STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
659 Degree Project in Economics
Spring 2018

Varying Winds

A Study of the Effect of Wind Power Production on Electricity Price Volatility in Southern Sweden

David Grünler (23493) and Hilla Inkinen (23551)

Abstract

Using an autoregressive time series framework, we exploit exogenous changes in forecasted wind power production to estimate the effect of temporarily increased production on electricity price volatility. Analyzing data of hourly day-ahead electricity prices and hourly forecasted wind power production in the south of Sweden from 2015 to 2018, we find that a temporary increase in the daily average level of wind power production is associated with decreased daily average volatility. The effect is robust to different specifications and to the inclusion of control variables, however, isolating the contribution from Swedish wind power production is difficult due to high correlation with Danish wind power production. Extending the analysis to the impact of daily variations in wind power production on daily average electricity price volatility, conflicting results are found. In the long run, the increased installed wind power capacity in Sweden is found to have been accompanied by a general increase in volatility, however, causality cannot be established due to endogeneity in the relationship and limitations in capacity data.

Keywords: Wind Power, Renewable Resources, Wholesale Electricity Market, Electricity Price Volatility, Time Series Analysis
JEL: L11, Q02, Q41, Q42

Supervisor:	Mark Bernard
Date submitted:	May 15, 2018
Date examined:	May 30, 2018
Discussants:	Axel Granström (23550) and Ludwig Tarnow (23248)
Examiner:	Johanna Wallenius

Acknowledgements

First and foremost, we are grateful to our supervisor, Mark Bernard, for contributing with many insightful tips and comments. Additionally, we would like to thank Cristian Huse for inspiration and literature recommendations and acknowledge Elle Parslow for her help with time series analysis. Finally, we express our gratitude to our friends Fabian, Nina, Marcus, and Olivia for their support in the writing process.

TABLE OF CONTENTS

1 Introduction 1

2 Background 3

2.1 Characteristics of Electricity and Different Energy Sources 3

2.2 Common Wholesale Market for Electricity 4

2.3 Electricity Production Statistics 6

3 Literature Review 9

3.1 Theory 9

3.2 Empirical Evidence 11

4 Empirical Strategy 15

4.1 Identification 15

4.2 Data 18

4.3 Method 20

5 Results 27

5.1 Long-Run Analysis 27

5.2 Model Specification for Daily Volatility 29

5.3 Short-Run Analysis 31

6 Discussion 36

6.1 Internal Validity 36

6.2 External Validity 36

6.3 Other Limitations and Considerations 37

7 Conclusion 37

References 39

APPENDICES 45

Appendix 1: Definitions 45
Appendix 2: Electricity Production Statistics 46
Appendix 3: Seasonal Adjustment 47
Appendix 4: Augmented Dickey-Fuller Test 48
Appendix 5: Alternative Model Specifications 49

1 Introduction

In 2017, the Swedish Commission on Energy announced a plan for future electricity production in Sweden, including the goal of 100 percent renewable energy by 2040 (Energikommissionen 2017, in Swedish). Nuclear power, the predominant non-renewable energy source in Sweden, accounts today for 40 percent of the total electricity production. The Swedish electricity transmission system operator, Svenska Kraftnät, estimates that the nuclear capacity will be replaced mainly with wind power (2017, p. 24). However, wind power is an energy source, variable by its nature, and this variability can have a large impact on the stability of the power system; if wind power increases in importance, the system will become more susceptible to variations in weather conditions.

Svenska Kraftnät expects that a larger installed capacity of wind power production will lead to increasing challenges in matching demand and supply, leading to higher volatility in wholesale electricity prices (pp. 25–26). Intuitively, higher volatility translates to higher uncertainty, and this uncertainty might deter investment in electricity-generating capacity. Analyzing the possible adverse effects of wind power on electricity price behavior, as well as, understanding the full consequences of supporting wind power, is of great importance from a policy standpoint, especially when wind power is promoted through investment or market subsidies. If wind power is related to a higher volatility and higher risks, responsive measures should be taken to avoid imposing unnecessary social costs.

Previous literature establishes a clear negative relationship between wind power production and electricity price level, however, the effect of wind power production on price volatility is not as clear-cut. Studies on the Nordic-Baltic region have focused on the common electricity market as a whole or on Denmark, most likely as it has the world's highest share of wind power production (IEA 2017). Literature on its neighboring country, Sweden, which has the same amount of wind power in absolute terms and ambitious plans for wind power in the future, is considerably scarcer. Analyzing the Nordic-Baltic electricity market as a whole overlooks characteristics that

are unique to Sweden, such as the vastness of the country, the large amounts of hydropower and wind power present, and heterogeneous electricity bidding areas[1]. Due to this, a more in-depth analysis of the country can be seen as a valuable contribution to the literature.

The aim of our Bachelor's thesis is to analyze the relationship between wind power and electricity price volatility in Sweden. Our specific object of interest is the southernmost bidding area, denoted Malmö or SE4, due to its high share of wind power and close geographic proximity to areas with large-scale wind power production. Moreover, Svenska Kraftnät estimates that the aforementioned challenges may be the most pronounced in this area (p. 26). The day-ahead area price of SE4 is analyzed as this measure represents the prices at which electricity is traded. We seek to answer the following questions:

(1) How does wind power capacity affect price volatility in the long term?

(2) How does the level and volatility of wind power production in SE4 affect the daily average volatility of the day-ahead area price in SE4?

Even though the effect of wind power on price volatility should be the most apparent in the long-run, a causal relationship is complicated by endogeneity in the relationship. Therefore, the empirical part of our thesis will focus on the short-run effects, which could give us an indication of the long-term implications of wind power as well. We utilize exogenous variations in wind power production to estimate the impact of increased production on the daily volatility of the day-ahead area price. We employ an autoregressive time series model with one lag of the dependent variable and exogenous inputs to estimate this relationship. The same framework is extended to the analysis of volatility in wind power production.

The rest of this thesis is organized as follows: section two provides background information and section three summarizes relevant theory and empirical evidence. The empirical framework applied in this thesis and a discussion of the data are introduced in section four, followed by a presentation and an analysis of our results in section five. In section six, we discuss the implications and limitations of our analysis. Finally, concluding remarks and suggestions for future research are given in section seven.

[1]Svenska Kraftnät uses the term *electricity area*. In this thesis, we use the term *bidding area*, which is more commonly used in the context of electricity trading.

2 Background

In the following section, we introduce the main terms that are used throughout our thesis. Furthermore, to provide an insight into the functioning of the common wholesale electricity market for the Nordic[2] and Baltic countries, we describe the characteristics of different energy sources, explain the price-setting mechanisms, and provide statistics on electricity production and consumption in the region, focusing especially on Sweden.

2.1 Characteristics of Electricity and Different Energy Sources

Electricity is a homogeneous good that cannot be conveniently stored in order to be sold at a later time like other commodities. Electricity is produced at the same time it is consumed, creating a need for a well-functioning system, from electricity producer to final consumer. Demand for electricity, commonly referred to as *load*[3], must be matched with adequate supply at each point in time as consumers expect to have access to electricity when needed. The demand that has to be met at all times is called *baseload*, while the hours when demand is at its highest are called *peak load*.

A general attribute of renewables such and wind and solar power is that they are not able to provide a constant supply of electricity due to meteorological reasons, a characteristic called *intermittency*. This entails that renewable energy is not suitable as a baseload generation capacity (van Kooten 2016) and that renewable electricity production is more or less uncontrollable from the producers' perspective (Cullen 2013). The intermittent nature of renewables poses certain challenges also to the power system as a whole, and these challenges are especially pronounced in areas with a high dependency on these energy sources. As suggested by Gowrisankaran et al. (2016), intermittent renewable energy can increase the need for backup electricity generation capacity and can affect the reliability of the electrical grid considerably. Reliability can be en-

[2]Iceland does not take part in the common wholesale market for electricity. For simplicity, we use the Nordic countries when referring to Sweden, Norway, Denmark, and Finland.

[3]Load and demand are used interchangeably throughout this thesis.

hanced with geographical dispersion of generation capacity since it is unlikely that production from intermittent resources is perfectly correlated. However, the risk of notable correlation of production despite dispersion remains (van Kooten)[4].

Nuclear power is part of the baseload and can be considered as inflexible (Söder and Ackermann 2005, p. 25) but can produce electricity constantly, except for maintenance and unforeseen shutdowns (van Kooten). Hydropower is a more flexible source of electricity as the production can be ramped up and down to balance intermittent energy sources. Certain limitations exist in Sweden today as most hydropower plants were built at a time with virtually no wind power in the system and are therefore designed to balance demand rather than other intermittent energy sources (Svenska Kraftnät 2017, p. 25). Additionally, low reservoir levels can severely limit the possibility for matching supply and demand in periods of low production from intermittent resources (Nord Pool 2017a).

2.2 Common Wholesale Market for Electricity

In the 1990's, the Nordic countries decided to leave the state-run model of the power markets and begin allowing competition. The company Nord Pool AS was created to provide a common marketplace for electricity trading within the Nordic countries. Estonia, Latvia and Lithuania joined the common market in the 2010's. Nord Pool is fully owned by the Nordic and Baltic transmission system operators and is the main platform for trading electricity in the region. (Nord Pool 2017b; Nord Pool 2017c)

Just like in all power markets, there are many parties involved in Nord Pool. The *transmission system operators* are responsible for balancing the power system in their national area. They maintain the electrical grid and assure that there is always a balance throughout the day between supply and demand. The transmission system operators must be independent and non-commercial in nature, making them usually state-owned. This is the case for the Swedish transmission system operator Svenska Kraftnät. Other market actors include *producers*, who generally sell their electricity on the wholesale power market to *suppliers* that enter into contracts with the *end consumer*, usually a company or a household. Some large end consumers

[4] As pointed out by van Kooten, the findings of Oswald et al. (2008) provide an example for this. The authors identify periods where no electricity from wind power was produced in the whole of Europe.

might buy electricity straight from the wholesale market. To ensure that electricity reaches the end consumer, there are local *distributors*. These are monopolistic in nature as each distributor is solely responsible for delivering the electricity in their local area. (Nord Pool 2017d)

Day-Ahead Market and Price-Setting Mechanisms

The main market for electricity trading in Nord Pool is the day-ahead market, where market actors bid for electricity to be transmitted or received during each hour of the day. Bids for the week are opened on Monday, two weeks before, and are accepted until mid-day the day before electricity is to be transmitted. Market clearing prices are determined from this, and bids outside the range are discarded. (Nord Pool 2017e) However, there are some restrictions on transmission capacity, making it infeasible in some instances to complete trades in all regions at the same price. For this reason, the algorithm used by Nord Pool computes two types of prices:

I. System price

The *system price* is determined as if there were no physical restrictions preventing electricity from flowing freely between regions (Nord Pool 2017d). The calculation also includes trade with the Netherlands and Germany, incorporating them into the regions they trade with. The system price is generally used as a reference price for contracts traded on financial markets, where no actual transfer of electricity takes place (Nasdaq OMX 2018).

II. Area prices

Area prices are calculated based on the location of the bids and the capacity available between areas. As specific area prices are based on available transmission capacity, it allows areas with low prices to export electricity to areas where the price and demand are higher. These are the prices that are paid for electricity in each region by the suppliers (Nord Pool 2017f). Since 2011, Sweden has been divided into four bidding areas: Luleå (SE1), Sundsvall (SE2), Stockholm (SE3), and Malmö (SE4). Denmark consists of two bidding areas: Western Denmark (DK1) and Eastern Denmark (DK2), while Norway has five bidding areas: Oslo (NO1), Kristiansand (NO2), Molde, Trondheim (NO3), Tromsø (NO4), and Bergen (NO5). Finland, Estonia, Latvia, and Lithuania only have one bidding area per country. (Nord Pool 2017g; Nord Pool 2017h) Both system and area prices are decided in euros, and all bids submitted in another currency are converted before the price is determined (Nord Pool 2017i).

Intraday Market and Reserves

The day-ahead market is complemented by an *intraday balancing market*, where trade happens on the same day, and buyers and sellers can correct for unexpected changes in supply and demand by bidding up to one hour before electricity is to be transmitted (Svenska Kraftnät 2017, p. 49). Whenever there is an unforeseen lack of balance in the system, there is a need for *balancing* so that the consumers' needs can be met at each point in time. This is done by upward or downward adjustment of the volume of transmitted electricity, which is mainly carried out through *reserves* and reserve balancing capacity (Svenska Kraftnät, pp. 8–9). The increase of renewables will increase the need for regulation (Svenska Kraftnät, p. 25). The reserves are only used for sudden variations during the day of delivery and should not have a direct effect on the day-ahead prices.

Interconnections Between the Electricity Areas

While Nord Pool is an integrated market, as previously mentioned, there are certain restrictions in how much electricity can be traded between bidding areas. The transmission between areas cannot exceed the cross-border capacity. Nord Pool calculates the prices assuming all interconnecting capacity is available to everyone, which means no area has priority when capacity is limited (Nord Pool 2017g). However, the kind of interconnections vary. SE4 is connected with DK2, Lithuania, Germany, and Poland, while SE3 is connected with Finland, DK2, and NO1. SE2 is connected with NO3 and NO4 and SE1 with NO4 and Finland (Nord Pool 2017j).

2.3 Electricity Production Statistics

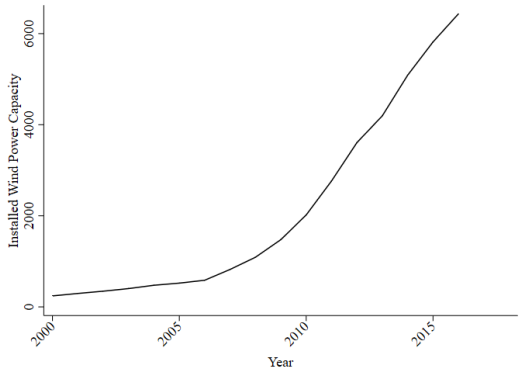
Different energy sources have a wide range of impact on the dynamics and price behavior of the Nord Pool market. Hydropower stands for almost the entirety of Norway's electricity production with 96 percent in 2016 (Statistics Norway 2017), while Denmark relies to a much larger extent on wind power. In 2015, wind power accounted for 41.8 percent of total production while the remaining 58.2 percent consisted mainly of combined heat and power (CHP) production, coal and biomass being the main fuels (Danish Energy Agency 2017). Norwegian producers would therefore have significantly more room for acting as a balancing actor than Denmark. Finland uses a wider combination of energy sources, with the share of nuclear power production at 33.7 percent, hydropower at 23.6 percent and wind power at 4.6 percent. CHP production accounts

for the majority of the remaining production (Statistics Finland 2017). Neighbouring countries like Germany and Lithuania also have substantial shares of their electricity production hailing from wind power, however, the former is not fully integrated into the market and the latter has a low total production. These countries do not have any sizable production of hydropower.

In Sweden, the main energy sources for electricity production are hydropower and nuclear power, each accounting for 40 percent of the total production. Wind and thermal power each constitute around ten percent of the remaining production (Statistics Sweden 2017). Sweden's total production surpasses three times that of Denmark and consequently, the wind power production in absolute terms in Sweden is comparable to Denmark. The large share of wind power production in Sweden is a result of an exponential increase in installed wind power production capacity during the past two decades. For the evolution of installed wind power capacity in each bidding area for the past four years, see Appendix 2.

To this day, the increasing wind power production capacity has not replaced that of other types of electricity production to a considerable extent, but changes in the Swedish energy mix are expected in the future due to the decision to gradually phase out Swedish nuclear power plants. Wind power is expected to replace most of the nuclear power production since the possibility to ramp up production of current hydropower plants is very limited, and the main rivers in Sweden are protected from being used for hydropower. Solar power, on the other hand, is an unattractive energy source due to a lack of profitability. (Svenska Kraftnät 2017, p. 24)

Figure 1: The Evolution of Wind Power Capacity Between 2000 and 2016



Note: Authors' own. Data retrieved from Nord Pool (2018).

The four Swedish bidding areas have differing characteristics. Hydropower represents a considerably larger share of total electricity production in SE1 and SE2 compared to SE3 and SE4. SE1 and SE2 are also bordered by regions with a lot of hydropower both in relative and absolute terms. Wind power production in absolute terms is the highest in SE3. Both SE3 and SE4 have cross-border transmission lines with countries in continental Europe, where hydropower generally accounts for a smaller share of total production, while wind power production accounts for a larger share of total production than in Nord Pool member countries. While SE1 and SE2 both produce more than they consume and are therefore net exporting areas, the average load in SE4 exceeds its production and consequently, is, a net importing area. In SE3 area, production is roughly equal to demand for electricity. See Appendix 2 for production and demand statistics for the different bidding areas.

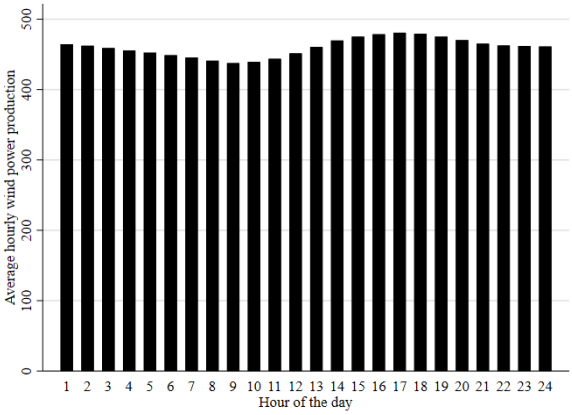
Table 1: Wind Power Production and Price Volatility

	SE1	SE2	SE3	SE4
Wind Share	0.06	0.10	0.06	0.31
Wind Penetration	0.14	0.30	0.07	0.17
Volatility	3.87	3.88	4.46	5.11

Note: Authors' own. Wind share is calculated as the share of wind power production of total production. Wind penetration is constructed taking the daily average wind production divided by the daily average load. Price volatility is calculated by taking the daily standard deviation using hourly prices. Data retrieved from Nord Pool (2018).

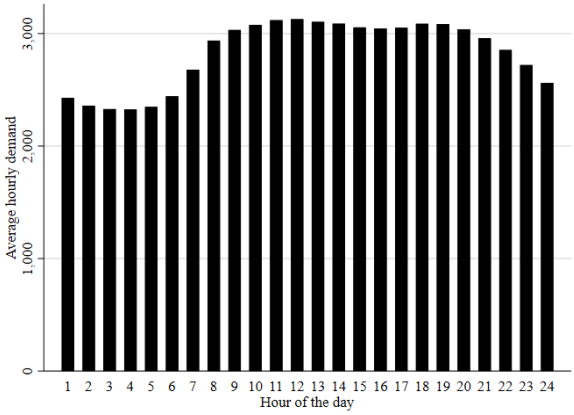
The wind share measure captures the proportion of wind power production to total electricity production. Wind penetration is highest in SE2 due to the low demand relative to production in the area. Volatility in SE1 and SE2 are very similar, which can be explained by less transmission constraints (Svenska Kraftnät, p. 54) and consequently, fewer periods where the prices differ. The high volatility in SE3 could possibly be explained by the geographical location close to regions with high wind shares. It has a connection with DK1, the main wind producing bidding area of Nord Pool, and a lack of hydropower resources to counterbalance these effects.

Figure 2: Wind Power Production by Hour



Note: Authors' adaptation of Rintamäki et al. (2017) with SE4 data. The distribution of the forecasted wind power production throughout the day measured in megawatt hours. Data is from the period January 1, 2015 to March 11, 2018 and is retrieved from Nord Pool (2018).

Figure 3: Demand by Hour



Note: Authors' adaptation of Rintamäki et al. (2017) with SE4 data. The distribution of the electricity demand prognosis throughout the day, measured in megawatt hours. The data is from the period January 1, 2015 to March 11, 2018 and is retrieved from Nord Pool (2018).

Notably, SE4 has at least three times higher wind share than the other bidding areas. It also has the highest price volatility. The distribution of wind power production and demand within the day can, as pointed out by Rintamäki et al. (2017), have substantial effects on the volatility. In SE4, demand varies on average more than wind power during the day. While wind power production peaks during hours of high demand, it is also high during the night when demand is low. Also, production is low in the morning when demand peaks.

3 Literature Review

3.1 Theory

Theoretically, the short-run relationship between wind power production and electricity prices can be explained by a phenomenon called the *merit order effect* (Ketterer 2014). The following description of the mechanisms behind the merit order effect is based on an article by van Kooten (2016), reviewing the economics of wind power.[5]

[5]If not otherwise noted, the observations in the following section are a summary of his review.

Supply of Electricity

The supply of electricity is determined in the bidding process. Electricity producers bid to produce electricity at a certain price that depends on their expected marginal cost when electricity is to be delivered. The producers are ranked according to their marginal costs to create the supply stack of electricity and to ensure that electricity is produced at the lowest possible cost. This ranking is called the *merit order*. Low expected marginal costs producers, such as nuclear power and hydropower producers, bid at low prices. Since nuclear power is very inflexible and can be considered non-dispatchable[6] the producers can sometimes bid to produce electricity at the price of zero, or below their expected marginal cost, to ensure continued production. Producers with high expected short-run marginal costs bid at higher prices. The supply curve takes the form of a step function where the steps represent the price levels at which the producers have to bid to produce electricity. The marginal producer is the producer with the highest marginal cost at a certain price level.

Subsidies

An important consideration when analyzing electricity markets is the presence of subsidies (Cullen 2013). Depending on their shape and size, subsidies can strongly affect the cost structure and the incentives of electricity producers. A subsidy for each megawatt hour produced decreases the marginal cost of production. A subsidy on investment presumably increases it but has little effect on the merit order. A special situation occurs when low marginal cost energy sources receive production subsidies, this may lead to a negative marginal cost of production and incentives to produce electricity, even when prices are negative (Cullen).

Demand of Electricity

The demand function can be modelled either as perfectly inelastic or as a downward-sloping function. If demand is perfectly inelastic, the price that clears the market is the price at which the marginal producer does not receive any producer surplus. Since the producer surplus would compensate for the fixed costs of electricity production, investment in capacity is disincentivized. On the other hand, if the demand function is assumed to be downward-sloping, this problem is not as pronounced, unless the transmission system operator sets a cap on electricity prices.

[6] i.e. it has to produce electricity at all times. Nuclear power can be adjusted but this is costly and slow.

With a downward-sloping demand function, the market-clearing price is the price at which the supply meets the demand and the marginal producer has the possibility to receive producer surplus. The demand and supply of electricity must balance at all times, and the market is to be cleared "continuously and instantaneously" (van Kooten 2016, p. 184).

Balancing Supply and Demand with Wind Power Production

The introduction of wind power production in the electrical grid shifts the electricity supply curve to the right. This effect is based on the assumption that wind power is non-dispatchable, which implies that all wind power produced is integrated in the electrical grid. As the marginal cost of wind power production is close to zero (Cullen 2013), it replaces higher marginal cost production, and thus, decreases the wholesale electricity prices. If wind power enters the grid when demand is low, either wind power production or baseload production must be reduced, in order to match supply and demand. In the case where all wind power produced is assumed to be integrated in the grid, baseload production needs to be adjusted, creating additional costs for the producers, as well as, the party responsible for balancing supply and demand.

If wind power replaces baseload capacity permanently, there is an increased need for high marginal cost backup capacity. Wind power cannot provide a constant supply of electricity, resulting in increased wholesale electricity prices. The variability in electricity production induced by intermittent wind power can then result in higher price volatility. This is the case when wind power replaces baseload thermal power. However, as suggested by Timilsina et al. (2013), a more flexible energy source, such as hydropower, does not necessarily face this problem as it can shift its production from providing baseload capacity to meeting peak load demand. Thus, if the system possesses large hydropower capacities, increased wind power capacity does not need to replace baseload capacity. The theory does not shed much light on the implications of short-run changes in wind power production on electricity price volatility.

3.2 Empirical Evidence

In vast amount of previous literature, a negative relationship between wind power and electricity prices is established empirically, either by simulating the effect of increased wind power on electricity prices by comparing a fictitious price with and without wind power or by using market data (Ketterer 2014). Regarding the impact of wind power on the electricity price volatility,

the empirical evidence is more divided (Rintamäki et al. 2017).[7] In these studies, different approaches and measures have been used, leading to differing and, in many cases, conflicting results. This includes, but is not limited to, data frequency, time frames, and measures of wind power and electricity price.

A distinct feature in electricity prices and their volatility that has been observed in the literature, is that the value of the variable today can to some extent be explained by its previous values. This indicates that autoregressive models can be useful in modelling electricity prices and their volatility, but since they cannot always be fully explained with these models, several authors use mixed autoregressive and moving average models. In addition to autocorrelation, electricity prices and their volatility often contain clear seasonal patterns that have been modelled, for example, through deseasonalization of price series (see e.g. Ketterer) or using time series models with seasonal components (see e.g. Rintamäki et al.). Lucía and Schwartz (2002) observe that electricity prices peak during the winter in Northern Europe due to higher demand for electricity during colder weather. The prices also display significantly lower values during weekends and holidays, which coincides with the days with the lowest load (Söder 2005, p. 177). Wind power production exhibits some seasonality as well; it tends to peak during the winter in Northern Europe (Holttinen and Hirvonen 2005, p. 152) and depending on the region, show different systematic patterns within the day (Holttinen and Hirvonen, p. 151).

Extensive research has been done on the effect of wind power in the context of the electrical grid managed by the Electricity Reliability Council of Texas (ERCOT). Woo et al. (2011) employ an autoregressive AR(1) model with exogenous inputs for 15-minute wind power generation market data. Controlling for the lagged price, nuclear power production, gas price, electricity load, and seasonal patterns, the authors find that increased wind power generation decreases the level of electricity spot prices, and that a ten percent capacity increase of wind power generation increases the variance of the prices in each of the four electricity zones in Texas. The effect of wind power does, however, differ in magnitude between the four zones. The findings of the report by Nicholson et al. (2010, cited by Woo et al., p. 3939) also suggest a negative relationship between wind power generation and the zonal electricity prices. The relationship

[7] Empirical evidence for increased (e.g. Nicholson et al. 2010; Woo et al. 2011; Ketterer 2014; Rintamäki et al. 2017) and decreased (e.g. Jónsson et al. 2010; Mauritzen 2010; Rintamäki et al. 2017) volatility are found.

is modelled using an autoregressive moving average model with exogenous inputs (ARMAX), and the authors find that the impact of wind power on price is stronger during the day than during the night, because the slope of the supply curve is steeper during the day (Nicholson et al.). The ERCOT grid differs substantially from the electrical grids in most of Europe as it is, more or less, isolated from its neighboring grids and exchange with other grids is very small in magnitude (Cullen 2013); these findings may not be directly applicable in other power markets.

The Spanish electricity market is another example of a more isolated market with average exports and imports accounting for merely 3.2 and 0.5 percent of demand, respectively (Pereira et al. 2017). Moreover, intermittent wind and solar power, as well as hydropower, represent a considerable part of total demand (IEA 2018). Estimating the effect of wind power and hydropower on electricity price volatility in Spain with an ARX-GARCHX model[8] on hourly data, Pereira et al. find that wind power increases volatility, while hydropower has a stabilizing effect on electricity prices. The authors do not control for solar power production that can have a differing impact on electricity prices compared to wind power production due to a different intraday distribution[9]. Solar power production could also be correlated with wind power production if more wind power is produced during the evening. The contradicting impacts of wind power and hydropower can be explained by their different natures. While wind power cannot be controlled by the producers, hydropower is dispatchable and allows for strategic production decisions (Pereira et al.). Therefore, the authors suggest that the magnitude of the positive effect of intermittent resources on electricity price volatility could be reduced if hydropower producers remained independent and electricity markets competitive.

Literature on more integrated electricity markets in Europe has largely focused on Germany and Denmark, that both have a considerable share of their electricity production coming from intermittent renewable energy. Jónsson et al. (2010) analyze the impact of day-ahead hourly wind power forecasts on day-ahead hourly electricity prices and their volatility in the Western Denmark price area (DK1) using a non-parametric regression model. The authors observe that increased forecasted wind power penetration, wind power production relative to demand,

[8]The authors remove seasonal variations from the dependent variable to construct a fitted price. Seasonal patterns and a time trend are removed from wind power production. A generalized autoregressive conditional heteroskedasticity model with exogenous inputs (GARCHX) is fitted to the data.

[9]Rintamäki et al. observe decreased volatility due to solar power production in Germany.

decreases the level and volatility of daily electricity prices in Western Denmark. Similar results are found by Mauritzen (2010) analyzing the Nord Pool daily system price and both Danish area prices, and by Rintamäki et al. analyzing solely the area prices on a daily level. Both use standard deviation as a measure of volatility. The decreased intraday volatility can be explained by wind power having a larger negative effect on peak prices compared to off-peak prices, which makes the daily electricity price distribution more even (Rintamäki et al.).

Ketterer analyzes the relationship between wind power production and the level and volatility of daily electricity prices in Germany using a generalized autoregressive conditional heteroskedasticity (GARCH) model with exogenous inputs. She estimates that wind power production decreases the level of electricity prices, but increases the daily volatility. The contradicting results regarding volatility of daily electricity prices are explored in more detail in the paper by Rintamäki et al., and the findings suggest that they are due to differing intraday distributions of wind power generation. In Germany, wind power has a stronger effect on off-peak prices because wind power generation is greater during the off-peak hours of the day. Germany's cross-border electricity transmission is smaller in magnitude and its access to flexible hydropower generation that could dampen the effect of intermittent wind power is more restricted. Therefore, wind power increases the daily spot price volatility instead of decreasing it, as in Denmark.

Analyses of electricity price volatility with a longer time horizon are considerably scarcer. Mauritzen (2010) argues that average wind power production increases price volatility in Denmark in the longer term but in a more recent working paper (Mauritzen 2011), he observes that the decreased intraday volatility carries over to daily volatility, however, not completely. Rintamäki et al. observe that increased weekly average wind power production increases the weekly volatility. Additionally, the authors find evidence for increased weekly price volatility in Denmark and Germany due to variation[10] in wind power production and combined wind and solar power production, respectively. The mechanism behind this is the merit order effect. As explained by the authors, since wind power production shifts the electricity supply curve horizontally, when production capacity increases, the shifts become larger. These larger shifts then translate into higher price volatility.

[10]Measured with standard deviation of daily average production.

In summary, even though a vast amount of previous literature establishes a negative relationship between wind power production and electricity prices, there appears to be no consensus on the impact of wind power on electricity price volatility. Moreover, since much of the previous literature has overlooked Sweden by focusing on the United States, other European countries or the Nord Pool market as a whole, more detailed analysis on electricity price volatility in this country can be seen as a valuable contribution to the research.

4 Empirical Strategy

The empirical part of our thesis is divided into two time horizons. The development of installed wind power capacity in Sweden and its possible long-run impacts on weekly SE4 price volatility are examined by using yearly observations. The focus of our study will lie on the short-run, daily, effects of wind power. First, we analyze the effect of the daily average level of wind power production in SE4 on the daily area price volatility of the same bidding area. Second, we proceed with exploring whether wind power production volatility has an impact on price volatility in SE4.

4.1 Identification

Electricity Price Volatility

We define the daily volatility as the daily standard deviation of the electricity prices, calculated using the difference of hourly observations p_h from the average daily price p_d.

$$vol_t = \sqrt{\frac{1}{24}\sum_{h=1}^{24}(p_h - p_d)^2} \tag{1}$$

This measure of volatility is the same as the one used by Rintamäki et al. (2017) and Mauritzen (2010; 2011) analyzing price volatility in Denmark and Germany. A more advanced approach to modelling electricity price volatility is to use some variant of an autoregressive conditional heteroskedasticity model (Engle 1982), see e.g. Pereira et al. (2017) or Ketterer (2014). For the purposes of this thesis, the simpler measure is preferred and applied.

Wind Power Production

The measure for wind power production we use is a forecast provided by Svenska Kraftnät. Forecasted wind power production is the most appropriate measure to be used, since bids from wind power producers will be based on the latest forecast available. Thus, the forecasted production has a direct effect on the day-ahead prices. Forecasted wind power production is arguably exogenous to the day-ahead prices, since in the short term, wind power production cannot be adjusted by the producers (Cullen 2013). Production is determined by wind speeds, which depend on meteorological conditions (Nicholson et al. 2010).

It is necessary to mention that on a particularly windy day, wind power producers might adjust production to avoid or alleviate congestion in electricity transmission, or if the wind speed is high and the turbine capacity is not sufficient (Cullen). This adjustment does not depend on electricity prices or their volatility. Also, as wind power is subsidized[11] in Sweden, decreasing the marginal cost of production that is already close to zero even further, it is reasonable to assume that wind power producers produce electricity whenever it is possible (Cullen).

Electricity Demand

Establishing a causal relationship between wind power production and electricity price volatility gets trickier in case electricity demand and wind power production affect electricity prices simultaneously. However, since wind power production can arguably be considered as an exogenous supply shock, we are likely to move along the demand curve that remains unaffected by wind power production. Furthermore, the particular measure of demand we use is a forecast published at 11 AM the day before the electricity is transferred. Since the day-ahead prices are established at 12 PM, our measure of demand should not be affected by the day-ahead prices.

Yet, as mentioned by Mauritzen (2011), endogeneity in wind power production can arise from the possible impact of weather conditions on both demand and wind power production. Despite the fact that demand and wind power production are both higher in the winter, the correlation is not particularly strong during these months (Holttinen and Hirvonen 2005, p. 163). However,

[11] Sweden and Norway share a market-based renewable energy subsidization program (*elcertifikatsmarknad* in Swedish) that allows the producers of renewable electricity to receive more revenue than what they would receive from the wholesale electricity prices. For a detailed description of the market, see the report by the Swedish Energy Agency and the Norwegian Water Resources and Energy Directorate (2016, in Swedish).

we analyze whether the estimated effect of wind power production on price volatility changes when controlling for demand of electricity by including daily average load in the model. In accordance with Mauritzen, since the coefficient of wind power production does not change significantly, we deem that it is improbable that a relationship between wind power production and price volatility is established merely because wind power production is correlated with demand.

Electricity Production from Other Energy

Solar power is another intermittent renewable energy source in Sweden, but it accounts for a very small part of the production of electricity. High wind power production correlates with low solar power production, as wind power production is generally higher during winter months than summer months (Holttinen and Hirvonen 2005, p. 163). In the winter, the available solar power is low in Sweden. Yet, this correlation can be ignored since the impact of solar power on electricity prices is deemed to be negligible in the case of Sweden.

Production from hydropower, while affecting the electricity price and stabilizing its volatility, is flexible and allows for strategic production decisions (Pereira et al. 2017), implying that hydropower production cannot be considered as exogenous to prices. The capacity to produce hydropower, which depends on water reservoir levels determined by weather conditions (Nord Pool 2017a), would be a more appropriate measure of hydropower production and would ideally be added in the model. Unfortunately, we lack data on hydropower capacity forecasts on a daily level. Rainfall levels and wind power can to some extent be correlated. Despite this, since the majority of Swedish hydropower production occurs in the northern parts of the country and our bidding area of interest is SE4, located in the south of Sweden, the correlation is low (Söder 2005, p. 188). Consequently, hydropower is not included in the model.

Since Sweden is a part of the common wholesale market for electricity, electricity production in other regions of the market affect SE4. Notably, SE4 is close to Denmark, which produces large amounts of wind power. Therefore, it is important to examine if the inclusion of Danish wind power production changes our results. On the one hand, Danish wind power production correlates with wind power production in SE4, and failing to control for this could cause us to overestimate the impact of wind power production in SE4. On the other hand, the correla-

tion is very high, and thus, including Denmark in the model could lead to misleading results. Additionally, we explore the possible non-linearities in the relationship, in the sense that the impact of wind production in SE4 is dependent on the production levels in Denmark. Except for Danish wind power production, we do not study the other interconnections in the market.

Long Run

In the long run, investment in wind power capacity could be affected by electricity prices since lower prices, due to wind power, might disincentivize new investment (Joskow 2006, cited by van Kooten 2016; van Kooten 2016)[12]. Higher price volatility implies higher revenue uncertainty, which might also contribute to reduced investment in installed capacity. This possible reversal causality brings endogeneity to the variable and complicates causal analysis with longer time horizons.

4.2 Data

Long-Run Analysis

For the long-run analysis we employ daily area price data for SE4 from Thomson Reuters Eikon. Before the introduction of different area prices in Sweden in November 2011, we approximate the SE4 price with the price for Sweden as a whole. The data for installed Swedish wind power capacity is provided by the Swedish Energy Agency. The time sample covers years 2004 to 2016, which implies that we have merely 13 data points as installed wind power capacity data is on a yearly level. No outlier correction is conducted for the measure of volatility used in our long-run analysis.

Short-Run Analysis

For the short-run analysis, hourly data is retrieved from Nord Pool. Since Nord Pool is the market operator, the day-ahead area price for SE4 comes directly from them, while load and wind power production forecasts for SE4 are reported to Nord Pool by the national transmission system operators. We employ data from January 1, 2015, the earliest date that data on demand is publicly available for each bidding area, until March 11, 2018. This results in 27,984

[12]Joskow discusses the view that competitive wholesale electricity markets are not able to provide sufficient revenues to producers and thus disincentivize investment in electricity generating capacity, the *problem of missing money*, whereas van Kooten argues that the price decreasing effect of wind power could exacerbate this problem.

observations on an hourly basis. As the data comes straight from the market operator or the national grid operators, it can be regarded as reliable and of high quality, and therefore, the risk of measurement errors in the variables leading to biased estimates should be low. From the hourly data, a daily measure for the area price and wind power production per area are constructed using an arithmetic average. After the hourly data is transformed into daily data, we are left with 1,166 observations.

Missing Values

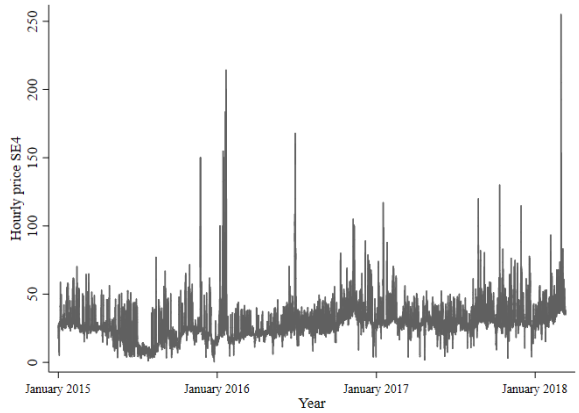
In the hourly raw data for all variables in the dataset, there is one gap and double observation per year, due to summer time. Therefore, the time series is adjusted so that every day in the year has 24 hours. The gap is filled with an average of the previous and following value when the day has 23 hours, and the second observation is dropped when the day has 25 hours. The clocks are turned forward, or back, during the night when variation between successive values is small, and that is why averaging should not have any noteworthy effect on our results. Moreover, the dataset from Nord Pool lacks data on demand for Sweden on May 8, 2015. This data is however found from the ENTSO-E Transparency platform that reports data directly from European transmission system operators, i.e. the original source is the same as for Nord Pool data.

Outlier Correction of the Area Price

When inspecting the raw hourly area price data graphically, we can observe multiple spikes. The electricity price volatility can be affected by a multitude of factors, many of which are not possible to include in our analysis. While in most cases they might be seen as different random shocks, the high price spikes could hardly be described as completely random, and could lead to a worse fit of the model.

Summarizing the SE4 area price for each day of the week, it is evident that there are differences between weekdays and weekends. The former have substantially higher means and standard deviations than the latter. Using a common mean and standard deviation for both weekdays and weekends when correcting for outliers could then result in a disproportionately large number of outliers for weekdays compared to weekends. Therefore, we calculate the mean and standard deviation of the price series separately for weekdays and weekends. Following Ketterer (2014), we correct for outliers that are further than three standard deviations from the mean.

Figure 4: Hourly Day-Ahead Prices in the SE4 Area



Note: Authors' own. The prices are measured in euros. Data retrieved from Nord Pool (2018).

We identify 191 outliers for weekdays and 11 for weekends for the SE4 area price. This corresponds to under one percent of the total number of observations.

4.3 Method

Long-Run Analysis

The long-run analysis is conducted by studying the relationship between Sweden's total installed wind power capacity and the weekly area price volatility for SE4. Similar to our measure of daily volatility, we construct a weekly standard deviation using the daily price and the corresponding weekly averages. As prices might change considerably between years, and outliers within the year could have large effects in such a small sample, a relative measure is used. We set the weekly standard deviation relative to the weekly average prices, and finally, take a yearly mean of these values. Optimally, the analysis would be separated into before and after the bidding areas were introduced but this would take away valuable data points from our sample.

Short-Run Model

In the short run, as suggested by the literature, we analyze the relationship between wind power production level and daily electricity price volatility in SE4 using autoregressive and moving average models. The same type of model is employed when analyzing the effect of wind power production volatility on price volatility.

An *autoregressive process* is a time series process that is determined by its previous values and a random component (Box et al. 2016, p. 8). The general form of an autoregressive process of order p, AR(p), can thus be written as:

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + e_t \tag{2}$$

where y_t denotes the dependent variable, y_{t-1} to y_{t-p} the lags of y_t, and e_t a random shock. Each of the lagged variables has a coefficient α_i and the letter p denotes the amount of lags included in the model. Thus, an AR(1) is a specification with one lag of y_t, and AR(2) with two. A *moving average process*, on the other hand, is a process determined by a contemporaneous shock, as well as a number of random shocks in previous periods (Box et al., p. 9). Using the same denotation, a MA(q) process can be expressed as:

$$y_t = \sum_{i=1}^{q} \beta_i e_{t-i} + e_t \tag{3}$$

where e_{t-1} to e_{t-q} denote the lagged random shocks, and q the number of lagged shocks. Similarly, an MA(1) is a specification with one lag of e_t and MA(2) with two. A combination of these two processes is possible through, a so-called *mixed autoregressive moving average process*, denoted as ARMA(p,q) (Box et al., p. 11). These models can also be applied with exogenous inputs when one is interested in causal analysis with autocorrelation in the dependent variable.

A common way of analyzing these models is through the *autocorrelation function* (ACF). The autocorrelation function describes the correlation between two variables in a sequence at a set time difference. Moreover, it reflects the "indirect correlations" between variables (Enders 2010, p. 65). As exemplified by Enders (p. 65): "In an AR(1) process, y_t and y_{t-2} are correlated even though y_{t-2} does not directly appear in the model. The correlation between y_t and y_{t-2} [...] is equal to the correlation between y_t and y_{t-1} [...] multiplied by the correlation between y_{t-1} and y_{t-2}." The *partial autocorrelation function* (PACF) is another relevant function in the analysis and identification of these models. In contrast with the ACF, the PACF does not display any indirect correlations between variables. The assumption that the correlations are constant over time needs to be fulfilled for these functions to be valid (Box et al., pp. 24–25).

Seasonal Patterns and Time Trends

To account for the clear seasonal patterns in daily average electricity price volatility, wind power production, and demand that are observed in the literature and in our data, variables are deseasonalized using seasonal dummy variables, as suggested by Ketterer (2014). Assuming that the magnitude of the seasonal patterns is constant over time, we apply an additive seasonal model to the variables. As it is not likely that all variables share the same seasonal patterns, we deseasonalize the variables separately instead of using dummy variables in the regression model.

The price volatility and demand are deseasonalized using day-of-the-week and monthly dummy variables, while wind power production is deseasonalized using merely monthly dummy variables since, intuitively, there should not be systematic differences in wind power production between days of the week. Each variable is regressed on a constant and the dummy variables, omitting Monday for the day-of-the-week dummy variables and January for the monthly dummy variables. The obtained residuals of the regressions represent the deseasonalized data (Wooldridge 2016, pp. 336–337). To facilitate comparison between the original and deseasonalized variables, we follow Ketterer and align the means of the original and deseasonalized variables by adding the mean of the original variable to the residuals. Ideally, we would follow the common practice in the literature and transform the variables into a logarithmic form which allows for interpreting the coefficients as percentage changes or elasticities. However, the deseasonalization results in negative values, for which a logarithm is not mathematically defined. The results of the deseasonalization can be found in Appendix 3.

Considering the possibility of trending factors that affect the dependent variable, but are also correlated with at least one of the independent variables, is crucial for establishing causality. If we do not control for trends, we might face a problem called spurious regression (Wooldridge, p. 332), where a causal relationship between variables is found merely because both are trending. The relationship in a spurious regression is highly significant but does not have any economic significance (Enders 2010, p. 196). In the graphical representation of our variables, we cannot identify clear time trends. In the long-term, installed wind power production capacity could certainly be a factor affecting both electricity price volatility and wind power production, but

as we analyze the effect of wind power production on price volatility in the short-term, we do not detrend the variables.

Stationarity and Persistence of Time Series

Stationarity of time series refers to the crucial assumption that the distribution of random variables in a sequence does not depend on time. The definition of a stationary time series, according to Wooldridge, is as follows: "A stationary time series process is one whose probability distributions are stable over time in the following sense: If we take any collection of random variables in the sequence and then shift that sequence ahead h time periods, the joint probability distribution must remain unchanged" (2016, p. 345). When analyzing causal relationships this property of time series is required; in case the relationship between variables is not stable over time, it is difficult to establish what kind of impact one variable has on another (Wooldridge, p. 346).

If a time series is highly persistent, it should not be included in the regression model without differencing if the classical linear assumptions do not hold (Wooldridge, p. 354). This is the case when a lagged dependent variable is included as an explanatory variable. High persistence of a time series refers to the phenomenon that the value of a variable today correlates with future values of the variable, even when the time distance between the values is large (Wooldridge, p. 355). If this is the case, new realizations of the time series process are to a large extent determined by the previous values of the variable, and do not provide us with additional information.

Wooldridge suggests that the *first order autocorrelation*, the sample correlation coefficient between a variable and its first lag when the time series follows a stable AR(1) process, can be used as a rough estimate for whether the time series are highly persistent (p. 359). We can observe from the autocorrelation functions that the first order autocorrelations do not exceed 0.8. As mentioned by Wooldridge, this method is quite unreliable since the first order autocorrelation is an estimate and the distribution of the population correlation coefficient is not constant (p. 359). Furthermore, using merely the autocorrelation functions can be misleading, since they take a similar form when the time series contains a trend and when the time series is close to a unit root process (Enders 2010, p. 200). The term unit root stems from the first

order autocorrelation of an AR(1) model; if it is equal to one, the time series is highly persistent (Wooldridge, p. 355).

To formally test for unit roots, we conduct augmented Dickey-Fuller (ADF) tests for each variable. The denomination *augmented* implies that we test for higher-order autoregressive processes. In the literature, the ADF is the most used method for unit root tests. There are several versions of the ADF test, and the most appropriate version is determined by the characteristics of the variables. It is important to consider the possibility of the variables containing time trends since failing to account for the trends reduces the ADF test's rejection power (Wooldridge, p. 577). We do not identify any clear time trends in the graphical representation of the variables[13] and, therefore, the tests are not adjusted for a time trend. Based on the graphs, the possibility of the time series following a random walk with drift[14] is very unlikely. We do not omit the constant intercept from the function since this causes bias if the intercept is not zero (Wooldridge, p. 578).

The variant of ADF test we use regresses the difference of the variable on a constant, the first lag of the variable, a number of lagged differences of the variable, and an error term. The equation is thus (Wooldridge, pp. 576–567):

$$\Delta y_t = \alpha + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + \gamma_2 \Delta y_{t-2} + ... + \gamma_p \Delta y_{t-p} + e_t \tag{4}$$

where y_t is the variable in question, p is the number of lags included in the model, and e_t is the error term that is assumed to be independent, identically distributed, and have a mean of zero conditional on past values of y_t (Wooldridge, p. 574). The null hypothesis is that the time series follows a unit root process, and the alternative hypothesis is that it does not, i.e. the ADF tests whether the coefficient of the first lag of the dependent variable is zero against the alternative that it is less than zero.

The t-statistic of the estimated coefficient θ is compared to the critical values tabulated originally by Dickey and Fuller in 1979. The critical values of the ADF test without trend are -3.43, -2.86

[13] Wooldridge (p. 578) suggests that intuition and graphical analysis are common ways to determine whether a time trend should be included in the Dickey-Fuller tests.

[14] A time series that is highly persistent and trending, however, the series does not often follow the trend line (Wooldridge, p. 357).

and -2.57 for one, five, and ten percent significance levels, respectively. These critical values are based on the assumption that the model is correctly specified, i.e. we have an appropriate amount of lagged differences in the model (Wooldridge, p. 577). Since the data is on a daily level and the sample is large, we run the ADF test with 7, 14, and 21 lagged differences included in the model, that is, three weeks of lags.[15] As opposed to the first lag of the variable y_{t-1}, the t-statistics of lagged differences of y_t follow a distribution close to the t-distribution. We can also test for their joint significance with an F-test (Wooldridge, p. 577).

The null hypothesis that the series follows a unit root is rejected at 7, 14, and 21 lags for all variables. This indicates that the variables do not need to be differenced to be included in the regression model. This result was somewhat expected from visually inspecting the volatility, wind power production, and demand since the time series vary around the mean and revert back to it after spikes. Also, the autocorrelation functions of the variables decay to zero fairly quickly. However, the ADF has the weakness of having a rather high Type I error (Kwiatkowski et al. 1992), so the results have to be interpreted with some caution. For the results from the ADF tests, see Appendix 4.

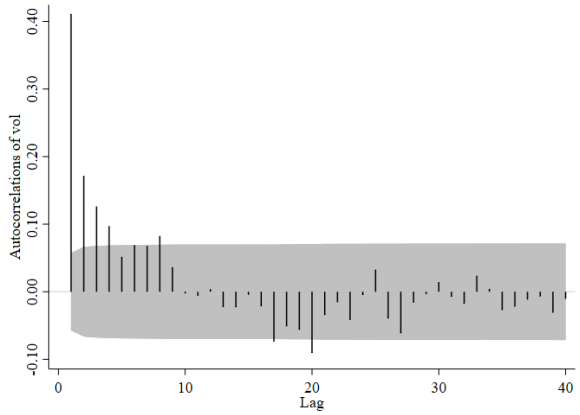
Model Selection

The correlograms of price volatility after deseasonalization indicate that there remains autocorrelation in the variable. However, the seasonal patterns that were visually apparent when examining the autocorrelations of the volatility before deseasonalization have disappeared. The autocorrelation function is exponentially decreasing, which usually indicates the need to use an autoregressive model or order one (Enders 2010, p. 68). According to Box et al. (2016, p. 64), the order p of the autoregressive model AR(p) can be identified by the lag after which the partial autocorrelation function becomes zero. Examining the plot, we can see the second lag is virtually zero. Therefore, the specification AR(1) is a natural starting point for us. To account for possible autocorrelation in the error term, we fit specifications with a moving average component as well.

To help determine which model specification provides the best fit to our data, we use the *information criteria approach* (Box et al., p. 193). This approach is based on comparing the

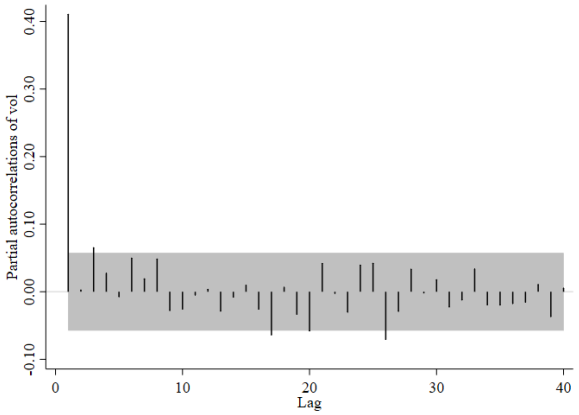
[15] Wooldridge (p. 577) mentions that there are no hard rules to determine the lag length and it should be in accordance with the frequency of the data and the number of observations.

Figure 5: Correlogram of the Electricity Price Volatility



Note: Authors' own. The gray area represents the 95% confidence bands.

Figure 6: Partial Correlogram of the Electricity Price Volatility



Note: Authors' own. The gray area represents the 95% confidence bands.

values of the information criteria yielded by different model specifications and choosing the specification that provides the smallest value (Box et al., p. 193). The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)[16] are the most used selection criteria and are therefore used in the analysis. AIC and BIC can be calculated as follows (Enders, p. 71)[17]:

$$AIC = Tln(SSR) + 2n \tag{5}$$

$$BIC = Tln(SSR) + nln(T) \tag{6}$$

where T is the "number of usable observations", the number of estimated parameters, including the constant, subtracted from the number of observations (Enders, p. 71). n is the number of estimated parameters including the constant, and SSR refers to the sum of squared residuals of the model.

To ensure comparability of the information criteria, the sample size must remain the same in all specifications (Enders, p. 71). Adding more parameters to the model reduces the sum of squared residuals but implies that more degrees of freedom are lost. The second term of both

[16]Enders uses denomination the *Schwartz Bayesian Criterion* (SBC).

[17]Statistical software packages can use different formulas when calculating AIC and BIC. STATA uses log-likelihood instead of sum of squared residuals.

formulas is the penalty associated with increasing the number of estimated parameters. The penalty set by BIC, $\ln(T)$, is larger than 2, and therefore, the preferred specification selected using BIC will not have more parameters than the one selected using AIC. (Box et al., p. 193)

Moreover, an important assumption in time series models is that the error term follows a *white noise process*, which is a sequence where each value is uncorrelated with all other values, has a zero mean, and a constant variance (Enders, p. 51). This is, however, not always the case in the data, but using a time series model with both autoregressive and moving average components is a way to circumvent this issue, converting the data into white noise (Box & Pierce 1970). Post estimation, a Ljung-Box test can be conducted to determine whether the residuals follow a white noise process (Enders, p. 70). Since we have daily data, we carry out the test with 7, 14, and 21 lags. The null hypothesis is that the residuals behave as a white noise process, the alternative hypothesis is that they do not.

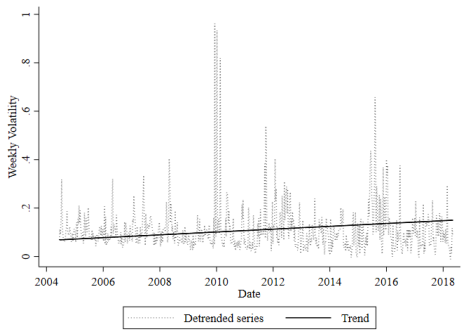
Selecting the model specification, we follow the process used by Rintamäki et al. and estimate the price volatility using different autoregressive and moving average specifications, omitting the exogenous variables. As mentioned by the authors, ideally, one would specify a separate specification for each variable, but this would make the interpretation of the effects of the variables more difficult. The specifications are evaluated using AIC, BIC, and the Ljung-Box Q-statistic for autocorrelation in the residuals after estimation. Autocorrelation in the error terms is also visually inspected. The models are estimated using Maximum Likelihood Estimation and we assume local linearity in the relationship, as suggested by Jónsson et al. (2010).

5 Results

5.1 Long-Run Analysis

Due to the longer time frame, we analyze the weekly price volatility relative to the average weekly price. This is important as the mean of the price might not be stable over such a long time horizon. Using a relative measure also handles the problem of influential outliers to a certain extent. Regressing the weekly volatility on time gives us a prediction of an upward trend, which is significant at the one percent level.

Figure 7: The Evolution of Weekly Volatility between Years 2004 and 2016



Note: Authors' own. Data retrieved from Nord Pool (2018).

The trend and the detrended series can be seen in Figure 7. Generally, we can observe a positive trend for the weekly price volatility during the period of analysis. A major change in electricity production that has occurred during this time is the exponential increase in installed wind power capacity, particularly after the year 2006. The graphical representation in Figure 8, plotting average weekly volatility and installed wind power capacity on a yearly basis, suggests that there is a positive relationship between the variables. The development of the variables is similar, with low levels in the early 2000's followed by a powerful increase. While parts of the development could possibly be attributed to other, random events, the fact that the volatility does not drop down to the level of the early 2000's suggests that something has caused a more permanent increase in price volatility.

It is important to note, however, that these common trends might be due to unobserved factors, and thus, causal analysis between installed wind power capacity and price volatility is not feasible. Other possible confounding factors could be the integration of the Baltic countries in the market and the division of Sweden in four bidding areas. However, if there is a positive relationship between increased wind power capacity and electricity price volatility, this is very essential from a policy perspective. The long-run analysis is complicated by quite apparent endogeneity, but the short-run effects of wind power production might be able to provide us with better insights on a causal relationship between wind power and price volatility.

Figure 8: Installed Wind Power Capacity and Average Weekly Volatility on a Yearly Basis



Note: Authors' own. Weekly volatility is measured as the weekly standard share of the weekly average price and is then averaged over the year. Data retrieved from Nord Pool (2018).

5.2 Model Specification for Daily Price Volatility

The results from the model selection process yield that the most appropriate specification to our data is a pure autoregressive model of order one, AR(1). When more lags are added into the model, the value of AIC does not decrease until a model with two autoregressive and two moving average lags, ARMA(2,2) is fitted. However, neither the second autoregressive lag, nor the first moving average lag, are significant at the five percent level. Therefore, this specification is not chosen even though it has the lowest AIC. The decision is supported by the principle of *parsimony*, which implies that models with fewer parameters are preferred (Enders 2010, pp. 78–79). This is the approach taken by Rintamäki et al. (2017) as well. The AR(1) has the lowest value of BIC since the criterion will always suggest a model with fewer parameters compared to AIC (Box et al. 2016, p. 193).

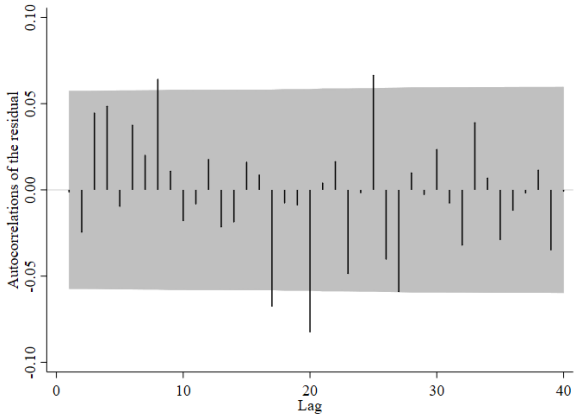
A requirement for stationarity of an AR(1) process is that the first order autocorrelation is less than one (Enders, p. 62), which we can observe from our AR(1) specification. When testing whether the model residuals for AR(1) follow a white noise process, we fail to reject the null hypothesis that the residuals are white noise at the five percent level for 7, 14, and 21 lags. For the other specifications, with the exception of ARMA(2,2), the Q-statistics and p-values are similar to the ones yielded by AR(1). For ARMA(2,2), the Q-statistics are considerably lower and p-values higher, as can be expected since we explicitly control for autocorrelation in the error term with the moving average lags.

Table 2: Different Model Specifications

	(1) AR(1)	(2) AR(2)	(3) ARMA(1,1)	(4) ARMA(2,1)	(5) ARMA(2,2)
vol_t					
α_0	4.794***	4.794***	4.794***	4.794***	4.794***
	(0.163)	(0.164)	(0.164)	(0.162)	(0.191)
ARMA					
α_1	0.410***	0.409***	0.418***	-0.0521	0.852***
	(0.0198)	(0.0212)	(0.0566)	(1.181)	(0.277)
α_2		0.00263		0.178	-0.0548
		(0.0250)		(0.495)	(0.158)
β_1			-0.00942	0.468	-0.446
			(0.0608)	(1.179)	(0.276)
β_2					-0.150**
					(0.0704)
AIC	5737.4	5739.4	5739.4	5741.1	5736.8
BIC	5752.6	5759.6	5759.6	5766.4	5767.1
Q(7)	7.991	7.966	7.954	7.714	2.336
p(7)	0.333	0.336	0.337	0.358	0.939
Q(14)	14.72	14.70	14.69	14.43	7.562
p(14)	0.397	0.399	0.400	0.418	0.911
Q(21)	28.71	28.67	28.65	28.31	20.53
p(21)	0.121	0.122	0.123	0.132	0.488
SSR	9310.3	9310.3	9310.2	9307.8	9257.5

Note: Standard errors in parentheses. Estimated using Maximum Likelihood.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Figure 9: Correlogram of the AR(1) Model Residuals



Note: Authors' own. Obtained by fitting an AR(1) model to vol_t using Maximum Likelihood estimation. The gray area represents the 95% confidence bands.

When visually inspecting residuals of the chosen AR(1) specification, we observe some lags that fall outside the 95 percent confidence interval, which implies that the value of the autocorrelation function for that lag is distinguishably different from zero. However, since we fail to reject the null hypothesis that the residuals follow a white noise process at the five percent, this should not pose any noteworthy problems for the validity of our analysis. Consequently, the model we employ is the following:

$$vol_t = \alpha_0 + \alpha_1 vol_{t-1} + \gamma_1 wprod_t + \epsilon_t \tag{7}$$

where vol_t is the daily average volatility, α_0 a constant, vol_{t-1} the first lag of vol_t, $wprod_t$ the level of wind power production, and ϵ_t the error term.

5.3 Short-Run Analysis

Level of Wind Power Production and Price Volatility

Regressing volatility on wind power production indicates that a higher level of wind power production has a clear, negative effect on volatility. The coefficient is interpreted as a one euro change in volatility induced by a one megawatt hour increase in wind power production. The evaluation of the economic significance of the coefficient can however be simplified by studying the effect of one standard deviation increase in wind power production relative to the

volatility. Thus, one standard deviation increase in wind power production, which is equal to 292.9 megawatt hours, is associated with a 1.10 euro decrease in volatility. The effect remains when controlling for demand, $load_t$, albeit it is slightly smaller, indicating a negative effect of 0.98 euro. Electricity load is found to have a significant, positive effect on the volatility. The average daily volatility of our time sample is 4.80 euros, which implies that the price-decreasing effect of wind power we observe is quite considerable.

Table 3: Wind on Electricity Price Volatility

	(1) vol_t	(2) vol_t	(3) vol_t	(4) $rvol_t$	(5) $rvol_t$	(6) $rvol_t$
y_t						
$wprod_t$	-0.00376***	-0.00337***		-0.0000525***	-0.0000471***	
	(0.000286)	(0.000281)		(0.00000877)	(0.00000879)	
$wpen_t$			-10.65***			-0.148***
			(0.775)			(0.0237)
$load_t$		0.00422***			0.0000649***	
		(0.000404)			(0.0000167)	
constant	6.523***	-5.586***	6.554***	0.189***	0.00270	0.189***
	(0.202)	(1.201)	(0.197)	(0.00704)	(0.0482)	(0.00698)
ARMA						
α_1	0.401***	0.361***	0.392***	0.421***	0.417***	0.420***
	(0.0205)	(0.0218)	(0.0205)	(0.0162)	(0.0159)	(0.0162)
p(21)	0.109	0.233	0.154	8.26e-14	1.55e-13	1.06e-13
Log-likelihood	-2795.4	-2758.9	-2789.5	1207.6	1215.3	1208.5

Note: Standard errors in parentheses. Estimated using Maximum Likelihood.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Robustness Checks

To examine the robustness of the results, we use daily average wind penetration, $wpen_t$ as an alternative main independent variable. This measure is used by Jónsson et al. (2010) among others, and it sets the daily average wind power production relative to the daily average load. When using wind penetration as the main independent variable, we do not control for load since the measure already sets wind power production in relation to it. Using both wind penetration and load could then lead to a large risk of multicollinearity. The results in column three indicate that one unit increase in wind penetration decreases the volatility by 10.65 euros. As wind penetration is a fraction, one unit represents 100 percentage points. Employing the alternative interpretation, one standard deviation increase in wind penetration, which equals to

10.8 percentage points, decreases the volatility by 1.15 euro.

Another way to measure volatility would be to set the daily standard deviation relative to the mean of the price that day. A day with a standard deviation of 1 euro would generally be considered as a stable day if the average price was 100 euros that day. However, if the average price was 10 cents, a standard deviation of one euro would imply high price volatility. Therefore, to explore whether different results are obtained setting volatility in relation to the average price, we include a relative measure of the dependent variable, $rvol_t$, in the model. Looking at the relative volatility, the sign or the significance of the coefficients do not change, even though the magnitude changes slightly. We observe that one standard deviation increase in the level of wind power production is associated with a 1.54 percentage point decrease in relative volatility. The average volatility of our sample in relative terms is 16.5 percents. Similar results are obtained when controlling for load and using wind penetration as the independent variable.

However, the p-values of the regressions presented in columns four to six indicate that we reject the null hypothesis that the residuals follow a white noise process. A simple explanation for this is that the model specification does not control for autocorrelation in the errors. Conducting the same model selection process as before, we establish that an ARMA(2,1) specification would fit the relative volatility the best. Using this specification, we fail to reject the null hypothesis of white noise in the residuals. The estimated coefficients do not differ significantly from the ones from the AR(1), for more details see Appendix 5.

The observed negative effect of wind power production on daily average price volatility is in line with the findings of Mauritzen (2010; 2011) and Rintamäki et al. (2017) for Denmark. The mechanism behind the decreased effect according to Rintamäki et al. is that a high level of wind power production during peak load, when prices are high, flattens the intraday distribution of the prices, and thus, decreases volatility. Examining Figures 2 and 3, we can observe that in SE4, high wind power production appears to coincide with high demand, indicating that this explanation might be plausible in our case as well.

Table 4: Wind on Electricity Price Volatility Controlling for Denmark

	(1)	(2)
y		
$wprod_t$	-0.000338	-0.00299***
	(0.000567)	(0.000767)
$load_t$	0.00418***	0.00406***
	(0.000408)	(0.000402)
$wprodDK_t$	-0.00106***	-0.00173***
	(0.000164)	(0.000189)
$wprod_t \times wprodDK_t$		0.00000133***
		(0.000000236)
constant	-5.196***	-3.879***
	(1.207)	(1.203)
ARMA		
α_1	0.390***	0.394***
	(0.0221)	(0.0221)
p(21)	0.0600	0.00673
Log-likelihood	-2735.0	-2720.5

Note: Standard errors in parentheses. Estimated using Maximum Likelihood.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Since SE4 is geographically close to Denmark, the patterns of wind power production are expected to be very similar. Including Denmark in the regression removes the significance of the estimated impact of wind power production in SE4 on volatility. However, since the correlation between the variables is very high, over 0.85, the results can be misleading, and should be analyzed with caution. Applying a model where the effect of the wind power production in SE4 is allowed to depend on the production in Denmark through interaction, the effect is significant. The interaction term being positive, the results suggest that covariance between Danish wind power production and wind power production in SE4 increases volatility. Intuitively, this makes sense; if wind power production is high in Denmark and SE4 simultaneously, the system might not be able to accommodate such amounts of wind power without imbalances in supply and demand.

Volatility of Wind Power Production and Price Volatility

We extend the analysis by studying the possible impact of volatility in wind power production on price volatility using the same AR(1) specification:

$$vol_t = \alpha_0 + \alpha_1 vol_{t-1} + \gamma_1 windvol_t + \epsilon_t \tag{8}$$

where vol_t is the daily average price volatility, α_0 a constant, vol_{t-1} the first lag of vol_t, $windvol_t$ the daily average volatility in wind power production, and ϵ_t the error term. The volatility of wind power production is measured by the daily average standard deviation. Regressions using an ARMA(2,1) specification can be found in Appendix 5. Surprisingly, we find a significant negative effect between volatility in wind power production and electricity price volatility. We test for robustness of the results by using a relative measure of volatility in both prices and wind power production. However, when regressing the relative price volatility on volatility in wind power production, the significance of the effect disappears. Since our model is not robust for different specifications and the significance of the results vary depending on the measure of volatility used, we cannot draw a conclusion regarding the impact of volatility in wind power production on electricity price volatility.

Table 5: Wind Volatility on Electricity Price Volatility

	(1) vol_t	(2) vol_t	(3) $rvol_t$	(4) $rvol_t$	(5) $rvol_t$	(6) $rvol_t$
y_t						
$windvol_t$	-0.00310***	-0.00254**	-0.0000450	-0.0000352		
	(0.00107)	(0.00101)	(0.0000323)	(0.0000319)		
$load_t$		0.00489***		0.0000742***		
		(0.000426)		(0.0000167)		
$rwindvol_t$					0.0588***	0.0588***
					(0.0114)	(0.0114)
constant	5.167***	-8.717***	0.170***	-0.0411	0.145***	0.145***
	(0.214)	(1.246)	(0.00685)	(0.0473)	(0.00670)	(0.00670)
ARMA						
α_1	0.401***	0.356***	0.419***	0.415***	0.427***	0.427***
	(0.0198)	(0.0209)	(0.0164)	(0.0160)	(0.0165)	(0.0165)
p(21)	0.154	0.298	1.92e-12	1.97e-12	9.06e-13	9.06e-13
Log-likelihood	-2861.1	-2816.1	1194.8	1204.8	1204.9	1204.9

Note: Standard errors in parentheses. Estimated using Maximum Likelihood.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

6 Discussion

6.1 Internal Validity

The wholesale electricity market is complicated, and the price of electricity is determined by many different aspects, such as demand for electricity, weather conditions, cross-border trade and market structure. Modelling all variables that could have a possible impact on the price and accounting for all possible interactions and interconnections, is not feasible. However, a simple, more parsimonious model can in many time series applications, provide better estimations. Naturally, in a market with many complexities and sometimes extreme price variations, there will be periods when our model cannot capture the dynamics as well as it could in others. Yet, analyzing the residuals of our model indicates that it approximates the behavior of the electricity price volatility in our time sample quite well.

6.2 External Validity

The effects of wind power in other time periods and in other geographical areas could be very different. The effects of wind power could depend highly on installed wind power capacity, which has seen an explosive development in the past two decades in Sweden. The rapid development of the capacity complicates the generalizability of our results to other time frames. Additionally, other areas and markets can have very different characteristics, and, the effects of increased wind power production will not be identical when market conditions, energy mixes, and consumption patterns vary. Notably, the intraday distribution of wind power production might differ between Sweden and its neighboring countries, which could lead to differing estimates for the price volatility (Jónsson et al. 2010) even though all countries are a part of the Nord Pool wholesale electricity market. The results can still give helpful indications on possible effects of wind power in southern Sweden in the future, and areas which share common attributes and preconditions with SE4 might see similar results.

6.3 Other Limitations and Considerations

There is also a possibility that the day-ahead market could be indirectly affected by the intraday market. One example of this would be if the cost for not delivering sufficient electricity or delivering too much electricity would be high enough for producers to change their production or bidding patterns. Since wind production is expected to increase the need for intraday adjustments (Svenska Kraftnät 2017, p. 45) this could cause endogeneity problems in the analysis of the effects wind power production in the future. In our thesis, we study merely the day-ahead electricity market and thus, may not capture the full effects of wind power production on electricity price volatility. Analyzing how wind power production might affect the electricity price volatility in the intraday balancing market would be interesting, but is, however, out of the scope of this thesis.

7 Conclusion

The rapid development of installed wind power capacity in Sweden has been accompanied by a general increase in volatility. However, no causal relationship can be established in the long run. Studying the short-run dynamics of changes in wind power production, we find that an increase in the daily average wind power production in the south of Sweden is associated with lower daily volatility of the day-ahead electricity price. Our results are not conclusive regarding the impact of daily variations in wind power production on the price volatility, and need to be examined further.

Our findings provide important insights into the effects of wind power on price behavior in a market where there already exists a large share of renewable production. The negative relationship between wind power production and volatility suggests that policymakers might need to target their actions on production that can provide sufficient electricity when there is little wind.

In the long run, if development of increased wind power causes a general increase in volatility, policymakers need to make sure that the costs related to higher volatility in the electricity market, and other possible adverse effects of wind power, do not exceed the environmental benefits of wind power production. A more detailed analysis needs to be done on the long-run effects of an increased wind power capacity on volatility to see if causality can be determined and if this result can be generalized to other areas and time periods.

References

Literature and Online Sources

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., and Ljung, G. M. (2015). *Time Series Analysis: Forecasting and Control*. 5th edition. Hoboken, New Jersey: John Wiley and Sons.

Box, G. E. P. and Pierce, D. A. (1970). Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models. *Journal of the American Statistical Association*, 65(332), pp. 1509–1526.

Cullen, J. (2013). Measuring the Environmental Benefits of Wind-Generated Electricity. *American Economic Journal: Economic Policy*, 5(4), pp. 107–133.

Danish Energy Agency (2017). Energy Statistics. https://ens.dk/sites/ens.dk/files/Statistik/energy_statistics_2015.pdf. Retrieved April 2, 2018.

Enders, W. (2010). *Applied Econometric Time Series*. 3rd edition. Hoboken, New Jersey: John Wiley and Sons.

Energikommissionen (2017). Kraftsamling för framtidens energi. SOU 2017:2.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), pp. 987–1007.

Gowrisankaran, G., Reynolds, S. S., and Samano, M. (2016). Intermittency and the Value of Renewable Energy. *Journal of Political Economy*, 124(4), pp. 1187–1234.

Holttinen, H. and Hirvonen, R. (2005). 'Power System Requirements for Wind Power', in Ackermann, T. (ed.) *Wind Power in Power Systems*. Chichester, England: John Wiley and Sons, pp. 143–167.

International Energy Agency (2018). Spain: Electricity and Heat for 2015. https://www.iea.org/statistics/statisticssearch/report/?country=SPAIN=&product=electricityandheat. Retrieved April 6, 2018.

International Energy Agency (2017). Energy Policies of IEA Countries Denmark 2017. http://www.iea.org/publications/freepublications/publication/EnergyPoliciesofIEACountriesDenmark2017Review.pdf. Retrieved May 13, 2018.

Jónsson, T., Pinson, P., and Madsen, H. (2010). On the Market Impact of Wind Energy Forecasts. *Energy Journal*, 32(2), pp. 125–139.

Joskow, P. L. (2006). Competitive Electricity Markets and Investment in New Generating Capacity. Working Paper 06–009, Center for Energy and Environmental Policy Research, Department of Economics, Sloan School of Management, MIT, Cambridge, Massachusetts.

Ketterer, J. C. (2014). The Impact of Wind Power Generation on the Electricity Price in Germany. *Energy Economics*, 44, pp. 270–280.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., and Shin, Y. (1992). Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root. *Journal of Econometrics*, 54, pp. 159–178.

Lucía, J. J. and Schwartz, E. S. (2002). Electricity Prices and Power Derivatives: Evidence from the Nordic Power Exchange. *Review of Derivatives Research*, 5, pp. 5–50.

Mauritzen, J. (2010). What Happens When It's Windy in Denmark? An Empirical Analysis of Wind Power on Price Volatility in the Nordic Electricity Market. Discussion Paper 2010/18, Department of Business and Management Science, Norwegian School of Economics, Bergen, Norway.

Mauritzen, J. (2011). What Happens When It's Windy in Denmark? An Empirical Analysis

of Wind Power on Price Variability in the Nordic Electricity Market. Working Paper No. 889, Research Institute of Industrial Economics (IFN), Stockholm, Sweden.

Nasdaq OMX (2018). Power. http://www.nasdaqomx.com/commodities/markets/power. Retrieved April 2, 2018.

Nicholson, E., Rogers, J., and Porter, K. (2010). The Relationship Between Wind Generation and Balancing Energy Market Prices in ERCOT: 2007–2009. Subcontract Report NREL/SR-5500-49415. National Renewable Energy Laboratory, Golden, Colorado.

Nord Pool (2017a). Producers. https://www.nordpoolgroup.com/the-power-market/The-market-members/Producers/. Retrieved April 30, 2018.

Nord Pool (2017b). History. https://www.nordpoolgroup.com/About-us/History/. Retrieved April 2, 2018.

Nord Pool (2017c). Organisation. https://www.nordpoolgroup.com/About-us/organisation/. Retrieved April 2, 2018.

Nord Pool (2017d). Market Members. https://www.nordpoolgroup.com/the-power-market/The-market-members/. Retrieved April 2, 2018.

Nord Pool (2017e). Product Specifications: Nordic/Baltic Market and Germany. https://www.nord-poolgroup.com/globalassets/download-center/rules-and-regulations/product-specifications-nordic-baltic-and-german-market_valid-from-26-march-2018.pdf. Retrieved May 11, 2018.

Nord Pool (2017f). Price Calculation. https://www.nordpoolgroup.com/TAS/Day-ahead-trading/Price-calculation/. Retrieved April 2, 2018.

Nord Pool (2017g). Bidding Areas. https://www.nordpoolgroup.com/the-power-market/

Bidding-areas/. Retrieved April 2, 2018.

Nord Pool (2017h). List of Changes in Elspot Area. https://www.nordpoolgroup.com/globalassets/download-center/day-ahead/elspot-area-change-log.pdf. Retrieved May 7, 2018.

Nord Pool (2017i). Day Ahead Market Regulations. https://www.nordpoolgroup.com/globalassets/download-center/rules-and-regulations/day-ahead-market-regulations_valid-from-15-august-2017.pdf. Retrieved April 2, 2018.

Nord Pool (2017j). Market Data. https://www.nordpoolgroup.com/Market-data1/Dayahead/Flow1/Flow/KEY/Norway1/. Retrieved June 13, 2018.

Oswald, J., Raine, M. and Ashraf-Ball, H. (2008). Will British Weather Provide Reliable Electricity? *Energy Policy*, 36(8), pp. 3212–3225.

Pereira, J. P., Pesquita, V., and Rodrigues, P. M. M. (2017). The Effect of Hydro and Wind Generation on the Mean and Volatility of Electricity Prices in Spain. 14th International Conference on the European Energy Market (EEM), June 6-9, 2017, Dresden, Germany.

Rintamäki, T., Siddiqui, A. S., and Salo, A. (2017). Does Renewable Energy Generation Decrease the Volatility of Electricity Prices? An Analysis of Denmark and Germany. *Energy Economics*, 62, pp. 270–282.

Söder, L. (2005). 'The Value of Wind Power', in Ackermann, T. (ed.) *Wind Power in Power Systems*. Chichester, England: John Wiley and Sons, pp. 169–195.

Söder, L. and Ackermann, T. (2005). 'Wind Power in Power Systems and Introduction', in Ackermann, T. (ed.) *Wind Power in Power Systems*. Chichester, England: John Wiley and Sons, pp. 25–51.

Statistics Finland (2017). Official Statistics of Finland (OSF): Production of Electricity and Heat. ISSN=1798-5099. http://www.stat.fi/til/salatuo/2016/salatuo_2016_2017-11-02_tie_001_en.html. Retrieved April 2, 2018.

Statistics Norway (2017). Electricity. https://www.ssb.no/en/energi-og-industri/statistikker/elektrisitet/aar. Retrieved April 2, 2018.

Statistics Sweden (2017). Electricity Energy Supply, District Heating and Supply of Natural and Gasworks Gas 2016. No. 1654-3661.

Svenska Kraftnät (2017). System Development Plan 2018–2027. https://www.svk.se/siteassets/om-oss/rapporter/2018/svenska-kraftnat-system-development-plan-2018-2027.pdf. Retrieved April 2, 2018.

Swedish Energy Agency and Norwegian Water Resources and Energy Directorate (2016). En svensk-norsk elcertifikatsmarknad: Årsrapport för 2016. https://www.energimyndigheten.se/globalassets/fornybart/elcertifikat/marknadsseminarium-2017/enmy-4597-elcertifikat-2016-se_web_ny.pdf. Retrieved April 2, 2018.

Timilsina, G. R., van Kooten, G. C., and Narbel, P. A. (2013). Global Wind Power Development: Economics and Policies. *Energy Policy*, 61, pp. 642—652

van Kooten, G. C. (2016). The Economics of Wind Power. *Annual Review of Resource Economics*, 8(1), pp. 181–205.

Woo, C. K., Horowitz, I., Moore, J., and Pacheco, A. (2011). The Impact of Wind Generation on the Electricity Spot-Market Price Level and Variance: The Texas Experience. *Energy Policy*, 39(7), pp. 3939–3944.

Wooldridge, J. M. (2016). *Introductory Econometrics: A Modern Approach.* 6th edition. Boston, Massachusetts: Cengage Learning.

Data Sources

ENTSO-E Transparency (2018). Total Load - Day Ahead/Actual. https://transparency.entsoe.eu/load-domain/r2/totalLoadR2/show. Retrieved May 2, 2018.

Nord Pool (2018). Historical Market Data. https://www.nordpoolgroup.com/historical-market-data/. Retrieved March 30, and April 27, 2018.

Swedish Energy Agency (2018). Wind Power Statistics. http://pxexternal.energimyndigheten.se/pxweb/en/Vindkraftsstatistik/?rxid=da53ae31-25c9-499e-9cc7-8b71641de466. Retrieved March 30, 2018.

Swedish Energy Agency (2018). Energy in Facts and Figures. http://www.energimyndigheten.se/en/news/2018/energy-in-sweden---facts-and-figures-2018-available-now/. Retrieved April 30, 2018.

Thomson Reuters Eikon (2018). Retrieved May 7, 2018.

Appendices

Appendix 1: Definitions

Volatility: The standard deviation of a variable.
Relative volatility: Deviation relative to its mean, i.e. changes in percentage terms.
Intermittency: The characteristic of renewable energy, i.e. it cannot provide a constant supply of electricity
Wind share: The fraction of wind power electricity production to total electricity production.
Wind penetration: The fraction of wind power electricity production to total electricity demand.

Appendix 2: Electricity Production Statistics

Table A2.1: Installed Wind Power Capacity per Bidding Area

	2014	2015	2016	2017
SE1	453	489	523	523
SE2	1393	1978	2297	2347
SE3	1812	1882	2018	2120
SE4	1429	1469	1596	1621

Note: Authors' own. Installed wind power capacity in the last years for the different bidding areas. All numbers are measured in megawatts. Data retrieved from the Swedish Energy Agency (2018).

Table A2.2: Average Production and Demand per Bidding Area

	SE1	SE2	SE3	SE4
Wind power	154	582	664	460
Total production	2695	5590	10199	1370
Demand	1114	1967	10070	2827

Note: Authors' own. Average hourly production and demand for the different bidding areas. All numbers are measured in megawatt hours and are rounded to closest integer. Data is from the period January 1, 2015 to March 11, 2018 and is retrieved from Nord Pool (2018).

Appendix 3: Seasonal Adjustment

Table 6: Deseasonalization

	(1) Volatility SE4	(2) Demand SE4	(3) Wind SE4	(4) Wind DK
February	-1.652***	25.50	-43.53	-51.49
March	-2.382***	-360.2***	-114.9***	-362.6***
April	-3.745***	-754.9***	-59.48	-294.1**
May	-2.924***	-1141.2***	-166.5***	-419.9***
June	0.424	-1306.0***	-145.6***	-472.7***
July	-3.611***	-1454.5***	-196.3***	-546.4***
August	-0.871	-1375.6***	-171.4***	-593.5***
September	-1.088	-1183.4***	-180.8***	-632.2***
October	-0.901	-892.0***	26.30	-168.9
November	-0.923	-489.4***	36.72	13.49
December	-1.418**	-362.8***	145.8***	449.3***
Tuesday	-0.00963	34.67		
Wednesday	-0.246	33.73		
Thursday	0.132	13.30		
Friday	-1.100**	-75.75***		
Saturday	-4.121***	-379.7***		
Sunday	-3.901***	-401.5***		
Constant	7.997***	3672.8***	530.4***	1823.1***
N	1166	1166	1166	1166

Note: Standard errors in parentheses. Estimated using Ordinary Least Squares.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Appendix 4: Augmented Dickey-Fuller Test

Table A4.1: Dickey-Fuller Test Statistics

	Lag 1	Lag 7	Lag 14	Lag 21
vol_t	-22.06	-9.53	-8.15	-7.43
$rvol_t$	-21.75	-7.49	-5.65	-4.55
$wprod_t$	-19.40	-11.18	-9.46	-7.41
$wpen_t$	-19.11	-10.99	-9.54	-7.48
$load_t$	-12.06	-8.43	-7.90	-6.69
$windDK_t$	-19.34	-11.29	-9.25	-7.13
$windvol_t$	-28.25	-10.71	-8.12	-6.38

Note: Dickey-Fuller test statistics with 1, 7, 14 and 21 lags for the variables. The critical values of the ADF test without trend are -3.43, -2.86 and -2.57 for one, five, and ten percent significance levels, respectively.

Appendix 5: Alternative Model Specifications

Table A5.1: Wind on Relative Price Volatility, ARMA(2,1)

	(1)	(2)	(3)
$rvol_t$			
$wprod_t$	-0.0000535***	-0.0000481***	
	(0.00000852)	(0.00000855)	
$wpen_t$			-0.150***
			(0.0230)
$load_t$		0.0000594***	
		(0.0000149)	
constant	0.189***	0.0180	0.189***
	(0.0189)	(0.0463)	(0.0190)
ARMA			
α_1	1.281***	1.281***	1.282***
	(0.0204)	(0.0203)	(0.0204)
α_2	-0.290***	-0.289***	-0.290***
	(0.0193)	(0.0192)	(0.0193)
β_1	-0.946***	-0.948***	-0.947***
	(0.0126)	(0.0123)	(0.0125)
p(21)	0.310	0.343	0.329
Log-likelihood	1238.2	1245.5	1238.9

Note: Standard errors in parentheses. Estimated using Maximum Likelihood.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

Table A5.2: Wind Volatility on Relative Price Volatility, ARMA(2,1)

	(1)	(2)	(3)	(4)
$rvol_t$				
$windvol_t$	-0.0000511	-0.0000399		
	(0.0000317)	(0.0000312)		
$load_t$		0.0000693***		
		(0.0000151)		
$rwindvol_t$			0.0602***	0.0602***
			(0.0116)	(0.0116)
constant	0.170***	-0.0277	0.144***	0.144***
	(0.0181)	(0.0454)	(0.0175)	(0.0175)
ARMA				
α_1	1.286***	1.285***	1.290***	1.290***
	(0.0205)	(0.0203)	(0.0208)	(0.0208)
α_2	-0.295***	-0.293***	-0.299***	-0.299***
	(0.0194)	(0.0193)	(0.0197)	(0.0197)
β_1	-0.948***	-0.950***	-0.946***	-0.946***
	(0.0125)	(0.0123)	(0.0129)	(0.0129)
p(21)	0.170	0.191	0.123	0.123
Log-likelihood	1223.6	1233.6	1234.1	1234.1

Note: Standard errors in parentheses. Estimated using Maximum Likelihood.
(* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)