Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Dept. of Industrial Economics and Technology Management

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Estimating Demand Response by Small Natural Gas Consumers in Germany

Master's thesis in Industrial Economics and Technology Management
Supervisor: Prof. Dr. Franziska Holz
Co-supervisor: Prof. Dr. Anne Neumann

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Preface

This Master's thesis is a product of the course TIØ4900 at the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU) in the spring of 2023.

The research presented builds upon our project thesis titled "Estimating elasticities of residential natural gas demand in Europe" (TIØ4550), which analyzes annual data from 13 EU countries covering the period from 1979 to 2020 (Jamissen & Vatne, 2022). In our Master's thesis, we zoom in on Germany and the recent period. Large market fluctuations, coupled with a global pandemic and dramatic supply disruptions, have created an interesting backdrop for our analysis.

Our sincere gratitude is due to our supervisors, Prof. Dr. Anne Neumann and Prof. Dr. Franziska Holz, for their invaluable guidance and continuous support. Their mentorship has provided us with clarity and confidence throughout the research process.

We would like to thank our supervisors for facilitating a highly motivating research visit to DIW Berlin. During this visit, we had the privilege of participating in workshops and presenting our findings to the researchers at the institute. It has been inspiring to discuss our research with prominent economists who were in the front line through the energy crisis and Germany's shift away from Russian imports.

We would also like to express our gratitude to THEMA Consulting Group for their generous sponsorship, without which our stay in Berlin would not have been possible.

Trondheim, June 2023

David Jamissen

Johanne Øderud Vatne

Abstract

Europe successfully averted a natural gas shortage this winter, largely due to a significant reduction in demand from households and small businesses. This study quantifies the key drivers of this decline and provides an estimate of the price elasticity of demand in a time of crisis. Using high-frequency data from Germany between 2018 and 2023, we estimate an ARDL cointegrating model. We find a price elasticity of demand for natural gas of -0.01 for wholesale prices and -0.04 for consumer end-use prices. Additionally, we quantify the effects of public awareness of the energy crisis and design a case-specific weather control. The results suggest that extreme price changes are required to trigger short-term demand adjustments and demonstrate the importance of public attention to the energy crisis.

Sammendrag

Europa avverget gassrasjonering denne vinteren, der et etterspørselsfall fra husholdninger og små virksomheter var et betydelig bidrag. Denne studien kvantifiserer de viktigste driverne bak dette fallet og gir et estimat på etterspørselens priselastisitet for naturgass i krisetid. Vi estimerer en kointegrerende ARDL-modell med høyfrekvente data fra Tyskland i perioden 2018 til 2023 og finner en priselastisitet på -0.01 for engrosspriser og -0.04 for sluttbrukerpriser. I tillegg estimerer vi effekten av den allmenne bevisstheten rundt energikrisen og lager en værkontroll tilpasset modellering av gassforbruk til oppvarming. Resultatene viser at det trengs ekstreme prisendringer for å utløse kortsiktige endringer i etterspørsel og demonstrerer viktigheten av oppmerksomhet rundt energikrisen.

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List of abbreviations

Abbreviation	Explanation
ADF	Augmented Dickey-Fuller (A unit root test)
AIC	Akaike Information Criteria
ARDL	Autoregressive distributed lag
BMWK	Federal Ministry for Economic Affairs and Climate Action
CPI	Consumer price index
Destatis	The German Federal Statistical Office
ECT	Error correction term
EEX	European Energy Exchange
EPEX	European Power Exchange
EU	European Union (The 27 member states as of 2023)
HDD	Heating degree days (A transformation of temperature)
IDW	Inverse distance weighting
IEA	International Energy Agency
IV	Instrumental variable
KPSS	Kwiatkowski-Phillips-Schmidt-Shin (Creators of a stationary test)
LNG	Liquefied Natural Gas
OECD	Organisation for Economic Co-operation and Development
PP	Phillips-Perron (Creators of a unit root test)
RECM	Restricted error correction model
RLM	Registering load measurement (Daily consumption metering of natural gas)
SLP	Standard Load Profile (A profile used to represent a typical pattern of energy consumption)
THE	Trading Hub Europe (The German market operator for natural gas)
UECM	Unrestricted error correction model
ZDF	Zweites Deutsches Fernsehen (A German public-service broadcaster)

1 Introduction

Following the Russian supply disruptions, German natural gas prices have reached new all-time highs. Although there has been a decrease in natural gas consumption during the energy crisis, there is a lack of understanding of the factors driving these changes. This paper quantifies the factors that influence demand in the residential and commercial sector. Based on these findings, we estimate the price elasticity of demand using both wholesale prices, which act as a short-term market signal, and slower-moving consumer end-use prices.

Understanding how consumers respond to turbulent market conditions is crucial for planning security of supply. The residential sector represents 40% of EU demand and primarily relies on natural gas for space heating. This usage pattern makes small consumers an interesting group to study in terms of energy security, as their basic heating needs are influenced by uncontrollable weather changes.

Our attention is directed towards Germany, formerly the largest importer of Russian natural gas through the Nord Stream pipeline (Eurostat, 2023d). Consequently, the German natural gas supply proved particularly sensitive to Russian deliveries. Additionally, with German natural gas consumption representing over a quarter of the EU total, the German demand reaction to market disturbances holds wider implications for the Union.

We find that the price elasticity of demand for wholesale prices is one-third of that for consumer end-use prices, indicating that market signals have limited reach to this large group of consumers. Interestingly, our findings also suggest that the consumer price elasticity during the sample period from 2018 to 2023 has been significantly lower than previously reported in the literature.

Unlike the majority of studies in this field, we address the issue of spurious regression by using an autoregressive distributed lag (ARDL) model and account for the simultaneity bias resulting from the endogeneity of price and demand. We also control for seasonality, weather effects and the awareness of the energy crisis. Together, these factors explain the observed reduction in demand in 2022 and provide insights for analyzing energy markets and planning security of supply.

In the following, we first give some background information on the European and German natural gas sector in Section 2 before reviewing the literature in Section 3. Our data and feature engineering are explained in Section 4. In Section 5, we introduce our empirical strategy. Section 6 presents the results which are further discussed in Section 7. Section 8 concludes.

2 Background

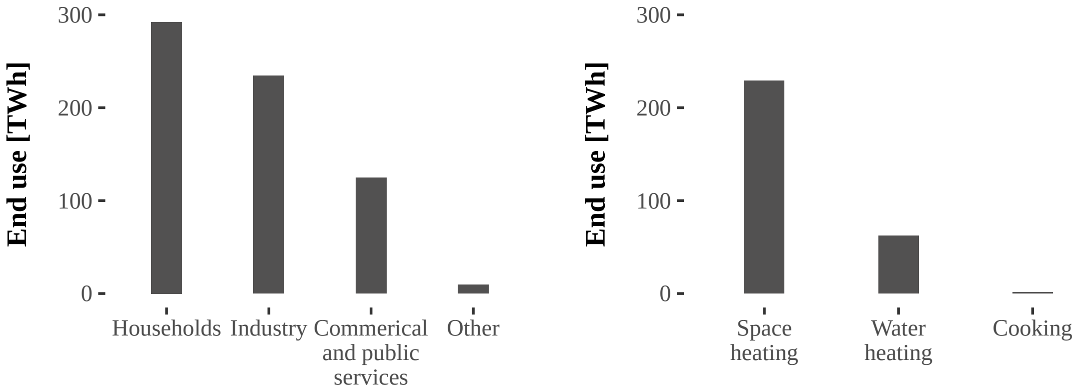
In this section, we describe the tight supply situation that Europe has been facing during the period of our analysis. We then characterize German small consumers, the focus of our study. Finally, we present previous calculations of the energy saved by this consumer group in the crisis year 2022.

2.1 The European energy crisis

The last two years, Europe has been navigating an energy crisis. In the fall of 2021, Russian exports to Europe dropped to a third of previous years' levels. In combination with high LNG demand in Asia and low European production, this led to low European storage levels and substantial price increases (Fulwood, 2022). Following the Russian invasion of Ukraine in February 2022, European import flows from Russia declined even further. Eventually, the Nord Stream pipeline was completely shut down during the summer 2022. During this period, the price of natural gas reached unprecedented levels along with the fear of shortages.

When the war broke out, the European natural gas market was highly reliant on natural gas supplies from Russia. Until the second half of 2021, Russia delivered around 50% of EU imports (European Council, 2023). In May 2022, the EU launched the REPowerEU strategy aiming to diversify supplies and ensure "affordable, secure and sustainable energy for Europe" (European Comission, 2022). In addition, the EU member states agreed to a specific savings target in June 2022, committing to reduce their gas demand by 15% compared to the average consumption in the past five years (European Council, 2022).

In a longer perspective, the climate crisis requires a rapid reduction in emissions and a shift away from fossil fuels, including natural gas. The European Green Deal has set a goal of achieving net-zero emissions by 2050, which requires a major transition in the European energy system (European Commission, 2019). In this context, the way consumers respond to price changes of fossil fuels will impact the effectiveness of price-based climate policies. To achieve the necessary emissions reductions, policy makers need a better understanding of these dynamics.



(a) End use by sector (b) End use within the household sector

Figure 1: German end use of natural gas in 2021 (Eurostat, 2023a) (Eurostat, 2023b)

2.2 Natural gas consumption in Germany

Natural gas makes up around a quarter of Germany's final energy consumption (IEA, 2022). Figure 1a shows that the residential sector represents the largest share of German natural gas consumption, followed by industry and the commercial sector. For households, Figure 1b illustrates that space and water heating are the major end uses of natural gas. Almost half of German homes use natural gas for heating, and despite energy transition targets, 70% of newly installed heating systems are based on natural gas (BMWK, 2022).

We analyze aggregated consumption data from households and small and medium-sized enterprises. This group, referred to as small consumers, report their yearly natural gas consumption by reading an analog gas meter. Their monthly bills are calculated based on their yearly consumption. Energy companies operate the gas grid by forecasting a Standard Load Profile (SLP) for small consumers. This SLP takes into account the building stocks' characteristics, the types of heat technologies and the changing weather. If the actual metered consumption during a 12-month-period exceeds the estimated amount, consumers need to pay for the additional usage. Conversely, if they have used less gas than predicted, they are refunded the difference (Trading Hub Europe, n.d.).

2.3 Investigating the demand reduction

First analyses have pointed out a considerable reduction in German natural gas consumption in 2022. The German broadcaster ZDF tracks the domestic natural gas savings and report a 24% reduction compared to previous years (Koberstein et al., 2023). Roth and Schmidt (2023) adjust for weather effects and find a total demand reduction from small consumers of 23 TWh in the period September-December 2022. Ruhnau et al. (2023) also find a weather-adjusted reduction in the same magnitude and discuss the drivers qualitatively. We expand their analyses by quantifying the components of the demand decline.

When investigating the behavioral reduction in demand for natural gas, classic economic theory points to the price elasticity of demand. We estimate this elasticity in response to both wholesale prices, serving as a market signal, and to consumer end-use prices, representing the price that appears on the bills of German consumers.

German small consumers typically have fixed energy price contracts, and are thereby not directly exposed to the wholesale market. However, in periods of tight supply, a demand-side response to the price signals is needed to avoid shortage. The wholesale market is intended to match supply and demand for natural gas efficiently. The resulting market price represents real-time information on supply levels, storage inventories, weather patterns and geopolitical events. Wholesale prices might also contain information on the future contract prices of small consumers. To gain novel insight into how small consumers interact with the wholesale market, we investigate their response to the wholesale price signal and quantify the wholesale price elasticity of demand. This is an extension to the existing literature, where this relationship has not been sufficiently investigated.

In addition, we estimate the price elasticity of demand to consumer prices. The literature on natural gas reports a wide range of estimates on the consumer price elasticity of demand. However, most of the reported estimates are not compatible with the observed developments in price and consumption in the latest period. Consumer prices, as calculated by the Verivox consumer price index, increased by 143% in 2022 compared to the yearly average between 2018 and 2021. In the same period, we observe a reduction in yearly demand of 11%, not adjusted for weather. Even if we assume that the demand reduction was driven by price in its entirety, an estimate of price elasticity of demand below $\frac{-11\%}{143\%} = -0.08$ would be nonsensical. We provide an updated estimate of the price elasticity of demand in a period of surging consumer prices.

3 Literature review

The literature on price elasticity of demand varies greatly in terms of estimation methods, data samples and results. This section focuses on studies on residential natural gas demand, including a selection of pioneering studies that creates the foundation for current research. Among modern studies, we focus on studies on natural gas demand in OECD countries. As research on natural gas price elasticities using daily data or wholesale prices is hardly available, we consider a handful of studies on the price elasticity of demand for electricity at a higher frequency.

The studies estimating the price elasticity of demand go back to the last century. The seminal study of Balestra and Nerlove (1966) recognizes the dynamic structure of natural gas demand and utilizes the panel structure to estimate elasticity of demand across 36 US states, obtaining a long run estimate of -0.63. In the wake of the oil price shocks of the 1970s, interest in estimating the price elasticity of energy demand increased. Bohi and Zimmerman (1984) offer an excellent survey of this period. With a structural model, Pindyck (1979) analyzes the energy demand based on the demand of energy services (lighting, heat and power) for nine OECD countries. He reports an estimate of -1.7 for the long run price elasticity of demand for natural gas. Griffin (1979) estimates a pooled dynamic model for 18 OECD countries, finding a strong demand response, with a short run elasticity of -0.95 and a long run elasticity of -2.61.

Compared to the classical studies, more recent studies find the demand for natural gas to be less elastic. Asche et al. (2012) combine the advantages of homogeneous type estimators and separate regression models using the shrinkage estimator proposed by Maddala et al. (1997). They find a price elasticity in the range -0.10 to 0 in the short run and from -0.60 to 0 in the long run, using a log-linear dynamic demand model to analyze residential natural gas demand in 12 European countries. Berkhout et al. (2004) estimate the residential demand for energy in the Netherlands using a two-stage budgeting model and includes indicators for the characteristics of the household, the building and its appliances. For natural gas, they find an average price elasticity of -0.28 between 1996 and 1999. Liu (2004) finds that residential price elasticity of demand for natural gas in the US is -0.10 in the short run and -0.36 in the long run. Across their selection of empirical literature, the meta-analysis of Labandeira et al. (2017) finds an average price elasticity of natural gas of -0.18 in the short run and -0.68 in the long run.

Joutz et al. (2009) investigates if there has been a significant change in demand after the turn of the millennium. Analyzing data from 41 local distribution companies

(LDC) in the US from 1996 to 2006, they note a decline in weather-adjusted demand since the 1980s, which accelerated after 2000. Estimating a separate OLS regression for each LDC, they find an average short-run elastiticty of -0.11 and a long-run elasticity of -0.20. A pooled approach finds a short-run price elasticity of -0.09 and a long-run price elasticity of -0.18. Joutz et al. (2009) find no evidence of an appreciable change in the price elasticity of demand after 2000 compared to the full sample. More recently, Burns (2021) evaluates if the price elasticity of demand changes over time, employing a state-space model for natural gas demand in the US from 1980 to 2016, reporting that the responsiveness to natural gas prices has declined in the period. Across the full sample, a significant price elasticity of -0.09 is reported, while for sub-samples the price elasticity is not significant. Testing whether the estimated coefficients are statistically different across sub-samples, she reports mixed results.

The newly published study of Ruhnau et al. (2023) investigates the natural gas savings in Germany during the energy crisis. They find that the industry started to reduce natural gas consumption in September 2021, while small consumers had a delayed response, starting their savings in March 2022. Adjusting for temperature and seasonality, they find a reduction in natural gas consumption of 23% in the second half of 2022. However, they exclude price from modeling, arguing that it would cause endogeneity bias. Instead, they report, in their own words, a rough descriptive estimate on the price elasticity of demand for natural gas of -0.16, calculated by the estimated consumption reduction from modeling in relation to the observed price surge in the period.

Over the last decade, error-correction-type models have become more prominent in the literature, addressing the issue of non-stationarity. The presence of non-stationary series may lead to spurious regression, driving incorrect conclusions about the relationship of the variables (Granger & Newbold, 1973). However, in the presence of non-stationary variables, there might be a cointegrating relationship between them. (Engle & Granger, 1987). Dagher (2012), Bernstein and Madlener (2011) and Erias and Iglesias (2022) adopt an autoregressive distributed lag (ARDL)-model, a dynamic model containing lags of both explanatory and explained variables. As highlighted by Bernstein and Madlener (2011) this method does not require that the order of integration is known pre-estimation and can handle a mixed order of integration. In their analysis of twelve OECD countries, they estimate a price elasticity of demand of -0.24 in the short run and -0.51 in the long run. Dagher (2012) examine natural gas demand in Colorado (US) from 1994 to 2006, using the ARDL technique to estimate a price elasticity of demand of -0.09 in the short run and -0.24 in the long run.

Another direction of recent studies make use of microdata to analyze natural gas demand. This approach allows researchers to match end-consumers to their end-use prices, and enables insight into the heterogeneity across consumer groups. Many of the studies on microdata address the simultaneity issue: The simultaneous determination of the equilibrium price and consumption. End-use prices often depend on tiered pricing regimes, and the price of the individual consumer could be a mechanical function of the quantify consumed. In the micro-data setting, the individual consumer could thereby have direct impact on the price they face, and it would be unreasonable to assume that price is exogenous Auffhammer and Rubin (2018) argue.

Auffhammer and Rubin (2018) and Alberini et al. (2020) employ the instrumental variable (IV) approach to address the issue of endogenous variables. Auffhammer and Rubin (2018) also make use of a spatial discontinuity between two natural gas utilities, using one group as a control when the two regions are exposed to different prices. With a dataset of 300 million residential energy bills from California, they estimate a short-run price elasticity of demand for natural gas in the range of -0.21 to -0.17. Alberini et al. (2020) find a price elasticity of demand of -0.16 in the short run analyzing a period of large price variations in Ukraine between 2013 and 2017, with data from 514 households. Overall, Bohi and Zimmerman (1984) and the meta study of Labandeira et al. (2017) suggest that studies on disaggregated data have shown to produce estimates of price elasticity of demand of a lower magnitude.

In this paper, we seek to examine the wholesale price elasticity of natural gas demand. To our knowledge, Erias and Iglesias (2022) is the only study to analyze price elasticities of natural gas demand in Europe using wholesale prices on a daily frequency. They use data from 15 European countries from 2016 to 2020 and find that the price elasticity of demand for natural gas is not significant in most countries. For some countries, they report positive price elasticities. They employ a log-log ARDL model, including seasonal and country-specific dummies as well as a lock-down term to account for effects of Covid-19. For all countries, they find short-run price elasticities in the range of -2.2 to 0, and long run elasticities of -0.94 to -4.3, which are considerably lower than the findings of earlier literature.

Although the literature using wholesale prices when calculating price elasticities of demand for natural gas is sparse, there are several studies on electricity demand using wholesale prices. Bönte et al. (2015) estimate the elasticity of demand for electricity in Germany and Austria, using EPEX day-ahead prices from 2010 to 2014, finding an average elasticity of demand of -0.43. They use a log-log specification with wind speed as an instrument for the market price. Knaut and Paulus (2016) estimate the hourly price elasticity of demand of electricity for the German day-ahead market, obtaining price elasticity estimates within the range of -0.13 to -0.02 depending on the hour of day. Genc (2016) investigates demand response to hourly wholesale price movements in Ontario, using a bottom-up Cornot modelling framework. The estimated elasticities are in the range of -0.13 to -0.013. Lijesen (2007) investigates the real-time price elasticity of electricity in the Netherlands, examining hour-to-hour demand response during peak hours. He reports a price elasticity of demand of -0.0043. Scaling by the fact that trade volume at spot is approx. 15% of total load, he obtains a price elasticity of demand of -0.029, which is still considerably lower in absolute terms than the existing literature. Malehmirchegini and Farzaneh (2022) analyze the day-ahead wholesale electricity market in Japan, using an hourly-based welfare-maximizing optimization model. They find an average hourly price elasticity of demand of -0.080. In comparison the meta-study Labandeira et al. (2017) finds an average price elasticity of -0.201 in the short run and -0.51 in the long run for electricity across studies, suggesting that studies on wholesale price elasticities seem to report weaker demand responses than studies on consumer end-use prices.

The estimates on price elasticities of demand collected in this section are summarized in Table 1.

Table 1: Summary of the results in the literature review

						Price elasticity of demand	
Study	Fuel	Countries	Period	Frequency	Type of study	Short run	Long run
Balestra and Nerlove (1966)	Natural gas	US, 36 states	1957-1962	Annual	Residential and commercial	-	-0.63
Pindyck (1979)	Natural gas	9 OECD countries	1960-1974	Annual	Residential	-	-1.7
Liu (2004)	Natural gas	23 OECD countries	1978-1999	Annual	Residential	-0.10	-0.36,
					Industry	-0.067	-0.24
Berkhout et al. (2004)	Natural gas	The Netherlands	1990-1999	Annual	Residential	-	-0.28
Lijesen (2007)	Electricity	The Netherlands	2003	Hourly	Wholesale prices	-0.0043	-
Joutz et al. (2009)	Natural gas	US	1980-2001	Annual	Residential		
					Pooled	-0.09	-0.18,
					Separate OLS	-0.11	-0.20
Serletis et al. (2010)	Natural gas	US	1960-2007	Annual	National,	-0.35	-
					Industry,	-0.50	-
					Commerical,	-0.30	-
					Residental	-0.31	-
					Incl. electricty generation	-0.14	-
Bernstein and Madlener (2011)	Natural gas	12 OECD countries	1980-2008	Annual	Residential	-0.24	-0.51
Alberini et al. (2011)	Natural gas	US	1997-2007	Monthly	Residential	-0.57	-0.65
Asche et al. (2012)	Natural gas	12 European countries	1978-2002	Annual	Residential	-0.10 to 0	-0.60 to 0
Bönte et al. (2015)	Electricity	Germany and Austria	2010-2014	Hourly	Wholesale, prices	-0.43	-
Knaut and Paulus (2016)	Electricity	Germany	2015	Hourly	Wholesale prices	-0.13 to -0.02	-
Genc (2016)	Electricity	Canada, Ontario	2006-2009	Hourly	Wholesale prices	-0.13 to -0.013	-
Burke and Yang (2016)	Natural gas	44 countries	1978-2011	Annual	Reidential and industry	-1.4 to -0.13	-
Auffhammer and Rubin (2018)	Natural gas	US, California	2010-2014	Monthly	Residential	-0.23	-0.17
Alberini et al. (2020)	Natural gas	Ukraine	2013-2017	Monthly	Residential	-0.16	-
Burns (2021)	Natural gas	US	1980-2016	Annual	Wholesale prices	-0.09	
Erias and Iglesias (2022)	Natural gas	15 European countries	2016-2020	Daily	Wholesale prices	-2.2 to 0	-4.3 to -0.94
Malehmirchegini and Farzaneh (2022)	Electricity	Japan	2016-2010	Hourly	Wholesale prices	-0.08	-
Ruhnau et al. (2023)	Natural gas	Germany	2018-2022	Monthly	Residential	-0.16	-
			2017-2022		Industry	-0.04	

Rounded to two significant figures when available

4 Data

In this section, we examine the consumption data for natural gas and the two different price series used to determine the elasticities of demand. We detail our efforts to engineer weather variables reflecting the areas where natural gas is used for heating. Additionally, we present indices for abnormal events during the observation period, namely the Covid-19 pandemic and the energy crisis. Finally, we explain our variable selection approach.

4.1 Consumption data

The German market area manager Trading Hub Europe (THE) publishes aggregate consumption data on natural gas. They divide the grid-connected natural gas customers into two groups. Customers with daily metering (RLM) and customers with manual metering whose daily consumption is estimated in a standard load profile (SLP). SLP customers primarily consist of households and small and medium-sized enterprises who use natural gas for space heating, water heating and cooking. The RLM costumers are, on the other hand, a heterogeneous group including industry and power plants with large differences in consumption patterns.

The actual consumption of SLP customers can be approximated by the residual load, calculated as "the sum of all measured inputs minus all measured offtakes in a network" (Trading Hub Europe, 2023).[1] THE reports three different states of the residual load observations, "preliminary", "corrected" and "final", that are published after different clearing periods. To ensure the highest possible reliability of the data, we include solely "final" records for the period 01-01-2018 to 01-03-2023.

Visualized in figure Figure 2,[2] the consumption series exhibits a strong seasonal trend in both the mean and the variance. The need for heating, and thereby the consumption of natural gas, is highest during the winter. On the other hand, typical summer consumption for water heating and cooking is lower and more stable.

[1]"Measured offtakes" include RLM consumption in addition to storage injection and exports.

[2]The outlier observed in Figure 2 on 01-01-2019 is not reflected in any of the predictors or referred to elsewhere. It is therefore likely an instance of measurement error and removed from the sample.

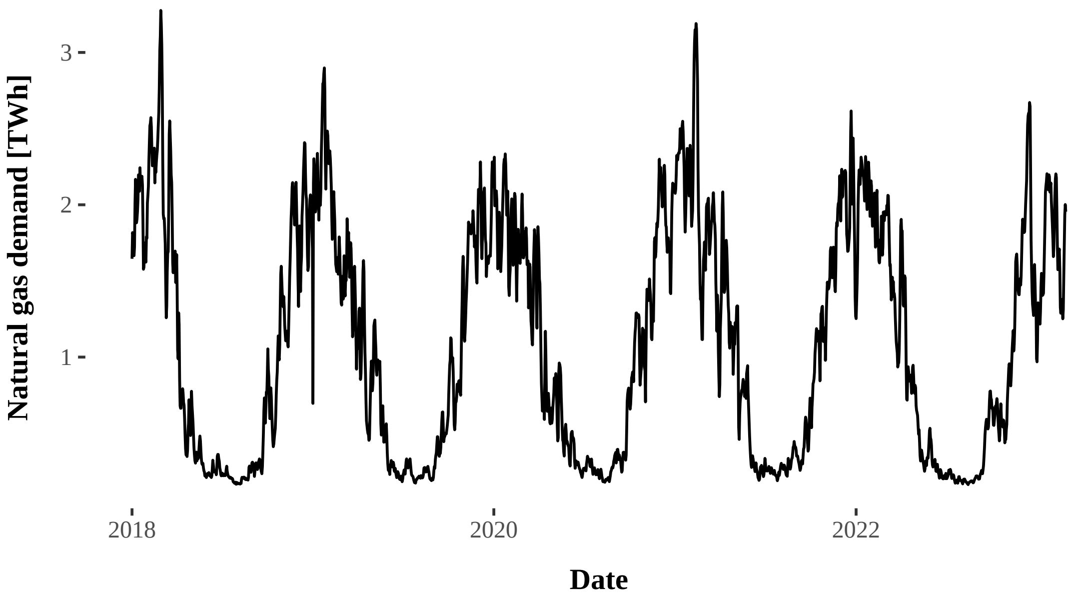


Figure 2: Aggregated German SLP consumption (Trading Hub Europe, 2023)

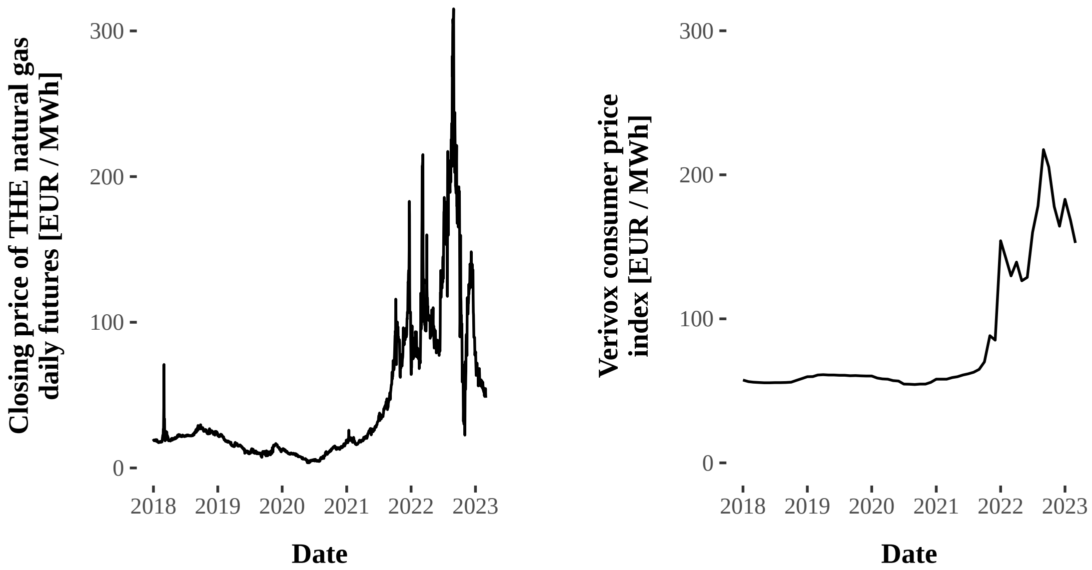
4.2 Wholesale prices

To evaluate the effects of wholesale market prices, we use closing day-ahead forward prices from the European Energy Exchange (EEX, 2023) in Germany, extracted from Bloomberg. The day-ahead series represent the prices for physical delivery of natural gas on the following working day. To avoid discontinuity during weekends and holidays, we incorporate the corresponding weekend-ahead forward price to the time series, also collected from Bloomberg.

Figure 3a shows the wholesale price series from 2018 to 2023. After a supply disruption from the Groningen field caused a short-run price rally in 2018, prices were relatively low and stable for a long period. In 2021, wholesale prices started to rise, reaching the highest peak in September 2022 following the Nord Stream 2 gas leaks. In the following months, prices fell distinctly before rising to a new spike at the end of the year. Since the beginning of 2023, wholesale prices have been decreasing.

Germany has experienced high inflation during our sample period. By our calculations, the monthly German CPI index rose by 20% during the period of analysis, adjusted for seasonality. To account for this inflation, we deflate the prices to the 2015-reference of the seasonally adjusted CPI index by OECD (2023).[3]

[3] In addition to CPI-adjusted prices, we have performed our analysis with nominal prices as well as a core inflation index that excludes food and energy prices. Both yield similar results which are available upon request.



(a) Wholesale prices, extracted from Bloomberg (EEX, 2023)

(b) Verivox consumer price index (Verivox GmbH, 2023)

Figure 3: Nominal price series for natural gas

4.3 Consumer end-use prices

Data on consumer end-use prices are not available on a daily frequency. We use a monthly index representing the end-use price, the Verivox consumer price index for natural gas (Verivox GmbH, 2023). Through its price comparison website, Verivox enables consumers to evaluate energy tariffs. The Verivox consumer price index represents the unit cost of natural gas for household end use, calculated based on an assumed annual consumption of 20.000 kWh. This index incorporates both the retail fixed-price contracts available on the Verivox website and the floating prices for customers without a supply contract. The contributions of individual suppliers to the price index are weighted based on the number of households they serve within the supply area. Unlike the wholesale price series, the Verivox price index also encompasses all applicable taxes and fees.

Examining the Verivox price series, we observe that end-use prices saw a rapid increase from late 2021, followed by some decline during the summer. As expected, end-use prices show less variation than the market prices.

4.4 Weather data

To account for the impact of weather on natural gas demand, we gather a range of daily indicators from 587 weather stations operated by the German Meteorological Service (Deutscher Wetterdienst, 2023).

Precise aggregation of the weather station data is crucial for obtaining reliable estimates, as weather is a predominant factor affecting heating needs[4]. Consequently, any biases introduced by inaccurate weather aggregation could compromise the reliability of the price effects we seek to estimate, especially considering their relatively smaller scale. Therefore, our objective is to calculate a weighted average of weather conditions across Germany that accurately reflects the total demand for natural gas-fired space heating.

From the temperature parameters, we engineer a Heating Degree Days (HDD) variable to establish a linear relationship between outdoor temperature and heating demand. The transformation in Eq. 1 is developed by the UK Met Office (Kendon et al., 2022). It incorporates the daily mean temperature T_{mean}, as well as the daily maximum and minimum temperatures T_{max} and T_{min}. The inclusion of the temperature range helps improve accuracy when the temperature is close to the base temperature $T_{\text{base}} = 15.5\,^{\circ}\text{C}$.

$$HDD = \begin{cases} T_{\text{base}} - T_{\text{mean}} & \text{if } T_{\text{max}} \leq T_{\text{base}} \\ \frac{T_{\text{base}} - T_{\text{min}}}{2} - \frac{T_{\text{max}} - T_{\text{base}}}{4} & \text{if } T_{\text{mean}} \leq T_{\text{base}} < T_{\text{max}} \\ \frac{T_{\text{base}} - T_{\text{min}}}{4} & \text{if } T_{\text{min}} \leq T_{\text{base}} < T_{\text{mean}} \\ 0 & \text{if } T_{\text{min}} \geq T_{\text{base}} \end{cases} \tag{1}$$

In energy demand analysis, it is common practice to use population-weighted weather variables. To establish our weighting framework, we employ a population density grid provided by the German Federal Statistical Office (Destatis, 2022). This data set, derived from mobile traffic data, provides population estimates at a high resolution of $1\,\text{km} \times 1\,\text{km}$ grid cells throughout Germany. As a result, we can accurately capture the prevailing weather conditions in inhabited areas with a high degree of precision.

However, it is important to note that the distribution of natural gas infrastructure and dwelling sizes is not uniform across Germany. For instance, the impact of

[4]The strong relationship between weather and natural gas demand has been widely described in the literature, see for instance Henley and Peirson (1998), EIA (2014) and Considine (2000).

weather changes in Niedersachsen, where 70% of homes are heated by natural gas, differs from the effects of a cold gust in Berlin, where only 37% of homes are equipped with gas heating facilities. Additionally, the average living space per capita in Niedersachsen is 25% larger than in Berlin.[5] Relying solely on population-based weighting would, therefore, lead to an under-representation of regions with a high dependence on natural gas.

To address these disparities, we incorporate detailed data from the German micro census (Destatis, 2019), which provides information on living area per capita and the share of natural gas-heated dwellings across 38 statistical regions. By multiplying these factors with the population densities, we create a fine-meshed grid with the estimated natural gas-heated living space across Germany to use as aggregation weights. Figure 4c illustrates these weights.

In each grid cell i, we estimate the weather parameter value $\hat{\theta}_i$ using Inverse Distance Weighting (IDW) based on data from the nearby weather stations illustrated in Figure 4a. This deterministic function, originally proposed by Shepard (1968), is on the form

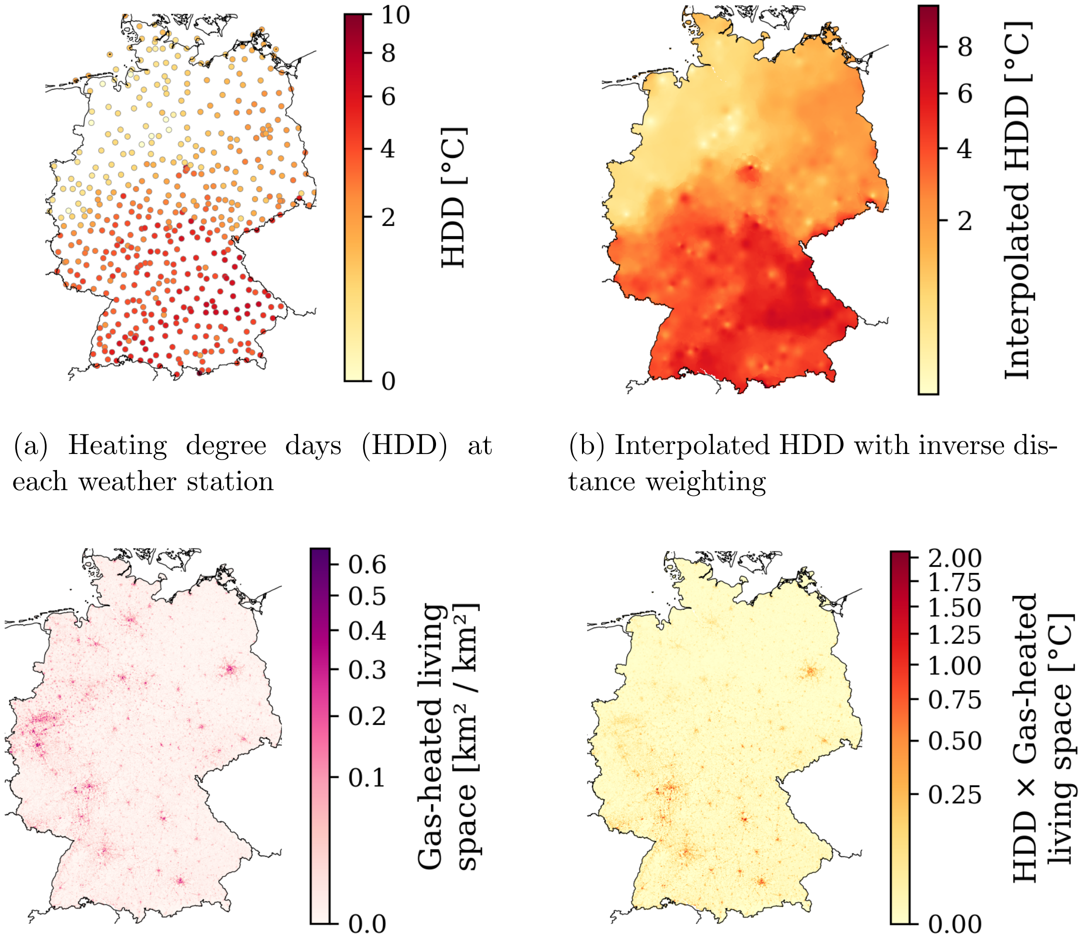
$$\hat{\theta}_i = \frac{\sum_{j=1}^{k} \theta_j d(x_i, x_j)^{-p}}{\sum_{j=1}^{k} d(x_i, x_j)^{-p}}, i \neq j. \tag{2}$$

Here, $d(x_i, x_j)^{-p}$ denotes the inverse Euclidean distance raised to the power $p = 2$ between locations x_i and x_j. This approach assigns higher weights to closer weather stations, based on the assumption of spatial autocorrelation in weather parameters. To preserve local variations and avoid over-smoothing, we limit the interpolation to the $k = 5$ nearest stations. Figure 4b illustrates this approach with HDDs. The daily weighted average is then calculated using the estimated weather parameters in each cell, with the estimated natural gas-heated living space within the cells as weights. See Figure 4d for the resulting HDD distribution on a sample day with mild temperatures in the North-West.

4.5 Crisis awareness indicator

We extract data from Google Trends to quantify the public awareness of the energy crisis. Given the Russian aggression in Ukraine and the resulting energy war, there has been extensive media coverage of feared gas supply disruptions. Ruhnau et al. (2023) argue that the reduction in natural gas consumption in response to the crisis

[5]The numbers are based on own calculations from the Destatis (2019) micro census data.



(a) Heating degree days (HDD) at each weather station

(b) Interpolated HDD with inverse distance weighting

(c) Density of natural gas-heated living space in Germany

(d) HDD weighted with gas-heated living space

Figure 4: Aggregating spatial weather data from Deutscher Wetterdienst (2023) on a sample day of October 26th, 2019

”could be driven by rising prices, anticipated future price increases, media attention on energy-related subjects, awareness of energy issues and conservation options, or, in the case of households, ethical considerations following the Russian invasion of Ukraine on 24 February 2022”. We aim to quantify the impact of increased awareness and information dissemination that has coincided with the rise in natural gas prices by measuring the popularity of related Google queries. Our objective is to assess how the awareness of the energy crisis may have contributed to energy conservation. By disentangling the awareness effect from the price effect, we can also make meaningful inferences about the price elasticity of demand.

We examine the relative frequency of Google queries from February 2022 to February 2023, following the invasion of Ukraine. First, we identify the top 25 trending queries within each of the ”Energie” (energy) and ”Erdgas” (natural gas) topics. To avoid colinearity, we select the highest-ranking search term from each group of related queries, excluding those directly related to natural gas prices. Appendix B provides the list of the 50 query candidates and their respective groupings.

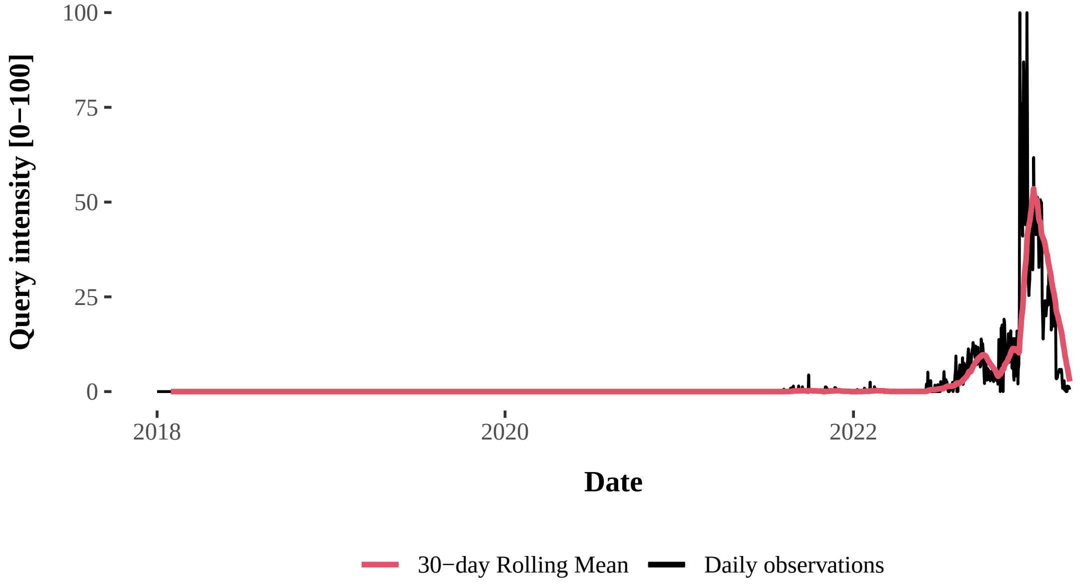


Figure 5: Crisis awareness indicator from web search traffic on ”Energiekrise” (Google Trends, n.d.)

Out of the 50 initial candidates, we select the ”Energiekrise” query as our indicator. This is both the most popular query, and the one with the lowest correlation to price. This last property is key, as we want to disentangle the price effect from other behavioral effects. We calculate a rolling mean over the past month to capture the sustained awareness beyond the specific query date.

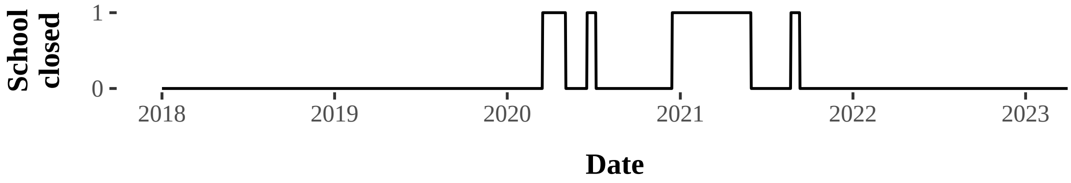


Figure 6: Days with closed schools in Germany as an indicator for lockdown measures during the pandemic (Hale et al., 2021)

From Figure 5 we observe that public awareness of the energy crisis remained low following the outbreak of the war in Ukraine, starting to rise only towards the fall of 2022. While wholesale price had its highest levels in September, the crisis awareness only increased, reaching its peaks around the turn of the year, when price levels were reverting.

4.6 Covid data

To account for the effects of the Covid-19 pandemic, we consider a selection of the indicators proposed by the Oxford Covid-19 Goverment Response Tracker (Hale et al., 2021):

- School closing: Required closing of schools.
- Workplace closing: Required closing of workplace
- Stay at home requirement: Requirement not to leave the house
- Government Response Index: A broad index of policy measures, including containment and closure policies, economic policies and health system policies
- Economic Support Index: An index of economic policies, such as income support and debt/contract relief for households.

The Oxford research team has encoded the indicator variables on a scale of 0 to 3, with 0 indicating the absence of measures and 3 representing the most stringent requirements. For the purpose of our analysis, the categorical variables are transformed to binary variables, set to 1 when there is a order 3 requirement, 0 otherwise.[6]

[6]The data is only available until 31.12.2022. However, for the categorical variables we can infer their current value, since they reverted to zero at the end of the lock down.

4.7 Variable selection

To accurately describe demand behavior, we consider a wide range of possible explanatory variables. The initial candidates and their correlations are visualized in Figure 4.7. We combine economic theory and data driven methods to select the appropriate variables. For instance, we know that there is a strong relationship between demand and weather, but are agnostic about which data series serves the best to explain the weather conditions experienced by the consumer. Thereby, we make use of the forward stepwise algorithm, as described by James et al. (2021) to guide variable selection based on goodness of fit.

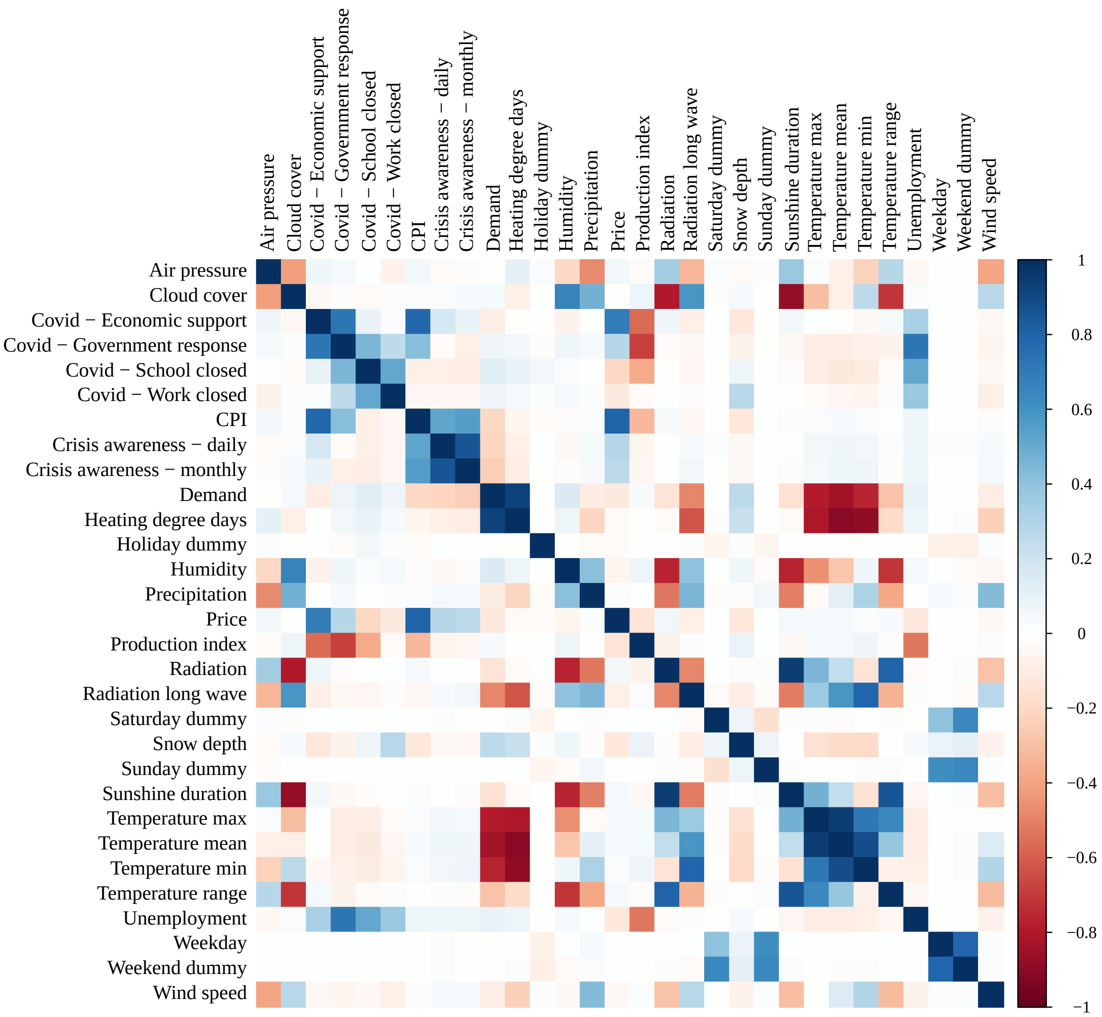


Figure 7: Correlation of the candidate variables

We start with the null model regressing demand on its own first lag and price, and add additional variables through the forward stepwise selection model. In each step, we add one of the candidate variables to the regression formula, fitting a model for each of the candidates, subsequently selecting the best among these models by

Algorithm 1 Forward stepwise selection

M_0: The null model
N: Number of predictors
$p_i, \quad i = 1, 2, ..., N$: Available predictors
$L(\hat{\beta})$: The likelihood function
for k=1,2,..N **do**

1. Consider all $N - k$ models that augment the predictors in the best model from last step, M_{k-1}, with one additional predictor
2. Select the best among these models, M_k, maximizing R^2.
3. When the best predictor $p_{i'}$ is chosen, all other candidate predictors $p_{i,i \neq i'}$ with $Cor(p_{i'}, p_i) > 0.5$ is discarded

end for
Select the single best model among $M_0, ..., M_p$ guided by
$AIC = -2\log(L(\hat{\beta})) + 2N$.

the R^2 of the regression. Many of our candidate variables are highly correlated, for instance solar radiation and sunshine hours. Thereby, we add a step to the approach of James et al. (2021), excluding any remaining candidates with a correlation above 0.5 when one variable is chosen. Finally, we use the Akaike infomation criterion (AIC) to evaluate the model.

Table 2: Descriptive statistics - Daily frequency

Variable	Unit	Obs	Mean	Sd	Min	Max
Demand†	MWh	1857	1066.89	278.74	-20.79	2521.77
HDD†	°C	1857	5.71	2.41	-3.67	17.82
Wholesale price†	EUR/MWh	1857	39.00	42.79	5.64	265.57
Wind speed†	m/s	1857	3.39	1.15	0.71	9.31
Radiation†	J/cm^2	1857	1173.29	346.92	-277.12	2082.88
Holiday × HDD†	°C	1857	0.10	0.79	0.00	10.00
Covid	Dummy	1857	0.14	0.34	0.00	1.00
Crisis awareness	Query intensity (0-100)	1857	2.08	7.83	0.00	53.53

†Deseasoned values

Table 3: Descriptive statistics - Monthly frequency

Variable	Unit	Obs	Mean	Sd	Min	Max
Demand†	MWh	61	1062.52	165.72	673.76	1544.22
HDD†	°C	61	5.73	1.13	3.39	10.09
Wholesale price†	EUR/MWh	61	38.71	41.88	6.93	200.07
Verivox CPI	EUR/MWh	61	75.12	36.41	51.59	182.47
Wind speed†	m/s	61	3.39	0.43	2.43	4.97
Radiation†	J/cm^2	61	1170.86	124.55	857.87	1548.27
Crisis awareness	Query intensity (0-100)	61	2.08	7.76	0.00	47.31
Covid	Dummy	61	0.14	0.31	0.00	1.00

†Deseasoned values

5 Econometric method

In this section, we describe the autoregressive distributed lag (ARDL) cointegrating model and the efforts to ensure its validity. Among these, we highlight the importance of correct functional form of the weather relationship and investigate efficient ways to adjust for seasonality with frequency analysis. Going further, we propose a solution for the simultaneity bias when using daily wholesale prices and test our time series for unit roots and cointegration.

5.1 Functional form

Following the ad hoc approach to energy demand estimation proposed by Houthakker and Taylor (1970), we assume that natural gas demand from small consumers q_t at time t in equilibrium can be expressed as a linear function of k exogenous variables $x_{i,t}$, $i = 1, 2, ..., k$.

$$q_t = \mu + \sum_{i=1}^{k} \beta_i x_{i,t} \tag{3}$$

Here, the intercept μ and variable coefficients β_i represent the equilibrium parameters to be estimated.

To unveil the relationship in Eq. 3, we estimate three distinct models: a daily model using wholesale prices as the price variable, as well as two monthly models to compare the demand response to wholesale prices to consumer end-use prices. The specific variables included in each of these models are provided in Table 2 and Table 3.

Our models have a linear functional form, in contrast to the majority of the literature using log-log and log-linear specifications in modelling natural gas demand (i.e. Erias and Iglesias (2022), Asche et al. (2012) and Bernstein and Madlener (2011)). All these studies report weather as one of the most important determinants of natural gas demand. They use HDD to control for weather effects, despite the fact that HDD is designed to have a linear relationship with energy consumption for space heating.

Figure 8 unmistakably demonstrates this relationship. However, the figure also reveals that applying log-transformations to either the HDD or demand variable disrupts the original linear correlation. This insight presents a matter of concern, especially in light of the common practice in the literature of modeling log-transformed demand with HDD. If the relationship with HDD is misspecified, it could lead to biased model estimates, including the price elasticity of demand.[7]

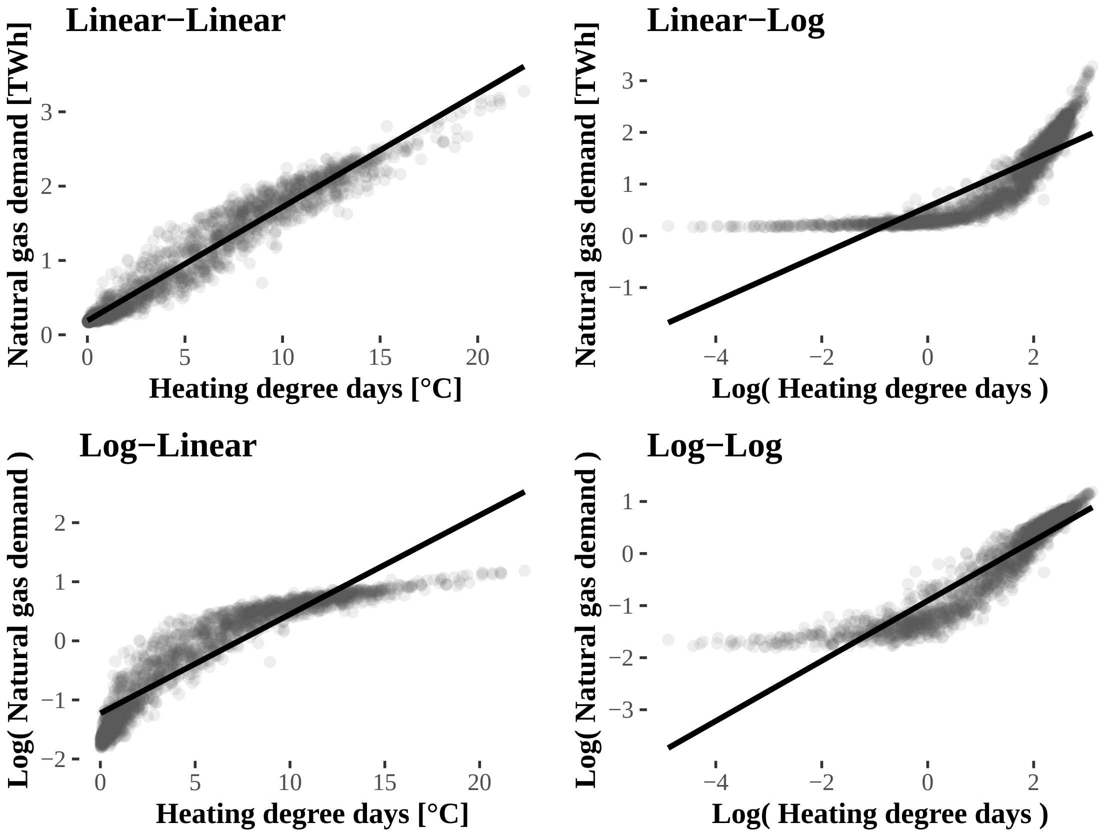


Figure 8: The relationship between demand and heating degree days for different transformations with linear regression lines

The popularity of log-log specifications could be explained by the convenient feature that the coefficients can be interpreted as elasticities directly. In contrast, the coefficient estimates in our models represent the unit changes of natural gas demand q for unit changes in the explanatory variables. We can then interpret the price estimate as the slope of the demand curve. To obtain the corresponding (arc) elasticity of demand, η_p, we calculate[8]

$$\eta_p = \frac{\partial q}{\partial p}\frac{\bar{p}}{\bar{q}}, \tag{4}$$

where $\frac{\partial q}{\partial p}$ is the coefficient estimate of price p and $\frac{\bar{p}}{\bar{q}}$ is the ratio of the mean estimates of price and demand.

The standard error for η_p, the product of a non-linear function, is calculated using

[7]Goff (2014) shows that misspecification of control variables in some situations can lead to higher bias in the estimate of interest than omitting them altogether.

[8]Here, we use the price p as an example due to the well-known interpretation of price elasticity of demand. We also calculate elasticities for the other explanatory variables with the same approach.

the statistical error propagation function given by

$$SE_{\eta_p} = \mathbf{g}^\top \mathbf{V} \mathbf{g}, \tag{5}$$

where $\mathbf{V}$ is the variance-covariance matrix of the variables $\bar{p}$, $\bar{q}$, and $\frac{\partial q}{\partial p}$, and $\mathbf{g}$ is a vector that contains the partial derivatives of the elasticity with respect to each of these variables.

5.2 Adjusting for seasonality

Sub-annual energy and weather data are characterized by the inherent seasonality stemming from the cyclical nature of Earth's orbit.[9] The standard approach to account for this would be to estimate the deterministic seasonality component S_t with T seasonal dummies D_s for period length T:

$$S_t = \sum_{i=1}^{T} D_{s,t}. \tag{6}$$

Estimating seasonal dummies on a high frequency with a low number of periods can yield imprecise estimates, as the variances of the dummy coefficients are inversely proportional to the number of observations in each season s. The sensitivity for noise is apparent in the red line in Figure 9, where a set of $T = 365$ day-of-year dummies is fitted to the daily demand series with only five whole periods from 2018-2023.

As pointed out by Cryer and Chan (2008), the dummy variable approach does not consider the shape of the seasonality. An alternative approach incorporating the smooth changes between seasons is to model the seasonal components with cosine curves.

To separate the dominant seasonal patterns from noise and other effects, we turn to spectral analysis of the time series. Using discrete Fourier expansions, Eq. 6 can be represented with pairs of sines and cosines:

$$S_t = A_0 + \sum_{j=1}^{H} (A_j \cos(2\pi f_j t) + B_j \sin(2\pi f_j t)), \tag{7}$$

where $f_j = \frac{j}{T}$ is the Fourier frequency for harmonic $j = 1, 2, ..., H$ and A_j and B_j are the respective amplitudes. The maximum number of harmonics is $H = \frac{T}{2} - 1$ when T is even and $H = \left\lfloor \frac{T}{2} \right\rfloor$ when T is odd. The components in Eq. 7 can be estimated

[9] Without further justification, we regard this as a deterministic process.

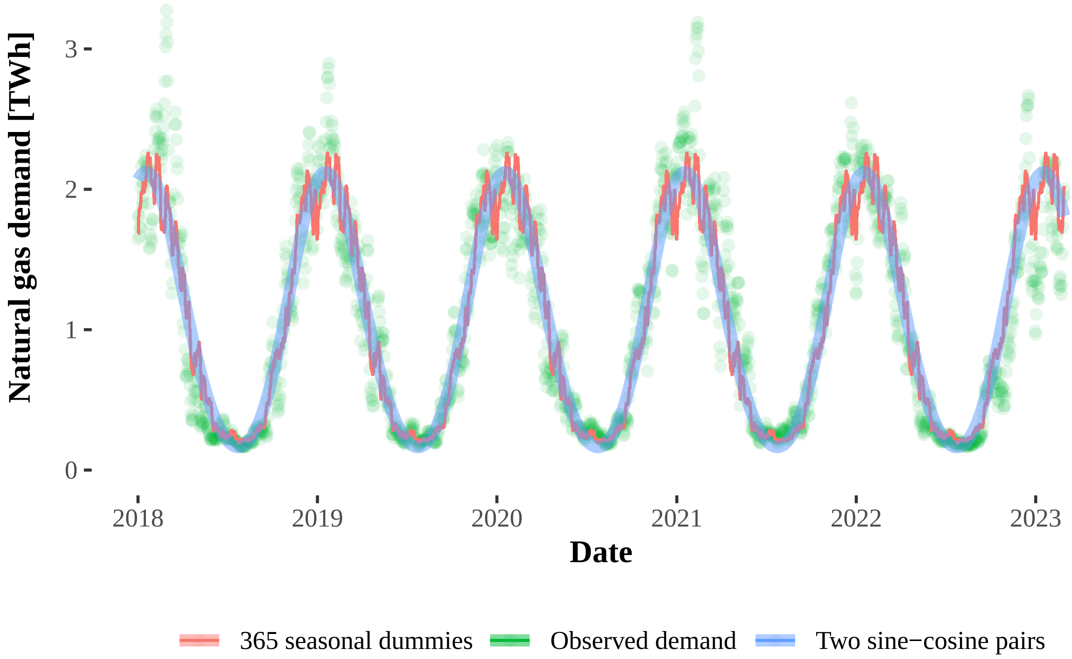


Figure 9: Modelling the deterministic seasonal component in demand using either dummies or sine-cosine pairs.

on the data with ordinary least squares (OLS) and yield identical fitted values as the dummy components in Eq. 6 (Ronderos, 2019). We can then evaluate the relative strength of each Fourier frequency by computing the periodogram defined by Cryer and Chan (2008) as

$$I(f_j) = \frac{T}{2}(\hat{A}_j^2 + \hat{B}_j^2), \tag{8}$$

where $\hat{A}_j$ and $\hat{B}_j$ are the OLS estimates of the amplitudes in Eq. 7.

The periodogram for the daily data is calculated with a yearly periodicity of $T = 365.24$ days. For natural gas demand and the weather variables in Figure 10, we see a clear spike at the fundamental frequency $f_1 = \frac{1}{T}$. This indicates a dominating annual seasonal trend. A spike at the second harmonic on f_2 indicates a bi-annual component, seen in Figure 9 as small asymmetries during summer and winter transitions. If intra-weekly and intra-monthly seasonality were present, we would see spikes in the periodogram around the 7th and the 12th harmonic, receptively. There are no signs thereof and we conclude that the seasonal components can sufficiently be captured by estimating the sine-cosine pairs for the first $k = 2$ harmonics[10], effectively reducing the degrees of freedom used from $T = 365$ (excluding

[10]For wholesale prices, we find evidence of a weaker seasonal component at the first harmonic before the fall of 2021. The following period is zero-weighted to reduce the risk of fitting seasonal

leap days) to $2k + 1 = 5$ with less risk of losing non-seasonal information.

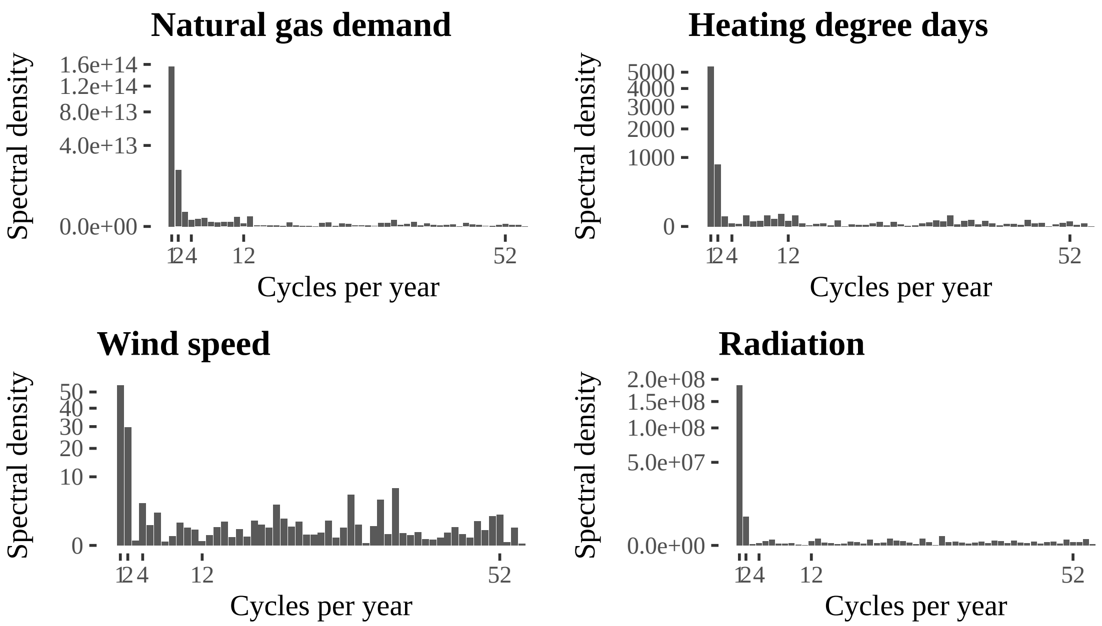


Figure 10: Periodograms showing the relative influence of different frequencies in model variables. The spectral density-axis is square-root scaled.

In addition to the seasonal trends modelled with sines and cosines, we subtract the calendar effects such as weekends and holidays evident in the natural gas demand data. We deliberetaly do not subtract the intercept to ensure that the full-period means of the variables are unaffected.

5.3 Simultaneity

A two-way causal relationship between the explained and the explanatory variable can be a source of endogeneity bias when estimating the price elasticity of demand. In this context, the theoretical simultaneous determination of supply and demand is particularly vulnerable to misspecification.

We evaluate the endogeneity of our initial specification with the Hausman test in Appendix A. Here, we observe that the fitted values of demand is a significant predictor for price, indicating that there is a two-way relationship between the variables.

We propose that a fundamental source of endogeneity could be weather, a dominating determinant of natural gas demand and information that is available to all market actors. A shock in weather conditions would therefore shift both demand

components to noise

and the wholesale price simultaneously, imposing a classic endogeneity bias.

Examining the autocorrelation function (ACF) plots for daily observations of price and weather, Figure 11 reveals that the wholesale price has a long memory, while seasonally adjusted HDD has not. In fact, the temperature is completely uncorrelated to its value 10 days earlier. Meanwhile, the price level is strongly correlated to its tenth lag. We therefore use the price with a ten-day lag to instrument the contemporaneous price, as there is no information left in HDD but a high degree of information in the lagged price. A contemporaneous shock to HDD would now only affect demand and not price, as information on the shock is not contained in the lagged price variable. We can therefore effectively gain inference from an instrument highly correlated to price, but avoid correlated innovations in price and demand originating from changing weather. After the lag transformation of the price variable, there is no longer evidence of endogeneity in the model, as demonstrated in Appendix A.

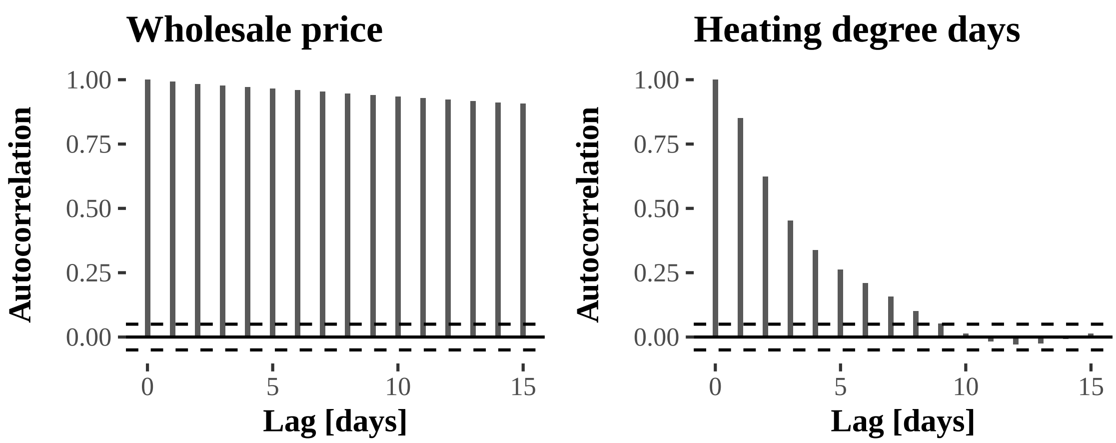


Figure 11: Autocorrelation function plots showing the different decay rates in wholesale price and HDD.

5.4 Unit root testing

We proceed to examine the stationarity of the seasonally adjusted time series. The inclusion of non-stationary variables could lead to spurious results and invalid inference. On the other hand, if there exists a cointegrating relationship between the variables, it enables us to examine the long-run relationship between the variables. Unit root tests are known to suffer from low power when distinguishing highly persistent I(0) stationary series that are close to I(1). Thereby, we perform three different tests to enhance the confidence of our conclusions.

The Augmented-Dickey Fuller (ADF) and Phillips-Perron (PP) tests are commonly used to test for unit roots. Both build on the work of Dickey and Fuller (1979) and the regression given by

$$\Delta q_t = \psi q_{t-1} + \mu + \lambda t + u_t \tag{9}$$

The null hypothesis $H_0 : \psi = 0$, the time series contains a unit root, is tested against the alternative $H_1 : \psi < 0$, the series is stationary.

The DF-test assumes that the error terms are not serially correlated, which would be the case if there is autocorrelation in Δq_t that has not been accounted for in the model. The ADF test adds to the traditional Dickey-Fuller test by introducing lags of Δq_t to control for autocorrelation. In our testing procedure, the appropriate numbers of lags is determined by information criteria. Phillips and Perron (1988) correct the DF-test with a non-parametric correction to the t-statistic to allow for autocorrelated residuals. Kwiatkowski et al. (1992) (KPSS) revert the null hypothesis of the ADF and PP unit root tests, and employ the null hypothesis $H_0 : q_t \sim I(0)$, the series is stationary, against the alternative $H_1 : q_t \sim I(1)$. The test is based on the residuals of the DF-regression.

5.5 Autoregressive distributed lag model

We employ an autoregressive distributed lag (ARDL) model, including u lags of the explained variable and v_i lags of explanatory variable x_i.

$$q_t = \alpha_0 + \sum_{l=1}^{u} \alpha_l q_{t-l} + \sum_{i=1}^{k} \sum_{l=0}^{v_i} \gamma_{i,l} x_{i,t-l} + \varepsilon_t \tag{10}$$

The ARDL has the flexibility to handle both I(0) and I(1) variables in a single regression framework, in contrast to the procedures of Engle and Granger (1987) and Johansen (1995), restricting all variables to have the same order of integration. We can assume that we have at least one non-stationary variable, as market prices are known to contain unit roots (Brooks, 2014). In addition, unit root tests are known to suffer from low power when the data-generating process is close to I(1), which may lead to misspecification.

Through the ARDL bounds test for cointegration introduced by Pesaran et al. (2001), we can test for cointegration without knowledge on the exact order of integration. In the case where a constant is included in the cointegrating relationship, the F-test is conducted on the following alternative representation of Eq. 10[11]:

$$\Delta q_t = a_0 + \phi q_{t-1} + \sum_{l=1}^{u-1} \omega_l \Delta q_{t-l} + \sum_{i=1}^{k} (\rho_i x_{t-1} + \sum_{l=0}^{v_i-1} \delta_{i,l} \Delta x_{i,t-l}) + \varepsilon_t. \tag{11}$$

The null hypothesis is then

$$H_0 : a_0 = \phi = \rho_i = 0, \forall i \in \{1, 2, ..., k\}.$$

The test statistic from the bounds test is compared against a set of critical value bounds for the two extreme cases where all variables are $I(0)$, the lower bound, and where all are $I(1)$, the upper bound. If the calculated F-statistic is above the upper bound, the null hypothesis of no cointegrating relationship between the variables is rejected, whereas if the F-statistic is within the critical value band, the test is inconclusive.

If a cointegrating relationship is present, the ARDL framework enables us to separate the cointegrating level relationship from the short-run dynamics . Eq. 11 can then be further reparameterized to a restricted error correction model (RECM):

$$\Delta q_t = \sum_{l=1}^{u-1} \omega_l \Delta q_{t-l} + \sum_{i=1}^{k} \sum_{l=0}^{v_i-1} \delta_{i,l} \Delta x_{i,t-l} + \phi ECT_{t-1} + \varepsilon_t. \tag{12}$$

Here, ϕ is defined as the speed of adjustment towards the equilibrium relationship in the error correction term (ECT). For convergence, ϕ must be negative, significant and less than unity in amplitude. The ECT given by

$$ECT_t = q_t - (\mu + \sum_{i=1}^{k} \beta_i x_{i,t}) \tag{13}$$

can be determined from the parameters in Eq. 11 with the transformations

$$\beta = -\frac{\rho_i}{\phi}, \forall i \in \{1, 2, ..., k\}$$

and

$$\mu = \frac{a_0}{\phi}.$$

From Eq. 12 and Eq. 13, it is clear that in equilibrium, where all the difference terms are zero, the RECM simplifies to the initial level relationship defined in Eq. 3.

[11]The EViews team (IHS Global Inc., 2017) provides a detailed demonstration of the algebraic steps involved in reparameterizing the ARDL.

6 Results

To investigate the order of integration of our data series, after adjusting for seasonality, we employ the augmented Dickey-Fuller test, the Phillips-Perron test and the KPSS stationarity test. The tests are performed on the variables in their levels and first differences.

Table 4: Unit root testing - Daily frequency

	ADF				PP		KPSS	
Null hypothesis	Unit root				Unit root		Stationarity	
Variable	Level Statistic	Lags	First difference Statistic	Lags	Level Statisic	First difference Statistic	Level Statistic	First difference Statisic
Demand	-1.01	25	-12.55***	24	-124.82***	-526.55***	0.63**	0.00
Wholesale price	-1.48	30	-8.65***	29	-22.27**	-1403.26***	10.68***	0.03
HDD	-1.57	21	-14.81***	20	-221.24***	-690.20***	0.08	0.00
Wind speed	-1.00	31	-12.37***	30	-643.74***	-1334.42***	0.17	0.00
Radiation	-0.64	30	-12.83***	29	-893.08***	-1550.03***	0.14	0.00
Crisis awareness	-3.27***	31	-5.06***	30	-12.64	-574.45***	4.19***	0.19
Covid	-3.20***	19	-12.68***	18	-36.64***	-1756.89***	1.75***	0.02
Covid × HDD	-2.87***	31	-10.74***	31	-61.56***	-802.009***	1.75***	0.02
Holiday × HDD	-10.42***	10	-13.28***	30	-2025.65***	-2088.59***	0.215	0.01

The lag column represents the number of lags included in the ADF regression, guided by AIC

Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *

Table 5: Unit root testing - Monthly frequency

	ADF				PP		KPSS	
Null hypothesis	Unit root				Unit root		Stationarity	
Variable	Level Statistic	Lags	First difference Statistic	Lags	Level Statisic	First difference Statistic	Level Statistic	First difference Statisic
Demand	-0.53	3	-7.03***	2	-57.54***	-60.41***	0.24	0.11
Wholesale price	-0.41	6	-3.55***	6	-11.53	-36.56***	0.96	0.08
End-use price	2.18	5	-5.19***	1	-6.21	-51.47***	1.02***	0.16
HDD	-0.20	3	-5.44***	6	-54.2***	-62.69***	0.09	0.06
Crisis awareness	3.53	6	-8.47***	1	-4.74	-68.02***	0.52**	0.35
Wind speed	-0.16	4	-6.76***	3	-81.43**	-80.59***	0.18	0.04
Radiation	-0.43	3	-7.76***	2	-74.87**	-77.28***	0.10	0.04
Covid	-2.56**	1	-6.32***	1	-14.80	-43.87***	0.22	0.05

The lag column represents the number of lags included in the ADF regression, guided by AIC

Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *

Table 4 and Table 5 presents the results of the selected unit root tests on the daily and monthly frequency, respectively. The three tests yield mixed results for some of the variables, preventing clear conclusions about the characteristics of our data. We can exploit the fact that the ARDL cointegration techique does not require the exact order of integration of the variables to be known in advance, and is appropriate when dealing with a mixture of $I(1)$ and $I(0)$ variables (Pesaran et al., 2001). Across all variables, we reject the null of a unit root in the first difference, indicating that none of the variables are $I(2)$, a prerequisite of the bounds test for cointegration.

We move on to conduct the ARDL bounds test to determine if a cointegrating relationship exists, using Eq. 11. The cointegrating relationship provides the basis for constructing an error correction model, allowing us to address the non-stationary variables and investigate their long-run relationship. The results of the bounds F-test is given in Table 6. The test statistic lies above the upper bound, indicating that a cointegrating relationship exists for all three specifications.

Table 6: Bounds test for cointegration

Frequency	F-statistic	Lower bound	Upper bound
Daily wholesale model	47.76***	2.88	3.99
Monthly wholesale model	151.09***	3.06	4.15
Monthly end-use price model	156.19***	3.06	4.15

Critical bounds provided at 1% significance level

The reparameterized results of our ARDL models are given in Table 7. The equilibrium relationship is contained in the ECT, and the speed of adjustment, given by its coefficient ϕ indicates a full adjustment within 5.7 days for the daily model, 1.15 months for the wholesale price monthly model and 1.16 for the end-use price monthly model, calculated by $1/\phi$. In the monthly models, no lags of the explanatory variables were selected with the AIC-criteria, cancelling out the Δ-terms in Eq. 12. To evaluate the impact of the level of the explanatory variables, we look to the components of the ECT.

Table 7: RECM results

Terms	Daily wholesale price	Monthly wholesale price	Monthly end-use price
Covid	3.01 (2.12)	12.5 (16.4)	12.6 (16.2)
Δ L(demand, 1))	0.110 *** (0.0103)	-	-
Δ HDD	76.1 *** (0.837)	-	-
Δ Wind speed	18.0 *** (0.863)	-	-
Δ Radiation	-0.0549 *** (0.00289)	-	-
Δ Holiday $\times$ HDD	12.5 *** (0.941)	-	-
ECT	-0.174 *** (0.0105)	-0.859 *** (0.0250)	-0.870 *** (0.0249)
R^2 (ex. seasonal trends)	0.92	0.95	0.95

Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *
Rounded to three significant figures

Table 8: ECT coefficients

Terms	Daily wholesale price	Monthly wholesale price	Monthly end-use price
(Intercept)	391 *** (30.6)	352 ** (167)	374 ** (163)
HDD	128 *** (2.41)	142 *** (10.4)	140 *** (10.1)
Wholesale price	-0.330 *** (0.0998)	-0.335 * (0.182)	-
End-use price	-	-	-0.523 ** (0.227)
Wind speed	41.4 *** (4.55)	41.4 * (20.8)	42.4 ** (20.2)
Radiation	-0.144 *** (0.0136)	-0.191 *** (0.0672)	-0.181 *** (0.0657)
Holiday × HDD	-7.31 (10.1)	-	-
Crisis awareness	-5.50*** (0.481)	-5.77 *** (0.956)	-5.06 *** (1.04)

Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *
Rounded to three significant figures

In Table 8, we see from the ECT coefficients how equilibrium demand will change (in GWh) from unit changes in the explanatory variables. The level of both the price variables, weather variables and the crisis awareness is significant in explaining natural gas demand.

Transforming the ECT coefficients to elasticities with Eq. 4, we find a wholesale price elasticity of demand of -0.012 on both daily and monthly frequencies. For end-use price prices, we find a price elasticity of demand of -0.037. Increased crisis awareness drives demand down, with an elasticity of approximately -0.01 across all models. Heating degree days has the strongest relative impact on demand with elasticities in the range 0.68-0.77.

Table 9: Elasticity estimates

Terms	Daily wholesale price	Monthly wholesale price	Monthly end-use price
HDD	0.680 *** (0.0129)	0.768 *** (0.0563)	0.757 *** (0.0545)
Wholesale price	-0.0120 *** (0.00363)	-0.0122 * (0.00663)	-
End-use price	-	-	-0.0369 ** (0.0161)
Wind speed	0.131 *** (0.0144)	0.132 * (0.0664)	0.135 ** (0.0646)
Radiation	-0.158 *** (0.0149)	-0.210 *** (0.0740)	-0.199 *** (0.0724)
Holiday × HDD	-0.000711 (0.000979)	-	-
Crisis awareness	-0.00824 *** (0.000720)	-0.0113 *** (0.00200)	-0.00993 *** (0.00213)

Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *
Rounded to three significant figures

Table 10: Residual diagnostics

Test	Daily wholesale price	Monthly wholesale price	Monthly end-use price
Jarque-Bera	159.817 ***	3.13	1.517
Ljung-Box	0.929	1.834	2.059
Breuch-Pagan	106.449 ***	2.14	4.004
Goldfeld-Quandt	1.078	1.717	1.483
Recursive CUMSUM	0.715	0.511	0.489

Test statistics reported with corresponding significance levels
Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *

When evaluating the residual diagnostics of our data, we observe that both monthly models pass all residual tests. In addition, the models all pass the parameter stability tests and Ljung-Box test, indicating that the residuals are not autocorrelated. However, on a daily frequency, our residuals do not pass the Jarque-Bera test for normally distributed errors or the Breusch-Pagan test for heteroskedasticity. We employ an additional heteroskedasticity test, the Goldfeld-Quandt test, investigating whether the volatility differs significantly when comparing two sub-periods of our data. By this test, we do not reject the null that the volatility is constant. This conclusion supports the hypothesis that the heteroskedasticity is caused by the seasonality in the volatility of the data and that we do not make consistently larger errors over time.

Our deseasoning efforts remove the seasonality in the means of the variables, but not in their variance. As we estimate a mean model, we are interested only in the central tendency of the distribution. We are not concerned with forecasting demand or estimating it's volatility, and accept that there is volatility clustering in our data as long as the mean is not affected by temporal dependencies in volatility. We use heteroskedasticity consistent standard errors to represent the uncertainty of our estimates. The fact that the estimates on a monthly frequency, passing all residual diagnostics, exhibit a similar magnitude to the daily results also serves as a benchmark to assess the reliability of our findings on the daily frequency. By comparing the two sets of results, we can ensure that the model's performance is consistent and stable across different time frequencies, an indication of the robustness and generalizability of our findings.

7 Discussion

In this section, we discuss the inelastic demand response to price and the high sensitivity to weather evident from our results. By analyzing the model outcomes, we draw inference about the significant decline in natural gas consumption during the crisis year of 2022. We then compare our results to the existing literature on the price elasticities of natural gas demand. Finally, we discuss policy measures to increase the responsiveness to market signals.

To make meaningful inference from our models, it is key to analyze the estimates of the ECT. As most of the literature estimating elasticities of natural gas demand has been done on yearly frequencies, the estimates on the differences terms have been referred to as short-run elasticities. For the typical yearly model, this would mean the impact of an innovation in a variable from one year to another. The estimates on the variables in their levels have then been referred to as long-run elasticities, representing stock adjustments and other economical changes over several years.

For our high-frequency data with a dominating cointegrating relationship, the division between short-run and long-run effects is not meaningful. Our ECT estimates indicate a full adjustment to the level relationship after six days on a daily frequency and shortly after one month for the monthly models. Hence, the level estimates in the ECT will capture adjustments over a short period of time and enable inference on the demand response of small consumers.

7.1 Interpreting the results

Examining the results for wholesale prices, we find that demand from small consumers is highly inelastic, with a price elasticity of -0.012 both on the daily frequency and monthly frequency. This means that a 1% increase in wholesale prices would lead to a demand reduction of around 0.012%. While this impact might sound negligible, the average wholesale price rose by a remarkable 433% in the crisis year 2022 compared to a reference period of the previous sample years 2018-2021. Combined, these estimates would imply a demand reduction of 5.3%, driven by wholesale prices.

For the monthly end-use prices, we find an elasticity of demand of -0.037. This implies that the reaction to a relative change in consumer end-use prices is around three times as strong as the reaction to a relative change in wholesale prices. Nonetheless, the small magnitude adds to the evidence that demand is inelastic in this period, also in response to prices directly affecting the consumer.

In quantities, our results imply that approximately 15 TWh of the observed demand reduction in 2022 is related to the increases in end-use prices. This calculation is based on the monthly price estimate[12], which reveals by how many GWh the average daily demand will change from a 1 EUR/MWh change in the average end-use price. Multiplying the coefficient with 365, we will then obtain the impact of a mean shift over a year. Figure 12 illustrates the impact of the observed mean shift in each variable between 2022 and the previous reference period.

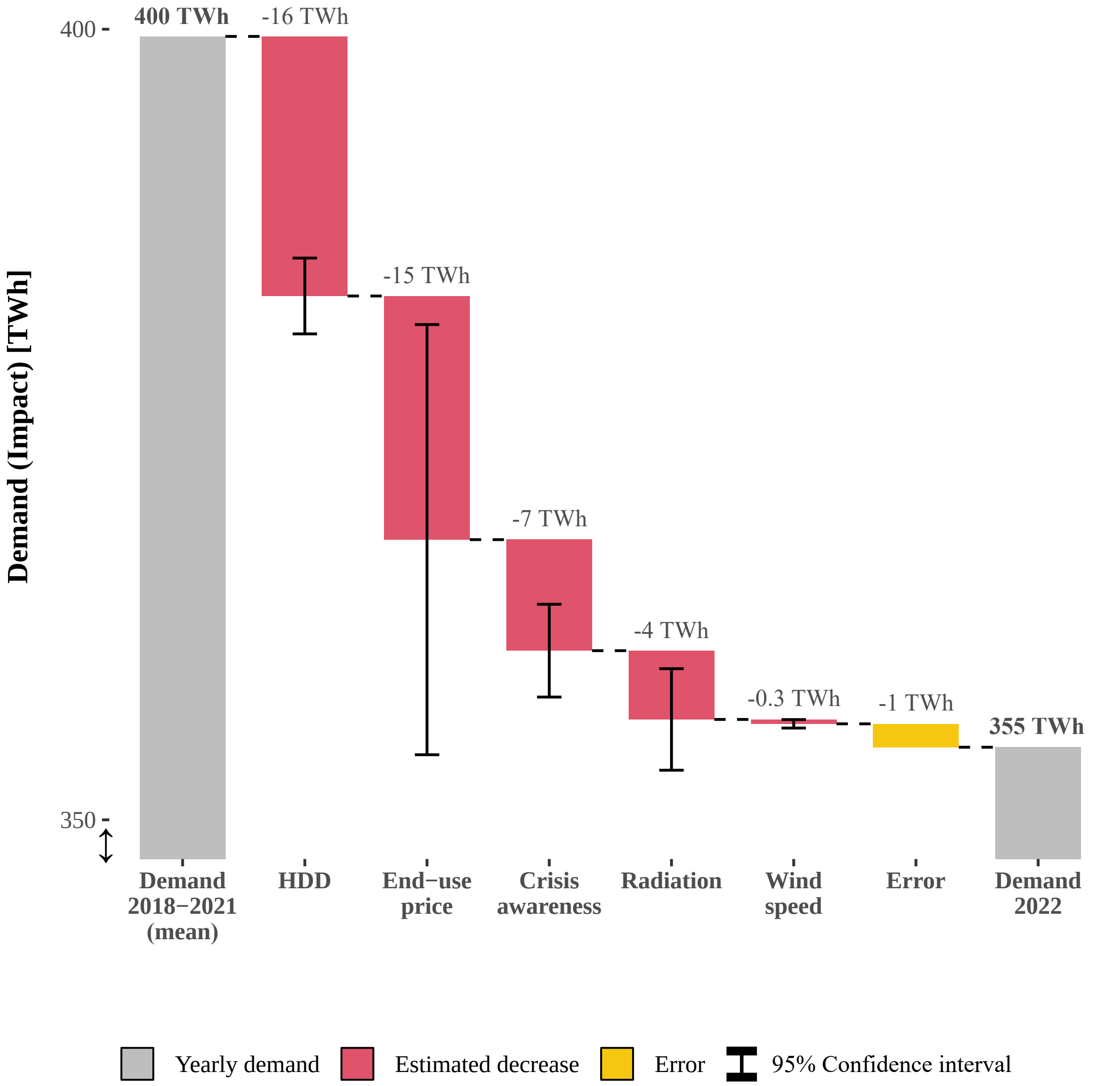


Figure 12: Decomposing the demand reduction in the crisis year 2022

Changes in crisis awareness have a dampening effect on demand, about half the size of the contribution of end-use prices in 2022. However, there is less uncertainty to the crisis awareness estimate. The low correlation between the crisis awareness variable

[12]Here, we base our calculations on the monthly frequency model with mean aggregations of the daily data, as it passes all residual diagnostics and has lower variance than the daily frequency model.

and the price series (below 0.25 on both frequencies) supports the assumption that the effects of prices and general crisis awareness can be separated. An estimated demand reduction of 7 TWh in 2022 from this awareness should serve as a motivation for policy makers to keep the general public informed.

While the crisis conditions prompted small consumers to decrease their consumption, our results reveal that the largest part of the demand variations is explained by weather conditions. We find that the reduction in HDD contributed to about 16 TWh demand reduction in 2022 compared to the reference period. Interestingly, 2022 had the mildest winter since 2015, in contrast to the previous year which was the coldest in the same period (Eurostat, 2023c). The solar radiation from the sky was also abnormally intense, contributing to an additional heating effect on the building envelopes. Next winter, Germany might not have this double advantage, and the sensitivity to weather of small consumers must not be neglected.

We find that the Covid-19 dummy is insignificant, adding to the insufficient research on the pandemic effects on natural gas demand. Only one study on price elasticity of demand, Erias and Iglesias (2022) includes the pandemic in their sample period, and the recent paper by Ruhnau et al. (2023) deliberately excludes the pandemic years from their sample. IEA (2020) highlights that 2020, the year of the first lockdown, was a warm year and that strong wind power generation contributed to low natural gas prices. They report a stronger decline in consumption during the lockdown but largely attributed it to the drop in demand from the industry. In line with our results, Honoré (2020) proposes that the effects of the pandemic on the consumption of natural gas were minor.

When comparing the reported price elasticity for consumer end-use prices to the literature, we observe that our result lie below the majority of previous studies. Our sample period from 2018 to 2023 is characterized by extreme price volatility, during which few other studies have examined the price elasticity of demand. As an exception, the recent study of Ruhnau et al. (2023) examines natural gas demand in a similar sample period, and provides a rough estimate on the price elasticity of demand of -0.16 given that behavioral changes in 2022 were driven by price. Similar to our findings, their calculation also indicates that the consumer price elasticity of demand has been lower in recent periods.

For the price elasticity of demand on wholesale prices, the available literature is limited. In our literature review, Erias and Iglesias (2022) and Burns (2021) are the only studies examining the wholesale price elasticity of demand for natural gas. Our estimates are lower than those of Erias and Iglesias (2022), reporting rather diverging estimates in the range of -2.2 to 0 in the short run and a long-run estimate between -4.3 and -0.94 in the period 2016 to 2020. Burns (2021) estimates an interannual elasticity of demand of -0.09 on US data from 1980-2016. Although this response is stronger than our results, her estimations on subsamples in the period provide elasticity estimates close to zero. Her results support our finding that natural gas demand is highly inelastic to wholesale prices. As discussed in Section 3, the literature on electricity demand, where there has been more research, shows that studies using wholesale prices and high-frequency data tend to report a lower price elasticity of demand than the average across studies, similar to our findings for natural gas.

Another reason we obtain lower estimates than prior literature can be attributed to the fact that our study controls for a combination of factors known to create upward bias to the price estimates. Firstly, we make deliberate modeling choices to create an appropriate control for weather effects. As the most important predictor of natural gas demand, misspecifications of the relationship between weather and demand would impact the estimate of price elasticity of demand. Secondly, we recognize the issue of spurious regression. Many prior studies have overlooked this concern, which can lead to false conclusions on the underlying relationship if the data are non-stationary. Lastly, we decompose the behavioral effect that has often been attributed to price in its entirety. Ruhnau et al. (2023) stress this issue and suggest that their own rough estimate of price elasticity of demand is inflated if an "increase in public attention and ethical considerations" are drivers of demand reduction. Our results suggest that public awareness does have a significant impact on demand. By addressing these issues, we mitigate the risk of inflated estimates on the price elasticity of demand.

7.2 Policy implications

For policy makers, the wholesale price elasticity of demand can indicate whether changes in market prices cause self-regulation among small consumers. We find evidence of a reaction to price signals in the wholesale market, although it is limited in magnitude and dominated by weather effects. This finding suggests that purely price-driven policy measures are ineffective in the short run. To exploit the saving potential from small consumers during periods of restricted supply, the price hikes must either be very large, or additional measures must be part of the policy mix.

Our results show a three times stronger response to the actual end-use prices than to wholesale prices. This implies that the demand response from small consumers to market changes could be far greater if the price signals were rapidly passed on to the consumer end-use prices. However, today's structure with yearly metering and fixed-price contracts makes such efforts impossible. In the absence of modern metering devices, there is no way of providing a fair dynamic pricing scheme without high-frequent information on consumption. Automatic meter reading have been widely discussed for electricity (Die Bundesregierung, 2023), but should also be considered for natural gas to meet the potential for increased market efficiency revealed in our results.

The consumer benefit from dynamic pricing schemes will depend on the demand flexibility. In a media interview, Germany's vice-chancellor Robert Habeck points to simple measures such as turning down the thermostat 1 °C and drawing the curtains to save energy (Tagesspiegel, 2022). In this sense, small consumers do have some short-term flexibility in adjusting their heating consumption. However, a basic consumption level is needed to maintain the standard of living. If consumption is close to this basic level, price fluctuations will directly impact either the indoor comfort of the consumers or the budget for other goods.

The welfare effect of more variable prices may vary across consumer groups. Analyzing the impact of energy price hikes in Norway, (Dalen & Halvorsen, 2022) find that the potential for energy saving is the lowest for low-income groups.[13] As an example, they highlight that turning down the heat in unused rooms is only feasible if you have the luxury of unused rooms. This illustrates that low-income groups have a modest consumption above the levels needed to fulfill basic needs and will be strongly affected by price fluctuations. This distributional effect should not be neglected when implementing policy.

[13]Here Norway is an interesting case study, as more than 90% of the household contracts follow the wholesale prices for heating energy and were rapidly exposed to the soaring energy prices from 2021.

8 Conclusion

This paper analyzes the drivers of natural gas demand from German small consumers in the period 2018 to 2023 using an ARDL cointegrating technique. Through the error correction framework, we account for the mixed orders of integration of the variables. For a precise weather control, we calculate the variations based on where natural gas is used for heating. Moreover, we quantify the impact of public crisis awareness and control for seasonality and pandemic restrictions. We report a price elasticity of demand of -0.01 for wholesale prices and -0.04 for consumer end-use prices.

These findings illustrate that demand from small consumers is highly inelastic in response to both consumer end-use prices and wholesale prices. Unless the price changes are extreme or there is a collective crisis awareness, demand variations are almost fully determined by weather. For energy security, these findings suggest that small consumers can play a role in balancing the market, but with a high social cost due to the drastic price changes needed to achieve significant demand adjustments.

With the crisis awareness indicator, we have identified a variable capturing the willingness to adjust energy consumption unrelated to price. To expand this research, sentiment analysis with modern machine learning techniques could allow a more comprehensive understanding of consumer awareness and non-financial motives for energy saving.

This study is limited by the country-wide aggregates of demand observations, as the consumption of individual consumers is only metered on an annual basis. This restricts the ability to exploit local variations in prices and examine the response across different income levels and consumer groups on a high frequency.

Our results reveal that small consumers do have some flexibility in demand, as demonstrated during the crisis year 2022. By making market signals more salient to the consumers, this capacity could be exploited in the joint European effort for energy security. However, further research into the distributional effects of greater market exposure is required to design policy protecting low-income consumers.

Based on this analysis, natural gas demand will recover as prices and attention on the energy crisis revert to normal levels. Until small consumers are offered adequate flexibility options, regulators are left to rely on the weather to trigger their demand response.

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A Endogeneity test results

Hausman test for endogeneity

Fitted values from:	Price ∼ HDD + Wind speed + Radiation + Holiday × HDD + Covid × HDD + Crisis awareness Demand ∼ HDD + Wind speed + Radiation + Holiday × HDD + Covid × HDD + Crisis awareness			
Dependent variable	Demand		Price	
Fitted values from	Price equation		Demand equation	
Term	Before price lag transform	After price lag transform	Before price lag transform	After price lag transform
(Intercept)	-3550 *** (44)	-9310 *** (93)	30.6 *** (8.9)	38 *** (8.7)
Wind speed	172 *** (2.6)	380 *** (4)	-1.49 (1)	-1.55 (1)
Radiation	-0.907 *** (0.009)	-1.27 *** (0.012)	0.00782 ** (0.0035)	0.00517 (0.0034)
Holiday × HDD	127 *** (2.8)	212 *** (3.1)	-1.09 (1.4)	-0.865 (1.4)
Covid × HDD	427 *** (3.5)	868 *** (7.3)	-3.68 *** (0.5)	-3.54 *** (0.49)
Crisis awareness	-238 *** (2)	-592 *** (5.1)	2.05 *** (0.17)	2.42 *** (0.17)
Price eq. fitted values	116 *** (1)	245 *** (2.1)	-	-
Demand eq. fitted values	-		0.00862 * (0.0048)	0.00408 (0.0048)

In this table, we observe that prior to the lag transformation to price, the fitted values of demand has a significant impact on price, indicating that endogeneity is present. This is not the case after transforming the price variable by a lag of 10.

B Supplementary table on Google Trends data

Top 25 rising queries within topics Energy and Natural gas

Ranking	Topic	Exact query	Our grouping
1	Natural gas	dezember abschlag gas	abschlag gas
2		gasumlage	gasumlage
3		gas in rubel	-excluded-
4		gaspreisbremse	gaspreisbremse
5		gasspeicher füllstand	gasspeicher
6		wieviel gas kommt aus russland	gas russland
7		gas sparen tipps	gas sparen
8		ukraine gas	gas ukraine
9		strompreis aktuell	-excluded-
10		nord stream gas pipelines	nord stream
11		was kostet 1 kwh gas 2022	-excluded-
12		fracking gas deutschland	-excluded-
13		gaspreis bremse	gaspreisbremse
14		nord stream 1	nord stream
15		eon grundversorgung strom	gas grundversorgung
16		russland gas	gas russland
17		wie teuer wird gas	-excluded-
18		umlage gas	-excluded-
19		gas aus russland	gas russland
20		gasversorgung deutschland	gas grundversorgung
21		gas pipeline ukraine	gas ukraine
22		gasspeicher deutschland	gasspeicher
23		gaspreis aktuell	-excluded-
24		eon gas grundversorgung	gas grundversorgung
25		gas grundversorgung	gas grundversorgung
1	Energy	entlastungspaket energie	entlastungspaket energie
2		energiepauschale	-excluded-
3		european energy crisis	energie krise
4		bion 3 energy	-excluded-
5		energie bonus 2022	entlastungspaket energie
6		entlastungspaket energie 300 euro	entlastungspaket energie
7		energie pauschale	-excluded-
8		energie preispauschale	-excluded-
9		energie zuschuss 2022	entlastungspaket energie
10		energie pauschale 300 euro	-excluded-
11		buhler energie	-excluded-
12		tagesschau fernseher energie erzeugt	-excluded-
13		energie embargo	energie krise
14		energie entlastung	entlastungspaket energie
15		sunny tripower smart energy	-excluded-
16		sma tripower smart energy	-excluded-
17		cheniere energy aktie	-excluded-
18		energie bonus	entlastungspaket energie
19		hamburg energie strompreis	-excluded-
20		energie zuschuss	entlastungspaket energie
21		wann wird die energie pauschale ausgezahlt	-excluded-
22		habeck energie sparen	gas sparen
23		cheniere energy	-excluded-
24		eckert new energy	-excluded-
25		energy crisis tarkov	energie krise

C Availability of code

The code written to conduct our analysis can be accessed openly at: https://gitfront.io/r/user-3955032/ubRT9TyGVhaz/jamissen-vatne-masterthesis/.

Kindly note that certain restrictions may apply to the sharing of market data obtained from Bloomberg. As a result, it is necessary for readers to collect the wholesale prices themselves in order to completely reproduce the analysis. If assistance is needed in this regard, the authors are pleased to offer their support upon request.

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