase as a result of the positive skewness in the distribution of the spot price (Bessembinder & Lemmon, 2002). During summer months the skewness of spot prices is negative due to lower expected demand and demand variance.[7] The power retailers do not feel the need to hedge themselves against unexpected losses as the distribution of the spot price is negative. This will lead to a downward pressure on the forward premium. Hence, the forward premium is likely to migrate to the non-normal regime in which the forward premium is lower but more volatile. However, being in the non-normal regime in which the forward premium is lower due to lower expected demand or demand variance, the power producers could adjust their output downwards to meet the lower demand. By doing so, the distribution of the spot price becomes less negatively skewed, such that the market returns to normal again (Huisman R. , 2008). As result, the forward premium will migrate from the non-normal regime to the normal regime. The probability of migrating from the non-normal regime to the normal regime is lower than the probability of migrating from the normal regime to the non-normal regime as result of the summer effect, which indicates that the negatively skewed distribution of the spot price is more profound than the adjustment of the output by the power producers.

K_1^{TS} and K_1^{TW} are 0.655 and 0.178 respectively. The positive estimates of the parameters indicate that when high capacity constraints occur, the probability of remaining in the normal regime increases. By definition, the probability of migrating to the non-normal regime decreases because $p_{2,1} = 1 - p_{1,1}$. The parameter estimates indicate that under tight market conditions, the probability of lower but more volatile forward premium, decreases. Thereby, the probability of higher and less volatile forward premia increases under tight market conditions. This results is in line with expectations as tight market conditions will induce higher forward prices due to the more positively skewed distribution of the spot price. Remarkably, this effect is more profound during summer months than during winter months. The difference between the parameter estimates is significant at the 1% and 5% level of significance (t-statistic = 14.711). This could be explained as follows. In the summer, the distribution of the spot price is negatively skewed and in the winter the distribution of the spot price is positively skewed. Under tight market conditions, high capacity constraints will induce higher demand and thus more skewness in the distribution of the spot price. Considering this effect in the summer, the distribution of the spot prices will become less negatively skewed and the spot prices will become more normally distributed. In the winter, the distribution will become even more positively skewed. Hence, the forward premium

[7] See the descriptive statistics in section 4.2 Data analysis.

is more likely to be in at the normal level in the summer compared to the winter. It can be concluded that high capacity constraints induce a higher increase in the probability of remaining in the normal regime during summer months than during winter months.

The estimates of parameters K_2^{TS} and K_2^{TW} are -0.279 and 0.231 respectively. The parameter estimate of K_2^{TS} is negative, which indicates being in the non-normal regime, the probability of remaining in the non-normal regime decreases. Consequently, the probability of migrating to the normal regime increases during summer months under tight market conditions. The distribution of the spot price tends to be negative in the summer. The skewness of the distribution of the spot price becomes less negatively skewed and more normal due to higher demand as a result of high capacity constraints. Consequently, the forward premium will move to the normal regime. Another explanation for the migration to the normal regime could be that power producers adjust their output such that markets can return to normal again (Huisman, 2008).

However, parameter K_2^{TW} is positive, which means that being in the non-normal regime, the probability of remaining in the non-normal regime increases under tight market conditions. This finding seems rather peculiar. During winter months the skewness is positive and the expected demand and demand variance are high.[8] According to these features, the forward premium should be high during winter months to compensate for this increased demand risk, and especially under tight market conditions. In this case, one would expect the forward premium to migrate back to the normal regime, in which the forward premium is higher and less volatile. However, the forward premium remains in the non-normal regime, in which the forward premium is lower and more volatile.

Recall that the Nord Pool is dominated by hydropower produced by flexible hydropower plants. Hydropower creates an option to delay power production based on current power prices and the expected opportunity loss that arises if the producers would use the hydro capacity for producing at a later time when power prices might be higher (Huisman, Stradnic, & Westgaard, 2003). In the winter, power producers are reluctant to adjust their power output downwards because of the positive skewness in the spot price distribution and higher expected demand, which leads to potential higher power prices. As consequence, they will keep producing power by deploying hydropower plants, leading to a surplus of power supply. This surplus of supply relatively to expected demand has a depressing effect on power prices. The depressing effect on the spot prices will eventually lead a downward spike in the forward premium, as power retailers do not feel the need to hedge themselves against spot price risk. Hence, the probability of remaining in the non-normal regime in increases during winter months, despite the fact that the market is under tight market conditions.

---

[8] See the descriptive statistics in section 4.2 Data analysis.

6 Conclusions and discussion

The introduction of renewable energy into the market for electricity has changed the dynamics significantly. Generally, renewable energy sources cause lower wholesale market clearing prices due to lower marginal costs and supporting incentives schemes provided by governments to stimulate the use of sustainable power generation. Lower wholesale market clearing prices are clearly economic beneficial to power retailers. However, the implication with renewable energy sources stems from the fact that these are highly unpredictable and very volatile in addition to load forecast errors, failure of power plants and demand variability. The uncertainty imposed by the system and the use of renewable energy sources causes electricity prices to be very volatile as electricity is still a non-storable commodity. The non-storable character of electricity mainly contributes to large price spikes. Large spikes in intraday spot prices are the result of sudden high short-term frictions in the supply and the expected demand. The short-term frictions in demand and supply are referred to as capacity constraints. Capacity constraints are defined as the ratio of demand over supply, namely the capacity constraints ratio. If this ratio exceeds the average capacity constraints ratio in the market, the capacity constraints are denoted as high and the market is under tight conditions. If the capacity constraints ratio is lower than or equal to the average ratio, the capacity constrains are low and the market is under normal conditions.

The Nord Pool power market is known for the employment of hydropower sources and increasingly wind power sources, thus one can consider the Nord Pool market as dominated by renewable energy. Therefore, this study analyses the Nord Pool market in order to measure the effect of capacity constraints driven by renewable energy on the forward premium. The goal of this study is to examine the effect of capacity constraints in the Nord Pool market on the forward premium the next day. In doing so, the expected spot price at maturity are forecasted by applying a one-factor model. The forward premium is constructed by means of the forecasted spot price at maturity and the observed M1-futures prices acquired from NASDAQ Commodities. The effect of capacity constraints is modelled by means of Markov regime-switching models with time-varying transition probabilities. This study analyses the effect of capacity constraints on the daily forward premium for the Nord Pool from 2013 to 2016 distinguishing between summer and winter months.

The results indicate that the expected spot price is lower during summer months than during winter months. Hydro units are dependent on precipitation and snowfall, which varies across seasons. The level of hydro reservoirs is highest in the summer. Higher levels of hydro reservoirs induce lower marginal costs of producing electricity and thereby lead to lower wholesale clearing prices.

The results show that the forward premium could be in two regimes, the normal regime and the non-normal regime. The normal regime is a state in which the forward premium is generally at the mean level and exhibits mean reversion. The forward premium could also be in the non-normal regime, in which the mean level is lower than the mean level in the normal regime. In addition, the mean level in the non-normal regime also exhibits high volatility. The lower mean level in the non-normal regime compared to the mean level in the normal regime, indicates a downward spike in the non-normal regime. The probability of remaining in the normal regime is higher than the probability of remaining in the non-normal regime. From this, it can be concluded that the forward premium is generally in the normal regime and does not exhibit spikes.

Regarding the effect of summer on the forward premium, it can be concluded that during summer months the forward premium is more likely to be in the non-normal regime than in the normal regime. This conclusion is based on the fact that the probability of remaining in the non-normal regime is significantly higher than the probability of remaining in the normal regime. In the non-normal regime, the forward premium is lower and more volatile. This finding is the result of the negative distribution of the spot price due to lower expected demand and demand variance during summer months. However, being in the non-normal regime, the forward premium returns to the normal regime because power producers adjust their output downwards to meet het lower demand. As consequence, the distribution of the spot price becomes less negatively skewed such that markets return to normal.

The implication of high capacity constraints does not significantly affect the forward premium. However, the probability of remaining in the normal regime or migrating from the non-normal regime to the normal regime, increases with the implication of high capacity constraints. The probability of remaining in the normal regime increases during winter and summer under tight market conditions. Hence, the probability of migrating to the non-normal regime decreases across both seasons. The probability of migrating from the non-normal regime to the normal regime increases only in the summer under tight market conditions (which means that the probability of remaining in the non-normal regime decreases in the summer under tight market conditions).

However, during the summer, the probability of remaining in the normal regime is significantly higher than during the winter. This is related to the difference in skewness in the distribution of the spot price across seasons. The distribution of the spot price is negatively skewed in the summer however, it is positively skewed in the winter. Tight market conditions mean higher expected demand relatively to supply and cause a more positively skewed distribution of the spot price. Under tight market conditions, the spot price becomes more normally distributed in the summer. Nonetheless, the distribution of the spot prices becomes even more positively skewed in the winter. As result, the probability of remaining in the normal regime is higher during summer than during winter under tight market conditions.

The probability of remaining in the non-normal regime is positive in the winter under tight market conditions. This finding seems rather peculiar. The probability of remaining in the non-normal regime increases in the winter under tight market conditions, which means that the forward premium is likely to be lower and more volatile in the winter. This is a result of the fact that power producers are unwilling to adjust their power output downwards such that markets can return to normal. They are reluctant to adjust their output downwards due to the positive skewness in the distribution of the spot price and increased expected demand during winter months. This forms an incentive to keep producing power, more than required by the market. As consequence, spot prices will decrease and the need of power retailers to hedge themselves against spot price risk is low, which will drive down forward premia. Hence, the probability of remaining in the non-normal regime increases in the winter in spite of high capacity constraints.

The findings in this study provide insights about the effect of increased uncertainty of renewable energy on the valuation of financial derivatives. The results suggest that in general, the forward premium is at the normal and stable level (normal regime) rather than at the lower and more volatile level (non-normal regime). With the implication of high capacity constraints, the probability of remaining in the normal regime or migrating from the non-normal regime to the normal regime, increases (the latter with the exception of winter months). Expected is that after the occurrence of high capacity constraints, the distribution of the spot price will become positively skewed as result of higher expected demand and demand variance. The positively skewed distribution of the spot price could induce higher expected spot prices. Assuming that the forward price is determined and fixed before the maturity date, the forward premium should decrease.

However, the results show evidence for the opposite, which means that the forward premium does not decrease but remains at the normal level. This suggests that power producers have anticipated the (higher) positive skewness in the distribution of the spot price by bidding up the forward price. Hence, this study provides evidence that capacity constraints do affect derivative pricing. Power retailers respond to the higher expected demand and demand risk by increasing forward purchases. As consequence, the forward premium does not exhibit downward spikes in general but remains at the normal level.

This study investigates the impact of capacity constraints on the magnitude of the forward premium as the model departs from the natural logarithm of the forward premium. Directions for further research could be to model the actual forward premium instead of the natural logarithm of the forward premium as the forward premium could be negative in the market. By doing so, one could obtain estimates of the parameters that would incorporate the magnitude and the sign of the forward premium. Furthermore, although the models are robust, not all the variables in model 3 are significant. This is probably because the capacity constraints do not have a direct effect on the forward premium but rather on the expected spot prices. Hydropower, which dominates the Nord Pool power market, is produced by an imperfectly storable underlying commodity. According to Huisman and Kilic (2011), imperfectly storable underlying commodities imply that forward prices embed information about expected spot prices rather than time-varying forward premia. Future research could disentangle the expected spot price and the forward price instead of calibrating the forward premium to obtain significant results. Even though the variables are not significant, they provide economic relevance in explaining the forward premium under tight market conditions.

At last, the forward premium is able to be at the normal level most of the time due to lack of risk sharing with outside speculators. When outside speculators are more present in the market, they could share the power price risk embedded in the forward premium. The lack of risk sharing suggests that the power market is not well-integrated with the broader financial market as outside speculators do not show their presence in the market (Bessembinder & Lemmon, 2002). It is of interest to see if the power markets will be better integrated in the financial markets in the future such that the risk premium will decline. This is also for future research.

References

Bessembinder, H., & Lemmon, M. L. (2002). Equilibrium pricing and optimal hedging in electricity forward markets. *The Journal of Finance*, 1347-1362.

Bierbrauer, M., Menn, C., Rachev, S., & Truck, S. (2007). Spot and derivative pricing in the EEX power market. *Journal of Banking & Finance*, 3462-3485.

Bierbrauer, M., Truck, S., & Weron, R. (2004). Modeling electricity prices with regime switching models. *Lecture Notes Comput Sci 3039*, 859-867.

Botterud, Kristiansen, & Ilic. (2008). The relationship between spot and futures prices in the Nord Pool electricity market. *Energy Economics*, 967-978.

Cartea, A., & Villaplana, P. (2008). Spot price modeling and the valuation of electricity forward contracts: The role of demand and capacity. *Journal of Banking and Finance, 32*, 2502-2519.

Cartea, Figueroa, & Geman. (2008). Modelling electricity prices with forward looking capacity constraints. *Applied Mathematical Science*, 103-122.

Cox, J., & Ross, S. (1976). The valuation of options for alternative stochastic processess. *Journal of Financial Economics* , 145-166.

European Commission . (2016, March 29). *Renewable Energy Directive*. Retrieved from Energy: https://ec.europa.eu/energy/en/topics/renewable-energy/renewable-energy-directive

European Commission. (2016, February 28). *Renewable energy*. Retrieved from European Commission: https://ec.europa.eu/energy/en/topics/renewable-energy

Fama, E., & French, K. (1987). Commodity future prices: Some evidence on forecast power, premiums, and the theory of storage. *The Journal of Business, 60*, 55-73.

Higgs, & Worthington. (2008). Stochastic price modeling of high volatility, mean-reverting, spike-prone commodities: The Australian wholesale spot electricity market. *Energy Economics, 30*, 3172–3185.

Huisman, R. (2008). The influence of temperature on spike probability in day-ahead power prices. *Energy Economics*, 2697-2704.

Huisman, R. (2009). *An introduction to models for the energy markets.* Riskbooks.

Huisman, R., & Kilic, M. (2011). Electricity Futures Prices: Indirect Storability, Expectations, and Risk Premiums. *Energy Economics, 34*, 892–898.

Huisman, R., & Mahieu, R. (2003). Regime jumps in electricity prices. *Energy Economics*, 425-434.

Huisman, Stradnic, & Westgaard. (2003). Renewable eneryg and eletricity price: indirect empirical evidence from hydro power. *Energy Economics*, 425-434.

Karakatsani, N., & Bunn, D. (2008). Intra-day and regime-switching dynamics in electricity price formation . *Energy Economics*, 1776-1797.

Kilic, M., & Truijillo-Baute, E. (2015). Flexibility in power generation enough to stabilize intraday power prices? *Working paper*, 1-19.

Longstaff, F., & Wang, A. (2004). Electricity forward prices: A high-frequency empirical analysis . *The Journal of Finance*, 1877-1900.

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

Mount, T. D., Ning, Y., & Cai, X. (2006). Predicting price spikes in electricity markets using a regime-switching model with time-varying parameters. *Energy Economics*, 62-80.

Nord Pool. (2016, 05 11). *The Power Market*. Retrieved from Nord Pool spot: http://www.nordpoolspot.com/How-does-it-work/

Schwartz, E., & Smith, J. (2000). Short-Term Variations and Long-Term Dynamics in Commodity Prices. *Management Science*, 893-911.