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Wind Power Production and Electricity Price Volatility

An empirical study of the effect of increased wind power production on electricity price volatility in Norway

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Abstract

As renewable energy sources are gaining increasing importance on the global electricity scene, the importance of understanding their implications increases accordingly. This thesis aims to increase electricity market participants' understanding of how the introduction of intermittent renewables in the energy mix will affect electricity price dynamics. Specifically, we examine whether wind power production has an effect on electricity price volatility in Norway. By doing so, we provide research on an unexamined market, which is particularly interesting due to its hydro-reliance and wind power potential.

In our analysis, based on electricity price data from 2013 to 2019, we have found that there is a significant positive relationship between wind power production and intra-weekly electricity price volatility in Norway. This finding has implications for Norwegian electricity consumers and producers, as increased price volatility creates both challenges and opportunities. Increased price volatility encourages investment in flexible supply and consumption, and we argue that such an investment may offset the disadvantages of the uncertainty associated with price fluctuations. In the analysis of wind power's effect on intra-daily volatility, however, we do not find an equivalent significance. Thus this finding provides interesting opportunities for future research as global investments in wind power continue to increase.

Keywords – Electricity prices, Volatility, Wind power, Norway

Contents

1 Introduction

Electricity markets are gaining increasing importance in the global economy. As the world is facing challenges related to climate change, depletion of natural resources, and growing energy demand, the involvement of the electricity markets is required beyond their core activities. There is undeniable evidence that electricity markets are going through an era of global change, and the changes are mostly related to the transition towards a more sustainable energy mix (Kyritsis et al., 2017). The integration of renewable energy sources is expected to minimize, and even prevent, some of the above-mentioned challenges through the mitigation of climate change, diversification of the energy mix and security of energy supply. To foster this integration, and the sustainable transition, governments across the globe, are implementing policies with the aim of incentivizing investment in renewables. These activities are reshaping today's electricity markets and provoking fundamental changes to the dynamics of deregulated electricity prices. The latter should be of great concern to electricity producers, consumers, and even policymakers, and is a direct effect of the increasing penetration of renewables in the energy mix.

Electricity prices display dynamics considerably different from those of financial assets and even other commodities (Vehviläinen and Pyykkönen, 2005; Kyritsis et al., 2017). These dynamics reflect the idiosyncrasies of the power system, which are mainly attributed to the instantaneous nature of electricity. Without the ability to store electricity, any changes in supply or demand result in frequent price jumps, and this trait is presumed to be enhanced by the introduction of intermittent renewable energy sources, namely solar and wind (Woo et al., 2011). Specifically, the intermittency of renewables is assumed to introduce unpredictability to a market that is fundamentally volatile due to its underlying properties. Hence, as the role of renewables becomes increasingly important, so does the need to have a clear understanding of their impact on electricity prices. Our research question arises from this and is stated as follows:

Can wind power production explain electricity price volatility in Norway?

The relationship between renewables and electricity price levels have been subject to thorough investigation in the field of energy economics (see Sensfuß et al., 2008; Brown, 2012; Cludius et al., 2014; Clò et al., 2015; Hu et al., 2010; Kyritsis et al., 2017). The findings conclude that when the share of intermittent renewables in the electricity mix increases, electricity price levels decrease. This price diminishing effect caused by renewable electricity generation is known in the literature as the merit-order effect, and its presence has been established in a number of electricity markets across the globe. The effect is attributed to the zero-marginal cost of renewables, which shifts the electricity supply curve, also called the merit-order curve, to the right, lowering the electricity prices. The literature on the merit-order effect establishes an important relationship between renewable energy sources and electricity price dynamics, and due to the conclusiveness of the findings, it has become a mainstay in the research on renewables and electricity prices.

The literature examining the effect of renewables on electricity price volatility is, however, inconclusive. Even though the number of studies is less compared to that of the merit-order effect, the research on volatility has increased over the years, both in the form of subordinate studies to a study of the price level and as stand-alone studies. There are, however, no clear consensus in the findings of the empirical studies. While the majority of the papers find a significant positive relationship between renewable electricity generation and electricity price volatility (Green and Vasilakos, 2010; Woo et al., 2011; Milstein and Tishler, 2011; Ketterer, 2014; Clò et al., 2015; Kyritsis et al., 2017), others argue partially for a negative relationship (Mauritzen, 2011; Rintamäki et al., 2017). Consequently, there is a need for more research on this topic as the importance of renewable energy sources continues to increase.

Among the research on the relationship between renewables and electricity price volatility, no thorough, empirical study has been conducted for a country strongly reliant on hydropower production, such as Norway. Hydropower displays extraordinary characteristics when exposed to electricity price fluctuations as it has the ability to make a commodity that is fundamentally non-storable, storable. Consequently, there is a gap in the literature regarding how an increasing intermittent renewable power generation will affect electricity price volatility in a hydro-reliant country. Norway has the last two years doubled its wind power capacity, and more importantly, it is considered to be one of three European countries best suited for further expansion (Enevoldsen et al., 2019). As the investments in wind power capacity increases, so does the relevance of its impact. Combined with the fact that Norway holds half of the European hydropower capacity, making it the largest producer of hydropower in Europe, the Norwegian conditions make a compelling case for why Norway should be investigated to fill the above gap in the literature.

The analysis of our research question is conducted in two turns. First, we use an Ordinary Least Square (OLS) estimation to examine the relationship between wind power production and electricity price volatility in Norway. We measure volatility as the standard deviation of prices and run two regressions, one with daily standard deviation as our dependent variable and one with weekly standard deviation. Secondly, in order to better argue for a causal relationship, we implement a Two-Stage Least Squares (2SLS) estimation by introducing wind speed as an instrumental variable for wind power production. In both analyses, we use time series regressions, and based on the literature review, we expect to observe a positive relationship between wind power production and electricity price volatility.

The results of our analysis of the relationship between wind power production and electricity price volatility indicate that the positive relationship found by several other researchers also holds for Norwegian electricity prices when looking at intra-weekly volatility. This implies that the increasing importance of wind power production in Norway will have implications for electricity producers and consumers. However, we do not find the same significance for intra-daily price volatility. We provide several explanations for why we observe the differing results and mainly attribute the differences to model weaknesses. Our findings of a positive impact of wind power production on intra-weekly price volatility have, nevertheless, implications for electricity market participants in the form of increased uncertainty. However, we argue that the increased price volatility also provides investment opportunities that would not be considered if prices were stable.

Through this thesis, we believe that contributions have been made to the existing literature. Firstly, we have added to the inconclusive base of research on the effect of wind power production on electricity price volatility by documenting a positive effect on Norwegian intra-weekly price volatility. We do so by using data as recent as 2019, which encompasses the recent period of increased renewable penetration in the Norwegian electricity market, making the research topical. Secondly, by investigating Norway, we provide research on a market with a rapidly growing wind power industry, which is particularly interesting due to its reliance on hydropower production. Thirdly, model-wise, we have accounted for more control variables than any other empirical research on this topic. Combined with our inclusion of a 2SLS analysis, we have thus devoted more focus to causality than any other related study, which argues for the reliance of our results.

The thesis will be structured as follows. In the next chapter, we will present the characteristics of electricity prices, followed by a review of existing literature on renewables and electricity price dynamics. Based on the literature review, we will then develop our hypotheses for the relationship between wind power production and electricity price volatility. The third chapter introduces the data used in this thesis and elaborates on the models and methodology used in our analyses. In addition, we present some descriptive statistics. In the fourth chapter, we present and discuss the results of our analyses with respect to our hypotheses and compare the different estimation approaches. In the fifth and final chapter, we conclude our findings and discuss any limitations to the thesis, in addition to suggestions for future research.

2 Literature Review

Our intention with this thesis is to examine whether wind power production can explain electricity price volatility in Norway. The relationship between intermittent renewables and electricity price dynamics has been widely investigated in the existing literature. However, no consensus has been reached for the effect on electricity price volatility. Further, no research has attempted to investigate whether the effect is present in a hydro-reliant country. In this chapter, we introduce the dynamics of electricity prices and elaborate on the existing findings and inconsistencies in the literature.

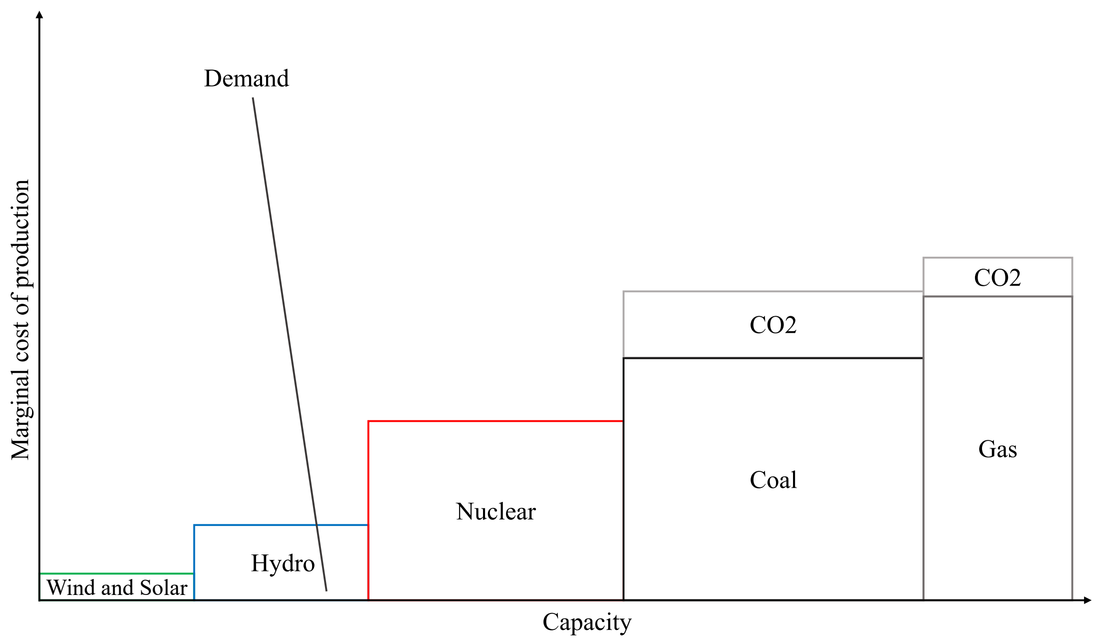
2.1 Electricity Price Dynamics and Drivers

The literary interest in electricity prices rose with the global deregulation of the electricity markets about three decades ago. The deregulation removed price controls and introduced competition, and hence price variations skyrocketed (Knittel and Roberts, 2005). In combination with the idiosyncrasies of the power system, the restructuring of the electricity markets brought about fundamental changes in the dynamics of wholesale electricity spot prices, which are significantly different from those of equity and commodity prices (Vehviläinen and Pyykkönen, 2005; Kyritsis et al., 2017). These dynamics have been researched by a number of studies, including studies by Nogales et al. (2002), Knittel and Roberts (2005), Karakatsani and Bunn (2008), Escribano et al. (2011), and Uritskaya and Uritsky (2015). We present these dynamics in the following.

Volatility is found to be one of the principal characteristics of the deregulated electricity prices, predominantly attributed to the non-storability of electricity. Due to its instantaneous nature, electricity consumption and production have to be continuously balanced, meaning any supply or demand shock will affect the prices immediately, resulting in frequent price jumps or spikes (Escribano et al., 2011). This effect is further amplified by an inelastic demand for electricity in the short run and a strong mean-reverting behavior, resulting in tremendous volatility (see Knittel and Roberts, 2005; Higgs and Worthington, 2008; Milstein and Tishler, 2011). Furthermore, electricity prices are known to display multiple seasonality, corresponding to a daily, weekly, and yearly periodicity and mainly due to a highly weather-dependent electricity demand (Nogales et al., 2002; Escribano et al., 2011). All of the above characteristics constitute the dynamics of electricity prices and should be accounted for in any attempt to model the prices.

The electricity price dynamics reflect the pricing mechanism. The electricity demand curve is steep and highly inelastic, reflecting the consumers' limited ability to change their consumption patterns in the short-run (Kyritsis et al., 2017). The complexity of electricity prices does, however, mostly arise from the shape of the supply curve, which is steeply increasing, discontinuous and convex (Karakatsani and Bunn, 2008) and composed of all electricity-producing energy sources, their capacities and their marginal costs of production. A stylized illustration of this curve is found in Figure 2.1. The energy sources appear on the curve in the order of their marginal costs, with the cheapest being situated to the far left, and the power sources with higher marginal costs constituting the right part of the curve. Due to this established order of the energy sources, the electricity supply curve is also known as the merit-order curve, and we will use the two names interchangeably. The order entails that the energy sources with lower marginal costs will always be prioritized in electricity production. As a result, the merit-order curve moves with the capacity of these energy sources, which are mainly intermittent renewables with near-zero marginal costs.

Figure 2.1: The Merit-Order-Curve



2.2 Renewables and Electricity Price Levels

The relationship between intermittent renewable energy production and electricity prices has been subject to thorough investigation. The studies find that there is a negative effect of increased renewable power generation on electricity spot price levels, and the findings are conclusive across markets. Due to the conclusiveness of the results, this effect has been established as the most important implication of an increasing share of renewables in the energy mix.

Sensfuß et al. (2008) were some of the first to establish a relationship between renewable electricity production and electricity price levels. By investigating the German electricity market, they found that the increasing share of renewables in the German energy mix reduced the average market spot price by 7.83 €/MWh. The findings by Sensfuß et al. (2008) were later followed by the studies of Nicolosi and Fürsch (2009) and Cludius et al. (2014), which confirmed the negative relationship between renewable power production and electricity prices in the German market. The price diminishing effect of renewables on the electricity spot prices was attributed to changes in the electricity supply curve, and thus it was named the merit-order effect. As renewable energy sources constitute the far left part of the merit-order curve, due to near-zero marginal costs, an increase in capacity for these energy sources would shift the merit-order curve to the right, resulting in the observed reduction in German electricity prices.

The merit-order effect is ultimately driven by electricity demand, the slope of the supply curve, and the variable renewable energy sources (Kyritsis et al., 2017). The demand, and particularly residual demand, which is the demand not served by intermittent renewables, determines the intersection with the supply curve. In turn, the slope of the supply curve decides which energy source's marginal costs set the prices. Thus the fuel and hydro prices constituting the supply curve play an important role in the size of the merit-order effect and the setting of the equilibrium electricity price (Kaminski, 1997; Mjelde and Bessler, 2009; Mohammadi, 2009; Huisman et al., 2014).

As Norway is highly reliant on hydropower, this has traditionally been the decisive energy source in the setting of Norwegian electricity prices (Kjaerland, 2007). Nevertheless, as Norwegian wind power production is increasing, this may be subject to change. The reason is that wind power displays even lower marginal costs than hydropower due to the latter considering the opportunity cost of postponing production. As a result, wind production appears to the left of hydropower on the merit-order curve, controlling the supply shifts. Regarding the conventional energy sources, such as coal and gas, they are barely used in Norwegian electricity production, with coal not even being present in the energy mix for mainland Norway. Gas, although previously important, is now only used to a limited extent in the northern parts of Norway. However, due to its importance in Europe and the increasing power exchange between Norway and Europe, gas' impact on Norwegian electricity prices should not be disregarded.

2.3 Wind Power and Electricity Price Volatility

Although an increase in renewable electricity production delights consumers and the Norwegian industry with lower electricity prices, there may be associated challenges. The theory of the merit-order effect suggests that the renewables' intermittency would lead to frequent changes in the supply curve, and consequently, price fluctuations. In contrast to the conclusive literature on electricity price levels, there is, however, no similar consensus in the findings of the effect of wind power production on electricity price volatility.

The majority of studies examining the effect of renewable power production on electricity price volatility find a positive relationship. A large proportion of these studies use a General Autoregressive Conditional Heteroscedastic (GARCH) model, as introduced by Bollerslev (1986), which investigates the effect of mostly wind power generation on the electricity price level and price volatility in an integrated approach. A noteworthy such study is a study from Ketterer (2014), which analyzes the effect of intermittent wind power on electricity price behavior in Germany. By using daily data on a basic GARCH model, Ketterer finds that the variable wind power production reduces the electricity price level and increases the price volatility. Her findings from the German market are further confirmed by the more recent study by Kyritsis et al. (2017), which extends the GARCH model of Ketterer to a GARCH-in-Mean model with both solar and wind power as exogenous variables. Kyritsis et al. (2017) find that both solar and wind power reduces German electricity prices; however, that they affect volatility in different ways. While solar power reduces the volatility of electricity prices due to its covariance with peak demand, wind power increases the price volatility by challenging the electricity market flexibility. Moving away from the German market, Pereira and Rodrigues (2015), using an ARX-ERGARCH model, investigate the behavior of electricity prices in Italy with the same conclusions reached. Their study finds the same negative impact of wind power on electricity price levels in Italy and the same significant positive relationship between intermittent wind power generation and Italian electricity price volatility. This argues that the results from the various GARCH analyses are consistent across markets.

The increasing effect on electricity price volatility from wind production has also been established using other model approaches. Through scenario analyses, Green and Vasilakos (2010) and Milstein and Tishler (2011) evaluate the impact of intermittent renewables on hourly electricity price dynamics in the UK and Israel, respectively, concluding that also for these markets the introduction of such energy sources amplifies price volatility. In addition, more traditional econometric models such as Ordinary Least Squares (OLS) were used in the studies by Woo et al. (2011) and Clò et al. (2015) with the same conclusion reached for the Texan and Italian market. Both of these studies include time fixed effects in their modeling, but while Clò et al. (2015) include wind exchange as an important driver of Italian electricity prices, Woo et al. (2011) has a greater focus on the inclusion of gas prices and nuclear production as these are essential drivers of Texan electricity prices. Regardless, both studies find significant results indicating that increased wind power increases electricity price volatility, though by modeling electricity prices rather than volatility and primarily viewing volatility as a measure of uncertainty rather than price fluctuations.

Even though the majority of the literature establishes a positive relationship between wind power production and electricity price volatility, some literature argues in the direction of a negative one. In their study, Rintamäki et al. (2017) find contradictory results for the German and Danish market, with wind power decreasing electricity price volatility in the latter market. Rintamäki et al. (2017) base their methodology on that of Mauritzen (2011) and use historical price fluctuations as their independent variable, calculated as the standard deviation of a day and a week. Through the application of a SARIMA model, both studies find that while daily and weekly electricity price volatility rises with increased wind power production in Germany, only intra-weekly price volatility increases correspondingly in Denmark. This means that they find a negative relationship between daily wind production and Danish intra-daily volatility. The negative relationship is explained by Denmark's interconnectedness to Norway and Norway's reliance on hydropower, as hydropower stabilizes the price fluctuations because hydropower reservoirs make electricity storable. Hydropower's stabilizing effect on volatility is also argued in the descriptive paper by Dong et al. (2019), which finds that electricity prices in Sweden are more stable compared to those in Denmark and the PJM area, attributing the findings to Sweden's investment in hydropower. Nevertheless, Dong et al. (2019) still observes a positive relationship between volatility in Sweden and wind power, which argues in favor of the majority of the results.

In between the significant empirical findings, we find a study that argues for a non-significant relationship between wind power production and electricity price volatility. In their study of the Nordic electricity market, Liski and Vehviläinen (2016) estimate the price reduction that follows from the entry of wind power, and they also comment on its effect on volatility. According to Liski and Vehviläinen (2016)'s findings, there is no significant relationship between wind power output and price volatility in Norden, which is not in line with the results from the above discussed empirical studies. A reason for this may be that the authors use the system price for the entire Nordic region in their regression analysis, rather than the clearing price for each bidding area. Hence, Liski and Vehviläinen (2016) use a theoretical and fictitious price instead of the actual equilibrium price affected by changes in supply and demand. Accordingly, we place little emphasis on this study.

2.4 Hypothesis Development

Based on the established dynamics of electricity prices and the above literary findings, we expect to find a positive relationship between Norwegian wind power production and electricity price volatility. We base this prediction on the largely consistent results across markets and model approaches, as well as the theoretical foundation of electricity supply and demand. An increase in intermittent wind power production is assumed to cause frequent changes in the supply curve, resulting in price fluctuations. Thus, we expect our results to be in line with those of Ketterer (2014), Kyritsis et al. (2017), Pereira and Rodrigues (2015), Woo et al. (2011) and Clò et al. (2015).

The results from Mauritzen (2011) and Rintamäki et al. (2017) may argue in the opposite direction and of a negative relationship between wind power production and price volatility in Norway. We emphasize the fact that the two studies view volatility as actual price fluctuations and that Denmark is part of the NordPool area, same as Norway. Nevertheless, Norway differs from Denmark with regard to its primary source of electricity, as Denmark is already primarily reliant on wind power. When Denmark increases its wind production, they sell their surplus to Norway, benefitting from Norway's historically stable hydro-driven prices. However, when wind production increases in Norway, it is solely used in the Norwegian electricity production as the intermittent, zero-cost renewables are always prioritized. Hydropower may be able to stabilize some of the price fluctuations. Thus, we may observe a less prominent relationship between wind power and Norwegian electricity price volatility, as Dong (2019) argues for the Swedish market. Nevertheless, we have no reason to believe that an increased wind production in Norway will lead to a decrease in volatility for Norwegian electricity prices, and thus the initial prediction stands. Based on the above discussion, we thus develop our first hypothesis regarding our results:

Hypothesis 1 (H_1): Increasing the wind power production leads to an increase in price volatility for Norwegian electricity spot prices.

Based on the theory of the merit-order effect, we want to extend on *Hypothesis 1* and take a closer look at the variations in the wind power production and its effect on price volatility. The average wind production within a day or a week encompasses periods of both stable and fluctuating wind production, and stable wind production is not expected to have the same effect on price volatility as a fluctuating one. The latter is associated with frequent changes to the merit-order curve, whereas the former may be linked to only one shift in the curve. To account for these varying effects, we would like to examine how the volatility of wind power production can explain the volatility in the electricity prices. As volatility is a measure of price variation, we believe the inclusion of variations of wind power production may better explain the price volatility. This reasoning leaves us with the following second hypothesis:

Hypothesis 2 (H_2): Increasing the wind power volatility leads to an increase in price volatility for Norwegian electricity spot prices.

We expect *Hypothesis 2* to hold if *Hypothesis 1* does, but we do not necessarily expect *Hypothesis 1* to hold even if *Hypothesis 2* does. This expectation is based on the assumption that if an increased level of wind production is associated with increased electricity price volatility, so should increased variations in wind production, as the latter is presumed to lead to more frequent changes in the merit-order curve.

3 Data and Methodology

In this chapter, we will present the data and methodology used to analyze our research question. First, we present the data sources and sample selection and explain any data modifications. Next, we introduce our model and the associated variables before we describe the methodology for the two hypotheses. Finally, we elaborate on the descriptive statistics.

3.1 Data Sources and Sample Selection

We use two primary sources of data in our analysis. NordPool provides us with data on day-ahead electricity spot prices and consumption. The rest of the data, including data on wind power production, is provided from Wattsight through Lyse. Since we use day-ahead prices in our modeling, we would prefer to use day-ahead forecasts of our independent variables. That way, we would be using the actual data used in the setting of electricity prices. However, since such forecasts are not available, and predicting the variables might lead to problems (see Pagan and Nicholls, 1984), we use actual data as a proxy for the forecasts, in line with the methodology of Nicolosi (2010) and Kyritsis et al. (2017). Accordingly, we assume perfect information about the conditions in the market the following day.

The data on electricity prices are obtained from Norway's NO2 bidding area, which encompasses the southwestern part of Norway. The area prices are the actual market clearing prices offered to consumers and producers, in contrast to the system price, which is a fictional price used as an indication of the price level in Norway. By using the area prices, we aim to correct for the possible mistake made by Liski and Vehviläinen (2016) in their analysis and to observe a more accurate relationship between wind production and price volatility. We choose NO2 as our area of interest as we want to correct for wind transmissions with Denmark, and NO2 is the only area connected to Denmark through a power cable.

The time span of our data set ranges from 2013 to 2019, which constitutes all data available at NordPool. The data from NordPool and Wattsight is all high frequency, and the majority of it is collected on an hourly basis, with some exceptions for the control variables. As we are interested in daily and weekly volatility, we aggregate our data in accordance with the current volatility measure. Hence, we create two different data sets, one with daily observations and the other with weekly observations. The first data set thus includes the daily standard deviation of electricity prices, the already available daily data as well as daily averages of the hourly data. A concern raised regarding this data set was the variations in observations for weekends, as some energy sources are not traded during the weekends. To avoid the possible bias related to any imputation method, we choose to remove the weekend observations from our data set, leaving us with a data set of only weekdays of 1826 observations. As for the second data set, no such removals have been made. In order to accord with a weekly volatility measure, we simply divide the weekly sum of the data on the number of observations per week, meaning the data including weekend observations is divided by seven, whereas the data with only weekdays is divided by five. This modification leaves us with 366 observations, which is still a substantial amount of observations due to our data's long time span.

Apart from the above modifications, no other changes have been made to the data set. We detect some outliers, or price spikes, in the data for electricity prices, as expected from the literature on electricity price dynamics. Due to these aforementioned dynamics, we do not consider these price spikes to be abnormal observations, and removal of them would contradict with our aim of explaining such spikes.

3.2 Discussion of Model and Variables

Our model aims to investigate the effect of wind power production on electricity price volatility in Norway. Hence, our dependent variable is the standard deviation of Norwegian electricity prices, and our independent variable is wind production in Norway. To account for other effects that might explain Norwegian electricity price volatility, we include selected control variables from the literature review.

3.2.1 Dependent Variable(s): Daily and Weekly Standard Deviation

Standard deviation is a well-established measure of volatility in financial markets. It is a measure of price dispersion or variance, and generally, it determines the variations between a group of observations and its mean.

There are several variations of the standard deviation formula, and the calculation methods differ somewhat across markets and literature. In finance, a standard deviation is almost exclusively applied to the rate of return of an investment. Another variant of this calculation is the use of log-returns rather than simple returns, which is mostly used for compounded returns (Calafiore and Massai, 2016). Both of these calculations are found in commodity markets as well, see studies from Karali and Power (2013) and Regnier (2007), respectively. However, in commodity markets, we also find instances where the rate of return has been replaced by prices. In their study of relative volatility of commodity prices, Arezki et al. (2014) subtract the price average from the price at time t to measure volatility, and this is also done by Fernandez-Perez et al. (2016) in their study of idiosyncratic volatility. In the literature on electricity price dynamics, we find the calculation of standard deviation of price to be most prevalent, also for the research similar to ours, including studies from Rintamäki et al. (2017) and Mauritzen (2011). In order to be able to compare our results, we base our calculations on the methodology of these two and thus calculate our standard deviation, and thus volatility, as the standard deviation of prices.

With regard to the time span of the volatility measure, most literature investigating electricity price dynamics examine the intra-day volatility, meaning they examine the price variations within a day, see Milstein and Tishler (2011), Ketterer (2014) and Dong et al. (2019) among others. In addition, a small sample of studies also addresses the weekly volatility in their analyses, including the studies by Mauritzen (2011) and Rintamäki et al. (2017). We choose to include both measures as independent variables for several reasons. Firstly, we would like to investigate whether the different measures provide different results. When we aggregate to weekly data, we may smooth out some of the spikes in our variables, including the price spikes, which might lead to less clear relationships. On the other hand, the analysis of *Hypotheses 2* may give us more prominent relationships for the weekly data, as the variations in the variables may appear to be greater than those of daily data. Secondly, one can argue that the intra-day volatility is not really volatility in terms of risk. In financial markets, volatility is usually a measure of the riskiness of an asset; however, as all prices for the day are set one day ahead, there really is no uncertainty related to the prices within a day. Consequently, a weekly measure might thus be a better measure of risk. Besides, we find it beneficial to be able to compare our results to studies such as the one of Rintamäki et al. (2017), which further argues for the inclusion of both measures.

As discussed in Chapter 2, most modeling of electricity price volatility has been done by using a variety of GARCH models. In these models, where the volatility analysis usually comes second to an analysis of the merit-order effect, the standard deviation is derived from the model, resulting in a conditional standard deviation that changes over time as a function of past errors (Bollerslev, 1986). Due to the fact that this standard deviation, or variance, is calculated only based on past observations, a GARCH variance is considered to be a prediction of volatility, rather than an actual measure. Thus, as we are looking to model an actual relationship between our variables, the inclusion of such a variance might bias our results. Furthermore, a GARCH model is only able to provide a volatility measure per hour, day, or week, predicted from past hours, days, and weeks. As a result, GARCH cannot provide us with measures of intra-daily or intra-weekly volatility, which are our dependent variables of interest. On top of this, the GARCH standard deviation is considered to be an abstract measure of volatility in the sense that it is less interpretable due to its calculation. In contrast, the standard deviation measure discussed initially is easily interpreted, comparable across markets, and with great applicability for power producers, hence we are confident in our decision of independent variables.

Based on the above discussions we calculate our dependent variables as follows:

$$SD_{Daily} = \sqrt{\tfrac{1}{24-1} \textstyle\sum_{h=1}^{24} (p_h - \bar{p}_d)^2} \qquad SD_{Weekly} = \sqrt{\tfrac{1}{7-1} \textstyle\sum_{d=1}^{7} (\bar{p}_d - \bar{p}_w)^2}$$

In the calculations of daily standard deviation, $\bar{p}_d$ is the average price within a day, and p_h is the hourly price. The weekly standard deviation is calculated similarly, only p_h is substituted by $\bar{p}_d$, and we subtract the daily average within that week, $\bar{p}_w$.

3.2.2 Independent Variable: Wind Power Production

Our main independent variable is wind power production in Norway. Due to data availability, we use production for the whole of Norway, not just the NO2 area, which is our bidding area in focus. By doing so, we assume an interconnectedness between the bidding areas without congestions and that a change in the national supply curve for the electricity market will lead to a change in the supply curve for the NO2 area. This is a legitimate assumption as the Norwegian power grid is well developed, and the five price areas are closely linked through seemingly well-functioning power cables. Furthermore, wind power production is dependent on the same drivers across Norway. These drivers constitute installed capacity of windmills, the angle of the windmills and thus the wind direction, and naturally, the amount of wind (Hau, 2013).

Even though we consider wind power production to be an exogenous variable due to it being fundamentally non-controllable, there may be some unobservable conditions affecting the dependent variable through the independent one. We formally test and control for this possibility in the second half of our analysis and evaluate the above-mentioned drivers of wind production as possible instruments in a 2SLS instrumental variable approach.

As mentioned in section 3.1 we emphasize that the wind power production we use in our analysis is the actual, historical wind power production in Norway. As electricity spot prices are set the day ahead, it is the forecasted determinants that are used in the price setting. Though, due to the lack of forecasted data, we use actual production and thus assume perfect information regarding the conditions the following day.

In the analysis of *Hypotheses 1* we use the natural logarithm of the wind power production, given as $ln(WindProd)$ in the model. In the analysis of *Hypothesis 2*, however, we use the standard deviation of wind power production in order to examine the effect of wind power variations on electricity price volatility. Thus the wind variable is given in the model as $ln(\sigma_{WindProd})$. In all models, wind power production is reported in MWh.

3.2.3 Control Variables

In this section, we discuss the control variables included in our model. The variables are mainly identified through the literature review as drivers of electricity prices and thus believed to affect volatility. We only include variables relevant for the Norwegian market, and to add additional credibility for their inclusion, they have been vouched for by Lyse.

3.2.3.1 Consumption NO2 *(Consumption)*

The first variable we control for is electricity consumption for the NO2 area. As electricity prices are set by supply and demand mechanics, demand is a fundamental variable in electricity price modeling (Knittel and Roberts, 2005; Karakatsani and Bunn, 2008). Furthermore, the demand affects the size of the previously introduced merit-order effect and, thus, the price fluctuations. Based on this and the prediction by Bessembinder and Lemmon (2002), which states that spot price volatility is higher (lower) during periods of high (low) demand, we expect to find a positive relationship between electricity price demand and price volatility. To account for this relationship, we include consumption in 100 MWh as a proxy for demand, as done by Huisman et al. (2014), among others. For countries with sufficient access to controllable energy sources, electricity supply will never be lower than demand, and consumption will always equal demand. As Norway has plenty of controllable hydropower, this applies to our data. Consumption is primarily driven by weather and temperature (Escribano et al., 2011), and consequently, the variable includes most of the seasonal effects found to be drivers of electricity prices.

3.2.3.2 Hydrological Balance *(Hydro)*

As the primary power source in Norway, hydropower needs to be accounted for due to its effect on electricity supply. The variable of hydrological balance shows the amount of water in the water reservoirs in Norway, including the surrounding snow, compared to what is considered normal. Hence, the variable takes the value of 0 for normal water levels, negative values for lower levels, and positive values for higher levels. The hydrological balance represents the marginal cost of producing hydropower, which essentially is the alternative cost of producing hydropower. A positive hydrological balance means much water stored in the reservoirs and hence a lower marginal cost of producing hydropower. Conversely, a negative hydrological balance means that the water level is low, resulting in a higher marginal cost. In the models, we include the data for hydrological balance as absolute values. However, as we believe the positive and negative values may influence the volatility differently, as argued by Simonsen (2005), we include an interaction term that takes the value of 1 for positive values.

3.2.3.3 Wind Production in Denmark *(WindProdDK)*

We include wind production in Denmark as a control variable. When it is windy in Denmark, Danish electricity prices decrease following the merit-order effect (see Hu et al., 2010), and Danish electricity is transmitted to Norway if the Norwegian prices are lower than Danish prices. This transmission happens exclusively through a cable that goes from the Danish DK1 area to Norway's NO2, and it results in a decrease in the prices in the NO2 area. Ideally, we would include the wind exchange from NO2 to Denmark's area to control for this effect. However, because of a possible simultaneity bias due to the exchange's dependence on the Norwegian price level, we use the Danish wind power production as a proxy. We quote the variable of $WindProdDK$ in 100 MWh.

3.2.3.4 Gas Price *(Gas)*

Fuel prices are found in the literature to be important determinants of the electricity supply curve (Mohammadi, 2009). The gas price determines the marginal cost of electricity production when gas production is part of the merit-order curve that intersects with the demand curve. Even though gas is only used to a certain extent in Norway, it still remains the third most preferred energy source after hydro and wind. Besides, it is an important electricity source in Europe, and with increasing power exchange between Norway and Europe, we need to consider its effect on Norwegian prices.

3.2.3.5 CO2 Certificate Price *(CO2)*

Changes in the CO2 price, which is the price of the EU CO2 emission allowance, are found in the literature to have an impact on electricity prices through its effect on fuel price (see Huisman et al., 2014). Despite the lack of use of fuel power in the Norwegian electricity grid, we choose to include the CO2 price due to its effect on European electricity prices, as the rest of Europe still includes much thermal power in their energy mix. When the prices increase in Europe, Norway benefits from exporting electricity. Though when we export to European markets, the European prices are imported to Norway, and consequently, it affects the Norwegian price level.

3.2.3.6 EUR/NOK Exchange Rate *(EURNOK)*

The EUR/NOK exchange rate is included to account for macroeconomic effects in Norway. In addition, the variable is included to separate out the effect on volatility that comes from changes in the CO2 price, and not changes in the exchange rate as the CO2 price is quoted in euros.

3.3 Methodology

In the following, we explain the econometric methods used to analyze our research question. We use time series regressions for all our models and run two main regressions for each of our two hypotheses, one with intra-daily volatility as a dependent variable and one with intra-weekly volatility. We include seasonal effects in the regressions to capture any seasonality that may affect price volatility, which may be different from the seasonality affecting price. For the intra-day models, we include day-of-week and month-of-year fixed effects, and for the intra-week models, we account only for monthly effects. With regard to the model specification, we create our base model based on the three most important drivers of electricity prices in Norway; wind power, consumption, and hydrological balance. Next, we add the other control variables in order of their presumed importance and check for significance and model fit improvements.

Time series regressions assume stationarity in their variables in order to detect relationships between two or more variables (Wooldridge, 2012). To account for this, we check for stationarity in all of the above-defined variables through an Augmented Dickey-Fuller (ADF) test for unit roots. To be certain of the results, we run additional tests with the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and difference the variables that show non-stationarity or questionable results. We provide explanations for the interpretation of these differenced variables when encountered. Further, we conduct formal tests for autocorrelation and heteroscedasticity and adjust for these features by adding Newey-West robust standard errors. In the following, we explain more thoroughly how we analyze our two hypotheses.

3.3.1 Wind Production and Electricity Price Volatility (H_1)

In order to analyze how wind power production affects electricity price volatility, we construct the following model:

$$ln(SD_t) = \alpha_0 + \beta_1 ln(WindProd_t) + \sum_{i=2} \beta_i X_t + \sum_{j=1} \gamma_j T_t$$

where the dependent variable $ln(SD_t)$ is the natural logarithm of the standard deviation measures defined in 3.2.1 for time t. The independent variable is given as the natural logarithm of wind power production at time t included in the model as $ln(WindProd_t)$.

All our previously defined control variables are included in X_t, and the final part of the equation includes the various time effects as the vector T_t.

We run two regressions with the above model. First, we regress the daily standard deviation on intra-daily averages or daily values of the previously defined variables. Secondly, we regress the weekly standard deviation on intra-weekly averages of the variables. To be able to interpret our wind coefficient as an elasticity, we have taken the natural logarithm of both the volatility metric and the variable of wind production. Consequently, the coefficient of wind can be interpreted as follows: A 1% increase in wind power production leads to a β_1% increase in the relevant standard deviation. With regard to the other variables, they are kept at levels as there is no interpretation reasoning for why they should be changed, nor does the modification improve the model fit or change the significance.

For this model, $ln(SD_t)$ is found to be stationary both for daily and weekly measures. As for the control variables, the daily data of $WindProd$, $Hydro$, and $WindProdDK$ are all found to be stationary at the 5% level. For the weekly data, however, $WindProd$, is found to be non-stationary, and thus we take the first difference of this variable, leaving us with the following interpretation: A 1% change from last week to this week will lead to an increase in intra-week volatility by β_1%. We follow the same procedure for all other variables found to be non-stationary and find them all to be stationary after taking the first difference. Thus they are integrated of order one, I(1), and we can use them in our regression (Wooldridge, 2012).

3.3.2 Wind Power Volatility and Electricity Price Volatility (H_2)

To analyze our second hypotheses, we modify the previous model to include the standard deviations of several of the independent variables:

$$ln(SD_t) = \alpha + \beta_1 ln(\sigma_{WindProd,t}) + \sum_{i=2} \beta_i \sigma_{X,t} + \sum_{j=i+1} \beta_j X_t + \sum_{k=1} \gamma_k T_t$$

Our dependent variable $ln(SD_t)$ remains unchanged and is still defined as the natural logarithm of the daily or weekly standard deviation for time t. The independent variable in this model is, however, now given as the natural logarithm of the standard deviation of wind power production at time t, included in the model as $ln(\sigma_{WindProd,t})$. This variable is thus aimed to capture the changes in wind power and its effect on price volatility. Accordingly, the standard deviations of the control variables are included in the vector

$\sigma_{X,t}$, and the variables that are left unchanged are found in the vector X_t. The final part of the model is the same as before and includes the various time effects as the vector T_t.

Also for this model, we run two regressions, one for daily data and one for weekly data. The wind power coefficient is kept as an elasticity, interpreted as explained in 3.3.1, but now as the standard deviation. All other variables are kept at levels as in the previous analysis. Concerning stationarity, SD and $WindProd$, as well as $Consumption$, $Hydro$, and $WindProdDK$ are found to be stationary by both the ADF and KPSS test, for both weekly and daily data. This implies that the variables are all integrated at order zero, I(0), and we can include them undifferenced in the model (Wooldridge, 2012). As for the remaining three variables, they are found to be non-stationary for daily data, and thus we include them as first-differences.

3.4 Descriptive Statistics

In the final part of this chapter, we present the descriptive statistics for the data used in our analysis. First, we present summary statistics for all of our variables and graphically illustrate the dynamics of our dependent and independent variable. We then elaborate on the results from a correlation matrix and address any possibility for multicollinearity.

3.4.1 Summary Statistics

The first table in the following contains summary statistics for the daily data. This means that it contains the already available daily data as well as daily averages of the hourly data, all weekends excluded. In the second table, we have aggregated to weekly data, leaving us with an average per week. Both of the data sets described below are used as a basis for the regressions in the subsequent chapter, though with some of the variables log-transformed, differenced or included as standard deviations in the final regression models. The data described in this section is thus the unmodified data set available prior to these transformations.

Table 3.1: Summary Statistics Daily Data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Price (EUR/MWh)	1,826	32.1	10.3	5.4	25.3	38.7	78.1
WindProd (MWh)	1,826	336	217	47	179	432	1,741
Consumption (100 MWh)	1,826	40.8	7.0	29.6	34.1	46.5	60.6
Hydro	1,826	−4.6	8.4	−25.0	−9.6	1.5	18.9
WindProdDK (100 MWh)	1,826	15.5	10.6	0.4	6.5	22.7	44.6
Gas (p/therm)	1,825	49.9	12.2	26.1	42.0	58.6	81.3
CO2 (EUR/ton)	1,826	10.0	7.3	2.8	5.1	13.0	29.8
EURNOK	1,826	9.0	0.7	7.3	8.4	9.6	10.3

Table 3.2: Summary Statistics Weekly Data

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Price (EUR/MWh)	366	31.6	9.9	8.1	24.8	37.5	63.9
WindProd (MWh)	366	339	192	67	195	414	1,574
Consumption (100 MWh)	359	40.0	6.9	29.6	33.5	46.3	56.6
Hydro	365	−4.6	8.3	−24.9	−9.6	1.4	17.9
WindProdDK (100 MWh)	366	15.6	6.7	3.4	10.7	20.2	34.1
Gas (p/therm)	365	49.9	12.2	26.3	42.2	58.4	79.2
CO2 (EUR/ton)	365	10.0	7.3	3.0	5.1	13.1	29.2
EURNOK	365	9.0	0.7	7.3	8.4	9.6	10.2

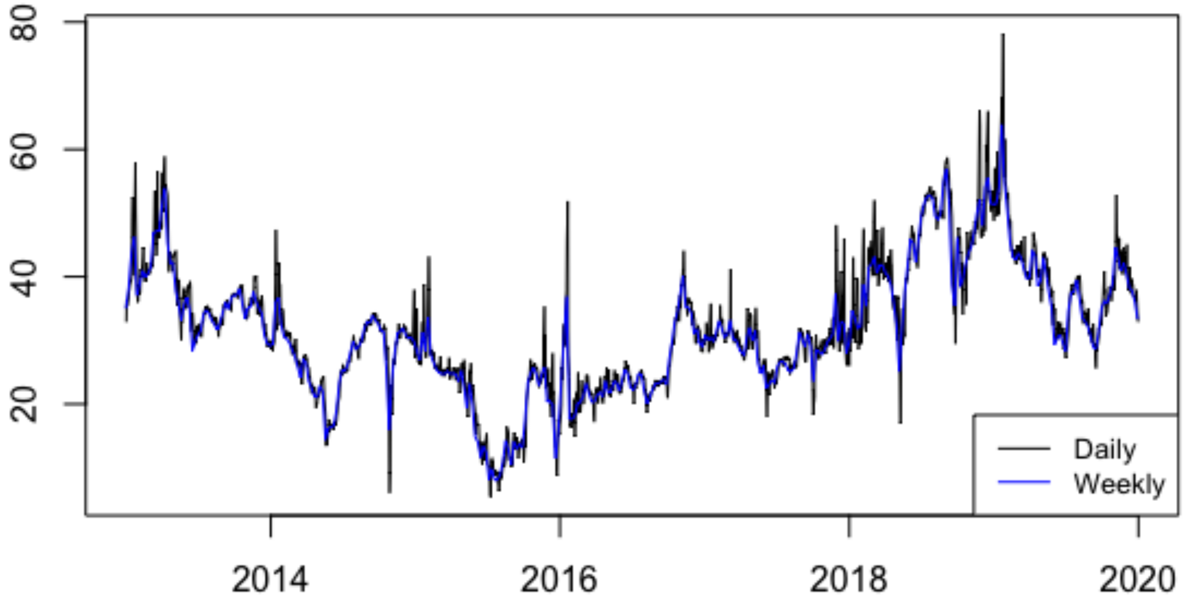
The electricity prices have a mean value of 32.1 and 31.6 EUR/MWh for the daily and weekly data set, respectively. As the two data sets are based on the same initial data, we would expect the two means to be the same, but the difference is attributed to the removal of the weekend observations in the daily data set. This causes the mean electricity price to decrease in the weekly data set, implying that weekend electricity prices tend to be lower than those of the weekdays. Gas, $CO2$, and $EURNOK$ all have the same mean in both data sets as the weekend data is not present in either of them.

Hydrological balance is the only control variable to hold negative values, which is explained by the aforementioned variable definition. Interestingly enough, we find the mean to be negative, implying that the water levels in the selected time period overall are below normal. We observe no negative values for Norwegian electricity prices, which has been observed for other countries, notably in windy Denmark. This is non-surprisingly not found for the NO2 area as hydropower is the dominant power source, and it always holds a marginal cost above 0.

Worth mentioning from the two above tables is that all of the variables' maximum values are lower for the weekly data, indicating that some of the highest values are evened out when aggregated to weekly averages. This is also illustrated in the plot in Figure 3.1 below, which show that the spikes observed in the electricity prices are lower and less frequent in the weekly data than in the daily.

Figure 3.1: Evolution of Norwegian Electricity Prices

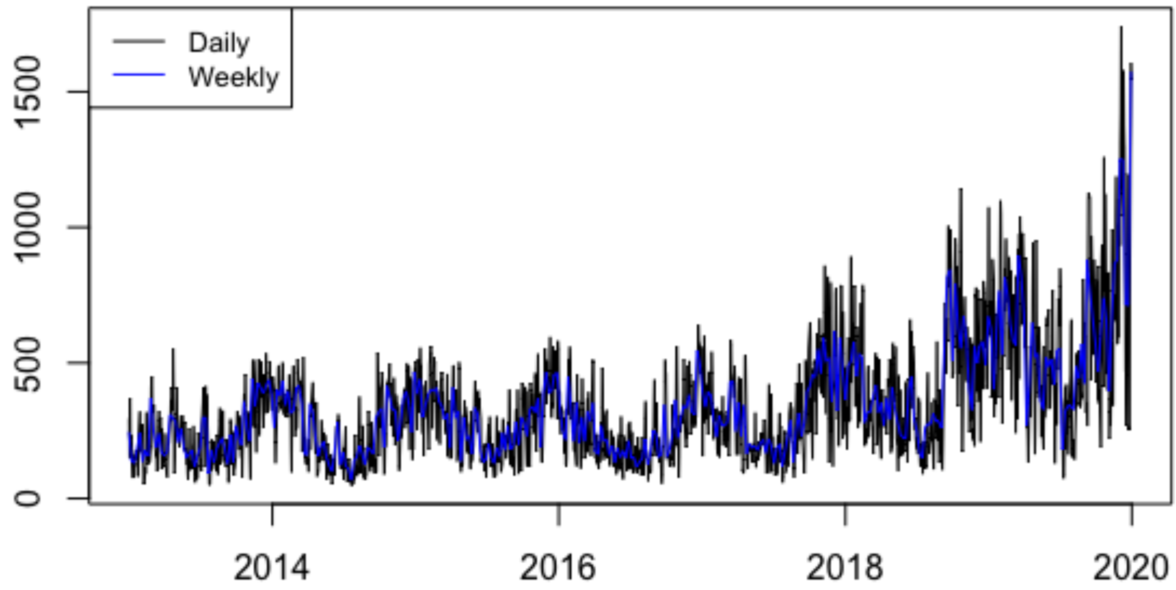
The figure displays the evolution of average daily and weekly electricity prices within the NO2 bidding area during the period 2013-2019. The prices are stated in EUR/MWh.



The summary statistics for wind power production do not truly illustrate the growth this sector has experienced in the last couple of years. To illustrate this, we include a plot with both the daily and the weekly average wind power production below in Figure 3.2. As displayed, the production has grown exponentially during the selected time span, and as the capacity has grown, so has the fluctuations in production levels. We also observe for this plot that the spikes are more prominent in the daily wind production than in the weekly production.

Figure 3.2: Evolution of Norwegian Wind Power Production

The figure displays the evolution of average daily and weekly wind power production in Norway during the period 2013-2019. The production is stated in MWh.



3.4.2 Pearson's Correlation Matrix

In the following, we analyze the Pearson's correlation coefficients between the variables included in our regression models. We do this to determine whether or not we should be concerned about multicollinearity, namely a high correlation between our independent variable of interest and the other exogenous variables. All variables appear in the form they take in the regressions, meaning some appear as first differences, natural logarithms, and standard deviations. That way, we reveal alarming correlations between the actual variables used in our analyses in the subsequent chapter. We present two correlation matrices associated with the analysis of each hypothesis, one for daily data and one for weekly data. In neither of the matrices, we find correlations above 0.5, which indicates a limited likelihood of a multicollinearity issue in either of our models. Despite this, there are a few correlations we would like to comment on.

In the matrices associated with *Hypothesis 1*, the correlation between daily $WindProd$ and $WindProdDK$ stands out as we find it to be 0.48. This raises a concern that the weather conditions in Norway and Denmark are so similar that the wind power plants produce electricity at the same time in both countries. To test whether we have a formal multicollinearity issue in our regression, which may harm the interpretability of the regressions, we conduct a Variance Inflation Factor (VIF) test. A VIF score of 1 indicates no collinearity, and any score below 5 is considered acceptable (Levshina, 2015). Our VIF test for the regression with daily data shows a value of 1.3, and we thus reject multicollinearity being an issue. For the weekly data, this correlation no longer stands out as it is there reduced to 0.194. None of the remaining control variables have a noteworthy high or low correlation with our variable of interest.

Table 3.3: Hypothesis 1, Daily Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $ln(\text{SD}_{Daily})$		0.2343	0.0847	0.1895	0.0824	-0.0046	0.0076	0.0119
(2) *ln(WindProd)*			-0.0857	0.0303	0.4784	-0.0505	-0.027	-0.018
(3) $\Delta Consumption$				0.0081	-0.108	-0.0709	-0.0161	0.0106
(4) *Hydro*					-0.0166	-0.0141	0.0294	0.0183
(5) *WindProdDK*						-0.0241	-0.0146	-0.027
(6) ΔGas							0.0592	-0.0013
(7) $\Delta CO2$								2e-04
(8) $\Delta EURNOK$								

Table 3.4: Hypothesis 1, Weekly Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $ln(\text{SD}_{Weekly})$		0.1005	0.3431	0.0961	0.1925	-0.0636	-0.0023	-0.0024
(2) $\Delta ln(WindProd)$			-0.031	0.0174	0.194	-0.0249	-0.0683	0.0551
(3) *Consumption*				0.1014	0.4122	-0.2395	-0.0345	-0.0429
(4) *Hydro*					-0.0238	0.0029	0.088	0.0694
(5) *WindProdDK*						-0.1155	-0.0936	0.0115
(6) ΔGas							0.2242	-0.0256
(7) $\Delta CO2$								-0.0146
(8) $\Delta EURNOK$								

For the data used in the analysis of *Hypothesis 2*, none of the correlation coefficients between our variable of interest and the control variables in the daily data stand out as possible issues. For the weekly data, on the other hand, there are a few variables that show slight correlations with $WindProd$ making them worth investigating. The standard deviations of $WindProdDK$, Gas, and $CO2$ correlate with the standard deviation of $WindProd$ with coefficients between 0.22-0.34. We, therefore, conduct another VIF test to check if this could cause any issues with the interpretation of the weekly regression models in *Hypothesis 2*. The VIF test is once again 1.3, indicating that the inclusion of these variables does not cause an issue and that we should include them to prevent any possible omitted variable bias.

Table 3.5: Hypothesis 2, Daily Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $ln(\mathrm{SD}_{Daily})$		0.1638	0.3267	0.1895	0.4376	-0.0046	0.0076	0.0119
(2) $ln(\sigma_{WindProd})$			0.0853	0.0227	0.1684	-0.038	-0.0235	-0.0119
(3) $\sigma_{Consumption}$				0.0655	0.3047	-0.0796	-0.0286	0.0019
(4) $Hydro$					0.1445	-0.0141	0.0294	0.0183
(5) $\sigma_{WindProdDK}$						-0.0061	0.012	-0.055
(6) ΔGas							0.0592	-0.0013
(7) $\Delta CO2$								2e-04
(8) $\Delta EURNOK$								

Table 3.6: Hypothesis 2, Weekly Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) $ln(\mathrm{SD}_{Weekly})$		0.2149	0.3484	0.1631	0.2778	0.0732	0.1892	-0.0287
(2) $ln(\sigma_{WindProd})$			0.08	0.1721	0.2825	0.2235	0.341	-0.0418
(3) $\sigma_{Consumption}$				0.2068	0.1926	0.0381	0.0479	-0.0599
(4) σ_{Hydro}					0.0844	0.0038	0.0782	0.0113
(5) $\sigma_{WindProdDK}$						0.0699	0.0342	0.0471
(6) σ_{Gas}							0.3084	-0.0698
(7) σ_{CO2}								-0.1116
(8) σ_{EURNOK}								

The correlation between our volatility measures and the wind production variables show correlations in the range of 0.1005-0.2343. This signifies a positive relationship between our dependent and independent variable, which is in line with our expectations. However, further analyses are necessary to fully test our hypotheses.

4 Results and Discussion

In this chapter, we will present the results from our analyses of *Hypothesis 1* and *2*. In the first section, we interpret the results from an OLS estimation, addressing the two hypotheses separately. Next, we use an instrumental variable approach to be better able to argue causality, and in the second section, we thus explore the results from a 2SLS estimation.

4.1 Determining Causal Effects through OLS

4.1.1 Wind Production and Electricity Price Volatility $(\boldsymbol{H}_1)$

In the following section, we will present the results from our analysis of *Hypothesis 1*, which aims to explain the effect of wind power production on electricity price volatility. We use the time series regression model outlined in 3.3.1 and run regressions for both daily and weekly observations. First, we start by regressing SD_{Daily} on $WindProd$ alone. In the next step, we include the control variables introduced in section 3.2.3 to reduce any omitted variable bias and increase estimate precision. As we do not detect any multicollinearity issue in 3.4.2 and thus have no reason to doubt the coefficient estimates, we choose to include them all in our final model. As the last step, we add day-of-week and month-of year fixed effects to the model to control for any unobserved seasonality that might affect the price volatility. The regressions are displayed in Table 4.1. We follow the same procedure for the weekly data and intra-week electricity price volatility and present the corresponding results in Table 4.2. The motivation for the two analyses is to see whether it is decisive, which volatility measure is used; hence, the inclusion serves as a robustness check. Based on the literature review, we however, expect wind power production to have a significant effect on price volatility in Norway for both time horizons.

The table below includes five different time series regressions. The first model regresses $ln(SD_{Daily})$ on $WindProd$. Model (2) controls for the presumed most important drivers of electricity prices in Norway and model (3) includes all variables defined in 3.2.3. Models (1) through (3) include no fixed effects, whereas regression (4) includes day-of-week fixed effects, and model (5) also adds month-of-year fixed effects. To correct for detected heteroscedasticity and autocorrelation, we use Newey-West standard errors in all regressions.

Table 4.1:
Intra-Daily Electricity Price Volatility and Wind Production in Norway

The table displays time series regressions for the relationship between Norwegian wind power production and intra-daily electricity price volatility in Norway's NO2 bidding area. The results are based on a sample of 1826 daily observations ranging from 2013 to 2019, excluding weekends. Models (1) through (3) include no seasonal fixed effects, whereas model (4) and (5) include fixed effects for day-of-week and month-of-year. Newey-West heteroscedasticity and autocorrelation corrected standard errors are displayed in parentheses.

	Dependent variable:				
	$\ln(\mathrm{SD}_{Daily})$				
	(1)	(2)	(3)	(4)	(5)
ln(WindProd)	0.321***	0.324***	0.341***	0.344***	0.268***
	(0.080)	(0.071)	(0.072)	(0.072)	(0.061)
Δ*Consumption*		0.058***	0.058***	0.056***	0.054***
		(0.014)	(0.013)	(0.013)	(0.012)
Hydro		0.027***	0.027***	0.027***	0.029***
		(0.007)	(0.007)	(0.007)	(0.006)
PosHydro		0.010	0.011	0.011	0.012
		(0.014)	(0.014)	(0.014)	(0.012)
WindProdDK			−0.002	−0.002	−0.004
			(0.004)	(0.004)	(0.004)
Δ*Gas*			0.013	0.015	0.024**
			(0.013)	(0.013)	(0.012)
Δ*CO2*			0.024	0.023	0.042
			(0.044)	(0.043)	(0.041)
Δ*EURNOK*			0.201	0.236	0.328
			(0.433)	(0.431)	(0.375)
D-O-W FE	No	No	No	Yes	Yes
M-O-Y FE	No	No	No	No	Yes
Observations	1,825	1,825	1,823	1,823	1,823
R^2	0.055	0.100	0.100	0.109	0.230
Adjusted R^2	0.054	0.098	0.096	0.103	0.220
F Statistic	105.927***	50.594***	25.289***	18.436***	23.342***
Note:					*p<0.1; **p<0.05; ***p<0.01

From the above regression table, we find that the coefficient for $WindProd$ is significant and positive through all models at the 1% level. This indicates that an increase in daily average wind production leads to an increase in electricity price volatility in Norway, and the results are therefore supportive of *Hypothesis 1.* The $WindProd$ coefficient stays relatively constant for models (1) through (4) but changes slightly in model (5) when monthly fixed effects are added. This suggests that the preceding coefficients are overestimated and that some of the volatility caused by seasonal variations is captured by the wind coefficients. When controlling for the monthly effects, we reduce the omitted variable bias, and with no previous indication of issues with multicollinearity, we argue that the inclusion of months increases the reliability of our $WindProd$ coefficient. Assuming that model (5) is our better model, the findings suggest that a 1% increase in Norwegian wind production is associated with a 0.268% increase in price volatility. The economic significance may seem questionable; however, as average daily wind production often increases by 50-100 percent, its impact on electricity price volatility is considered to be sizeable. Hence, our first analysis argues in favor of *Hypothesis 1.*

As to our control variables, we observe variations with regard to significance. $Consumption$ is significant for all regressions and rather constant with a narrow range of 0.054-0.058. The sign of the coefficient is consistently positive, which is in line with microeconomic theory and the literary findings. The statistical significance is solid at a 1% level, with increasingly precise estimates as more control variables are added to the models. Also the economic significance is considered solid as the variable is quoted in 100 MWh, and the average change in demand from one day to another is 105 MWh. Given table (5), it signifies that a change in the demand from day to day of 100 MWh results in a change in volatility of 5.4%, given the differenced variable and the log-level regression.

The coefficient for $Hydro$ is significant and positive for all regressions, and it remains relatively stable. The output thus complies with our literary findings that hydropower is an important driver of electricity prices in Norway. With a level-log interpretation, the coefficient is also economically significant, as the results signify that a 1 unit increase or decrease in hydrological balance, which is associated with a change in the marginal cost of hydropower production, is associated with a 2.9% change in Norwegian intra-daily electricity price volatility. Interestingly enough, the interaction term of $PosHydro$ shows no significance, implying that there is no difference between the effect from positive or negative abnormality to the hydrological balance on daily volatility.

The coefficient for $WindProdDK$ is surprisingly not positive, which is contradictory to the findings of Rintamäki et al. (2017), emphasizing the importance of transmission lines between Denmark and Norway on volatility. As we cannot say from our analysis that the coefficient for $WindProdDK$ is significantly different from zero, we cannot interpret it, nor can we say anything about the impact of transmission with Denmark on Norwegian price volatility. We note that we are not using the exchange data from Denmark to NO2 due to potential biases but rather the total wind production in Denmark, which may affect the results.

The remaining variables are consistently not significant, with the exception of Gas turning significant in model (5) when controlling for monthly fixed effects. This implies that the gas price follows a seasonal pattern and that gas does have a significant effect on intra-daily price volatility when monthly effects are controlled for. As for $CO2$ and $EURNOK$, their coefficients show no significance, and thus we cannot interpret the coefficients as being different from zero.

Addressing the seasonal effects, we see that the day-of-week effects have no noteworthy effect on either of the coefficients. We find this reasonable as we have excluded the weekends from the daily data sets, and one could suspect that any change in volatility during the week would be related to changes in the pattern of behavior during the weekend. Conversely, we observe changes in several of our coefficients when monthly fixed effects are added to the model, and most notably, we observe changes in our coefficient of interest, as discussed above. We are, however, slightly surprised that the coefficient for consumption does not display any changes when adding the monthly effects, as we would assume consumption to vary slightly with the months. However, as this variable is first-differenced, it makes sense that the changes in consumption from day to day does not vary much with the months, and we would rather expect to see a different result in this coefficient for a non-differenced variable. Nevertheless, we observe that the adjusted R^2 for the model almost doubles when adding monthly fixed effects, which argues for continuing the inclusion of them in the succeeding models.

Even though some of the coefficients are not as expected, they are not unreasonable, and hence we have no reason to doubt the accuracy of the model as a whole or the initial interpretation of our variable of interest.

Table 4.2:
Intra-Weekly Electricity Price Volatility and Wind Production in Norway

The table displays time series regressions for the relationship between wind power production in Norway and intra-weekly electricity price volatility in Norway's NO2 bidding area. The results are based on a sample of 366 weekly observations during the period of 2013 to 2019. Models (1) through (3) include no seasonal fixed effects, whereas model (4) includes fixed effects for month-of-year. Newey-West heteroskedasticity and autocorrelation corrected standard errors are displayed in parentheses.

	Dependent variable:			
	$\ln(\text{SD}_{Weekly})$			
	(1)	(2)	(3)	(4)
Δ*ln(WindProd)*	0.225^{**}	0.242^{**}	0.232^{**}	0.239^{**}
	(0.099)	(0.096)	(0.103)	(0.097)
Consumption		0.039^{***}	0.038^{***}	0.135^{***}
		(0.009)	(0.010)	(0.020)
Hydro		0.009	0.010	0.007
		(0.008)	(0.008)	(0.008)
PosHydro		0.027	0.027	0.030^{***}
		(0.018)	(0.018)	(0.010)
WindProdDK			0.004	0.011
			(0.008)	(0.007)
Δ*Gas*			0.010	−0.003
			(0.016)	(0.017)
Δ*CO2*			0.015	0.027
			(0.062)	(0.071)
Δ*EURNOK*			−0.090	−0.194
			(0.534)	(0.456)
M-O-Y FE	No	No	No	Yes
Observations	365	357	357	357
R^2	0.010	0.146	0.148	0.321
Adjusted R^2	0.007	0.136	0.128	0.282
F Statistic	3.707^{*}	15.029^{***}	7.541^{***}	8.368^{***}
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.2 displays the corresponding results from the analysis of intra-weekly volatility and weekly data. For these regressions, $WindProd$ is also found to be significant for all models. The coefficient ranges from 0.225-0.242, which shows that it remains relatively constant even when monthly effects are added, indicating that weekly wind production does not capture the same seasonality as the daily production. However, we note that $WindProd$ in these regressions is given as the first difference of the natural logarithm of the weekly average wind production. This leaves us with the following interpretation of the estimated coefficient of model (5): A 1% increase in wind production from last week to this week leads to an increase in volatility of approximately 0.239%. The differencing of the variable may thus be the reason why we do not observe the same change in the coefficient when controlling for months. The different interpretation also affects our ability to compare the magnitude of the coefficients with the daily model. Nevertheless, more importantly, we see that the estimated $WindProd$ coefficients are significant and positive, which shows that despite using different volatility measures and aggregation levels, the wind production holds its significance, further supporting *Hypothesis 1*.

The $Consumption$ coefficient is also significant for this analysis. The coefficient is relatively consistent through models (2) and (3), however, it increases in model (4) when monthly effects are included. This result is more consistent with our belief that consumption includes some monthly seasonality, which becomes apparent in this model when the variable is included as a non-differenced variable. Assuming model (4) is the better model, the coefficient estimate of $Consumption$ implies that a change in demand of 100 MWh is associated with a 13,5% change in volatility, which is a considerable amount.

The estimated coefficient for $Hydro$ shows no significance in either of the weekly models displayed above, implying that the weekly average of the hydrological balance does not have a significant impact on Norwegian electricity price volatility. This is interesting as we observe a significance for the daily data set. However, with weekly hydrological balance being the average of the daily observations within a week, the averaging may smooth out the peaks, making it harder to establish a relationship between $Hydro$ and SD_{Weekly}. Nevertheless, we observe for this analysis that the coefficient for $PosHydro$ becomes significant when monthly fixed effects are added. This indicates that when water levels are higher than normal, a change in the hydrological balance will impact weekly volatility, which is in line with the findings of Simonsen (2005).

We observe no significance in the remaining control variables, which mostly reflects the results from the analysis of daily volatility. We find the coefficients in this model to be reasonable as well, and thus we see no reason to doubt the accuracy of the model and its estimates.

4.1.2 Wind Power Volatility and Electricity Price Volatility *(H_2)*

In this section, we present the results from our analysis of *Hypothesis 2*. In this hypothesis, we explain the effect of the variations in wind power production on electricity price volatility and include the standard deviation of the control variables where possible. The motivation for this second analysis is that we believe the variations in the variables can better explain variations in electricity prices, and more so than a single decrease and increase in the variables. For the analysis of *Hypothesis 2* , we use the time series regression model outlined in 3.3.2 for daily and weekly volatility and data. We follow the same procedure as for *Hypothesis 1* and start by regressing SD_{Daily} on the new $\sigma_{WindProd}$ before we stepwise include the control variables and seasonal effects. The regressions for the daily data are displayed in Table 4.3, whereas the analysis for weekly is presented in Table 4.4. Same as for *Hypothesis 1*, we expect our second hypothesis to hold and thus expect wind power volatility to have a significant effect on price volatility in Norway. In addition, we expect the regression models in the analysis of this hypothesis to explain more of the variation in our dependent variable compared to the models used for our first hypothesis.

The following table includes five different time series regressions. The first model regresses SD_{Daily} on $\sigma_{WindProd}$. Model (2) includes the daily standard deviation of consumption as well as hydrological balance and its interaction term. In model (3), we include all variables defined in 3.2.3, however, we now include the standard deviation of wind production in Denmark. As in the daily analysis of *Hypothesis 1*, model (1) through (3) includes no fixed effects, whereas regression (4) includes day-of-week fixed effects and model (5) also adds month-of-year fixed effects. Also for this analysis, we correct for detected heteroscedasticity and autocorrelation by using Newey-West standard errors in all the regressions.

Table 4.3:
Intra-Daily Electricity Price Volatility and Norwegian Wind Power Volatility

The table displays time series regressions for the relationship between Norwegian wind power volatility and intra-daily electricity price volatility in Norway's NO2 bidding area. The results are based on a sample of 1826 daily observations ranging from 2013 to 2019, excluding weekends. Models (1) through (3) include no seasonal fixed effects, whereas model (4) and (5) include fixed effects for day-of-week and month-of-year. Newey-West heteroskedasticity and autocorrelation corrected standard errors are displayed in parentheses.

	Dependent variable:				
	$\ln(\mathrm{SD}_{Daily})$				
	(1)	(2)	(3)	(4)	(5)
$\ln(\sigma_{WindProd})$	0.199***	0.164***	0.104**	0.104**	0.110***
	(0.059)	(0.051)	(0.044)	(0.044)	(0.039)
$\sigma_{Consumption}$		0.342***	0.233***	0.228***	0.236***
		(0.066)	(0.061)	(0.062)	(0.061)
Hydro		0.025***	0.018***	0.019***	0.023***
		(0.007)	(0.006)	(0.006)	(0.006)
PosHydro		0.008	0.012	0.012	0.015
		(0.015)	(0.013)	(0.013)	(0.011)
$\sigma_{WindProdDK}$			0.001***	0.001***	0.001***
			(0.0001)	(0.0001)	(0.0001)
ΔGas			0.014	0.016	0.016
			(0.011)	(0.011)	(0.011)
$\Delta CO2$			0.017	0.016	0.031
			(0.039)	(0.040)	(0.040)
$\Delta EURNOK$			0.581	0.601	0.609
			(0.402)	(0.401)	(0.373)
D-O-W FE	No	No	No	Yes	Yes
M-O-Y FE	No	No	No	No	Yes
Observations	1,825	1,825	1,821	1,821	1,821
R^2	0.027	0.154	0.257	0.260	0.322
Adjusted R^2	0.026	0.152	0.254	0.255	0.313
F Statistic	50.289***	82.673***	78.530***	52.852***	37.031***
Note:					*p<0.1; **p<0.05; ***p<0.01

From the analysis of *Hypothesis 2* with daily data, we find that the coefficient for $\sigma_{WindProd}$ is significant and positive through all models in the range of 0.10-0.199. Its standard errors decrease as control variables are included, indicating that the coefficient estimate for wind power volatility becomes increasingly efficient when more of the variance in the error term is accounted for. Also, in this analysis, day-of-week fixed effects have a minimal effect on the coefficients; in fact, our coefficient of interest remains constant between model (3) and (4). Conversely, $\sigma_{WindProd}$ becomes more significant in model (5) when the monthly effects are included, making us more certain that the coefficient estimate in model (5) is significantly different from zero. The coefficient in our final regression shows that a 1% increase in wind power volatility is associated with a 0.11% increase in the electricity price volatility. This finding supports *Hypothesis 2* stating that intra-daily variance in wind production has a significant impact on intra-daily electricity price volatility. In addition, as suspected, the adjusted R^2 for this model is higher than for the model used in *Hypothesis 1*, implying that the variance of the variables may better explain the variation in daily electricity prices than single changes in the values.

For the control variables, they mostly display the same significance as the analysis of the daily data in *Hypothesis 1*, but with the exception of $WindProdDK$. The coefficient for $WindProdDK$ is now significant when we control for its variations, meaning that a one-unit increase in Danish wind power volatility is associated with a 0.1% increase in Norwegian electricity price volatility. The economic significance for this may seem questionable, but as the standard deviation of $WindProdDK$ changes on average by approximately 210.2 units from one day to the other, the impact on electricity price volatility is on average 21.02%. This indicates that there, in fact, is a relationship between Danish wind production and Norwegian price volatility, but only apparent when we control for the variations of the variable.

Table 4.4:
Intra-Weekly Electricity Price Volatility and Norwegian Wind Power Volatility

The table displays time series regressions for the relationship between Norwegian wind power volatility and intra-weekly electricity price volatility in Norway's NO2 bidding area. The results are based on a sample of 366 daily observations ranging from 2013 to 2019. Models (1) through (3) include no seasonal fixed effects, whereas model (4) includes fixed effects for month-of-year. Newey-West heteroskedasticity and autocorrelation corrected standard errors are displayed in parentheses.

	Dependent variable:			
	$\ln(\text{SD}_{Weekly})$			
	(1)	(2)	(3)	(4)
$ln(\sigma_{WindProd})$	0.297***	0.243***	0.088	0.167**
	(0.093)	(0.085)	(0.078)	(0.069)
$\sigma_{Consumption}$		0.344***	0.305***	0.274***
		(0.047)	(0.045)	(0.054)
σ_{Hydro}		0.033	0.033	0.071
		(0.082)	(0.084)	(0.088)
PosHydro		0.189**	0.211**	0.193**
		(0.090)	(0.089)	(0.077)
$\sigma_{WindProdDK}$			0.045***	0.050***
			(0.013)	(0.013)
σ_{Gas}			−0.018	−0.052
			(0.036)	(0.034)
σ_{CO2}			0.583***	0.671***
			(0.178)	(0.184)
σ_{EURNOK}			−0.446	0.085
			(1.681)	(1.651)
M-O-Y FE	No	No	No	Yes
Observations	366	358	357	357
R^2	0.046	0.174	0.227	0.330
Adjusted R^2	0.044	0.164	0.210	0.292
F Statistic	17.621***	18.527***	12.798***	8.740***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4.4 displays the regressions from our analysis of *Hypothesis 2* with weekly data. Model (3) stands out in this table, as the variable of interest for the first time turns out to be non-significant. This indicates that some of the variations in $WindProdDK$, Gas, $CO2$, and $EURNOK$ may be absorbed by the wind coefficient in model (2), making it overestimated. This raises the concern of multicollinearity. Even though the correlation between wind production and these variables is modest as seen in 3.4.2 and our official VIF test is passed with no values higher than 1.3, the results may indicate that the modest correlation we see between the standard deviation of wind power production and the control variables may, in fact, bias our results when the latter variables are omitted. We investigate this further by adding the relevant control variables to the model one by one and find that the decrease in the $\sigma_{WindProd}$ coefficient is primarily a consequence of adding $\sigma_{WindProdDK}$ and σ_{CO2} to the model (see Appendix A1). This signifies that we are able to control for the co-varying effect between variations in Norwegian wind production and variations in Danish wind production and the CO2 price when adding the latter two to the model. This again is, to some extent, confirmed by the significant positive coefficients for $\sigma_{WindProdDK}$ and σ_{CO2}.

Furthermore, from the same regression table, we observe that the coefficient for $\sigma_{WindProd}$ turns significant again in model (4) when the monthly effects are added. This, in turn, indicates that the wind production coefficient also captures time-varying fixed effects, making it underestimated. When adding the month-of-year dummies to the model, we control for the contradictory effect that there is less volatility in some months where it is also windy, notably the months of winter and fall, which are significant and negative (shown in Appendix A2). When controlling for both the co-varying control variables and the contradictory fixed effects, we believe we are able to successfully reduce the omitted variable bias and increase the reliability of our main coefficient of interest. Based on the successive result in model (5), we interpret that a 1% increase in weekly wind power standard deviation is associated with an increase of 0.167% in the standard deviation of electricity prices. This complies with our previous results, and once again, the findings are supportive of our hypothesis.

The control variables display similar results as in the analysis of weekly volatility in *Hypothesis 1*. $Hydro$ is still not significant even though we here include the standard deviation, but *PosHydro* is, indicating that the variation in the positive values of hydrological balance has an effect on price volatility. More interesting is the change in the coefficient for σ_{CO2}. For the first time, we include the standard deviation of the CO2 price as we can only calculate this for the weekly data, and this variable's significance indicates that the variations in CO2 prices have an effect on electricity price volatility. This is surprising compared to the previous analysis; however, it somehow confirms our suspicions that variations in the independent variables may better explain variations in electricity prices.

4.2 Determining Causal Effects through 2SLS

To better be able to argue for causality between wind production and electricity price volatility in Norway, we choose to conduct a Two-Stage Least Squares (2SLS) estimation. So, we control for a situation where the assumption of exogeneity does not hold and any issue related to unobservable macroeconomic conditions affecting our main independent variable. We start by discussing the possible instruments for wind power production. Next, we present our analyses and compare the results to those of OLS.

4.2.1 Discussion of Instrument

As introduced in 3.2.2, wind power production is primarily driven by installed wind power capacity and wind speed. These variables do not impact electricity prices or volatility directly, only indirectly through their effect on wind production. Hence, we consider them as possible instruments for wind production in a 2SLS analysis.

For an instrument to be considered good, it has to fulfill the conditions of exclusion and relevance (Wooldridge, 2012). We can formally test the relevance condition by regressing wind production on the two instruments separately. By doing so, we find both wind power capacity and wind speed to be relevant in explaining wind production. The exclusion condition, on the other hand, needs to be discussed, and we raise some concerns regarding the exogeneity of wind power capacity. Changes in wind power capacity are likely to be driven by macroeconomic factors that may also affect electricity prices or volatility, such as political incentives or economic growth. We run a Sargan test for overidentification with the two potential instruments, and the test results indicate that at least one of the instruments is endogeneous. In addition, we run a weak instrument test, which concludes that at least one instrument is strong. As we consider wind speed to be completely exogenous, we conclude that wind power capacity is the endogenous instrument, and thus we proceed with wind speed as our instrument.

We use wind speed data from Lista in Agder in Norway, which contains the largest wind park within the NO2 area that has been operating continuously throughout our selected time period. The data is gathered from Meterologisk Institutt's database. We would have preferred to use data for wind speed captured by all Norwegian wind farms, however as very few wind parks have been operating since 2013 and creating such a data set would result in much manual work, we test with the data from Lista. Regressing wind speed from Lista on Norwegian wind power production results in an F statistic above the rule of thumb of 10 (Wooldridge, 2012) (see Appendix A3 and A4), and we conclude that also the relevance assumption is met for this instrument.

4.2.2 Wind Production and Electricity Price Volatility (H_1)

Table 4.5 constitutes two regression tables which encompass the final OLS regressions from table 4.1 and 4.2 together with the 2SLS versions of the models for both daily and weekly data. The models with daily data are displayed to the left, and the models with weekly data are placed to the right. The associated first stage regressions can be found in Appendix A3. For the daily data, we observe that the coefficients for $WindProd$ differ greatly between the two model approaches. For the Instrumental Variable estimation, we find our variable to be non-significant and negative, which is very different from our previous OLS results and from what we have seen in the literature. In the table with weekly data, we again find the wind production variable to be non-significant also for this data, even when controlling for all seasonal fixed effects and control variables. The different results question our initial OLS analysis and raise a concern of whether those results are valid or if we are looking at a potential rejection of our *Hypothesis 1*.

Table 4.5:
2SLS Estimation of Norwegian Wind Power Production on Intra-Daily and Intra-Weekly Electricity Price Volatility

The table displays the estimated OLS and 2SLS coefficients for the effect of Norwegian wind power production on intra-daily and intra-weekly electricity price volatility in Norway's NO2 bidding area. The models with daily data are displayed to the left, and the models with weekly data are placed to the right. The 2SLS model uses wind speed from Lista in Agder in Norway as instrument for wind power production. The results are based on a sample of 1826 daily and 366 weekly observations raging from 2013 to 2019, and all models include time fixed effects. Newey-West heteroskedasticity and autocorrelation corrected standard errors are displayed in parentheses.

	Dependent variable:	
	$\ln(SD_{Daily})$	
	OLS	*2SLS*
	(1)	(2)
ln(WindProd)	0.268***	−0.170
	(0.061)	(0.157)
$\Delta Consumption$	0.054***	0.043***
	(0.012)	(0.012)
Hydro	0.029***	0.031***
	(0.006)	(0.007)
PosHydro	0.012	0.009
	(0.012)	(0.013)
WindProdDK	−0.004	0.006
	(0.004)	(0.005)
ΔGas	0.024**	0.021
	(0.012)	(0.013)
$\Delta CO2$	0.042	0.027
	(0.041)	(0.046)
$\Delta EURNOK$	0.328	0.258
	(0.375)	(0.377)
D-O-W FE	Yes	Yes
M-O-Y FE	Yes	Yes
Observations	1,823	1,823
R^2	0.230	0.164
Adjusted R^2	0.220	0.153
F Statistic	23.342***	

Note: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:	
	$\ln(SD_{Weekly})$	
	OLS	*2SLS*
	(1)	(2)
$\Delta ln(WindProd)$	0.239**	0.094
	(0.097)	(0.152)
Consumption	0.135***	0.134***
	(0.020)	(0.020)
Hydro	0.007	0.008
	(0.008)	(0.008)
PosHydro	0.030***	0.029***
	(0.010)	(0.010)
WindProdDK	0.011	0.013*
	(0.007)	(0.007)
ΔGas	−0.003	−0.004
	(0.017)	(0.017)
$\Delta CO2$	0.027	0.024
	(0.071)	(0.071)
$\Delta EURNOK$	−0.194	−0.162
	(0.456)	(0.458)
M-O-Y FE	Yes	Yes
Observations	357	357
R^2	0.321	0.317
Adjusted R^2	0.282	0.278
F Statistic	8.368***	

Note: *p<0.1; **p<0.05; ***p<0.01

4.2.3 Wind Power Volatility and Electricity Price Volatility (H_2)

Similar to the observations above, we find the same striking results of no significance for our $\sigma_{WindProd}$ variable in the 2SLS estimation, as displayed in Table 4.6. The first stage regressions can be found in Appendix A4. The 2SLS estimation thus implies that the variations of wind production do not have an impact on Norwegian electricity price volatility when using wind speed from Lista as an instrument, for either one of the two volatility measures. This again questions our OLS results in section 4.1 and whether or not *Hypothesis 2* should be rejected.

Table 4.6:
2SLS Estimation of Norwegian Wind Power Volatility on Intra-Daily and Intra-Weekly Electricity Price Volatility

The tables displays the estimated OLS and 2SLS coefficients for the effect of Norwegian wind power volatility on intra-daily and intra-weekly electricity price volatility in Norway's NO2 bidding. The models with daily data are displayed to the left, and the models with weekly data are placed to the right. The 2SLS model uses wind speed from Lista in Agder Norway as instrument for wind power production. The results are based on a samples of 1826 daily and 366 weekly observations raging from 2013 to 2019, and all models include time fixed effects. Newey-West heteroskedasticity and autocorrelation corrected standard errors are displayed in parentheses.

	Dependent variable:	
	$\ln(SD_{Daily})$	
	OLS	*2SLS*
	(1)	(2)
$ln(\sigma_{WindProd})$	0.104**	−0.195
	(0.044)	(0.141)
$\sigma_{Consumption}$	0.228***	0.194***
	(0.062)	(0.063)
Hydro	0.019***	0.023***
	(0.006)	(0.007)
PosHydro	0.012	0.012
	(0.013)	(0.011)
$\sigma_{WindProdDK}$	0.001***	0.001***
	(0.0001)	(0.0001)
ΔGas	0.016	0.012
	(0.011)	(0.012)
$\Delta CO2$	0.016	0.015
	(0.040)	(0.040)
$\Delta EURNOK$	0.601	0.575*
	(0.401)	(0.349)
D-O-W FE	Yes	Yes
M-O-Y FE	Yes	Yes
Observations	1,821	1,821
R^2	0.260	0.263
Adjusted R^2	0.255	0.254
F Statistic	52.852***	
Note: *p<0.1; **p<0.05; ***p<0.01		

	Dependent variable:	
	$\ln(SD_{Weekly})$	
	OLS	*2SLS*
	(1)	(2)
$ln(\sigma_{WindProd})$	0.167**	1.020
	(0.069)	(1.539)
$\sigma_{Consumption}$	0.274***	0.303***
	(0.054)	(0.088)
σ_{Hydro}	0.071	−0.014
	(0.088)	(0.190)
PosHydro	0.193**	0.183*
	(0.077)	(0.098)
$\sigma_{WindProdDK}$	0.050***	0.015
	(0.013)	(0.066)
σ_{Gas}	−0.052	−0.118
	(0.034)	(0.127)
σ_{CO2}	0.671***	0.155
	(0.184)	(0.918)
σ_{EURNOK}	0.085	0.970
	(1.651)	(2.185)
M-O-Y FE	Yes	Yes
Observations	357	357
R^2	0.330	0.076
Adjusted R^2	0.292	0.024
F Statistic	8.740***	
Note: *p<0.1; **p<0.05; ***p<0.01		

4.3 Comparing OLS and 2SLS

From the above regression tables, we see that the results from the OLS and 2SLS estimations differ widely. The OLS estimation displays a positive and significant relationship between our wind power production coefficient, both in the analysis of *Hypothesis 1* and *Hypothesis 2* for both daily and weekly volatility. In contrast, the 2SLS analysis shows no significance for our variable of interest in either of the regressions, meaning we cannot interpret the coefficient as being different from zero. The differing results raise the question of which estimation approach to rely on, and consequently, whether or not we should reject our hypotheses.

OLS provides the best linear unbiased estimates for a regression, given that its assumptions hold. If, however, the endogeneity assumption is violated, the OLS coefficient estimates are biased, and we would not be able to rely on the regression results. To determine which estimation to base our conclusions on, we test for endogeneity in our initial OLS model. We run a Durbin-Wu-Hausman test for each of the four final models, and the results find no indication of endogeneity in the weekly models. Accordingly, we base our interpretation of these models on the OLS estimations. For the daily models, however, we reject the null hypothesis of no endogeneity, both in the analysis of *Hypothesis 1* and *Hypothesis 2*. This result implies that the OLS estimates for daily wind power production are biased, and consequently, we rely on the 2SLS results in the interpretation of the relationship between daily wind power production and price volatility.

At first glance, it is difficult to comprehend what can cause the endogeneity issue, as wind power production is fundamentally non-controllable (Jacobsen and Zvingilaite, 2010; Kyritsis et al., 2017). Wind production is further mainly driven by wind speed, which is clearly exogenous to our model. The issue is thus assumed to be related to the other main driver of wind power production, namely the wind power capacity. Capacity expansions are likely to be driven by macroeconomic factors, such as political incentives, that also affect electricity prices and volatility. When not accounted for, these correlations may cause an omitted variable bias, resulting in endogeneity. Furthermore, the model may be subject to a simultaneity bias caused by the relationship between electricity prices and wind power capacity. An increase in electricity prices increases the expected profitability of an installed wind turbine, which may motivate a capacity expansion. Assuming that the increase in capacity leads to an increase in wind power production, we have a simultaneity bias causing an endogeneity issue.

Another simultaneity bias may be related to the maintenance of the wind turbines. When the wind turbines are under maintenance, the wind power capacity is reduced for a short period of time, which likely reduces the total wind power production. In order to optimize the maintenance activities and reduce the associated costs, maintenance may be moved to periods with stable lower electricity prices in an attempt to reduce the revenues lost due to the shut down of the turbines. If the case is that the timing of the wind turbine maintenance depends on electricity price dynamics, our dependent variable has an effect on our main independent variable, which leaves us with a second possible simultaneity bias.

In addition to the above issues, we may have a bias in our coefficient estimates related to the exclusion of the interactions constituting a 'perfect storm'. A perfect storm is a meteorological phenomenon that occurs when strong wind, mild temperature, and heavy rain hit simultaneously (J.E. Høie, personal communication, February 18, 2020). The event results in a collective effect on prices and price spikes much stronger than that caused by any of the variables alone. By not accounting for these interactions, it may appear as wind power has a more significant effect on volatility than it has because the estimated coefficient captures the effect caused by the perfect storm. Ideally, we would control for these interactions in our models. Still, due to the uncertainty related to when the storm strikes and thus, the impossible task of recognizing the phenomenon in the data, we have not been able to do so.

Despite the above discussions, it is difficult to fully grasp why we observe endogeneity only in our models of daily volatility. The changes in wind power capacity are massive operations that require substantial planning and organizing. Thus it is not reasonable to believe that macroeconomic factors or changes in electricity prices will have an effect on installed capacity in a day, or a week for that matter. More plausible is the discussion of the perfect storm if one assumes that the storm lasts a couple of hours. If so, the bias may be decisive in the daily calculations, but less important when the data is averaged over a week. However, as a perfect storm normally lasts for several days or even weeks, it suggests that the exclusion of the perfect storm interactions is not the issue. Thus, we rely the most on our discussion of the bias related to maintenance. The maintenance of the wind turbines normally lasts 12-18 hours, meaning that it has a sizeable effect on daily wind production. When we aggregate to weekly data, the same effect may be less prominent as the data is averaged over a longer period. This may be the reason why we observe the differing results from the endogeneity tests. Based on the above discussions, we believe the latter issue constitutes the most plausible explanation as to why we observe endogeneity only in our daily models. However, we do not rule out that there may be other unexplained factors that affect our OLS results.

As we base our analysis of the relationship between wind production and intra-daily volatility on the 2SLS estimates, we find no significance for our wind production coefficient. This finding is contrary to the majority of previous research investigating daily volatility, which finds a positive relationship between the two variables in question. There may be several reasons why we observe this. Firstly, we may have a bias also in our 2SLS estimates. Even though our instrument of wind speed at Lista passes the formal tests, it may be weak enough to increase the variance in the error term such that it is difficult to prove statistical significance. This increased variance is one of the disadvantages of the 2SLS method. We know that our instrument is not perfect as it only represents wind surrounding one wind park, whereas our independent variable of interest is the total Norwegian wind production.

Secondly, we may have an issue regarding the use of actual wind power production as a proxy for forecasted wind production. Because electricity prices are based on day-ahead weather forecasts, we may have cases where we find no relationship between actual wind production and price volatility, simply because the forecast is slightly off. This may be a more significant issue for the daily data than weekly because one day of mismatch may have a greater impact on the relationship between wind power and price volatility for a day than for a week. Thirdly, even though we have a hard time explaining it, it may be that the non-significant relationship we observe between daily wind production and price volatility is true, simply because there is no relationship.

Coming back to our hypotheses, the results from our 2SLS analysis of daily volatility argue in favor of a rejection of our two hypotheses. Conversely, for our analysis of weekly volatility, we rely on the results from the OLS analyses, which argues in favor of our hypotheses. Due to the spread in our discoveries, we can only conclude that Norwegian wind power and wind power volatility has a significant effect on intra-weekly Norwegian electricity price volatility. However, we cannot conclude when it comes to intra-daily volatility. We thus find that our hypotheses hold partially.

4.4 Implications

Our findings of a positive relationship between wind power production and intra-weekly volatility have implications for energy market participants. As wind production increases in Norway, due to more extreme weather and a further commitment to renewable energy sources, this established relationship becomes more important. More volatile electricity prices are often associated with the disadvantages of uncertainty, but we believe increased price volatility also provides opportunities for consumers and certain producers of electricity. By investing in flexibility, hydropower producers and consumers can increase earnings and save costs by exploiting the electricity price peaks and troughs. That way, the disadvantages frequently attributed to the increased price volatility caused by increased wind power production can be partially offset by the benefits of adjusting to it.

Norway's hydropower reliance provides unique flexibility to a market that is fundamentally rigid. By storing water, the hydropower reservoirs operate as electricity batteries that can be utilized to even out the price peaks (Regjeringen, 2019). The level of flexibility is, however, limited by the size of the water reservoirs and how fast the water is converted to electricity. While changes to the first factor require unpopular interventions in nature, the latter can be improved by investing in another water turbine. When electricity demand and prices are high, producers find it profitable to increase the production, and with several water turbines, they can produce more electricity within the profitable periods. Ultimately, the increased supply will lower the prices and smooth out the price spikes. Consequently, an investment in additional water turbines results in profits for producers and stability for consumers.

Hydropower producers can also exploit the electricity price troughs by investing in technology that increases the inflow of water to the reservoirs. Such an investment could be the installment of electric pumps. When electricity prices are low, the pumps enable the transmission of water from low-level reservoirs to high-level ones, so that the water can be stored in the latter reservoir until electricity demand and prices increase. Thus, producers buy cheap electricity to pump up the water and receive high prices for the electricity when released. Again, this technology enables producers to control the supply and smooth out the price fluctuations. Today, this is already done to some extent in Norway through seasonal storage, however, our findings suggest that this technology could also be implemented on a weekly basis.

Norway's ability to exploit the price peaks and troughs are attributed to the country's large water reservoirs and elevation differences. Due to the low marginal costs of operating hydropower, the storage of electricity is cheaper in Norway than in countries more reliant on conventional energy sources. In addition, only hydropower enables the storage of a considerable amount of electricity. With the increased importance of wind power production in Norway and the rest of Europe, Norway's ability to stabilize the price volatility also increases in importance. Increasing wind production in Europe, in combination with the development of several new transmission cables, facilitates that Norway can serve as a battery for the whole of Europe (Graabak et al., 2017).

Increased intra-weekly volatility also creates opportunities for consumers. The above adjustments made by hydropower producers are relatively expensive and only profitable in periods with high volatility. The consumers, on the other hand, can implement less costly technologies to adjust to the volatile electricity prices by making their consumption more elastic to price changes, also in the short term. Such technologies take the form of electricity consuming devices which are automatically turned on and off based on the electricity prices, such as automatic water heaters and electric vehicle chargers. As of now, only a part of a consumer's electricity demand is flexible, due to electricity being a necessity. However, in line with increasing price volatility, we expect to see increasing innovation in this field and new ways to make consumption more flexible.

To conclude, the predicted increase in intra-weekly electricity price volatility, caused by an increase in wind power production, creates not only threats, but also opportunities for consumers and producers. The key to the possibilities is an investment in flexibility. Consumers are most likely unable to adjust their demand to the point where they can completely smooth out the price fluctuations alone, as they need some electricity to function. However, if the producers adjust their supply first, the importance of consumer flexibility may decrease. Nevertheless, due to the costly investments for electricity producers, we would most likely be looking at an investment in flexibility from both parties. If the market participants succeed with their adjustments, the disadvantages of the volatile electricity prices may be offset.

5 Conclusion and Limitations

5.1 Conclusion

The aim of this thesis has been to examine the effect of increased wind power production on electricity price volatility in Norway. As renewable energy sources are gaining increasing importance on the global electricity scene, through its mitigation of climate change and security of energy supply, the importance of understanding its implications increases accordingly. In Norway, wind power has penetrated the electricity mix through extensive investments in wind power capacity. In combination with the ongoing development of electricity transmission systems between European countries, the capacity expansion is predicted to affect future Norwegian electricity supply. We wanted to investigate how this change to the electricity mix will affect the already volatile electricity prices, and how Norway's reliance on hydropower affects the results. Hence, our research question was stated as the following:

Can wind power production explain electricity price volatility in Norway?

In order to answer the research question, we formulated two hypotheses for the relationship between wind power production and electricity price volatility, based on a literary review of research on renewables and electricity prices. Despite the lack of consensus in previous studies investigating the relationship between wind power production and electricity price volatility, we landed on the two hypotheses based on our accumulated knowledge of electricity price dynamics and the merit-order effect. The intuition behind the hypotheses is that the intermittency of wind power results in frequent shifts in the merit-order curve as renewable, zero-marginal cost energy sources are always prioritized in electricity production. Accordingly, we expected to find a positive relationship between wind power production and electricity price volatility and wind power volatility and electricity price volatility for both intra-daily and intra-weekly volatility.

In our results chapter, we present the findings from an Ordinary Least Square (OLS) estimation and an Two-Stage Least Squares (2SLS) analysis with wind speed as an instrument for wind power production. The two estimation methods display differing results with regard to the significance of our independent variable of interest, which we mainly attribute to a bias in our OLS analysis of daily data. We thus rely more on the 2SLS estimations in the interpretation of the relationship between daily wind production and intra-daily volatility. Our empirical findings suggest that there is a positive relationship between weekly wind power production and intra-weekly electricity price volatility in Norway. This finding is in line with the results from the other studies examining intra-weekly volatility, hereunder the studies from Rintamäki et al. (2017) and Mauritzen (2011). Conversely, we find no significance for our wind power coefficient in the 2SLS analysis of intra-daily volatility, and thus we cannot say anything about the relationship between daily wind power production and intra-daily price volatility. This finding is surprising, as the majority of literature finds significance for daily wind production, either positive or negative (Mauritzen, 2011; Woo et al., 2011; Ketterer, 2014; Pereira and Rodrigues, 2015; Clò et al., 2015; Kyritsis et al., 2017; Rintamäki et al., 2017). We provide explanations for why we observe this result, and we suggest that it might be related to a bias also in our 2SLS model related to our available instrument. However, we cannot rule out that there simply is no relationship between Norwegian daily wind power production and intra-daily price volatility, as this market has never been investigated before.

Our finding of a positive relationship between weekly wind power production and intra-weekly electricity price volatility has implications for Norwegian electricity producers and consumers. As the importance of wind power continues to increase, so does the benefits of investing in flexible supply and consumption. Norwegian hydropower producers can exploit the price peaks and troughs by installing additional water turbines or electro pumps. As a result, they can smooth out the price fluctuations while profiting on the actions. Consumers can invest in technology that automatically adjusts their consumption based on the current electricity price levels, resulting in a more elastic demand curve and presumably less frequent price spikes. All in all, the increasing focus on environmental concerns and the integration of renewables in the energy mix, provokes changes to the electricity markets, and these changes will affect market participants whether they appreciate it or not.

5.2 Limitations

In this section, we elaborate on the limitations of the thesis and discuss the implications they may have had for our analysis and the subsequent results.

Firstly, we have made noteworthy modifications to our dataset. The dataset was modified to correspond to our two volatility measures, and accordingly, our hourly observations were aggregated to daily and weekly data. This particular data aggregation has been done for most studies examining the electricity price dynamics, however, it may still affect our results. The aggregation smoothes out some of the spikes in our variables, which may cause us to dismiss some less prominent relationships. Also, due to the non-existence of weekend data for fuel prices, we were forced to remove all weekend observations from the daily data sets. Although the data set remained large, we omit some information about changes in behavioral patterns. Nevertheless, the potential issue related to the data removals may still be secondary to the issues likely to arise from an imputation method.

Further, we have used several proxies to make up for the lack of data on our independent variables. Mainly, we have substituted day-ahead forecasts with actual data and thus assumed perfect information regarding the conditions the following day. This assumption does not necessarily hold. Hence, the use of proxies may cause us to draw conclusions based on imperfect measures. Data availability also affected our choice of instrument in the 2SLS analysis. As there exists no complete data of the total wind speed surrounding all wind parks in Norway given our selected time period, we may have ended up with a weaker instrument for Norwegian wind power production than if this data was available. Consequently, the non-significance we observe for our analysis of intra-daily volatility may be attributed to this limitation.

Lastly, we need to discuss the possible limitations to our assumption of no congestions in the Norwegian power grid. Again due to data availability, we mostly use variable data for the whole of Norway rather than data specific for the NO2 area. In fact, only the data on consumption is available as region-specific. This is plausible under the above assumption, however, if the assumption does not hold, we may observe changes in the independent variables without observing an effect in the prices of the NO2 area, even though there could be one. A violation of the above assumption would also affect the applicability of our results. As there is no national bidding price for the Norwegian market, we were forced to select the prices of one of the bidding areas. Thus, if the assumption of no congestions in the power grid does not hold, then the established relationship between wind power production and electricity price volatility may not apply to the whole of Norway. Ideally, the latter issue could be limited by conducting analyses for all bidding areas, however, due to the time restrictions of this thesis, this is out of our scope.

5.3 Future Research

Our main recommendation for future research is to further investigate the relationship between wind power production and intra-daily electricity price volatility in hydro-reliant markets. One approach is to examine the presence of such a relationship in other hydro-reliant countries such as Sweden or Switzerland, in order to draw a common conclusion for hydro-dependent markets. Another approach is to investigate the other bidding areas of Norway, to examine whether our results in fact do apply to the whole of Norway. This would help extend the inconclusive base of literature on wind power production and intra-daily electricity price volatility, and understand the true causes of our non-significant result. The analysis should also be done for intra-weekly volatility, as although we find results concluding with the literature for this volatility measure, the research is still scarce.

Secondly, we would encourage future research to dig deeper into the possible implications of our findings of a positive effect of wind power production on intra-weekly electricity price volatility. As we discuss in the final part of our analysis, we believe increased volatility creates both challenges and opportunities for consumers and producers, and a broader understanding of these becomes increasingly important as investment in wind production increases. One angle is to conduct a qualitative analysis through interviews of the Norwegian industry, households, or hydropower producers in order to map how increased volatility would affect their activities. Once these effects are established, and perhaps later quantified, a new research opportunity could arise in the form of optimization of investments in flexibility, given different volatility levels.

Furthermore, there are future research opportunities related to the impact of the development of transnational electricity transmission cables on electricity price dynamics. In some of our results, we find a significant effect of wind power production in Denmark on Norwegian electricity price volatility, implying that there may exist a relationship there that is not yet fully explored. At the time of writing, new transmission cables are being built between Norway and Germany and Norway and the UK. Accordingly, it would be interesting to explore whether an increased interconnectedness between more countries increasingly reliant on wind power production will affect Norwegian electricity price behavior.

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Appendix

Table A0.1:
Investigation of non-significant main independent variable in model (3) of Table 4.4

This table displays the adding of the control variable one by one to better understand what makes the independent variable go from significant to non-significant in model (3) in Table 4.4. The data used is exactly the same, the only difference is the inclusion of variables. Also here, Newey-West standard errors are the ones displayed in parenthesis.

	Dependent variable:				
	$\ln(\mathrm{SD}_{Weekly})$				
	(1)	(2)	(3)	(4)	(5)
$ln(\sigma_{WindProd})$	0.243***	0.179**	0.175**	0.088	0.088
	(0.085)	(0.082)	(0.081)	(0.079)	(0.078)
$\sigma_{Consumption}$	0.344***	0.314***	0.314***	0.306***	0.305***
	(0.047)	(0.046)	(0.046)	(0.045)	(0.045)
σ_{Hydro}	0.033	0.049	0.048	0.033	0.033
	(0.082)	(0.085)	(0.086)	(0.084)	(0.084)
PosHydro	0.189**	0.152*	0.155*	0.209**	0.211**
	(0.090)	(0.090)	(0.090)	(0.089)	(0.089)
$\sigma_{WindProdDK}$		0.043***	0.043***	0.045***	0.045***
		(0.013)	(0.013)	(0.013)	(0.013)
σ_{Gas}			0.026	−0.017	−0.018
			(0.039)	(0.037)	(0.036)
σ_{Co2}				0.586***	0.583***
				(0.177)	(0.178)
σ_{EURNOK}					−0.0446
					(1.681)
M-O-Y FE	No	No	No	No	No
Observations	358	358	357	357	357
R^2	0.174	0.196	0.197	0.227	0.227
Adjusted R^2	0.164	0.185	0.184	0.212	0.210
F Statistic	18.527***	17.174***	14.355***	14.653***	12.798***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A0.2

Model (4) in Table 4.4 is extended to display the dummy variables for each month.

	Dependent variable:
	$ln(\text{SD}_{Weekly})$
$ln(\sigma_{WindProd})$	0.167**
$\sigma_{Consumption}$	0.274***
σ_{Hydro}	0.071
PosHydro	0.193**
$\sigma_{WindProdDK}$	0.050***
σ_{Gas}	−0.052
σ_{Co2}	0.671***
σ_{EURNOK}	0.085
February	−0.644***
March	−0.506**
April	−0.458**
May	0.116
June	−0.040
July	−0.535***
August	−0.425**
September	−0.775***
October	−0.539***
November	−0.377**
December	−0.519***
Observations	357
R^2	0.330
Adjusted R^2	0.292
F Statistic	8.740***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A0.3: First Stage of 2SLS Estimation of Norwegian Wind Power Production on Intra-Daily and Intra-Weekly Electricity Price Volatility

The tables display the first stage of the 2SLS estimations of *Hypothesis 1.* The models with daily data are displayed to the left, and the models with weekly data are placed to the right. The instument used to estimate wind power production is wind speed from Lista in Agder, Norway. The results are based on a samples of 1826 daily and 366 weekly observations raging from 2013 to 2019, and all models include time fixed effects.

	Dependent variable:
	ln(WindProd)
ln(Windspeed)	0.496***
	(0.034)
$\Delta Consumption$	−0.019**
	(0.008)
Hydro	0.006***
	(0.002)
PosHydro	0.007***
	(0.002)
WindProdDK	−0.006
	(0.009)
ΔGas	−0.044
	(0.031)
$\Delta Co2$	−0.207
	(0.258)
$\Delta EURNOK$	−0.009**
	(0.004)
D-O-W FE	Yes
M-O-Y FE	Yes
Observations	1,823
R^2	0.424
Adjusted R^2	0.417
F Statistic	57.568***
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	Δ*ln(WindProd)*
Δ*ln(Windspeed)*	0.659***
	(0.053)
Consumption	0.005
	(0.007)
Hydro	−0.00002
	(0.003)
PosHydro	−0.004
	(0.003)
WindProdDK	−0.008
	(0.008)
ΔGas	−0.030
	(0.026)
$\Delta Co2$	0.178
	(0.210)
$\Delta EURNOK$	0.003
	(0.005)
D-O-W FE	No
M-O-Y FE	Yes
Observations	357
R^2	0.360
Adjusted R^2	0.324
F Statistic	10.272***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A0.4:
First Stage of 2SLS Estimation of Norwegian Wind Power Volatility on Intra-Daily and Intra-Weekly Electricity Price Volatility

The tables display the first stage of the 2SLS estimations of *Hypothesis 2*. The models with daily data are displayed to the left, and the models with weekly data are placed to the right. The instument used to estimate the standard deviation of wind power is wind speed from Lista in Agder, Norway. The results are based on a samples of 1826 daily and 366 weekly observations raging from 2013 to 2019, and all models include time fixed effects.

	Dependent variable:
	$ln(\sigma_{WindProd})$
$ln(\sigma_{Windspeed})$	0.206***
	(0.018)
$\sigma_{Consumption}$	−0.133***
	(0.032)
Hydro	0.002
	(0.003)
PosHydro	0.0002***
	(0.0001)
$\sigma_{WindProdDK}$	−0.010
	(0.013)
ΔGas	−0.048
	(0.043)
$\Delta Co2$	−0.068
	(0.356)
$\Delta EURNOK$	−0.015***
	(0.005)
D-O-W FE	Yes
M-O-Y FE	Yes
Observations	1,821
R^2	0.143
Adjusted R^2	0.132
F Statistic	12.989***
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	$ln(\sigma_{WindProd})$
$ln(\sigma_{Windspeed})$	0.001***
	(0.0001)
$\sigma_{Consumption}$	−0.024
	(0.032)
σ_{Hydro}	0.0003
	(0.047)
PosHydro	0.025***
	(0.008)
$\sigma_{WindProdDK}$	0.040
	(0.025)
σ_{Gas}	−0.173*
	(0.102)
σ_{Co2}	0.133
	(0.863)
σ_{EURNOK}	0.074*
	(0.041)
D-O-W FE	No
M-O-Y FE	Yes
Observations	357
R^2	0.564
Adjusted R^2	0.540
F Statistic	22.956***
Note:	*p<0.1; **p<0.05; ***p<0.01