# Norway: A War Profiteer or Equitable Market Participant?"

How much of Norway's 2022 natural gas export revenues to the EU can be explained by the influence of the Russia-Ukraine conflict on natural gas prices - using Russian supply shortfall of pipeline gas as a proxy.

A Structural VAR Approach

Eirik Hjalte & Ida Elisabeth Uberg Gaasland

### Supervisors: Julio Cesar Góez & Lars Jonas Andersson

MSc in Economics and Business Administration Majors in Business Analytics, and Energy, Natural Resources and The Environment

# NORWEGIAN SCHOOL OF ECONOMICS

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible – through the approval of this thesis – for the theories and methods used, or results and conclusions drawn in this work.

# Acknowledgments

First and foremost, we extend our sincerest gratitude to our supervisors, Julio Cesar Góez and Lars Jonas Andersson from the Department of Business and Management Science for their invaluable guidance and unwavering support throughout the course of this thesis. We appreciate the time, effort, and knowledge you contributed to guide our research.

In addition to our supervisors, we would like to extend our gratitude to our peers, friends, and families for their encouragement and support throughout the writing process. This accomplishment would not have been possible without you.

Finally, we want to express our appreciation to the Norwegian School of Economics for providing an enriching environment that has fostered our intellectual growth. The combined knowledge accumulated through our individual specializations in Business Analytics and Energy, Natural Resources, and The Environment is what laid the groundwork for this collaborative endeavor.

Norwegian School of Economics

Bergen, Spring of 2023

Eirik Hjalte

Ida Elisabeth Uberg Gaasland

### Abstract

On the 24<sup>th</sup> of February 2022, Russia invaded Ukraine. The following months were characterized by major supply disruptions of Russian pipeline gas, soaring prices, and record revenues for Norwegian natural gas exports. This resulted in prominent political figures accusing Norway of being a war profiteer. In this thesis, we estimate how much of Norway's 2022 revenues from natural gas export to the EU can be explained by the influence of the Russia-Ukraine conflict on natural gas prices – using Russian supply shortfall of pipeline gas as a proxy.

We construct a Structural Vector Autoregressive (SVAR) model for the EU-27 natural gas market. The main drivers of the natural gas price, in addition to the volume of Russian supply shortfall, are used in the SVAR model. Based on economic theory, the model has been constrained such that shocks in the individual drivers only affect other drivers contemporaneously if this reaction can be supported from a theoretical standpoint. This allows us to disentangle the relationship between the variables and it helps with interpreting the result and validating the model. The model is built with data on a daily frequency for seven key drivers of the natural gas price from 2016 - 2022. Utilizing a Historical Decomposition (HD), we break down the natural gas price changes into contributions from structural shocks in our model variables.

We find the price of coal and Russian supply shortfall to explain the majority of the fluctuations in the natural gas price over 2022. The share of the fluctuations in the *Natural gas price* that is explained by the *Supply Shortfall* in the HD is extracted. This share is multiplied with Norwegian export volumes, and the natural gas price, to estimate the Norwegian natural gas export revenues of 2022. This approach attributes 334 billion NOK, or 27.18%, of Norway's natural gas revenues for 2022 to the Russian supply shortfall. This estimate nuances the debate on Norway as a war profiteer as it indicates how much of the revenues can be attributed to the war. Context and validity are established by comparing our estimate to the government-published historical natural gas revenues, including 2022.

**Keywords:** Natural Gas Market, Structural VAR, Supply shortfall, The European transmission system, Norwegian gas exports, Historical Decomposition, Energy security

# **Table of Contents**

1.0 INTRODUCTION	
2.0 LITERATURE REVIEW	14
3.0 BACKGROUND	
3.1 THE EUROPEAN NATURAL GAS MARKET	
3.1.1 Market structure	
3.1.2 Trading	
3.2 THE MAIN DRIVERS OF THE EUROPEAN NATURAL GAS MARKET	
3.2.1 Storage	
3.2.2 LNG imports	
3.2.3 Crude oil	
3.2.4 Coal	
3.2.5 Temperature	
3.3 NORWAY'S ROLE IN THE EUROPEAN NATURAL GAS MARKET	
3.4 THE IMPACT OF THE WAR ON EUROPEAN ENERGY PRICES	
4.0 DATA	
4.1 DESCRIPTIVE STATISTICS	
4.2 Comprehensive data description and transformation	
4.2.1 Heating Degree Days	
4.2.2 Supply Shortfall	
4.2.3 Price of Brent crude oil	
4.2.4 Price of coal	
4.2.5 LNG imports to EU-27	
4.2.6 Storage	
4.2.7 Natural Gas Price	
4.2.8 Norwegian export volumes	
4.3 Stationarity	
5.0 METHODOLOGY	
5.1 THE VECTOR AUTOREGRESSIVE MODEL	
5.2 STRUCTURAL VECTOR AUTO REGRESSION MODEL	
5.3 IDENTIFICATION METHOD	

5.4 SVAR model specification	
5.5 LAG SELECTION	
5.6 HISTORICAL DECOMPOSITION	54
5.7 Method application	55
5.8 Norwegian export revenues	
6.0 RESULTS & DISCUSSION	
6.1 HISTORICAL DECOMPOSITION	
6.1.1 Estimation- and Approximation Error in the HD of 2022	
6.2 Norwegian export revenues	61
6.3 HISTORICAL DECOMPOSITION FOR 2021	64
6.3.1 Estimation- and Approximation Error in the HD of 2021	
6.4 Robustness	67
7.0 CONCLUSION	69
8.0 REFERENCES	71
APPENDIX	85
A1 DATA	
A1.1 Summary Statistics	
A1.2 Pipeline entry points	
A1.3 Unit transformations	
A1.4 Variables pre-detrending	
A2 MODEL	
A2.1 Matrix of canonical moving average representation	
A2.2 Matrix of structural impulse responses	
A3 RESULTS	
A3.1 Column chart representation of the 2022 HD per month	
A3.2 Aggregated mean coefficients from the HD by each month for all v	ariables over
2022	

# List of figures

3.1	Cross border transmission capacities and import points	
3.2	The energy mix of the European Union in 2020	19
3.3	2019 Energy imports in the European Union by exporter and transportation	20
3.4	EU storage capacities by country	23
3.5	Gas pipelines on the Norwegian continental shelf	28
3.6	Energy price development from 2016-2022	30
3.7	Timeline of events impacting the TTF natural gas price in EUR/MWh	30
3.8	Russian pipeline exports to the EU by pipeline expressed in million MWH	31
3.9	The supply shortfall (MWH) and the natural gas price development 2021-2022	33
3.10	Norwegian yearly pipeline gas export revenues from 1977-2022	33
4.1	Daily deviations between HDD of the year 2022 and the historical average	37
4.2	Russian supply shortfall and surplus compared to historical export volumes	38
4.3	LNG imports to the EU from 2016-2022 pre- and post-detrending	40
4.4	Storage volumes in the EU from 2016-2022 pre-and post-detrending	41
4.5	Norwegian export volumes to the EU-27 through different pipeline entry points	43
4.6	OLS-CUSUM stability test results for each variable	45
6.1	Historical decomposition of the natural gas price for the year 2022	59
6.2	The discrepancy between the cumulative sum of the historical decomposition (total) and the demeaned natural gas price for 2022	61

6.3	Norwegian natural gas revenues over 2022 attributed to the supply shortfall of Russian pipeline gas	62
6.4	Historical decomposition of the natural gas price for 2021	64
6.5	Norwegian natural gas revenues attributed to the supply shortfall of Russian pipeline gas	65
6.6	The discrepancy between the cumulative sum of the historical decomposition (total) and the demeaned natural gas price for 2021	67
A1.4a	Heating degree days	86
A1.4b	Supply shortfall and surplus given historical export volumes in TWh	87
A1.4c	Brent crude price in USD/barrel	87
A1.4d	Coal price in USD/ton	88
A1.4e	LNG import volumes in the EU expressed in MWh	88
A1.4f	Storage volumes in the EU expressed in MWh	89
A1.4g	The TTF natural gas price expressed in USD/MWh	89

# List of tables

4.1	Data variables	36
6.1	Aggregated monthly mean coefficients of the historical decomposition for each month of the SVAR variables for 2022	57
6.2	Aggregated monthly mean coefficients of the historical decomposition for each month per SVAR variable for 2021	63
A1.2	Pipeline entry points	80
A2.3	Aggregated weekly mean of the HD table 6.1 per SVAR variable for 2022	85

# List of abbreviations

- EU The European Union
- EU-27 The 27 EU countries
- FRSU Floating Storage Regasification Unit
- HD Historical Decomposition
- HDD Heating Degree Days
- LNG Liquified Natural Gas
- MWH Mega Watt Hour
- OLS Ordinary Least Squares
- SM3 Standard Cubic Meters
- SVAR Structural Vector Auto Regression
- TWH Terra Watt hour
- UK United Kingdom
- VAR Vector Auto Regression

## **1.0 Introduction**

Norway currently finds itself in a geopolitically controversial but financially blessed situation, having displaced Russia as Europe's top supplier of pipelined gas during record-breaking natural gas prices. Norway's beneficiary status as the EU's leading supplier during this time of high prices and crisis has, however, not come without scrutiny. Current discussions revolve around whether Norway should relinquish some of its natural gas profits, which are mainly funneled into the government pension fund for apolitical foreign investments.

In an article titled "*Norway is profiting embarrassingly from war in Europe*" published by The Economist, Norway is accused of forcing Europe into a "*My way or Norway*" situation where Norway is unwilling to cap prices despite Europe finding itself in a time of crisis due to Russian supply shortfall (The Economist, 2022). Politico discusses the desire of Rasmus Hansson from the Norwegian Green Party to determine a "normal" price and funnel all profits made from selling natural gas above that price into a solidarity fund to rebuild Ukraine after the war (Duxbury, 2022). The EU Commission President Ursula Von der Leyen attempted to persuade Norway to lower the price of gas. However, Norwegian Prime Minister Jonas Gahr Støre has repeatedly stated that Norway will not cap prices.

On the question of whether Norway should be considered a war profiteer, Lars-Henrik Paarup Michelsen, director of the Norwegian Climate Foundation think tank, firmly claims that the excess revenues are war profits. Støre, however, rejects the notion that Norway is a war profiteer (Euronews, 2023). The Norwegian Ministry of Energy and Petroleum state secretary, Andreas Bjelland Eriksen, also denies any war profiteering to The Washington Post (Rauhala, 2022). They are both supported by David Sheppard from the Financial Times who argues that nobody should treat Norway as a war profiteer or forget its contribution to European energy security during this crisis (Sheppard, 2022). In an interview with CNBC, Deputy Foreign Minister Eivind Vad Petersson views the excess revenues as an indirect effect of Norway's participation in the European energy market (Meredith, 2023). Finally, Karin Thorburn, a professor at the Norwegian School of Economics, weighs in on the debate as two-sided when interviewed by TIME Magazine. Thorburn discusses if either "*it*'s a moral obligation that money that comes from the war should be used to help Ukraine" or "*is it just that we are another player in the oil industry and anyone who has oil and gas resources benefits*?" (Abend, 2022).

With this debate as a backdrop, it is interesting to perform a statistical analysis of how much of Norway's soaring export revenues from natural gas can realistically be attributed to the Russia-Ukraine conflict. Assessing economic consequences of major intricate conflicts through statistical analysis is a complex task. Following previous research, we model the impact of such a conflict on the price of the commodity in question. A conflict or war, however, is not a directly measurable concept in and of itself, and therefore one or more proxies for the conflict can be applied to capture its effects on the price of the commodity in question. The share of the Norwegian natural gas revenues that can be attributed to the proxy can then be calculated by taking into account the actual export volumes and the natural gas price. The resulting export revenues could thus be attributed to the conflict through the proxy with natural limitations. After balancing our research aims with the statistical requirements of our proposed model, as well as the existing evidence for the feasibility of the model, we developed the following research question:

"How much of Norway's 2022 natural gas export revenues to the EU can be explained by the influence of the Russia-Ukraine conflict on natural gas prices – using Russian supply shortfall of pipeline gas as a proxy."

Our thesis applies a *Structural Vector Autoregressive* (SVAR) model to make sense of the surge in Norwegian natural gas export revenues during 2022. Through the SVAR we can analyze the key drivers of the natural gas price. The model has built-in restrictions on which of the variables are allowed to contemporaneously affect each other in the system. These restrictions allow us to directly impose assumptions from economic- and natural gas market theory on our model and thereby control the direction and strength of the causal link between the variables.

We further apply a key tool within the SVAR named the *Historical Decomposition* (HD). By utilizing the HD, we estimate the share of the fluctuations in the *Natural gas price* that can be attributed to each of the variables in the system for each day of the period of interest, 2022. The share attributed to Supply Shortfall is extracted and multiplied with Norwegian export volumes and the natural gas price. The result represents an estimate of how much of Norway's natural gas export revenues to the EU that can be explained by the influence of the Russia-Ukraine conflict on natural gas prices throughout 2022. The results follow the natural limitations associated with the choice of using a single proxy to encapsulate the intricate concept of the Russia-Ukraine conflict.

Potential deviations due to estimation errors in the model are acknowledged. Ideas for further research on the topic using different variables, other combinations of restrictions, or on different historical periods of interest is both suggested and facilitated by this paper. As far as our knowledge goes, our analysis is the first to examine the European natural gas market in the context of the Ukraine conflict of 2022 using a SVAR approach. This approach distinguishes itself from most gas market research by focusing on the dynamic interactions between fundamental drivers of the natural gas price and by allowing for endogeneity between the variables in the system.

An important contribution of our research is the historical decomposition of the fluctuations in the European natural gas price into the distinct influences from both fundamental drivers and the supply shortfall of Russian pipeline gas. Hence, we distinguish the contribution of the different variables on the natural gas price fluctuations. Nick & Thoenes (2014) use an equivalent approach. They decompose the natural gas price into the contributions from the same drivers of the natural gas price as used in our model, but for three different periods of supply disruptions between 2009 and 2011. We build on their approach for the supply disruptions related to the Russia-Ukraine conflict in 2022. By utilizing the contribution from supply shortfall in explaining the natural gas price fluctuations, along with export volumes, we infer the share of the total Norwegian export revenue for 2022 that can be attributed to Russian supply shortfall. The SVAR model is valuable for this purpose because the natural gas price is affected not only by the supply shortfall shock, but also by multiple coinciding exogenous shocks to all variables, which our model accounts for. Thereby, the model provides empirical insights into EU security of supply and sheds light on the role of the Russia-Ukraine conflict in determining the 2022 Norwegian natural gas export revenues.

*Chapter 2* is a literature review of relevant research on the subject and establishes a theoretical framework based on findings and limitations in the existing literature. *Chapter 3* provides an overview of the natural gas market and elaborates on the fundamental components, developments, and drivers of the natural gas price. This material provides the necessary foundation for the reader to comprehend the market structure behind the model. It simultaneously supports the variable selection of the key drivers of the natural gas price, the restrictions placed on said variables, and the realization of the model. *Chapter 4* presents the collection- and transformation methods utilized to develop each variable that is used in the model. We strive for transparency and replicability by providing information on how the data was obtained, including its origin, collection process, and any transformation done to the

original data. Descriptive statistics and steps taken to ensure data quality are also accounted for. *Chapter 5* on methodology is focused on how our research was conducted in the modeling stage. We thoroughly outline the model's statistical- and mathematical properties in the sequence that the model was developed. *Chapter 6* discusses the analysis results considering the topic and background, and *Chapter 7* presents our concluding remarks.

### 2.0 Literature review

The natural gas market is a complex system influenced by multiple factors, including economic, political, and environmental conditions. Additionally, there are complex relationships between the drivers in the market. As our research revolves around a very recent event, few studies are published on this specific matter. However, several researchers have explored the drivers of natural gas prices, and the effects of supply disruptions of Russian gas. This chapter provides insight into common models and methods relevant to investigate similar topics.

Some authors explore the role of supply and demand fundamentals in short-term natural gas price development. Brown & Yücel (2008) apply a vector error correction model and find that temperatures, storage levels, and movements in crude oil prices play a significant role in shaping natural gas prices. Hulshof et al. (2016) analyze the development of spot market TTF prices from 2011-2014 by assessing the contribution of several supply and demand fundamentals<sup>1</sup>. The authors conclude that gas-market fundamentals predominantly determine day-ahead gas prices.

Several studies take a special interest in security of supply and focus specifically on potential or former supply disruptions. A supply shock is an unexpected event that suddenly changes the conditions for the supply of a product or commodity, resulting in an unforeseen change in price (Tarver, 2022). These studies primarily focus on gas transport disruptions and Russia's use of gas supplies as a political tool. Russia restricted natural gas flows to Europe several times due to disputes with Ukraine in 2005, 2009, 2014, and 2017 (Lawson, 2022).

Martinez et al. (2015) evaluated the Russia-Ukraine tensions and the possible impacts of supply disruptions to the Ukraine transit pipelines. They concluded that the 2014 crisis had a limited impact on the Northwestern European markets. They attributed this outcome mainly to the existence of the Nord Stream I pipeline. However, the authors emphasized that Southern and Eastern European countries remained susceptible to potential supply disruptions along the transit route through Ukraine. Growitsch et al. (2014) concluded that if such a Russian disruption to the EU persisted for at least six months, it would have significant implications

<sup>&</sup>lt;sup>1</sup> Supply and demand fundamentals explored in Hulshof et al. (2016): EU storage levels, LNG imports, temperature, the Brent crude price, the coal price, the CO2 price, wind generation levels in Germany, and global gas discoveries.

for European gas security. Furthermore, they estimated that a nine-month disruption could potentially result in a deficit of 46 billion cubic meters (BCM) in the total European gas supplies.

According to analyses conducted by Holz et al. (2015), short-term Russian disruptions would cause only a modest price increase for the EU. However, specific East European countries would face more significant consequences. In contrast, the long-term disruption scenario would have a more substantial impact overall. The authors emphasize the potential significance of liquified natural gas (LNG) in addressing these challenges but note that substantial investments in transportation infrastructure would be necessary to facilitate the transportation of LNG.

Egging et al. (2008) indicated that a disruption in Russian exports through the Ukraine transit would severely affect Ukraine and some Eastern European countries. However, the EU would experience only a minor price increase on average. Huppmann et al. (2009) use the World Gas Model, a dynamic representation of world natural gas production, trade, and consumption between 2005 and 2030, to model the effect of a complete disruption in Russian supply to Europe. They concluded that all EU countries would be impacted, with an average price increase of over 40% in the first year of the shock. The results of these studies show how previous Russian supply disruptions have affected the European gas market and provide insight into the effects of current supply disruptions.

The SVAR model has been used extensively in research on the evolution of the real price of oil and its effect on the macroeconomy (Kilian & Zhou, 2020). Kilian & Lee (2014) build a SVAR model and use the HD to attribute fluctuations in the oil price over an extended period to shocks in four key drivers of the oil price<sup>2</sup> to understand the evolution of the oil price for that period. The HD is a SVAR tool that permits the researcher to examine the cumulative effect of the shocks in the system on individual variables and to assess the relative importance of the shocks in explaining the variation in that particular variable. The Kilian & Lee (2014) study uses the HD to aggregate the determinants of the oil price increase between 2003 and 2008. Their total, the sum of each cumulative shock across the time series, shows that the oil

 $<sup>^{2}</sup>$  The four key drivers of the oil price in Kilian & Lee (2014) are a flow supply shock, a flow demand shock, a speculative shock, and a residual shock.

price increased by \$95 in real terms. Furthermore, they divide how much of said increase must be attributed to each of the four structural shocks, which sum makes up the total increase of \$95.

The natural gas market has traditionally been considered an extension of the oil market. However, it has become a sizeable stand-alone market over the last decades. Thus, in more recent literature, the SVAR model is applied in analyses of the natural gas market. Both Wiggins & Etienne (2017) and Hailemariam & Smyth (2019) investigate what drives fluctuations in US natural gas prices using variations of the SVAR. The former investigates three different periods using HDs and concludes that supply- and aggregate demand shocks account for the majority of the fluctuations in the price. The latter uses HDs to determine the relative contributions of structural shocks to the natural gas price volatility. As they decompose the natural gas price from 1978 to 2018, they find significant time variations. Furthermore, they find the effects of supply and demand shocks to be the most persistent and to have the largest effect over time.

Domfeh (2021) applies a SVAR model to explain the determinants of the natural gas price in the US by modeling the interactions between the main gas market fundamentals. He identifies the five key drivers of the natural gas price: storage, coal prices, temperature deviations, short-term interest rates, and crude oil prices. He places equivalent restrictions on the instantaneous coefficient matrix to identify his model, as is done in Nick & Thoenes (2014). These restrictions, which are based on economic theory, determine if the variables in the system are allowed to interact instantaneously. This approach allows him to disentangle the effect of the different variables on the natural gas price. Using impulse response functions and a forecast error variance decomposition, he identifies coal prices as the most significant determinant of natural gas price development.

Nick & Thoenes (2014) apply a SVAR to explain to which degree different drivers affect the natural gas price in Europe. Their focus is on the influence of supply shortfalls, and the fundamental drivers of the natural gas price in the German market. The variables they model are gas supply disruptions, weather conditions, storage levels, and LNG imports. They also include the coal and crude oil prices to capture the substitutive relationships between the gas, coal, and crude oil prices. They then perform a HD to estimate how much of the natural gas price can be attributed to each of the system's seven variables for three different cases of supply disruptions from 2009 to 2011. In the short run, they find that supply shortfall, coal,

crude oil, storage, and temperature deviations affect the natural gas price. One of the supply disruptions they decomposed was the Russia-Ukraine gas transit conflict of 2009. Through the HD, they find that supply shortfall of natural gas exports from Russia accounted for an increase of more than 30% in the European gas price, making it the primary driver of the price surge during the supply disruption. Their results also indicate that coal prices have an immediate and persistent impact on natural gas prices. In contrast, oil prices are important determinants of the natural gas price in the long run – capturing important substitution effects between the energy commodities.

### 3.0 Background

In this chapter we provide a brief historical background of the European natural gas market, its defining characteristics, and drivers of the natural gas price. It provides insight into the most recent developments and challenges prior to and after the commencement of the Russia-Ukraine conflict. The background makes sense of how and why we selected the specific key drivers of the natural gas price by elaborating on their role in the market and determining the price. By delving into how the drivers interact in the market we help establish the theoretical assumptions behind the restrictions placed on the variables in the model.

#### 3.1 The European Natural gas market

The modern history of natural gas in Europe began in 1959 with the discovery of the Groningen field in the Netherlands, which was soon followed by the first discoveries in the United Kingdom (UK) sector of the North Sea. Subsequently, in the 1970s, Norway also made significant discoveries of gas in its sector (Stern, 2003). These discoveries marked the beginnings of a Europe-wide transmission system.

Although the Soviet Union had been exporting limited amounts of gas to Poland since the late 1940s, many people considered it impossible to import significant quantities of Soviet gas to Western Europe. In the 1970s and 80s, the Siberian gas development eliminated the transport problem by utilizing the giant fields found in the West Siberian areas of Medvezhye, Urengoy, and Yamburg. By constructing several large-diameter pipelines from Siberia to Ukraine, only a small extension of the pipelines was required for the gas to reach Europe (Stern, 2003). In the following years, deliveries of Soviet gas to Western Europe increased substantially, and by 1990, Western Europe had become the Soviet Union's largest market. In the 1980s a pipeline from Algeria to the Italian mainland was completed, and later transmissions to Spain and Portugal were established (Stern, 2003).

Today, more than two-thirds of the global cross-border pipeline capacity is concentrated in Europe (Snam, 2023), and the European natural gas network is comprised of approximately 200 000 kilometers of high-pressure gas pipelines (ACER, 2022). The primary entry points to the European natural gas network are in the east from Russia, north from Norway, and south from Algeria. Figure 2.1 illustrates the main transmission pipelines from Russia to the EU: the *Baltic Connector, Nord Stream, Yamal*, the *Ukraine Transit*, and *Turkstream*.



Figure 3.1. Cross-Border Transmission Capacities and Import Points. Illustration made based on ENTSO-G (Di Bella et al., 2022). The yellow lines represent the domestic European transmission system. The other colored lines represent import pipelines to Europe. The green triangles represent LNG receiving terminals (EC, 2023b).

The demand for natural gas within the European Union is estimated to be approximately 400 bcm per year (EC, 2023b). A quarter of the European Union's total energy consumption comes from natural gas, while the remaining shares come from coal, oil, nuclear and, renewables as seen in figure 3.2.



Figure 3.2 The energy mix of the European Union in 2020. Illustration made with data from Eurostat (2023).

Finland, Latvia and Bulgaria followed by Germany and Italy, are the nations most dependent on Russian natural gas within the European Union (Buchholz, 2022). The power generation sector, which includes combined heat and power plants, accounts for approximately 26% of the EU's gas consumption, while the industrial sector utilizes around 23%. Most of the remaining natural gas is used for heating purposes in residential and service-oriented buildings (Eurostat, 2020). The share of natural gas consumption in the EU energy mix has increased in recent years due to higher carbon pricing strategies designed to phase out the more carbonintensive coal consumption.

The two once pioneering natural gas producers, the Netherlands and the UK, have transitioned from net exporters to net importers of natural gas<sup>3</sup>. By 2019, Russia had become the primary exporter of natural gas to the Euro area via pipelines, accounting for 57% of the imports, followed by Norway at 35% and Algeria at 7%. Long-distance oversea transport requires gas liquefaction<sup>4</sup>. Regardless of delivery method, the EU's total natural gas imports consisted of 47% Russian natural gas, as illustrated in figure 3.3.



Figure 3.3. 2019 Energy imports in the European Union by exporter and transportation mode. The illustration is made with data from EWI (2022).

<sup>&</sup>lt;sup>3</sup> The UK gas fields in the North Sea were rapidly depleted. More than 70% of the reserves in the Groningen gas field, are extracted, and the majority of its remaining output is utilized domestically. After increasing frequencies of earthquakes due to gas extraction, the field was capped in 2014. This contributed to increase demand for gas imports (Egging-Bratseth, 2023).

<sup>&</sup>lt;sup>4</sup> Liquefaction involves cooling the gas to -162 degrees Celsius in order to shrink the volume of the gas 600-fold (EC, 2023b)

#### 3.1.1 Market structure

The natural gas industry can be divided into three primary segments. In the upstream segment, natural gas is explored and produced. The midstream segment involves transportation, storage, refining, and processing. The gas is transported to local distribution grids, large-scale industrial users, and power plants. Finally, in the downstream segment, local distribution grids deliver gas to small domestic- and business consumers (Correljé, 2016). The significant investments in national- and international infrastructure led to the establishment of natural monopolies in the transportation and sale of gas. The EU's extensive- and escalating reliance on external natural gas sources created a necessity for measures aimed at mitigating supply risks to ensure a steady energy supply.

Concerns have been raised about an EU over-reliance on natural gas imports, as a small number of non-EU producers hold a large share of the market power (Fermann, 2009). The European Commission has tried to limit the concentration of market power and improve efficiency and energy security by implementing market liberalization measures: *The Third Energy Package* and *The Gas Directive*, which both entered into force in 2009. These contain clear regulations that limit the vertical integration of the three primary segments. The main objectives include the legal splitting of gas sellers and network operators through ownership unbundling and regulatory supervision of the member states<sup>5</sup> (Hamie et al., 2020).

#### 3.1.2 Trading

As natural gas infrastructure is capital intensive and largely irreversible, supply and demand actors face uncertainty in short- and long-term volumes and prices. These risks are managed through contracts. Contract duration typically ranges from 10 to 34 years, while the most common duration is 15 years<sup>6</sup> (Sergeeva, 2023). The gas network must always be in balance<sup>7</sup>. An unbalanced network is less efficient, poses a higher safety risk, and could cause damage to equipment and lead to supply disruptions (ENTSOG, 2023a). The supplier is more exposed to

<sup>&</sup>lt;sup>5</sup> Major developments in these regulatory reforms include providing customers and suppliers with third party access to infrastructure to avoid obstruction of competition and to ensure energy security. The regulations further aim to ensure increased cross-border cooperation and fair and open retail markets (EC, 2022b).

<sup>&</sup>lt;sup>6</sup> The largest contracted gas volumes are also under 15-year contracts (Sergeeva, 2023).

<sup>&</sup>lt;sup>7</sup> Network balance means that the overall gas removed from the network should match the volume entering in order to secure that the gas transmissions always are correctly pressurized.

volume risk than price risk, as changes in volumes are more critical than price changes when dealing with the large margins of this industry. Therefore, in long-term contracts, the volume risk is imposed on the buyer in as a "take-or-pay" clause. The clause guarantees the seller a minimum portion of the agreed-on payment if the buyer does not purchase the agreed-on quantity of goods. (Sergeeva, 2023).

The price risk is more crucial to the buyer as switching to another energy source on short notice can be difficult. Historically, the natural gas price was determined according to the crude oil price through oil indexation. Since 2000, gas prices in Europe have moved towards natural gas hub pricing. The share of crude oil indexation of European natural gas prices was 72% in 2005 (IGU, 2014), but only 23% in 2021 (Egging-Bratseth, 2023). The decline in oil-indexed long-term contracts is the result of the liberalization and integration of the natural gas market, and the elimination of oil products from many stationary energy sectors (Stern & Rogers, 2011). Additionally, there is a higher demand for natural gas as coal and crude oil are slowly phased out due to environmental concerns (OECD, 2022).

The Dutch Title Transfer Facility (TTF) is considered the European gas price benchmark. LNG cargoes, as well as other hubs, price against it. In 2019, 79% of the total volumes in Europe were traded on the TTF (Heather, 2020). Benchmarks play a vital role in the natural gas markets by providing access to reliable and accessible prices in markets with little transparency (OECD, 2022). The regional gas markets are not independent and Stern & Rogers (2014) argue that they seem to become increasingly tied to each other. Nevertheless, regional prices can move in very different directions as seen from the divergence between European and North American gas prices (Mulder, 2013).

#### 3.2 The main drivers of the European natural gas market

The Energy Information Administration (EIA, 2022) and the Organization for Economic Cooperation and Development (OECD, 2022) classify the main natural gas price drivers as the following supply- and demand factors: storage, LNG imports, crude oil, coal, and temperatures. In addition to Russian supply shortfall, these fundamental drivers will be used as variables in the SVAR. Understanding the economic relevance of these variables is important, as the interpretative advantages of the SVAR rely on the strength of the underlying economic model. Therefore, a solid theoretical foundation for both the choice of variables and for determining the causal link between them through contemporaneous restrictions is

necessary to be able to later extract clear interpretations and meaningful insights from the model results.

#### 3.2.1 Storage

The amount of natural gas in underground storage fields significantly affects the overall supply. It is mainly used to smooth out the seasonal demand pattern but also plays an essential role in hub prices as storages can be used for inter-temporal arbitrage (Hulshof et al., 2016). During periods of low demand, excess domestic supply can be absorbed by storage. Moreover, storage facilities support pipeline operations and trading hub services. Typically, the level of natural gas in storage rises from April to October when the demand for natural gas is low. Conversely, the level of natural gas in storage decreases from November to March when there is a high demand for heating (IEA, 2022a).



Figure 3.4 EU Storage capacities by country. Illustration made based on data from the EC (2023) and a generic map made by (Grajeda, 2023).

Although the European storage facilities are a cooperation project, they are unevenly distributed across the continent as shown in figure 3.4. Germany has the largest capacity in the European Union. The largest Russian state-owned energy corporation Gazprom also owns major storage facilities in Germany and Austria, accounting for 7 % of total EU storage capacity (Di Bella et al., 2022). Natural gas storage facilities can be divided into two types: aboveground- and underground storage. Aboveground storages barely contribute and are merely used to balance short-term demands due to its small size (INES, 2023). Underground storages can be divided into cavern storage facilities and porous rock storage facilities. The properties of cavern storage facilities allow the storage of large quantities of gas and allow gas to be rapidly injected and withdrawn from storage. Therefore, these storage facilities are especially well-suited for compensating for severe short-term demand fluctuations. The porous rock storage facilities are used for storing large quantities of gas. However, the maximum injection and withdrawal rates are relatively low due to the geophysical properties of porous rock. Natural gas stored in facilities of this type is therefore used mainly to compensate for seasonal fluctuations in gas demand (INES, 2023). To summarize, the cavern storage facilities are flexible, while the porous rock storage facilities are inflexible in the short run.

#### 3.2.2 LNG imports

The majority of Europe's LNG supply in recent decades comes from three countries: the United States, Qatar, and Russia. Together, these nations were responsible for almost 70 % of Europe's total LNG imports in 2021. The liquefaction process makes it possible to safely ship large quantities of gas, as liquified natural gas cannot ignite (Shell, 2023). Natural gas produced far from Europe, such as in the US, needs to be liquified and transported by LNG carriers to reach Europe. When the LNG vessels arrive in Europe, they must go through a regasification process, passing through receiving terminals before entering the pipeline networks. The liquefaction process and subsequent regasification increase the cost of importing LNG, making it economically viable only in cases where the geographical distance is too great to establish pipeline infrastructure. In contrast to pipelined gas, the LNG market is exposed to global competition, especially from Asia.

The EU's overall LNG import capacity is approximately 157 bcm in regasified form per year, enough to meet around 40% of the total EU gas demand. However, bottlenecks and infrastructural limitations exist in some regions, thereby limiting the actual capacity (EC,

2023b). As a result, LNG regasification capacity in the EU-27<sup>8</sup> has remained relatively stable and expanded modestly during the last decade while capacity utilization has grown significantly (EC, 2022a).

#### 3.2.3 Crude oil

The price of crude oil is related to the natural gas price in three main ways: competition in fossil fuel extraction, fuel substitution, and through arbitrage on oil-indexed contracts. Price linkages between crude oil and natural gas are primarily driven by direct competition for drilling resources on the supply side. The equipment needed to extract oil and gas is essentially the same; most fields can produce both commodities. Price signals can prompt suppliers to prioritize one fuel source over another to maximize profits.

Price linkages exist because some industrial users and electricity generators can alternate between crude oil and natural gas (OECD, 2022). The price of oil can impact both the demandand supply of gas due to the substitutability between the two fuels, as noted by Villar & Joutz (2006). This substitution property is especially relevant when dealing with large-volume fuel consumers, as can be found in electricity generation and heavy industries dedicated to producing iron, steel, and paper.

The substitutability of both supply and demand sides means that the value of the two commodities typically moves in parallel. Therefore, indexing the price of natural gas to that of oil has historically provided a good approximation of the actual value but has now largely decoupled. Still, price arbitrage between the remaining oil-indexed contracts could result in changes in the natural gas price. For example, when the spot price of gas is lower than the price of gas indexed to oil contracts, the demand for spot-priced gas in hubs will increase, while the demand for oil-indexed gas will decrease. This, in turn, will make buyers with long-term contracts reduce their nominations to the minimum required amount, resulting in lower upstream production and reduced market supply (Hulshof et al., 2016).

<sup>&</sup>lt;sup>8</sup> The EU-27 countries are the following. Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

#### 3.2.4 Coal

The demand for gas by gas-fired electricity generators depends primarily on the natural gas price relative to other fuels used for electricity generation, particularly coal (Hulshof et al., 2016). Coal is one of the primary energy sources in the European energy mix and accounts for about one-fifth of the total electricity production in the EU (EC, 2023a). Gas plants are preferred to coal plants as they are more flexible and have lower emissions. In addition, the increasing carbon emission prices have reduced the competitiveness of coal power plants, even in countries like Germany, where the prices of coal are typically low. In 2019, Poland, Bulgaria, the Czech Republic, and Germany mostly used coal-based electricity generation despite the European Union's efforts to reduce carbon emissions. This was reflected in electricity prices, which were influenced by coal generation over 75% of the time in Germany, 82% in the Czech Republic, and over 90% in Poland and Bulgaria (Zakeri et al., 2022). Thus, coal remains a dominant fossil fuel in electricity generation, and there is significant competition between gas and coal (Zakeri et al., 2022).

#### 3.2.5 Temperature

Natural gas is the EU's primary energy source for household heating, making up 39% in 2019 (Odyssee-Mure, 2021). When demand for heating by residential- and commercial consumers increases, price pressure increases. This effect on prices can intensify during extraordinarily low temperatures, as the supply is often unable to react quickly to short-term increases in demand. Given the limited availability of alternative fuels for heating, gas demand related to heating is considered inelastic<sup>9</sup> in the short term (Hulshof et al., 2016). Additionally, if the natural gas transmission system is already operating at or near full capacity, the effect of weather on natural gas prices may be even greater (EIA, 2022). As a result, a significant seasonal pattern emerges in the natural gas price (Hulshof et al., 2016). However, natural gas supplies stored in reserves can help to cushion the impact of high demand in periods of cold weather (EIA, 2022). Additionally, the increased consumption of natural gas during the summer due to the demand for air conditioning could lead to smaller injections of natural gas into seasonal storages than usual, affecting prices (EIA, 2022).

<sup>&</sup>lt;sup>9</sup> The level of supply does not change as much as the change in prices does. The natural gas supply is considered inelastic in the short run due to production and capacity constraints.

#### 3.3 Norway's role in the European natural gas market

Since the beginning of natural gas production on the Norwegian shelf in 1977, Norwegian gas production and exports have experienced significant growth. Once a byproduct of oil production, natural gas has now evolved into a competitive product in its own right. In 2021, Norway covered around 3% of the global natural gas demand and 20-25% of the total gas consumption in the EU and Great Britain. This placed Norway as the world's third-largest gas exporter, surpassed only by Russia and Qatar (NPD, 2023a). Norway stands apart from 70% of the world's gas-exporting nations in that it exports nearly all the gas it produces (Egging-Bratseth, 2023). Only a small fraction is consumed domestically, as the country relies primarily on hydropower for electricity generation. Consequently, the Norwegian export value of oil and gas makes up over half of the total Norwegian export value (NPD, 2023a). Natural gas exports have been an increasingly important source of revenue for Norway for almost 50 years (SSB, 2023). There have only been four years where revenues from natural gas have exceeded revenues from oil since Norway started exporting and all of them have occurred since 2015. This development highlights the growing significance of natural gas exports for Norway.

The transmission system has since the 1970s expanded to 8800 km of pipelines. The Norwegian pipeline transport capacity is 120 billion standard cubic meters<sup>10</sup> ( $SM^3$ ). The authorities largely control the transmission system, a natural monopoly central to Norwegian petroleum activities. The gas transport infrastructure is jointly owned by Gassled<sup>11</sup> and Gassco<sup>12</sup> (NPD, 2023a). As illustrated in figure 3.5, the Norwegian transmission pipelines have receiving terminals in Belgium (Zeebrugge), France (Dunkerque), England (Easington), Scotland (St. Fergus), Germany (Emdem & Dornum), and Denmark (Nybro) (Gassco, 2023). Additionally, LNG is shipped from the LNG terminal at Melkøya off the coast of Hammerfest on LNG carriers. The LNG is extracted from the Snøhvit field, and the export makes up about 5% of Norwegian gas exports (NPD, 2023a).

<sup>&</sup>lt;sup>10</sup> Oil and gas volumes are often stated in standard cubic meters. The standard conditions are a temperature of 15 °C and normal atmospheric pressure (1013.25 hectopascal (hPa)) (NPD, 2023b).

<sup>&</sup>lt;sup>11</sup> Gassled is the official owner of the transmission system on the Norwegian shelf and is itself owned by large petroleum producers and state-owned Petoro (NPD, 2023a).

<sup>&</sup>lt;sup>12</sup> Gassco is the operator of the Norwegian transmission system and is owned by the Norwegian state (Gassco, 2023).



Figure 3.5 Gas pipelines on the Norwegian continental shelf. Illustration made by Norsk Petroleum (NPD, 2021).

#### 3.4 The impact of the war on European energy prices

Since early 2020, energy prices have experienced significant fluctuations due to the pandemicinduced disruptions to the global economy. Even before Russia invaded Ukraine, international commodity markets were already experiencing the effects of these disruptions. These fluctuations in global energy prices resulted in an average increase of over 80% in 2021 compared to 2020, leading to inflationary pressures, rising demand, and constrained supply across several commodity markets (Benton et al., 2022).

Despite high energy prices, the supply-side responsiveness has been limited. Investments in oil and gas production decreased by 23% between 2019 and 2021 as producers preferred to reward shareholders using record free cash flow (Sheppard et al., 2020). This trend can be attributed to various factors, including the severe impact of the commodity price collapse in 2014-15 and 2020 on producers, which decreased the risk appetite for new long-term projects

(Alvarez & Molnar, 2021). In addition, the transition to *Net Zero* has further reduced the appetite for fossil fuel projects as government carbon-reduction policies become more ambitious and technological advancements reduce fossil fuel demand (Crowley & Hurst, 2022). As a result, some of the investments in fossil fuel production have been redirected towards renewable energy. Despite the EU's commitment to a low-carbon future, investments in renewable energy have been insufficient to reduce fossil fuel reliance (Benton et al., 2022). Also, the EU has become increasingly dependent on Russian energy, mainly due to the fact that carbon-intensive energy sources are being phased out, and alternative domestic production is declining.

In the summer months of 2021, gas consumption by power plants increased significantly due to a lower supply of renewable energy resulting from low winds in the summer months of 2021. This increase in consumption led to a depletion of European storage facilities, which were 28% below their five-year average levels (IEA, 2022b). Furthermore, as tensions escalated in the fall of 2021, Gazprom reduced natural gas exports through the Yamal pipeline following Germany's refusal to certify the new pipeline, Nord Stream II (OECD, 2022).

On the 24<sup>th</sup> of February 2022, Russia initiated a full-scale invasion of Ukraine, resulting in a severe conflict. The threat of an interruption of energy supply from Russia has triggered unprecedented rises in fossil fuel prices, as shown in figure 3.6. In the EU, the relative inflexibility of the movement of gas, and the dependence on Russian supply, led to a particularly large price spike (Benton et al., 2022). The natural gas price peaked at 339 EUR/MWh on the 26<sup>th</sup> of August 2022, the highest price ever recorded on the TTF. See figure 3.7 for the timeline of events impacting the TTF natural gas price.





Figure 3.6 From the top one can observe the the coal price (USD/ton), then the Brent crude price (USD/Barrel), and at the bottom the natural gas price (USD/MWh). The development shown is from 2016-2022.

The high dependency of certain EU member states on Russian energy imports makes fossil fuel sanctions economically and politically difficult. On the 3<sup>rd</sup> of June, the EU banned the import of Russian oil and certain petroleum products, although with some exceptions, notably for crude oil imports by pipeline into member states with specific dependence on Russian supplies (OECD, 2022). By August 2022, an import ban on Russian coal was enforced in the EU. However, due to high gas prices, demand for coal in power generation remained strong. In the autumn of 2022, coal prices followed a similar trend as the natural gas prices.



Figure 3.7 Timeline of events impacting the TTF natural gas price in EUR/MWh made by the authors and inspired by Elliott (2023).

After the invasion and the imposition of extensive sanctions, Gazprom unilaterally amended existing natural gas contracts, requiring payment in Russian rubles from "unfriendly countries" (Hernandez, 2022). Following a refusal to pay in rubles, Gazprom halted natural

gas deliveries to Poland and Bulgaria on the 26<sup>th</sup> of April, with several other countries and firms experiencing similar disruptions in the following months. The Nord Stream I pipeline, the largest pipeline for transporting Russian natural gas to Europe, was entirely shut down in late August 2022<sup>13</sup>. On the 26<sup>th</sup> of September, the yet-to-be-opened Nord Stream II was hit by a suspected sabotage attack which is still under investigation (Elliott, 2023). By September 2022, natural gas flows to the EU had decreased by more than 75% compared to 2021 (Ferris, 2022), as can be observed in figure 3.8. The same month, Russian pipeline exports made up only 9% of the total supply to Europe (EC, 2023d). Norway has since become the most important source of pipeline gas imports to the EU, followed by Algeria.



Figure 3.8 Russian pipeline exports to the EU by pipeline expressed in million MWh<sup>14</sup> Made with data from ENTSOG (2023b).

In response to the invasion, the EU launched the REPowerEU plan to ensure affordable, secure, and sustainable energy for Europe (EC, 2023c). As the natural gas supply is inelastic

<sup>&</sup>lt;sup>13</sup> Russian authorities initially claimed the Nord Stream I pipeline was shut down due to a maintenance issue, an explanation refuted by European authorities.

<sup>&</sup>lt;sup>14</sup> The negative values of the Yamal pipeline in 2022 are caused by the reversal of pipeline flows from the usual westbound flow (Russian-Poland-Germany) to an eastbound flow (Germany-Poland). This is explained by Poland's choice to utilize stored reserves from Germany instead of purchasing additional Russian gas at inflated spot prices (Soldatkin, 2022).

in the short run, the following measures have been implemented to increase supply (OECD, 2022). European countries have made significant investments to increase the imports of LNG. In September 2022, two floating storage regasification units were established in the Netherlands, and seven were chartered by Germany, allowing for the pumping of LNG into onshore networks. However, limited pipeline capacity to Central and Northern Europe hinders further LNG imports, preventing supply diversification. In response, the EU required all member states to have sufficient natural gas storage, and to fill underground natural gas storages to at least 80% capacity before the winter of 2022 and 90% by the winter of 2023. This regulation successfully filled natural gas storage facilities, but increased demand for natural gas, resulting in higher prices and distortions to the typical shape of the forward price curve (OECD, 2022). During the spring of 2022, storages previously managed by Gazprom were practically speaking requisitioned by the European governments upon the "use it or lose it" principles of gas security of supply regulations (EC, 2022a). However, the volume of Russian LNG reaching European LNG terminals has remained unaffected<sup>15</sup> (Zachmann et al., 2023).

As can be observed in figure 3.9, the shortfall continued to increase after the invasion, but the market was able to adapt. On the demand side, the EU has implemented measures designed to increase home energy efficiency. The measures include incentives for inhabitants to change their energy consumption patterns and to accelerate heat pump investments (Benton et al., 2022). The European Council passed a regulation<sup>16</sup> on the 5<sup>th</sup> of August 2022 that proposes voluntary natural gas demand reductions of 15% for the winter of 2023 and for the following winter of 2024 (EC, 2022a).

<sup>&</sup>lt;sup>15</sup> The main Russian LNG supplier to Europe is the privately owned company Novatek (Staalesen, 2023).

<sup>&</sup>lt;sup>16</sup> The European Council could trigger a "Union alert" to implement mandatory gas demand reductions for industry and households.



Figure 3.9 The supply shortfall (MWh) and the natural gas price development 2021-2022

For Norway, the culmination of these events led to record-high prices of natural gas. As illustrated in figure 3.10, already in 2021, the natural gas revenues increased five-fold from the year before, reaching a record high of 578 billion NOK. In 2022 the revenues more than doubled from the past year to another record-high of 1378 billion NOK. These record revenues sparked the debate on Norway's role as a gas supplier in the midst of a war-induced energy crisis.



Figure 3.10 Norwegian yearly pipeline gas export revenues from 1977-2022 (SSB, 2023).

### **4.0 Data**

Our thesis develops a SVAR model in combination with a HD to determine the degree to which shocks to the different fundamental drivers of the natural gas price account for the fluctuations in the natural gas price over a historical period. The variables applied in the SVAR model are chosen based on the IEA and OECD's empirical findings of the main drivers of the natural gas price, elaborated on in Chapter 2.2. The model variables are in accordance with those applied by Nick & Thoenes (2014) in a similar model for the German natural gas market and Domfeh (2021) in a similar model for the US natural gas market. Our model is equal to that of Nick & Thoenes (2014) in terms of variables and restrictions on the model, but we extend the scope to the EU market for a longer period, namely 2016-2022, and decompose a far more recent period, 2022, in context of the Russia-Ukraine conflict. As our data extends for several years longer than what was available to Nick & Thoenes (2014), our basis for the HD in the SVAR is well equipped to reflect historical events leading up to 2022 and the nuances they generate in the HD. Furthermore, our data are on a daily frequency, which allows us to capture short-term effects more accurately in the model.

The following section offers a comprehensive description of the collection- and transformation methods utilized to develop each variable in the model. The source and collection process, in addition to why and how transformations are done to the variables, is elaborated on in sufficient detail to ensure replicability of the dataset. Finally, we discuss how we have utilized relevant statistical tests, and their results, to pre-process the data so that we were able to ensure valid results from the model.

#### 4.1 Descriptive statistics

All 7 variables are on a daily frequency, with 2557 days representing the period from 2016-2022<sup>17</sup>. This period represents the years from which we were able to retrieve an adequate amount of continuous daily observations for all variables. The EU started to publicly disclose high-quality daily gas transmission data through the European Network of Transmission System Operators for Gas ENTSOG (2023a) in November 2015. Due to the critical need for

<sup>&</sup>lt;sup>17</sup> Historical data dating back to 2010 and 2011 for the variables of *heating degree days* and *storage* were available and utilized to compute historical averages.

high-quality data on transmissions for our analysis, our time series dataset runs from the 1<sup>st</sup> of January 2016 to the 31<sup>st</sup> of December 2022.

We depend on spot prices for natural gas, Brent crude, and coal as we assume that certain short-term effects are essential to the contemporaneous modeling of the shocks to the natural gas price. For example, spikes in demand induced by temperature or unexpected supply shortages are more accurately represented in the spot market than in the futures market. All currency exchange rate conversions done in this thesis are done using the European Central Bank's (ECB) daily rates (Condylios, 2022). See A1.1 for the summary statistics for our input dataset, where all variable transformations have been carried out. For a graphical illustration of the data pre-detrending, see appendix A1.4.

Variable	Description	Unit	Source
Heating degree days	Heating degree days in the EU-27.	Degree Celsius	The Global Historical Climatology Network (GHCN) (NOAA, 2023).
Supply Shortfall	Shortfall in Russian gas transmissions to the EU-27 countries through the main pipelines Yamal, Ukraine transit, Nord- Stream 1, Turkstream and Baltic.	TWh	European Network of Transmission System Operators for Gas ENTSOG (2023).
Price of Brent crude oil	Spot price of the North Sea Brent Crude oil.	\$/barrel	Energy Information Administration EIA (2023).
Price of coal	Price of Coal in Northwestern Europe, API2.	\$/ton	Refinitiv EIKON (Eikon, 2023).
LNG imports to EU-27	LNG imports to the EU-27 countries.	TWh	Gas Infrastructure Europe – Aggregated LNG Storage Inventory GIE ALSI (2023).
Storage	EU-27 natural gas storages, both flexible and inflexible storages.	TWh	Gas Infrastructure Europe – Aggregated Gas Storage Inventory GIE AGSI (2023).
Natural gas price	Natural gas spot price from Northwestern Europe, TTF.	\$/MWh	Refinitiv EIKON (Eikon, 2023).

Table 5.1 Data variables

#### 4.2 Comprehensive data description and transformation

#### 4.2.1 Heating Degree Days

Heating degree days (HDD) is a weather-based technical index designed to describe the energy requirements of buildings in terms of heating. These indexes can contribute to the correctly interpretating energy consumption for cooling and heating buildings (Eurostat, 2023). HDD calculations assume a threshold for when a household will use heating. Such a threshold could be, for instance, 15,5 degrees Celsius. If the temperature drops below 15,5 degrees, the HDD is calculated by subtracting the average temperature on a given day from the threshold. For instance, 15,5 - 10 degrees Celsius gives an HDD of 5,5. The HDD is zero if the average temperature a given day is more than or equal to 15,5 degrees.

The Global Historical Climatology Network Daily (GHCN) is an integrated database of daily climate summaries from land surface stations across the globe and is comprised of daily climate records from over 100 000 stations in 180 countries and territories (NOAA, 2023). We retrieved HDD observations for the years 2010 to 2022 on a daily frequency. The threshold for the HDD calculations is 15,5 degrees Celsius, according to GHCN. We excluded all non-EU countries from the data and calculated the mean daily temperature for those countries based on multiple key temperature locations in each country<sup>18</sup>. Then we created a variable with the daily historical average for the EU based on 2010 - 2021. Furthermore, we made a variable containing the daily observed HDD data for 2022. Finally, we found the deviations in HDD from the observed 2022 values and the historical average. By utilizing the temperature deviation, we can estimate the effects of unexpected temperature conditions on the TTF natural gas price for the historical period of interest, 2022.

Our year of interest, 2022, was generally warmer than the historical average, as there were significantly fewer HDDs. This coincides with the Copernicus Climate Change Service report for 2022, Global Climate Highlights. The report states that 2022 was the second warmest year on record for Europe (Copernicus, 2023). Figure 4.1 shows that there were 132 days where

<sup>&</sup>lt;sup>18</sup> The dataset did not include the EU nations Cyprus and Malta. One can assume the climate in those countries will be comparable to that of nearby ones, such as Italy and Greece.
the average temperature in 2022 was colder, while 233 days were warmer than the historical seasonal average.



Figure 4.1. Daily deviations between the HDD of the year 2022 and the historical seasonal average.

## 4.2.2 Supply Shortfall

As mentioned in the introduction, a conflict, or war, is not a directly measurable concept in and of itself. Therefore, one or more proxies will have to be used to capture the effects caused by a conflict or a war on the variable of interest. The word "conflict" is repeatedly used in this thesis, where some might consider "war" more appropriate. However, we make this distinction because we model the entirety of 2022, which stretches further back in time than the official breakout date of the war. Conflict, however, is fitting for the situation across all of 2022. As elaborated on in Chapter 3.4, the conflict has arguably caused the Russian supply shortfall of pipeline gas. This shortfall has to a large extent had a direct impact on the natural gas price and simultaneously reflected the conflict's influence on the natural gas price. Therefore, we use the supply shortfall volumes as a proxy for the conflict in our model as is done in Nick & Thoenes (2014) and Domfeh (2021). The Russian supply shortfall is defined as the 2022 deviation from the historical average export volumes in pipeline transmissions from Russia to the EU-27. As the EU-27 continued to buy and in fact increased their imports of Russian LNG during 2022, LNG imports from Russia are not included in the proxy (Elliott, 2023).

Considering the high level of integration between national gas markets in Europe, we assert that any instance of supply or import deficit in the European market will have comparable economic ramifications across the EU-27.

The *Supply Shortfall* variable is constructed with data from the European Network of Transmission System Operators for Gas (ENTSOG, 2023b). We tap into the ENTSOG open application programming interface (API) using the R wrapper package *entsog* written by Rose (2019/2023). A custom script is written to facilitate the retrieval of daily transmission volumes from the specific from-and-to points of Russian pipeline gas to the EU-27. The retrieved data consists of daily transmissions for the relevant pipeline entry points, see table A1.2 in the appendix. These points are aggregated into the main pipelines connecting Russia to the EU-27: the Baltic Connector, Ukraine Transit, Nord Stream, Turkstream, and Yamal. First, we construct a variable for the historical daily average transmissions of total Russian pipeline exports to the EU-27 for 2016-2021. Then, the historical daily averages are subtracted from the actual observed values for 2022 to obtain the variable *Supply Shortfall* used in our model.



Figure 4.2. Russian supply shortfall and surplus compared to historical export volumes

As shown in figure 4.2, the "missing" supply in 2022 compared to 2021 is according to our data 69%. To check the validity of the results, we compare it to previous estimates. For example, Ferris (2022) estimates that the Russian natural gas flows to the EU have decreased by more than 75% while Bruegel analyst Sgaravatti estimates a 76% decline (Kaya, 2023).

### 4.2.3 Price of Brent crude oil

The Brent Crude oil price variable is the closing price determined in dollars per barrel on a daily frequency for 2016-2022, and is retrieved from the EIA (2023). The Brent Crude oil is the most traded of the global oil benchmarks and consists of crude oil drilled in the North Sea (Wittner, 2020). Thus, the data are the closest measure geographically for the European market. As there are no data points for weekends, we carry the last weekday price forward through the weekend. Finally, the data are transformed by applying the natural logarithm to the series to stabilize the variance and make it more closely conform to a normal distribution. This procedure is common practice for vector autoregressive models (Mayr & Ulbricht, 2015) and is equivalently applied to the later described variables *Price of coal* and *Natural gas price*.

### 4.2.4 Price of coal

The coal price used in our model is the closing price determined in dollars per ton on a daily frequency for the period 2016-2022. The data are Benchmark European Thermal Coal "TRAPI2Mc1" prices and are retrieved from the Refinitiv EIKON platform. There are no data points for weekends, so the last weekday price is carried on through the weekend. There are 296 missing prices for weekdays across 2016-2022. These missing values are relatively evenly distributed across the period. Therefore, we apply linear interpolation<sup>19</sup> on all missing weekday values without concern of interpolating too large gaps in the weekday dates. We expect that any deviations from actual values through linear interpolation are minor compared to the benefit of including the coal prices in the model.

#### 4.2.5 LNG imports to EU-27

The data consist of LNG imports in TWh per day for 2016-2022. The data is retrieved from the Gas Infrastructure Europe Aggregated LNG Storage Inventory Transparency Platform (GIE ALSI, 2023). The GIE ALSI platform covers all large-scale LNG terminals within the EU-27 (GIE, 2022). We use the R wrapper package *gie* for the GIE API written by Rose (2022) to retrieve the data. The variable is included to serve as a measure of the current supply

<sup>&</sup>lt;sup>19</sup> Linear interpolation is a technique employed to approximate values between two given data points. It involves drawing a straight line connecting the two points on a graph and estimating the value of an unknown point by considering its position along that line. This approach assumes that the connection between the two known points is linear in nature and can be reasonably approximated by a straight line (Kong et al., 2020)

conditions. As mentioned in Chapter 3.2.2, the LNG market in Europe has experienced steady growth over time creating a trend. Therefore, we detrend the LNG imports variable by regressing the time series against time. The result of this transformation can be observed in figure 4.3. According to the IEA, LNG inflows to the European Union rose by 70% in 2022 compared to the previous year – almost twice the increase in global LNG production (IEA, 2023). Our data show that LNG imports to the EU-27 have increased by 73% from 2021 to 2022.



Figure 4.3 LNG imports to the EU from 2016-2022 pre- and post-detrending.

#### 4.2.6 Storage

Most storage facilities operate on a yearly planned cycle. Cartea & Williams (2008) argue that deviations from the expected storage cycle are most relevant for spot price development. Thus, we are interested only in the flexible cavern storage capacities. The storage data are retrieved from the Gas Infrastructure Europe Aggregated Gas Storage Inventory Transparency Platform (GIE AGSI, 2023). These data are also retrieved using the *gie* package of Rose (2022). The GIE AGSI platform provides day-by-day inventory reports for underground gas storage and covers around 98% of the underground gas storage market in the EU-27. Since the data do not differentiate between cavern- and porous storage facilities, we had to separate these two underground storage options. The technical procedure for separating the two is explained in more detail in the following paragraphs.

Following the approach of Cartea & Williams (2008) and Brown & Yücel (2008), we calculate the storage filling rate. To adjust for the fact that the total storage volume capacity may change over the years, we estimate the filling rate of the storages. The storage filling rate is defined as the gas in storage (MWh/day) divided by the total technical capacity of the storage<sup>20</sup> (MWh/day).

Storage filling rate (%) = 
$$\frac{Gas \text{ in storage}}{Technical capacity}$$
 (1)

Furthermore, we create a variable for the actual storage filling rate between 2011-2022, calculated as the actual storage of gas divided by the total storage capacity, which equals the filling rate. This dataset contains the actual filling rate over the 11 years. Then we create a yearly historical average filling rate computed as the mean filling rate per day across 2011-2021. This dataset contains 365 observations which represent the mean across the 10 years. Next, we calculate the daily difference between the current day's filling rate and the previous day's filling rate for both the actual storage filling rate dataset and the historical average filling rate dataset. These represent the change in the filling rate for both series from day to day. Lastly, we subtract the historical change in the filling rate from the actual change in the filling rate based on the day of the year as a proxy for the flexible cavern storage. This variable can be assumed to represent the deviation from the seasonal storage utilization pattern. The transformation is illustrated in figure 4.4.



Figure 4.4 Storage volumes in the EU from 2016-2022 pre- and post-detrending.

#### 4.2.7 Natural Gas Price

The natural gas spot price data are retrieved as the closing price in dollars per MWh. The data are on a daily frequency and retrieved from the *Refinitiv EIKON* platform under the name

<sup>&</sup>lt;sup>20</sup> The total technical capacity is named "working" in the GIE AGSI Platform

*"TRPC Natural Gas TTF Day 1"*. More specifically, the data is from the European benchmark virtual hub TTF and were originally noted in Euro/MWh. We transformed the prices to USD using the API for daily ECB currency exchange rates available from the *priceR* package in R (Condylios, 2022). There are no data points for weekends, so the last weekday price is carried on through the weekend.

## 4.2.8 Norwegian export volumes

This variable is not included in the SVAR model but is applied to calculate the share of the Norwegian natural gas export revenues that can be attributed to Russian supply shortfall for 2022 and the total revenues for 2022. The same is done for the 2021 revenues for comparison purposes. The Norwegian export volumes consist of daily actual export volumes listed by Gassco, see figure 4.5. Gassco is the sole operator of the Norwegian natural gas system and is owned by the Norwegian government. The Norwegian ministry of Oil and Energy manages the operator and oversees all gas exports from Norway to Europe (Oil- and Energy Department, 2022). These exports are measured in  $SM^3$  on a daily frequency from 2016-2022. The exports include all pipeline export nominations from the Norwegian shelf to Europe, including Scotland and England. Due to limited data on storage levels and LNG imports for the UK market, only the EU-27 countries are included in our model. As pipelines transport 95% of Norwegian gas exports to Europe, the remaining LNG exports from Melkøya are not included (NPD, 2023a). The export nominations provided by Gassco can deviate from physical deliveries due to maintenance and capacity restrictions, as informed by Ine Høines from Gassco (Personal communication, April 2023).



Figure 4.5 Norwegian export volumes to the EU-27 through the different pipeline entry points for 2016-2022. Illustration made with data from Gassco (2023).

# 4.3 Stationarity

An important concept in time series analysis and for most VAR models is stationarity, i.e., the assumption that the statistical properties of the time series are constant over time. A requirement of stationarity is time-invariant first- and second unconditional moments (Kilian & Lütkepohl, 2017). In this section, we elaborate on which type of non-stationarity we are concerned with for our modeling purposes and how we test for, and handle said non-stationarity. Suppose a variable is non-stationary, and stationarity is a prerequisite for valid results in a model. In that case, transformations can be applied to the variable to increase its level of stationarity. An example of this transformation is to apply the natural logarithms to stabilize the variance or to remove the trend in a variable. In our case, non-stationarity comes from potential structural breaks and unit roots in the economic variables. The presence of structural breaks or unit roots hinder time invariance, which complicates the interpretation of the structural shocks in the SVAR model.

Structural breaks in the series are a key characteristic to look out for in a SVAR model. In a time-series context, stability refers to time-invariant means, variances, and covariance structures (Pfaff, 2008). If the stability of a time series is observed to be severely broken at single or multiple points, this indicates structural breaks at those points. We fit the model to

increasingly long samples to test for structural breaks to obtain cumulative recursive residuals. The procedure is done using an *Ordinary Least Squares Cumulative Sum* (OLS-CUSUM) test as described in (Lütkepohl & Krätzig, 2004). It is performed using the Empirical Fluctuation Process (EFP) method, a non-parametric test<sup>21</sup> for detecting structural breaks in a time series through stability changes. The test is based on the CUSUM of the OLS residuals from the VAR model. This process estimates the stability of the time series with a moving data interval of constant bandwidth, which is then compared to the estimates based on the entire sample (Zeileis et al., 2002). The output of each test includes the results of the EFP test, which consists of a graph of the CUSUM statistic and a critical value band that is used to test for structural breaks. Figure 4.6 plots the CUSUM statistic over time, and the critical value band indicates the range within which the statistic falls outside of the critical value band, it indicates that the VAR model has periods of instability which could indicate the presence structural breaks. On the contrary, if the CUSUM statistic stays within the critical value band, it indicates that the stability of the VAR model can be trusted, and that there are no structural breaks.



<sup>&</sup>lt;sup>21</sup> Nonparametric tests are referred to as distribution-free tests as they are based on fewer assumptions (e.g., they do not assume the outcome to be approximately normally distributed). Parametric tests include specific probability distributions, and the tests involve estimation of the key parameters of that distribution from the data sample. The cost of fewer assumptions is that nonparametric tests are in general less powerful than their parametric tests (Sullivan, n.d.).



Figure 4.6. OLS-CUSUM stability test results for each variable

Based on the OLS-CUSUM test results, our VAR model appears to be generally stable without signs of significant structural breaks in any of the variables. More specifically, five of the seven variables in the VAR model are within the critical value band for the entire time series period. The model shows, however, some indication of structural breaks for *LNG imports* and *Storage* around the center of the time series. Examining the CUSUM statistics for each variable reveals that the CUSUM statistic only slightly, and for a short period, exceeds the

critical value band. More specifically, they are observed to be slightly outside of the critical value band for approximately 1/10<sup>th</sup> of the time series period. For these reasons, the indications of structural breaks we observe may not be a significant cause for concern. In addition, there are no indications of structural breaks in any of the variables during the period where the results are drawn from the HD, which is 2022.

In time series analysis, a unit root signifies that the data has a stochastic trend, resulting in persistent deviations from the mean that do not dissipate over time. Because of the effects of potential unit roots in one or more variables on both the econometric method and the economic interpretation of the model, it is regular practice to test the data for unit roots (G. Elliott & Jansson, 2003, p. 20). The most common approach is to test the variables one-by-one for unit roots with the Augmented Dickey Fuller (ADF) test (Dickey & Fuller, 1979). The regular Dickey Fuller (DF) test checks for unit roots in the model variables with stationarity as the alternative hypothesis.

The ADF test expands the DF test equation with a high-order regressive process. A result of concern was that the *Supply Shortfall* variable yielded a p-value of 0.17 on a 5% significance level. As the p-value is larger than 0.05, we cannot reject the null hypothesis of non-stationarity. In other words, the *Supply Shortfall* displays a certain degree of non-stationarity, where it does not exhibit constant variance over time. The *Supply Shortfall* is calculated as the historical mean subtracted from the 2022 actual values. We could have performed further transformations on the *Supply Shortfall variable* to reach a higher level of stationarity. However, we refrained from said measures to avoid losing information critical to the HD (Kilian & Lütkepohl, 2017, p. 120). Even though cointegration or non-stationarity might occur among some of our model variables, we cannot assertively claim that none contain a unit root, as unit root tests are weak in cases of near-unit root processes, as described in G. Elliott (1998).

The natural gas price, Brent crude price, and coal price have all been transformed to their natural logarithms as we are not interested in the potential properties of stationarity or cointegration by themselves but instead in the dynamic economic relationships between the variables driving the natural gas price as is done by Nick & Thoenes (2014), and Domfeh (2021). This procedure is in agreement with similar implementations of SVAR models thereof Abhyankar et al. (2013), Kilian (2009), Kilian (2010), and Kim & Roubini (2000).

# 5.0 Methodology

The SVAR model is a time-series econometric model that allows us to investigate complex relationships, such as those in the natural gas market, as one can set aside the standard OLS assumptions of no endogeneity and autocorrelation (Foroni, 2014). The model is an extension of vector autoregressive (VAR) models, which explain endogenous variables based only on their own history. In contrast, SVAR models enable the explicit modeling of contemporaneous interdependence between the left-hand side variables, enabling direct estimation of one variable's effects on another in the same time period (Pfaff, 2008).

To allow for contemporaneous modeling, SVAR models impose restrictions on the relationships among the variables in the model. These restrictions are typically based on economic theory about the relationships among the variables. By imposing these restrictions, SVAR models can identify the causal relationships among the variables and trace the propagation of shocks through the system. The SVAR thus provides the opportunity to extract clear interpretations from an underlying economic model through mutually uncorrelated shocks. For example, the natural gas market is a highly interdependent system subject to both supply and demand shocks. With the SVAR model's incorporation of *a priori* information about the relationship among the variables, the accuracy of the model and its ability to generate meaningful insights is enhanced.

Once the SVAR model is estimated, we explore the causal inference and the empirical model's dynamic behavior. Through a HD, the SVAR model will provide an estimate of the influence of Russian supply shortfall on the European TTF natural gas price over 2022. This estimate is then used to calculate the share of the Norwegian export revenues for 2022 that can be attributed to the Russia-Ukraine conflict. This chapter will provide further details on the methodology of both VAR and SVAR models, as the SVAR model is estimated from the reduced form VAR. Then, we will elaborate on the chosen restrictions imposed on the model and their underlying theoretical assumptions. We explain and illustrate how the SVAR model is identified through the ordering of the variables. Finally, we elaborate on how and why we use the HD for our research purpose and how this is connected to the SVAR.

#### 5.1 The Vector Autoregressive Model

The vector autoregressive (VAR) model is widely used for multivariate time series analysis. It consists of a system of regression equations producing estimates by regressing each variable on its lags and the lags of all other variables in the model up to a prespecified lag order (Gottschalk, 2001). This structure permits a VAR to be estimated by ordinary least squares (OLS). The reduced form VAR can be noted as the following.

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t \tag{2}$$

The left side variable  $y_t$  is a K-dimensional stochastic process of observed variables  $y_t = (y_{1t} \dots y_{Kt})$  for  $k = 1, \dots K$  and  $A_1, \dots, A_p$  are K \* K reduced form VAR coefficient matrices for  $i =, \dots, p$ . The reduced form errors  $u_t$  is a K-dimensional process with  $E(u_t) = 0$  and time-invariant positive definitive covariance matrix  $E(u_t u_t') = \sum_u$  (Pfaff, 2008). The latter white noise assumption rules out serial correlation in the errors (Kilian & Lütkepohl, 2017, p. 24). The *p* represents the number of lags included in the model. The lag length of the VAR model is specified to be nine, as indicated by the Akaike Information Criterion (AIC) elaborated on in Chapter 5.6. Following Pfaff (2018, p.21), the Wold moving average (MA) representation for a stable VAR process is defined as

$$y_t = \Phi_0 u_t + \Phi_1 u_{t-1} + \Phi_2 u_{t-2} + \dots, \tag{3}$$

 $\Phi_i$ , the coefficient matrix of the canonical MA representation can be computed recursively according to

$$\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j \quad i = 1, 2, \dots,$$
(4)

where  $A_j = 0$  for j > p. The matrix elements represent the impulse responses of the components of  $y_t$  with respect to the shocks  $u_t$  (Kilian & Lütkepohl, 2017, p. 718). See appendix A2.1 for the matrix representation of  $\Phi_i$ .

## 5.2 Structural Vector Auto Regression Model

In contrast to the VAR model, SVAR models allow for the explicit modelling of contemporaneous interdependence between the left-hand side variables. Hence, these models

try to bypass the shortcomings of VAR models (Pfaff, 2008). The SVAR representation expresses the reduced-form VAR errors as a linear combination of structural shocks that allows for economic interpretation. Thus, the SVAR is based on the premise that the structural shocks can be recovered from the reduced-form prediction errors (Kilian & Lütkepohl, 2017, p. 6). The SVAR has the following representation:

$$B_0 y_t = B_1 y_{t-1} + \dots + B_p y_{t-p} + w_t$$
(5)

 $B_i$  is a structural form VAR coefficient matrix and  $w_t$  is a K-dimensional structural error vector. The model is structural in the sense that the elements of  $w_t$  are mutually uncorrelated and have clear interpretations in terms of an underlying economic model (Kilian & Lütkepohl, 2017, p. 109). The economic model for this thesis is introduced in section 5.4. The estimation method of the SVAR model is done by the scoring algorithm as proposed by Amisano & Giannini (1997). In the case of a SVAR, the multivariate MA representation is the following:

$$y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i} \tag{6}$$

 $w_{t-i} = B_0 u_{t-i}$  and the matrix of structural impulse responses  $\Theta_i = \Phi_i B_0^{-1}$  as suggested by Kilian & Lütkepohl (2017, p.111). See appendix A2.2 for the matrix representation of  $\Theta_i$ .

#### 5.3 Identification method

To perform the structural analysis, we need to make the shocks uncorrelated. That is, the model will be developed with the moving average representation where the residuals are orthogonal. The most common way to do this is through the Cholesky decomposition, from which the orthogonal impulse responses are derived (Bjørnland & Thorsrud, 2015). The Cholesky decomposition is a way of identifying the SVAR model by imposing a recursive structure on the model. The recursive structure implies that the ordering of the variables in  $y_t$  matters (Carstensen, 2012). Ideally one should use economic theory to decide on the order of the variables and the type of restrictions imposed (Bjørnland & Thorsrud, 2015, p. 216). By using Cholesky's method one decomposes the positive-definitive matrix into the product of a lower triangular matrix and its conjugate transpose (Bjørnland & Thorsrud, 2015, p. 215). An example of a bivariate Cholesky decomposition is presented in equation 7.

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} b_{0,11} & 0 \\ b_{0,21} & b_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$$
(7)

To identify the structural form of the VAR, one must set contemporaneous restrictions on the structural-form VAR coefficient matrix, often referred to as the contemporaneous matrix. A requirement for deriving the structural representation is to impose in total K(K-1)/2 restrictions on the contemporaneous matrix so that the model's coefficients are identified (Pfaff & Stigler, 2018). In our model, these restrictions are determined based on empirically supported assumptions from natural gas market theory.

## 5.4 SVAR model specification

The contemporaneous matrix allows for any structure as long as it has sufficient restrictions (Kim & Roubini, 2000). In our model, as K = 7, the number of restrictions is K(K-1)/2 = 21. The identification scheme is recursive except for cases where our theoretical expectations of the economic dynamics between the variables deviate from the recursive ordering. This allows us to deviate from the lower triangular ordering in cases where economic theory and empirics justify it, as is done in Shokr et al., (2019) and Nick & Thoenes (2014). The ordering is important to determine how the different shocks will affect each other contemporaneously. A solid theoretical foundation for both the choice of variables and for determining the causal link between them through the contemporaneous restrictions, is necessary to interpret the model results clearly. The vector for the SVAR model contains the following variables: *the heating degree days*  $(v_h)$ , *the supply shortfall*  $(v_s)$ , *the price of Brent crude oil*  $(v_o)$ , *the price of coal*  $(v_c)$ , *the LNG imports to EU-27*  $(v_l)$ , *storage*  $(v_y)$  and the *natural gas price*  $(v_n)$ .

$$\begin{bmatrix} v_h \\ v_s \\ v_o \\ v_c \\ v_l \\ v_y \\ v_n \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & 1 & 0 & 0 & 0 & 0 \\ b_{41} & 0 & b_{43} & 1 & 0 & 0 & b_{47} \\ b_{51} & b_{52} & 0 & 0 & 1 & b_{56} & b_{57} \\ b_{61} & b_{62} & b_{63} & b_{64} & 0 & 1 & b_{67} \\ b_{71} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & 1 \end{bmatrix} \begin{bmatrix} u_h \\ u_s \\ u_o \\ u_l \\ u_y \\ u_n \end{bmatrix}$$
(8)

The contemporaneous matrix implies the following restrictions on the variables:

•  $(v_h)$ : Only shocks to *HDD* can affect *HDD* contemporaneously.

- $(v_s)$ : Only shocks to *HDD* and *supply shortfall* can affect *supply shortfall* contemporaneously.
- (v<sub>o</sub>): Only shocks to HDD, supply shortfall and Brent crude price can affect the Brent crude price contemporaneously.
- (v<sub>c</sub>): Only shocks to *HDD*, *Brent crude price*, *coal price* and *natural gas price* can affect *coal price* contemporaneously.
- (v<sub>l</sub>): Only shocks to HDD, supply shortfall, LNG imports, storage, and gas price can affect LNG imports contemporaneously.
- $(v_y)$ : Only shocks to *HDD*, *supply shortfall*, *Brent crude price*, *coal price*, *storage*, and *natural gas price* can affect storage contemporaneously.
- $(v_n)$ : Shocks to all variables can affect the *natural gas price* contemporaneously.

Further, we delve deeper into the rationale behind the order of the variables and the restrictions placed upon them. The most exogenous variable is the HDD which is derived from temperature changes. Thus, this variable is placed first in the ordered sequence. The supply shortfall can also be considered exogenous in relation to the other variables in the system, except for the heating degree days variable. In historical cases of supply shortfall, the natural gas price can be increased even further if the shortfall coincides with extraordinary cold weather, such as in the Russia-Ukraine dispute of 2009 modelled by Nick & Thoenes (2014). Thus, the instantaneous impact of temperature deviations on supply shortfall is left unrestricted.

The Brent crude oil price is expected to be affected by extraordinarily low temperatures contemporaneously as both oil and gas are used for peak power production. In addition, the supply shortfall on crude oil is left unrestricted due to Europe's high share of dual- and multi-fuel electric power capacity, permitting short-run switching behaviour between these two fuels in power production (Pettersson et al., 2012).

The price of coal is also assumed to be contemporaneously affected by extraordinary cold temperatures through increased demand, as coal accounts for about one-fifth of total electricity production in the EU (EC, 2023a). The conversion from gas to coal firing typically requires more expensive investments. Therefore, it is regarded as an intermediate-term response (IEA, 1987, referred to in Pettersson et al 2012), and will not have a contemporaneous effect. Gas is often provided to the electric utilities instantaneously with pipelines. Thus the need for storing

the gas becomes less critical, but this is not the case for coal, which must be stored before being crushed and fed to the plant (Pettersson et al., 2012). The supply shortfall is therefore left restricted from contemporaneously impacting the coal price.

Furthermore, a crude oil price shock on the coal price is left unrestricted. This is because the power of cartels, the most important being OPEC, leads to a highly integrated economic market for crude oil Bachmeier & Griffin (2006), referred to in Zamani (2016). Given its concentration of power, the oil market is believed to be more exogenous than the coal market and can impact the coal market as an alternative fossil energy source. Zamani (2016) performed a SVAR on the relationship between crude oil and coal markets and found a significant effect on coal prices by oil supply shocks due to substitutability on a global level. Finally, natural gas shocks are expected to impact the coal price contemporaneously as natural gas and coal are the most dominant fossil fuels in electricity generation, and there is significant competition between the two commodities (Zakeri et al., 2022).

The LNG imports are expected to be contemporaneously affected by unexpectedly cold weather and natural gas supply shocks through increased demand. While pipelined natural gas has historically been oil-indexed on long-term contracts, Wood (2012) argues that a fair amount of LNG entering Europe is traded against natural gas benchmarks like the TTF and therefore should, in theory, be more independent of oil prices. The LNG imports are thus restricted from being contemporaneously affected by shocks to the crude and coal prices. The LNG imports are however expected to be affected by contemporaneous shocks to storage and the natural gas price as argued by (Hauser, 2021).

The flexible storages will be sensitive to sudden and unexpected changes in temperature and supply shortfalls. The storage facilities demand gas in the warm period of the year when gas is injected and become suppliers in the colder periods when gas is withdrawn (Hulshof et al., 2016). The flexible storages are also used to balance temporary supply and demand divergence caused by unforeseen shifts in market conditions (Nick & Thoenes, 2014). Thus, the storage variable leaves oil and coal prices unrestricted. Brown & Yücel (2008) find that the storage volumes of natural gas influence the price of gas.

Furthermore, the storage of gas is important for hub prices as storages can be used for intertemporal arbitrage (Hulshof et al., 2016). Due to the capacity restrictions elaborated on in Chapter 3.2.1. and the uneven distribution of EU storages, it is assumed that shocks in LNG imports do not have a contemporaneous effect on the storage variable. Therefore, the LNG import variable is left restricted.

Finally, the least exogenous variable, the natural gas price, is the main variable of interest. It is the last in the sequence of variables and is therefore affected contemporaneously by shocks to all the variables above it.

The orthogonalization process means imposing a particular causal chain on the model. This mechanical solution does not make economic sense without a plausible economic interpretation of the ordering (Kilian & Lütkhepohl 2017, p. 220). In practice, a different solution exists for each order of the *K* variables in the model. It is sometimes argued that one should conduct a sensitivity analysis based on alternative orderings of the *K* variables as a form of robustness test. Kilian and Lütkepohl (2017, p. 220) argue that this proposal is problematic. Even for a small SVAR model with K = 4, there are 4 \* 3 \* 2 \* 1 = 24 permutations of the ordering. Not many researchers would want to attempt this many model specifications, nor is it likely that the results would be equal (Kilian & Lütkepohl, 2017, p. 220). Thus, one must rely on the theoretical assumptions behind the model restrictions to be well substantiated.

#### 5.5 Lag selection

To select the lag order for the VAR model we use an information criteria<sup>22</sup>. Information criteria are based on the premise that there is a trade-off between the improved fit of the SVAR model as the lag order by which the criterion function is evaluated (*m*) increases, and the parsimony of the model (Kilian & Lütkepohl, 2017, p. 54). We employ the *Akaike Information Criterion* (AIC) introduced by Akaike et al. (1973) to determine the lag length of our model. The equation of the AIC is shown in equation 9.

$$AIC(m) = \log \left(\det \left(\sum_{u}^{\infty} (m)\right)\right) + \frac{2}{T}(mK^{2} + K)$$
<sup>(9)</sup>

Where 2/T is a sequence of weights that depends on the sample size. The AIC uses the loglikelihood to assess the model fit, but also adds a penalizing term associated with the number

<sup>&</sup>lt;sup>22</sup> See appendix A2.3 for the general information criterion formula

of variables (Lord et al., 2021). Selecting the appropriate lag order allows for capturing dynamic relationships between the variables in the model by determining the number of lagged values to be included in the model (Kilian & Lütkepohl, 2017).

### 5.6 Historical Decomposition

One of the main applications of a SVAR model is to generate HDs which measure each structural shocks' cumulative contribution to each variable's evolution over time (Kilian, 2013). Kilian deems the HD as essential in understanding recessions or surges in energy prices. The HD can reveal the cumulative effect of a shock in each variable in the SVAR system on a variable of interest over a specific time period. Each component in the HD reveals what the historical development of the target variable would look like if the shock in one of the variables were the only shock affecting the target variable. Henceforth, the cumulative HD can be considered as the isolated contribution of a shock to each variable in the system to the target variable. With time series data from 1 to t, then for any t,

$$y_t = \sum_{s=0}^{t-1} \Theta_s w_{t-s} + \sum_{s=t}^{\infty} \Theta_s w_{t-s},$$
(10)

where the value of  $y_t$  ( $y_{1t} \dots y_{Kt}$  for  $k = 1, \dots K$ ) is dependent on the shocks from the Kdimensional structural error vectors  $w_{1,} \dots, w_t$  (Kilian & Lütkepohl, 2017, p. 116). The structural MA coefficient matrices ( $\Theta_0, \dots, \Theta_{t-1}$ ) will have a continuously lesser effect when moving further into the past in the HD. This approximation can be denoted as in equation 11 (Kilian & Lütkepohl, 2017. p. 117).

$$\hat{y}_t = \sum_{s=0}^{t-1} \Theta_s w_{t-s}.$$
(11)

After computing the structural coefficient matrices and the structural shocks, each shock will be matched with the opposite impulse response weight, as determined by the structural MA representation. The sum in equation 11 can be decomposed to isolate the cumulative contribution of each shock to each element of  $\hat{y}_t$  which we discuss in section 5.8 on method application. Kilian & Lütkepohl (2017, p. 120) describe the importance of HDs as underappreciated in empirical macroeconomics. According to them, "only the historical decomposition allows us to assess the cumulative effect of these shocks on the business cycle and the relative importance of the different shocks in explaining particular recessions or expansions". The HD is best understood as a time series plot where the observations that occurred before and after the period of interest are discarded. Usually, the demeaned variable of interest is plotted alongside the HD coefficients of the cumulative shocks in each variable on the variable of interest. The sum of these coefficients is plotted to compare against the demeaned variable of interest.

# **5.7 Method application**

The HD of the *Natural gas price* variable in our SVAR model is used to infer how large a share of the Norwegian oil and gas revenues of 2022 can be attributed to the Russian supply shortfall of natural gas. As the HD is not a part of the *vars* package for the R programming language we use to develop the SVAR model (Pfaff & Stigler, 2018), we developed a custom script to manually conduct the HD based on Murao (2021). We are interested in examining the cumulative effect of the seven structural shocks on the seventh variable in the SVAR system, the *Natural gas price*. To retrieve this information, we computed the weighted sums for t = 1, ..., T, which can be shown as

$$\hat{y}_{7t}^{(1)} = \sum_{i=0}^{t-1} \Theta_{71,i} w_{1,t-i,}$$
(12)

$$\hat{y}_{7t}^{(2)} = \sum_{i=0}^{t-1} \Theta_{72,i} w_{2,t-i}, \qquad \hat{y}_{7t}^{(3)} = \sum_{i=0}^{t-1} \Theta_{73,i} w_{3,t-i}, \qquad \hat{y}_{7t}^{(4)} = \sum_{i=0}^{t-1} \Theta_{74,i} w_{4,t-i},$$
$$\hat{y}_{7t}^{(5)} = \sum_{i=0}^{t-1} \Theta_{75,i} w_{5,t-i}, \qquad \hat{y}_{7t}^{(6)} = \sum_{i=0}^{t-1} \Theta_{76,i} w_{6,t-i}, \qquad \hat{y}_{7t}^{(7)} = \sum_{i=0}^{t-1} \Theta_{77,i} w_{7,t-i}.$$

Here,  $\theta_{jk,i}$  represents the response of variable *j* to the shock *k* at time horizon *i*.  $w_{k,t}$  denotes the structural shock at time *t* (Kilian & Lütkepohl, 2017, p.118). Each vector contains the cumulative contribution of the *Natural gas price* in the SVAR system over time, and the value for  $\hat{y}_{7t}$  is computed as the sum of

$$\hat{y}_{7t} = \sum_{j=1}^{K} \hat{y}_{7t}^{(j)} \tag{13}$$

The SVAR model is estimated with enough iterations to achieve an optimal model fit based on the maximum log-likelihood. HDs involve an approximation error that arises as a result of the truncation of the MA representation (Kilian & Lütkepohl, 2017, p. 118). The decomposition depends on the structural shocks on the starting date, and the history of structural shocks. Therefore, the initial approximation is bound to be poor but then be improved as  $\hat{y}_{kt}$  is recursively updated. The optimal way to evaluate at which time points the HD is accurate is by plotting the sum of the cumulative contributions of the *Natural gas price* against the demeaned natural gas price. The deterministic component is removed from the *Natural gas price*, as the HD data produced by the structural MA representation are zero mean. The HD recursively updates  $\hat{y}_{kt}$ , thereby improving the approximation by approaching  $y_{kt}$ . This translates into the HD of the *Natural gas price* approaching our model's demeaned natural gas price. Finally, we discard the data predating the point of convergence by considering approximately the first month of the data as transient in the HD. We determine this point of convergence by visually inspecting the time series plot of the HD as recommended by Kilian & Lütkepohl (2017).

# 5.8 Norwegian export revenues

The Norwegian export revenues attributed to the supply shortfall in Russian natural gas transmissions to the EU-27 countries over 2022 are calculated the following way. First, the share of the decomposed *Natural gas price* attributed to *Supply Shortfall* is multiplied with the actual TTF spot price in euro. This product is multiplied with the Norwegian export volume to the EU-27 countries of natural gas in MWh<sup>23</sup>. All multiplied values are on a daily frequency. Revenues calculated in euros are converted to NOK using the ECB daily exchange rates (Condylios, 2022). The currency transformation is conducted to compare the result of our method with the officially listed Norwegian natural gas export revenues. Equation 14 shows how the Norwegian export revenues are calculated.

# Supply shortfall share \*TTF spot $(\in) *Norwegian export volume (MWh)$ (14)

The ability to build the model with data on a daily frequency not only allows us to capture short-term effects in the SVAR model, but also enables us to capture the unique daily combinations of the natural gas price, Norwegian export volume to the EU, and the attributed

 $<sup>^{23}</sup>$  The natural gas export volume from Norway to the EU-27 are expressed in SM3. To calculate the Norwegian income from natural gas, we must express the gas volumes in SM3 as the natural gas price are expressed in MWh. See appendix A1.3 for the unit transformation formula.

57

supply shortfall share from the HD. With natural gas prices as volatile as they were in 2022, these unique daily combinations that shape the development secure a more accurate representation of the Norwegian gas revenues throughout 2022. Using this method of calculation, we also more accurately take into consideration that Norwegian suppliers are not completely inelastic and can, in the medium- to longer term, react by increasing the production volume.

# 6.0 Results & discussion

In this chapter, we present and discuss the results of the HD, followed by our estimation of the Norwegian natural gas revenues that we attribute to the Russian supply shortfall over 2022. The output of the HD is described and compared to the findings in the existing literature to evaluate if the degree to which the different variables explain the *Natural gas price* can be supported by theory on gas market fundamentals. Next, the results of the revenue analysis are discussed against the backdrop of the thesis and compared to empirical data. The HD of 2022 is then compared to the HD of 2021, when the supply shortfall's effects were not yet as prominent. Finally, the results are discussed together with a validity and reliability evaluation of the revenue estimate.

# 6.1 Historical Decomposition

The HD time series plot of the *Natural gas price* allows us to determine which combinations of structural shocks accounts for the fluctuations in  $\hat{y}_{kt*}$ , ...,  $y_{kt}$  during particular periods of interest within the data set. As is done in Kilian & Lee (2014) for the oil price for another historical context, our model assesses how much of the changes in the *Natural gas price* can be attributed to each of the seven structural shocks in our model for every day of 2022. The overall aim of the HD is to determine how much of the surge in the TTF price during 2022 can be attributed to the supply shortfall of Russian natural gas exports, which in our model is considered a proxy for the Russia-Ukraine conflict. Figure 6.1 displays the HD of the variable *Natural gas price* for 2022. The series named *Total* represents the sum of the cumulative shocks from each variable amounting to the decomposed *Natural gas price*  $\hat{y}_{kt}^{7}$ .<sup>24</sup>

<sup>&</sup>lt;sup>24</sup> A column chart representation of the HD is also available in appendix A3.1 Also, in appendix A3.2, table 6.1 is provided on a weekly frequency, instead of monthly, to display the development of the coefficients more accurately.



Figure 6.1 Historical Decomposition of the *Natural gas price* for the year 2022.

	Heating degree days deviation	Supply Shortfall	Price of Brent crude oil	Price of coal	LNG imports to EU-27	Storage	Natural gas price
January	0.00	0.20	-0.08	0.83	-0.04	0.00	0.25
February	-0.01	0.24	-0.01	0.71	-0.03	0.07	0.13
March	0.01	0.24	0.06	0.92	-0.01	0.23	0.08
April	0.02	0.22	0.05	0.79	-0.01	0.21	0.02
Мау	0.00	0.20	0.05	0.71	-0.01	0.22	-0.04
June	0.00	0.20	0.06	0.85	-0.02	0.25	-0.05
July	0.00	0.24	0.05	1.26	-0.03	0.29	-0.08
August	0.00	0.28	0.03	1.65	-0.04	0.28	-0.15
September	0.01	0.32	-0.01	1.36	-0.04	0.28	-0.15
October	-0.01	0.35	-0.02	0.34	-0.03	0.26	-0.13
November	-0.01	0.35	-0.02	0.66	-0.01	0.20	-0.10
December	0.00	0.37	-0.02	0.93	-0.02	0.19	-0.13
Mean	0.00	0.27	0.01	0.92	-0.02	0.21	-0.03

Table 6.1 Aggregated mean coefficients from the HD by each month for all variables over 2022.

Table 6.1 displays the how much of the *Natural gas price* is explained by each variable in the HD per month of 2022. One can observe that the results returned by the HD are consistent with the economic theory discussed in Chapter 5.4, and that the fluctuations in the *Natural gas price* correspond to changes in the underlying supply- and demand factors. The results show that the aggregated effect of temperature shocks is small. This could because there have been fewer than average heating degree days in 2022, as illustrated in figure 4.1. The *Supply Shortfall* coefficients starts high and increases throughout the year. One can expect that this is due to the constrictions on the Yamal pipeline that were implemented as early as December

2021. Later, as Yamal and Nord Stream I are further constrained, and finally shut down, the supply shortfall increases substantially. Thus, the rising supply shortfall explains a significant share of the natural gas price increases during this period. This these results are in line with the findings of Nick & Thoenes (2014), as discussed in Chapter 2.

In 2022, the *Brent crude oil price* only has a marginal effect on the *Natural gas price*. The previously discussed decline in oil-indexed natural gas contracts could be part of the explanation for these results. The *coal price* is the variable that explains most of the fluctuations in the *Natural gas price* over 2022. The degree of influence from the *Brent crude oil price* and the *coal price* are consistent with the findings of Domfeh (2021) and Nick & Thoenes (2014), who find the coal price to have a persistent impact on natural gas prices, while crude oil prices are of smaller importance. *LNG imports* have a small but negative effect, which indicates that *LNG imports* slightly helped drive the natural gas prices down, consistent with natural gas price. During 2022 however, the flexible filling rates were generally low due to high prices until the EU mandatory filling rate levels were implemented. These mandatory measures also contributed to increase the price even further as argued by the OECD (2022), which we discussed in Chapter 3.4. In conclusion, we find that the coal price, supply shortfall, and storage, together explain the majority of the fluctuations in the *Natural gas price* over our historical period of interest, 2022.

## 6.1.1 Estimation- and Approximation Error in the HD of 2022

The sum total of the HD for the *Natural gas price* is equal to the demeaned natural gas price except for model estimation error and approximation error due to the truncation process (Kilian & Lütkepohl, 2017. p. 119). The distance between the cumulative sum of the HD and the demeaned natural gas price in figure 6.2 is the result of the aforementioned errors. As explained in section 5.7, the HD estimation improves as the series are recursively updated. As our dataset consists of six full years of daily data prior to the year of the HD, it enables for a far more accurate approximation than if the dataset was very short, which can sometimes preclude the use of the HD as a tool (Kilian & Lütkepohl, 2017, p. 118).



Figure 6.2 The discrepancy between the cumulative sum of the historical decomposition (Total) and the demeaned natural gas price for 2022.

#### 6.2 Norwegian export revenues

We calculated the Norwegian natural gas export revenues<sup>25</sup> following equation 14 in Chapter 5.8. The increase in natural gas prices attributed to supply shortfall amounted to an average revenue of 916 million NOK per day over 2022, as shown in figure 6.3. The total export revenue for 2022 is calculated to be 1 229 billion NOK. The increase in natural gas prices attributed to supply shortfall thus amounted to a revenue of 334 billion NOK, or 27.18%, of the total revenue. On the day when the natural gas price was at its peak, on the 26<sup>th</sup> of August 2022, the increase in natural gas prices attributed to supply shortfall amounted to a revenue of over 2,5 billion NOK for that day. By utilizing this calculation method, we also consider that the Norwegian suppliers are not entirely inelastic and can, in the medium- to longer term, react by increasing the production volume and thus the export volumes. The export volume increased 6,6% from 2021 to 2022 as a response to the surge in demand.

<sup>&</sup>lt;sup>25</sup> These revenues only include pipeline gas, not revenues from Norwegian LNG exports.



Figure 6.3. Norwegian natural gas revenues over 2022 attributed to the supply shortfall of Russian pipeline gas.

In a well-estimated and realistic model, we expect the estimated total export revenue to be close to the export value reported by the Norwegian government. The government-reported natural gas revenues were 1 356,5 billion NOK for 2022 (SSB, 2023). This total is higher than the total from our model (1 229 billion NOK) but includes the revenues from natural gas sales to the UK as well, and not just to the EU-27 countries. In order to compare the totals, we added the UK export volumes to our revenue model. The result is a total revenue of 1 585,8 billion NOK – which is a higher revenue than what is reported by the government. A possible explanation for this discrepancy is our model's assumption that Norwegian export volumes are sold at the daily spot price. In reality, the Norwegian exports are sold on short- and long-term contracts with negotiated prices which are to a varying degree linked to the spot market. The difference between the officially listed revenues, and the total model revenues including UK exports, amounts to 229,8 billion NOK. Interestingly, this can be considered the natural gas revenues that Norway was unable to capitalize on, due to market constraints and contracted prices, had the model been calibrated to include the UK.

Our results indicate that a significant share of Norway's natural gas revenues from 2022 can be attributed to the price increase caused by the Russian supply shortfall. As discussed in the introduction, several political figures claim that a large share, if not all, of Norway's natural gas earnings in excess of the average earnings should be considered war profits. In light of those arguments, and to evaluate the validity of our results, we will briefly compare them to historical government-published revenues. According to SSB (2023), the average yearly natural gas revenue from 2010 to 2021 was 221 billion NOK, while the 2022 revenue alone was 1 356 billion. In our model, we find that the revenues attributed to our proxy for the conflict, *Supply Shortfall*, of 334 billion NOK, is alone larger than the actual average revenues of 221 billion NOK from 2010 to 2021. This is despite being calculated as a share of a smaller total revenue than the SSB reported revenue for 2022 which includes sales to the UK market and contracted prices. Even though the numbers are not strictly comparable, they indicate that the supply shortfall alone is not important enough to explain the discrepancy between the historical and the 2022 export revenues. When examined through the lens of our proxy results, it is hard to argue that the entirety of the excess profits of 2022, compared to 2021, is solely a result of the Russia-Ukraine conflict.

A perfect model would incorporate every effect the Russia-Ukraine conflict has had on the natural gas price over 2022, but that is not attainable. *Supply Shortfall*, the proxy for the conflict in our model, does not include factors such as negative market sentiment, speculation, economic slowdowns, political actions, currency fluctuations, inflation- and interest rate responses, to mention a few examples. However, it could be assumed that the revenues attributed to the conflict in our model would increase if the proxy, or proxies, used for the conflict, were able to incorporate more relevant factors related to the Russia-Ukraine conflict that affected the price of natural gas over 2022. Given these constraints, the model appears well estimated. The revenue model shows little discrepancy when compared to external sources for total natural gas revenues. Also, the economic interpretations of the HD results coincide with the empirically supported rationale we presented for both the variable ordering and for determining the contemporaneous restrictions.

As elaborated on in Chapter 3.4, the current high coal- and gas prices are not exclusively the result of a single shock event on the demand- or supply side. Rather, they result from a combination of supply- and demand factors that gradually tightened markets over several months and even years . Furthermore, the decline in oil and gas investments in recent years, and the delayed scale-up of clean energy sources, have made supplies more vulnerable to the exceptional circumstances observed today. However, the culmination of these factors into a 2022 of record natural gas prices and, as a result of it, soaring revenues for Norway as a producer is beyond question related to Russia-Ukraine conflict and has therefore been analyzed accordingly.

## 6.3 Historical Decomposition for 2021

In this section, we estimate the Norwegian natural gas revenues for 2021 by conducting a HD of 2021 to compare with the results for 2022. This comparison allows us to evaluate if the theoretical assumptions behind the variable ordering and the restrictions placed on the model can be sensibly economically interpreted for years other than 2022. It also allows us to assess if the revenues are close to the actual numbers for 2021 and if the development across 2021 and 2022 coincides with our theoretical assumptions.



Figure 6.4. Historical Decomposition of the Natural gas price for 2021.

	Heating degree days deviation	Supply Shortfall	Price of Brent crude oil	Price of coal	LNG imports to EU-27	Storage	Natural gas price
January	-0.03	0.03	0.01	0.91	0.28	-0.26	-0.55
February	-0.02	0.05	0.02	0.54	0.30	-0.28	-0.40
March	-0.02	0.06	0.04	0.45	0.32	-0.28	-0.34
April	0.00	0.07	0.03	0.57	0.31	-0.25	-0.35
Мау	0.01	0.08	0.03	0.71	0.30	-0.17	-0.36
June	0.00	0.08	0.03	0.71	0.30	-0.05	-0.34
July	-0.01	0.08	0.02	0.76	0.29	0.03	-0.24
August	-0.02	0.08	-0.02	0.81	0.27	0.11	-0.12
September	-0.02	0.08	-0.05	1.02	0.24	0.21	-0.01
October	-0.03	0.09	-0.05	1.14	0.19	0.36	0.05
November	-0.01	0.09	-0.05	1.29	0.15	0.19	0.04
December	0.00	0.09	-0.05	1.62	0.13	0.21	-0.02
Mean	-0.01	0.07	0.00	0.88	0.26	-0.02	-0.22

Table 6.2. Aggregated mean coefficients from the HD by each month for all variables over 2021.

Table 6.2 displays the how much of the Natural gas price is explained by each variable in the HD per month of 2021. Supply Shortfall explains far less of the fluctuations in the Natural gas price over 2021 than it does over 2022. As shown in figure 6.4 the trend is upwards, supported by moderate reductions in Russian transmissions from multiple pipelines already in 2021. As we saw for 2022, the price of Brent crude oil has a marginal effect on the natural gas price also in 2021. The coal price explains most of the fluctuations in the natural gas price over 2021, which we found consistent with previous literature when discussing the results of 2022. In 2021, LNG imports explain more of the increase in the Natural gas price than for 2022. This could be caused by the significantly lower levels of LNG imports in 2021 than in 2022, as seen in appendix A1.4e. Equal to in 2022, the results show that the aggregated effect of temperature shocks is small. During the first half of 2021, Storage volumes contributed to pulling down the Natural gas price as the stored gas supplied the market during the winter. As mentioned in Chapter 3.4, the gas consumption in power plants increased significantly in the summer months of 2021 due to low wind generation levels. This consumption led to a depletion of storage facilities which were already below their five-year average levels (IEA, 2022a). Over the last half of 2021, prices continued to increase as natural gas was bought and stored.



Figure 6.5 Norwegian natural gas revenues in 2021 attributed to the supply shortfall of Russian pipeline gas.

We calculate the Norwegian natural gas export revenues for 2021 as shown in equation 14 in Chapter 5.8. As illustrated in figure 6.5, the increase in natural gas prices attributed to *Supply Shortfall* amounted to an average revenue of 101 million NOK per day during 2021, over nine times less than in 2022. The total export revenue in 2021 is estimated to be 450 billion NOK, which is 37% of what we estimated for 2022. The increase in natural gas prices attributed to *Supply Shortfall* amounted to a revenue of 37 billion NOK, which is 11% of what it was in 2022, and 8.2% of the total. As done for 2022, we compared the total revenue calculated in our model with those published by the Norwegian government. We expected our estimate to be lower due to the exclusion of UK exports in our model. The government-reported total revenues were 577 billion NOK for 2021, compared to our estimate of 450 billion NOK.

To conclude, the results for 2021 show that the coal price explains the majority of the fluctuations in the *Natural gas price*, as it did in 2022. As expected, the share explained by *Supply Shortfall* is significantly lower in 2021, but it displays an increasing trend throughout 2021, heading into 2022. The increasing importance of *Supply Shortfall* in explaining the fluctuations in the *Natural gas price* over 2021 is in line with the market events of that period, including escalating Russian supply disruptions. The over three-fold jump in the revenues attributed to *Supply Shortfall* from 2021 to 2022 supports the decision to select Russian supply shortfall as a fitting proxy for the Russia-Ukraine conflict.

# 6.3.1 Estimation- and Approximation Error in the HD of 2021

The same estimation- and approximation error which applied for the HD of 2022 also applies for the HD of 2021. This is illustrated in figure 6.6 in figure as the distance between the cumulative sum of the HD and the demeaned natural gas price.



Figure 6.6 The discrepancy between the cumulative sum of the historical decomposition (Total) and the demeaned natural gas price for 2021.

## 6.4 Robustness

We have tested the robustness of our model on multiple levels. Firstly, the economic theory used to set contemporaneous restrictions on the SVAR is supported by empirical data and well-established theory on the drivers of the natural gas price. The results of the HD have been compared with the same theoretical basis to see if they are consistent with the theory's assumptions. Secondly, we have performed statistical pre-processing tests on the variables used in the model, testing for unit roots and structural breaks. We also tested if the results vary across different lag lengths and selected the optimal lag length using the AIC criteria. Thirdly, we compared the results of our model with external measures which, can be seen as benchmarks. This applies to the government-released revenue numbers from natural gas sales and for Norwegian natural gas export volumes. By estimating the revenue model for 2021 and comparing this to the results of 2022, we assessed if the theoretical assumptions behind the variable ordering and contemporaneous restrictions placed on the model held for another year than 2022. It also allowed us to evaluate the quality of the revenue model for another year compared to official numbers and to inspect if the development across 2021 and 2022 was interpretable in terms of the underlying economic model. Lastly, we compared our results with

the findings of other published studies that also examine the drivers of the natural gas price for different historical periods of interest, but which share a similar model specification.

# 7.0 Conclusion

Our findings contribute to current research by focusing on the degree to which Russian supply shortfall of natural gas can be attributed as the driver of natural gas price fluctuations in the EU-27 market during 2022. A backdrop of soaring natural gas prices, record revenues, and prominent political figures labeling Norway as a war profiteer, makes an empirical investigation into how much of the natural gas revenues can be attributed to the Russia-Ukraine conflict interesting. We expand the research of Nick & Thoenes (2014) on the German market by modeling the EU-27 natural gas market with its fundamental drivers using a SVAR model, but for a different period, and with higher frequency data. We add the volume of Russian supply shortfall in the EU-27 market to the model as a proxy for the Russia-Ukraine conflict. By extracting the share of the natural gas price explained by supply shortfall from a HD of the SVAR model, we calculated the daily revenues across 2022 by multiplying the share of supply shortfall with the natural gas price and the Norwegian daily export volumes.

The results from the HD are that throughout 2022, the Russian supply shortfall and the price of coal explain the majority of the fluctuations in the natural gas price in the EU-27 market. The HD of 2021 also showed the price coal to be the main contributor, but also that gas storage and LNG imports were larger contributors than for 2022. There is a sharp and steady increase in the degree to which supply shortfall explains the fluctuations in the natural gas price from 2021 to 2022. This reflects the development in supply disruptions of Russian natural gas which started slowly in 2021 and reached full effect by mid-2022. We estimate that over 27%, or 334 billion NOK, of Norway's record natural gas revenues in 2022 can be attributed to the increase in natural gas prices caused by the Russian supply shortfall. A comparison of the total revenues in the model with the official numbers released by the Norwegian government supported the validity of the estimates. By calculating the revenues with shares from the HD, volumes, and prices, all on a daily frequency, we control for how the Norwegian exporters reacted to price changes, and also pick up short-term reactions to the shocks in the structural model. Reflection on the results, we took the shortcomings of using supply shortfall as a proxy for the conflict and the risks associated with estimation- and approximation error in our model into consideration.

Our thesis contributes with insights into the EU dependency on Russian natural gas in terms of security of supply, and its effect on the market price. To the best of our knowledge, we are

the first to apply a SVAR model to investigate the effects of the Russian supply shortfall over 2022 on the natural gas price, and its impact on Norwegian natural gas revenues.

We believe our model can be extended in multiple ways. Firstly, it can be extended to different natural gas markets or adapted to different energy commodities. For example, if the relevant data are available, the model can be expanded to include the UK market, thereby capturing the revenues from all Norwegian entry points to Europe. Secondly, the SVAR can be altered to model different drivers of the natural gas price, and the HD can be used to estimate a different measure than the Norwegian natural gas revenues of 2022. Wind and solar are becoming increasingly important sources of electricity that compete with fossil fuels, shaping the price of natural gas. It could be of interest for further research to either include them or substitute existing variables with them in a similar model. Thirdly, our model can also be replicated to further explore the dynamic relationships between the variables in the model during different historical periods of interest.

Price volatility and supply disruptions have characterized the development of the EU natural gas market since the outbreak of the Russia-Ukraine conflict, and the situation is still precarious. Further decline in Russian pipeline gas is a risk, and it is uncertain whether the European storages will be sufficient for the winter of 2024. The danger of LNG shortages could add to the severity of the forecasted situation. Even though Norway increased exports to the EU by 6,6 % from 2021 to 2022, more supply is needed to meet the demand. For these reasons, empirical investigations into the effect of supply disruptions are increasingly relevant. This thesis sheds light on the EU market's vulnerability to Russian gas supply disruptions and the significant role of these disruptions in Norway's record gas revenues from 2022. It contributes an empirical basis of knowledge to the debate around EU energy security, policy implications, and Norwegian war profiteering of the Russia-Ukraine conflict.

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# Appendix

## A1 Data

#### A1.1 Summary Statistics

	Observations	Min	Max	Mean	Median	Standard Deviation
Heating degree days deviation	2,557	-8.64	10.53	-0.23	-0.17	1.65
Supply Shortfall	2,557	-1.90	4.25	0.25	0.00	1.33
Price of Brent crude oil	2,557	2.21	4.89	4.10	4.14	0.34
Price of coal	2,557	3.73	6.24	4.59	4.47	0.55
LNG imports to EU-27	2,557	-1.93	2.24	-0.04	-0.10	0.69
Storage	2,557	-0.02	0.02	0.00	0.00	0.00
Natural gas price	2,557	1.22	5.80	3.21	3.00	0.85

### A1.2 Pipeline entry points

Main pipelines	Entry points
Baltic Connector	Varska and Imatra
Ukraine Transit	Velke Kapusany and Budnice
Nord Stream	Nord Stream Nel and Nord Stream Opal
Turk stream	Turk Stream
Yamal	Mallnow, Mallnow Reverse and Kondratki

### A1.3 Unit transformations

The natural gas export volume from Norway to the EU-27 are expressed in SM<sup>3</sup>. To calculate the Norwegian income from natural gas, we must express the gas volumes in SM<sup>3</sup> as the natural gas price is expressed in MWh. Following the Norwegian Petroleum Directorate that are based on the properties of Norwegian natural gas,  $1 \text{ SM}^3 = 40 \text{ MJ} = 11,111 \text{ kWh}$  (NPD, 2023b). The result in kWh is then divided by 1000 to achieve the result in MWh.





Figure A1.4a. Heating Degree days





Figure A1.4b Supply shortfall and surplus given historical export volumes in TWh

Figure A1.4c Brent crude price in USD/barrel





Figure A1.4d Coal price in USD/ton

Figure A1.4e LNG import volumes to the EU expressed in MWH



Figure A1.4f Storage volumes in the EU expressed in MWH



Figure A2.4g The TTF natural gas price expressed in USD/MWh

#### A2 Model

A2.1 Matrix of canonical moving average representation

$$\Phi_i = \begin{bmatrix} \Phi_{11,i} & \dots & \Phi_{1K,i} \\ \vdots & \ddots & \vdots \\ \Phi_{K1,i} & \dots & \Phi_{KK,i} \end{bmatrix}$$

Kilian and Lütkepohl, (2017, p. 717).

A2.2 Matrix of structural impulse responses

$$\Theta_i = \begin{bmatrix} \Theta_{11,i} & \dots & \Theta_{1K,i} \\ \vdots & \ddots & \vdots \\ \Theta_{K1,i} & \dots & \Theta_{KK,i} \end{bmatrix}$$

Kilian & Lütkepohl, (2017, p. 717).

A2.3 Information criteria general form

$$C(m) = \log \left( \det \left( \sum_{u}^{\widetilde{}} (m) \right) \right) + c_T \varphi(m)$$

Where  $\sum_{u}^{\infty}(m) = T^{-1} \sum_{t=1}^{T} \hat{u}_{t} \hat{u}_{t}'$  is the residual covariance matrix estimator for a reduced form VAR model of the order m. This is based on the least square residuals  $\hat{u}_{t}$ , while m is the candidate lag order at which the criterion function is evaluated. The  $\varphi(m)$  is a function of the order m that penalizes large lag orders and corresponds to the total number of regressors in the system of VAR equations. and  $c_{T}$  is a sequence of weights that may depend on the sample size.

#### A3 Results



A3.1 Column chart representation of the 2022 HD per month

Weels	the stars down down down and star	0		Data at an at	1.110		N	<b>T</b> 1
Week	Heating degree days deviation	Supply Shortfall	Price of Brent crude oil	Price of coal	LNG imports to EU-27	Storage	Natural gas price	Total
1	0.00	0.18	-0.10	0.88	-0.03	-0.06	0.28	1.14
2	0.02	0.18	-0.09	0.85	-0.03	-0.04	0.27	1.17
3	0.00	0.20	-0.07	0.74	-0.04	0.02	0.25	1.11
4	0.00	0.22	-0.06	0.85	-0.04	0.06	0.21	1.24
5	0.00	0.23	-0.04	0.77	-0.04	0.04	0.18	1.13
6	-0.02	0.24	-0.02	0.69	-0.03	0.06	0.15	1.07
7	-0.02	0.25	-0.01	0.63	-0.02	0.06	0.13	1.02
8	0.00	0.25	0.01	0.77	-0.02	0.08	0.11	1.19
9	0.02	0.25	0.03	1.05	-0.01	0.21	0.11	1.66
10	0.02	0.25	0.06	1.06	-0.01	0.33	0.10	1.80
11	0.00	0.24	0.05	0.77	-0.01	0.23	0.08	1.38
12	0.01	0.23	0.08	0.78	-0.01	0.15	0.07	1.31
13	0.02	0.23	0.07	0.88	-0.01	0.18	0.04	1.41
14	0.03	0.23	0.06	0.86	-0.01	0.17	0.04	1.36
15	0.01	0.22	0.05	0.80	-0.02	0.21	0.03	1.31
16	0.01	0.21	0.05	0.71	-0.01	0.25	0.02	1.24
17	0.01	0.21	0.04	0.76	-0.01	0.22	0.01	1.23
18	0.00	0.21	0.05	0.80	-0.01	0.19	-0.02	1.21
19	0.00	0.21	0.04	0.72	-0.02	0.21	-0.03	1.13
20	-0.01	0.20	0.05	0.72	-0.02	0.24	-0.04	1.14
21	0.01	0.20	0.05	0.63	-0.02	0.24	-0.05	1.06
22	0.02	0.20	0.06	0.65	-0.02	0.24	-0.06	1.08
23	0.00	0.20	0.07	0.63	-0.02	0.23	-0.06	1.04
24	0.00	0.20	0.07	0.85	-0.03	0.21	-0.05	1.26
25	-0.01	0.20	0.06	1.03	-0.03	0.27	-0.05	1.47
26	-0.01	0.21	0.06	1.07	-0.03	0.31	-0.06	1.56
27	0.00	0.22	0.06	1.25	-0.03	0.29	-0.06	1.73
28	0.00	0.24	0.05	1.23	-0.03	0.29	-0.06	1.71
29	0.01	0.24	0.05	1.20	-0.04	0.27	-0.08	1.65
30	0.01	0.26	0.04	1.39	-0.04	0.29	-0.12	1.83
31	0.00	0.27	0.04	1.48	-0.04	0.28	-0.14	1.88
32	0.00	0.27	0.04	1.55	-0.04	0.23	-0.15	1.90
33	0.00	0.28	0.02	1.63	-0.04	0.28	-0.15	2.02
34	-0.01	0.29	0.02	1.81	-0.04	0.31	-0.14	2.24
35	-0.01	0.30	0.02	1.66	-0.04	0.28	-0.14	2.07
36	0.02	0.31	0.00	1.44	-0.04	0.31	-0.15	1.89
37	0.01	0.32	0.00	1.37	-0.04	0.29	-0.15	1.80
38	0.02	0.33	-0.01	126	-0.04	0.26	-0.14	1.69
39	0.01	0.34	-0.02	1.30	-0.03	0.27	-0.14	1.72
40	0.00	0.34	-0.01	0.85	-0.03	0.27	-0.14	1.28
41	0.00	0.35	-0.01	0.63	-0.03	0.23	-0.13	1.02
42	-0.01	0.35	-0.02	0.25	-0.04	0.26	-0.14	0.65
43	-0.02	0.35	-0.02	-0.25	-0.04	0.29	-0.13	0.00
45	-0.02	0.35	-0.02	-0.20	-0.03	0.29	-0.13	0.19
45	-0.04	0.35	-0.02	0.49	-0.03	0.20	-0.10	0.23
46	-0.04	0.35	-0.01	0.45	_0.03	0.14	-0.10	1 10
40	-0.02	0.35	-0.01	0.00	-0.01	0.14	-0.11	1.13
47	0.01	0.30	-0.02	1.04	0.00	0.19	-0.11	1.3/
40	0.00	0.30	-0.02	1.04	0.00	0.21	-0.12	1.40
49	0.01	0.37	-0.03	1.07	-0.01	0.21	-0.12	1.03
50	0.04	0.37	-0.02	1.05	-0.03	0.21	-0.13	1.49
51	0.01	0.37	-0.02	0.82	-0.03	0.17	-0.13	1.18
52	-0.04	0.37	-0.02	0.69	-0.03	0.15	-0.13	0.99

A3.2 Aggregated mean coefficients from the HD by each month for all variables over 2022.