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An Empirical Analysis of the Effect of Wind Power on the Level and the Volatility of the Electricity Price in the Nordic-Baltic Market

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The recent rise in wind power in Europe may have important consequences for electricity markets. This study analyses the effect of the combined volume of Danish and Swedish wind power on the level and the volatility of the system price in the Nordic-Baltic day-ahead wholesale electricity market. Hourly data between 2014 and 2016 are employed in an ARX-GARCHX framework. Wind power is found to decrease the price level and increase price volatility. The results are robust to various model specifications. Furthermore, the effect of adding wind power is simulated for various levels of demand and existing wind power supply. The impact of wind power on both the level and the volatility of the price is amplified when either demand is relatively high or existing wind power supply is relatively low. Moreover, other variables are also found to affect the price level and volatility. Demand, market coupling and the oil price increase the price level. Hydro power, on the other hand, has an ambiguous impact. A positive effect on price volatility is shown for market coupling and hydro power whereas the oil price decreases the volatility. The impact of demand on price volatility is less clear cut however, as both a positive and negative relationship are found.

Keywords: Wind power, Electricity price, Merit order effect, Price volatility, Nord Pool Spot

JEL: C32, L94, Q41, Q42

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1 Introduction

Wind is the fastest growing source of power generation in Europe. (Vattenfall, 2016) Between 2000 and 2015, the wind power capacity of the EU increased more than ten-fold (Figure 1) while its share of total power capacity grew from 2.4 percent to 15.6 percent. By the end of 2015, wind power accounted for 11.4 percent of the EU's electricity consumption and had surpassed hydro power as the region's third biggest power source. (EWEA, 2016) Wind generation emits virtually zero CO2 emissions and may have positive economic externalities. (Clò et al., 2015) Many European countries are therefore promoting this technology in order to meet the renewable energy share targets set by the EU[1]. In Sweden and Denmark, wind power is playing a key role in the transition from fossil fuel based to renewable energy sources. (Swedish Wind Energy, 2016) As shown in Figure 1, both countries have expanded their wind power capacity in the past decade and a half. Sweden and Denmark are currently the largest producers in the Nordic-Baltic region, and have some of the highest shares of installed capacity in the world. (GWEC, 2016) Wind power is expected to play an increasingly important role in the two countries, as they aim to further increase the share of renewables in their power portfolios. (State of Green, 2015; Swedish Wind Energy, 2016)

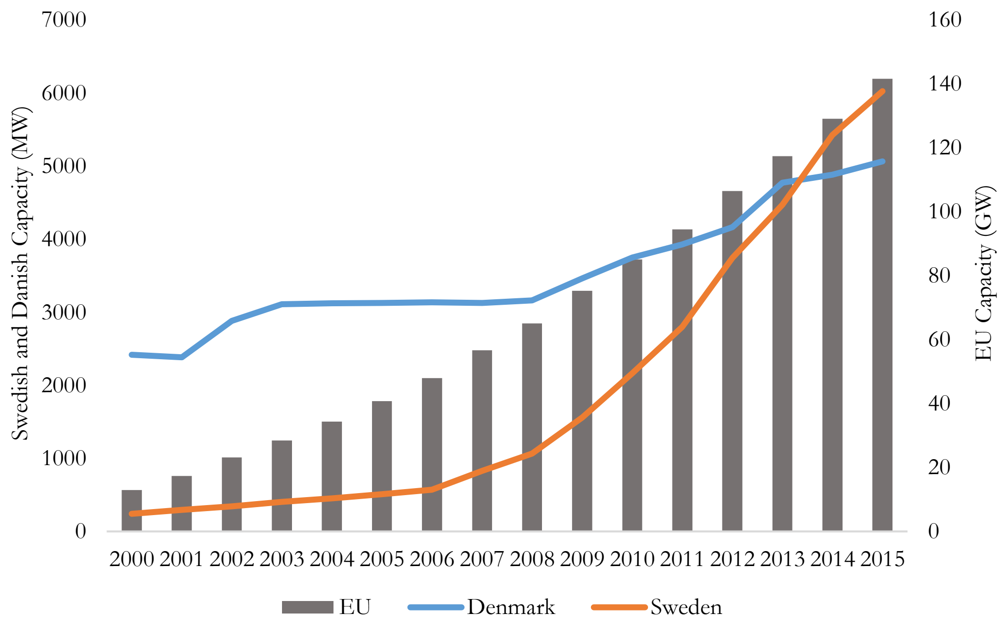

Figure 1. Cumulative Capacity of Wind Power Generation in the EU, Sweden and Denmark
Source: The data were obtained from EWEA (2016) and The Wind Power (2016)

[1] The EU has a target of deriving 20 percent of its energy from renewable sources by 2020. The equivalent targets for Sweden and Denmark are 50 and 35 percent respectively.

Integrating more wind power in electricity systems is not without challenges. (Chang, 2014) Wind power possesses several distinct features that may impact both the level and the volatility of the wholesale electricity price. Firstly, wind power is generated at a very low marginal cost, making it cheaper than traditional sources of power such as oil and coal. (Sáenz de Miera et al., 2008) More wind power in the electricity grid may thus decrease the wholesale electricity price. Though this may translate into a lower retail price for end consumers, some dispatchable sources of power may consequently find production unprofitable due to high marginal costs. These technologies are used to stabilise overall supply and are crucial to the balance of the electricity system. Secondly, wind is an intermittent power source that cannot easily be switched on and off. The volume of generation is exogenous to demand and price, and is instead determined by the level of wind, which is highly volatile. The production of wind power is consequently also erratic (Figure 2). As storing electricity from wind is economically unfeasible, this cheap power source is immediately dispatched into the transmission grid whenever it is produced. The variable in-feed may cause large and unpredictable swings in the electricity price, which may increase the uncertainty of operating power generating technologies. A more volatile price may furthermore accentuate the risk of activating non-dispatchable sources of power, such as wind and solar, that cannot easily be switched off.

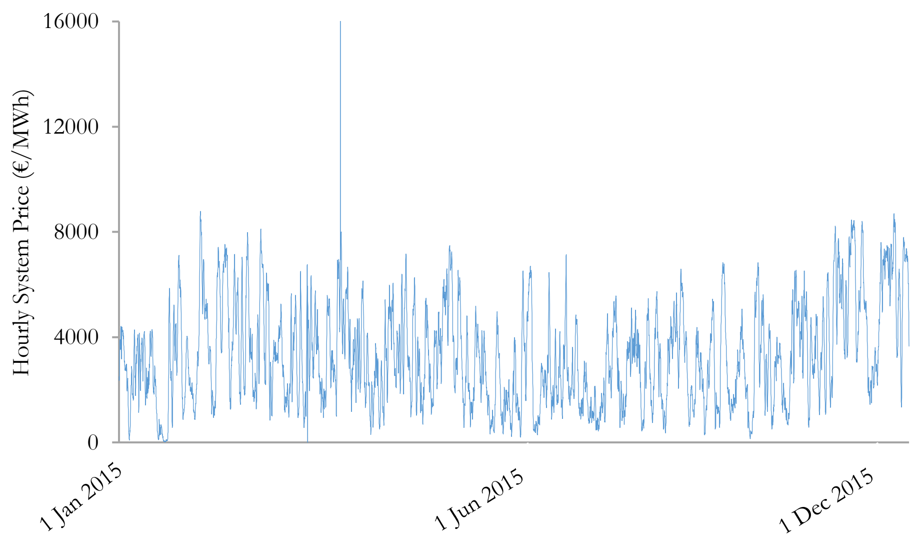

Figure 2. Combined Swedish and Danish Wind Power in 2015
Source: Author's own illustration based on data from Nord Pool Spot (2016a)

An increased risk of operating in the power market, due to a lower and more volatile electricity price, may in turn reduce investment in the long run and destabilise electricity markets. These concerns pertain to the Nordic-Baltic electricity market, in which a large share of wind power is traded. (Mauritzen, 2012) Against the above, this study examines the impact of the wind power of the largest producers in the Nordic-Baltic market – Sweden and Denmark - on both the level and the volatility of the day-ahead wholesale system price. Thus, the main research question is as follows:

To what extent has the combined volume of Swedish and Danish wind power impacted the level and the volatility of the system price in the day-ahead wholesale Nordic-Baltic electricity market?

A number of related topics, which have received scarce attention from the empirical literature, are also investigated. The impact of wind power on both the level and the volatility of the electricity price may vary depending on several factors. Firstly, wind power likely crowds out more expensive technologies during periods of high demand. The impact of wind power on both the level and the volatility of the price may therefore be amplified when demand is relatively high. Secondly, the price effects of adding more wind power may be larger when the existing supply of wind power is relatively low. The differential impact of wind power on the price depending on demand and existing wind power supply are also analysed.

This study makes a number of other contributions. Little research has used historical data to examine the impact of wind power on the level and, in particular, the volatility of the wholesale electricity price. Moreover, few studies employ high frequency data to analyse the short run relationship between wind power and the price. (Li, 2015) This study uses *hourly* data in an ARX-GARCHX framework. The short run impact of wind power on the level and the volatility can thereby be evaluated in an integrated approach. Using hourly data furthermore accounts for large intraday variations in wind power supply, which allows for an analysis of the instantaneous impact of this energy source on the electricity price. Moreover, the analysis is undertaken on the Nordic-Baltic wholesale electricity market, which has so far received limited attention. In fact, to the best of my knowledge, no previous empirical study has used both Swedish and Danish wind power to examine the effects on the wholesale price. Accounting for both countries captures most of the impact of wind power on the Nordic-Baltic electricity market. Finally, this study controls for exogenous factors that may affect the electricity price, including demand, hydro power, the oil price and market coupling.

The results essentially indicate that wind power reduces the price level and increases price volatility in the Nordic-Baltic electricity market. Both effects are significant at a one percent level and robust to various model specifications. Moreover, the magnitude of the impact of wind power on the price level and the volatility is amplified when either demand is relatively high or the existing wind power supply is relatively low. Other variables also have statistically significant effects on the price level and the volatility. Market coupling, demand and the oil price increase the price level. An ambiguous impact is, however, found for hydro power. Moreover, market coupling and hydro power increase price volatility, while the oil price exerts a negative influence. Only partial support is provided for demand increasing price volatility.

The remainder of the paper is structured as follows. Section two presents the theoretical framework and a review of relevant literature. A description of the Nordic-Baltic electricity market, as well as the Swedish and Danish wind power sectors, is provided in section three. The hypotheses are stipulated in the subsequent section, and the data and methodology are outlined in section five. The following two sections present the results and sensitivity analysis, respectively. Section eight discusses the policy implications of the findings and the limitations of the study. Section nine concludes.

2 Theory and Literature Review

2.1 Theory

Electricity is a homogeneous good for which differentiation is difficult. (Thoenes, 2014) Producers face capacity constraints as they cannot supply more electricity than they generate. A Cournot oligopoly model is therefore suitable to evaluate the theoretical impact of increased wind power generation on the electricity price level. (O'Mahoney & Denny, 2011) In this model, firms compete by simultaneously choosing the quantity supplied, while taking the market price P as given. Following Ledvina and Sircar (2011), the inverse demand curve is assumed a linear function of industry supply Q:

$$P = P(Q) = a - bQ$$

where the industry supply is split equally between n firms:

$$Q = q_1 + q_2 + q_3 + \cdots + q_n = \sum_{i=1}^{n} q_i$$

If firm i produces q_i units, the output of the remaining firms is $q_{-i} = Q - q_i$. Firm i takes its competitors' behaviour into account and thereby chooses the profit maximising level of output q_i^* given the quantity supplied by its rivals. As all firms are rational, they maximise profit by equating marginal revenue MR to marginal cost MC. I assume for simplicity that the marginal cost is constant, implying $MC_i = c_i$. Solving for the marginal revenue of firm i yields:

$$TR_i = P(Q)q_i$$

$$MR_i = \frac{\partial TR_i}{\partial q_i} = \frac{\partial P}{\partial q_i}q_i + P$$

Letting MR_i=$MC_i = c_i$ gives:

$$\frac{\partial P}{\partial q_i}q_i + P = c_i$$

Recalling that $P = a - bQ = a - b(q_i + q_{-i})$ yields the profit maximising condition:

$$\frac{\partial P}{\partial q_i}q_i + P = -bq_i + a - b(q_i + q_{-i}) = c_i$$

$$-b(2q_i + q_{-i}) + a = c_i$$

Solving for the optimal level of output for firm i q_i^* gives firm i's reaction function $f(q_{-i})$:

$$q_i^* = f(q_{-i}) = \frac{a - c_i}{2b} - \frac{q_{-i}}{2} \tag{1}$$

The reaction function shows the optimal output of firm i, given the output of its competitors. As all firms are rational and maximise profit given their expectations of q_{-i}, the reaction function in (1) holds for all $i \in [1, n]$. Thus:

$$q_1^* = f(q_{-1}) = \frac{a - c_1}{2b} - \frac{q_{-1}}{2}$$

$$q_2^* = f(q_{-2}) = \frac{a - c_2}{2b} - \frac{q_{-2}}{2}$$

$$\vdots$$

$$q_n^* = f(q_{-n}) = \frac{a - c_n}{2b} - \frac{q_{-n}}{2}$$

The sum of the individual outputs equals industry output. Adding the reaction functions together and recalling $q_{-i} = Q - q_i$ gives the optimal industry output Q^*:

$$Q^* = n\frac{a}{2b} - n\frac{\bar{c}}{2b} - n\frac{(Q^* - q_i^*)}{2}$$

$$2Q^* + nQ^* - Q^* = n\frac{a}{b} - n\frac{\bar{c}}{b}$$

$$Q^*(1 + n) = n\frac{a}{b} - n\frac{\bar{c}}{b}$$

where:

$$\bar{c} \equiv \frac{\sum_{i=1}^{n} c_i}{n}$$

Simplifying and solving for Q^* yields:

$$Q^* = \frac{n}{(1+n)} \frac{(a-\bar{c})}{b} \tag{2}$$

Substituting Q^* into (1) gives:

$$P^* = a - bQ = a - b\frac{n}{(1+n)}\frac{(a-\bar{c})}{b}$$

Simplifying yields the industry price P^*, assuming optimal behaviour by firms:

$$P^* = \frac{a}{(1+n)} + \frac{n\bar{c}}{(1+n)} \tag{3}$$

As (3) shows, the price is determined by the number of firms and the average marginal cost of the industry. Electricity is typically produced from a broad range of energy sources, including wind power, nuclear, condensing plants and hydro power. Each power source differs with respect to its marginal cost of production. Wind power has virtually zero marginal cost whereas condensing plants, that use inputs such as oil and natural gas, have high marginal costs. (Forrest & MacGill, 2013) Suppose, therefore, that all firms initially use the same non-wind power source to produce electricity, and thereby that $c_i = c_{-i} \neq 0$. If firm 1 begins generating its electricity from wind, its marginal cost would decrease.[2] This would reduce the average marginal cost in the industry and thereby the market price as $\frac{\partial P^*}{\partial \bar{c}} > 0$. The total amount of electricity produced would remain unchanged, assuming demand remains constant. Thus, the model predicts that more wind power decreases the price of electricity.

Similar results are obtained in a supply and demand framework. Figure 3 represents the Nordic-Baltic market for electricity, in which the price, known as the system price, is determined by the intersection of the merit order (supply) and demand curves. The system price equals the cost of supplying the last unit of electricity to meet demand in the Nordic-Baltic market. (Ei, 2014) Only units produced at a cost below or equal to the system price are sold. Wind power enters the merit

[2] For simplicity, I assume that the marginal cost of all firms remains below the market price such that there is no market exit when one firm switches production technology. This assumption is reasonable for the power market in the short term, since it takes time for cheap intermittent technology to completely displace alternative technologies.

order from the bottom as it is generated at nearly zero marginal cost. This implies that wind power is always dispatched when available, leaving the other power sources to compete for the residual demand. (Munksgaard & Morthorst, 2008; Steggals et al., 2011) As illustrated in Figure 4, greater wind generation increases the supply of electricity, thus shifting the merit order curve to the right. The additional wind power crowds out the most expensive marginal plants, thereby dampening the market price. (Clò et al., 2015) This is known as the merit order effect.

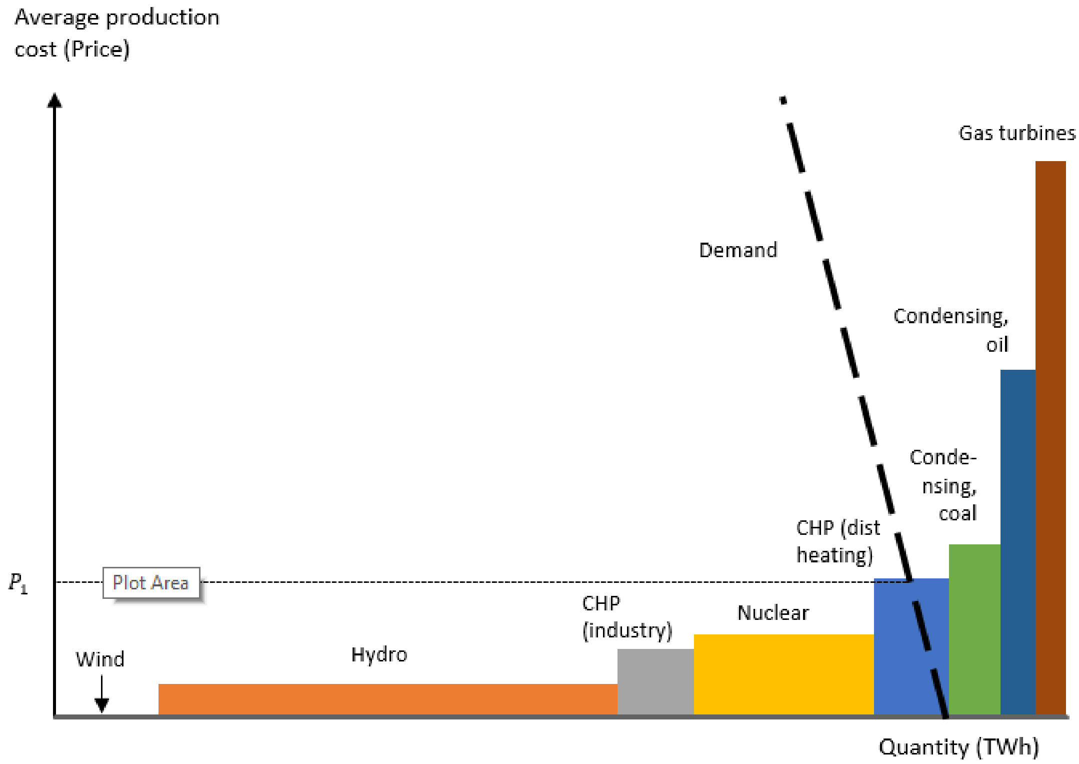

Figure 3. A Simplistic Hypothetical Illustration of the Nordic-Baltic Electricity Market
Source: Author's own illustration
Note: The width of the bars approximately corresponds to the share of each power source in the total supply in the Nordic-Baltic market. The bars are not completely flat in practice since the production cost varies within each power source. (Söder, 2014) Moreover, as demand is volatile, the market equilibrium may frequently move along the entire supply curve. (Söder, 2014)

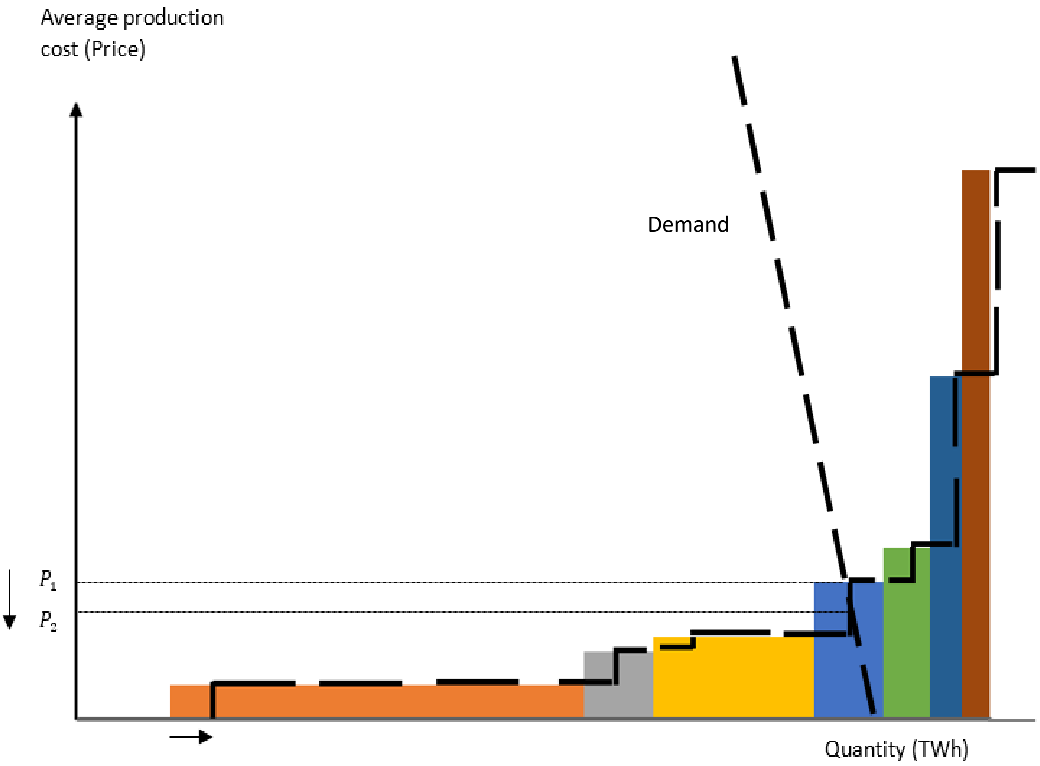

Figure 4. A Hypothetical Illustration of the Merit Order Effect
Source: Author's own illustration
Note: Since the bars are not completely flat in practice, even a movement along a given technology may change the price level.

As electricity has few substitutes and is increasingly vital to modern, digitally enabled societies, the demand for electricity is highly inelastic in the short run. (Steggals et al., 2011; EWEA, 2009) Even small changes in supply can significantly alter the price. The magnitude of the merit order effect may depend on two key factors in particular: the existing demand for power and the amount of wind power already in the transmission system. (EWEA, 2009) The hypothetical impact of wind power in different demand scenarios is illustrated in Figure 5. During times of peak power demand, most of the available supply is consumed, meaning that demand intersects at the steep end of the merit order curve. An increase in wind power in this case is expected to cause a large price decrease (from P_1^{High} to P_2^{High}), since the wind power displaces more expensive electricity sources. On the other hand, if the demand for electricity is low in a given hour, additional wind power may crowd out relatively inexpensive technologies, resulting in a smaller price reduction (from P_1^{Low} to P_2^{Low}). Similarly, the magnitude of the impact of wind power depends on the degree of wind power in the generation mix. If the latter is high, adding wind power may lead to a smaller reduction in the price compared to when existing wind volumes are low, since the expensive technologies have more likely already been crowded out when a lot of wind power is already produced.

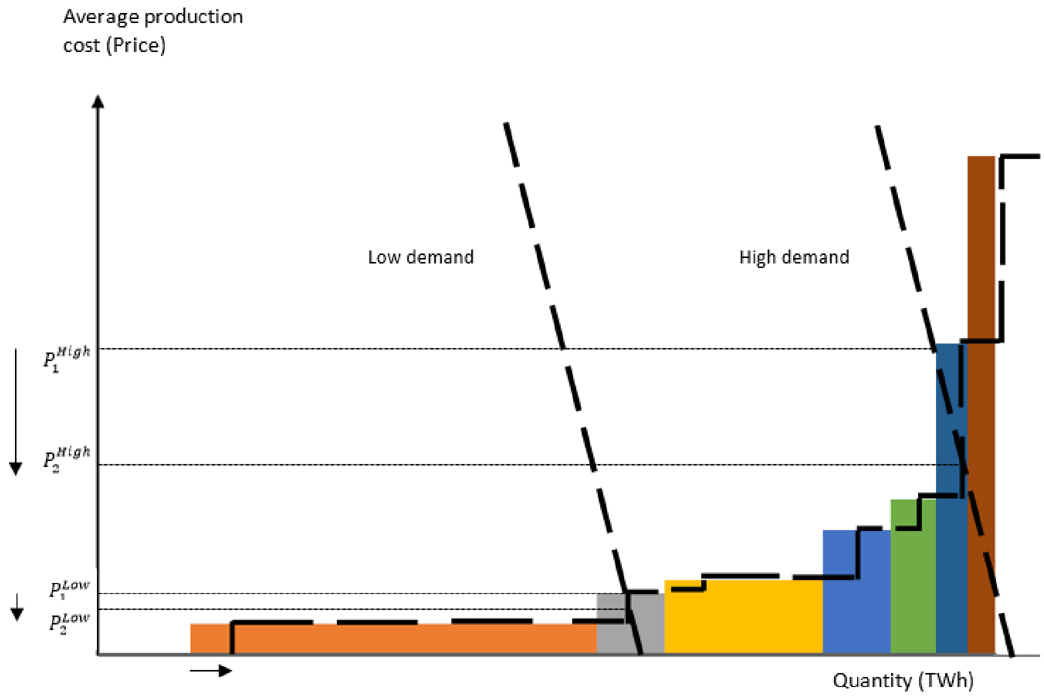

Figure 5. A Hypothetical Illustration of the Merit Order Effect of Wind Power in Low and High Demand Scenarios
Source: Author's own illustration

Wind power may also impact the *volatility* of the electricity price. (Jónsson et al., 2010; Woo et al., 2011) Wind is an intermittent power source which cannot be switched on and off in response to demand movements. Instead, the volume of electricity generated is determined by volatile wind conditions. (Ketterer, 2014; Li, 2015) As storage is economically unfeasible, electricity generated from wind is immediately dispatched into the transmission system. (Mauritzen, 2012) The variable nature of wind therefore translates into frequent fluctuations in the supply of electricity. As demand is highly inelastic, the volatile in-feed may create large swings in the price. The increased price volatility is likely larger when either demand is high or the existing volume of wind power in the market is low. (Forrest & MacGill, 2013) In these situations, more expensive technologies operate in the market, resulting in larger price movements when wind power is added to the transmission system and displaces other technologies.

2.2 Literature Review

A growing body of research is examining the impact of wind power on electricity prices, as a result of the expansion of this renewable technology and the potential difficulty of incorporating it in the power generation mix. (Ketterer, 2014) In particular, the merit order effect of wind power has gathered attention. (Azofra et al., 2014) The majority of studies employ theoretical models that simulate market interactions under various scenarios. (Mauritzen, 2012) Sáenz de Miera et al. (2008) estimate the merit order effect in Spain by simulating the wholesale electricity price with and without wind power. They find that wind generation reduced the wholesale price by between 8.6 and 25.1 percent from 2005 to 2007, and led to net energy savings in all three years. A negative relationship between the level of the wholesale price and volume of wind power is also shown for Germany (Sensfuss, 2011). Further, Ray et al. (2010) conduct a literature review of the merit order effect in European electricity markets and conclude that most studies find that, *ceteris paribus*, increased use of wind power lowers the wholesale price. Figure 6 is replicated from Ray et al. (2010) and summarises the results of four of these studies.

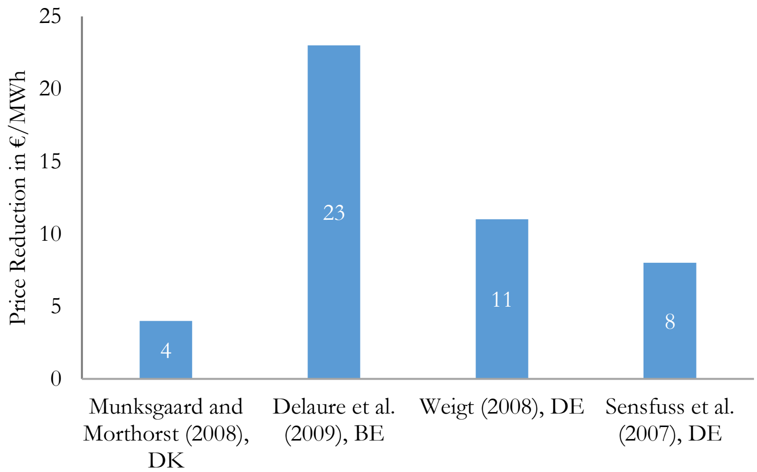

Figure 6. Empirical Findings on the Reduction in the Electricity Wholesale Price from an Increased Supply of Wind Power in Belgium, Denmark and Germany
Source: Figure is replicated from Ray et al. (2010)

A key drawback of the abovementioned studies is that their results are highly sensitive to a set of simplistic assumptions regarding certain economic and physical relationships in the market. (Forrest & MacGill, 2013; Weron, 2014) One empirical strand of the literature has sought to overcome this issue by instead using historical market data instead of theoretical simulations. (Azofra et al., 2014) Though the econometric literature on electricity price forecasting is rich, few empirical studies examine the impact of intermittent technologies, such as wind power, on either the level or variability of electricity prices. (Forrest & MacGill, 2013; Woo et al., 2011) Using an ARMAX-GARCHX model and daily data to study the effect of wind power on wholesale prices, Ketterer (2014) shows that wind power decreased electricity prices and increased price uncertainty in Germany. Clò et al. (2015) employ daily averages of hourly prices to analyse the impact of renewable technology on the Italian wholesale electricity market between 2005 and 2013. They conclude that a greater volume of wind and solar power decreased the price level and amplified the volatility. Interestingly, the effect on the price level was lower over time due to greater penetration of the two technologies. Using a non-parametric model, Jónsson et al. (2010) similarly establish that the short run impact of wind power on the price level in the Western Danish bidding area lessened as the share of wind in the power supply mix increased. The authors furthermore conclude that price variability was lower at higher wind power proportions. Forrest and MacGill (2013) illustrate that the strength of the merit order effect may depend on the existing demand for electricity. The authors find that the short run negative impact of wind power on the Australian wholesale price level is stronger when demand is high. A similar result is shown for Denmark by Enevoldsen et al. (2006) who use a non-parametric model. The latter study does not adequately account for other variables potentially affecting the price, however, which may bias the results. (Mauritzen, 2012)

Several studies argue in favour of employing *hourly*, as opposed to *daily*, data in order to reflect wind's erratic nature (Figure 2). (See for instance Li, 2015; Huisman et al., 2007) Indeed, using averages of daily wholesale prices hides the intraday variability of wind power, which may be significant. (Jónsson et al., 2010) The few studies that use high frequency data generally observe a negative effect of wind power on the level of electricity prices (see for instance O'Mahoney & Denny, 2011 for Ireland and Woo et al., 2011 for Texas). Little research has explored this relationship in the Nordic-Baltic electricity market. Using a GARCH-type model, Li (2015) finds a negative effect of Danish wind power on both the level and volatility of the day-ahead wholesale system price, after controlling for market coupling and the exchange of hydro and wind power between the Nordic countries. The model in the analysis is non-stationary, however, which undermines the validity of the results. Moreover, the study only takes into account Danish wind power, which constitutes a small fraction of the electricity traded in the Nordic-Baltic market. The additional influence of Swedish wind power has to the best of my knowledge never been investigated before.

3 Background on the Electricity Market and Wind Power Sectors

3.1 The Nordic-Baltic Electricity Market

The Nordic countries (Denmark, Finland, Norway and Sweden) deregulated their electricity markets in the 1990s and formed a common market, known as Nord Pool. Estonia, Latvia and Lithuania subsequently joined in the 2000s, thus creating a joint Nordic-Baltic market for electricity. (Nord Pool Spot, 2016b) In Nord Pool, producers sell electricity to traders in the wholesale market. The electricity is thereafter resold to end consumers in the retail market. (Svenska Kraftnät, 2011) Figure 7 provides an overview of the Nordic-Baltic electricity market.

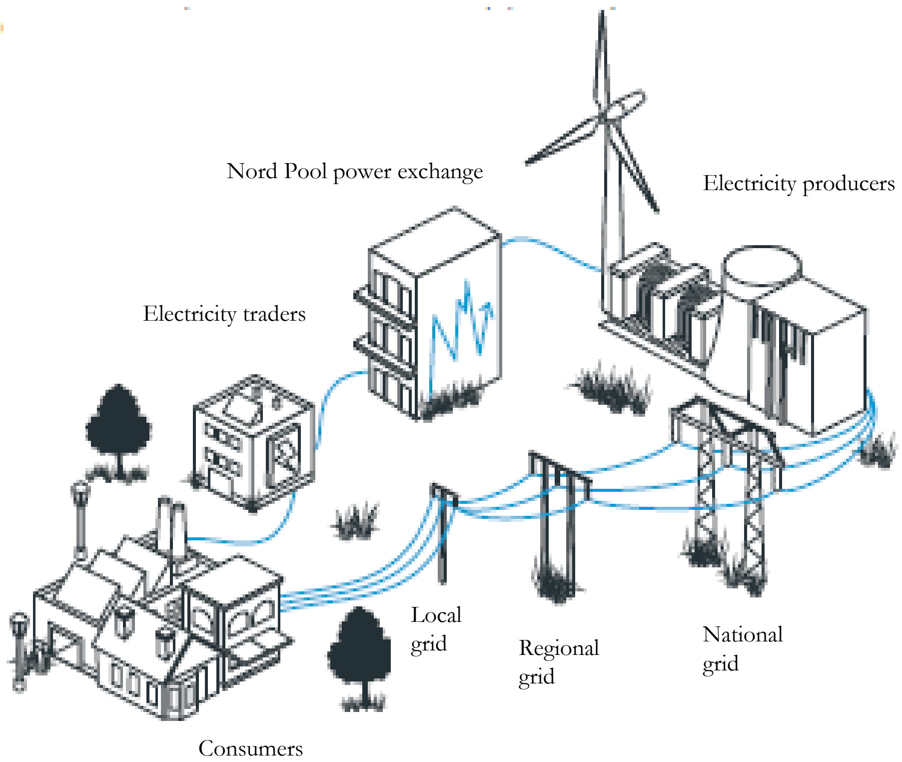

Figure 7. A Simple Representation of the Nordic-Baltic Electricity Market
Source: Figure is obtained from Svenska Kraftnät (2011)

The physical market of Nord Pool is known as Nord Pool Spot, in which 379 TWh of Nordic-Baltic electricity (equivalent to 95 percent of total production) was traded in 2015.[3] (Ei, 2016) Nord

[3] Nord Pool also has a financial market, NASDAQ OMX Commodities, where financial instruments are traded and actors can hedge against price risk.

Pool Spot consists of the Elspot market for day-ahead trading and the Elbas intraday market.[4] Elspot is by far the biggest platform, accounting for 98.7 percent of the Nordic-Baltic power exchanged on Nord Pool Spot in 2015. (Ei, 2016) This makes it the world's largest power market for day-ahead trading. (Empower, 2016)

In Elspot, producers and buyers submit their bids and offers for each hour of the following day before gate closure at noon. The bids and offers for the entire trading region are thereafter aggregated into a supply and demand curve for each hour. The hourly system price is determined by the intersections of these curves, as shown in Figure 3. Once prices have been set, trades are carried out. Bids and orders below or equal to the system price are settled at the given price. (Swedish Energy Agency, 2006) The power is physically delivered hour by hour the next day, from midnight to midnight, in line with the agreed contracts. (Nord Pool Spot, 2016d)

Nord Pool Spot is divided into bidding areas (see Figure A in the appendix) in order to prevent congestion due to transmission constraints. In particular, bottlenecks may arise if large volumes of power flow to bidding areas of high demand. Prices for each bidding area are established alongside the hourly system price. When transmission capacity between two areas is limited, the area price increases in the high demand area to eliminate any power shortage. In contrast to area prices, the system price represents an unconstrained market clearing price which disregards the transmission capacities between bidding areas. (Nord Pool Spot, 2016e) The system price therefore equals the area price in the absence of grid congestions. The former is furthermore the reference price for most financial contracts exchanged in the Nordic-Baltic region. (Nord Pool Spot, 2016e)

As illustrated in Figure 8, more than half of the total electricity produced by the members of Nord Pool Spot stems from hydro power. Around nine percent of total electricity is produced from wind power. Sweden and Denmark are by far the largest producers of wind power, as they accounted for 45 and 39 percent respectively of total production in 2015.[5] Both countries are comprised into bidding areas. Denmark is divided into Denmark West (DK1) and Denmark East (DK2), while Sweden is split into SE1, SE2, SE3 and SE4. (Nord Pool Spot, 2016f) The regions are well connected with the other bidding areas of Nord Pool Spot as well as neighbouring countries. (Söder, 2014) Figure B in the appendix depicts the large transmission capacities of the Nord Pool Spot members. The interconnectivity enables trade between countries, whereby power flows from low to high price areas. As elaborated on in the following sections, the trade of power is a key

[4] Technically, Nord Pool Spot also runs N2EX, which is Nord Pool's UK power market. 110 TWh of power was traded there in 2015. (Nord Pool Spot, 2016c)

[5] The shares were calculated by hand using data from ENTSO-E (2016).

component of the energy strategy of Sweden and Denmark to maintain balance between supply and demand.

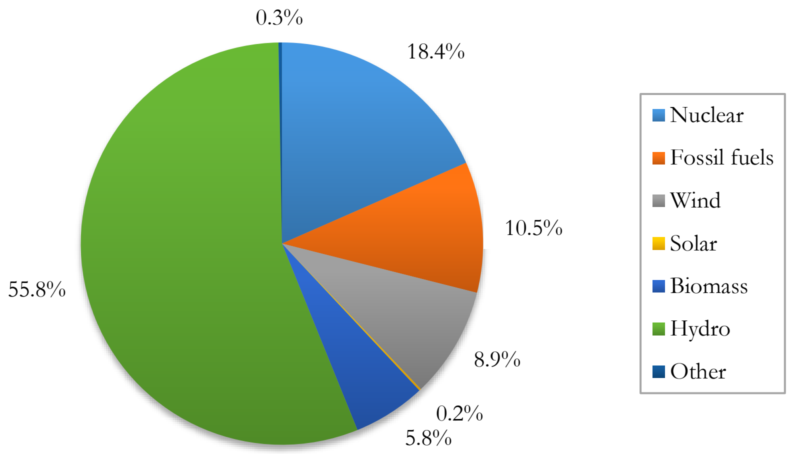

Figure 8. Combined Power Production of the Nord Pool Spot Members in 2015
Source: Author's own illustration using data obtained from ENTSO-E (2016)
Note: As 95 percent of the power produced by the Nord Pool Spot member countries is traded on the power exchange, the power decomposition of Nord Pool Spot is assumed the same as in the figure.

In the analysis, the impact of both Swedish and Danish wind power on the Elspot system price is investigated. These countries produce the vast majority of the wind power in Elspot, and are therefore pertinent for studying the overall effect of wind power on that market. An overview of the wind power sectors in both countries is provided in the following two sections.

3.2 Wind Power in Sweden

Sweden has witnessed considerable growth in wind power in the past decade. The share of wind source in total power production increased from 0.5 percent (less than 1 TWh) in 2005 to 10 percent (16 TWh) in 2015. (Swedish Energy Agency, 2016a) Some 354 new wind power plants were constructed in 2011, followed by another 366 plants in 2012. (Swedish Wind Energy, 2013) By the end of 2015, 3,233 wind power plants, capable of producing 6,029 MW of power, had been installed. (Swedish Wind Energy, 2016) Sweden is the biggest producer of wind power in absolute terms on Nord Pool Spot. (EWEA, 2016) The main policy tool to support wind power deployment is the market-based electricity certificate system. It entitles owners of approved renewable energy plants a certificate for every MWh of electricity produced. Electricity suppliers and some consumers are obliged to purchase a specific proportion of certificates relative to their electricity sales or consumption. (Swedish Energy Agency, 2015) The proportion is specified annually through a quota mechanism.[6] (Swedish Wind Energy, 2013)

As Figure C in the appendix illustrates, the majority of Swedish wind power is produced in SE2 and SE3. SE1 and SE2 are typically net exporters of electricity whereas consumption usually exceeds production in the other two bidding areas. According to the Swedish Energy Agency (2016), a bidding area is more likely a net exporter if its population is low and if it has access to hydro power. Indeed, as shown in Figure D in the appendix, Sweden derives most of its electricity from the latter energy source. In contrast to wind power, hydro power is a dispatchable energy source, which can be turned on and off fairly quickly. Hydro power is therefore used to counterbalance the fluctuating supply of wind power in Sweden and Denmark. (Svenska Kraftnät, 2015) Indeed, the latter country imports Swedish and Norwegian hydro power when domestic wind power production is insufficiently high to meet demand. This topic is elaborated on in the following section.

3.3 Wind Power in Denmark

Denmark has the highest proportion of wind generation in the world, and attained a wind power capacity of 5,070 MW by the end of 2015. (Danish Wind Industry Association, 2016) Wind power contributed to 42 percent of Danish electricity consumption in 2015, breaking the country's previous world record in 2014 by three percentage points. (Energinet.dk, 2016) Most of the remaining production stems from combined heat and power (CHP) plants. (Li, 2015) The development of Danish wind power dates back to the late 1970s and early 1980s when the country began diversifying away from imported oil. As a result of public support for the development of wind power, through most notably a fixed feed-in tariff mechanism and tax refunds for wind projects, wind power production proliferated between the mid 1990s and early 2000s. (IRENA, 2012) Capacity expanded from 500 MW to 3,000 MW between 1993 and 2004. (IRENA, 2012) Growth subsequently slowed down, however, following the abolishment of the feed-in tariff in 2004. (Li, 2015) In 2009, support for new installations of wind power plants was rejuvenated, as the government launched a scheme guaranteeing producers a premium above the market price.

[6] The certificate system was expanded in January 2012 to Norway, which created a joint market for the certificates between the two countries. (Swedish Wind Energy, 2013)

(IRENA, 2012) A broad energy agreement was reached in 2012, which outlined Denmark's goal of sourcing 50 percent of its electricity consumption from wind by 2020. (IRENA, 2012)

Denmark is highly integrated with the electricity markets of Germany, Norway and Sweden, which enables trade and balancing of electrical power. Norway and Sweden have abundant hydro power,[7] which varies in a predictable pattern according to the rainy and dry seasons of the year. This lends Denmark an important shield against the uncontrollable nature of wind power. According to Green (2012), Denmark's strategy to ensure a secure supply of electricity is to balance domestic wind power generation with Norwegian and Swedish hydro power. When Danish wind generation cannot meet domestic consumption, Denmark either imports hydro power from its Scandinavian neighbours or increases thermal generation at home. (Li, 2015) Importing is particularly advantageous when water levels in hydro reservoirs in Norway and Sweden are high, since imports thereby becomes cheaper relative to domestic generation. Conversely, when Denmark produces an excess of wind power, the surplus can be exported to its neighbours at a premium. (Green & Vasilaskos, 2012) The link between Danish wind power and Scandinavian hydro power is exploited in this study to proxy Swedish hydro power production. This is further discussed in section 5.1.

[7] 99 percent of power in Norway is produced from hydro power. (Statkraft, 2016) The corresponding figure in Sweden was 47 percent in 2015. (Swedish Energy Agency, 2016a)

4 Hypotheses

Against the above theoretical discussion and literature review, a set of hypotheses regarding the relationship between the supply of wind power and the electricity price in the Nordic-Baltic market can be formulated. Both theory and previous empirical research suggest that wind power replaces more costly technologies, leading to a lower electricity price. Predicting the effect of wind power on price volatility is less clear-cut. The empirical evidence is ambivalent, as both a negative and positive relationship have been found. More wind power can be expected to increase volatility, however, due to its intermittent nature and relatively low marginal cost. The first and second hypotheses are therefore as follows:

Hypothesis 1: An increase in the combined supply of wind power of Sweden and Denmark decreases the level of the Elspot system price.[8]

Hypothesis 2: An increase in the combined supply of wind power of Sweden and Denmark increases the volatility of the Elspot system price.

As discussed, the relationship between wind power and the electricity price may vary depending on demand and the volume of existing wind power. Theory suggests that wind power exerts a larger influence on both the level and volatility of the price when demand is high or existing wind power supply is low. The literature provides empirical support for these differential impacts, even though little research has evaluated the varying strength of the relationship between the volume of wind power and price volatility caused by demand. Thus, against the above, four hypotheses are formulated:

Hypothesis 3: An increase in the supply of wind power decreases the level of the Elspot system price by a larger extent when the demand for electricity is relatively high.[9]

Hypothesis 4: An increase in the supply of wind power increases the volatility of the Elspot system price by a larger extent when the demand for electricity is relatively high.

Hypothesis 5: An increase in the supply of wind power decreases the level of the Elspot system price by a larger extent when the volume of wind power already in the transmission system is relatively low.

Hypothesis 6: An increase in the supply of wind power increases the volatility of the Elspot system price by a larger extent when the volume of wind power already in the transmission system is relatively low.

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[8] It should be noted that an increase in the wind power supply is expected to alter the price level even if the marginal technology-type does not change. (Söder, 2014) Indeed, as noted in Figure 3, the production cost may vary within each power source. Hydro power plants, for instance, have different marginal costs. (Söder, 2014) If demand is initially low and hydro power is the marginal technology, a small shift in the merit order curve (due to more wind power) that does not change the marginal technology, may therefore still change the price level (and volatility).

[9] In line with the previous footnote, adding wind power is expected to change the price level and volatility even if the marginal technology-type remains the same. Thus, though hypotheses 3 and 4 state that the change in the price level and volatility is larger when demand is *relatively* high, adding wind power is nonetheless expected to decrease the price level and volatility in *absolute* terms for all volumes of demand. A similar reasoning applies to hypotheses 5 and 6.

5 Data and Methodology

5.1 Data

This section presents the variables and data used in this study. Table A in the appendix presents descriptive statistics. The aim of this study is to investigate the impact of the volume of Danish and Swedish wind power on the level and the volatility of the electricity system price of Elspot. Hourly data between 12 May 2014 and 19 September 2016 are used in order to capture the intraday variability of the electricity price. Each day consists of 24 hours, implying that a total of 20,688 observations are available per variable.[10]

The Dependent Variable

The data on the hourly system price in the Nordic-Baltic day-ahead wholesale electricity market, measured in Euro per megawatt hour (€/MWh), are sourced from Nord Pool Spot (2016a). The system price is calculated based on the day-ahead supply bids and demand offers for the entire Nord Pool Spot area as well as the imports and exports with the Netherlands and Germany. (Nord Pool Spot, 2016e) As this study considers the impact of wind power on the entire Nordic-Baltic market, the system price is more relevant to use than local area prices. The system price is furthermore the main reference for the financial contracts at Nord Pool Spot and for bilateral agreements. (Svenska Kraftnät, 2011) It has been used by other studies that have analysed the effects of wind power in the Nordic wholesale electricity market (e.g. Jónsson et al., 2010; Li, 2015).

Several diagnostic tests were carried out to explore the properties of the system price data. Table A in the appendix shows that the variable exhibits both extreme kurtosis and skewness, which may arise from autocorrelation or outliers. (Ketterer, 2014) A visual inspection of the Elspot system price reveals several spikes, particularly in January 2016 (Figure 9). As highlighted by Li (2015), unusually high or low prices do not reflect the general behaviour of the price level and volatility caused by wind generation. This point is corroborated by Contreras et al. (2003) who recommend filtering outliers before running AR-type models. An outlier filter is therefore applied to eliminate the influence of extreme values. I follow the methodology of Li (2015) and define an outlier as a

[10] Data are missing for all variables sourced from Nord Pool Spot (2016a) for 29-03-2015 (hour: 02-03) and 27-03-2016 (hour: 02-03). The missing values are replaced with the average of the previous and following value, in order to eliminate gaps from the sample when running the ARX-GARCHX models. This should not impact the results, since the previous observations in the previous and following hour are very similar.

value that exceeds six times the standard deviation or is lower than 3.7 times the standard deviation of the mean.[11] A total of 31 outliers are detected in the price series, which is a very small number relative to the sample size of 20,688 observations. The outliers are replaced with the mean price averaged over 24 and 48 hours prior to and 24 and 48 hours after the given outlier.

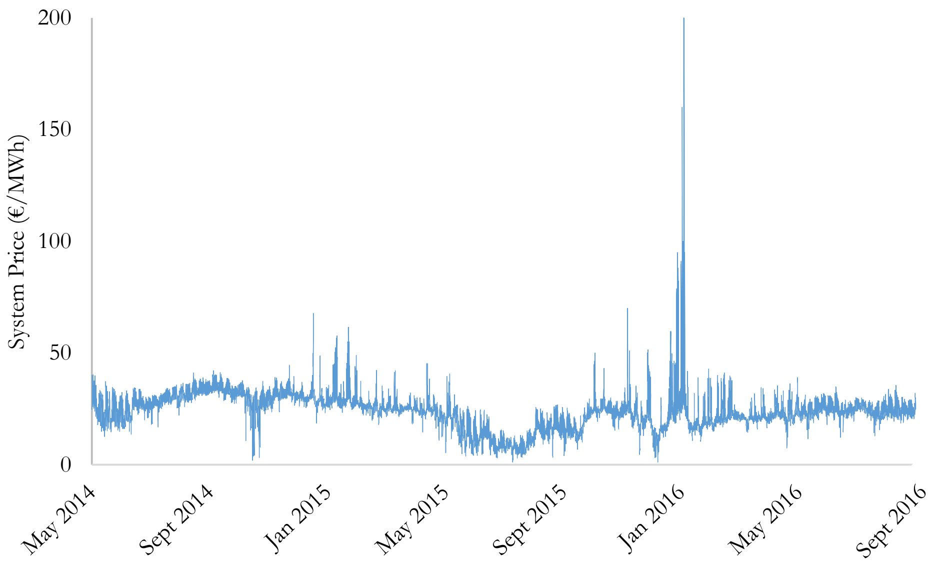

Figure 9. The Hourly Elspot System Price
Source: Author's own illustration based on data from Nord Pool Spot (2016a)

A common feature of wholesale electricity prices is seasonality, whereby the price varies based on the time of the year, month, day or hour. (Li, 2015) The electricity price may be highest in winter, for instance, due to high demand arising from cold temperatures. Similarly, the price may be greater during daytime than at night. The variation in the price caused by seasonality does not arise from market conditions or generation intermittency. (Li, 2015) Seasonality should therefore be removed from the price data. Following the procedure of Ketterer (2014), the electricity price pr_t at time t is decomposed into a seasonal component s_t and a stochastic component u_t as follows:

$$pr_t = s_t + u_t$$

The deseasonalised price is obtained by subtracting the seasonal component from the original series to obtain u_t. As shown below, the seasonal component s_t is derived using a constant step function, composed of a constant c and dummies for each year y_i, month m_i, day of the week d_i hour of the day h_i, and for all week-day holidays in Sweden and Denmark: [12]

[11] Other studies use an outlier threshold of three times the standard deviation of the mean (e.g. Ketterer, 2014). However, as noted by Li (2015), it is preferable to allow for more variation in the electricity price due to its highly volatile nature and the frequent occurrence of spikes.
[12] The reference dummies are excluded from the model equation.

$$s_t = c + \sum_{i=1}^{2} \beta_{1i} y_i + \sum_{i=1}^{11} \beta_{2i} m_i + \sum_{i=1}^{6} \beta_{3i} d_i + \sum_{i=1}^{23} \beta_{4i} h_i + \beta_5 Holiday \tag{4}$$

Table B in the appendix presents the coefficients from the regression in (4). On average, the price tends to peak in the mornings between 8:00 and 11:00 while it is low during the night. Colder months are associated with more expensive electricity while the price peaks in January. Wholesale electricity is furthermore cheaper on weekends.

The seasonal component is deducted from the original price series and the means of the two series are aligned to obtain the fitted deseasonalised prices. A similar outlier treatment is applied as on the original series to remove any extreme observations. A total of 42 outliers are detected and replaced. Taking logarithms to further smoothen the data yields a fitted logarithmic deseasonalised price series. This series is smoother than the original price data (see Figures 10 and 11), and is used as the dependent variable in the analysis.

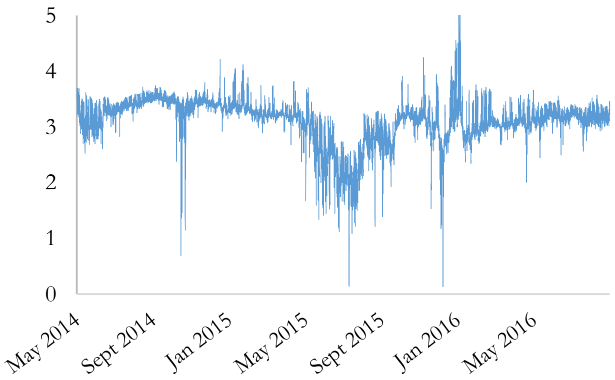

Figure 10. Logarithm of Original Hourly Price Series
Source: Author's own illustration based on data from Nord Pool Spot (2016a)

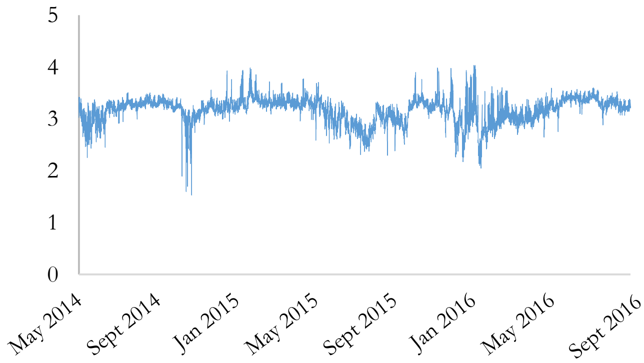

Figure 11. Logarithm of Deseasonalised Hourly Price Series
Source: Author's own illustration based on data from Nord Pool Spot (2016a)

The Independent Variable of Interest

In order to test the hypotheses, forecasts of the combined hourly wind power generation in Sweden and Denmark are used as the main independent variable. The generation is measured in megawatt hours (MWh) and data are acquired from Nord Pool Spot (2016a). Both Sweden and Denmark are considered in order to account for most of the wind generation in Elspot. Further, the combined wind power of the two countries is preferred to the individual volumes, given the strong correlation between Swedish and Danish wind power.[13] The forecasts are published for the following day by the Swedish and Danish transmission system operators (TSOs), and therefore match the day-ahead nature of the price. They are reliable and mirror the information in the day-ahead market on the basis of which bids and offers are formulated. (Ketterer, 2014) The forecasted volumes depend on the amount of wind and installed capacity, and do not respond to price movements. This variable is hence exogenous to the system price.[14]

In contrast to electricity prices, the combined wind power forecasts of Sweden and Denmark do not follow an hourly pattern. As shown in Figure E in the appendix, the average forecasted wind power remains fairly constant during the day in winter and summer, and peaks slightly in the afternoon in spring and fall. Overall, the variable appears independent from the time of day. There is, however, some variation across the year. Though the average hourly forecasted wind power hovers around 3,000 MWh between March and November, it increases to around 4,300 MWh in winter. Volumes range from 2,100 MWh to 4,390 MWh across the year. In contrast to the mean, the variance remains steady for both hours and seasons. It is furthermore as large as 2,000 MWh, which reflects the intermittent nature of wind. As noted by Li (2015), the sizable and continuous volatility of wind power, resulting from intermittency, reduces the need to adjust for the disproportionally higher mean in winter, since there is sizable deviation from the mean of the respective season. In addition, the magnitude of the forecasts does not vary according to an hourly pattern. I therefore follow the standard procedure in the literature (see for instance Ketterer, 2014; Clò et al., 2015; Li, 2015) and refrain from deseasonalising the wind power forecast data.

The Control Variables

As the system price is determined by the demand for and supply of electricity in the day-ahead wholesale market, there is a need to control for variables affecting the demand and supply. These are outlined below.

Net market coupling. As discussed in section three, the Nordic countries trade a significant amount of electricity with Germany and the Netherlands. The cross-border exchange, known as

[13] The correlation between Swedish and Danish wind power is 0.63, which is very high. A strong correlation increases the risk of collinearity which makes it difficult to disentangle the individual effects. This may, in turn, reduce the predictive power of the model.

[14] In contrast, the actual wind power generation is an outcome variable of the price, as it is determined after the price has been set. Even though wind power is almost always dispatched when produced due to its low marginal cost, the volume of wind power may be affected by the price during times of (very) low demand. In order to sidestep this concern, the exogenous forecasts are used instead.

market coupling, is included in the bids and offers that determine equilibrium between demand and supply on Elspot. (Nord Pool Spot, 2016g) Market coupling therefore directly impacts the system price. The data used to calculate hourly net market coupling between Elspot and the Netherlands and Germany are acquired from Nord Pool Spot (2016a). This study defines net market coupling as the difference between the sum of all exports to and the sum of all imports from the Netherlands and Germany. These data are submitted to Nord Pool Spot prior to the price setting and are taken into account when calculating the price. They are therefore exogenous to the dependent variable. The data are not deseasonalised in line with previous studies (e.g. Ketterer, 2014; Li, 2015), and due to the lack of seasonal variation in the variable (see Figure F in the appendix). Net market coupling is expected to positively impact the system price, as an increase in the former may either reflect greater demand for Nordic-Baltic exports of electricity or lower supply of electricity on Elspot due to decreased imports. Higher net market coupling may furthermore crowd in expensive technologies, resulting in large price swings. Thus, this variable is hypothesised to exert a positive impact on price volatility.

Demand. A number of authors have stressed the importance of controlling for the demand profile of the electricity market (e.g. Clò et al., 2015; Li, 2015). The interaction between wind power and demand may furthermore be relevant. Jónsson et al. (2010) show that wind power has a stronger impact on the price of electricity in the Western Danish bidding area when demand is high. Wind power may thereby displace more expensive power sources as a larger share of the power portfolio is used to meet demand. Data on the demand for electricity should therefore be included to fully assess the impact of wind power on electricity prices.

Hourly forecasts of electricity consumption in Elspot are included as a proxy for the (forecasted) electricity demand.[15] These data are obtained from Nord Pool Spot (2016a), which in turn received the forecasts from the transmission system operators of the member countries. The consumption forecasts are made before the system price is set, and are therefore exogenous to the latter. They are furthermore independent from the forecasted wind power. (Ketterer, 2014) Figure G in the appendix shows that forecasted demand follows a strong seasonal pattern, which is likely due to the correlation between demand and meteorological factors such as temperature. As the seasonal trend does not arise from wind power intermittency and does not reflect underlying market behaviour, it is removed using the same methodology as on the price series. The coefficients from the deseasonalisation process can be found in Table C in the appendix. An increase in the (deseasonalised) forecasted consumption can be considered equivalent to an increase in demand.

[15] Forecasted electricity consumption is therefore used interchangeably with forecasted demand in this study.

The former is consequently expected to have a positive effect on both the level and volatility of the system price.

A potential concern is if net market coupling is endogenous to the forecasted demand. Pursuing energy independent policies may lead countries to prioritise domestic over foreign demand. When domestic demand is high, there may be little residual power to export, lowering net market coupling. Though I bear this concern in mind, two reasons lend support to including both net market coupling and forecasted demand in the model. Firstly, the correlation coefficient between the two is fairly low (0.22). Secondly, the two variables have previously been used together (see e.g. Li, 2015).

Oil price. Other sources of power besides wind naturally influence the electricity price. Care must be taken when including these power sources due to endogeneity concerns. (Clò et al., 2015; Woo et al., 2011) Nord Pool Spot's least-cost dispatching rule implies that additional wind power crowds out more expensive alternatives, such as coal and oil based condensing plants. Similarly, a low price may prevent costly technologies from being produced. The volume of power produced by expensive sources may therefore be endogenous to both the supply of wind power and the price.

In order to avoid the endogeneity concerns, I use the hourly US light crude oil price as traded on the Swiss FX Marketplace (SWFX) as a proxy for the cost of fossil fuel based alternatives to wind power.[16] The data are sourced from Dukascopy (2016)[17] and are converted manually from US dollars to euros[18]. In line with O'Mahoney and Denny (2011), I lag the data by 24 hours in order to reflect the oil price when the bids and offers were submitted in the day-ahead market for electricity. Previous empirical research suggests that the oil price varies according to a yearly and monthly pattern (see for instance Möbert, 2007). This point of view is further corroborated by Table D in the appendix which shows that the year and month are significant predictors of the oil price, in contrast to the day of the week and hour. Thus, applying the same methodology as for the electricity price series data, the monthly and yearly trends are removed from the data and the new mean is aligned. Table E in the appendix contains the coefficients from the deseasonalisation process.

The (deseasonalised) oil price should be exogenous to the Elspot system price and the independent variables as they unlikely significantly influence a commodity like oil traded on a global trading

[16] Six observations were missing and were therefore extrapolated using the previous and next hour's value. This is of minor concern since the oil price fluctuates little from hour to hour. In addition, six observations constitutes a tiny fraction of the total sample size of 20,688.
[17] Dukascopy Bank is a Swiss online bank and security dealer that operates the online trading platform SWFX.
[18] Data on the hourly USD-EUR exchange rate are also sourced from Dukascopy (2016).

platform in Switzerland. The oil price is hypothesised to have a positive influence on the Elspot system price level. Indeed, a higher oil price may increase the cost of expensive sources of power, such as CHP used in district heating and oil condensing technologies. If the demand for electricity is sufficiently high, the market equilibrium would consequently shift to the right, resulting in a higher price level. Hypothesising the impact of the oil price on the volatility of the electricity price is more difficult. On the one hand, a higher oil price implies an increased cost of oil-based technologies and thus larger price swings when these technologies operate in the market. On the other hand, oil based technologies are dispatchable and may therefore smooth price fluctuations from intermittent sources like wind. Overall, however, a positive impact on price volatility is hypothesised. Indeed, the large standard deviation of the oil price (see Table A in the appendix) suggests large swings in the cost of this technology, and consequently the system price, may occur.

Hydro power. The abundance of hydro power in Norway and Sweden impacts the system price. Though hydro power is a low cost technology, it may be endogenous to the price. Hydro power is a dispatchable energy source, which means that producers can produce strategically according to the price level. (Huisman et al., 2015) A higher price may therefore induce more hydro power generation. Thus, data on hydro power production should not be included in the model.

In order to sidestep the endogeneity concern, the hydro power production *capacity* of Elspot could ideally have been used to proxy hydro power generation. Indeed, as evidenced by Huisman et al. (2015), greater hydro power capacity positively impacts generation in Nord Pool. Unfortunately, data on hydro power capacity are unavailable on an hourly basis. I therefore exploit hourly data on the overall power production capacity of Norway and the power export capacity of Sweden to Denmark, which are sourced from Nord Pool Spot (2016a). These data are used as a proxy for the hydro power production of the Nordic-Baltic countries. This approach is justified as follows. Firstly, Norway derives 99 percent of its power from hydro. (Statkraft, 2016) Using total Norwegian power capacity as a proxy for its hydro power generation therefore seems reasonable. Secondly, for the case of Sweden, I exploit the relationship between Swedish hydro power and Danish wind power as discussed in section 3.3. According to Green and Vasilaskos (2012), Denmark's strategy is to import hydro power from Sweden and Norway during domestic shortages of electricity. Thus, the Swedish capacity to export electricity to Denmark is used as a proxy for Sweden's production of hydro power. Thirdly, Norway and Sweden accounted for 95 percent[19] of the hydro power capacity of Nord Pool Spot in 2015, implying that they should adequately proxy the entire trading region.

[19] Calculated manually using data obtained from Nord Pool Spot (2016a).

Reservoir content follows monthly and annual patterns. (Huisman et al., 2015; Li, 2015). In line with the methodology of Li (2015), the monthly and yearly effects are removed from the hydro power data and the means are aligned (see Table F in the appendix for the coefficients from the deseasonalisation process). The resulting deseasonalised values are used in the analysis. An increase in hydro power generation may crowd out more expensive technologies, thereby reducing the price. As hydro power capacity is positively correlated with generation (see Huisman et al., 2015), the fitted capacity is hypothesised to negatively impact the system price. The hypothesised impact on price volatility is less clear cut. As hydro power is a relatively cheap power source that crowds out more expensive technologies, higher fitted capacity may increase price volatility. Conversely, hydro power is dispatchable that can be used to smooth price variability from the erratic in-feed of wind power. The former effect is expected to dominate, however, given the potential large cost difference between hydro power and the technology which is crowded out. Thus, hydro power is hypothesised to increase price volatility.

5.2 Methodology

Electricity prices display a number of idiosyncrasies that should be considered when specifying an empirical model. (Knittel & Roberts, 2005) Previous studies highlight the mean reverting property of electricity prices (see for instance Cartea & Figueroa, 2005; Escribano et al., 2011). As electricity cannot be stored, the price may temporarily jump when production increases and quickly revert to the mean once equilibrium between demand and supply has been restored. A visual inspection of Figure 11 suggests the (logarithmic deseasonalised) Elspot system price is autocorrelated, implying that the current and past values are correlated. The Ljung-Box test (Ljung & Box, 1978) for autocorrelation is therefore carried out for various lag lengths. The null hypothesis of no serial autocorrelation is always rejected, as shown in Table 1, confirming the presence of autocorrelation in the price.

Table 1. Results from the Ljung-Box Test for Autocorrelation in the Logarithmic Deseasonalised Price Series

Lag Length	Ljung-Box Q Statistic	P-value
1	19,287	0.000
4	67,991	0.000
6	95,469	0.000
8	121,100	0.000
12	169,100	0.000

The autocorrelation in the price series suggests an AutoRegressive (AR) model is suitable. AR-type models are commonly used to analyse electricity price series. (Weron, 2014) In a pure AR model, the current value of the dependent variable is linearly explained by p lags of itself (the autoregressive components). An AR(p) model of the system price therefore takes the following form:

$$sp_t = c + \sum_{i=1}^{p} a_i sp_{t-i} + \varepsilon_t \tag{5}$$

where sp_t corresponds to the logarithmic deseasonalised system price at time t; c is the mean of the system price; a_i is the autoregressive coefficient; ε_t is the error term; and p is the number of autoregressive lags. In a simple AR(p) framework, stationarity requires the following condition:

$$\sum_{i=1}^{p} a_i - 1 \in (-1,1) \tag{6}$$

The system price is unlikely only explained by its own past. As discussed in section 5.1, it is important to account for covariates. Modifying equation (5) to an ARX(p, b) model incorporates the information contained in these exogenous series and gives the following specification:

$$sp_t = c + \sum_{i=1}^{p} a_i sp_{t-i} + \sum_{k=1}^{b} \gamma_k x_{k,t} + \varepsilon_t \tag{7}$$

where γ_k is the coefficient of the kth exogenous covariate x; and b is the number of exogenous variables.

The erratic behaviour of the system price, as illustrated in Figure 11, may also arise from unobserved noise that is not captured by the autoregressive components and the exogenous covariates. (Li, 2015) Accounting for the noise may add explanatory power to the model. An AutoRegressive Moving Average with exogenous covariates (ARMAX) model, which incorporates a noise (or moving average) component, is therefore also specified. Extending model (7) to an ARMAX(p, q, b) model gives the following:

$$sp_t = c + \sum_{i=1}^{p} a_i sp_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} + \sum_{k=1}^{b} \gamma_k x_{k,t} + \varepsilon_t \tag{8}$$

where β_j is the moving average coefficient; and q is the number of lags of the moving average terms.

An important assumption underlying models (5), (7) and (8) is a constant variance of the error term over time. Empirical evidence suggests this assumption is violated for electricity spot prices (see for instance Keles et al., 2012; Bhar et al., 2013). According to Weron (2014), the variance of these series' error term often depends on its own past and thus varies over time. The volatility is said to cluster, implying that periods of high uncertainty are followed by more uncertainty and vice versa. The system price series is tested for volatility clustering using both Engle's multiplier test (Engle, 1982) and the Ljung-Box test on the squared residuals. Table 2 illustrates that the null hypothesis of a constant variance over time is rejected, implying that the variance is conditional on time. The assumption of homoscedasticity is therefore rejected.

Table 2. Homoscedasticity Tests for the Error Term of the Logarithmic Deseasonalised Price Series

Lag Length	Engle's Multiplier Test Statistic	Ljung-Box Q Statistic
1	2,600***	2,592***
4	2,671***	3,329***
6	2,948***	3,955***
8	2,953***	4,253***
12	2,977***	4,499***

Note: ***Significant at 1 percent level, **significant at 5 percent level, and *significant at 10 percent level
Note: The results in Table 2 are obtained using an ARX(1,5) (i.e. the mean equation with all covariates in Table 4). However, as shown in Tables 4-6, the null hypothesis of homoscedasticity is rejected for the mean equation of all models. Thus, using a GARCH-type model is always justified.

In order to overcome the heteroscedasticity, a GARCH[20] model extended by exogenous variables (i.e. a GARCHX) can be used together with an AR-type model. Introduced by Bollerslev (1986), GARCH-type models effectively capture volatility clustering and are commonly applied to mean reverting series such as electricity prices. (Engle, 2001) In a GARCH(X) framework, the impact of wind power on the price level and the volatility is modelled in an integrated approach. The identification and estimation of AR(MAX) and GARCH(X) models are indeed performed analogously as the residuals obtained from the former model are used in the GARCH(X) process. More formally, the residuals ε_t obtained from, for instance, model (8), known as the 'mean equation' in an AR(MAX)-GARCH(X) framework, are used in the below 'variance equation' to describe the volatility of the system price:

[20] GARCH stands for 'general autoregressive conditional heteroscedasticity'.

$$h_t = \delta + \sum_{l=1}^{u} \omega_l h_{t-l} + \sum_{m=1}^{v} \theta_m \varepsilon_{t-m}^2 + \sum_{n=1}^{w} \pi_n x_{n,t} \tag{9}$$

where h_t is the conditional variance; ε_t^2 is the squared residuals of the mean equation; δ is a constant; u and v are the orders of the lagged conditional variance terms and lagged squared residual terms respectively; w is the number of exogenous variables; and ω_l, θ_m and x_n are the coefficients of the lagged conditional variance terms, lagged squared residual terms and the kth exogenous variable respectively. The conditional variance h_t of the system price is explained by its own past values, the squared residuals from previous periods and a set of exogenous variables. The lagged conditional variance and lagged squared residuals are commonly referred to as the GARCH and ARCH terms respectively. In a GARCH(X) framework, the error term in the mean equation ε_t is defined as follows:

$$\varepsilon_t = \sqrt{h_t} z_t$$

where z_t is assumed a sequence of independent and identically distributed random variables, with zero mean and variance one. (Zivot, 2008) The error term in the mean equation is therefore serially uncorrelated while the conditional variance h_t varies over time. (Tsai & Chan, 2008) The GARCH(X) is stationary if the following condition holds:

$$\sum_{l=1}^{u} \omega_l + \sum_{m=1}^{v} \theta_m < 1 \tag{10}$$

In this case, shocks only have a temporary impact on the conditional variance as the variance reverts to its long run mean. (Engle, 2001) Following the methodology proposed by Bollerslev (1986), a GARCHX(u, v) refers to u lags of the conditional variance and v lags of the squared residuals. In a GARCH(1,1), the speed of the mean reversion is given by:

$$1 - (\omega_1 + \theta_1) \tag{11}$$

The empirical strategy of this thesis is to first apply a simple AR(1) process in order to explore the autocorrelation in the system price. The number of autoregressive lags that minimise the Akaike information criterion (AIC) are thereafter added to account for serial autocorrelation in the error term. In order to investigate the hypotheses, the mean and volatility equation in (7) and (9) respectively are modelled in an ARX(1,b)-GARCHX(1,1) framework. The results are compared to ARX(p, b)-GARCHX(u, v) and ARMAX(p, q, b)-GARCHX(u, v) models in the sensitivity analysis, which takes into account a larger share of the autocorrelation in the system price and residual noise. In line with previous studies (see for instance Ketterer, 2014; Woo et al., 2011), all models are estimated using maximum likelihood.

Prior to undertaking the analysis, all variables besides net market coupling[21] are transformed logarithmically. Taking the natural logarithm helps to normalise the error term and reduces skew. The coefficients of the independent variables can thereby also be interpreted as elasticities. Moreover, an assumption underlying AR(MAX)-GARCH(X) processes is that both the dependent and independent variables are stationary. Table G in the appendix presents the results from various stationarity tests. For the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), the null hypothesis of a unit root process is rejected at a one percent level of significance for all variables.[22] The same results are obtained when running the Dickey-Fuller Generalised Least-Squares (DF-GLS) test (Elliott et al., 1996). All variables are therefore stationary.

6 Results

6.1 Overall Impact of Wind Power on the Price Level and Volatility

Various AR processes are first used to explore the overall properties of the logarithmic deseasonalised system price. The results from regressing a simple AR(1) process are shown in the second column of Table 3.[23] The model is stationary since $a_1 < 1$. Though not explicitly shown in the table, the R squared indicates that the first lag explains 93.2 percent of the variation in the price.[24] The first lag is furthermore statistically significant at a one percent level. Since the dependent and independent variable are both in logarithmic form, the coefficient of the lagged value represents the elasticity of the current price with respect to the previous hour. Thus, an increase in the price in the previous hour by one percent raises the current price by 0.965 percent. The one period autocorrelation between hourly prices is, in other words, very large.

The Ljung-Box test on the error term of the AR(1) process is conducted for various lag lengths to examine whether any serial correlation remains in the error term. The null hypothesis of no remaining autocorrelation is always rejected at a one percent level of significance (Table H in the

[21] The natural logarithm of net market coupling is not taken, since this variable contains many negative observations (indicating net imports).
[22] The lag length which minimises the AIC is chosen for the ADF test for each variable. The highest possible lag length is 10.
[23] A constant was included in the model since the price series have a non-zero mean.
[24] The R squared values are excluded from Tables 3-6 since using the AIC and log likelihood is more relevant when evaluating the model fit due to the strong autocorrelation in the price series.

appendix). The AR(1) process therefore fails to capture all the serial correlation in the error term. Autoregressive components p are consequently added one by one until $p = 10$.[25, 26] The results of the various AR(p) processes are depicted in Table 3. All models are stationary as they satisfy condition (6) in section 5.2. The AIC is minimised at the ninth lag, suggesting an AR(9) is most appropriate. The R squared of the AR(9) is only slightly higher than in the AR(1) process,[27] while the coefficient of the first autoregressive term is by far the largest. The results therefore underline the importance of the price in the previous hour in predicting the current value.

Table 3. Results for Various AR(p) Processes

	AR(1)	AR(2)	AR(5)	AR(7)	AR(8)	AR(9)	AR(10)
Constant	3.16659*** (0.01)	3.16661*** (0.01)	3.16661*** (0.01)	3.16662*** (0.01)	3.16664*** (0.02)	3.16671*** (0.02)	3.16671*** (0.02)
a_1	0.96547*** (0.00)	1.09301*** (0.00)	1.08880*** (0.00)	1.07946*** (0.00)	1.07740*** (0.00)	1.07316*** (0.00)	1.07323*** (0.00)
a_2		-0.13209*** (0.00)	-0.13843*** (0.00)	-0.13707*** (0.00)	-0.14209*** (0.00)	-0.13897*** (0.00)	-0.13895*** (0.00)
a_3			-0.05005*** (0.00)	-0.04553*** (0.00)	-0.04360*** (0.00)	-0.04774*** (0.00)	-0.04780*** (0.00)
a_4			-0.00640 (0.00)	0.00775* (0.00)	0.00715* (0.00)	0.00833** (0.00)	0.00843** (0.00)
a_5			0.07320*** (0.00)	-0.02494*** (0.00)	-0.02141*** (0.00)	-0.02180*** (0.00)	-0.02182*** (0.00)
a_6				0.06471*** (0.00)	0.07529*** (0.00)	0.07768*** (0.00)	0.07769*** (0.00)
a_7				0.02660*** (0.00)	-0.05688*** (0.00)	-0.04911*** (0.00)	-0.04917*** (0.00)
a_8					0.07734*** (0.00)	0.01831*** (0.00)	0.01814*** (0.00)
a_9						0.05480*** (0.00)	0.05617*** (0.00)
a_{10}							-0.00128 (0.00)
AIC	-56,896	-57,258	-57,484	-57,847	-57,798	-57,859	-57,857
Log likelihood	28,451	28,633	28,749	28,847	28,909	28,940	28,940

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level
Note: The dependent variable is the logarithm of the deseasonalised electricity price series. Standard errors are in parentheses.
Note: a_i given $i \in [1,10]$ is the ith autoregressive component of the deseasonalised logarithmic price series.

The first and second hypotheses are subsequently tested using an ARX($1, b$)-GARCHX(1,1) framework. Table 4 illustrates the results of the mean and variance equations for different models. All models satisfy condition (6), as the coefficient of the autoregressive lag a_1 is smaller than unity, which implies that the mean processes are stationary. Further, the sum of the GARCH term ω_1

25 A maximum lag length of 10 should provide an adequate indication of the nature of the autocorrelation in the price series.
26 As discussed in the previous section, the presence of serial correlation in the error term motivates using a GARCHX model. The autocorrelation is thereby captured, as the conditional variance is regressed on lagged values of the error term. Furthermore, including exogenous covariates, as in Tables 4-6, accounts for some of the serial correlation. In the sensitivity analysis, a moving average term is also included which should further improve the model fit.
27 The R squared of the AR(9) is 0.967.

and ARCH term θ_1 is always smaller than one. The variance processes therefore satisfy conditions (10) and are stationary. The conditional variance of the price reverts to the mean while shocks only temporarily impact the conditional variance. The reversion is slow, however, since the sum is close to unity. The size of the GARCH term in the model with all covariates is 0.55, which is fairly small. The conditional variance process is therefore weakly persistent. Further, the ARCH term is also small (0.44), implying that shocks to the conditional variance, passed through the error term in the mean equation, only have a limited effect. The AIC and log likelihood values of the various models suggest the model fit improves for each added covariate. A potential concern with the results in Table 4 is the negative constant terms in the variance processes. In theory, the conditional variance can thereby take on negative values which is unreasonable. Three reasons suggest the negative constant is of limited concern, however. Firstly, the conditional variance is always positive in practice, as shown in Figure H in the appendix. Secondly, the results in Table 4 remain largely similar to the models in the sensitivity analysis that contain a positive constant. Thirdly, as shown by Nelson and Cao (1992), the negative coefficients may reflect the true data generating process, and are not uncommon in the literature. Thus, the negative constant terms are maintained.

Forecasted wind power has a negative effect on the level of the price in all models. The effect is always significant at a one percent level. Controlling for demand, hydro power capacity, the oil price and coupling yields a coefficient of -0.04 in model (E). Thus, an increase in forecasted Swedish and Danish wind power by one percent decreases the Elspot system price, on average, by 0.04 percent. The result underlines the merit order effect of wind power in the Nordic-Baltic wholesale electricity market and confirms the first hypothesis. More wind power crowds out expensive technologies which reduces the price. The impact is economically significant, given the highly volatile nature of wind power generation. As shown in Table A in the appendix, the standard deviation of wind power is 64 percent of the mean. Thus, an increase in wind power by one standard deviation (from its mean value) decreases the price by 2.56 percent.[28] This may have important consequences for the stability of the electricity market. A lower price may crowd out costly dispatchable power plants that are crucial to offsetting the intermittent supply from renewable sources. The risk of power imbalances may consequently increase, since supply thereby become more erratic.

Table 4 furthermore shows that an increase in hydro power production lowers the electricity price. This suggests that hydro power replaces more costly technologies which explains the negative and statistically significant coefficient of this variable. Examining the other covariates reveals that price

[28] This equates to a price reduction of 0.62€/MWh for a price level originally at the sample mean.

surges are predominantly driven by demand. A one percent increase in demand raises the price by 0.84 percent, which is much larger in absolute terms than the effects of hydro and wind power. The renewable technology can therefore be said to offset some of the upward pressure on the price caused by demand. Overall, however, the demand effect dominates the merit order effect in the Nordic-Baltic electricity market. This finding is in line with Li (2015). Moreover, as expected, Table 4 shows both the oil price and net market coupling positively impact the electricity price level. The effects are statistically significant at a one percent level. An increase in the oil price therefore reflects a higher cost of production of oil based technologies, which increases the average marginal cost and price in the market. Greater net market coupling, on the other hand, can be considered equivalent to more demand, which increases the price.

Turning to the variance equation, wind power has a positive and statistically significant impact on price volatility in all model specifications. When accounting for all exogenous covariates, an increase in wind power by one percent raises the hourly volatility of the Elspot system price by 0.12 percent. The finding confirms the second hypothesis and is in line with Woo et al. (2011) and Ketterer (2014), but contradicts the results of Li (2015) for Denmark. The effect is sizable, in absolute terms, given the large intraday variability of wind power. A more volatile price due to added wind power may deter market entry in the long run as investments become more uncertain. In the short run, activating intermittent sources becomes riskier since they cannot easily be switched off in response to price fluctuation. This may reduce the supply of power, and make it more difficult to balance the electricity transmission system.

The effect of all covariates in model (E) on price volatility is statistically significant at a one percent level. As hypothesised, greater demand and hydro power generation increase volatility. The impact of these variables is interestingly much larger than for wind power, suggesting demand and hydro power exacerbate price uncertainty to a relatively large extent. It should be noted, however, that hydro power displays less intraday variability than wind power. Thus, even though the former technology has a larger effect, wind power may cause more price fluctuation in practice due to its highly variable nature. Examining the remaining covariates in model (E) shows that net market coupling, as expected, increases price volatility. The oil price, on the other hand, has a negative effect. This suggests that dispatchable oil based technologies smooth price fluctuations from intermittent sources like wind power.

Table 4. Results for ARX(1, b)-GARCHX(1,1) Processes

	(A)	(B)	(C)	(D)	(E)
Mean Equation					
Constant	3.56674***	-6.03478***	-5.19348***	-6.18050***	-5.65816***
	(0.02)	(0.05)	(0.08)	(0.16)	(0.17)
Log wind	-0.04666***	-0.05010***	-0.05295***	-0.05282***	-0.04196***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log demand		0.90247***	0.88001***	0.88253***	0.84119***
		(0.00)	(0.00)	(0.00)	(0.01)
Log hydro			-0.05738***	-0.03801***	-0.04695***
			(0.01)	(0.01)	(0.01)
Log oil price				0.19687***	0.17389***
				(0.02)	(0.02)
Coupling					0.00001***
					(0.00)
a_1	0.97824***	0.97931***	0.97576***	0.97424***	0.97593***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Variance Equation					
Constant	-12.86606***	-61.61967***	-93.96049***	-85.96385***	-83.52218***
	(0.20)	(0.94)	(1.17)	(1.42)	(1.36)
Log wind	0.32643***	0.06071***	0.06716***	0.05821***	0.11658***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Log demand		4.94831***	4.81785***	4.65825***	4.49980***
		(0.08)	(0.08)	(0.08)	(0.08)
Log hydro			3.34989***	3.03922***	2.85777***
			(0.07)	(0.08)	(0.08)
Log oil price				-0.79405***	-0.64624***
				(0.09)	(0.10)
Coupling					0.00018***
					(0.00)
ARCH(1)	0.07454***	0.39661***	0.39453***	0.39263***	0.43984***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
GARCH(1)	0.91886***	0.59347***	0.59113***	0.58937***	0.54518***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
AIC	-69,709	-71,837	-72,121	-72,148	-72,939
Log likelihood	34,890	35,297	36,072	36,087	36,484
Engle's multiplier test statistic (using one lag)	2,617***	2,645***	2,630***	2,601***	2,600***

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level
Note: The dependent variable is the logarithm of the deseasonalised electricity price series. Standard errors are in parentheses.
Note: *Log wind* refers to the logarithm of the combined Swedish and Danish wind power. *Log demand* is the logarithm of the deseasonalised projected consumption of power on Elspot. *Log hydro* alludes to the logarithm of the deseasonalised proxy for the combined Norwegian and Swedish hydro power generation. *Log oil price* alludes to the logarithm of the deseasonalised price of oil. *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands. a_1 is the first autoregressive component of the deseasonalised logarithmic price series. Finally, *ARCH(1)* and *GARCH(1)* are the respective first lags of the squared residuals and conditional variance.

6.2 Differential Impact of Wind Power Based on Demand

The above results show that an increased supply of wind power, on average, decreases the electricity price and increases the price volatility. The magnitude of the effects may vary, however, depending on the demand for power. This topic has received surprisingly little attention from empirical research, and is therefore investigated here. Using the methodology of Li (2015), the hypothetical impact of adding 500 MWh of (forecasted) wind power on the level and the volatility of the price is simulated for different volumes of (deseasonalised forecasted) demand.[29] The data are sorted in ascending order according to demand, after which they are split into six intervals. Increments of 2,000 MWh are used such that the first interval contains values of demand below or equal to 40,000 MWh and the last interval includes values above or equal to 48,000 MWh. Each interval contains at least 1,500 observations, as shown in Table I in the appendix. The mean of the variables used in the original analysis is calculated for each interval (see Table I in the appendix for the results). Assuming the price elasticity of each independent variable is the same across intervals, the means are multiplied by the coefficients in model (E) in Table 4, which gives the average price for each interval of demand in the absence of variation in wind power. The impact of suddenly adding 500 MWh of wind power on the price level and volatility is thereafter simulated for each interval, holding everything else constant. The effect of adding wind power given various levels of demand is thereby estimated. The analysis is static and does not take into account the past behaviour of variables.

Figures 12 and 13 illustrate the impact of adding the wind power on the level and the volatility of the price respectively, for each interval of demand. The results are also contained in Table J in the appendix. Figure 12 shows that adding wind power always decreases the price level. The reduction is generally larger when demand is relatively high. Adding 500 MWh of wind power when demand is equal to or above 48,000 MWh decreases the price by an additional 0.14 percentage points relative to when demand is equal to or below 40,000 MWh. Surprisingly, the largest price reduction occurs when demand is between 44,000 MWh and 46,000 MWh. In general though, the findings are intuitive and confirm the third hypothesis. When demand is high, more expensive technologies operate in the market. Adding wind power thereby greatly reduces the average marginal cost in the market, decreasing the price level to a large extent.

As illustrated in Figure 13, adding wind power increases the price volatility for all intervals. The increase is largest, however, when demand is between 44,000 MWh and 46,000 MWh. The overall pattern suggests the price becomes more volatile as demand increases. The results confirm the fourth hypothesis, and imply that the price uncertainty from greater wind power supply is exacerbated when demand is relatively high. The increased uncertainty may reduce supply, as non-dispatchable sources may be unwilling to produce during hours when the price is erratic. As the increased price volatility coincides with periods of high demand (Figure 13), the reduction in supply may be paralleled with high demand. Countries relying on wind power may consequently be

[29] As data on *forecasted* demand are used as a proxy for *actual* demand in this study, the two are used interchangeably in section six. Similarly, *forecasted* wind power is used synonymously with *actual* wind power in section six.

vulnerable to power imbalances. A mitigating measure could be integrating national power markets in order to diversify the supply across countries. This topic is elaborated on in section 8.1.

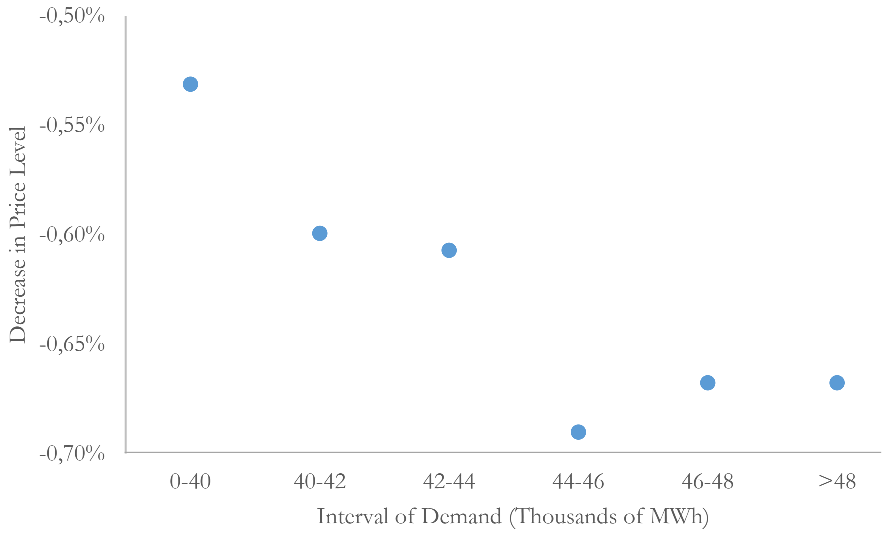

Figure 12. The Impact of Adding 500 MWh of Wind Power on the Price Level Given Different Levels of Demand

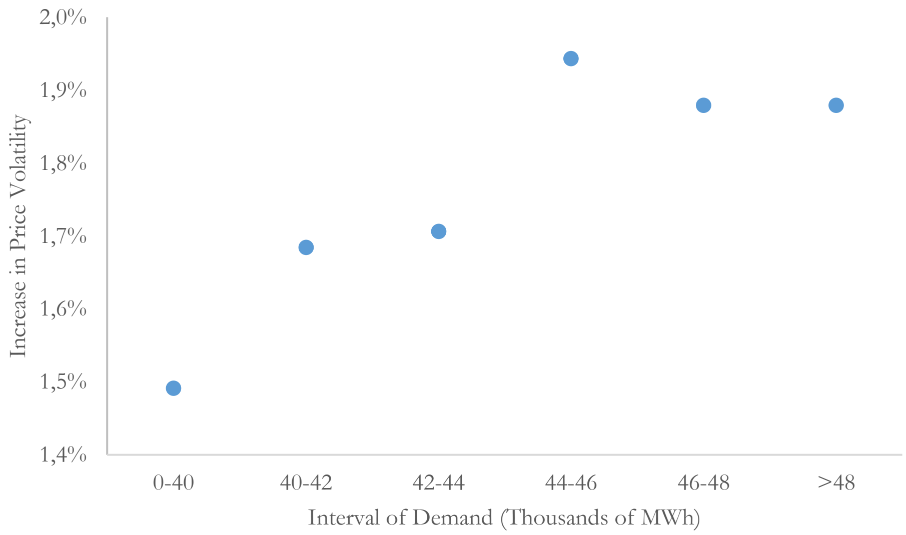

Figure 13. The Impact of Adding 500 MWh of Wind Power on the Price Volatility Given Different Levels of Demand

6.3 Differential Impact of Wind Power Based on Existing Wind Power

The impact of wind power on the electricity price may also vary based on the volume of wind power already in the market. The same methodology as in the previous section is used to investigate this topic. This time, though, the data are split into eight intervals of 800 MWh of wind power, such that the cutting values range from 800 MWh to 5,600 MWh. Table K in the appendix shows the average price for each interval, which is obtained by multiplying the coefficients in model (E) in Table 4 with the mean of each variable. As before, the impact of adding 500 MWh of wind power on the price level and volatility is simulated for each interval, assuming all other conditions remain constant.

The results in Table L in the appendix are replicated in Figures 14 and 15. As illustrated in the former figure, adding wind power results in a larger decrease in the price level when the existing wind power supply is relatively low. Suddenly increasing the wind power supply by 500 MWh decreases the price by 2.58 percent when almost zero wind power originally exists, compared to 0.3 percent when this power source initially exceeds 5,600 MWh. The results indicate that the merit order effect of wind is stronger when the supply of wind power is initially low. The added wind power crowds out more expensive technologies in such situations, which reduces the average cost and price in the market to a large extent. The fifth hypothesis is therefore confirmed.

Turning to Figure 15, adding wind power always increases the price volatility. The positive effect is greater at lower volumes of existing wind power supply. The difference in impacts can furthermore be large. Injecting 500 MWh in the transmission system when 0 to 800 MWh of wind power is already supplied increases price volatility by more than seven percent. The effect is almost halved for the next interval, while volatility increases by less than one percent if more than 5,600 MWh wind power initially exists. The results confirm the sixth hypothesis and shed light on the operating climate in the power market given different distributions of the generation mix. When little wind is originally used, adding wind power suppresses the price level and increases its volatility to a large extent. The reduced price level decreases industry profitability and crowds out expensive dispatchable sources. The increased volatility, on the other hand, enhances the risk of producing intermittent power, which may further reduce the overall power supply. However, when medium to large amounts of wind already exist, adding wind power distorts incentives to produce both dispatchable and intermittent power to a lower extent.

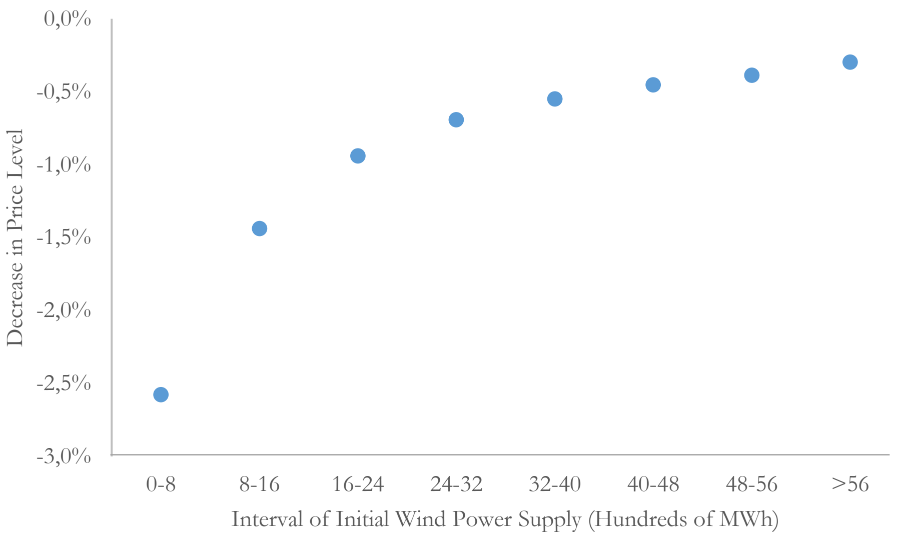

Figure 14. The Impact of Adding 500 MWh of Wind Power on the Price Level Given Different Levels of Initial Wind Power Supply

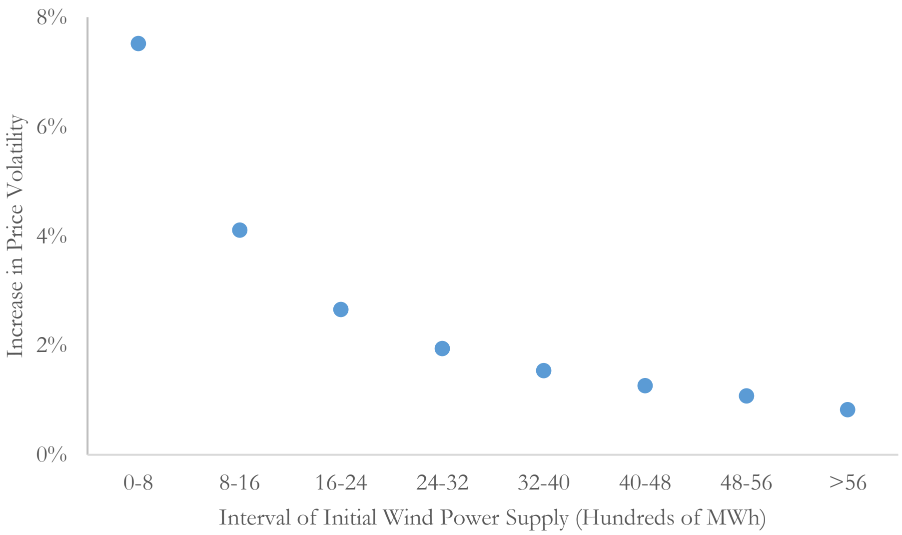

Figure 15. The Impact of Adding 500 MWh of Wind Power on the Price Volatility Given Different Levels of Initial Wind Power Supply

7 Sensitivity Analysis

7.1 Adding Autoregressive Components

In order to verify the robustness of the results in Table 4, a number of alternative model specifications are employed. As discussed in section 6.1, the price is correlated across several lags. A lone autoregressive component may fail to capture all of the autocorrelation. A second lag is therefore added to the model. The coefficients from the resulting ARX(2,5)-GARCHX(1,1) framework are shown in the second column of Table 5. The AIC and log likelihood values suggest including the second lag improves the model fit, compared to the complete model in Table 4. The mean equation satisfies condition (6), implying that the mean process is stationary. All variables in the mean equation remain statistically significant at a one percent level and none of the coefficients change sign. The negative effect of wind power on the price level increases slightly in magnitude, while the impacts of hydro power and demand decrease in absolute terms. A positive effect is once more found for the oil price and market coupling. Turning to the variance equation, the results largely mimic the complete model in Table 4. The positive effect of wind power remains statistically significant at a one percent level. Interestingly, the sum of the GARCH and ARCH terms exceeds unity. The inclusion of the second autoregressive lag therefore makes the variance process non-stationary, which highlights the sensitivity of the process to the autoregressive lag length. The non-stationarity implies that the conditional variance diverts from the long run mean and gets infinitely large as the sample size grows. The coefficients may therefore be spurious. Thus, though the results lend some support to the validity of the findings in Table 4, the results from the model should be interpreted with care.

A potential remedy to the non-stationarity of the variance process is to review the lag order of the GARCHX model. (Engle, 2001) As shown in the third column of Table 5, replacing the first with the second lag of the squared residuals makes the variance process stationary, since the sum of the GARCH and ARCH terms is below unity. The AIC of the model increases, however, which suggests a poorer model fit. This is intuitive, as the current value is likely more correlated with the first than the second lag of the squared residuals. As the model fit is worse than in Table 4, the results should again be interpreted with caution. The coefficients in the mean equation paint a similar picture to those in Table 4. The sum of the autoregressive components is below unity, indicating that the mean process is stationary. A negative effect is found for wind power, while coupling and the oil price increase the price level. A surprising result is the insignificance of hydro power and the reduction of its effect. However, the coefficient may be biased by the omission of the first lag of the squared residuals, since the second lag explains less of the variation in the conditional variance than the first lag. In the variance equation, the constant term turns positive while wind power once more has a statistically significant positive effect. The size of the impact increases by almost four fold though. This may be due to the reversed sign of demand, which is now negative and statistically significant. The result is surprising since demand is expected to increase price volatility. The change of sign may again reflect, however, omitted variable bias from excluding the first lag of the squared residuals.

Table 3 suggests the autocorrelation in the price is persistent across more than two lags. Expanding the lag length may thus improve the model fit. Autoregressive lags p are added until p =10, whereby the AIC is minimised. The results from the ARX(10,5)-GARCHX(1,1,5) are illustrated in the fourth column of Table 5. Most autoregressive lags are statistically significant at a one percent level, and the AIC and log likelihood values indicate that the model fit is improved. The coefficients of the covariates are similar to the model with two autoregressive lags (second column). Wind power has a negative effect on the price level and a positive effect on volatility. Both effects remain statistically significant at a one percent level. The signs of the remaining coefficients are also unchanged compared to the results in the second column of Table 5 and the original results in Table 4. However, the oil price becomes insignificant in the mean equation. Examining the ARCH and GARCH terms suggests the variance process is non-stationary, since their sum exceeds unity. The results may therefore be spurious. The fifth column of Table 5 addresses this issue by substituting the first lag with the second lag of the squared error term. The model fit is slightly better than the complete process in Table 4, in spite of the omission of the second lag. The model in the fifth column of Table 5 provides further evidence of a negative effect of wind power on the price level and a positive effect on price volatility. The findings are robust to the inclusion of more autoregressive lags. Most of the remaining coefficients show the same sign as in Table 4. However, hydro power surprisingly has a positive impact on the price level while demand reduces volatility. Though these results suggest the effects in Table 4 should be interpreted with care, they may have arisen from omitted variable bias of first lag of the squared residuals.

Table 5. Results from Various ARX-GARCHX Specifications

	ARX(2,5)-GARCHX(1,1,5)	ARX(2,5)-GARCHX(1,(2,2),5)	ARX(10,5)-GARCHX(1,1,5)	ARX(10,5)-GARCHX(1,(2,2),10)
Mean Equation				
Constant	-4.37791***	-5.05712***	-2.48935***	-4.21559***
	(0.16)	(0.21)	(0.14)	(0.22)
Log wind	-0.04534***	-0.04804***	-0.04701***	-0.05415***
	(0.00)	(0.00)	(0.00)	(0.00)
Log demand	0.75831***	0.76670***	0.59476***	0.68312***
	(0.01)	(0.01)	(0.00)	(0.01)
Log hydro	-0.07655***	-0.00100	-0.04306***	0.03310***
	(0.01)	(0.01)	(0.01)	(0.01)
Log oil price	0.15690***	0.11285***	0.03441	0.04692*
	(0.02)	(0.03)	(0.02)	(0.02)
Coupling	0.00002***	0.00001***	0.00002***	0.00001***
	(0.00)	(0.00)	(0.00)	(0.00)
a_1	1.33024***	1.17807***	1.31204***	1.16468***
	(0.01)	(0.00)	(0.00)	(0.00)
a_2	-0.35875***	-0.20021***	-0.41344***	-0.25166***
	(0.01)	(0.00)	(0.01)	(0.01)
a_3			-0.00390	0.01804
			(0.01)	(0.01)
a_4			0.06511***	-0.01487
			(0.00)	(0.01)
a_5			-0.09073***	-0.03762***
			(0.01)	(0.01)
a_6			0.10084***	0.03716***
			(0.10)	(0.01)
a_7			-0.07239***	-0.00399
			(0.00)	(0.01)
a_8			0.09230***	0.00119
			(0.00)	(0.01)
a_9			-0.03268***	0.06490***
			(0.00)	(0.01)
a_{10}			0.03264***	0.01001
			(0.00)	(0.01)
Variance Equation				
Constant	-68.60085***	34.39555***	-82.39949***	29.54435***
	(1.21)	(2.31)	(1.20)	(2.20)
Log wind	0.10876***	0.39937***	0.05417***	0.39508***
	(0.01)	(0.02)	(0.01)	(0.01)
Log demand	3.69131***	-5.58970***	6.14313***	-5.25377***
	(0.07)	(0.16)	(0.08)	(0.15)
Log hydro	2.42721***	1.94081***	1.49745***	2.03071***
	(0.07)	(0.10)	(0.06)	(0.10)
Log oil price	-1.10512***	-1.99066***	-1.69803***	-1.87914***
	(0.09)	(0.13)	(0.09)	(0.12)
Coupling	0.00017***	0.00010***	0.00012***	0.00010***
	(0.00)	(0.00)	(0.00)	(0.00)
ARCH(1)	0.52538***		1.23027***	
	(0.01)		(0.01)	
ARCH(2)		0.05372***		0.05451***
		(0.00)		(0.00)
GARCH(1)	0.48656***	0.93873***	0.16237***	0.93685***
	(0.00)	(0.00)	(0.00)	(0.01)
AIC	-74,388	-72,331	-75,849	-72,982
Log likelihood	37,210	36,182	37,949	36,515
Engle's multiplier test statistic (using one lag)	2,942***	2,942***	2,841***	2,841***

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level

Note: The dependent variable is the logarithm of the deseasonalised electricity price series. Standard errors are in parentheses.

Note: *Log wind* refers to the logarithm of the combined Swedish and Danish wind power. *Log demand* is the logarithm of the deseasonalised projected consumption of power on Elspot. *Log hydro* alludes to the logarithm of the deseasonalised proxy for the combined Norwegian and Swedish hydro power generation. *Log oil price* alludes to the logarithm of the deseasonalised price of oil. *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands. a_i given $i \in [1,10]$ is the ith autoregressive component of the deseasonalised logarithmic price series. *ARCH(1)* and *GARCH(1)* are the respective first lags of the squared residuals and conditional variance. *ARCH(2)* is the second lag of the squared residuals.

7.2 Adding a Moving Average Component

The exogenous covariates and the autoregressive lags may fail to explain all of the variation in the electricity price. A moving average term is therefore added to all models in Table 5 to further verify the robustness of the original results. The coefficients from the resulting ARMAX-GARCHX models are reported in Table 6. In essence, similar results to Table 5 are obtained. Wind power reduces the price and increases price volatility in all models. The effects are always significant at a one percent level. Moreover, the positive and significant impact of market coupling on both the level and volatility is confirmed. The merit order effect of hydro power is statistically significant in only two models, both of which are non-stationary. This sheds doubt on the robustness of the negative relationship between this variable and the price level. On the other hand, hydro power is always found to increase price volatility, in line with the original results. The oil price generally has a positive effect on the price level, though it is only significant when two autoregressive components are included. The variable always reduces price volatility, however, in line with the original findings in Table 4. Less clear-cut results are obtained for demand. On the one hand, demand has, as expected, a positive effect on the price level which is both statistically and economically significant. The coefficient ranges from 0.77 to 0.51, suggesting that an increase in demand by one percent raises the price by at least 0.5 percent. On the other hand, the positive effect of demand on volatility, as observed in Table 4, is only confirmed in the non-stationary models. In the stationary models, demand decreases volatility. Though this suggests the positive effect of this variable on price volatility in Table 4 should be interpreted with care, the fit of the stationary models are poor (as suggested by the AIC and log likelihood values). Indeed, the exclusion of the first lag of the squared residuals likely leaves some of the variation in the conditional variance unexplained. As this may bias the coefficients, the internal validity of these models is reduced. Further investigating the effect of demand on price volatility in the Nordic-Baltic market is thus desirable for future research.

Table 6. Results from Various ARMAX-GARCHX Specifications

	ARMAX(2,1,5)-GARCHX(1,1,5)	ARMAX(2,1,5)-GARCHX(1,(2,2),5)	ARMAX(10,1,5)-GARCHX(1,1,5)	ARMAX(10,1,5)-GARCHX(1,(2,2),5)
Mean Equation				
Constant	-4.19380***	-5.05440***	-1.90287***	-3.14254***
	(0.15)	(0.21)	(0.14)	(0.22)
Log wind	-0.04536***	-0.04785***	-0.04902***	-0.06135***
	(0.00)	(0.00)	(0.00)	(0.00)
Log demand	0.75100***	0.76559***	0.51647***	0.58241***
	(0.01)	(0.01)	(0.00)	(0.01)
Log hydro	-0.08102***	-0.00053	-0.03367***	0.05104***
	(0.01)	(0.01)	(0.01)	(0.01)
Log oil price	0.14087***	0.11054***	0.02830	-0.00102
	(0.02)	(0.03)	(0.02)	(0.02)
Coupling	0.00002***	0.00001***	0.00002***	0.00001***
	(0.00)	(0.00)	(0.00)	(0.00)
a_1	1.13467***	0.98547***	2.18230***	2.06818***
	(0.02)	(0.03)	(0.01)	(0.01)
a_2	-0.16886***	-0.01211***	-1.59665***	-1.31581***
	(0.02)	(0.03)	(0.01)	(0.01)
a_3			0.40934***	0.25282***
			(0.01)	(0.02)
a_4			0.04027***	-0.03201
			(0.01)	(0.02)
a_5			-0.12595***	-0.02397
			(0.01)	(0.03)
a_6			0.16154***	0.06943***
			(0.01)	(0.02)
a_7			-0.14674***	-0.03137
			(0.01)	(0.02)
a_8			0.15218***	0.01819
			(0.00)	(0.02)
a_9			-0.10339***	-0.00360
			(0.00)	(0.02)
a_{10}			0.02586***	-0.00227
			(0.00)	(0.01)
MA(1)	0.24105***	0.20111***	-0.87184***	-0.92017***
	(0.02)	(0.03)	(0.01)	(0.01)
Variance Equation				
Constant	-67.84296***	34.72332***	-89.87614***	27.98807***
	(1.17)	(2.31)	(1.28)	(2.34)
Log wind	0.09586***	0.39798***	0.05425***	0.40191***
	(0.01)	(0.01)	(0.01)	(0.01)
Log demand	3.72594***	-5.60242***	6.84635***	-5.19340***
	(0.07)	(0.16)	(0.08)	(0.16)
Log hydro	2.34765***	1.93430***	1.44024***	2.09892***
	(0.07)	(0.10)	(0.06)	(0.10)
Log oil price	-1.16178***	-2.01880***	-1.59639***	-1.84216***
	(0.09)	(0.13)	(0.09)	(0.13)
Coupling	0.00017***	0.00010***	0.00013***	0.00012***
	(0.00)	(0.00)	(0.00)	(0.00)
ARCH(1)	0.54752***		1.04403***	
	(0.01)		(0.01)	
ARCH(2)		0.05398***		0.05599***
		(0.00)		(0.00)
GARCH(1)	0.47039***	0.93842***	0.23134***	0.93575***
	(0.00)	(0.00)	(0.00)	(0.00)
AIC	-74,517	-72,361	-75,967	-73,338
Log likelihood	37,276	36,198	38,009	36,694
Engle's multiplier test statistic (using one lag)	2,942***	2,942***	2,841***	2,841***

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level

Note: The dependent variable is the logarithm of the deseasonalised electricity price series. Standard errors are in parentheses.

Note: *Log wind* is the logarithm of the combined Swedish and Danish wind power. *Log demand* is the logarithm of the deseasonalised projected consumption of power. *Log hydro* is the logarithm of the deseasonalised proxy for hydro power generation. *Log oil price* alludes to the logarithm of the deseasonalised oil price. *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands. a_i given $i \in [1,10]$ is the ith autoregressive component of the deseasonalised logarithmic price. *MA(1)* is the moving average component. *ARCH(1)* and G*ARCH(1)* are the respective first lags of the squared residuals and conditional variance. *ARCH(2)* is the second lag of the squared residuals.

8 Discussion

8.1 Policy Implications

The above analysis suggests integrating additional wind power in the transmission system has important consequences for both producers and policy makers. More wind power decreases the wholesale price of electricity, and consequently the industry profitability. The existence of power plants with high marginal costs may in particular be threatened by the reduced price level. As these plants are typically dispatchable, they are integral to a stable electricity supply and balanced electricity system. The positive impact of wind power on price volatility may further accentuate the likelihood of power imbalances. Indeed, greater price uncertainty increases the risk of activating non-dispatchable power sources, such as wind power, that cannot easily be switched off. Increased reliance on these technologies may thus limit the supply of power during certain hours of the day. If the reduction of supply coincides with periods of high demand, when the positive impact of wind power on price uncertainty is particularly pronounced, domestic supply may fall behind to demand.

The enhanced risk of power imbalances as a result of more wind power may necessitate a number of policy interventions. Regionally diversifying the supply of power in Nord Pool Spot is desirable. The concentration of wind power generation in Sweden and Denmark makes these countries particularly vulnerable to domestic power shortages. A more even distribution of wind power production across Nord Pool Spot may reduce the risk of regional imbalances. Moreover, increased reliance on wind power in the Nordic-Baltic market as a whole underlines the need for enhanced market integration with the rest of Europe. As suggested by Schaber et al. (2012), connecting European power grids may increase revenues for producers, as well as stabilise prices and supply. A similar conclusion is drawn by Hulle (2009). The increased integration could be realised by extending power grids across borders. Policy makers could furthermore facilitate market coupling in order to allocate existing supply more effectively. (Hulle, 2009)

Another method of mitigating risk is to promote a diversified power supply. In particular, dispatchable plants can be used to offset the intermittent nature of wind power. Incentivising uptake of dispatchable technologies may be challenging, however, due to high investment costs. (Ketterer, 2014) Moreover, a lower market price, due to more wind power, decreases the number of hours in which it is profitable to operate these plants. It may therefore take longer to recover the high investment cost. Investors may also need compensation for the increased price uncertainty arising from greater generation of wind power. Ketterer (2014) highlights a number of ways in which policy makers could incentivise uptake, including promoting capacity payments and access to capacity markets. The literature is divided, however, on the effectiveness of such interventions. (Ketterer, 2014) Further research is required to assess the ability of such measures to incentivise investment in dispatchable power in the Nordic-Baltic market.

Two additional policy tools merit consideration. Firstly, promoting research in cost effective storage of electricity may be beneficial. If electricity could be stored at a sufficiently low cost, any excess could be used to offset shortages during periods of low wind supply, and smooth price jumps caused by wind generation. Currently, however, storage is economically unfeasible. Secondly, energy agencies and relevant stakeholders could encourage better risk management by producers. The financial market of Nord Pool Spot contains instruments allowing producers to hedge against price risk. However, as noted by Woo et al. (2011), uptake of these instruments may be limited by a lack of awareness. Sensitising producers about the available products may increase familiarity and ultimately use.

8.2 Limitations

Several constraints are inherent to this study. Firstly, the external validity of the distributional impact of wind power is circumscribed by the idiosyncrasies of the Nordic-Baltic electricity market. The member countries of Nord Pool Spot are highly integrated which lends them a shield against the intermittency of wind. Erratic in-feed of wind power in Sweden and Denmark can be balanced by generating dispatchable power in other regions of Nord Pool Spot. The effect of wind power on price volatility in Nord Pool Spot may therefore be lower in absolute terms than in isolated markets. Secondly, it is beyond the scope of this study to juxtapose all the costs and benefits of integrating more wind power. Such an analysis would be relevant, however, in order to fully assess whether promoting wind power increases societal welfare. Thirdly, the impact on the price level and volatility in the *retail* market is not considered. Indeed, this study focuses on the *wholesale* market and does not examine the extent to which the effects are transmitted to end consumers. Finally, the analysis on the differential impact of wind power on the price level and volatility is static and assumes a constant price elasticity across the independent variables. Relaxing these assumptions may change the effect of wind power under different demand and wind power supply scenarios.

9 Conclusion

The impact of the recent rise in wind power on electricity markets in Europe is increasingly attracting attention. This study examines the effect of the volume of Swedish and Danish wind power on the level and the volatility of the electricity price in the Nordic-Baltic day-ahead wholesale market. Hourly data are used in an ARX-GARCHX framework. The results indicate that more wind power reduces the price level. A merit order effect of wind power is therefore found. Additional wind power is furthermore shown to increase the price volatility. The effects on the price level and volatility are economically significant, and robust to alternative model specifications, including the addition of autoregressive and moving average components. A lower and more volatile price may have important consequences for the stability of the Nordic-Baltic electricity market. A reduced price may decrease industry profitability and threaten the existence of costly dispatchable plants. Greater price volatility may increase the risk of activating non-dispatchable sources of power. Supply may therefore decline while maintaining the electricity balance may become more difficult.

Several exogenous variables are controlled for. Market coupling, demand and the oil price increase the price level, while hydro power exerts an ambiguous influence. Thus, only partial evidence for a merit order effect of hydro power in the Nordic-Baltic electricity market is provided. An increase in market coupling and hydro power furthermore increase price volatility, while the opposite effect is observed for the oil price. The hypothesised positive relationship between demand and price volatility is only partially supported, as both a positive and negative relationship are found. The role of demand in the Nordic-Baltic electricity market may therefore be less clear cut than theory suggests.

The differential impact of wind power is also investigated. The effect of adding wind power on the price level and volatility is simulated for different levels of demand and existing wind power supply. When demand is relatively high, the effects of wind power are generally accentuated. Thus, adding wind power reduces the price and increases its volatility to a larger extent in these situations. Similarly, the impact of increasing the volume of wind power on both the price level and volatility is stronger when the existing supply of wind power is relatively low. The findings are in line with theory and suggest that wind power crowds out more expensive technologies when either demand is relatively high or existing wind power supply is relatively low.

For future research, a cost benefit analysis of integrating more wind power in the transmission system would paint a clearer picture of the overall effect on producer and consumer surplus.

Understanding whether more wind power translates into higher welfare is indeed pertinent. Forecasting the effect of adding more wind power in the future is also desirable, as both Sweden and Denmark aim to further expand their generation capacity. The impact of demand on price volatility as well as the effect of hydro power on the price level furthermore merit more attention, given the ambiguous relationships observed in this study. Finally, future research could focus on ways of mitigating the price uncertainty risk from increased wind power. Exploring the feasibility and impact of further integrating the Nordic-Baltic electricity market with the rest of Europe may in particular be relevant.

10 Bibliography

Azofra, D., Jiménez, E., Martínez, E., Blanco, J., & Saenz-Díez, J. (2014). Wind power merit-order and feed-in-tariffs effect: A variability analysis. *Energy Conversion and Management, 83*, 19-27.

Bhar, R., Colwell, D. B., & Xiao, Y. (2013). A jump diffusion model for spot electricity prices and market price of risk. *Physica A: Statistical Mechanics and its Applications, 392*(15), 3213-3222.

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

Cartea, A., & Figueroa, M. G. (2005). Pricing in electricity markets: A mean reverting jump diffusion model with seasonality. *Applied Mathematical Finance, 12*(4), 313-335.

Chang, W. (2014). A Literature Review of Wind Forecasting Methods. *Journal of Power and Energy Engineering, 2*(4), 161-168.

Clò, S., Cataldi, A., & Zoppoli, P. (2015). The merit-order effect in the Italian power market: The impact of solar and wind generation on national wholesale electricity prices. *Energy Policy, 77*, 79–88.

Contreras, J., Espinola, R., Nogales, F. J., & Conejo, A. J. (2003). 2003. *IEEE transactions on power systems, 18*(3), 1014-1020.

Danish Wind Industry Association. (2016). *The Danish Market.* Retrieved October 5, 2016, from the web site of the Danish Wind Industry Association: http://www.windpower.org/en/knowledge/statistics/the_danish_market.html

Delarue, E. D., Luickx, P. J., & D'haeseleer, W. D. (2009). The Actual Effect of Wind Power on Overall Electricity Generation Costs and CO2 Emissions. *Energy Conversion and Management, 50*, 1450-1456.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association, 74*(366), 427-431.

Dukascopy. (2016). *Historical Data Feed.* Retrieved November 2, 2016, from the web site of Dukascopy: https://www.dukascopy.com/swiss/english/marketwatch/historical/

Ei. (2014). *Ett faktablad från Energimarknadsinspektionen.* Energimarknadsinspektionen.

Ei. (2016). *The Swedish electricity and natural gas market 2015.* Energimarknadsinspektionen.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica, 64*(4), 813-836.

Empower. (2016). *Elspot trading.* Retrieved October 20, 2016, from the web site of Empower: http://www.empower.eu/elspot-trading

Energinet.dk. (2016). *New record-breaking year for Danish wind power.* Retrieved October 10, 2016, from the web site of Energinet.dk: http://energinet.dk/EN/El/Nyheder/Sider/Dansk-vindstroem-slaar-igen-rekord-42-procent.aspx

Enevoldsen, S. W., Østergaard, P. A., Morthorst, P. E., & Moesgaard, R. (2006). *Vindkraftens betydning for elprisen i Danmark.* IBT Wind.

Engle, R. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*, 987-1007.

Engle, R. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives*, 157-168.

ENTSO-E. (2016). *Elspot capacities.* Retrieved 5 November, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/Market-data1/Elspot/Capacities1/Capacities/KEY/Norway/?view=table

ENTSO-E. (2016). *Statistical database.* Retrieved September 15, 2016, from the web site of ENTSO-E: https://www.entsoe.eu/data/data-portal/Pages/default.aspx

Escribano, A., Pena, I., & Villaplana, P. (2011). Modeling electricity prices: International evidence. *Oxford Bulletin of Economics and Statistics*, 622-650.

EWEA. (2009). *The Economics of Wind Energy* . European Wind Energy Association.

EWEA. (2016). *Wind in power: 2015 European statistics.* EWEA.

Forrest, S., & MacGill, I. (2013). Assessing the impact of wind generation on wholesale prices and generator dispatch in the Australian National Electricity Market. *Energy Policy, 59*, 120-132.

Green, R. (2012). How Denmark manages its wind power. *IAEE Energy Forum, 3rd Quarter*, (pp. 9-11).

Green, R., & Vasilaskos, N. (2012). Storing Wind for a Rainy Day: What kind of electricity does Denmark export? *Energy policy, 33*(3), 1-22.

GWEC. (2016). *Global Wind 2015 Report.* Brussels: Global Wind Energy Council.

Huisman, R., Huurman, C., & Mahieu, R. (2007). Hourly electricity prices in day-ahead markets. *Energy Economics, 29*(2), 240-248.

Huisman, R., Michels, D., & Westgaard, S. (2015). Hydro reservoir levels and power price dynamics. Empirical insight on the nonlinear influence of fuel and emission cost on Nord Pool day-ahead electricity prices. *Journal of Energy and Development*, 149-187.

Hulle, F. v. (2009). *Integrating wind. Final report of the TradeWind project, European Wind Energy Association and TradeWind Consortium.* TradeWind.

IRENA. (2012). *30 Years of Policies for Wind Energy.* IRENA.

Jónsson, T., Pinson, P., & Madsen, H. (2010). On the market impact of wind energy forecasts. *Energy Economics, 32*(2), 313-320.

Keles, D., Genoese, M., Möst, D., & Fichtner, W. (2012). Comparison of extended mean-reversion and time series models for electricity spot price simulation considering negative prices. *Energy Economics, 34*(4), 1012-1032.

Ketterer, J. C. (2014). The impact of wind power generation on the electricity price in Germany. *Energy Economics, 44*, 270-280.

Knittel, C., & Roberts, M. (2005). An empirical examination of restructured electricity prices. *Energy Economics, 27*(5), 791-817.

Ledvina, A., & Sircar, R. (2011). Bertrand and Cournot Competition Under Asymmetric Costs: Number of Active Firms in Equilibrium. *SSRN Electronic Journal.*

Li, Y. (2015). Quantifying the impacts of wind power generation in the day-ahead market: The case of Denmark. *AFSE 2015 64th Congress.* Rennes.

Ljung, G., & Box, G. (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrika*, 297-303.

Mauritzen, J. (2012). What happens when it's wind in Denmark? An empirical analysis of wind power on price variability in the Nordic electricity market. *Research Institute of Industrial Economics*.

Munksgaard, J., & Morthorst, P. E. (2008). Wind power in the Danish liberalised power market - Policy measures, price impact and investor incentives. *Energy Policy, 36*(10), 3940-3947.

Möbert, J. (2007). *Crude Oil Price Determinants.* Darmstadt: Darmstadt Discussion Papers in Economics.

Nelson, D. B., & Cao, C. Q. (1992). Inequality constraints in the univariate GARCH model. *Journal of Business & Economic Statistics, 10*(2), 229-235.

Nord Pool Spot. (2016a). *Historical Market Data.* Retrieved September 20, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/historical-market-data/

Nord Pool Spot. (2016b). *The power market.* Retrieved September 10, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/How-does-it-work/

Nord Pool Spot. (2016c, January 13). *Nord Pool Spot 2015 Traded Volumes - New all-time high in the Nordic/Baltic market*. Retrieved September 11, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/message-center-container/nordicbaltic/exchange-message-list/2016/q1/no.-42016---nord-pool-spot-2015-traded-volumes---new-all-time-high-in-the-nordicbaltic-market/

Nord Pool Spot. (2016d). *Day-ahead market.* Retrieved September 30, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/How-does-it-work/Day-ahead-market-Elspot-/

Nord Pool Spot. (2016e). *Price calculation.* Retrieved October 9, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/TAS/Day-ahead-market-Elspot/Price-calculation/

Nord Pool Spot. (2016f). *Bidding areas.* Retrieved September 11, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/How-does-it-work/Bidding-areas/

Nord Pool Spot. (2016g). *System price.* Retrieved September 20, 2016, from the web site of Nord Pool Spot: http://www.nordpoolspot.com/Market-data1/Elspot/Area-Prices/SYS1/Hourly/?view=table

O'Mahoney, A., & Denny, E. (2011). The merit order effect of wind generation in the Irish electricity market. *30th USAEE/IAEEE North American Conference.* Washington DC.

Ray, S., Munksgaard, J., Morthorst, P. E., & Sinner, A.-F. (2010). *Wind Energy and Electricity Prices: Exploring the 'merit order effect'*. Brussels: European Wind Energy Association.

Sáenz de Miera, G., del Río González, P., & Vizcaíno, I. (2008). Analysing the impact of renewable electricity support schemes on power prices: The case of wind electricity in Spain. *Energy Policy, 36*(9), 3345-3359.

Schaber, K., Steinke, F., & Hamacher, T. (2012). Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? *Energy Policy, 43*, 123-135.

Sensfuss, F. (2011). *Analysen zum Merit-Order Effekt erneuerbarer Energien: Update für das Jahr 2010.* Karlsruhe: Fraunhofer Institute for Systems and Innovation Research.

Sensfuss, F., Mario, R., & Genoese, M. (2007). Merit Order Effect: A Detailed Analysis of the Price Effect of Renewable Electricity Generation on Spot Prices in Germany. *Energy Policy, 36*, 3086-3094.

State of Green. (2015). *Wind Energy Moving Ahead.* State of Green.

Statkraft. (2016). *Hydropower.* Retrieved October 5, 2016, from the web site of Statkraft: http://www.statkraft.com/energy-sources/hydropower/

Steggals, W., Gross, R., & Heptonstall, P. (2011). Winds of change: How high wind penetrations will affect investment incentives in the GB electricity sector. *Energy Policy, 39*(3), 1389-1396.

Swedish Energy Agency. (2006). *Price Formation and Competition in the Swedish Electricity Market, Main findings of ER 2006:13 EMIR 2006:02.* Swedish Energy Agency.

Swedish Energy Agency. (2015). *Energy in Sweden 2015.* Swedish Energy Agency.

Swedish Energy Agency. (2016a). *Vindkraftstatistik 2015.* Swedish Energy Agency.

Swedish Energy Agency. (2016b). *Vindkraft i Sverige.* Retrieved October 26, 2016, from the web site of the Swedish Energy Agency: http://www.energimyndigheten.se/fornybart/vindkraft/marknadsstatistik/ny-sida/

Swedish Wind Energy. (2013). *På väg mot ett förnybart elsystem - möjligheter till 2030.* Swedish Wind Energy.

Swedish Wind Energy. (2016). *Vindkraftstatistik och prognos.* Swedish Wind Energy.

Svenska Kraftnät. (2011). *The electricity market in Sweden and the role of Svenska Kraftnät.* Svenska Kraftnät.

Svenska Kraftnät. (2015). *Anpassning av elsystemet med en stor mängd förnybar elproduktion.* Svenska Kraftnät.

Söder, L. (2014). *På väg mot en elförsörjning baserad på enbart förnybar el i Sverige.* Kungliga Tekniska Högskolan.

The Wind Power. (2016, December 12). *Countries.* Retrieved from the web site of The Wind Power: http://www.thewindpower.net/country_list_en.php

Thoenes, S. (2014). Understanding the determinants of electricity prices and the impact of the German Nuclear Moratorium in 2011. *Energy Journal, 35*(4), 61-78.

Tsai, H., & Chan, K.-S. (2008). A Note on Inequality Constraints in the Garch Model. *Econometric Theory, 24*(3), 823-828.

Vattenfall. (2016). *Wind power at Vattenfall.* Retrieved October 4, 2016, from the web site of Vattenfall: https://corporate.vattenfall.com/about-energy/renewable-energy-sources/wind_power/wind-power-at-vattenfall/

Weigt, H. (2008). Germany's Wind Energy: The Potential for Fossil Capacity Replacement and Cost Saving. *Applied Energy, 86*, 1857-1863.

Weron, R. (2014). Electricity price forecasting: A review of the state-of-the-art with a look into the future. *30*(4), 1030-1081.

Woo, C., Horowitz, I., Moore, J., & Pacheco, A. (2011). The impact of wind generation on the electricity spot-market price level and variance: The Texas experience. *Energy Policy, 39*(7), 3939-3944.

Zivot, E. (2008). Practical Issues in the Analysis of Univariate GARCH. In T. Mikosch, J.-P. Kreiss, R. A. Davis, & T. G. Andersen, *Handbook of Financial Time Series* (pp. 113-155). Berlin: Springer Berlin Heidelberg.

11 Appendix

Table A. Descriptive Statistics

	Unit	Obs.	Mean	Min	Max	Std. dev.	Skewness	Kurtosis
Price	€/MWh	20,688	24.46	1.14	200	8.35	2.53	43.39
Deseasonalised price	€/MWh	20,688	24.35	4.61	56.61	5.31	0.14	4.81
Log deseasonalised price	-	20,688	3.17	1.53	4.04	0.23	-0.89	4.64
Wind	MWh	20,688	3,000	133	9,771	1,907	0.89	3.14
Log wind	-	20,688	7.79	4.89	9.19	0.70	-0.43	2.79
Demand	MWh	20,688	45,143	23,919	74,774	8,859	0.51	2.68
Deseasonalised demand	MWh	20,688	45,143	24,824	58,097	3,329	-0.40	4.08
Log deseasonalised demand	-	20,688	10.71	10.12	10.97	0.08	-0.76	5.10
Hydro	MW	20,688	23,317	9,600	29,812	6,449	-0.68	1.83
Deseasonalised hydro	MW	20,688	23,317	12,025	28,254	2,213	-1.42	7.74
Log deseasonalised hydro	-	20,688	10.05	9.39	10.25	0.11	-2.42	14.70
Oil price	€	20,688	48.45	23.18	79.00	14.26	0.77	2.45
Deseasonalised oil price	€	20,688	48.45	35.72	59.13	11.83	-0.45	3.42
Log deseasonalised oil price	-	20,688	3.88	3.58	4.08	0.07	-0.70	3.78
Coupling	MWh/h	20,688	763	-3,438	3,500	1,365	-0.68	2.58

Note: *Price* refers to the original system price series. *Deseasonalised price* is the price series after outliers have been removed (twice) and deseasonalisation. *Log deseasonalised price* is the logarithm of the deseasonalised price. *Wind* is the combined Swedish and Danish wind power and *Log wind* is its logarithm. *Demand* refers to the original forecasted consumption series. *Deseasonalised demand* and *Log deseasonalised demand* refer to the deseasonalised forecasted consumption series in level and logarithmic format respectively. *Hydro* is the proxy for the combined Norwegian and Swedish hydro power generation. *Deseasonalised hydro* is the hydro power series after deseasonalisation. *Log deseasonalised hydro* is the logarithm of the deseasonalised hydro series. *Oil price* alludes to the price of oil. *Deseasonalised oil price* and *Log deseasonalised oil price* are the deseasonalised oil price series in level and logarithmic format respectively. *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands.

Table B. Coefficients from the Deseasonalisation of the Electricity Price Series

Variable	Coefficient	Month	Coefficient	Day	Coefficient	Hour	Coefficient
Constant	36.01*** (0.27)	Feb	-4.43*** (0.21)	Tue	-0.13 (0.14)	01-02	-0.8*** (0.26)
2015	-10.3*** (0.1)	Mar	-5.09*** (0.2)	Wed	0.03 (0.14)	02-03	-1.26*** (0.26)
2016	-7.18*** (0.11)	Apr	-4.90*** (0.2)	Thu	0.21 (0.14)	03-04	-1.48*** (0.26)
Holiday	-3.8*** (0.25)	May	-7.2*** (0.19)	Fri	-0.69*** (0.14)	04-05	-1.21*** (0.26)
		Jun	-9.48*** (0.19)	Sat	-3.16*** (0.14)	05-06	-0.12 (0.26)
		Jul	-10.6*** (0.19)	Sun	-3.82*** (0.14)	06-07	1.80*** (0.26)
		Aug	-8.22*** (0.19)			07-08	4.27*** (0.26)
		Sep	-6.00*** (0.19)			08-09	5.55*** (0.26)
		Oct	-6.04*** (0.21)			09-10	5.42*** (0.26)
		Nov	-4.91*** (0.21)			10-11	5.14*** (0.26)
		Dec	-6.86*** (0.21)			11-12	4.69*** (0.26)
						12-13	4.14*** (0.26)
						13-14	3.78*** (0.26)
						14-15	3.50*** (0.26)
						15-16	3.49*** (0.26)
						16-17	3.68*** (0.26)
						17-18	4.43*** (0.26)
						18-19	4.66*** (0.26)
						19-20	4.06*** (0.26)
						20-21	3.26*** (0.26)
						21-22	2.78*** (0.26)
						22-23	2.06*** (0.26)
						23-00	0.80*** (0.26)

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level. Standard errors are in parentheses.

Table C. Coefficients from the Deseasonalisation of the Forecasted Demand Series[30]

Variable	Coefficient	Month	Coefficient	Hour	Coefficient
Cons	40*** (60)	Feb	-2477*** (125)	01-02	-1041*** (161)
2015	842 (69)	Mar	-6588*** (122)	02-03	-1526*** (161)
2016	-2539*** (147)	Apr	-11849*** (123)	03-04	-1607*** (161)
Holiday	52841*** (152)	May	-17674*** (115)	04-05	-1175*** (161)
		Jun	-19485*** (114)	05-06	558*** (161)
		Jul	-21781*** (113)	06-07	3629*** (161)
		Aug	-20258*** (113)	07-08	6837*** (161)
		Sep	-17780*** (118)	08-09	8434*** (161)
		Oct	-12657*** (127)	09-10	9009*** (161)
		Nov	-8309*** (128)	10-11	9291*** (161)
		Dec	-4695*** (127)	11-12	9097*** (161)
				12-13	8759*** (161)
				13-14	8424*** (161)
				14-15	8157*** (161)
				15-16	8032*** (161)
				16-17	8182*** (161)
				17-18	8554*** (161)
				18-19	8462*** (161)
				19-20	7874*** (161)
				20-21	6778*** (161)
				21-22	5701*** (161)
				22-23	4050*** (161)
				23-00	1878*** (161)

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level. Standard errors are in parentheses.

[30] Ideally, the daily variation could also have been removed from the series. The AR(MA)X-GARCHX processes become non-stationary when removing the daily trend, however. It was consequently kept for the demand series.

Table D. Coefficients from a *Hypothetical* Deseasonalisation of the Oil Price Series

Variable	Coefficient	Month	Coefficient	Day	Coefficient	Hour	Coefficient
Cons	64.67*** (0.17)	Feb	0.58*** (0.13)	Tue	-0.1 (0.09)	01-02	0.00 (0.17)
2015	-24.18*** (0.06)	Mar	3.56*** (0.13)	Wed	-0.18* (0.09)	02-03	0.00 (0.17)
2016	-33.78*** (0.07)	Apr	7.18*** (0.13)	Thu	-0.01 (0.09)	03-04	0.00 (0.17)
Holiday	-0.78*** (0.15)	May	11.5*** (0.12)	Fri	-0.08 (0.09)	04-05	0.00 (0.17)
		Jun	12.66*** (0.12)	Sat	-0.05 (0.09)	05-06	0.00 (0.17)
		Jul	9.42*** (0.12)	Sun	-0.11 (0.09)	06-07	-0.01 (0.17)
		Aug	5.00*** (0.12)			07-08	0.00 (0.17)
		Sep	5.04*** (0.12)			08-09	-0.01 (0.17)
		Oct	1.69*** (0.13)			09-10	-0.01 (0.17)
		Nov	-1.87*** (0.13)			10-11	-0.01 (0.17)
		Dec	-10.93*** (0.13)			11-12	0.00 (0.17)
						12-13	0.01 (0.17)
						13-14	0.01 (0.17)
						14-15	0.00 (0.17)
						15-16	-0.02 (0.17)
						16-17	-0.02 (0.17)
						17-18	-0.03 (0.17)
						18-19	-0.03 (0.17)
						19-20	-0.03 (0.17)
						20-21	-0.04 (0.17)
						21-22	-0.04 (0.17)
						22-23	-0.04 (0.17)
						23-00	-0.04 (0.17)

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level. Standard errors are in parentheses.

Table E. Coefficients from the *Actual* Deseasonalisation of the Oil Price Series

Variable	Coefficient	Month	Coefficient
Cons	64.55*** (0.11)	Feb	0.60*** (0.13)
2015	-24.18*** (0.06)	Mar	3.56*** (0.13)
2016	-33.77*** (0.07)	Apr	7.17*** (0.13)
		May	11.47*** (0.12)
		Jun	12.65*** (0.12)
		Jul	9.45*** (0.12)
		Aug	5.03*** (0.12)
		Sep	5.06*** (0.12)
		Oct	1.72*** (0.13)
		Nov	-1.85*** (0.13)
		Dec	-10.97*** (0.13)

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level. Standard errors are in parentheses.

Table F. Coefficients from the Deseasonalisation of the Hydro Power Series

Variable	Coefficient	Month	Coefficient
Cons	15181*** (69)	Feb	1590*** (83)
2015	12962*** (40)	Mar	1550*** (81)
2016	11470*** (46)	Apr	328*** (82)
		May	-386*** (77)
		Jun	-1826*** (76)
		Jul	-2802*** (75)
		Aug	-3644*** (75)
		Sep	-2335*** (78)
		Oct	-519*** (84)
		Nov	385*** (85)
		Dec	766*** (84)

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level. Standard errors are in parentheses.

Table G. Stationarity Test Statistics

	Optimal lag length of Augmented Dickey-Fuller test	Augmented Dickey-Fuller test statistics	Dicky-Fuller GLS test statistics
Log price	8	-13.40***	-5.32***
Log wind	6	-15.23***	-10.61***
Log demand	9	-18.91***	-15.77***
Log hydro	9	-8.11***	-3.93***
Log oil price	0	-5.28***	-3.53***
Coupling	9	-20.26***	-3.09***

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level
Note: Log price is the logarithm of the deseasonalised price series. *Log wind* refers to the logarithm of the combined Swedish and Danish wind power. *Log demand* is the logarithm of the deseasonalised projected consumption of power on Elspot. *Log hydro* alludes to the logarithm of the deseasonalised proxy for the combined Norwegian and Swedish hydro power generation. *Log oil price* alludes to the logarithm of the deseasonalised price of oil. Finally, *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands.

Table H. Ljung-Box Q Statistics for the Error Term of an AR(1) process of the logarithmic deseasonalised price

Lag length	Ljung-Box Q Statistics
1	2,622***
4	3,376***
6	4,006***
8	4,310***
12	4,572***

Note: ***Significant at one percent level, **significant at five percent level, and *significant at 10 percent level

Table I. Summary Statistics of Variables per Interval of Demand

	Mean per Interval							
Intervals of demand (MWh)	Number of observations	Log price level (€/MWh)	Log price variance (€/MWh)	Log wind	Log demand	Log hydro	Log oil price	Coupling (MWh/h)
0-40000	1,551	21.73	0.00012	8.21	10.55	10.02	3.91	-190.30
40,000-42,000	1,993	23.19	0.00020	8.09	10.62	10.06	3.89	224.14
42,000-44,000	2,9	24.33	0.00026	8.07	10.67	10.04	3.89	735.74
44,000-46,000	5,372	25.40	0.00033	7.93	10.72	10.05	3.88	841.72
46,000-48,000	5,408	26.19	0.00042	7.97	10.76	10.06	3.87	943.18
>48,000	3,464	27.48	0.00057	7.97	10.81	10.07	3.86	1119.82

Note: The table refers to the *simulated* mean of each variable for each interval of demand using the coefficients in column (E) of Table 4, given zero variation in wind power. *Log price level* is the logarithm of the deseasonalised price series. *Log price variance* is the logarithm of the conditional variance of the price series. *Log wind* refers to the logarithm of the combined Swedish and Danish wind power. *Log demand* is the logarithm of the deseasonalised projected consumption of power on Elspot. *Log hydro* alludes to the logarithm of the deseasonalised proxy for the combined Norwegian and Swedish hydro power generation. *Log oil price* alludes to the logarithm of the deseasonalised price of oil. Finally, *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands.

Table J. Change in the Price Level and Volatility for each Interval of Demand Given a Sudden Increase in Wind Power Supply by 500 MWh

Interval of demand (MWh)	Change in the Price Level	Change in the Price Volatility
0-40,000	-0.53%	1.49%
40,000-42,000	-0.60%	1.68%
42,000-44,000	-0.61%	1.71%
44,000-46,000	-0.69%	1.94%
46,000-48,000	-0.67%	1.88%
>48,000	-0.67%	1.88%

Table K. Summary Statistics per Interval of Initial Wind Power Supply

	Mean per Interval							
Intervals of initial wind power supply (MWh)	Number of observations	Price level (€/MWh)	Price variance (€/MWh)	Log wind	Log demand	Log hydro	Log oil price	Coupling (MWh/h)
0-800	1,447	27.04	0.00026	6.36	10.71	10.04	3.88	698.91
800-1,600	4,233	26.28	0.00031	7.10	10.72	10.06	3.88	704.65
1,600-2,400	4,135	25.91	0.00034	7.59	10.72	10.06	3.88	917.15
2,400-3,200	3,010	25.40	0.00034	7.93	10.72	10.06	3.87	839.79
3,200-4,000	2,456	25.08	0.00035	8.18	10.71	10.05	3.87	882.85
4,000-4,800	1,625	24.95	0.00036	8.39	10.72	10.05	3.87	779.40
4,800-5,600	1,344	24.62	0.00034	8.55	10.71	10.05	3.87	603.63
>5,600	2,438	23.88	0.00028	8.83	10.69	10.03	3.90	503.00

Note: The table refers to the *simulated* mean of each variable for each interval of existing wind power supply using the coefficients in column (E) of Table 4, given zero variation in wind power. *Log price level* is the logarithm of the deseasonalised price series. *Log price variance* is the logarithm of the conditional variance of the price series. *Log wind* refers to the logarithm of the combined Swedish and Danish wind power. *Log demand* is the logarithm of the deseasonalised projected consumption of power on Elspot. *Log hydro* alludes to the logarithm of the deseasonalised proxy for the combined Norwegian and Swedish hydro power generation. *Log oil price* alludes to the logarithm of the deseasonalised price of oil. Finally, *Coupling* is the net market coupling between Nord Pool Spot and Germany as well as the Netherlands.

Table L. Change in the Price Level and Volatility for each Interval of Initial Wind Power Supply Given a Sudden Increase in Wind Power Supply by 500 MWh

Interval of Initial Wind Power Supply (MWh)	Change in the Price Level	Change in the Price Volatility
0-800	-2.58%	7.52%
800-1,600	-1.44%	4.11%
1,600-2,400	-0.94%	2.66%
2,400-3,200	-0.69%	1.94%
3,200-4,000	-0.55%	1.54%
4,000-4,800	-0.45%	1.26%
4,800-5,600	-0.39%	1.08%
>5,600	-0.30%	0.83%

Figure A. The Bidding Areas of Nord Pool Spot
Source: Figure obtained from Ei (2016)

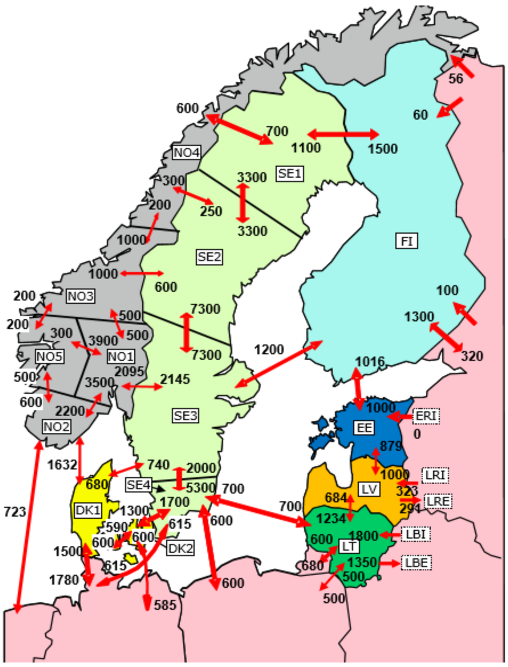

Figure B. Maximum Net Transmission Capacities (MW) of Nord Pool Spot Members
Source: Figure obtained from ENTSO-E (2016)

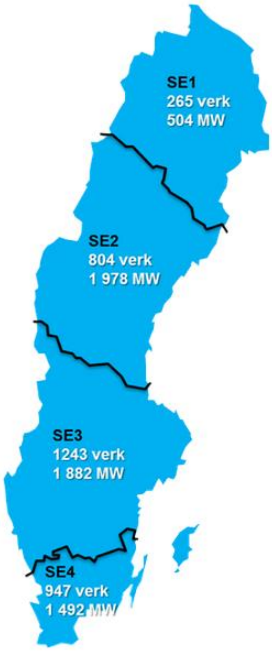

Figure C. Geographical Distribution of Wind Power capacity in Sweden in 2015
Source: Figure obtained from the Swedish Energy Agency (2016b)

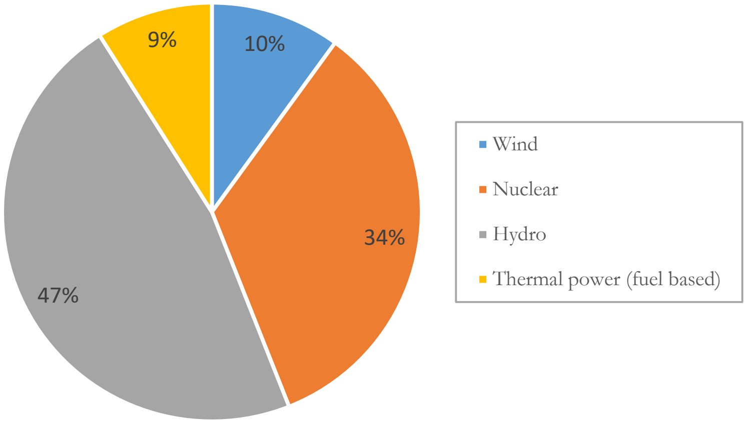

Figure D. Composition of the Electricity Production in Sweden in 2015
Source: Author's own illustration based on data from the Swedish Energy Agency (2016a)

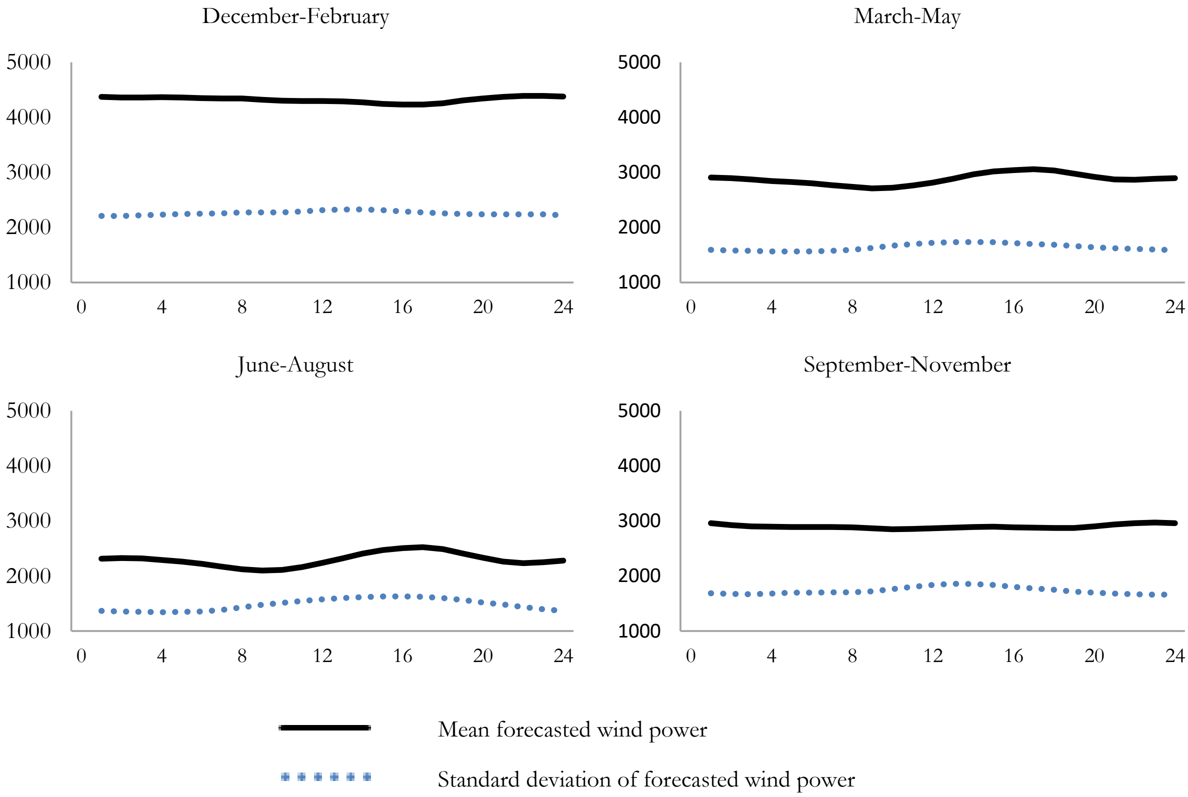

Figure E. Average Forecasted Wind Power (MWh) per Hour of the Day and Season
Source: Author's own illustrations based on data from Nord Pool Spot (2016a)

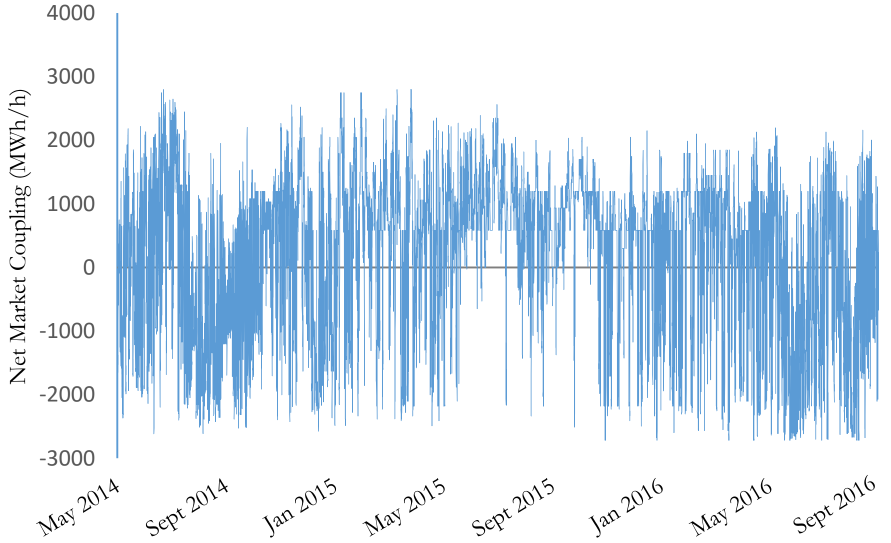

Figure F. Net Market Coupling Series
Source: Author's own illustration based on data from Nord Pool Spot (2016a)

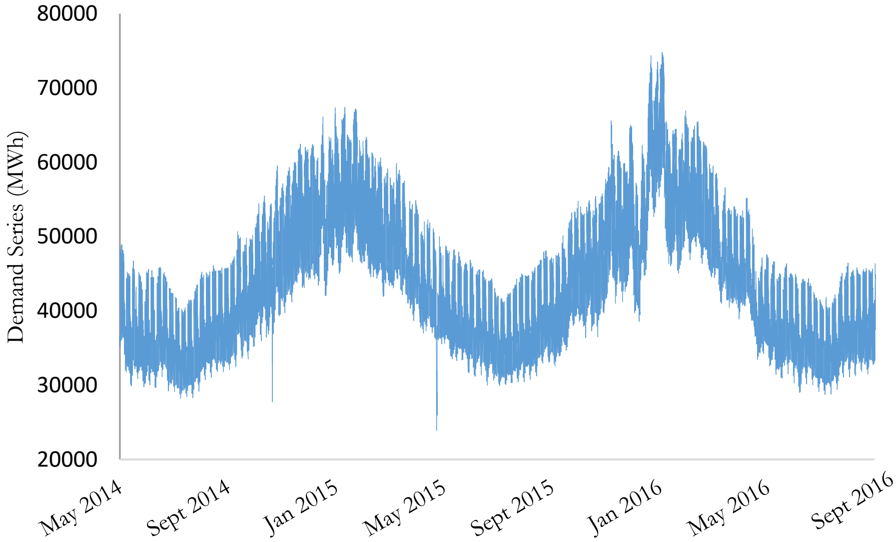

Figure G. Forecasted Demand Series
Source: Author's own illustrations based on data from Nord Pool Spot (2016a)

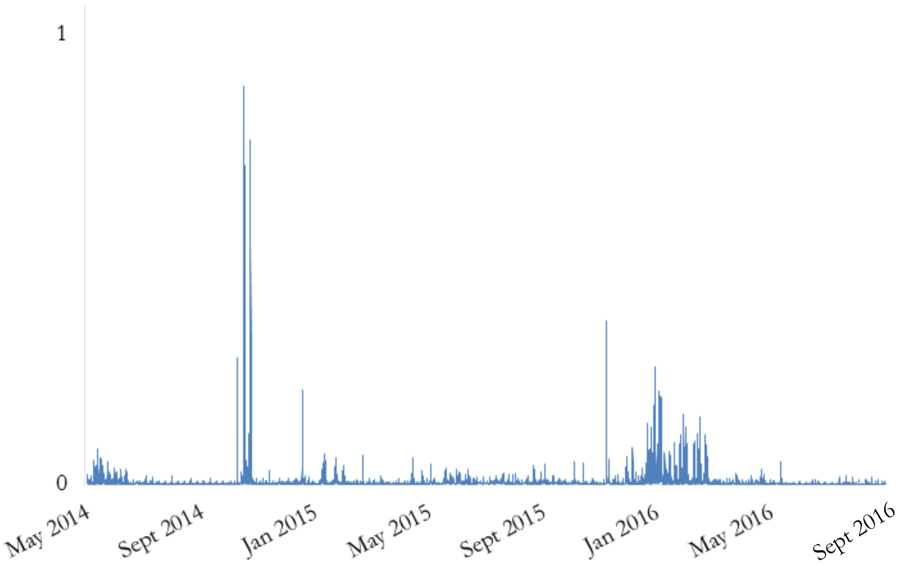

Figure H. Conditional Variance of ARX(1,5)-GARCHX(1,1)
Source: Author's own illustrations based on data from Nord Pool Spot (2016a)