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Abstract

The Nordic power market is a key player in facilitating the production of green energy. Especially in recent time, the market has seen a substantial increase in power prices and volatility. A tool for hedging this exposure is the Nasdaq Commodities exchange, which offers Nordic power derivatives. However, Nasdaq themselves has claimed this market is relatively illiquid.

Our thesis aims to investigate how volatility in Nordic power prices affects the liquidity in the Nordic power derivative market, with special emphasis on the 2022 power crisis. Our analysis is based on daily orderbooks from different power derivatives, as well as daily Nordic system prices from 2016 to 2023. We use OLS regression in order to examine any possible relationship between volatility and liquidity.

We find volatility and liquidity to have a negative relationship. This is in line with present literature, due to liquidity providers being less attracted to volatile markets, although empirical testing has given different results. We found volatility in 2022 to bid-ask spread, but lack statistical significance to back up this result. In 2022, we observed that market participants were more willing to add orders despite volatile system prices compared to 2019.

Key words: liquidity, volatility, power derivatives, Nordic, energy crisis

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1 Introduction

The Nordic power market has seen substantially high prices and volatility during 2022. It is expected that energy prices will continue to be volatile due to the fast transition to low-carbon energy. Furthermore, Nordic energy consumption is projected to increase by 50% by 2050, with the possibility of increasing as much as 100% (Wråke et al., 2021). The increased prices and volatility have caused financial problems for households, corporations, and producers alike. If clean energy production does not increase by a similar amount as projected consumption, managing electricity price risk may become even more important in the future.

A tool for handling electricity exposure in the Nordics is the Nasdaq Commodities Exchange. They offer power derivatives for the entire Nordic area. These instruments can be used either for hedging power exposure or for speculative trading. However, in an interview we conducted with Nasdaq, they described the Nordic power derivative market as "relatively illiquid" compared to other financial markets. With the growing need to hedge volatile energy prices, understanding the volatility and liquidity of the power derivative market is crucial for effective risk management, stability, and efficiency of the market. Given the increased focus on Nordic power prices and its volatility, has there been an increase in interest in power derivatives, and if so, has liquidity improved?

In the commodity futures market, the demand for liquidity is considered high (Grossman & Miller, 1988). This is because hedgers need to buy continues, due to inflow of commodities in the supply chain. This is especially true in volatile markets, and liquidity becomes crucial for this reason. Moreover, futures markets involve high level based on margin requirements that vary with the volatility of the underlying asset. Trading therefore becomes riskier for speculators during high volatility scenarios, which may affect liquidity (Haugom & Ray, 2017).

The relationship between volatility and liquidity have been studied for other derivatives such as oil futures (Haugom &Ray, 2017) and stocks (Ma et al., 2018). Although there is some literature on the Nordic power derivative market, most of these papers investigate specific price dynamics. Our thesis aims to investigate the liquidity in the Nordic power derivative market, how it relates to liquidity in the underlying power prices, and how this may have changed during the 2022 energy crisis. To our knowledge, we are the first to provide a research paper that investigates this.

We are expecting to find volatility to have a negative relationship with liquidity. This is based on work such as Amihud and Mendelseon (1980) who find liquidity providers to be less attracted to volatile markets. We are unsure to what extent the 2022 energy crisis affected liquidity. Results from Chang, Chou and Nelling (2000) found the demand of hedgers to increase with volatility in the underlying asset, especially during shocks. However, results from Amihud and Mendelson (1980) still apply, where liquidity providers will be less inclined to provide liquidity.

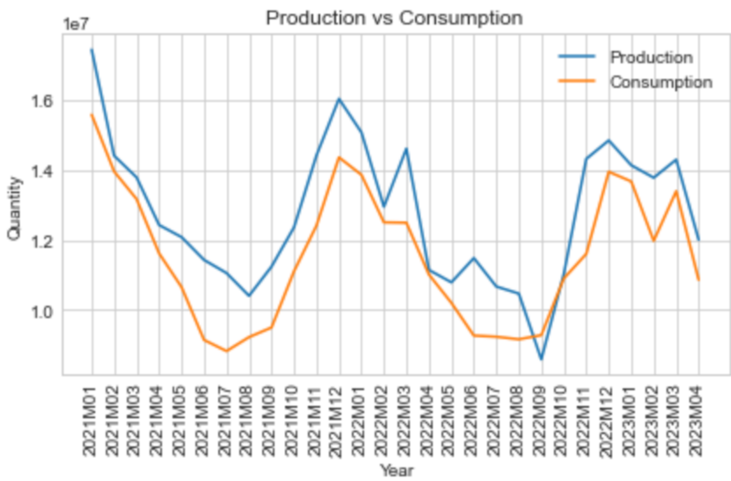
To investigate this further, we will deploy OLS regressions with daily data ranging from 2016-2022 provided by Nasdaq. Furthermore, we will analyze if the 2022 crisis brought more attention to the Nordic power market.

We have structured our thesis as follows: We will first present a background of the market, followed by existing literature on volatility, liquidity and shocks. Based on our literature review, we will introduce our hypotheses and look further into what data and methodologies we have used to perform our research. Thereafter, we discuss and validate our results based on our hypotheses. In the final chapter, we conclude our findings with discussion of limitations, weaknesses and future research.

2 The Nordic Power market

2.1 Electricity

Electricity has unique qualities that distinguish it from other commodities. First, electricity is completely interchangeable. This means one unit of electricity contains the same amount of energy, regardless of its source. Secondly, production and consumption must occur at the same time. Power storage is currently expensive and inefficient. While most commodities have the option of being stored for later usage, this is not currently applicable to electricity. As a result of this, any imbalance in supply and demand can cause big fluctuations in price. Electricity is also difficult to transport over long distances. This can make the price of electricity vary across regions, as some regions may not be able to supply their own electricity demand, and therefore must rely on importation (and vice versa) (Bessembinder & Lemmon, 2002; Çanakoğlu & Adıyeke, 2020; Lucia & Schwatz, 2002). Electricity markets, especially in the Nordics, are largely temperature driven. There will be higher demand during the colder months, as residents need heating for their homes (Espen Benth & Meyer-Brandis, 2009). In addition, most forms of electricity production have some dependencies on weather conditions, which are seasonal as well.



Graph 1: Seasonality in energy consumption

There has been an increasing focus on the development of green energy in the Nordic countries. According to Sovacool et al. (2018), 83% of all electricity generated in the Nordic countries is considered low carbon, with a significant portion coming from renewable sources. Furthermore, Saranyaa & Fathima (2023) indicate that there is a strong shift towards renewable energy sources in the global power market, and Wörner et al. (2022) say policymakers aim to make renewable energy sources more accessible and attractive to customers. With this in mind, it should come as no surprise that the Nordic power market has become more attractive to outside markets in recent years. A recent example of this is the newfound connection between Norway and Germany, so called NordLink, which allows for power transmission between the two countries. With Germany's recent investment in wind- and solar energy, they are now able to substitute this energy with Norwegian hydro energy in periods with low wind and/or sun (*NordLink*, 2023).

The Nordic countries, especially Norway, export some of their electricity production. Norway can do this reliably due to its production portfolio being dominated by hydropower (about 95%). While electricity cannot be stored, water can be stored in reservoirs and used for power production later. When reservoir levels are higher than needed in order to supply electricity for the foreseeable future, Norway can use this excess water and export it to other nations. Bolwig et al. (2020) noted that Norwegian households and firms were opposed to the exportation of Norwegian power to other nations. This is because the exportation of power will reduce the available supply in Norway. However, there has been no evidence of this being the case just yet. This is possibly due to the level of exportation fluctuating with seasonal precipitation and thus reservoir levels (Lenzen et al., 2010). Either way, Norwegian reservoir levels are a very significant determinant of the power price, both nationally and in the Nordics as a whole.

2.2 Nord Pool

Nord Pool was created in 1993 and has since established itself as the second largest power market in Europe. It offers clearing, trading (intraday and day-ahead) and settlements across 14 European countries. We have decided to focus solely on the Nordic Power Market, consisting of countries such as Norway, Sweden, Denmark, and Finland (Nord Pool [a], 2023).

Nord Pool is responsible for calculating the system price for the day ahead. The system price is the benchmark for price fixing in the Nordic region. The price is made up of producers submitting bids that delineate the desired quantities they are willing to produce and for what price. Meanwhile, end-users give their estimation of how much they are willing to consume and for what price.

The Nordic areas are further divided into several bidding areas, where electricity will flow to areas where demand and prices are higher (Nord Pool [b], 2023). This is known as the area price, which is the price consumers are familiar with. Area prices can differ from system prices based on the demand of different areas compared to transmission capacity. For our thesis, we will focus on the system price, as this serves as a more unbiased price of electricity, as possible congestion in different areas is not considered. Furthermore, according to Nord Pool, the system price is also the most common reference price in financial contracts traded in the Nordics (Nord Pool [b], 2023).

2.3 Nasdaq

Nasdaq Commodities is a division under the Nasdaq umbrella, which is one of the biggest marketplaces in the world for trading stocks, options, and futures (Nasdaq [a], 2023). Nasdaq Commodities offers power derivatives, such as futures and options. These derivatives can be used by both power producers and consumers to hedge their exposure to fluctuating power prices. Nasdaq Commodities is an exchange, meaning it connects potential buyers and sellers for different products. This makes finding a counterparty easier and eliminates counterparty risk, as this is taken care of by the exchange.

2.4 Power Futures Contracts

In our thesis, we are going to be focusing on futures contracts. Futures- and forward contracts are financial instruments where two parties agree on buying/selling a set quantity of an asset at a set price on a set date or month (Hull, 2018). Futures contracts differ from forward contracts in that they are standardized. While forward contracts are traded over the counter (OTC), futures are sold and bought at exchanges. The exchange guarantees the execution of the contract, which eliminates counterparty risk. For the exchange to offset this risk, collateral is required in the form of margin accounts. The value of the account will fluctuate according to the underlying asset. Once the account falls below a certain threshold, additional funds are required in the form of a margin call. If the party is not available to provide further collateral, the position is liquidated. Because of the margin account, engaging in a futures contract can be very expensive, especially if the underlying asset is volatile.

Futures are priced in a non-arbitrage fashion. The theoretical price of any given futures contract is a combination of spot price, yield, cost of carry, and time to maturity. However, since these instruments are traded on exchanges, futures contracts are not initially priced, instead, the price must be discovered through bidding and offering.

3 Literature Review

3.1 Liquidity and Volatility

Due to several factors, the Nordic power futures market has received little research. First, the primary areas of interest for financial market research have historically been stocks, bonds, and commodities such as oil and gold. These markets are more appealing for research because they have a longer history and are traded more frequently. Because of this, there has been much more research done and more established methodologies for analyzing these markets (Kiesel et al., 2009)

Second of all, the Nordic power market, which focuses on electricity contracts in the Nordic region, is relatively small and less significant globally. For researchers who lack domain expertise, the market's specialized nature, which necessitates a thorough understanding of the electricity industry, may limit its accessibility. Data accessibility and transparency may also be lower than in established financial markets. The market's make-up, particularly the utilities and energy companies, may also be a factor in the decline in research interest.

Even though liquidity and volatility have not been studied for the Nordic Power Derivative market, these two factors have been studied for other markets, such as other futures markets and the stock market. Original papers such as Corwin & Schultz (2012) and Roll (1984) have studied liquidity for the stock market and the bond market, but their research has also been applied to the futures market as well. Examples of this are Bryant et al. (2006) and Locke & Venkatesh (1997).

Amihud and Mendelson (1980) showed that there is a negative relationship between asset volatility and liquidity in the stock market. They did this through an inventory model. While Nasdaq themselves do not have inventories of these derivatives, the institutions that provide liquidity to the market do, and they will be less inclined to provide said liquidity when volatility in the underlying asset increases (Drechsler et al., 2021). Empirical evidence on this subject of liquidity and volatility shows different results, however. Pastor and Stambaugh (2003) find there to be a negative correlation between volatility and liquidity, whereas Menyah and Paudyal (1996) find there to be a positive one. Parlour and Seppi (2008) found prices to be more volatile in thin markets, as the lack of liquidity hinders the price discovery process, causing more uncertainty about the security's value. Furthermore, Acharya and Pedersen (2005) find that when aggregate market liquidity falls, it falls primarily for already illiquid assets.

Andersen (1996), Clark (1973), Tauchen and Pitts (1983), Epps and Epps (1976), and Gallant, Rossi, and Tauchen (1992) all find a positive relationship between trading volume and volatility. Trading volume inherently has a negative impact on liquidity, as it shrinks the order book. However, trading volume is often correlated with more market interest/activity, which has a positive impact on liquidity. Therefore, the effect this will have on liquidity is uncertain.

The link between the bid-ask spread and volatility has been studied by Stockton & Glassman (1987). He finds volatility to be an important factor in the bid-ask spread in the exchange rate market. This is in line with the conclusion presented by Bollerslev & Melvin (1994), where they found a positive connection between the bid-ask spread and volatility.

Huberman & Stanzl (2005) find that traders are risk-averse, tend to decrease their trade sizes over time, and conduct a larger proportion of their trades during periods of high price volatility or liquidity. When transaction fees are involved, traders prefer to trade less frequently when volatility or liquidity increase.

Chung & Chuwongnant (2018) found that the relationship between market volatility and stock returns is twofold. Volatility directly affects returns, while also influencing liquidity provision. This in turn affects returns, where greater liquidity premiums are associated with higher market volatility.

Chan, Hameed & Kang (2013) find that stock price synchronicity impacts stock liquidity, with higher co-movement in returns and systematic volatility improving liquidity. Their findings support both the relative synchronicity hypothesis (higher co-movement relative to total volatility improves liquidity) and the absolute synchronicity hypothesis (stocks with higher systematic volatility or beta exhibit better liquidity). They observe a positive relationship between the measures of liquidity and stock return co-movement as well as systematic volatility.

In line with what was mentioned earlier, Garleanu and Pedersen (2007) found institutions to become more cautious and less likely to engage in risky activities during times of higher volatility. They further argue that this can create a feedback loop, where risk management in corporations is less inclined to engage in hedging activities due to institutions providing less liquidity. This further decreases the liquidity in the market. Brunnermeier and Pedersen (2009) examined previous shocks and its effect on liquidity. They found that after big shocks occurred, affected markets tended to be caught in downward liquidity spirals, and margin requirements were substantially increased. This resulted in the markets becoming less efficient, and trades were harder to execute at desired prices.

Beltran-Lopez, Durre & Giot (2004) found evidence that the provision of liquidity remained adequate when volatility increased but found it more costly to trade. When the volatility was high, the liquidity dynamics were affected, but not by much. Locke & Sarkar (2001), on the other hand, found that customer trading and its costs do not increase with volatility as a measure.

Chang, Chou, & Nelling (2000) studied the effect of stock market volatility on the open interest of S&P 500 stock index futures contracts. They found open interest in the derivative to increase when both expected and unexpected volatility in the underlying increased. Furthermore, they were also able to identify large hedgers, large speculators, and small traders. They found the increase in open interest to be significantly larger for hedgers, suggesting that an increase in volatility also increases hedging demand.

3.2 Hypotheses

We will first investigate how volatility in the Nordic system price affects liquidity in the power derivative market. Our first hypothesis is:

H_1 : In general, increased volatility in the underlying will negatively impact the liquidity of the derivative.

This is in line with the findings of Amihud and Mendelson (1980), Drechsler et al. (2021), and Garlenau & Pedersen (2007), who all find volatility to decrease market liquidity due to liquidity providers being less attracted to the market. The Nordic power derivative market is first and foremost made up of liquidity providers and firms wanting to hedge their electricity exposure. It has also been categorized as a relatively illiquid market, suggesting that firms may not be willing to hedge exposure to fluctuating power prices. However, from 2022 and on, the volatility of power prices increased substantially. As mentioned above, Chang, Chou & Nelling's (2000) found hedging demand to increase when expected- and unexpected volatility increased. Hypotheses 2 and 3 are therefore:

H_2 : During 2022, increased volatility in the system price positively impacted the liquidity of power derivatives.

H_3 : During 2022, increased volatility in system prices led to more market activity in the Nordic power futures market.

While higher volatility will incentivize firms to hedge, liquidity providers will also be less attracted to the market. The result of H_2 will therefore depend on which of these two forces has the most impact. Increased volatility will also make hedging more expensive, as outlined by Brunnermeier & Pedersen (2009). This is due to the possibility of exchanges increasing collateral requirements. Furthermore, the chance of a margin call happening will also increase with more volatility. The cost of hedging may at some point become so big that it is not attractive anymore.

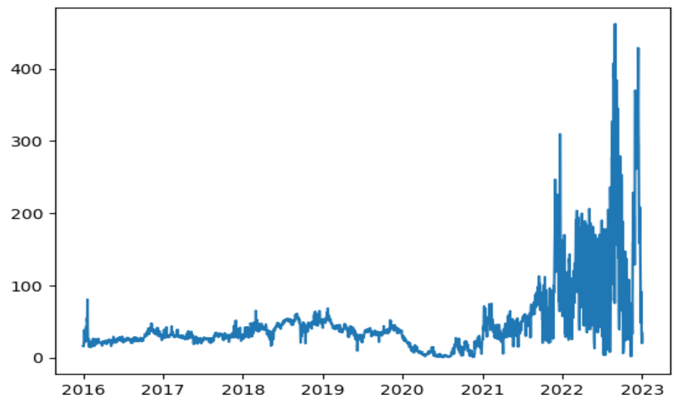
4 Data and Methodology

4.1 Data description

Our dataset is self-constructed and contains data from many different sources. The first and most important source is the ITCH log files from Nasdaq OMX. This data contains order messages directly from Nasdaq's order books from 2016 to 2023, for a total of about 133 million messages. This allows us to see every order added, deleted, and executed during the time period, and we can use this to build up the different order books. From this data, we can infer different metrics such as midpoint price, bid-ask spread, volume, etc. Nasdaq Power futures are standardized to 100 MW/h per contract, and the price is denoted in Euro. Nasdaq offers five different maturities/exercise dates for their futures: daily, weekly, monthly, quarterly, and annually. The difference between these products is the time frame within which the future can be exercised. Daily futures can only be exercised on the day they mature, weekly futures can be exercised any time during the week in which they mature, etc. We further sample the data on futures using the Nordic system price as the underlying. This gives us 2722 different derivatives. The main differences between the futures are the date of maturity and exercise period. As we infer different liquidity measures for a given derivative each day from origination to maturity, our dataset contains 82416 observations.

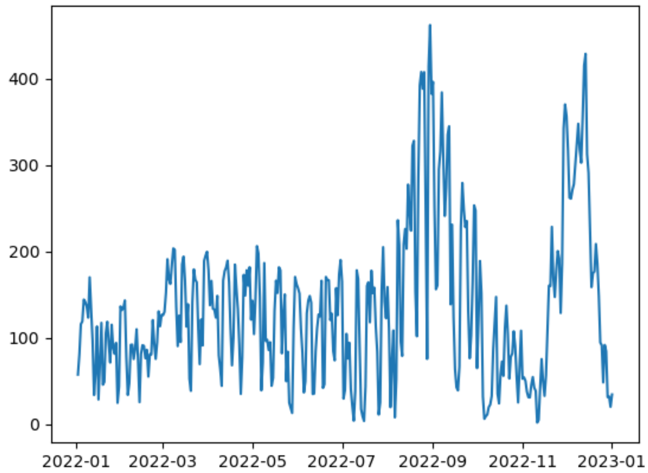
We also have daily Nordic day-ahead system prices collected from Nord Pool and their FTP-servers. The prices are denoted in euros and are for 1 MW/h.

We also include Norwegian reservoir levels, and the Oslo Stock Exchange Index returns in our dataset. This data has been downloaded online. Norwegian reservoir levels contain the weekly percentage levels of Norwegian reservoirs used by hydropower plants from 2016-2023. The Oslo Stock Exchange Index contains daily prices and returns from 2016-2023.



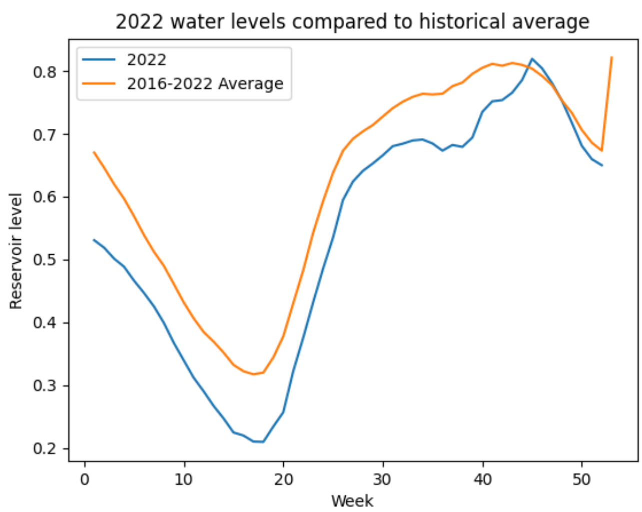
Graph 2: Nordic system power prices 2016-2022

Power prices have always been volatile, having the possibility of being very cheap or very expensive given differences in supply and demand. As we can see from *Graph 1*, the volatility increased exponentially in 2022.



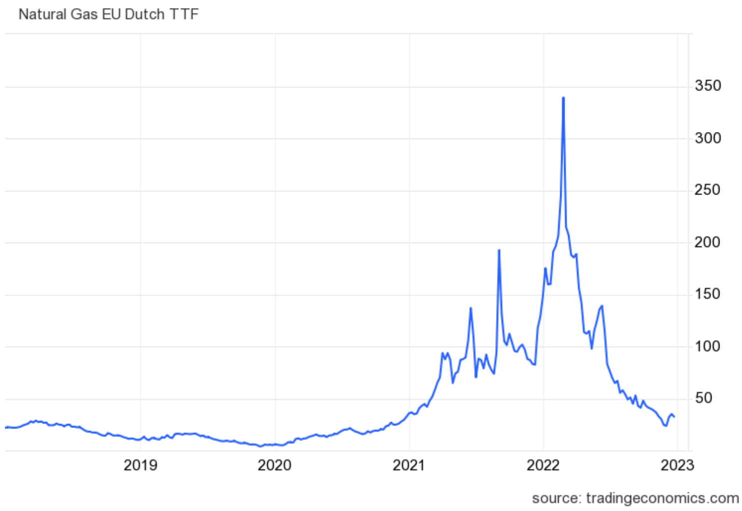
Graph 3: Nordic system power prices Jan-Dec 2022

According to Nordic Energy Regulators (*NordREG Annual Report 2022*, 2023), the increase in both prices and volatility was due to a multitude of reasons. First of all, the Nordics experienced a longer and colder winter than usual, resulting in more demand for electricity. Norwegian water reservoir levels were also low this year, meaning there was less capability for production.



Graph 4: Norwegian Reservoir Levels 2022

Lastly, following the Russian invasion of Ukraine, Russia cut its gas pipelines to Europe as a response to sanctions. Russia is an important player in the European gas market, with their gas accounting for roughly 40% of all imported gas (Ben Hassen & El Bilali, 2022). This sudden drop in gas supply led to the commodity's price rising, making electricity production through gas a lot more expensive. The interplay of these three factors led to a significant imbalance in the supply and demand of electricity.



Graph 5: European natural gas prices 2018-2023

From *Table 1,* we can see that Nordic system prices are very volatile. The prices are right-skewed, as the mean is substantially higher than the median (50%). This makes sense due to the fact that there is a price floor of zero but no price ceiling. This is further illustrated by the difference between the 75th percentile and the maximum value. As expected from the graphs above, the values are much higher in 2022 than in previous years.

SYS	*n*	*Mean*	*Std*	*Min*	*25%*	*50%*	*75%*	*Max*
2016-2023	2557	49	53	1	25	35	49	462
<2022	2191	35	23	1	24	31	34	309
>2022	366	135	91	2	72	121	174	462

Table 1: Descriptive statistics of Nordic system prices.

4.1.1 Liquidity

In the context of asset pricing, liquidity refers to the ability to buy or sell a large position quickly without it influencing the price of the asset to a large degree (Lee & Lee, 2015). According to Amihud et al. (2005), market liquidity is a multi-faceted concept that encompasses several dimensions. The authors name five main dimensions of market liquidity: tightness, depth, resiliency, immediacy, and breadth. For our thesis, we will focus on tightness and depth.

Tightness refers to the bid-ask spread, which measures the difference between the highest price a buyer is willing to pay and the lowest price a seller is willing to sell for. A smaller bid-ask spread is indicative of more liquidity, as it is less costly to enter and exit positions.

$$\%BAS = \frac{Ask - Bid}{(Ask + Bid)/2}$$

Depth refers to the market´s ability to absorb large trading volumes. As mentioned earlier, trades will mechanically shrink the order book, as the order(s) get deleted once the trade has occurred. A deep market therefore has enough orders that a large trade will have little impact on the new trading price of the asset.

Amihud's (2002) illiquidity measure measures the effect of trading volumes on asset returns. If the measure has a high value, then this would indicate little depth in the orderbook. This, in turn, will lead to larger trading volumes, which will have a significant impact on price.

$$ILLIQ = \frac{1}{n} \Sigma_{i=1}^{n} \frac{|r_i|}{p_i * v_i}$$

Where *ILLIQ* is the illiquidity measure for a given asset over a given time interval. Furthermore, r is the absolute daily return of the asset, p is the daily trading price, and v is the trading volume during the day.

A problem with Amihud's illiquidity measure is that it does not perform well in less traded markets, such as the Nordic power derivative market. This is because there may be days where a given asset is not traded during the day, which causes a severe lack in the performance of the measure (Fong et al., 2017). To counteract this, Kang and Zhang (2014) found an alteration to the measure, *AdjILLIQ,* to allow for better performance in less traded markets.

$$AdjILLIQ = \left[ln\left(\frac{1}{n}\Sigma_{i=1}^{n}\frac{|r_i|}{p_i * v_i}\right)\right] \times (1 + ZeroVol_n)$$

Where ln is the natural logarithm change, and ZeroVol is the percentage of zero trading days during the time interval, which in our case is going to be the last 30 days of the observation.

Other measures that will be used in this thesis are volume, depth, and width. Volume is the number of trades during a time period. Depth is the number of unique price points within +/- 2% of the midpoint price, and width is the number of quantities within +/- 2% of the midpoint price in the orderbook.

4.1.2 Volatility

Volatility in financial markets refers to the degree of variation or fluctuation in the prices/returns of financial assets over a specific period of time. It is a measure of the uncertainty and risk associated with investing in these assets (Lempérière et al., 2017). Market volatility can be influenced by various factors, including economic conditions, geopolitical events, investor sentiment, and market participants' behavior (Wei & Kong, 2016). Changes in market volatility can have significant implications for investors, as they can impact the profitability and risk of investment portfolios (Abduh, 2020).

For our volatility measure of the underlying system prices, we will use the rolling standard deviation. According to Duxbury and Summers (2018), the standard deviation is the most commonly used volatility measure for financial markets. The standard deviation of returns measures the dispersion centered around the mean, which captures price fluctuations and uncertainty in financial markets. The standard deviation can be sensitive to the time interval used in the measurement. For this reason, we will test several time periods (N) in order to see what measure fits our model the best and see how different volatility parameters affect liquidity.

$$Volatility = \sqrt{\frac{\Sigma_{i=1}^{N}(x_i - \mu)^2}{N}}$$

4.2 Methodology

In order to examine H_1, we will deploy two models. These models use OLS regressions to regress different liquidity measures on market volatility, as well as controlling for other variables. The liquidity measures are the bid-ask spread and the Amihud illiquidity measure. We will test the model using different specifications of volatility by alternating the number of days used for the calculations. We will use six different volatility parameters, spanning from 3- to 180 days. This allows us to both find what measure fits our model best and see how short-term and long-term volatilities impact liquidity.

While there have been several studies on the liquidity of a financial asset, most of these have focused on equities. A challenge this imposes on us is that the models mostly deploy firm characteristics as control variables, such as Amihud (1980) using SIZE, the market capitalization of the firm. Some of the relevant control variables we found include trading day dummy variables from both McInish (1992) and Chordia et al. (2001). However, due to the issue of seasonality in the power market, we include a dummy for both the current year and the current month. Similar to Chordia et al. (2001), also include market index returns, to control for general economic activity and market sentiment. Interestingly, Chordia et al. (2001) also included dummy variables for regularly scheduled announcements such as US Nonfarm Payrolls and US Employment rates, as there is typically more trading activity as a response to the announcement. However, we could not find any regularly scheduled announcements related to the Nordic energy sector. Finally, McInish (1992) controls for the current price of the underlying in his model, which we will do as well.

In addition to this, we also control for time-to-maturity (TTM), volume, depth, width, Norwegian reservoir levels, and month of maturity.

We control for TTM, as the closer a futures contract is to maturity, the more certain one can be of its fundamental value. This would mean tightness (the bid-ask spread) decreases as maturity gets closer, as there is less room to speculate over the fundamental value. However, as these derivatives are used for hedging purposes, it is reasonable to assume these hedging activities are done some time before the cash flow occurs. Therefore, the effect of TTM is unclear.

Volume is controlled for, as increased trading volume will mechanically shrink the orderbook, which decreases liquidity. However, an increased trading volume is also indicative of more market activity, which is a positive for liquidity. It is therefore uncertain to what extent volume will impact liquidity.

Depth and width are control variables that help us distinguish between more- and less liquid order books. If an order book is very liquid prior to a volatility shock, it is reasonable to believe liquidity will be less impacted by this compared to a less liquid orderbook.

As mentioned earlier, Norwegian reservoir levels are a big determinant of the Nordic system's price. In order to control for this, we deploy the control variable “Water Reservoir Difference” (WRD), which is the difference between the current reservoir level and the average reservoir level during 2016-2023.

We control for month of maturity due to the seasonal aspect of power prices. For instance, there may be more incentive to hedge cash flows during the winter, when electricity prices are higher. We therefore expect to see increased liquidity in futures contracts that expire during colder months, although we are unsure to what degree this will be.

Model 1:

$$\%BAS = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots +$$

$$D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December +$$

$$D_{23} * Date\_2017 + \ldots + D_{28} * Date\_2022 + \mathcal{E}$$

Model 2:

$$AdjILLIQ = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots +$$

$$D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December +$$

$$D_{23} * Date\_2017 + \ldots + D_{28} * Date\_2022 + \mathcal{E}$$

	Variables	Measurement	Description
Dependant variables	%BAS	Percentage	Bid-ask spread as a percentage of the midpoint price. A higher value indicates less liquidity
	AdjILLIQ	Percentage	Change in midpoint price (%) per Euro traded[1]
Independent variables	Volatility	Percentage	Standard deviation of Nordic system prices over a set number of days

[1] In order to avoid scientific notations in our models, the measure has been multiplied.

	TTM	$\frac{Time\ to\ maturity}{7}$	Amount of weeks until the derivative matures
	Volume	$\frac{Trading\ volume}{10000}$	Number of trades per 10 000 units
	Width	Integer	Number of quantities within 2% of the midpoint price
	Depth	Depth	Number of orders within 2% of the midpoint price
	SYS	Integer	Nordic system price
	RetOBX	Percentage	30 days return of Oslo Stock Exchange index
	WRD (Water Reservoir difference)	Percentage	Difference between current water reservoir levels and historical average reservoir levels in Norway.
Dummy variables	Month of maturity		Dummy variable for which month the derivative matures
	Current year		Dummy variable for what year the observation happens
	Current month		Dummy variable for month

Table 2: Summary of variables

For H_1 to be true, all volatility parameter coefficients must be negative and statistically significant. This is because higher values of %BAS and the Amihud illiquidity measure indicate lower levels of liquidity. If only a sample of the volatility parameters is negative and/or statistically significant, an individual assessment will be made based on our findings.

In order to test H_2, we will run the same models as earlier. However, this time we will sample the data for observations in 2022. This will allow us to examine how volatility impacted liquidity during that given year, and also compare the results to the model using the full dataset.

For H_2 to be true, the inverse rationale of H_1 applies, where we would need to see negative coefficients for the volatility parameters. In the event that H_1 is confirmed, but we find the volatility in 2022 to contribute to less illiquidity, we would still reject H_2.

In order to test H_3, we will deploy a very similar model to Models 1 and 2. However, this time we will use *BidOrders and AskOrders* as our dependent variables. Due to our unique data, we have access to every new order added to any power derivative order book from 2016 to 2023. Most data available online only contains Bid and Ask, which are the best offers at any given time. We are, on the other hand, able to see how all orders change over time, and the quantities of these orders. *BidOrders* and *AskOrders* measure how many times a new bid/ask order was added during the day, regardless of the quantity of the order. Chang, Chou & Nelling's (2000) used open interest as their dependent variable when modelling how interest/activity changed over time in the derivative market. Since we do not have identification of orders, we are unable to compute this measure. Despite *BidOrders* and *AskOrders* measuring a very different thing than open interest, it can still be used as a proxy for market interest.

We will sample the data into a 2022 sample and a 2019 sample. 2022 is the year we are interested in, and 2019 was a year with low volatility in power prices.

In order for H_3 to be true, we would need to see positive volatility coefficients in the 2022 model. If the volatility coefficients are positive in the 2019 model as well, the 2022 coefficients would need to be substantially higher.

Model 3:

$BidOrders = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots +$

$D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December +$

$D_{23} * Date\_2017 + \ldots + D_{28} * Date\_2022 + \mathcal{E}$

Model 4:

$AskOrders = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots +$

$D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December +$

$D_{23} * Date\_2017 + \ldots + D_{28} * Date\_2022 + \mathcal{E}$

5 Results

This section presents the results of our different models and discusses our findings. We present each model, as well as a table presenting the different volatility coefficients when we run the model using the different volatility measures. We use Newey-West's heteroskedastic and autocorrelation consistent (HAC) standard errors in all models (more on this later). All models contain coefficients and their respective z-values. *, ** and *** are representative of a significance level of 10%, 5% and 1% respectively.

For models that have different samples, a merged version of these is given in the appendix for comparative purposes. A summary of the number of observations and R-squared for each model is also available in the appendix.

5.1 Hypothesis 1

Our first hypothesis is that volatility in the Nordic system price will, in general, lead to less liquidity in Nordic power futures. We investigate this by running models 1 and 2, which use liquidity measures as dependent variables, and volatility as our main independent variable of interest.

5.1.1 Model 1 Overview

Model 1: $\%BAS = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots + D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December + D_{23} * Date\_2017 + \ldots + D_{28} * Date\_2022 + \mathcal{E}$

N: 81 831, R^2*: 0.139*

Independent variables

Intercept	Volatility 30 Days	TTM	Volume	Width	Depth	SYS	RetOBX	WRD
0.0445	0.0095	-0.0001	-0.0005	0.0013	-0.0312	0.0006	0.0246	-0.0203
(23.326***)	(3.811***)	(-24.658***)	(-4.053***)	(6.326***)	(-30.987***)	(2.821***)	(2.531**)	(-3.162***)

Maturity dummy variables

Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
-0.0042	0.0024	-0.0023	-0.0020	-0.0003	0.0082	0.0082	-0.0028	0.0001
(-1.840*)	(0.949)	(-1.266)	(-0.913)	(-0.183)	(6.599***)	(3.095***)	(-1.579)	(0.039)

Nov	Dec
0.0057	-0.0001
(2.06**)	(-0.016)

Date dummy variables

Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
-0.0019	-0.0019	-0.0069	0.0036	-0.0027	-0.0026	0.0002	0.0003	0.0024
(-5.171***)	(-1.536)	(-5.910***)	(2.620***)	(-2.113**)	(-2.119**)	(0.189)	(0.249)	(1.684*)

Nov	Dec	2017	2018	2019	2020	2021	2022
0.0064	-0.0036	-0.0051	-0.0027	-0.0018	0.0382	0.0022	0.0526
(4.474***)	(-2.997***)	(-9.347***)	(-3.604***)	(-2.535***)	(26.233***)	(1.806*)	(15.808***)

This regression regresses the percentage bid-ask spread on several factors, with the point of interest being β_1 (30 days). Since a higher bid-ask spread means less liquidity, a positive variable coefficient means a negative relationship to liquidity, and a negative coefficient means a positive relationship to liquidity.

This data set contains all observations from 2016-2022. From the results, we observe that volatility has a positive coefficient of 0.0095. In other words, a 10-percentage point increase in 30-day volatility will result in a bid-ask spread increase of 0.1 percentage points. This means volatility in Nordic system prices in general leads to less liquidity (tightness) in the Nasdaq power derivative. We also observe the coefficient to be statistically significant at a 1% level. A more detailed overview of our volatility coefficients in models 1 and 2 will be presented later.

In our non-categorical control variables, we do, for the most part, see expected results. First, all of them are statistically significant at a 1% level, except for *RetOBX*, which is significant at a 5% level. Time-to-maturity ("TTM") is positively associated with liquidity, but not by much. This could indicate the conflict between the certainty of fundamental value the closer it gets to maturity, and hedgers not wanting/needing to hedge into the immediate future. A similar story could be drawn for volume, where it is positively associated with liquidity in our model, but not by much given the counteracting forces explained earlier. RetOBX is positive, suggesting there is greater liquidity when the equity markets are not doing well. We do not see much statistical significance in our maturity dummies, nor do we see any pattern of seasonality. We see a lot more statistical significance in our date dummies and some patterns of seasonality where liquidity is slightly higher at the start and end of the year. Furthermore, we also observe that liquidity was lower in 2022 through the dummy variable. To what extent this is driven by increased volatility will be investigated in Hypothesis 2.

5.1.2 Model 2 Overview

Model 2: $AdjILLIQ = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots + D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December + D_{23} * Date\_2017 + \ldots + D_{28} * Date\_2022 + \mathcal{E}$

N: 57 285, R^2*: 0.505*

Intercept	Volatility $_{30\ Days}$	TTM	Volume	Width	Depth	SYS	RetOBX	WRD
4.6967	0.2677	0.0062	-0.0718	-1.1525	-1.6235	-0.0060	-0.9785	-0.5528
(64.181***)	(6.443***)	(56.870***)	(-41.807***)	(-84.870***)	(-44.581***)	(-1.959**)	(-6.045***)	(-3.360***)

Maturity dummy variables								
Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
0.5441	0.5345	-1.0400	0.5869	-0.5263	0.9875	0.7357	-0.6863	0.8928
(6.348***)	(6.136***)	(-17.163***)	(7.522***)	(-8.876***)	(11.410***)	(8.579***)	(-11.557)	(8.926***)

Nov	Dec
0.6977	-2.1000
(8.563***)	(-34.679***)

Date dummy variables								
Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
0.1229	0.3838	0.1755	-0.2597	-0.3187	-0.4748	-0.7453	-0.3534	-0.2579
(3.075***)	(9.412***)	(4.697***)	(-6.631***)	(-8.421***)	(-12.409***)	(-18.680***)	(-8.876***)	(-6.631***)

Nov	Dec	2017	2018	2019	2020	2021	2022
-0.1956	-0.0866	-1.1092	-1.8749	-1.6642	-1.0709	-1.3992	-2.3422
(-4.477***)	(-1.919*)	(-28.520***)	(-44.048***)	(-38.294***)	(-24.092***)	(-30.061***)	(-32.735***)

This model regresses the adjusted Amihud liquidity measure on several factors, once again with volatility as the main variable of interest. As explained earlier, the Amihud liquidity measure measures how the price (return) of the asset is affected when trades occur. A positive variable coefficient is associated with less liquidity, and a negative coefficient is associated with more liquidity.

This model seems to fit better than model 1, due to a higher R-squared and more statistically significant variables. We find the volatility variable to have a coefficient of 0.2677, meaning we once again find volatility to have a negative impact on liquidity (depth). This coefficient is also statistically significant at a 1% level.

For our non-categorical control variables, we see some different results from model 1. Unlike the previous model, *TTM* is positive. However, the coefficient value is small relative to the other coefficients, telling a similar story as *TTM* in model 1. *SYS* and *RetOBX* improved liquidity in this model, whereas they decreased liquidity in model 1. The maturity dummies are all statistically significant. In addition, there seems to be a pattern of seasonality, where futures that mature in the early months of the year are less liquid. Similar conclusions can be drawn regarding the date dummy variables, where all are statistically significant and there seems to be less liquidity at the start of the year. Unlike model 1, liquidity seems to have improved in 2022. It should be noted that all years improved liquidity compared to the reference year (2016), but 2022 improved it the most.

The diversions in coefficients from this model to model 1 are likely due to the differences in liquidity dimensions. Tightness (model 1) and depth (model 2) measure liquidity in different ways, and certain factors may affect these dimensions differently.

5.1.3 Volatility Overview

	Volatility	3 days	7 days	14 days	30 days	45 days	90 days	180 days
Model 1	**Coeff**	0.0008	-0.0002	0.0038	0.0095	0.0170	0.0359	0.0439
		(0.479)	(-0.100)	(1.813*)	(3.811***)	(5.928***)	(10.212***)	(10.733***)
Model 2	**Coeff**	0.0465	0.0779	0.1176	0.2677	0.3453	0.1152	0.0030
		(1.555)	(2.572***)	(3.423***)	(6.443***)	(7.237***)	(2.076**)	(0.043)
	VIF	1.4	1.7	2.2	2.9	3.8	4.9	5.9

Table 3: Volatility summary of Model 1 and Model 2

Table 3 summarizes the different volatility time periods, spanning from 3- to 180 days, in models 1 and 2. Our first hypothesis is that increased volatility in the Nordic system price will decrease liquidity in the Nordic power derivative market. For this to be true, we expect the volatility coefficients to be positive under both models.

In model 1, we observe all coefficients except 7-day volatility to be negative. Neither the 3-day nor the 7-day volatility measures seem to be able to capture any significant effect of volatility on liquidity, as they are both far from statistically significant on any ordinary level. This indicates that short-term volatility does not seem to affect liquidity (tightness). From the perspective of hedgers, this makes sense, as the same argument as for *TTM* can be used here. Hedgers are typically not interested in hedging short-term (intra-week) cash flows, as there is a small chance of the price diverging to a drastic level. In line with Beltran-Lopez, Durre & Giot's (2004) findings, trading costs typically increase when volatility increases. Thus, there is little incentive for increased hedging activity when short-term volatility increases.

We find all coefficients in model 1 to be positive and statistically significant for 14-days and beyond. This is in line with Amihud & Mendelson (1980), Drechsler, Savov & Schnabl (2021), and Garlenau & Pedersen (2007), who all find liquidity providers to be less active when markets are volatile, resulting in less liquidity. In addition, if trading costs also increase with volatility, this would further reduce liquidity on the demand side as well. However, as outlined by Chang, Chou, & Nelling (2000), the demand for hedging instruments is also higher during volatile times (Chang et al., 2000). The results from this model would indicate that the decrease in supply during volatile times out-weights any increases on the demand side.

Furthermore, we also observe both the coefficient and statistical significance increasing in tandem with the volatility period (for 14 days and beyond). This suggests that liquidity providers devalue long-term volatility over short-term volatility. This seems in line with the literature mentioned above. We find model 1 to be highly supportive of our first hypothesis.

In model 2, all coefficients are positive, meaning volatility was negatively associated with liquidity (depth) in this model as well. All coefficients between 7- and 90 days are statistically significant. Similarly to model 1, we find that between 7- to 45 days, an increase in the number of days increases both the coefficient and the statistical significance. This implies that short- and long-term volatility affect the adjusted Amihud illiquidity measure the most. A possible explanation for this is Huberman and Stanzl (2005), who found that traders conduct a larger proportion of their trades during periods of high volatility. This would imply a large number of trades occurring once market volatility is established, meaning there is less of an effect if volatility remains in the long term, as a large number of the trades have already been done. We find model 2 to be highly supportive of hypothesis 1 as well.

Through models 1 and 2, we find good evidence that volatility in the Nordic system price led to weakened liquidity in the Nordic power derivative market. This is most likely due to liquidity providers, typically financial institutions, being less attracted to the market. We also found the different volatility time periods to affect liquidity differently. Tightness (model 1) was more affected by long-term volatility.

Meanwhile, depth (model 2) was more affected by short- to mid-term volatilities. Because of this, we confirm Hypothesis 1, which states that volatility in system prices leads to less liquidity in the power futures market.

5.2 Hypothesis 2

Our second hypothesis is that volatility in the Nordic system price positively impacted liquidity during 2022. We investigate this by running the same models as in Hypothesis 1, but this time sampling for observations during 2022. This allows us to see if volatility in the underlying asset affected the liquidity of the derivative differently during the 2022 energy crisis.

5.2.1 Model 1 Overview

Model 1: %BAS = $\alpha + \beta_1 *$ *Volatility* + $\beta_2 *$ *TTM* + $\beta_3 *$ *Volume* + $\beta_4 *$ *Width* + $\beta_5 *$ *Depth* + $\beta_6 *$ *RetOBX* + $D_1 *$*January_maturity* + ... + $D_{11} *$ *December_maturity* + $D_{12} *$ *Date_January* + ... + $D_{22} *$ *Date_December* + $\mathcal{E}$

N: 9 213, R^2*: 0.135*

Independent variables							
Intercept	**Volatility $_{7\ Days}$**	**TTM**	**Volume**	**Width**	**Depth**	**SYS**	**RetOBX**
0.1234	-0.0086	-0.0005	-0.0118	-0.0371	-0.0528	0.0002	-0.0543
(12.826***)	(-3.195***)	(-18.319***)	(-13.449***)	(-6.258***)	(-13.538***)	(0.541)	(-1.161)

Maturity dummy variables								
Jan	**Feb**	**Mar**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**
-0.0366	-0.0015	0.0393	0.0015	0.0440	0.0678	0.0204	0.0177	0.0516
(-2.876***)	(-0.137)	(4.199***)	(0.129)	(4.768***)	(4.296***)	(1.321)	(1.989**)	(3.557***)

Nov	Dec
0.0958	0.0660
(5.513***)	(6.541***)

Date dummy variables								
Jan	**Feb**	**Mar**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**
-0.0174	-0.0135	-0.0238	0.0042	0.0124	0.0175	0.0469	0.0199	0.0232
(-3.192***)	(-2.129**)	(-4.080***)	(0.676)	(1.866*)	(1.791*)	(5.933***)	(2.427**)	(2.540**)

Nov	Dec
0.0099	-0.0015
(1.207)	(-0.050)

Again, this model regresses the bid-ask spread of Nordic power futures on the volatility in the Nordic system price, while controlling for several variables. It is worth mentioning that the volatility time period displayed is the 7-day volatility, as this fits the model the best. In Hypothesis 1, we displayed the 30-day volatility. We do not include water reservoir difference (WRD) in this model, because it would induce multicollinearity in the model. More on this in the robustness check section. We do not use any dummy variables for the year of the observation either, since the data is only sampled for 2022.

First and foremost, we find the volatility measure to have a coefficient of -0.0086 and be statistically significant on a 1% level. This indicates that volatility in power prices led to more liquidity in the derivative market. The 7-day volatility in hypothesis 1 was also negative for model 1. However, it was not statistically significant. This is evidence for Hypothesis 2.

We find most of our non-categorical dummy variables have a similar relationship to liquidity as in the full sample model. However, the coefficients seem to be larger in the 2022 sample. A possible explanation for this is the removal of year dummy variables. We find a lot more statistical significance in the maturity date variables, with 7 out of 11 being statistically significant on at least a 5% level. We also see a pattern of seasonality, where contracts that mature at the start- and end of the year are more liquid. We see a lot of statistical significance in our date dummy variables. In our full sample model, we found some pattern in seasonality, where there was less liquidity at the start of the year. In the 2022 sample, we find the opposite, where liquidity was higher at the start of the year. This could possibly be a result of growing market concern as the crisis evolved.

5.2.2 Model 2 Overview

$$\textit{Model 2: AdjILLIQ} = \alpha + \beta_1 * \textit{Volatility} + \beta_2 * \textit{TTM} + \beta_3 * \textit{Volume} + \beta_4 * \textit{Width} + \beta_5 * \textit{Depth} + \beta_6 * \textit{RetOBX} + D_1 * \textit{January\_maturity} + \ldots +$$

$$D_{11} * \textit{December\_maturity} + D_{12} * \textit{Date\_January} + \ldots + D_{22} * \textit{Date\_December} + \mathcal{E}$$

N: 6 705, R^2: 0.497

Intercept	Volatility $_{45\ Days}$	TTM	Volume	Width	Depth	SYS	RetOBX
2.6011	0.3563	0.0028	-0.1836	-3.4007	-1.9115	-0.0073	-0.3450
(11.401***)	(2.623***)	(7.706***)	(-13.769***)	(-22.182***)	(-15.155***)	(-1.861*)	(-0.513)

Maturity dummy variables

Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
0.2324	0.4535	0.2464	0.5093	1.0896	0.8474	0.6674	0.2266	-0.6916
(0.885)	(1.702*)	(1.232)	(2.563***)	(5.471***)	(3.477***)	(2.896***)	(1.167)	(-3.258***)

Nov	Dec
0.4659	-1.2259
(2.046**)	(-6.145***)

Date dummy variables

Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
0.0210	0.2976	0.1749	-0.0885	-0.2607	-1.0734	-1.1414	-1.0192	-1.1643
(0.188)	(2.669***)	(1.617)	(-0.760)	(-1.859*)	(-5.418***)	(-4.647***)	(-7.004***)	

Nov	Dec
-0.9320	-0.8433
(-6.753***)	(-1.991**)

Again, this model regresses the adjusted Amihud illiquidity measure on system price volatility, but this time sampled on 2022 observations. The volatility time period is 45 days, and WRD and yearly dummies are omitted for the same reasons as above.

Unlike the 2022 sample for model 1, we find system price volatility to negatively impact liquidity power derivatives when using the Amihud illiquidity measure as our volatility measure, as volatility has a coefficient of 0.3536. This works as evidence against hypothesis 2. We also find the coefficient to be larger than in the full sample model, indicating that volatility in system prices increased the liquidity in power futures even more.

For model 2, we find our non-categorical control variables to have the exact same relationship to liquidity in 2022 as in the full sample model. Much like in model 1, the coefficients are also larger in 2022. Most likely due to the same reason as in model 1. For the maturity dummy variables, the relationships are very similar to those in the full sample. Most of them are also statistically significant, much like in the full sample. The month dummy variables are coefficients are very similar as well. We see the same pattern of seasonality as in the 2022 sample, where there is less liquidity at the start of the year.

5.2.3 Volatility Overview

	Volatility	3 days	7 days	14 days	30 days	45 days	90 days	180 days
Model 1	**Coeff**	-0.0035	-0.0086	-0.0078	-0.0050	-0.0091	0.0198	0.0004
		(-1.479)	(-3.195***)	(-2.084**)	(-0.901)	(-0.887)	(1.426)	(0.015)
Model 2	**Coeff**	-0.0152	0.0049	0.0479	0.1034	0.3563	0.1424	0.3467
		(-0.417)	(0.127)	(0.969)	(1.435)	(2.623***)	(0.813)	(1.053)
	VIF	1.2	1.5	2.1	3.5	10.2	13.9	41.8

Table 4: Volatility summary of Model 1 and Model 2, 2022 sample

Table 4 summarizes the different volatility time periods in models 1 and 2. when sampled for 2022 observations. Since our second hypothesis is that increased volatility in the Nordic system price will lead to more liquidity in the Nordic power market during 2022, we expect volatility coefficients in both models to be negative.

For model 1, we find volatility coefficients to be negative for volatility periods ranging from 3 to 45 days. However, only the 7-day and 14-day coefficients are statistically significant. Both the 90-day and 180-day coefficients are positive, but neither is statistically significant. While this leaves some room for arguing that short-term volatility increased liquidity (tightness) during 2022, the lack of statistical significance in most of the coefficients makes it hard to be confident in the results. Due to a lack of confidence in the results, this works as evidence against Hypothesis 2.

For model 2, all coefficients are positive except for the 3-day volatility. In addition, only the 45-day volatility is statistically significant. Based on this, it is very hard to argue that system price volatility impacted the Amihud illiquidity measure in 2022. This serves as evidence against hypothesis 2.

Overall, we find it hard to make any empirical judgments based on these results, due to the lack of statistical significance when only sampling for 2022. In model 1, we find the 7- and 14-day coefficient to be statistically significant, which signals that short-term volatility impacted liquidity (tightness) in 2022. In model 2, we find the 45-day coefficient to be statistically significant and negative as well. However, in the broad picture, we do not see any clear trajectory. We therefore reject hypothesis 2.

5.3 Hypothesis 3

Our third and final hypothesis is that increased volatility in system prices during the 2022 energy crisis led to increased market activity for Nordic power futures. This will be done by deploying similar models as in our previous hypotheses, but this time using the amount of added bid- and ask orders as the dependent variable. We use 2019 as the benchmark year, which was a year where the Nordic system price was relatively stable. We will compare the different volatility coefficients between the 2019- and 2022 models and see if volatility affected liquidity differently during these years.

5.3.1 Model 3 Overview

Model 3: BidOrders = $\alpha + \beta_1$ * *Volatility* + β_2 * *TTM* + β_3 * *Volume* + β_4 * *Width* + β_5 * *Depth* + β_6 * *SYS* + β_7 * *RetOBX* + β_8 **WRD* + D_1 **January_maturity* + … + D_{11} * *December_maturity* + D_{12} * *Date_January* + … + D_{22} * *Date_December* + $\mathcal{E}$

2019 – N: 12 015, R^2: 0.496, 2022 – N: 9 164, R^2: 0.518

	Independent variables								
	Intercept	***Volatility*** $_{90\ Days}$	***TTM***	***Volume***	***Width***	***Depth***	***SYS***	***RetOBX***	***WRD***
2019	3.0067	-359.8762	-0.3808	17.8739	6.5867	148.0433	-5.6434	112.3921	-196.2488
	(0.285)	(-10.959***)	(-19.574***)	(16.098***)	(3.532***)	(21.756***)	(-2.658***)	(2.473**)	(-4.791***)
2022	-10.1565	-20.8284	-0.2025	33.4406	357.3449	50.5832	-0.0615	151.2209	-219.4085
	(-1.747*)	(-8.717***)	(-8.717***)	(11.727)	(14.701***)	(5.280***)	(-3.602***)	(4.413***)	(6.608***)

	Maturity dummy variables								
	Jan	***Feb***	***Mar***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***
2019	16.9489	8.2848	24.6510	23.2451	51.0732	37.1668	46.7149	60.9280	23.9601
	(2.880***)	(1.169)	(4.209***)	(3.823***)	(9.535***)	(5.827***)	(8.352***)	(10.479***)	(3.648***)
2022	24.7209	0.8057	31.6360	2.4939	34.4543	0.1296	19.2487	44.4607	16.9426
	(4.234***)	(0.136)	(5.846***)	(0.338)	(5.501***)	(0.022)	(3.718***)	(7.147***)	(3.002***)

	Nov	***Dec***
2019	22.7209	84.9175
	(3.801***)	(11.957***)
2022	28.3760	-4.5672
	(5.247***)	(-0.801)

This model regresses bid orders added to Nordic power futures order books on Nordic system price volatility, while controlling for other variables. As we are interested in any possible changes between 2019 and 2022, both samples are illustrated at the same time.

We find both volatility coefficients to be negative and statistically significant. The 2019 coefficient is -359, and the 2022 coefficient is -20. This suggests that increased volatility in system prices reduces market activity, at least on the bid side. However, the 2022 coefficient is substantially smaller than the 2019 one. This could possibly mean that a volatility increase has disincentivized market participants less than in previous years.

For our control variables, we find them to be rather similar across both time periods. The only exceptions to this are width and depth, which control for which order books are more/less liquid by default.

5.3.2 Model 4 Overview

Model 4: $AskOrders = \alpha + \beta_1 * Volatility + \beta_2 * TTM + \beta_3 * Volume + \beta_4 * Width + \beta_5 * Depth + \beta_6 * SYS + \beta_7 * RetOBX + \beta_8 * WRD + D_1 * January\_maturity + \ldots + D_{11} * December\_maturity + D_{12} * Date\_January + \ldots + D_{22} * Date\_December + \mathcal{E}$

2019 – N: 12 015, R^2: 0.541, 2022 – N: 9 164, R^2: 0.508

	Independent variables								
	Intercept	***Volatility*** $_{\textit{90 Days}}$	***TTM***	***Volume***	***Width***	***Depth***	***SYS***	***RetOBX***	***WRD***
2019	-10.9593	-343.5600	-0.2839	18.3217	7.0929	127.2949	-0.6713	-11.4048	-110.9577
	(-1.117)	(-12.601***)	('-17.601***)	(16.166)	(4.786***)	(19.424***)	(-0.338)	(-0.314)	(-2.752***)
2022	-5.8842	-22.6638	-0.1933	36.3976	322.5737	47.1129	-0.5945	150.7400	-226.7248
	(-0.981)	(-9.741***)	(-8.362***)	(11.974***)	(13.979***)	(4.867***)	(-3.411***)	(4.242***)	(-6.918***)
	Maturity dummy variables								
	Jan	***Feb***	***Mar***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***
2019	13.9173	14.5728	26.1055	22.6026	48.3622	31.9982	49.9785	51.3348	15.8207
	(2.358**)	(2.003**)	(4.535***)	(3.765***)	(8.719***)	(5.164***)	(9.242***)	(9.097***)	(2.570***)
2022	21.9287	-1.3356	20.7459	-7.1941	29.9771	0.4235	12.7890	42.1470	14.0220
	(3.593***)	(-0.224)	(3.695***)	(-0.928)	(4.632***)	(0.067)	(2.326**)	(6.638***)	(2.397**)
	Nov	***Dec***							
2019	16.8150	59.5388							
	(2.898***)	(9.410***)							
2022	25.6954	-5.4017							
	(4.557***)	(-0.916)							

This model is the same as model 3 above, but this time we use new ask orders as our dependent variable. We once again sampled for both 2019 and 2022 observations to examine any possible differences between the two years.

Similar to model 3, we find the volatility coefficients to be both negative and statistically significant for both years. The 2019 coefficient is -343, and the 2022 coefficient is -22. We also observe the 2022 coefficient to be substantially smaller compared to the 2019 coefficient. The size of the volatility coefficients is also very similar to those of model 3. This would imply that volatility impacts both the bid- and the ask sides similarly. Considering we cannot distinguish between hedgers, speculators, and liquidity providers, this suggests they are evenly spread among both sides of the order book.

Interestingly, we find almost all coefficients to be very similar between models 3 and 4. This further implies that different players in the market are split evenly between the bid- and the ask side, and that there are few differences between the two in terms of how they respond to different factors.

5.3.3 Volatility Overview

	Volatility	*3 days*	*7 days*	*14 days*	*30 days*	*45 days*	*90 days*	*180 days*
2019	***Coeff***	-34.0957	-12.9894	-47.4492	-91.7215	-171.7909	-359.8762	9.4226
		(-1.661*)	(-0.749)	(-2.471**)	(-4.163***)	(-6.365***)	(-10.959***)	(0.122)
2022	***Coeff***	-1.4540	-5.4720	-3.2514	-9.3453	-15.1321	-20.8284	-28.5598
		(-1.035)	(4.153***)	(-1.929*)	(-5.011***)	(-7.221***)	(-8.767***)	(-8.117***)

Table 5: Volatility summary of Model 3

This table summarizes the different volatility coefficients in Model 3, the model that uses *BidOrders* as the dependent variable.

We first observe that all variables (except 2019, 180 days) are negative. Two variables are statistically significant at a 10% level, one variable is statistically significant at a 5% level; and eight variables are statistically significant at a 1% level. This encourages confidence in claiming that increased volatility leads to less activity on the bid side of the order book.

Although volatility led to less market activity in 2022, the effect of volatility was much less in all measures (except 180 days) than in 2019. The effect of volatility is about 10 times larger in 2019 when using the 14-, 30-, 45- and 90-day volatility measures.

We cannot say that the increased system price volatility in 2022 directly caused more market activity for power futures as a consequence of the coefficients being negative. This is evidence against hypothesis 3. However, the results show that market participants (on the bid side) were less disincentivized by volatility in 2022 compared to 2019. This is because of the large deviations in coefficient sizes between 2019 and 2022. Even so, this does not serve as evidence for hypothesis 1, as liquidity was not improved, but rather "less worsened".

	Volatility	*3 days*	*7 days*	*14 days*	*30 days*	*45 days*	*90 days*	*180 days*
2019	***Coeff***	7.3988	25.0064	-5.0181	-54.6902	-139.1832	-343.5600	-166.0654
		(0.353)	(1.500)	(-0.279)	(2.641***)	(-5.567***)	(-12.601***)	(-2.324**)
2022	***Coeff***	-1.8798	-4.6124	-2.0391	-9.0214	-15.7120	-22.6638	-31.3752
		(-1.180)	(-3.036***)	(-1.088)	(-4.553***)	(-7.002***)	(-9.741***)	(8.239***)

Table 6: Volatility summary of Model 4

This table summarizes the different volatility coefficients in model 4, which uses *AskOrders* as the dependent variable.

In 2019, we find short-term volatility (3- and 7 days) to be positively associated with activity on the ask side, given the positive coefficient. However, none of these are statistically significant, making drawing any inference hard. The 30-day volatility measure is negative, but not statistically significant. Mid- to long-term volatilities (30- to 180 days) are all negative and statistically significant at a 1% level. This suggests that the ask-side activity is sensitive to mid- and short-term volatilities, and the relationship is negative.

In 2022, we find all volatility coefficients to be negative. Furthermore, all coefficients except 3- and 14 days are statistically significant at a 1% level. This makes us confident in saying there was a negative relationship between mid- to short-term volatilities and market activity, just like in 2019.

We find similar differences between the 2019- and 2022 volatilities as we did in model 3. The coefficients for mid- to long-term volatilities are much larger in 2019 than in 2022, generally by a factor of 5 to 10. This leads us to a similar conclusion as in model 3, where system price volatility did not directly lead to more market activity in 2022, but rather disincentivized market participants less than in 2019.

Based on our findings in models 3 and 4, we find that volatility led to less market activity in 2022. However, compared to 2019, the effect of this was substantially smaller. From this, we conclude that volatility in system prices in 2022 incentivized market participants less than in 2019. We also find there to be no big differences between the behavior of the bid- and ask side. We reject hypothesis 3, as volatility had a negative impact on market activity, although the impact was much less compared to 2019.

5.4 Robustness check

5.4.1 Heteroscedasticity

One of the OLS assumptions is that the residuals are homoscedastic. Homoscedasticity is observed when the residuals are constant (no variations over time). If the residuals are not constant, the standard errors will become inappropriate, and therefore the OLS estimator will no longer be BLUE. Therefore, the inference might be wrong, and we have Heteroscedastic residuals.
To detect heteroskedasticity, one common approach is to visually examine the scatterplot of the residuals (the differences between the observed and predicted values) against the predicted values or independent variables (Brooks, 2018).

Another way to detect Heteroskedasticity is to perform a White's test. To perform this test, we run the first regression to obtain the residuals, $\widehat{U_t}$, so we can run the auxiliary regression. Thereafter, we extract the R^2 and multiply this measure with the number of observations, T. We will then be able to observe the test statistic. Lastly, we will then extract the critical value, $\chi^2(m)$, and compare it to the t-stat. If the null hypothesis gets rejected, we conclude that we have residuals that are heteroskedastic (Brooks, 2018).

The regressions are as follows:

$$y_t = \beta_o + \beta_1 x_{1,t} + \beta_2 x_{2,t} \ldots + \beta_n x_{n,t} + v_t$$

$$\hat{u}_t^2 = \alpha_0 + \alpha_1 x_{1,t} + \alpha_2 x_{2,t} + \alpha_3 x_{1,t}^2 + \alpha_4 x_{2,t}^2 + \alpha_5 x_{1,t} x_{2,t} + v_t$$

$$H_0: \alpha_1 = 0 \; and \; \alpha_2 = 0 \; and \; \alpha_3 = 0 \text{ and } \alpha_4 = 0$$

$$H_A: \alpha_1 \neq 0 \; and \; \alpha_2 \neq 0 \; and \; \alpha_3 \neq 0 \text{ and } \alpha_4 \neq 0$$

If there is a sign for heteroskedasticity in the residuals in our regression, we can use Heteroskedastic Robust Standard Errors to correct for heteroskedasticity and proceed.

5.4.2 Autocorrelation

Usually referred to as the correlation between consecutive observations in a time series.

It is assumption 3 for the OLS, where the assumption is no autocorrelated residuals. Autocorrelations can both be positive and negative, and they occur when there is a relationship between the current and past values of a variable, where $Cov(u_i, u_j) \neq 0$. It is essential to see no pattern in the plots of the residuals because this would conclude autocorrelated errors. The OLS estimator will therefore not be BLUE, because it will be inefficient. R^2 will likely be inflated, and we might observe inappropriate standard errors, which can lead to an inference that is misleading. We use the *Breusch-Godfrey-test* to test for autocorrelated residuals (Brooks, 2018).

We can run the OLS regression to collect the estimated residuals. Thereafter, we can run the auxiliary regression. We can then use the lagged estimated residuals and test the coefficients:

$$y_t = \beta_o + \beta_1 x_{1,t} + u_t$$

$$\hat{u}_t = \beta_o + \beta_1 x_{1,t} + \rho_1 \hat{u}_{t-1} + \ldots + \rho_r \hat{u}_{t-r} + v_t \qquad v_t \sim N(0, \sigma_v^2)$$

The null and the alternative hypothesis is:

$$H_0: \rho_1 = 0 \; and \; \rho_2 = 0 \; and \ldots and \; \rho_r = 0$$

$$H_A: \rho_1 \neq 0 \; or \; \rho_2 = 0 \; or \ldots or \; \rho_r = 0$$

$$\text{Test statistic: } (T - t)R^2 \sim \chi_r^2$$

Critical value $x^2(r)$. Where (r) is the maximal order of autocorrelation.

5.4.3 Multicollinearity

Multicollinearity refers to a situation when two or more independent variables in a regression model are highly correlated with one another. It can cause issues for our statistical analysis because it indicates a strong linear relationship between the predictor variables (Brooks, 2008).

There are several problems that might occur in the presence of multicollinearity:
The coefficient estimates will be unreliable. Differentiating the individual impacts of the associated factors on the dependent variable becomes challenging. The estimates may have inflated standard errors, which can reduce the statistical significance, or they might be unstable, which can make the interpretation unreliable. It will become harder to choose those variables that are truly influential for our case, since highly correlated variables might show redundant information.

One popular way to address multicollinearity is by using a *Variance Inflation Factor (VIF). We chose to use VIF.* This factor measures the degree to which the variance is overstated in comparison to what it would be, if the variables weren't connected. It can be calculated as follows (Velleman & Welsch, 1981):

$$VIFk = (1 - R^2k)^{-1}$$

R^2k represents the coefficient of determination for a specific independent variable, xk, when this variable is regressed on all the other independent variables in the model. A VIF value above 10 is a typical threshold for multicollinearity detection. If the VIF for any variable is higher than this limit, there may be significant multicollinearity present, and the coefficient is likely to be underestimated (Velleman & Welsch, 1981).

If multicollinearity is present in the data, there are many alternative techniques to apply to the given problem, such as ridge regressions and principal component analysis. These techniques are quite complex and not very well understood. Therefore, many researchers do not use them. They argue further that the estimation method might not be the problematic variable in this case, but rather the data (Brooks, 2018). There are more easily and conveniently available ways to deal with multicollinearity:

1. You can ignore it if the adequacy of the model is statistically acceptable.
2. Drop one of the variables that are collinear, and the problem disappears.
3. Transform the correlated variables into a given ratio.

5.4.4 Stationarity

A strictly stationary process is expressed as:

$$t_1, t_1, \ldots, t_T \in \text{Z, any k} \in \text{Z and T} = 1,2, \ldots$$

$$Fy_{t_{1+k}}, y_{t_{2+k}}, \ldots, Fy_{t_{T+k}}(y_1, \ldots, y_T)$$

Where F represents the collection of random variables' joint distribution function (Tong, 1990). If a series' value distribution is constant through time, it is said to be strictly stationary. This means that the chance that y falls inside a certain interval is constant across time, now or in the future.

For any given lag, a stationary series is one with a constant mean, constant variance, and constant autocovariances. This is mathematically formulated as follows:

$$E_{(y_t)} = \mu$$

$$E_{(y_t - \mu)(y_t - \mu)} = \sigma^2 < \infty$$

$$E_{(y_{t_1} - \mu)(y_{t_2} - \mu)} = \gamma_{t_2 - t_1} \qquad \forall t_1, t_2$$

It is important to test for Stationarity because shocks that appear in non-stationary data, will last for an infinite time. It can also lead to high R^2 but have attributes that lead to insignificant coefficients for the slope because of spurious regressions. One other problem that might occur, is that the slope coefficients for the t-ratios will not be distributed correctly (t-distribution), which will give lower p-values (Brooks, 2018).

To describe non-stationarity, two models have been frequently used:

Random walk with drift:

$$y_t = \phi y_{t-1} + u_t$$

And the *deterministic process*:

$$y_t = \beta_o + \beta_1 t + u_t$$

if $\phi = 1$, the process is considered non-stationary.

Since the null is one of non-stationarity, the test statistics under the null hypothesis do not follow the ordinary t-distribution but follow a non-standard distribution. The critical values are derived from the models and experiments conducted by Dickey Fuller:

$$y_t = \phi y_{t-1} + u_t$$

$$H_0: \phi = 1 \quad H_A: \phi < 1$$

Test statistic: $\tau = \frac{\widehat{\phi}-1}{SE\widehat{\phi}}$

A limitation with the use of DF-test is that it is only valid U_t is a white noise process. where no autocorrelation is present. With our data, this is the case, and we therefore must look for a different option. We therefore used the *Augmented Dickey Fuller test (ADF).* The ADF process can be expressed as follows:

$$\Delta y_t = \psi y_{t-1} \sum_{i=1}^{p} \alpha \Delta y_t + u_t$$

Where the main objective is to examine if $\phi = 1$, (H_0), against the alternative hypothesis $\phi < 1$. In other words, we are interested in examining(H_A): contains a unit root, vs H_A: stationary series:

$$H_0: \phi = 1 \text{ or } \psi = 1. \quad H_a: \phi < 1 \text{ or } \psi < 1$$

ADF has the following test statistics:

$$Test\ statistic\colon \frac{\psi}{SE(\psi)}$$

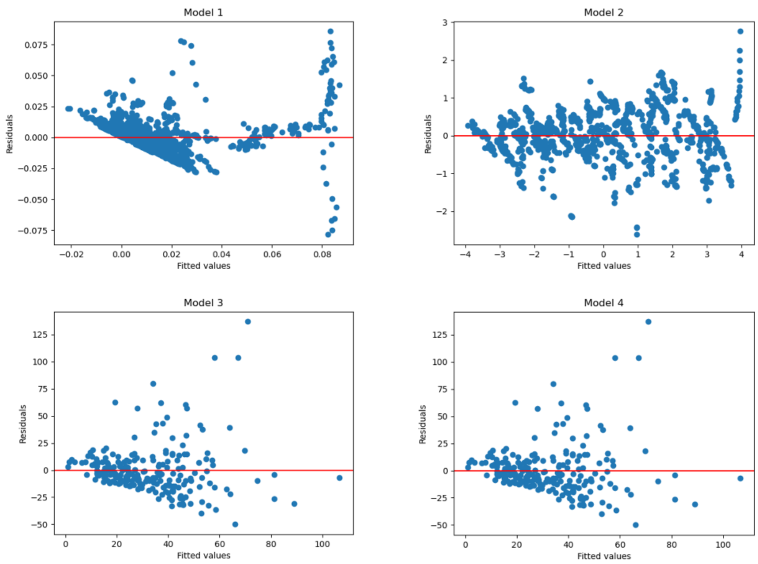
To prevent U_t from being autocorrelated, the dependent variable's dynamic structure is now "absorbed" by the lags of Δy_t. As is customary, information criteria or data frequency establish the optimal lag duration. We take the initial differences and keep testing until there are no more unit roots if the null hypothesis is not disproved. The exam has its detractors. The major one has to do with the test's power; it performs poorly at identifying roots that are near the non-stationary border, such as = 1 versus = 0.95. Using stationarity tests in addition to unit root tests like the ADF is one approach to getting around this issue (Brooks, 2018).

5.5 Robustness check results

This section presents the results of our different robustness tests on our models.

5.5.1 Heteroscedasticity and Autocorrelation

To examine the presence of heteroscedasticity, we initially plotted the residuals against the fitted values for both Model 1 and Model 2. The graphical analysis revealed evidence of heteroskedasticity, as the spread of residuals appeared to vary systematically across the range of fitted values. We could have used White's test, but the visual examination of the residuals was sufficient in this case.



Graph 6: Summary of heteroskedasticity plots

While investigating heteroscedasticity, we also examined the presence of autocorrelation in our models. We utilized the Breusch-Godfrey test, to identify potential autocorrelation. The test results indicated the presence of autocorrelation in our data. A summary of the test is available in the appendix.

To address both heteroscedasticity and autocorrelation, we employed Newey-West's heteroskedastic and autocorrelation consistent (HAC) standard error estimation. This technique adjusts the standard errors, which will help with our problem, by providing more accurate inference.

5.5.2 Multicollinearity

To check for multicollinearity, we calculated the variance inflation factors (VIFs) for each variable in our models. After we examined the different variables, we found that OBX_Price induced multicollinearity in all our models, as it exceeded the VIF threshold of 10. We also observed water reservoir difference (WRD) to induce multicollinearity in models 1 and 2 when sampling for 2022, for the same reason. We deleted these variables from our analysis because it was necessary to mitigate the impact of multicollinearity and to ensure the reliability of our regression results, as their high correlation could potentially introduce bias and instability into our estimates.

5.5.3 Stationarity

In the analysis of stationarity, we performed unit root tests such as the Augmented Dickey-Fuller (ADF) test to examine the stationarity of our variables. The results showed that all our data were stationary in the regressions. This is a desirable property for time series data, as it implies that the statistical properties of the variables remain constant over time. Our finding provides a solid foundation for the analysis we have performed because it allows us to utilize standard regression models and conduct reliable inference on the estimated parameters, since these methods are based on stationarity.

6 Conclusion

This thesis has aimed to investigate the relationship between volatility in the Nordic system price and liquidity in the Nordic power derivative market. From our research, we are the first to investigate this topic in the Nordic power derivative market. We place special emphasis on the 2022 power crisis, and how this shock specifically impacted the power derivative market. More specifically, we investigated if

- Volatility in Nordic system price, in general, leads to less liquidity in the Nordic power derivative market
- Volatility in Nordic system price positively impacted the liquidity in the Nordic power derivative market in 2022
- Volatility in the Nordic system price led to more market activity in the Nordic power derivative market

We investigated these questions through OLS regressions, using different dependent variables available through our dataset. We further sampled our data for 2022 observations, to find out how the energy crisis impacted the derivative market. Our dataset is self-constructed, and contains daily data from different sources, such as Nasdaq and Nord Pool.

We found volatility in the Nordic system price to have a negative relationship to the liquidity in the Nordic power derivative market, both when measuring the tightness and depth of the orderbooks. We suspect this is because of financial institutions being less incentivized to provide liquidity to the market, although we have no way of verifying this through our data. We did not find volatility in power prices to improve liquidity in the Nordic derivative market during 2022 either. Despite our volatility coefficients in model 1 looks promising, the lack of statistical significance deters us from making any empirical judgements. While the need for hedging may have been higher in 2022, the effect of financial institutions providing less liquidity probably overruled the added need for hedging. We did not find volatility in Nordic system prices to improve market activity in 2022 either. However, we did find it to have a substantially lessened negative effect compared to 2019.

7 Limitations, weaknesses and further research

One of the big limitations encountered during this master's thesis was the significant amount of time required to handle and process the data obtained from Nasdaq, specifically the ITCH files. It also took some valuable time to receive it due to some challenges on their part. The process was quite time-consuming and demanding, as we had to clean the data, decode messages, and create variables to construct an understandable dataset. This process also required significant computational power, which resulted in significant processing time. It took us approximately two weeks of continues computer operation to generate the required dataset each time. This substantial data processing phase took longer than expected, resulting in time constraints and potential limitations on the depth and complexity of the study.

Regarding model 1, it would be necessary to address the relatively low R-squared values of 0.139 and 0.134. This is indicating that the model's explanatory power is limited, where it suggests that the chosen model may not be the most optimal for the given dataset. It may not fully capture the complexity of the underlying relationship between the variables. If we had more time, we could have been conducting alternative models that could improve the fit and explanatory power of the potential model.

Gas prices play a role in the overall market dynamics, and to determine it, these variables would have a certain impact, explaining the volatility and liquidity of the derivatives in the Nordic power market. Considering the interdependencies between power markets and gas prices, since we were not able to extract gas prices for the European market, we consider the absence of gas prices to restrict the comprehensiveness of this analysis to some degree. For future potential research, it would be suggested to incorporate gas prices in the model to get a better comprehensive understanding of the relationships between power derivatives, liquidity, volatility, and gas prices.

In hypothesis 3, it would be ideal to compare 2022 results to a model with all observations in our dataset (2016-2022). Due to a late development of this hypothesis, we did not have the required time to construct this dataset due to long processing times. We therefore had to use a smaller sample to shorten the time the program ran.

An intriguing avenue for future research would be to investigate power markets beyond the Nordic region and compare their behavior to gain a broader understanding of market dynamics. It would be interesting to further analyze power markets in different European countries or even globally. This can shed light on variations in trading patterns and market structures, where we can gain insights into the unique factors influencing volatility and liquidity in various power markets.

Another interesting direction for future research would be the exploration of other derivatives markets for commodities such as oil and gas. These markets are often considered more liquid and actively traded compared to power derivatives. It would therefore be interesting to look at the derivatives markets for oil and gas because it can provide valuable insights into the dynamics of highly liquid markets. By making these comparisons between liquid and illiquid markets, it would be possible to identify potential differences in market liquidity & volatility, the impact of fundamental factors, and the effectiveness of risk strategies.

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Appendix

Appendix 1. Observations and R-squared, all models

	Model 1	Model 1 (2022)	Model 2	Model2 (2022)	Model 3 (2019)	Model 3 (2022)	Model 4 (2019)	Model 4 (2022)
Observations	81 831	9 213	57 285	6 705	12 015	9 164	12 015	9 164
R^2	0.139	0.134	0.505	0.497	0.496	0.518	0.541	0.508

Appendix 2. Models 1 and 2, all samples

	Independent variables								
	Intercept	***Volatility*** $_{30\ Days}$	***TTM***	***Volume***	***Width***	***Depth***	***SYS***	***RetOBX***	***WRD***
Model 1	0.0445	0.0095	-0.0001	-0.0005	0.0013	-0.0312	0.0006	0.0246	-0.0203
	(23.326***)	(3.811***)	(-24.658***)	(-4.053***)	(6.326***)	(-30.987***)	(2.821***)	(2.531**)	(-3.162***)
Model 1 (2022)	0.1234	-0.0086	-0.0005	-0.0118	-0.0371	-0.0528	0.0002	-0.0543	
	(12.826***)	(-3.195***)	(-18.319***)	(-13.449***)	(-6.258***)	(-13.538***)	(0.541)	(-1.161)	
Model 2	4.6967	0.2677	0.0062	-0.0718	-1.1525	-1.6235	-0.0060	-0.9785	-0.5528
	(64.181***)	(6.443***)	(56.870***)	(-41.807***)	(-84.870***)	(-44.581***)	(-1.959**)	(-6.045***)	(-3.360***)
Model 2 (2022)	2.6011	0.3563	0.0028	-0.1836	-3.4007	-1.9115	-0.0073	-0.3450	
	(11.401***)	(2.623***)	(7.706***)	(-13.769***)	(-22.182***)	(-15.155***)	(-1.861*)	(-0.513)	

	Maturity dummy variables								
	Jan	***Feb***	***Mar***	***May***	***Jun***	***Jul***	***Aug***	***Sep***	***Oct***
Model 1	-0.0042	0.0024	-0.0023	-0.0020	-0.0003	0.0082	0.0082	-0.0028	0.0001
	(-1.840*)	(0.949)	(-1.266)	(-0.913)	(-0.183)	(6.599***)	(3.095***)	(-1.579)	(0.039)
Model 1 (2022)	-0.0366	-0.0015	0.0393	0.0015	0.0440	0.0678	0.0204	0.0177	0.0516
	(-2.876***)	(-0.137)	(4.199***)	(0.129)	(4.768***)	(4.296***)	(1.321)	(1.989**)	(3.557***)
Model 2	0.5441	0.5345	-1.0400	0.5869	-0.5263	0.9875	0.7357	-0.6863	0.8928
	(6.348***)	(6.136***)	(-17.163***)	(7.522***)	(-8.876***)	(11.410***)	(8.579***)	(-11.557)	(8.926***)
Model 2 (2022)	0.2324	0.4535	0.2464	0.5093	1.0896	0.8474	0.6674	0.2266	-0.6916
	(0.885)	(1.702*)	(1.232)	(2.563***)	(5.471***)	(3.477***)	(2.896***)	(1.167)	(-3.258***)

	Nov	***Dec***
Model 1	0.0057	-0.0001
	(2.06**)	(-0.016)
Model 1 (2022)	0.0958	0.0660
	(5.513***)	(6.541***)
Model 2	0.6977	-2.1000
	(8.563***)	(-34.679***)
Model 2 (2022)	-0.9320	-0.8433
	(-6.753***)	(-1.991**)

	Date dummy variables								
	Jan	Feb	Mar	May	Jun	Jul	Aug	Sep	Oct
Model 1	-0.0019	-0.0019	-0.0069	0.0036	-0.0027	-0.0026	0.0002	0.0003	0.0024
	(-5.171***)	(-1.536)	(-5.910***)	(2.620***)	(-2.113**)	(-2.119**)	(0.189)	(0.249)	(1.684*)
Model 1 (2022)	-0.0174	-0.0135	-0.0238	0.0042	0.0124	0.0175	0.0469	0.0199	0.0232
	(-3.192***)	(-2.129**)	(-4.080***)	(0.676)	(1.866*)	(1.791*)	(5.933***)	(2.427**)	(2.540**)
Model 2	0.1229	0.3838	0.1755	-0.2597	-0.3187	-0.4748	-0.7453	-0.3534	-0.2579
	(3.075***)	(9.412***)	(4.697***)	(-6.631***)	(-8.421***)	(-12.409***)	(-18.680***)	(-8.876***)	(-6.631***)
Model 2 (2022)	0.0210	0.2976	0.1749	-0.0885	-0.2607	-1.0734	-1.1414	-1.0192	-1.1643
	(0.188)	(2.669***)	(1.617)	(-0.760)	(-1.859*)	(-5.418***)	(-4.647***)	(-7.004***)	

	Nov	Dec	2017	2018	2019	2020	2021	2022
Model 1	0.0064	-0.0036	-0.0051	-0.0027	-0.0018	0.0382	0.0022	0.0526
	(4.474***)	(-2.997***)	(-9.347***)	(-3.604***)	(-2.535***)	(26.233***)	(1.806*)	(15.808***)
Model 1 (2022)	0.0099	-0.0015						
	(1.207)	(-0.050)						
Model 2	-0.1956	-0.0866	-1.1092	-1.8749	-1.6642	-1.0709	-1.3992	-2.3422
	(-4.477***)	(-1.919*)	(-28.520***)	(-44.048***)	(-38.294***)	(-24.092***)	(-30.061***)	(-32.735***)
Model 2 (2022)	-0.9320	-0.8433						
	(-6.753***)	(-1.991**)						

Appendix 3. Robustness test

Breusch-Godfrey test	X^2	$P>\|X^2\|$
Model 1	1107	0
Model 2	1138	0
Model 3	62	0
Model 4	64	0