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Winds of Change
How Swedish Wind Power Generation is Impacting Electricity Prices

Karolina Sundell (24662) and Liv Nyström (24633)

Abstract: This study provides fresh evidence on the impact of wind power generation on Swedish electricity prices. Hourly observations from the Nord Pool electricity market dated January 1, 2019 to December 31, 2021 are used to investigate the relationship between wind power generation and electricity spot price level and volatility. A time series analysis is performed with the use of an integrated ARMAX-GARCHX model, which is optimized for the data set. The ARMAX models the electricity spot price level in terms of wind power generation, controlling for consumption, net exchange, and oil price. Similarly, the GARCHX models the electricity spot price volatility in terms of the selected explanatory variables. The results conclude that wind power generation significantly lowers the electricity spot price level, and increases the spot price volatility. Understanding how variable renewable energy sources impact electricity market conditions has important implications for the design of energy policy. Our findings add to the energy political debate by providing insight on how a drastic expansion of wind power in Sweden may impact electricity markets.

Key words: electricity spot price, price volatility, wind power, merit order theory, time series analysis

JEL: C32, L94, Q41, Q42

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Examiner:	Johanna Wallenius

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1. Introduction

At the time of writing this paper, war is raging in Europe. The Russian invasion of Ukraine on February 24, 2022 has caused immense suffering and left us wondering where it will end. Amongst this uncertainty, one thing has become abundantly clear: Europe must free itself from dependence on Russian fossil fuels. The urgent need for a green energy transition has seldom been as evident as right now. A shift to renewable sources of energy is a crucial step to securing European energy supply while mitigating climate change.

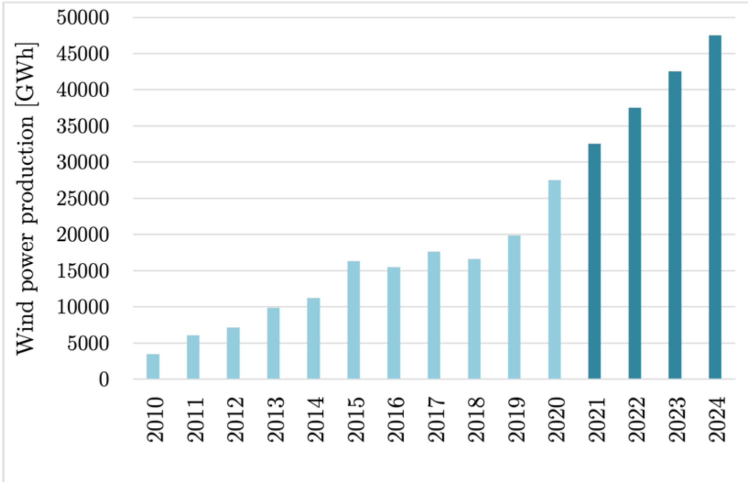
Wind power is expected to play a central role as the global economy commits to reducing its dependence on fossil fuels. Wind is a clean energy source that produces close to zero greenhouse gas emissions and no air pollutants, making it an attractive alternative to fossil fuels (Wind Europe, 2022). In Sweden, wind power production has increased remarkably over the past two decades (figure 1). Wind power is a source of variable renewable energy (VRE), different from conventional energy sources in that its production is intermittent, exogenously dependent on weather conditions, and cannot be planned by power generating companies (Wind Europe, 2022). An increased dependence on intermittent energy sources will likely have impacts on the behavior of electricity prices (Rintamäki et al., 2016). Knowledge about the impact on electricity spot prices of increased reliance on VRE is therefore important for risk management purposes. To this end, this study seeks to examine the effect of increased wind power generation on electricity prices. A thorough empirical analysis will be undertaken in an attempt to answer the following question:

How has the generation of wind power in Sweden impacted the level and volatility of the Swedish electricity spot price?

On February 3, 2022, a commission issued by the Swedish government published the *Electrification strategy* – a national strategy formulated to serve as the basis for the electrification of Sweden. The strategy includes an ambitious expansion of wind power, whereby land-based wind power production is planned to increase with a minimum of 5 terawatt hour (TWh) per year until 2024 (illustrated in figure 1). Additionally, sea-based wind power production is projected to increase from today's yearly capacity of 0.3 TWh, to 34 TWh by 2050 (Elektrifieringsstrategin, 2022). Before Sweden commits to the Electrification strategy, it is important to understand how an increased share of wind power impacts Swedish electricity prices.

Figure 1

Historical and forecasted wind power production in Sweden.[1]



Source: Energimyndighetens statistikdatabas (2022).

Because wind power production has a low marginal cost relative to non-renewable sources of energy, wind power generation is expected to have a dampening effect on electricity spot prices. Moreover, the intermittent and unplannable nature of wind power, accompanied by the current inability to efficiently store large amounts of electricity, should entail a positive correlation between wind power and electricity spot price volatility. The predicted effects will be investigated using hourly data on the Swedish market from January 1, 2019 to December 31, 2021. Using an ARMAX-GARCHX framework, we find that 1 MWh increase in wind power generation significantly lowers the average spot price by 0.0180 SEK, and increases the variance by 0.0004, equivalent to a volatility increase of 0.020 SEK (2 öre). The effects are reliable as various model specifications are made without altering the significance or the effects.

The paper will adhere to the following structure: it will begin with a background section, providing information about electricity as a commodity, characteristics of the Swedish electricity market, as well as the Nordic-Baltic marketplace for electricity trade called Nord Pool. This section will be followed by a review of previous literature on the subject, after which the theoretical foundation of the study will be outlined. In the fourth section of the paper, our hypotheses will be presented, before we move onto describing the data and methodology parts of our paper. The subsequent sections will present the results and a discussion of these, including possible policy implications. In the final section of the paper, conclusions will be drawn together with suggestions for possible future research.

[1] Figure includes land-based wind power only.

2. Background

2.1 Electricity as a Commodity

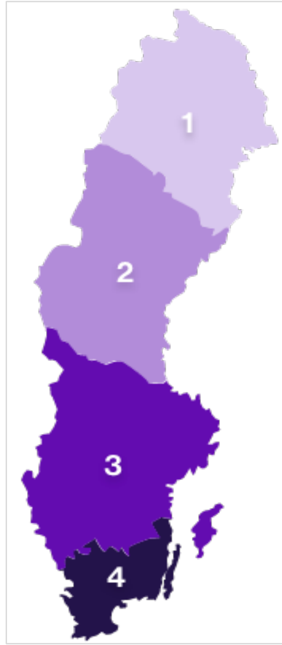
Electricity is an important commodity, which possesses characteristics that differentiate it from other commodities like crude oil or natural gas (CME Group, 2022). Firstly, electricity is interchangeable – one produced unit of electricity is equivalent to any other, that is, there are no variations in quality, efficiency, or energy content between units of electricity. Secondly, electricity is virtually non-storable. Much research and development are being directed towards the future implementation of hydrogen technology that potentially can store large amounts of energy (Ny Teknik, 2021). However, there is today no cost-efficient technology that allows for large-scale storage of electricity, requiring it to be produced and consumed simultaneously. This makes the electricity market unique. As opposed to other free markets, there must always be a balance between supply and demand. This non-storability makes electricity a commodity with naturally high price volatility; changes in demand and supply drive prices up and down because storage cannot be used as a hedging tool to reduce shocks. The physical power grid constitutes the basis of the market and sets a cap on market capacity as all energy that is produced or consumed must be transferred via the physical grid. Prices of electricity are then determined by a combination of factors linked to supply and demand (Svenska Kraftnät, 2021).

2.2 The Swedish Electricity Market

The Swedish electricity market was deregulated in 1996. Following the deregulation, the industry underwent substantial consolidation (Swedish Competition Authority, 2018). The European electricity markets are interconnected, and electricity can be traded across country borders (Svenska Kraftnät, 2021). In 2011, the Swedish market was divided into four bidding areas, illustrated in figure 2. The rationale behind the market division was to make it easier to oversee where in the market there is a capacity excess or shortage. This to better match demand with supply, in an effort to avoid costly transportation of electricity. A consequence of the division into four bidding areas is that the price of electricity can differ substantially between the areas. Northern Sweden is the region which produces the largest amount of electricity due to extensive hydropower capacity. This region is also the most sparsely populated, meaning that high levels of supply are met by low levels of demand, entailing lower prices. Correspondingly, southern Sweden enjoys less production capacity but is more densely populated. This creates excess demand, resulting in significantly higher electricity prices in southern Sweden than in the north (Konsumenternas energimarknadsbyrå, 2021).

Figure 2

Sweden's bidding areas SE1, SE2, SE3, SE4

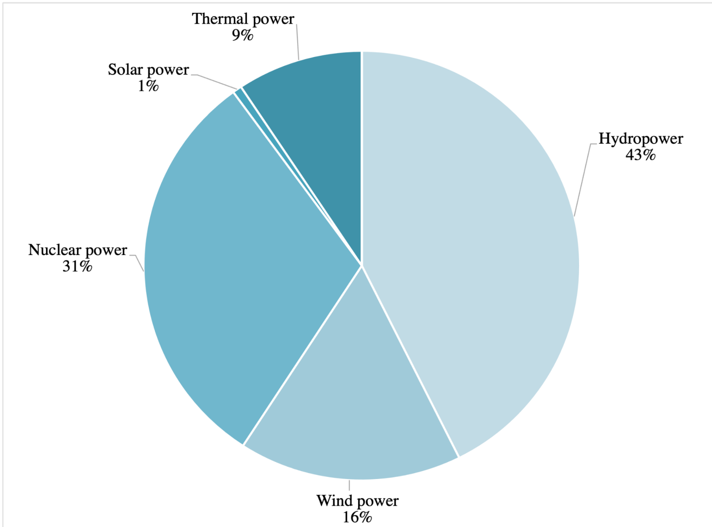


Source: Kundkraft (2022)

Seeing to the production side, the Swedish electricity market is dominated by hydropower, accounting for 43 percent of the supply, followed by nuclear power, accounting for 31 percent of the supply, and by wind power, accounting for 17 percent (figure 3). Sweden's access to large-scale hydropower generation is important for the stability of Swedish electricity supply (Rintamäki et al., 2016). Hydro reservoirs create flexibility in the production of power, and the marginal cost is low relative to non-renewable sources. Solar power currently makes up only a small portion of the total Swedish energy supply but is being expanded. However, solar power supply and demand are poorly matched; during the darker periods of the year, demand for electricity is typically high while the supply of solar power is small due to fewer hours of daylight (Energimyndigheten, 2018). Given the inability to storge large amounts of energy, Sweden cannot readily rely on solar power as a central source of energy.

Figure 3

Swedish electricity production by source in 2021.



Source: Statistics Sweden (2022)

Note: Thermal power consists mainly of fossil fuels and biofuels (Energiföretagen, 2022)

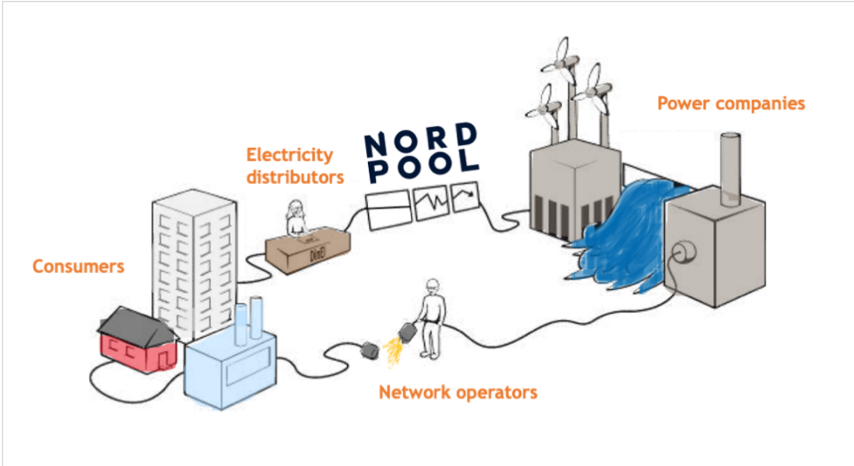
The market for electricity is one characterized by low price elasticity of demand, as our societal structure is reliant on electricity use. The share of electricity generated by wind power in Sweden has increased steadily over the past decades. In an attempt to promote investments in sustainable energy sources, the Swedish government introduced a subsidy system in 2012, called the electricity certificate system (Energimyndigheten, 2021). Producers of renewable energy such as wind power are eligible for the subsidy, further reducing the already relatively low operational costs.

The unplannable nature of VRE sources may give rise to fluctuations in market prices, causing destabilization (Mwampashi et al., 2021). An increasingly volatile market with a lower average electricity price has negative implications for its actors and risks deterring producers and investors (Mauritzen, 2012). Therefore, a volatile, price-pressured market may counteract the goal of substantially increasing electricity production in Sweden.

2.3 Nord Pool

Electricity trade in the Nordics and the Baltics is organized on the marketplace called Nord Pool, which includes Sweden, Norway, Finland, Denmark, Estonia, Latvia, and Lithuania. 85 percent of the electricity consumed in the Nordic region is bought and sold via this joint Nordic-Baltic power exchange. Nord Pool provides a trading space where power companies (producers of electricity) and electricity distributors, that sell electricity to consuming households and the industry, engage in trade, as illustrated in figure 4. Based on supply and demand, Nord Pool sets market clearing spot prices. There is a combined system price for the whole of Nord Pool as well as prices for the individual market areas (Nord Pool, 2021).

Figure 4
Swedish electricity market and its actors



Source: Illustration is authors' own, inspired by image from Göteborg Energi (2014)

The lion part of all electricity trade on Nord Pool is carried out in the day-ahead market, called *Elspot*. A smaller portion of electricity trade takes place on the intraday market, called *Elbas*, where market players can balance trade up until one hour before delivery (Swedish Competition Authority, 2018). As Elspot is the dominant trading place, it will serve as the basis for this study.

At the Elspot market, the bidding process is initiated at 10:00 CET every day. Electricity distributors acting as buyers and power producing companies acting as sellers can then place bids on electricity to be delivered the following day. These bids specify the volume of electricity the participating actors want to buy or sell at a given hour the next day. The bidding process ends at 12:00 CET, and one aggregated demand and supply curve is created for each hour of the following day, for each of the bidding areas. In this way, area spot prices are set (Energimarknadsinspektionen, 2021).

3. Literature Review and Theory

3.1 Previous Literature

The increased integration of renewable energy sources into Western power markets has given rise to a growing body of literature on the topic. Scholars are interested in understanding the implications of VRE sources for different actors in the electricity market. Interest is particularly devoted to understanding the behavior of electricity prices, in terms of level and volatility. The statistical properties of electricity price data make certain modeling approaches more suitable than others. This section of our paper merely focuses on previous literature; however, a detailed description of these statistical properties will be included in the methodology section (6) of this paper.

The theoretical presumption of wind power having a negative effect on electricity price level due to its lower marginal cost has been tested empirically on a range of markets and confirmed by multiple scholars (e.g. Hagfors et al., 2016; Mwampashi et al., 2021; Woo et al., 2011). A second widespread conclusion is that increased shares of non-dispatchable energy sources like wind and solar power in the energy mix lead to increased price volatility (Auer, 2016; Hagfors et al, 2016; Huisman et al., 2021). However, there is also literature, specifically on the Nordic market, which presents contradicting evidence and finds that wind power generation decreases intraday volatility (e.g. Li, 2015; Mauritzen, 2010; Rintamäki et al., 2016).

ARMA Approach

A number of scholars have investigated wind power production and spot price volatility using autoregressive moving average (ARMA) models. Mauritzen (2010) studies the Danish electricity market and uses an ARMA approach to conclude that wind power generation reduces intraday volatility, a finding which challenges a large body of literature. Mauritzen also looks at volatility over longer time periods and finds that wind power instead seems to increase weekly volatility of spot prices. Rintamäki et al. (2016) compare the Danish and German electricity markets using a SARMA model, which is an ARMA model with the addition of a seasonal component often found in electricity price data. They find some contradicting evidence; in Denmark, daily spot price volatility decreases with wind power, whereas the opposite trend is observed in Germany. This result is explained to stem from differing access to flexible generation capacity, as the Danish market is coupled to other Nordic markets and their large-scale hydro reservoirs. Moreover, Rintamäki et al. (2016) find that weekly spot price volatility increases in both Denmark and Germany due to the intermittent characteristics of VRE.

ARMA-GARCH Approach

An integrated ARMA-GARCH framework is commonly used by scholars, where ARMA is used to model the mean equation, that is, the price level, and a generalized autoregressive conditional heteroscedasticity (GARCH) models the variance equation. Mwampashi et al. (2021) use this approach to investigate the Australian National Electricity market. They confirm the negative effect of wind power on price level, often referred to as the 'merit order effect'. Moreover, they find that a 1 MWh increase in wind power generation increases price volatility by 2 percent. The ARMA-GARCH model is also used by Kyritsis et al. (2016) who study the German electricity market and the effect of wind and photovoltaic power sources on electricity spot price volatility. The authors conclude that solar power generation in general reduces electricity price volatility, whereas wind power generation increases volatility. Li (2015) and Fredriksson (2017) employ a similar ARMA-GARCH model to investigate the Nordic day-ahead system price and its volatility in response to wind power generation. Li (2015) finds that wind power generation seems to reduce spot price volatility in the Nordic day-ahead market, contradicting the results found by Fredriksson (2017), Mwampashi et al. (2021) and Kyritsis et al. (2016).

Other Modeling Approaches

Some papers use a conditional autoregressive model, such as Auer (2016) who uses data from the European Energy Exchange to investigate how the shift toward green energy in Germany is affecting electricity prices. He investigates the hypothesis that although renewables generally exhibit lower variable costs that translate into lower variable prices, their non-dispatchable nature may lead to price spikes causing greater overall market volatility. Auer (2016) finds a reduction of volatility in response to increased VRE generation, suggesting that Germany has been successful in integrating renewable sources in the electricity market without compromising its stability.

Another way of investigating the effects of VRE on price level and volatility is with a quantile regression model. Both Maciejowska (2018) and Hagfors et al. (2016) look specifically into the German market and conclude that wind and solar power have negative effects on price level. Conclusions regarding the effect on volatility are however more ambiguous. Maciejowska (2018) finds that the effect of wind power generation on volatility, measured by the inter-quantile range, increases when demand is low, and decreases when demand is high.

Focusing on the Danish market, Jónsson (2010) investigates the market impact of wind energy forecasts by using a non-parametric regression model. Drawing on existing literature, Jónsson (2010) formulates a hypothesis that increased wind power production bears responsibility for increasingly "extreme" electricity prices. He finds a reduction in prices as a result of wind power generation, while intra-day variations seem to diminish in a non-linear manner.

Studies Focused on the Swedish Market

Alam (2021) uses a GARCH model to study the Swedish market and, more specifically, analyze the extent to which wind power generation impacts the long-term electricity price volatility. He finds that a more inflexible wind power supply leads to an increase of long-term volatility. Moreover, Dong et al. (2018) use a non-parametric model to investigate the influence of VRE on electricity price volatility in the Swedish, Danish, and North-Eastern American markets. They find that electricity prices are more stable in the Swedish market, suggesting hydropower as an enabler of a stable market environment.

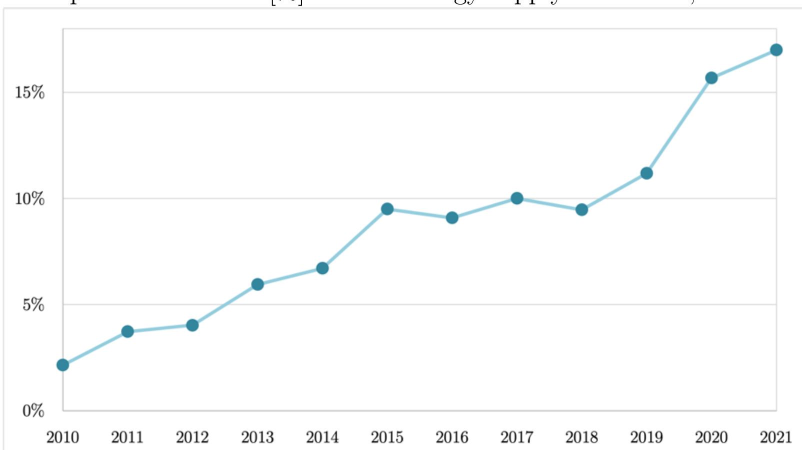
3.2 Our Contribution

The review of previous literature reveals a convincing argument for the negative effect of wind power generation on the electricity spot price level. Additionally, there is currently a large body of literature suggesting that volatility increases with wind power generation (Kyritsis et al., 2016; Mwampashi et al, 2021). However, there is also evidence of wind power generation reducing price volatility in the Nordic market (Jónsson, 2009; Li, 2015; Mauritzen, 2019; Rintamäki et al., 2016). The lack of consensus on the effect of renewable energy on electricity spot price volatility calls for further studies of an increasingly renewable energy mix.

A suggested explanation for why wind power generation has been found to reduce volatility of electricity prices in some parts of the Nordics is the access to large hydro reservoirs in Norway and Sweden working as a stabilizing factor (Li, 2015; Rintamäki et al., 2016). Sweden is pointed out to have good base-load capacity through its hydropower, which should entail resistance to volatility, as is pointed out by Dong et al. (2018). The unique characteristics of the Swedish power mix make it interesting to further investigate the Swedish market. This especially because the current body of research focused on Sweden is limited in scope.

Figure 5

Wind power as a share [%] of total energy supply in Sweden, 2010-2021



Source: Statistics Sweden (2022)

As is seen in figure 5, the Swedish energy sector has changed remarkably over the past decade towards more dependence on wind power, which calls for continuous reassessment of the electricity market dynamics. When Sweden commits to the Electrification strategy, it is of utmost importance to have an up-to-date evaluation regarding the effects of wind power. This in order for suppliers, consumers and the government to anticipate any challenges that may follow from an expansion of wind power production. The importance is reinforced by the war in Ukraine, as Sweden and the EU want to speed up the green transition to become less dependent on Russian resources (European Commission, 2022). Using recent data, this paper will add to the existing body of research an updated investigation of the impacts of wind power in Sweden.

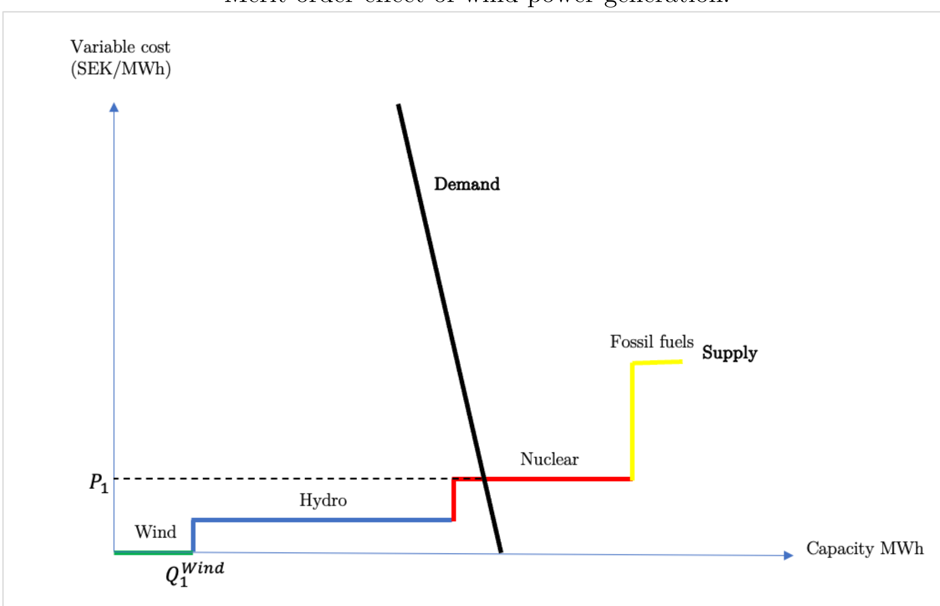
3.3 Theory

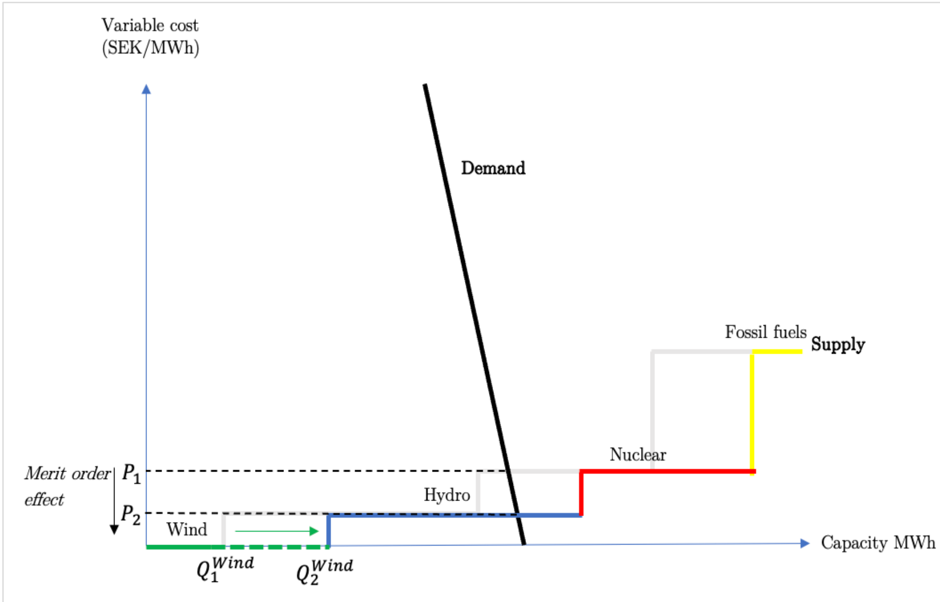
Electricity demand is typically considered highly price inelastic as consumption is essentially independent of the spot price – at least in the short term (Forrest et al., 2013; Huisman et al., 2021; Jónsson et al., 2009; Michelfelder & Pilotte, 2019). This has to do with electricity being a commodity without efficient substitutes: we are completely dependent on it in our day-to-day lives. Hence, the slope of the demand curve is close to vertical. The supply curve in electricity markets can be drawn as a 'merit order curve'. The curve illustrates the marginal cost of production and total supply of each available electricity source in the energy mix. The quantity produced by each source of energy is represented by a step in the curve (figure 6). Wind power generation has a low marginal cost, placing wind at the lowest level in the supply curve. Fossil fuels, on the other hand, have a high marginal cost. As such, the supply of fossil fuels appears at a higher level in the supply curve (The European Wind Energy Association, 2020).

The spot prices for electricity are driven by supply, and therefore, by marginal costs (Swedish Competition Authority, 2018). The idea of the merit order curve is to illustrate the 'crowding out effect' of energy sources with a high marginal cost. For lower levels of demand, wind power and other low marginal cost sources of energy can supply the demanded quantity, eliminating the demand for fossil fuels which, due to their higher marginal costs, would operate at a loss when prices are low. The supply of fossil fuels kicks in only at higher levels of demand when prices are higher. This is called the merit order effect (The European Wind Energy Association, 2020).

Figure 6

Merit order effect of wind power generation.





Source: Authors' own, inspired by Forrest & MacGill (2013)
Note: As the supply of wind power increases from Q_1 to Q_2, the price falls from P_1 to P_2, 'crowding out' the more expensive energy source (nuclear power at this level of demand).

If wind power supply was constantly large, the merit order theory would indicate a permanently lower price level, leading to other non-renewable sources being partially or fully pushed out of the market. However, wind power generation is unpredictable. Today, it is not possible to efficiently store large amounts of electricity, meaning that the power generation mix varies across each point in time (Mauritzen, 2012). If the wind speed is low during a given hour, this will cause the supply curve to shift left and supply to become more reliant on other power sources with higher marginal costs to meet the demand. As a result, the electricity spot price will increase. However, when wind speeds are high, the supply curve shifts right and prices go down (The European Wind Energy Association, 2020).

Due to the low price elasticity of demand, these changes in the electricity supply mix will lead to large price swings. The supply curve with a larger share of unplannable wind power generation should therefore entail greater variations in the electricity price. Increased wind power generation should intuitively increase volatility as a result of this mechanism (Jónsson et al., 2010; Woo et al., 2011).

4. Hypotheses

The theoretical framework presented in the theory section of this paper gives rise to predictions about how electricity prices should behave in response to wind power generation. Together with the results found in previous literature, these predictions have been used to develop two hypotheses that will be empirically assessed in this paper. Our hypotheses are specified as follows:

Hypothesis 1: Wind power generation is negatively correlated with the average Swedish electricity spot price level.

Hypothesis 2: Wind power generation is positively correlated with the Swedish electricity spot price volatility.

5. Data

5.1 Input Data Selection

The time series data used in this paper has primarily been retrieved from the Nord Pool Group (2022). The Nord Pool ftp servers contain hourly observations of our variables of interest, including day-ahead electricity spot prices, forecasted wind power generation, forecasted consumption of electricity, and forecasted net exchange (imports – exports). To capture the intra-day variation of electricity spot prices, we have chosen to use hourly data, which is in line with the method employed by the majority of previous studies on the subject (e.g. Jónsson et al, 2009; Mwampashi, 2021; Rintamäki et al., 2016). The high frequency data is studied for a limited time period in order to keep the data set to a workable size. We have decided to limit the scope of our study to include hourly data from January 1, 2019 to December 31, 2021. With 24 hours in each day, this implies that a total of 26,304 observations are available per variable.[2]

A second reason for using data from a relatively short period, apart from keeping the data set to a manageable size, is that the energy market is continuously changing in terms of composition. For our results to bear relevance for general audiences and policymakers in 2022, we have decided to use the most recent data available, making us opt for data leading up to December 31, 2021.

5.2 The Dependent Variables

In our study, there are two different dependent variables of interest, namely, the electricity spot price level and the electricity spot price volatility. The volatility variable will be defined in the methodology section (6) of this paper.

This study concerns the Swedish market as we seek to investigate how wind power generation in Sweden impacts Swedish electricity spot prices. The system price for the entire Nordic-Baltic market is therefore less relevant. Simply considering the system price for the entire market would decrease any effect Swedish wind power generation might have on prices. Meanwhile, looking at only one of the four Swedish bidding areas would fail to capture the substantial variations across the regions. For instance, the effect of increased wind power is expected to have a greater impact on electricity

[2] Note that 2020 was a leap year with 366 days.

prices in areas where the majority of windmill installations are located, than it would in those heavily dominated by hydropower.

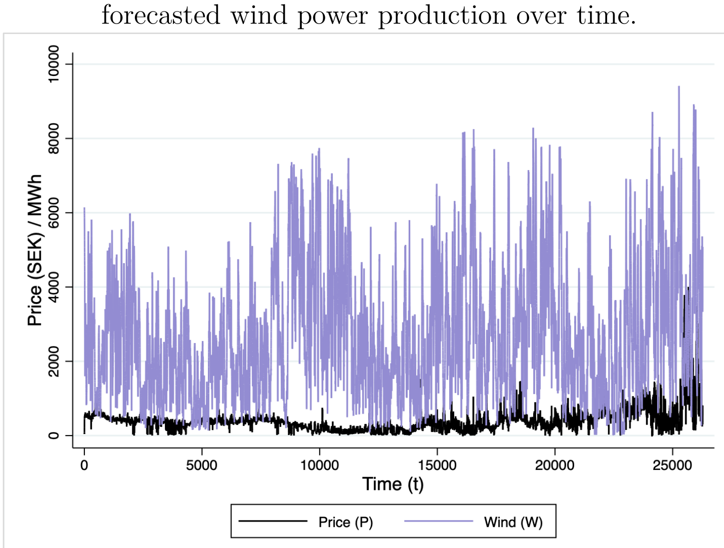
In order to be able to draw conclusions on the national level, an average for hourly electricity spot prices has been calculated, using prices from the four bidding areas. By calculating an average, we have generated data for a Sweden specific system price of electricity. Prices are measured in SEK per megawatt hour (SEK/MWh). Potentially, using an average could reduce the volatility of prices, weakening our findings. However, we have judged the scope of this paper insufficient to motivate a four-part assessment of the bidding zones separately. Moreover, as outlined above, we aim for results that can have a national implication, which is why we opt for a Swedish system price, rather than a Nordic-Baltic system price. Taking the average of the four Swedish bidding zones is also done by Alam (2021).

5.3 The Independent Variable

The independent variable of interest is the forecasted generation of wind power in Sweden. The price of electricity in the day-ahead market is formed on the basis of forecasted supply and demand, which is why forecasted rather than actualized values are used (Fredriksson, 2017). The forecasted production of wind power is a product of installed capacity, and more importantly, the wind speed. The independent variable is exogenously determined and driven by the current weather conditions. Wind power generation is measured in megawatt hours (MWh).

Figure 7

Plot of dependent variable electricity spot price and independent variable forecasted wind power production over time.



Source: Authors' own illustration based on data from Nord Pool Group (2022)

According to the merit order theory, wind power generation is expected to have a price dampening effect. As is illustrated in figure 7, the predicted wind power generation is highly volatile exhibiting large swings. Due to the unpredictable nature of weather conditions, it is intuitive that increased reliance on wind power should transmit some of the wind volatility into price risks.

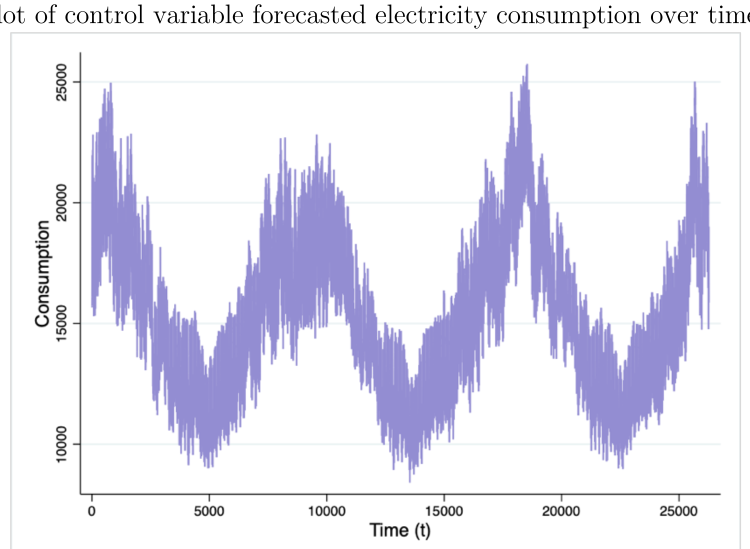
5.4 Control Variables

Consumption of Electricity

Data regarding the forecasted electricity consumption is expected to bear relevance for price setting in the electricity spot price market (Forrest & MacGill, 2013; Mwampashi et al., 2021). Like the wind variable, day-ahead electricity prices are set based on forecasted consumption rather than actualized demand. The consumption forecasts are set before the electricity prices, and are therefore exogenous to the spot price. On the Nord Pool power exchange electricity spot prices are determined by supply and demand. Much like the supply of electricity, demanded consumption for electricity fluctuates and follows a seasonal pattern. For example, electricity consumption is higher during business hours than during night-time, and generally higher during peak winter months, when the Swedish climate serves cold temperatures, than in summer. The seasonality in demand in turn drives the seasonal variations of the electricity spot price. The seasonality in consumption can be clearly observed in figure 8 which shows a plot of the forecasted consumption variable.

Figure 8

Plot of control variable forecasted electricity consumption over time.[3]



Source: Authors' own illustration based on data from Nord Pool Group (2022)

The seasonal and intra-day variations in consumption impact the price of electricity at any given time. To isolate the impact of our independent variable of interest on the electricity price, it is of

[3] The plot in figure 8 shows corrected forecasted consumption variable. For further information, see appendix B.

interest to eliminate the seasonal variations in electricity spot prices. A common method to control for these seasonal variations is to deseasonalize the price data with the use of dummy variables, as is done by Li (2015).
An alternative approach, which is simpler but meets the same objective, is to control for forecasted consumption. By including this variable as a control variable, the seasonal and intra-day variations of the electricity spot price is captured. Because the two variables move in tandem, controlling for demand is in effect a way of deseasonalizing the price data.

In line with the theory of supply and demand, forecasted consumption is expected to exhibit a positive relationship with the price level, as is found by other scholars (see for instance Li, 2015; Mwampashi et al., 2021). Moreover, because the supply curve is steeper at higher levels of demanded consumption as seen in the merit order diagram (figure 6), small consumption changes will cause greater price swings at higher levels of demanded consumption. The effect is amplified due to the inelasticity of the demand curve. This predicts a positive relationship between consumption and electricity price volatility.

Net Exchange

The European market for electricity is interconnected and allows for transmission of electricity across country borders. This means that the Swedish market for electricity is not a closed system – what is produced in Sweden is not necessarily consumed within the country. The net exchange refers to the sum of imports minus the sum of exports. Hence, a negative number indicates net exports, whereas a positive number is indicative of net imports for that particular hour. On a yearly basis, Sweden is a net exporter of electricity (Energimyndigheten, 2022).

Contracts for exports and imports are signed before the bidding process takes place, meaning that the volume of electricity that is exported or imported affects the supply of electricity available for domestic market actors to bid for, and therefore also the price. This entails that the dependent variable of interest, the price of electricity, is exogenously impacted by the volume of exports and imports. It follows that net exchange of electricity should be controlled for to avoid an omitted variable bias.

Imports increase the supply of electricity available for buyers in the Swedish market. Therefore, basic supply and demand frameworks suggest that the variable net exchange should exhibit a negative correlation with the spot price level. The Swedish power mix is dominated by stable, low-cost hydropower. Imported energy originates from a range of sources, many of which are more expensive than the domestically produced electricity. Imports from other countries can thus crowd in expensive technologies. This could in turn give rise to larger price swings and greater price volatility in the Swedish market (Fredriksson, 2017). For this reason, a positive relationship between the variable net exchange and the price volatility is expected.

Oil Price

It can be reasonably assumed that the price of electricity is influenced by the price of other sources of energy, such as fossil fuels (Woo et al., 2011). As a proxy for fossil fuel prices, we will use the price of US light crude oil. The use of US light crude oil rather than Brent crude oil is due to potential endogeneity concerns associated with the latter (Ketterer, 2014; Woo et al., 2011). Nord Pool has a least-cost dispatching rule which means that the volume of energy produced from oil is endogenous to electricity price and wind power production. If the wind speed is high, less oil will be used in the production of electricity. If the electricity price is low, less oil will be produced due to its higher marginal cost. A strategy to avoid this endogeneity is therefore to use US light crude oil as a proxy for fossil fuels. A positive effect is expected with regards to the effect of oil on price level, as its higher marginal cost should force prices upwards. It is however more difficult to hypothesize the effect of oil on electricity price volatility. On one hand it is dispatchable, meaning that it could smoothen the supply curve from other intermittent sources when needed. On the other hand, the high cost of the technologies needed when operating in the market can lead to large price swings (Fredriksson, 2017).

From Dukascopy (2022) we have retrieved hourly prices for US light crude oil as traded on the Swiss FX marketplace (SWFX). The oil price data is reported in USD. Therefore, the prices have been manually converted to SEK for the purpose of this paper, using official exchange rates from the Swedish Central Bank (Sveriges Riksbank, 2022). Official exchange rate data is available only with daily frequency, meaning that the daily exchange rates have been used to convert oil prices for the full 24 hours of each day. While hourly conversion rates would have been ideal, we have settled for the use of daily rates for access purposes. Moreover, the exchange rates from the Swedish central bank are updated only for business days (Monday through Friday, public holidays excluded). For this reason, we have used the exchange rate for the most recent business day, and prolonged it to cover for adjacent days of the weekend and, where applicable, public holidays. The same method is used to account for missing oil price data on weekends and public holidays, when no oil trade takes place.

To capture the effect the oil price is predicted to have on the electricity spot price, we have chosen to include the control variable with a 24-hour lag, as was done by O'Mahoney and Denny (2014). The rationale is that it is the close price of the day before which is used as the basis for energy supply and demand in the market. The natural logarithm of the oil price is used, and the first difference is taken, to achieve stationarity.[4] This is illustrated in appendix C.

5.5 Missing Values

Our raw data features missing values. For the variable wind, 51 observations are missing, and for net exchange, 27 are missing. For the variable consumption, 3 are missing, and for the variables

[4] The model used (ARMAX) requires stationary variables. This will be elaborated on in the methodology section (6).

electricity price and oil price, no data points are missing. The reason for the missing values is simply that the data points are absent in the raw data retrieved from the Nord Pool ftp server, without further information as to why these are missing. We use linear interpolation to handle the missing values. In practice, this means that the missing values are estimated as a linear trend from the last to the next existing value, to ensure continuity of the time series. This method is suitable for variables with a small number of missing values grouped together, which is the case for the variable consumption. For the variable wind, there are 24 missing values grouped together, after each other, in two sequences. For the variable net exchange, the same problem of 23 missing values grouped together is found. The relatively large number of consecutive missing values creates a problem with linear interpolation as the smoothing period becomes very long. However, due to the limited scope of this paper, we have decided to simplify the procedure and use linear interpolation for all variables.

Table 1

Descriptive statistics.[6]

Variable	Observations	Unit	Mean	St.d.	Minimum	Maximum
Price	26 279	SEK/MWh	397.889	301.961	-20.000	4 003.355
Wind	26 279	MWh/h	2 771.391	1 768.699	9.000	9 414.000
Consumption	26 279	MWh/h	15 128.250	4 040.054	828.000	25 254.000
Net exchange	26 279	MWh/h	-2 924.134	1 563.405	-8 047.000	2 276.000
Oil price	26 279	SEK	0.000	0.009	-0.519	0.314

Source: Authors' own illustration based on data from Nord Pool Group (2022) and Dukascopy (2022)

6. Methodology

6.1 Time Series Properties of the Data

Electricity spot price data have important characteristics that must be accounted for when choosing how to model the relationship between electricity prices and wind power generation. Previous literature suggests that electricity spot prices are autocorrelated (see for instance Kyritsis et al., 2016; Mwampashi et al., 2021; Rintamäki et al., 2016). This means that the electricity spot price at a given time in part can be explained by the spot price in the previous period or periods. The Ljung-Box test will be performed on the dependent variable, the electricity spot price, to confirm this autocorrelation in our data for different lagged values (Ljung & Box, 1978).

[6] The descriptive statistics are presented after manipulation of the data is done (i.e. linear interpolation and first difference of the natural logarithm of the oil price variable).

Table 2

Result of Ljung-Box test for autocorrelation in the dependent variable, the electricity spot price, for three different lag lengths

Lag length	Ljung-Box Q Statistic
5	1.066e+05***
10	1.829e+05***
15	2.504e+05***

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

The null hypothesis of zero autocorrelation is rejected for all chosen lag lengths, confirming presence of autocorrelation in our time series data. Table 2 indicates that the price of electricity at a given hour is influenced by the price up to 15 hours earlier.

The presence of autocorrelation in electricity spot prices indicates that our regression model needs to include lagged values of the price as variables, to capture the autocorrelation effect. A model for electricity prices which omits lagged values of the dependent variable will inevitably give rise to an omitted variable bias, whereby explanatory information is lost, and misplaced among the included variables. This would lead to biased coefficients, meaning that we would not be able to trust the precision of the results. For this reason, a suitable model for the price level should be autoregressive, to account for the autocorrelation of electricity prices.

6.2 Conditional Mean Equation: AutoRegressive Moving Average (ARMA) Model

Autoregressive (AR) models allow for predicting a dependent variable based on the past values of that same variable. In a pure AR(p) model, the electricity spot price level at time t is linearly explained by the electricity price p hours back in time, as follows (Stock & Watson, 2020):

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

(Equation 1)

where sp_t is the electricity spot price at time t, a_i is the coefficient for the autoregressive terms, and p is the number of lags.

A multitude of previous studies have recognized that the addition of a moving average (MA) component is informational for electricity prices and improves the fit of the model (Mauritzen, 2010; Mwampashi et al., 2021; Rintamäki, 2016). The MA component implies including past error terms, in addition to the past values of the dependent variable at hand. The ARMA equation is specified as follows:

$$sp_t = c + \sum_{i=1}^{p} a_i \, sp_{t-i} + \sum_{j=1}^{q} \beta_j \, \varepsilon_{t-j} + \varepsilon_t$$

(Equation 2)

where q is the number of moving average lags and β_j is the coefficient for the respective MA term.

Previous literature has also found that electricity spot prices are not only affected by their own past, but also by exogenous factors x_k (Alam, 2021; Kyritsis et al., 2016; Mwamphasi et al., 2021). The purpose of this paper is to examine the impact of the exogenous variable wind power production on the electricity spot price. Therefore, we are interested in applying a version of the ARMA model which adds the exogenous variable of interest and the exogenous control variables. Including all exogenous factors gives an ARMAX(p, q, b) model with the following specification:

$$sp_t = c + \sum_{i=1}^{p} a_i \, sp_{t-i} + \sum_{j=1}^{q} \beta_j \, \varepsilon_{t-j} + \sum_{k=1}^{b} \gamma_k \, x_{k,t} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_t^2)$$

(Equation 3)

where b is the number of exogenous variables, and γ_k are the coefficients of each of the exogenous variables. The error terms (ε_t) are assumed to be white noise, meaning that they have a mean of zero and a constant variance. This ARMAX(p, q, b) model fits the mean equation, in which the electricity price level is linearly expressed by its past values, by the past values of the error terms, and by other exogenous factors (Weron, 2014).

One key assumption of the ARMAX model is that all variables are weakly stationary, meaning that the mean, variance, and covariance are constant over time (Weron, 2014). The augmented Dickey-Fuller (ADF) test is therefore performed on all variables with the null hypothesis of non-stationarity (Clò, 2014). The null hypothesis is rejected for all variables as seen in table 3, confirming stationarity of the time series data.[7]

Table 3

Augmented Dickey-Fuller test for stationarity on all variables.

The fist difference of the natural logarithm of the oil price is used as variable, to achieve stationarity.

Variable	ADF test statistics
Price	-17.246***
Wind	-7.466***
Consumption	-14.267***
Oil price	-161.749***
Net exchange	-17.493***

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

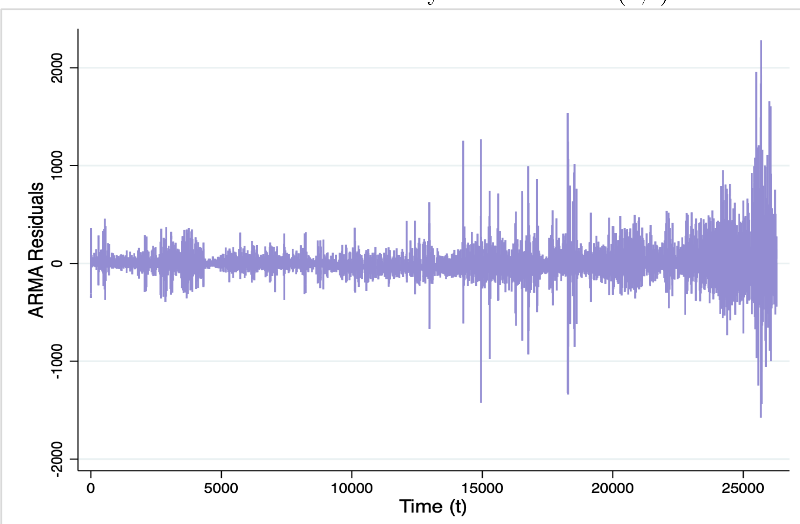
[7] The price of crude oil is found to be non-stationary. The natural logarithm of the oil price is used, and the first order difference is taken, to achieve stationarity. Therefore, the coefficients of the oil price will be interpreted in a different way than all other coefficients in the results section.

6.3 Conditional Variance Equation: Generalized AutoRegressive Conditional Heteroscedastic (GARCH) Model

Moving over to the volatility of electricity prices, some key characteristics of the error terms in the ARMAX equation must be considered. As is stated in the previous section, an important assumption underlying the ARMAX model is homoscedasticity in the error terms; that is, constant variance over time. Weron (2014) states that the volatility of electricity prices is often non-constant, implying heteroscedastic error terms. Moreover, periods of high volatility tend to be followed by periods of high volatility, and vice versa. This phenomenon is within finance often referred to as *volatility clustering* (Engle, 2001). These characteristics are reasonably expected to be present in our data. An arbitrarily chosen ARMA model with 3 p and 3 q lags is constructed to investigate the properties of the error terms. The plot in figure 9 is indicative of non-constant variance over time and volatility clustering; the volatility is clearly higher around $t = 25\ 000$ than $t = 5\ 000$.

Figure 9

Plotted residuals of an arbitrarily chosen ARMA(3,3) model.



Source: Authors' own illustration based on data from Nord Pool Group (2022)

One way to formally investigate the error term properties indicated in figure 9 is by applying the Engle's multiplier test for residual heteroscedasticity (Engle, 1982). The null hypothesis of homoscedasticity is rejected for all tested lag lengths (table 4), confirming heteroscedasticity. This implies that the variance of the error terms depends on its own past and is conditional on time (Bollerslev, 1986). Heteroscedasticity in the error terms violates the assumption of constant variance, which calls for further modeling to improve precision and reliability of our variance model output (Engle, 1982).

Table 4

Engle's multiplier test for heteroscedasticity in the squared residuals for various lag lengths, of an arbitrarily chosen ARMA(3,3) model.

Lag length	Engle's Multiplier Test Statistic
5	1205.526***
10	1281.166***
15	2552.766***

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

Engle (1982) developed an autoregressive conditional heteroscedastic (ARCH) model to account for heteroscedastic error terms. Effectively, the heteroscedasticity is treated as a variance that needs to be modeled, rather than a forecasting issue that needs to be corrected (Engle, 2001). ARCH type models are often used to model the variance of electricity prices, given an already fitted ARMAX(p, q, b) model (Kyritsis et al., 2016; Li, 2015; Mwampashi et al., 2021). The dependent variable in an ARCH model is the conditional variance of the electricity price data. In short, this means that the modeled variance is allowed to change over time as a function of lagged squared errors from a previously specified ARMAX model. An ARCH(u) model has the following equation:

$$\sigma_t^2 = \alpha + \sum_{l=1}^{u} \theta_l \varepsilon_{t-l}^2$$

(Equation 4)

where σ_t^2 is the conditional variance, u is the number of past squared errors, ε_t^2 is the squared error term from the ARMAX equation, and θ_l is the coefficient for the respective squared error term.

Bollerslev (1986) extended the model to form a generalized autoregressive conditional heteroscedastic (GARCH) model. A GARCH(u, v) model is an ARCH(u) model which also includes v lagged conditional variances σ_t^2 with coefficients ϖ_m(Bollerslev, 1986). A GARCH model is superior to an ARCH model because it permits a more flexible lag structure and allows for a more parsimonious description (Bollerslev, 1986). Most scholars use this generalized form instead of a simple ARCH model when modeling electricity price data (Kyritsis et al., 2016; Li, 2015; Mwampashi et al., 2021). Including w exogenous variables x_n with coefficients π_n, a GARCHX(u, v, w) approach to modeling the conditional variance will allow us to find the effect of wind power generation on electricity price variance as follows (Fredriksson, 2017):

$$\sigma_t^2 = \alpha + \sum_{l=1}^{u} \theta_l \, {\varepsilon_{t-l}}^2 + \sum_{m=1}^{v} \varpi_m \, \sigma_{t-m}^2 + \sum_{n=1}^{w} \pi_n x_{n,t}$$

(Equation 5)

6.4 Integrated Framework: ARMAX-GARCHX Model

An integrated framework will hereby be applied where an ARMAX(p, q, b) model is used to describe the relationship between wind power generation and the electricity price level. A GARCHX(u, v, w) model will then be used to describe the relationship between wind power generation and the electricity spot price volatility.

In practical terms, we will first optimize the ARMAX(p, q, b) model by choosing the number of lags p and q that best fit our data, given the inclusion of our four exogenous variables. This optimization process will be performed using the Akaike Information Criterion (AIC), which is a measure of the relative quality of a statistical model for a given data set (Stock & Watson, 2020). The best fitted ARMAX(p, q, b) model exhibits the combination of p and q which optimizes the AIC by minimizing the information loss. In practice, the marginal benefit of adding an extra lag is weighted against the marginal cost of additional estimation error which stems from the addition of an explanatory variable (Stock & Watson, 2020). The AIC, which we seek to minimize, can be expressed as follows:

$$AIC \ = \ 2K \ - \ 2ln(L)$$

(Equation 6)

where K is the number of estimated parameters in the model, and L is the likelihood that the model can produce our observed y-values (Stock & Watson, 2020). Hence, the AIC penalizes overly complex models with many parameters, and rewards good data fit. The best model according to the AIC will as such be the one that best describes the changes in the dependent variable, with the smallest number of explanatory variables.

After finding the optimal ARMAX(p, q, b) model, the squared residuals obtained will be used as input (the ARCH component) in a GARCHX(u, v, w) equation to find the conditional variance. Various iterations are made to find the optimal integrated ARMAX-GARCHX model which minimizes the AIC (Mwamphasi et al., 2021). The optimized integrated model is used to test the two hypotheses that wind power generation is negatively correlated with electricity spot price level, and positively correlated with electricity spot price volatility.

7. Results

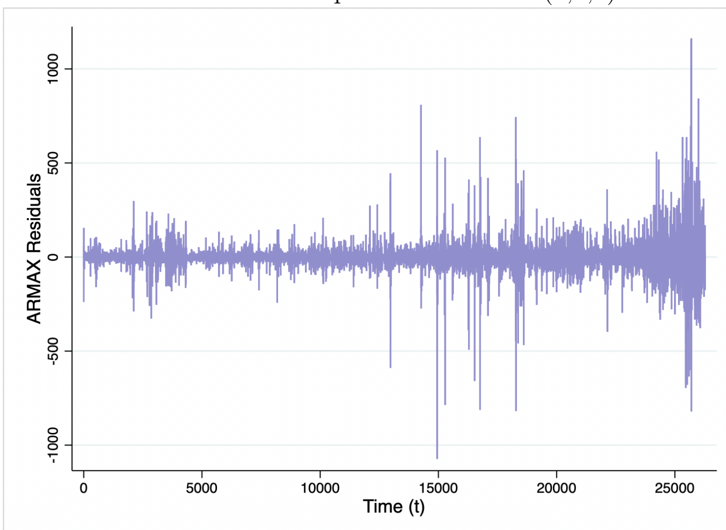
7.1 Mean Equation: ARMAX Results

To optimize the ARMAX(p, q, b) model describing the conditional mean, we would ideally test all possible combinations of p and q lags. It is not feasible to test every potential model to find the one optimizing the AIC, as the number of possible combinations increases exponentially. Different numbers of p and q lags, ranging from 0 to 3, are combined and their fit is assessed using AIC, as reported in appendix D. The best fitted model, with the minimized AIC, is an ARMAX(3,3,4) model with p=3 and q=3, including all four exogenous variables which are expected to have explanatory value.

In order to confirm the usage of an integrated ARMAX-GARCHX framework for modeling the level and volatility of Swedish electricity prices, we need to verify the existence of ARCH effects in the ARMAX(3,3,4) error terms, as predicted in the methodology section. Plotting the error terms of the optimized model ARMAX(3,3,4) in figure 10, it can be deduced that the variance is non-constant and that the error terms exhibit volatility clustering: periods of high variance are followed by periods of high variance.

Figure 10

Plotted residuals of the optimized ARMAX(3,3,4) model



Source: Authors' own illustration based on data from Nord Pool Group (2022)

Both hypotheses are therefore tested using an integrated ARMAX(3,3,4)-GARCHX(1,1,4) approach. The output is reported as model A in table 5. Adhering to a common approach, we choose ARCH and GARCH lags of 1 (see for instance Kyritsis et al., 2016; Li, 2015; Mwampashi et al., 2021).

Apart from the fact that electricity prices are autocorrelated, prices are also found to have a strong daily pattern (see for instance, Rintamäki et al., 2016). Therefore, including a 24 hour AR(p) lag could be informative for prices of the kind we are using. Adding this to model B in table 5, we find that the AR(p) 24 hour lag has a significant impact of the electricity spot price and the addition also improves the AIC for the integrated model. As the daily pattern of electricity prices might not exhibit a perfect integer periodicity, one could potentially improve model fit further by including AR(p) lags at hour 23 and 25 (Jakobsson, 2019). In model C, these additions are made, resulting in significant results for both lag 23 and lag 25, and a drastically lowered AIC.
As seen in models A to C, the variable oil price lacks significance which could have various explanations, a plausible one being the substantial manipulation performed to the oil price data. Because the oil price variable lacks explanatory value, we improve our model by excluding this variable, resulting in model D.

Engle's multiplier test for residual heteroscedasticity is presented in the bottom row of table 5 to formally test for heteroscedasticity in the error terms for each mean equation. The null hypothesis of homoscedasticity is rejected for all ARMAX models, formally confirming usage of a GARCHX equation to model the variance in the integrated ARMAX-GARCHX framework.

Table 5

Results for ARMAX-GARCHX processes.

Variables	**Model A**	**Model B**	**Model C**	**Model D**
		Mean Equation		
Wind	-0.0177***	-0.0197***	-0.0180***	-0.0180***
	(0.000)	(0.000)	(0.000)	(0.000)
Consumption	0.0137***	0.0140***	0.0074***	0.0074***
	(0.000)	(0.000)	(0.000)	(0.000)
Net exchange	-0.0002	-0.0039***	-0.0032***	-0.0032***
	(0.409)	(0.000)	(0.000)	(0.000)
Oil price	2.1773	0.5367	3.4551	
	(0.880)	(0.969)	(0.812)	
Constant	189.604***	131.0271***	224.4423***	224.4307***
	(0.000)	(0.000)	(0.000)	(0.000)
AR lags				
a_1	2.7178***	0.4162***	1.3805***	1.3802***
	(0.000)	(0.000)	(0.000)	(0.000)
a_2	-2.7049***	0.0260	-0.5383***	-0.5378***
	(0.000)	(0.206)	(0.000)	(0.000)
a_3	0.9840***	0.2613***	0.0987***	0.0985***
	(0.000)	(0.000)	(0.000)	(0.000)
a_{23}			0.1590***	0.1590***
			(0.000)	(0.000)
a_{24}		0.2786***	0.1434***	0.1434***
		(0.000)	(0.000)	(0.000)
a_{25}			-0.2491***	-0.2492***
			(0.000)	(0.000)
MA lags				
β_1	-1.5285***	0.7649***	-0.2160***	-0.2156***
	(0.000)	(0.000)	(0.000)	(0.000)
β_2	0.6511***	0.5826***	0.0324**	0.0323**
	(0.000)	(0.000)	(0.049)	(0.050)
β_3	0.1811***	0.1892***	-0.0387***	-0.0387***
	(0.000)	(0.000)	(0.000)	(0.000)
		Variance Equation		
Wind	0.0004***	0.0005***	0.0004***	0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)
Consumption	-0.0002***	-0.0002***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Net exchange	0.0001***	0.0001***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Oil price	19.2695***	19.0495***	17.9246***	17.9572***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	4.074689	3.7282***	2.9899***	2.9900***
	(0.000)	(0.000)	(0.000)	(0.000)
ARCH lags				
θ_1	0.1432***	0.1209***	0.1151***	0.1151***
	(0.000)	(0.000)	(0.000)	(0.000)
GARCH lags				
ϖ_1	0.8853***	0.8979***	0.9007***	0.9008***
	(0.000)	(0.000)	(0.000)	(0.000)
AIC	254 616.3	253 844.0	252 169.9	252 168.0
Engle's multiplier test statistic (using one lag)	933.630***	730.215***	540.090***	539.532***

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

The results in the mean equation of all models A to D confirm the first hypothesis of wind power generation having a significantly negative impact on the electricity price level. This illustrates the merit order effect of wind crowding out more expensive energy sources, and is consistent with findings made by other scholars (see for instance Hagfors et al., 2016; Li, 2015; Maciejowska, 2018;).

Through the various model iterations A, B C, and D, our coefficient of interest is not altered to a noteworthy extent which speaks towards a credible result. Model D, our best fitted model, implies that for each unit (MWh) of wind power generation, the average electricity price level decreases by 0.0180 SEK. Moreover, all control variables except for the oil price have significant impact on the price level. For each unit increase in consumption, the average price level increases by 0.0074 SEK. This is consistent with basic supply and demand theory, as a demand curve that shifts right increases prices, all else fixed. For an additional unit net exchanged (imported) electricity, the price decreases by 0.0032 SEK (0.32 öre), on average. The result is in line with what is found by Li (2015) on the Danish market. Intuitively, as more energy is imported, the available supply of electricity in the Swedish market is increased. An upward shift in supply should, in line with standard supply and demand theory, drive down prices in the Swedish market. Therefore, the result is expected.

The specification of our best fitted model (D) shows that AR(p) lags 1, 2, 3, 23, 24 and 25 all have significant explanatory power for the electricity price level. Some of the lags (2 and 25) are negatively correlated with the price, whereas the rest exhibit a positive correlation. Had all lags been positive, the electricity spot price would increase indefinitely. The different signs indicate mean reversion, that is, stationarity of our chosen model (Stock & Watson, 2020).

The regression results presented in table 5 also illustrate the significant impact of the MA lag components, which improves model fit.

7.2 Variance Equation: GARCHX Results[8]

The results for the variance equation shown in table 5 confirm our second hypothesis: that wind power generation increases volatility of electricity spot prices. For each additional unit of wind power generation, the variance in electricity spot prices increases by 0.0004, equivalent to a volatility increase of 0.020 SEK (2 öre). This significant and positive effect of wind power generation on volatility is consistent with what other scholars have found, such as Mwampashi et al. (2021) who study the Australian market, Fredriksson (2017) who investigates the Nordic market, and Alam

[8] For an ARCH process to generate real results, the conditional variance must exhibit mean reversion, also known as process stationarity. A mean reverting variance process requires the sum of the ARCH and GARCH coefficients to be less than one. Otherwise, the conditional variance grows infinitely large, which undermines the modeling process (Engle, 2001). The GARCH(1,1,4) process that is modeled and displayed in table 5 generates ARCH and GARCH coefficients with a sum that marginally exceeds unity. This implies a non-stationary GARCH process. To avoid this so-called integrated volatility problem, standard errors would need to be calculated in a different way. However, that is beyond the scope of this paper.

(2021) who analyzes the Swedish market. Thereby, our results contribute to this perspective within the body of contradicting evidence in the Nordic market.

It is found that the consumption variable is negatively correlated with the variance of the electricity spot price. As is shown in the merit order framework (figure 6), the supply curve is steeper at higher levels of demand, which should entail that changes in demand at high levels cause greater variations in electricity price than changes in demand at low levels. Thus, a positive coefficient was expected for the consumption variable. As such, the observed result is somewhat surprising, and a plausible explanation is likely found in a methodology shortcoming as seen in footnote 8. Alternatively, the result could derive from suboptimal data handling, further discussed in the limitations section of this paper.

Net exchange is correlated with an increase in volatility. The result contradicts what is found by Li (2015). However, she defines Danish imports as electricity transmitted from Norway and Sweden – countries with relatively high shares of hydropower which has a low marginal cost. As Sweden is largely self-sufficient with relatively cheap electricity, a potential explanation for the observed result could be that more expensive energy sources are crowded in when there is a shortage in domestic electricity supply, leading to larger price swings and increased volatility.

As opposed to the mean equation, the oil price variable is highly significant in our variance equation. Oil prices have a positive effect on the volatility, suggesting that the dispatchable nature of oil does not dampen the volatility, but the contrary. The result is in line with the presumption that increased oil prices drive up differences in relative prices of different sources of energy in the mix. The magnitude of the coefficient is large relative to the other explanatory variables. This is related to the heavy manipulation performed on the oil price data to achieve stationarity (see appendix C). The manipulation complicates intuitive interpretation of the coefficient.

7.3 Goodness of Fit Tests

Testing the ARMAX Model

An additional step to securing the reliability of our model output is to test the specification of our optimized model. The Ljung-Box test on the residuals of our optimized ARMAX(p, q, b) model (table 5, model D) tests for any remaining autocorrelation not captured by the lagged values p and q, or by the exogenous variables (Ljung & Box, 1978). In an ARMAX(p, q, b) model with perfect explanatory power, the residuals would be white noise only. That is, the residuals would be random error terms with a zero mean and constant variance, and no autocorrelation should remain. Therefore, we want the null hypothesis of zero remaining autocorrelation to hold in the Ljung-Box test. As displayed in table 6, the null hypothesis cannot be rejected at a 1 percent significance level. This indicates good fit of our model and appropriate specification of our p and q lags.

Table 6

Ljung-Box test for remaining autocorrelation in the residuals of the ARMAX model with AR lags = 1, 2, 3, 23, 24, 25; MA lags = 1, 2, 3; Exogenous variables = wind, consumption, net exchange, for various lag lengths.

Lag length	Ljung-Box Q Statistic	P-value
1	0.0170	0.8963
2	0.1733	0.9170
3	3.3354	0.3428

Interpretation: If the p-value exceeds the significance level (e.g. 0.001), the null hypothesis of no remaining autocorrelation cannot be rejected

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

Testing the GARCHX Model

Like the ARMAX model, the specification of the GARCHX model should be assessed. Performing the Ljung-Box test on the squared residuals of the GARCHX model instead tests for remaining ARCH effects in the residuals of the model (Ljung & Box, 1978). Ideally, there should be no remaining ARCH effects as a well-fitted GARCHX model would capture all of these in the variance modeling process. Therefore, we want the null hypothesis of zero remaining ARCH effects to hold. As displayed in table 7, the null hypothesis cannot be rejected at a 1 percent significance level.[9] This indicates that our model is sufficiently well-fitted.

Table 7

Ljung-Box test for remaining ARCH effects in the squared residuals of the GARCHX model with ARCH lag = 1; GARCH lag = 1; Exogenous variables = wind, consumption, net exchange, oil, for various lag lengths.

Lag length	Ljung-Box Q Statistic	P-value
1	5.1514	0.0232**
2	6.2406	0.0441**
3	6.2406	0.1005

Interpretation: If the p-value exceeds the significance level (e.g. 0.001), the null hypothesis of no remaining ARCH effects cannot be rejected

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

[9] As seen, the null hypothesis for lags 1 and 2 would be rejected at a 5 percent significance level, indicating that ARCH effects may still be present. As such, it is likely that the GARCH(1,1,4) model does not capture the full ARCH effect and would benefit from additional optimization methods that go beyond the scope of this paper.

8. Sensitivity Analysis

A shortcoming to our study is the model specification process, specifically, the chosen number of p and q lags included in the mean equation (ARMAX model) and the number of u and v lags in the variance equation (GARCHX model). We have only tested a limited number of lag combinations to avoid an overwhelming set of results. Our selected models do indeed perform relatively well in the goodness of fit tests, however, one could question the decision to only test models under strict lag length constraints.

The optimized ARMAX-GARCHX model equation displayed in table 5 has been derived using maximum lag lengths of 3 for both ARMAX lags p and q, with the exemption of AR lags 23, 24, and 25. For the GARCHX lags u and v the maximum lag length tested was 1. Therefore, there may exist a combination of lags p, q, u, and v that better captures the characteristics of the time series data at hand, and consequently offers a better model fit. To verify the reliability of our findings, and legitimize our choice to test for a maximum of 3 AR/MA lags, and 1 ARCH/GARCH lags respectively, a sensitivity analysis is conducted. Various alternative model specifications are tested in addition to our optimized model D.

Table 8

Specification of tested models with arbitrarily chosen lag combinations.[10]

Model Specification		
Name	ARMAX	GARCHX
Test Model 1	(4, 4)	(1, 1)
Test Model 2	(4, 5)	(1, 2)
Test Model 3	(5, 4)	(1, 2)
Test Model 4	(6, 6)	(1, 1)
Test Model 5	(4, 4)	(1, 3)
Test Model 6	(7, 3)	(1, 1)
Test Model 7	(6, 4)	(1, 3)
Test Model 8	(5, 5)	(1, 3)
Test Model 9	(8, 2)	(1, 1)
Test Model 10	(10, 10)	(1, 1)

Note: All tested ARMAX specifications include the exogenous variables wind, demand, and net exchange, as well as AR lags 23, 24 and 25, to make the test models 1-10 comparable to our previously optimized model D. All tested GARCH specifications include the exogenous variables wind, demand, net exchange, and oil price.

[10] The ARCH lag is still restricted to 1 due to infeasibility to increase its lag length in the statistical software used.

Table 9[11]

Specification of coefficients for the exogenous variables for each test model.[12]

Variables	Test model 1	Test model 2	Test model 3	Test model 4	Test model 5	Test model 6	Test model 7	Test model 8	Test model 9	Test model 10
Mean equation										
Wind	-0.0178***	-0.0179***	-0.0178***	-0.0176***	-0.0173***	-0.0176***	-0.0177***	-0.0177***	-0.0176***	-0.0177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Consumption	0.0075***	0.0077***	0.0078***	0.0079***	0.0066***	0.0079***	0.0081***	0.0080***	0.0080***	0.0082***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net exchange	-0.0032***	-0.0034***	-0.0032***	-0.0029***	-0.0032***	-0.0028***	-0.0035***	-0.0035***	-0.0027***	-0.0027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	223.0557***	218.7815***	215.8549***	213.5365***	231.1080***	210.8380***	208.1408***	210.8576***	206.3847***	197.5979***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance equation										
Wind	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0004***	0.0005***	0.0005***	0.0004***	0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Consumption	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net exchange	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil price	19.0467***	18.2451***	18.2415***	18.1351***	19.8197***	18.1247***	19.8827***	19.8463***	18.1455***	18.1587***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3.0239***	3.4199***	3.4264***	3.0560***	3.4764***	3.0747***	3.7218***	3.7091***	3.0716***	3.0616***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AIC	252 101.6	251 557.6	251 537.2	252 004.4	251 054.7	251 996.6	251 076.8	251 104.5	251 990.3	251 939.0

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.

[11] The coefficients for the lags are excluded in the table due to limited space.

[12] All GARCH processes in the test models are, as in the results section, non-stationary, meaning that the conditional variance does not exhibit mean reversion (Engle, 2001). This undermines the modeling processes and implies that standard errors would need to be calculated in a different way. However, this is beyond of the scope of this paper.

The AIC is lower for all above tested ARMAX-GARCHX processes, indicating that the inclusion of more lags indeed gives rise to a better model fit. This is not surprising, as the addition of more explanatory variables increases the explanatory capacity of the model. However, worth noting is that the coefficients for all variables of interest exhibit little to no deviations regardless of how many lags are included, and they are all significant at the 1 percent level. This verifies the accuracy and reliability of the results generated by our optimized model D in table 5.

Even if the theoretical best-fitting model for our data contains a different lag combination than our optimized model D, including different $p, q, u,$ and v lags does not seem to alter the results. As illustrated in table 9, the number of ARMAX lags does not change the result that for each unit (MWh) of wind power generation, the electricity price level decreases by approximately 0.0180 SEK. Similarly, a unit (MWh) increase of wind power generation increases volatility by approximately 0.020 SEK.

9. Discussion

9.1 Policy Implications

Implications of Lowered Price Levels

In order to make our results comparable to other studies, we convert our results into percentage terms of the mean values seen in table 1. A 1 percent increase of wind power generation decreases the average electricity spot price by 0.13 percent. This can be compared to Fredriksson (2017) who studies the effect of Danish and Swedish wind power production on the Nordic system price. He finds that a 1 percent increase in wind power generation reduces the average price by 0.04 percent. Similarly, Li (2015) who studies the Danish market, finds an effect of 0.03 percent. It can be deduced that the effect we found is of comparable magnitude, but greater. The two studies date back five and seven years respectively, a time when wind power production in the Nordics was smaller. The greater effect found in this paper could be attributable to the past few years' growth of the wind power share in the energy mix. The difference between our results and those in previous studies indicate that the transformation of the energy sector affects how policy should be formulated, which emphasizes the need for continuous reassessment on the subject.

At first sight, an electrification strategy based on wind power which significantly lowers the price of electricity seems attractive. Lower prices should be at the benefit of consumers and society as a whole. However, reality is more complex. The green transition requires that we maximize the production of sustainable energy in order to steer away from fossil fuel dependency. The electrification of Sweden will cause a drastic increase in the demand for electricity; according to some estimates, the demand for electricity in 2045 will exceed today's levels by up to 120 percent (Borglund, 2021). To sustain an electrified Sweden, we need to make sure that the market conditions are attractive enough for power generating companies to remain in the market – otherwise we are unlikely to achieve the necessary increase in capacity.

Supported by the results presented in this paper, investing in wind power risks setting the scene for an unattractive market, characterized by low profit margins. Power companies with high marginal costs, such as those burning fossil fuels or produce nuclear energy, may struggle to stay afloat in such a market, ultimately, being forced to exit. The typical high-cost power sources are dispatchable, making them integral to a stable and balanced electricity supply in Sweden (Fredriksson, 2017). Without these plannable energy sources stabilizing on non-windy days, the market is poorly equipped to meet demand. Unless accompanied by appropriate measures, an expansion of wind power may result in generation capacity shortages.

Implications of Increased Price Volatility

In contrast to lowered electricity prices, which benefit some groups at the expense of others, increased price volatility is unambiguously undesirable. All parties suffer from a volatile market. Producers will struggle to predict cash flows, and will therefore require a larger buffer to meet unexpectedly low prices, and consumers will be exposed to large price swings. Risk averse investors will seek other investment opportunities, possibly depriving the energy sector of the necessary influx of capital.

Possible Remedies for Increased Price Volatility

The policy implications of increased price volatility due to increased wind power production have been discussed by previous scholars. Woo et al. (2011) encourage the principal actors in the electricity market to meet the challenge through increased efforts at risk management. An efficient way to deal with risk for economic actors with large stakes in the electricity market is to engage in the energy security market and invest in financial products like electricity futures and forward contracts with important hedging abilities. Mwampashi et al. (2021) instead emphasize the importance of adequate infrastructure, and an expansion of the electricity grid. A drastic expansion of wind power and a subsequent loss of stabilizing dispatchable power sources requires improved integration of the Swedish market with the rest of Europe to avoid domestic power outages. Further connecting the power grids with Europe can also increase profitability for producers, and stabilize supply and prices (Schaber et al., 2012).

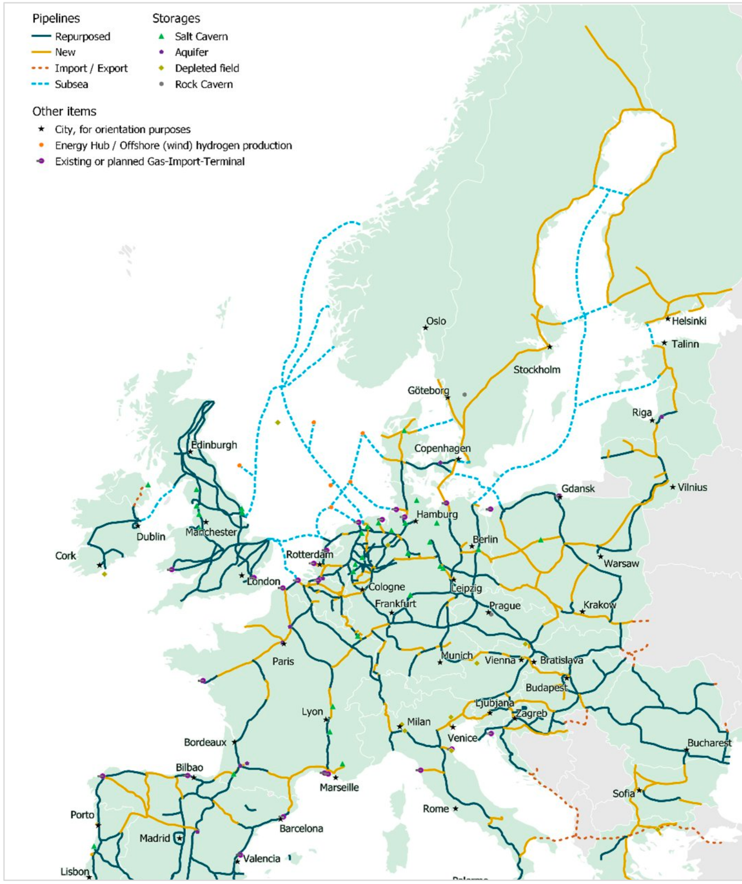
Aside from financial products and expanding electricity grids, new technology may be the solution to increasingly volatile markets. For example, large investments are being made within the market for frequency containment reserves (FCR). In 2019, Svenska Kraftnät, the electricity transmission system operator in Sweden, opened up for more intermittent energy sources in the electricity grid by enabling consumers to make money through flexible electricity consumption (Vattenfall, 2021). This is an example of how technology can be used to hedge market risk, which presents great potential for counteracting the volatility induced by intermittent energy sources like wind power in the electricity grid.

Up until this point, the discussion in this paper has only been about wind power directly being converted to electricity. However, resources are being directed toward the research, development, and future implementation of hydrogen technology. Dr. Mats Lundberg, Head of Sustainability at Sandvik, elaborates on the development in an interview. As previously discussed, we currently lack technology for efficient large-scale storage of electricity. Electricity transmission causes substantial energy losses, sometimes as high as 15 percent. Energy converted into hydrogen, on the other hand, allows for storage and transmission without energy losses. A combination of batteries, for short-term storage, and hydrogen, for longer-term storage, can have important smoothening effects, reducing the negative impacts of intermittent energy sources on the Swedish electricity market. Apart from alleviating the impact of wind power on price volatility, this can also improve the business case for the wind power producers. With a storage option, producers can maximize production without worrying about price drops when wind speeds are high, which today can incentivize shutting off windmills to avoid operating at a loss (Lundberg, 2022). This could in turn reduce the negative profitability effects that wind power generation otherwise may have on the electricity market.

As a consequence of the war in Ukraine, efforts in line with the green transition, including investments in hydrogen technology, have been accelerated in the European Union. In fact, Dr. Lundberg (2022) claims that the sense of urgency has never been greater. Despite its status as a sustainability pioneer, Sweden has fallen behind the rest of Europe when it comes to the development and implementation of appropriate infrastructure. Figure 11 shows the network of hydrogen compatible pipes, which are evenly distributed across Europe but with a clear gap in Sweden, Norway, and Finland. This further emphasizes the need for additional investments into research and development to keep up with technology advancements.

Figure 11

Map of Europe, illustrating stretches of pipe capable of transporting hydrogen.



Source: Gas for Climate 2050 (2022)

The Benefits of Self Sufficiency

Despite some undesirable effects on the electricity market, there are aspects beyond climate considerations that motivate an expansion of wind power production. As illustrated by recent geopolitical events, a strive towards self-sufficiency in energy supply has valuable security implications, as it can provide protection in terms of crisis. It builds resilience in international conflict, by effectively reducing the threat of aggressions intended to put energy supply on the line. Sweden has no independent supply of oil or gas, meaning that all fossil fuel driven energy production relies on international trade and import of these fuels. The intrinsic value in being self-sufficient creates additional support for moving away from fossil fuels, and heavily investing in types of energy that Sweden is capable of producing on its own. Most Swedish hydropower plants date back to the 1960s and 1970s, and the installation of new plants is limited due to their impacts on ecosystems and biodiversity (Energiföretagen, 2022). Wind power is therefore a natural step to electrify Sweden, without increasing dependency on international trade. It is crucial to securing Swedish independence, and the possibility to opt for neutrality in a crisis.

9.2 Limitations

Input Data Selection

There are inherent limitations to this study which may have undermined the findings. One limitation is our manipulation of the input price data. As described in section 5.1, we use the national average prices of the different bidding zones in Sweden, rather than the separate prices for each area. Using an averaged value as input may have omitted important information, preventing us from fully understanding the relationship between our investigated variables. Particularly, it is possible that the investigation of how wind power impacts electricity spot price volatility may have been hampered by our decision to use averaged data, as any volatility effects are expected to have been reduced. The same manipulation is however done by Alam (2021), which should legitimize the approach.

Another limitation regarding our input data is our choice not to include Danish wind power production in our analysis. Danish wind power accounts for a substantial portion of the total wind power produced within the Nord Pool market (Li, 2015). Because the market is highly integrated, the ideal way to investigate and understand the relationship between wind power production and electricity spot prices would arguably have been to include Danish production. Our choice of a pure Swedish focus made us opt for Sweden specific input values, and we instead attempted to mitigate this shortcoming by controlling for net exchange.

Possible Impacts of the Covid-19 Pandemic

Attention must be directed to the fact that our time series stretches across the Covid-19 pandemic. The years 2020 and 2021 were characterized by unusual circumstances, impacting society and the economy on a wide front, possible affecting variables such as electricity consumption. We chose not to dedicate time or effort into investigating the possible effects the pandemic may have had on our study. Our devotion to producing time relevant results made us use current day data in spite of a possible pandemic effect. This is in part motivated by Sweden's relatively soft approach to the pandemic, with no official lockdowns (Our world in data, 2022), which arguably entails that any effects are limited in size.

Manual Data Entry

The raw data retrieved from the Nord Pool data base had to be converted into a format that could readily be used as input for our regression analysis in our chosen statistical software tool. For a number of steps in this process, manual data entry was required. Manual data entry is prone to human error (Barchard & Pace, 2011). Upon thorough examination of our data set done in the final stage of writing this paper, existence of human error was confirmed. The inspection revealed that 720 values of the variable forecasted consumption had been entered incorrectly. A plot of the consumption variable containing these errors is seen in appendix B, along with a table of the corrected summary statistics. With a total of 26 279 observations of this same variable, the incorrectly entered values result in an error rate of approximately 2.7 percent. A rule of thumb in statistics is that manual data entry generates an error rate of approximately 1 percent, which should be considered acceptable (Laurila, 2022). We deem our error rate of 2.7 percent to fall within an acceptable range, and therefore, made the decision to keep our faulty variable as an input in our regression analysis to avoid excessive reworking. However, it should be mentioned that the confirmed existence of error may have, albeit negligibly, altered our results.

10. Conclusion

The aim of this study was to contribute to the current energy political debate by investigating how Swedish wind power generation impacts electricity spot prices in terms of level and volatility. To this end, we have specified and applied an ARMAX-GARCHX model to our set of hourly electricity price and wind power generation data, together with a number of control variables. The model has subsequently been altered with regard to lag lengths and control variables in order to achieve optimal fit. Using the optimized model, we tested our two hypotheses; that wind power generation is negatively correlated with electricity spot price level, and positively correlated with electricity spot price volatility. Both hypotheses were confirmed at a 1 percent significance level. More specifically, increasing wind power generation by 1 MWh lowers the average electricity spot price by 0.018 SEK (1.8 öre), and increases the volatility by 0.020 SEK (2 öre). Lowered price levels combined with high volatility risks setting the scene for an unprofitable and unstable electricity market, potentially unattractive for both producers and investors. As Sweden embarks on an ambitious electrification journey, in which wind power is to play a major part, these risks must be accounted for. In an effort to stabilize an electricity market with a large share of VRE, extensive resources are currently being invested in the development of volatility dampening tools, including hydrogen technology and frequency containment reserves. However, Sweden has a long way to go in terms of building new infrastructure before the country is adequately equipped for a green energy transition. Unless accompanied by a rigorous risk management strategy, a rapid expansion of wind power could challenge the long-term goal of substantially and sustainably increasing Swedish electricity production.

The results presented in this study have partial support in previous literature, but the lack of consensus regarding the effect of wind power generation on electricity price volatility calls for further research. A suggestion is to particularly focus on Sweden and other countries with a high penetration of wind power. Moreover, the ongoing transformation of the energy market composition requires continuous reassessment of effects, as changed circumstances seem to impact results. Reaching a consensus regarding the impacts of a green transition on electricity price behavior will be crucial to designing the optimal electrification strategy for Sweden – a strategy that paves way for efficient and sustainable electricity production without compromising market stability.

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Appendices

Appendix A

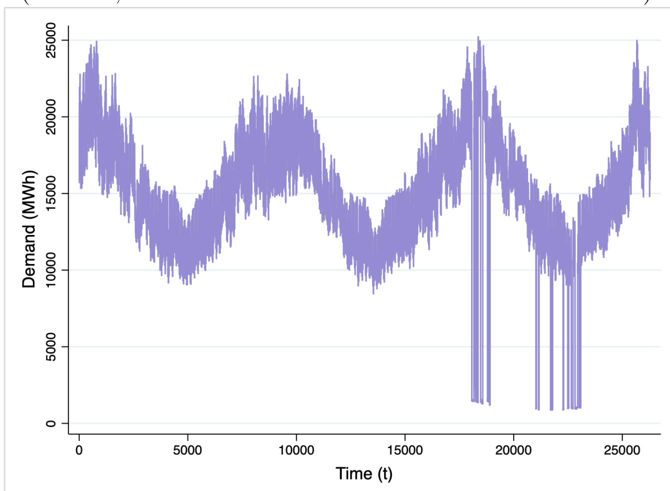
Definition of the dependent variable, the independent variable of interest, and all control variables.

Variable	Definition
Electricity spot price	Hourly price of electricity set on day-ahead market (average of SE1, SE2, SE3, and SE4 prices)
Forecasted wind power production	Day-ahead hourly Swedish wind power production prognosis
Forecasted electricity consumption	Day-ahead hourly Swedish consumption prognosis
Net exchange	Day-ahead hourly Swedish net import - net export prognosis
Oil price	Hourly US crude oil price with a 24 hour lag (natural logarithm, first difference)

Appendix B

B.1

Figure shows plot of the (faulty) consumption variable which has been used as input in the regression analysis. Faulty values (outliers, observed between t = 18 000 and t = 23 000) are visible in the graph.



Source: Authors' own illustration based on data from Nord Pool Group (2022)

B.2

Table showing consumption variable corrected for faulty values. Mean, st.d., min, and max. can be compared to the descriptive statistics in table 1, where the consumption variable exhibits different numbers.

Variable	Observations	Unit	Mean	St.d.	Minimum	Maximum
Consumption	26 279	MWh/h	15 574.090	3 348.947	8 415.000	25 745.000

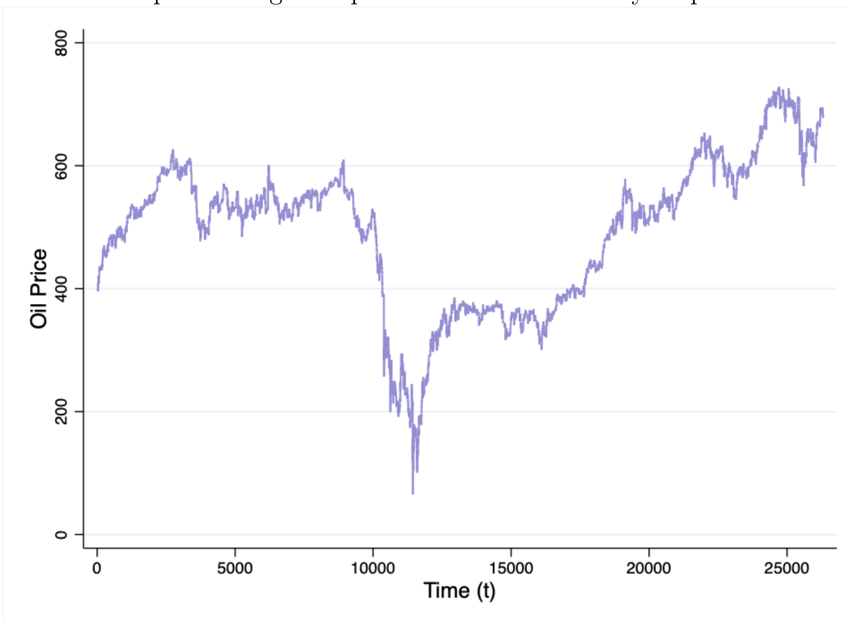
Source: Authors' own illustration based on data from Nord Pool Group (2022)

Comment: The faulty values were noticed at a late stage in the process of writing this paper. The faulty values are attributable to manual data entry, whereby inaccurate data points were entered in the data set. This resulted in the consumption variable exhibiting an unexpected pattern. Upon notice, the faulty data was corrected, and a plot of the corrected data points was included in figure 8 to illustrate the seasonal behavior of the consumption variable. However, the faulty variable, including a total of 720 faulty values (equal to an error rate of 2.7 percent) was still used as input in the regression analysis.

Appendix C

C.1

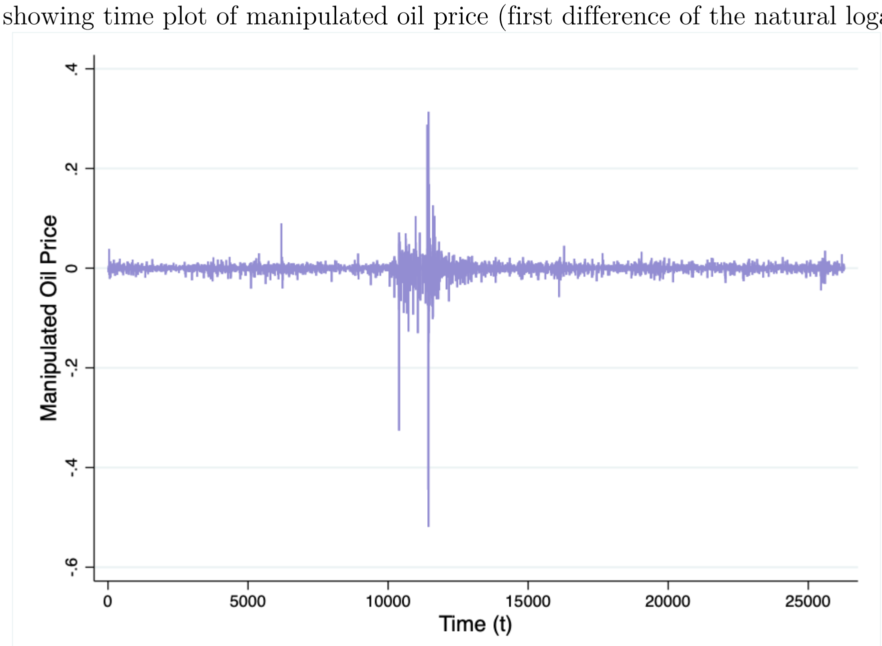
Graph showing time plot of the non-stationary oil price.



Source: Authors' own illustration based on data from Dukascopy (2022)

C.2

Graph showing time plot of manipulated oil price (first difference of the natural logarithm).



Source: Authors' own illustration based on data from Dukascopy (2022)

Appendix D

Specification and AIC for various combinations of p and q lags in the ARMAX(p,q,4) model.

ARMAX(p,q,b)	1,0,4	1,1,4	1,2,4	1,3,4	2,0,4	2,1,4	2,2,4	2,3,4	3,0,4	3,1,4	3,2,4	3,3,4
Wind	-0.03183***	-0.0343***	-0.0346***	-0.0346***	-0.0347***	-0.0346***	-0.0346***	-0.0346***	-0.0346***	-0.0345***	-0.0360***	-0.0336***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Consumption	0.0256***	0.0194***	0.0186***	0.0183***	0.0184***	0.0185***	0.0185***	0.0183***	0.0185***	0.0184***	0.01590***	0.0155***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net exchange	0.0259***	0.0223***	0.0218***	0.0218***	0.0219***	0.0219***	0.0218***	0.0218***	0.0218***	0.0220***	0.0221***	0.0197***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Oil price	-6.5815	-13.0021	-10.6532	-11.2666	-9.5750	-11.0844	-10.7729	-11.0954	-10.9852	-11.8048	-9.3491	-13.2367***
	(0.895)	(0.774)	(0.815)	(0.805)	(0.835)	(0.808)	(0.813)	(0.808)	(0.809)	(0.795)	(0.824)	(0.757)
Constant	155.9973***	252.4922***	265.4000***	269.2289***	269.3460***	266.4310***	266.6280***	269.7242***	265.8089***	268.0985***	240.6660***	265.8466***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR lags												
a_1	0.9779***	0.9658***	0.9621***	0.9602***	1.2583***	1.1380***	1.0632***	0.2843***	1.2704***	0.4958***	2.3347***	2.7987***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_2					-0.2875***	-0.1698***	-0.0978**	0.6498***	-0.3413***	0.6473***	-1.8057***	-2.6552***
					(0.000)	(0.000)	(0.025)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
a_3									0.0431***	-0.1938***	0.4707***	0.8561***
									(0.000)	(0.000)	(0.000)	(0.000)
MA lags												
β_1		0.2882***	0.3059***	0.3115***		0.1313***	0.2061***	0.9876***		0.7718***	-1.1070***	-1.5779***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
β_2			0.0530***	0.0633***			0.0254*	0.27360***			0.1511***	0.3787***
			(0.000)	(0.000)			(0.066)	(0.000)			(0.000)	(0.000)
β_3				0.0217***				0.0654***				0.2289***
				(0.000)				(0.000)				(0.000)
AIC	289 201.0	287 178.4	287 119.3	287 112.2	287 158.8	287 118.8	287 119.0	287 087.0	287 112.1	287 113.8	285 927.5	285 758.3

Note: ***Significant at 1 percent level, **significant at 5 percent level, *significant at 10 percent level.