Understanding Gas Price Shocks: Elasticities, Volatility, and Macroeconomic Transmission*

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Abstract

We identify supply and demand shocks to the real price of natural gas in the Euro Area and the United States. Demand shocks are identified using exogenous temperature variations, while supply shocks are identified through a high-frequency strategy based on an extensive collection of market-relevant news. This approach enables us to estimate gas market elasticities and uncover key transmission channels through which gas price shocks affect the broader macroeconomy. Our findings show that gas demand in the Euro Area adjusts more slowly than in the United States, amplifying the inflationary impact of supply shocks. This effect is reinforced by inventory accumulation and financial volatility, pointing to a transmission channel driven by expectations and uncertainty. The aggregate real effects appear limited, though we document substantial sectoral heterogeneity.

Keywords: Gas price shocks, gas supply, gas demand, elasticities, proxy-VAR, external instruments, temperature deviations, inflation.

JEL classification: C32, E31, Q38, Q41, Q43.

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1 Introduction

The recent outbreak of war between Russia and Ukraine has driven natural gas prices to unprecedented levels, particularly in Europe, sparking significant interest in a commodity that had previously received relatively little attention. Moreover, the surge in gas and broader energy prices coincided with rising inflation worldwide (see Figure 1). These developments have raised several critical economic questions that have shaped both political and academic debates: To what extent, and how quickly, can economies respond to supply disruptions by substituting to alternative gas supplies or to other energy sources, and how elastic is natural gas demand in response to price increases (Moll et al., 2023)? How does the segmentation of natural gas markets affect the transmission of regional shocks compared to the more integrated crude oil market? To what degree do gas prices reflect fundamental supply and demand dynamics, as opposed to non-fundamental factors such as speculative activity (Knittel & Pindyck, 2016)? How much of the recent inflation surge can be attributed to gas prices as opposed to other factors, such as the post-pandemic economic recovery? Addressing these questions is challenging, as energy prices are endogenous and respond to economic conditions, while the assessment of macroeconomic effects is further complicated by a range of confounding factors that have been particularly relevant in recent years.

This paper proposes a novel approach to identifying structural supply and demand shocks in natural gas prices. Demand shocks are identified leveraging variation in temperatures, while supply shocks are isolated using market-relevant news and high-frequency data. Using the resulting series as external instruments in a Bayesian VAR setting, we analyze gas market dynamics and the broader macroeconomic transmission of these shocks. To the best of our knowledge, this allows us to provide the first macro-level estimates of gas market elasticities based on exogenous variation for both the Euro Area and the United States. Building on these estimates, we then study the key transmission channels through which gas price shocks influence the broader economy, highlighting significant differences between the Euro Area and the United States. While many of these differences are attributable to well-known disparities in gas balances and to fundamental supply and demand dynamics, we also find evidence that supply shocks can be amplified through an expectations and market volatility channel, with differing strength across the two regions. Moreover, we show that CO_2 emissions tend to rise in response to gas price shocks in the short to medium term. Finally, we compare the identified gas shocks with other structural drivers of inflation to assess the extent to which the recent surge in inflation can be attributed to gas price shocks relative to other contributing factors.

Preview of results. Gas price shocks have economically meaningful effects. However, our analysis reveals significant regional differences in both the magnitude and transmission of these shocks between the Euro Area and the United States, shaped by structural differences in supply composition, demand elasticity, and market dynamics. In the United States, domestic production is the primary margin of supply adjustment, with this quantity gradually increasing over time; with a peak response of 0.1% after one year, following a 1% increase in price. In contrast, in the Euro Area, where imports play a larger role, supply adjusts more rapidly—reflected in an adjustment of around 0.2% observed shortly after the shock. However, reliance on external sources of supply offers limited insulation from import-related disruptions. On the demand side, gas consumption in the Euro Area is highly inelastic on impact, with noticeable adjustment occurring only after several months. In the United States, by contrast, greater potential for interfuel substitution enables a faster demand response. We estimate the underlying structural short-run elasticities as follows: for the Euro Area, the demand elasticity is -0.10 and the supply elasticity is 0.75; for the United States, the demand elasticity is -0.05 and the supply elasticity is 0.24.

Inflationary effects are more pronounced in the Euro Area, with demand shocks contributing up to a 2.5% increase in headline inflation and supply shocks up to 3%, also feeding into core inflation. In contrast, the impact in the United States is smaller and less persistent, with supply shocks showing no significant effect. These inflationary dynamics reflect spot price movements, which are shaped by demand adjustments and gas inventory responses. The inventory response in the Euro Area, where stock levels do not offset price increases following supply shocks but instead rise over the long run, gives evidence of an expectation-driven mechanism. Heightened uncertainty appears to prompt stockpiling and precautionary demand, similar to the channel identified by Kilian and Murphy (2014) for the oil market, further amplifying inflationary pressures. Consistently, we observe a rise in financial uncertainty, likely reflecting concerns over future gas supply. This differs from the oil market shock identified by Känzig (2021a), where volatility remains unchanged. Additionally, the near one-to-one pass-through of gas prices to electricity prices in the European market further reinforces inflation persistence.

The aggregate real effects of gas price shocks are limited but exhibit significant sectoral variation. In the United States, gas demand shocks lead to a temporary increase in industrial production, driven by heightened activity in the energy sector. In contrast, in the Euro Area, supply shocks have a moderate negative impact, with energy-intensive industries such as electricity, gas and steam, and chemicals experiencing the largest declines. Over time, cost increases are largely passed downstream, mitigating the effects on output but leading to inflationary pressures, which are more pronounced in goods-producing sectors than in services.

Our findings have important implications for the green transition. The estimated consumption elasticities indicate that price-based policies alone may be insufficient to induce a significant shift away from natural gas. In the short to medium term, gas supply shocks tend to lead to substitution toward coal and oil rather than renewables, thereby hindering progress in reducing emissions. As a result, both demand- and supply-driven gas price shocks increase CO_2 emissions.

A comprehensive set of sensitivity checks confirms the robustness of our results across various dimensions, including model specification, estimation sample, estimation technique, and instrument construction. We show that the qualitative findings remain consistent when estimating responses to the identified shocks using a frequentist VAR-OLS instead of Bayesian estimation, while the quantitative results remain unchanged when employing an informationally robust gas supply instrument that accounts for potential confounding factors and background information over event windows. Furthermore, we demonstrate that the constructed instruments do not capture unintended mechanisms, as they exhibit no correlation with other macroeconomic shocks.

Related Literature and contribution. The starting point of this paper is to isolate exogenous variation to construct instruments for natural gas demand and supply, which serves as the foundation for the broader macroeconomic analysis. In this sense, it contributes to the literature examining temperature as a key determinant of natural gas prices. Most studies rely on heating and cooling degree days (Mu, 2007; Nick and Thoenes, 2014; Wang et al., 2019, among others), while others employ extreme temperature indexes (Dubin & Gamponia, 2007; Chen et al., 2023; Baumeister & Hamilton, 2024). To the best of our knowledge, however, this paper is the first to use temperature as an instrument for gas demand and to analyze the broader macroeconomic effects of gas demand shocks. Similarly, a substantial body of research applies event-study techniques to assess the impact of various announcements on gas prices, including EIA's Weekly Natural Gas Storage Reports (Gay et al., 2009; Bjursell et al., 2010; Halova et al., 2014; Prokopczuk et al., 2021), policy measures (Goodell et al., 2024), and supply-related announcements or disruptions (Bartelet & Mulder, 2020; Goodell et al., 2023). This paper integrates this event-study literature with traditional VAR analysis by constructing an instrument for gas supply using market-relevant announcements. Methodologically, we employ a high-frequency identification strategy developed in the monetary policy literature (e.g. Kuttner, 2001; Gertler and Karadi, 2015; Altavilla et al., 2019) and subsequently applied to other domains (Wu & Cavallo, 2012; Känzig, 2021a, 2021b). Additionally, we also propose an informationally robust version of the supply news instrument, to obtain cleaner identification (Romer & Romer, 2004; Nakamura & Steinsson, 2018; Miranda-Agrippino & Ricco, 2021).

A key contribution of this study is the estimation of elasticities of gas demand and supply in both the United States and the Euro Area using external instruments. This analysis is related to a well-established body of research in the oil market literature, which seeks to estimate such elasticities and assess the relative importance of supply and demand forces (Hamilton, 2003; Kilian, 2009; Baumeister & Hamilton, 2019; Caldara et al., 2019; Baumeister & Hamilton, 2023). The limited number of studies estimating gas market elasticities has largely drawn from this literature. Early contributions relied on recursively identified VAR models (Wiggins & Etienne, 2017; Hou & Nguyen, 2018; Nguyen & Okimoto, 2019; Rubaszek & Uddin, 2020), which impose a zero short-run supply elasticity. More recent work has adapted the approach of Baumeister and Hamilton (2019), incorporating both zero and magnitude restrictions while integrating prior beliefs (Rubaszek et al., 2021; Casoli et al., 2022; Farag, 2024).

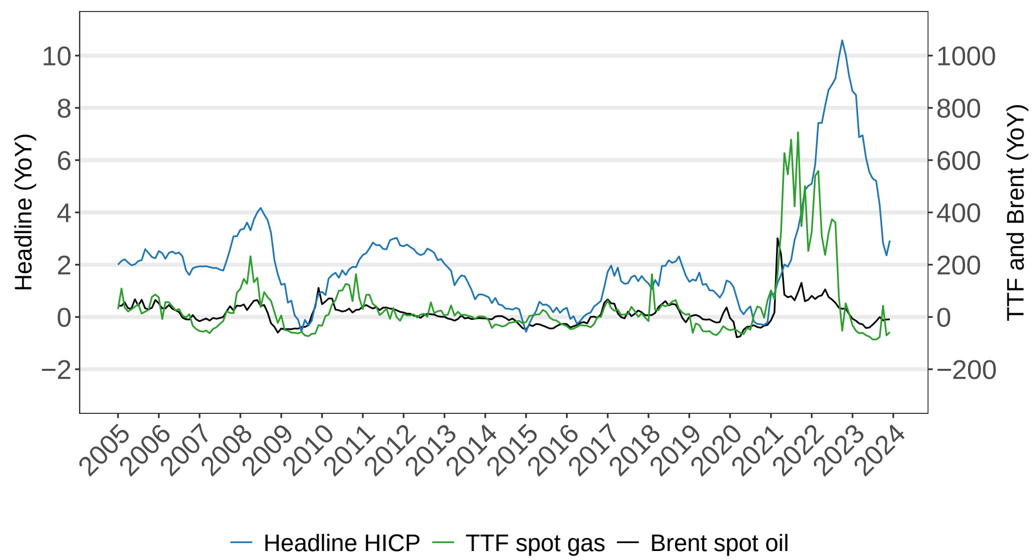
In addition, some studies estimate sector-specific demand elasticities using static approaches (Asche et al., 2008; Andersen et al., 2011; Pettersson et al., 2012; Auffhammer & Rubin, 2018). However, their external validity is likely limited, and simultaneity issues remain a common concern in this literature (Labandeira et al., 2017). By leveraging exogenous variation in both the demand and supply of natural gas, we estimate both elasticities without relying on sign or zero restrictions. Moreover, constructing distinct instruments for the United States and the Euro Area allows us to address the challenge of natural gas market fragmentation—unlike the globally integrated oil market—where the absence of a unified market structure prevents the estimation of "global" elasticities (Szafranek & Rubaszek, 2023).

This study also relates to a well-established body of literature examining the broader economic effects of commodity price shocks, which has traditionally focused on oil price shocks in the United States (Zhou, 2020; Känzig, 2021a, as well as many of the works previously discussed in the context of oil market elasticities). In contrast, research on the macroeconomic impact of natural gas shocks is more recent and still developing. The Russian invasion of Ukraine in 2022 heightened concerns about the potential economic consequences of gas supply disruptions, prompting an initial wave of theoretical studies on their macroeconomic effects. Most of these studies suggest relatively limited output losses (Bachmann et al., 2022; Albrizio et al., 2023; Di Bella et al., 2024), though some early assessments warned of far more severe economic consequences (Lan et al., 2022). Empirical research using VAR techniques has also begun to examine the macroeconomic implications of gas shocks in the Euro Area. Boeck et al. (2023) analyze the effects of natural gas price fluctuations using a Bayesian VAR with sign restrictions, focusing on inflation expectations. Adolfsen et al. (2024) likewise employ sign restrictions to identify three structural shocks: supply, demand (economic activity), and inventory shocks. Alessandri and Gazzani (2025) adopt a high-frequency approach similar to ours to construct a gas supply shock instrument for the Euro Area. However, we find evidence that their instrument also captures some demand-side dynamics. A detailed discussion of this is provided in Appendix J. We contribute to this growing literature in several ways. First, we introduce a novel approach to identifying gas demand and supply shocks using external instruments (Lunsford, 2015; Stock & Watson, 2018). This method yields gas balance responses that align with, but are not restricted by, standard theoretical predictions on prices and quantities. Second, we provide a comparative analysis of the macroeconomic effects of gas shocks in the Euro Area and the United States within a unified framework. Third, we develop an informationally robust version of the supply instrument, which accounts for high-frequency movements in potential confounding factors, ensuring a more precise identification of supply-driven shocks. Finally, for the Euro Area, we conduct a detailed sectoral analysis, examining both prices and quantities to capture potential heterogeneous effects and explore direct and indirect transmission channels.

Moreover, this study also relates to the literature on the pass-through of energy shocks to inflation, which, once again, has primarily focused on oil price shocks in the United States. Existing estimates suggest that while energy price shocks have a strong impact on headline inflation, their effect on core inflation is less pronounced (Gao et al., 2014; Känzig, 2021a; Kilian & Zhou, 2022). Recent studies estimating the pass-through of gas price shocks in the Euro Area report a wide range of estimates. Headline inflation pass-through varies from 1.9% to 8.5%, while core inflation effects range from 1.1% to 4.5% (López et al., 2022; Boeck et al., 2023; Adolfsen et al., 2024), while broader estimates of energy price pass-through to inflation, based on firm-level data, suggest an impact of up to 7.3% (Joussier et al., 2023). Using an external instrument approach, we find that in the United States, only gas demand shocks exhibit a significant yet moderate pass-through to headline inflation. In contrast, in the Euro Area—where gas price shocks fully transmit to electricity prices—the peak pass-through reaches approximately 2.5% for demand shocks and 3% for supply shocks. Notably, supply shocks also affect core inflation, with a peak pass-through of 1%. Our findings indicate that gas price shocks, alongside supply chain bottlenecks, have played a central role in the post-pandemic inflation surge in the Euro Area. In this context, we also contribute to the literature examining the factors driving the recent rise in inflation (Bańbura et al., 2023; Baumeister, 2023; Bordo et al., 2023; Stiglitz & Regmi, 2023; De Santis, 2024).

Finally, this paper contributes to the literature on the environmental effects of energy shocks. Previous studies find that in the short run, lower gas prices reduce emissions by encouraging coal-to-gas substitution in the power sector (Knittel et al., 2015; Cullen & Mansur, 2017; Brehm, 2019). Over the long run, however, rising gas prices can promote investment in renewables and help lower emissions (Stock & Zaragoza-Watkins, 2024). This has led some authors to highlight a time inconsistency problem: while gas can reduce emissions in the near term, its continued use may hinder the transition to cleaner energy sources (Acemoglu et al., 2023; Harstad & Holtsmark, 2024). Our findings show that gas price increases raise CO_2 emissions in the short to medium term by prompting substitution toward more polluting fuels. Combined with our estimates of demand elasticity, this suggests that price-based mechanisms alone may be insufficient to achieve meaningful emissions reductions.

Layout. The rest of this work is structured as follows. Section 2 provides key background information on the gas markets. Section 3 outlines our identification strategy, with a focus on the separate identification of supply and demand shocks to the price of gas. Section 4 describes the econometric framework and estimation approach. Section 5 presents the main results. Finally, section 6 concludes. Several appendices follow with additional details on the data, the Bayesian framework, supplementary empirical results, and robustness checks.



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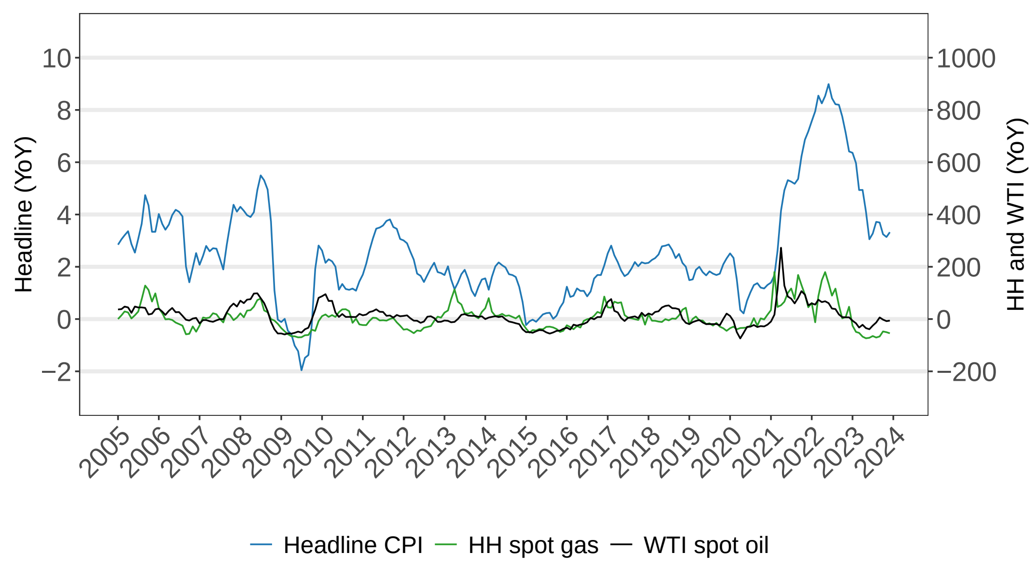


US

Figure 1: *Inflation and energy prices*

Notes: The top panel displays the Year-on-Year (YoY) headline inflation rate in the Euro Area, along with the YoY inflation rates of Title Transfer Facility (TTF) natural gas and Brent crude oil prices—benchmark indicators for European gas and oil markets. The bottom panel shows the equivalent series for the US, where the benchmarks are the NYMEX Henry Hub (gas) and WTI (oil). Gas and oil spot prices are referenced to the right-hand scale.

2 Gas market background

This section outlines important characteristics of the natural gas market in the Euro Area and the United States, emphasizing regional differences and comparing them to the more globally integrated crude oil market. These distinctions underscore the need for a region-specific interpretation of gas price shocks and provide the foundation for our empirical strategy. Additional supporting figures and tables are available in Appendix C.

The global natural gas market is regionally fragmented, with prices for the same commodity differing markedly across areas. This contrasts with the crude oil market, which tends to be more integrated, trading at a relatively uniform price in most places.[1] The consequences of this segmentation became particularly evident during Russia's invasion of Ukraine, which led to a drastic reduction in pipeline flows to Europe. European spot gas prices surged to a record high in August 2022, increasing nearly 30-fold compared to August 2019, while gas prices in the United States remained considerably lower. The difference in price movements is driven by regional gas supply balances and variations in transportation infrastructure. In particular, the United States is less affected by gas price shocks originating abroad due to its self-sufficiency and limitations on LNG export capacity, which constrain the ability of domestic production to reach international markets (IMF Blog, 2023).

Natural gas is a critical energy source in both the EA and the US, accounting for one quarter of total energy consumption in both the Euro Area and the United States. It plays a crucial role as a primary fuel in residential and commercial heating, and it also serves as an important input for industrial activities and electricity generation. Residential consumption represents a substantial share of total demand — 35% in the EA and 22% in the US— primarily for heating purposes.[2] For a detailed breakdown of natural gas consumption by end use, see Figure C19 in the Appendix. Gas demand is highly sensitive to temperature fluctuations, particularly in winter (Chen et al., 2023). Consequently, anomalous weather-driven variability can be exploited as a source of exogenous variation to study the effects of gas demand shocks.

The supply structure of the gas market differs markedly between the two regions. In the Euro Area, natural gas production has steadily declined, with monthly output falling to negligible levels—below 100 PJ in recent years. As a result, import dependence has risen sharply, increasing from around 50% of total gas energy use in the early 1990s to a record 90% by 2019. Illustrative trends are shown in Figure C20 in the Appendix. The region sources gas from a select group of major suppliers, including Russia, Norway, Algeria, and the US. Prior to the war in Ukraine, Russia dominated the EU gas market, supplying 41% of gross available energy by

[1] For example, Brent and WTI prices, the respective benchmarks for crude oil in the Euro Area and the United States, have typically been highly integrated (Reboredo, 2011). Nonetheless, there have been isolated episodes of limited decoupling (Baumeister & Kilian, 2016). For a more recent examination of crude oil prices integration, see Mastroeni et al. (2021).

[2] These figures refer to the average for the period 2004–2022, own calculations based on (IEA, 2024a) and (IEA, 2024b).

2020, making it the fuel with the highest exposure to Russian imports. This share further increased to approximately 50% of total imports by 2021, when imported gas accounted for over 80% of EU consumption (European Council, 2023). Due to the heavy dependence on imports from a limited number of suppliers, disruptions to gas flows—whether actual or simply perceived as potential—are closely monitored by financial markets and can result in significant price fluctuations. The price fluctuations that follow market-relevant events can be leveraged to study the effects of gas price shocks using high-frequency identification techniques.

In contrast, the United States stands as the world's largest natural gas producer. Domestic production has grown substantially, doubling from approximately 2000 PJ per month in the early 2000s to 4000 PJ in 2023. This remarkable expansion has been largely driven by advancements in shale gas extraction (Acemoglu et al., 2023; Stock & Zaragoza-Watkins, 2024).[3] The US has progressively become a natural gas exporter, particularly in the form of LNG to European and Asian markets. In the aftermath of Russia's invasion of Ukraine, exports saw a further sharp increase, with volumes more than doubling imports in recent years. This trend is illustrated in the lower panel of Figure C21 in the Appendix.

A second key difference lies in market structure and maturity.The US pioneered gas market liberalization in the 1970s, adopting a gas-on-gas pricing model, and the Henry Hub (HH) has served as the benchmark price since 1990. In contrast, historically, natural gas pricing in Europe has been predominantly linked to oil products. Over the last two decades, gas prices have moved away from oil indexation to spot pricing through a series of regulatory reforms aimed at liberalizing the European gas market. The European Union began its liberalization process in 1992 with the EU energy market regulatory framework. However, meaningful developments only started in the late 1990s, leading to the issuance of three European Directives designed to foster competition and create a single market for natural gas. This reform process culminated in the "Gas Regulation" of 2009, which further strengthened market integration efforts.[4] These regulatory reforms led to the development of trading hubs across Europe, with 11 main active hubs as of 2021, though varying significantly in liquidity and infrastructure (Heather, 2021).[5]

After more than two decades, full liberalization is not yet completed in Europe (Cardinale, 2019; ACER, 2022). Nevertheless, the gas market is increasingly integrated regionally. The Dutch Title Transfer Facility (TTF) gas hub, recognized as the most liquid trading hub, has emerged as the benchmark for European gas prices. The TTF, listed on the ICE ENDEX futures exchange in Amsterdam, was established in 2003, whereas the first gas hub in the region, the National Balancing

[3]Shale gas refers to natural gas confined within shale formations. Shales are fine-grained sedimentary rocks that can be rich sources of petroleum and natural gas. Over the past decade, advancements associated with supply reliability, coupled with developments in horizontal drilling and hydraulic fracturing, commonly known as "fracking", have boosted natural gas production from tight shale formations.

[4]Regulation (EC) No 715/2009 (the "Gas Regulation").

[5]While there are approximately 30 gas trading hubs in Europe, not all of them are actively operational.

Point (NBP), was created in the United Kingdom in 1996. TTF overtook NBP as the largest gas hub in 2017, accounting for approximately 75% of the total European gas trade in 2022 Q4.[6]

Additionally, the share of hub-indexed imported gas relative to fixed contracted prices has grown significantly over time, representing approximately 80% of total gas imports in the European Union in 2021 (IEA, 2021). As part of this trend, oil-indexed contracts, which constituted over 90% of European gas imports in 2005, declined sharply to only 25% by 2019 (IEA, 2020). These developments enable the analysis of the economic effects of gas price variations through the use of the TTF. Indeed, most studies that examine the role of gas prices in Europe focus on the TTF price (e.g. Boeck et al., 2023; Adolfsen et al., 2024; López et al., 2024). Jotanovic and D'Ecclesia (2021) provide detailed evidence of a high level of integration among the European trading hubs, with the TTF playing the role of the reference trading hub. In support of this, Figure C24 and Table C7 in the Appendix show that price dynamics across the various hubs are highly correlated.

Crucially, while LNG has become increasingly important in the European market, its expansion has not resulted in greater price divergence within the region. On the contrary, the integration between European and global LNG markets has strengthened significantly, driven by the substantial growth of seaborne gas trade (Albrizio et al., 2023). Historically, LNG prices did not closely track the TTF, reflecting its limited role in the European market at the time. However, as LNG has gained prominence, its price has become more closely aligned with the TTF, reducing divergence. This convergence is documented in Figures C25 and C26, as well as in Table C7 in the Appendix.

Finally, the futures natural gas market is well-developed and characterized by high liquidity and substantial transaction volumes. These attributes are crucial to our high-frequency identification approach, which studies intra-day changes in gas futures prices. The Henry Hub futures, introduced at the New York Mercantile Exchange (NYMEX) in 1990, are the most actively traded worldwide (CME Group, 2021). Moreover, these futures have the longest available history, thus making them a natural choice for analysis in the US. TTF is the most liquid and most widely traded future for natural gas in Europe, hitting a record of 5.7 million contracts per month in May 2023 (ICE, 2023).

The structural characteristics of natural gas markets in the Euro Area and the United States inform our empirical strategy for analyzing the macroeconomic effects of gas price shocks. In the Euro Area, the heavy reliance on imports and frequent supply disruptions justify the use of high-frequency variations in futures prices following import flow disruptions to identify supply shocks to natural gas prices. In contrast, in the United States, where domestic production is the primary source of supply, supply shocks are identified by analyzing disruptions to domestic production. On the demand side, the extensive use of natural gas for heating and its strong sensitivity to temperature fluctuations enable the identification of demand shifts. Regarding

[6] European Commission (2022).

the choice of a price benchmark that best represents overall market conditions, the Henry Hub price effectively proxies natural gas prices in the United States due to its role as the primary reference price. Similarly, in the Euro Area, the Title Transfer Facility has emerged as the key benchmark for natural gas prices, given its status as the most liquid and widely traded market. While liquefied natural gas has grown in importance, the TTF remains a reliable proxy for overall gas prices, as its increased integration with LNG markets has strengthened its correlation with TTF spot prices. Furthermore, the increased importance of hub-based pricing mechanisms in the Euro Area further reinforces the TTF's suitability as the region's reference price.

3 Identification strategy

To study the impact of gas price shocks on the macroeconomy, our main model of choice is the literature-standard structural vector auto-regression, which we identify with external instruments (proxy-SVAR). We identify both demand and supply shocks to the price of gas, exploiting exogenous variation in temperatures and in futures prices in a tight window around gas market-relevant news, respectively. We then assess the responses to gas shocks in a model that includes gas balances as well as several commonly studied macroeconomic variables. We also present results on the interrelation of the natural gas and crude oil markets, as well as detailed sectoral responses for the Euro Area. Finally, we examine in greater detail the impact of gas shocks on inflation in the Euro Area via a historical decomposition exercise. We also compare the impact of gas price shocks to other key drivers such as supply chain bottlenecks, oil prices, and monetary policy shocks.

We estimate the models using Bayesian techniques. All the technical details on the econometric modelling are given in Appendix A, and the results are presented in Section 5. The rest of this section details our identification strategy.

3.1 Gas price shocks

We identify a supply shock to gas prices using market-relevant news and high-frequency data on natural gas futures prices. We also identify a demand shock by exploiting exogenous variation induced by large deviations from seasonal averages in temperatures. Gas surprises, constructed as high-frequency changes in gas prices around exogenous market-relevant news, reflect variations driven by supply factors. Conversely, temperatures provide exogenous variations in gas prices through their impact on demand. For example, an unexpected warm spell during a typically cold month reduces gas consumption for heating. The construction of these instruments is detailed in the following subsections.

3.1.1 Market-relevant news and high-frequency data

To identify the effects of a gas price increase driven by supply factors, we adopt a high-frequency identification strategy inspired by methodologies developed in the monetary policy literature (Cochrane & Piazzesi, 2002; Nakamura & Steinsson, 2018;

Altavilla et al., 2019) and more recently adapted to the crude oil market (Wu & Cavallo, 2012; Känzig, 2021a). Specifically, we analyze changes in gas prices occurring around market-relevant announcements. Provided that the news are exogenous to broader economic conditions and that these changes are measured within a sufficiently tight window, these surprises—unexpected information that has not yet been incorporated into market prices—can be interpreted as *shocks* (Ramey, 2016). Indeed, reverse causality from economic conditions can be plausibly dismissed, as these factors are typically already priced prior to the announcement and unlikely to change significantly within the narrowly defined time window. Daily surprises that satisfy these requirements can then be aggregated to monthly and used to instrument the price of gas in a proxy-VAR setting.

In the gas market, identifying relevant gas-related news poses a substantial challenge due to the absence of a single, authoritative entity consistently capable of influencing price movements, such as OPEC in the oil market or central banks for monetary policy.[7] To address this, we collect gas supply-related news from multiple sources, relying on Reuters for both the Euro Area and the United States, and carefully assess the exogeneity of each news. Additionally, we cross-reference the most followed news on each release date to ensure that our event window is not contaminated by concurrent significant news. We also exclude news from months in which gas prices are mostly driven by temperature variations, as these represent a confounding demand factor through the heating-related gas demand channel (see the next section). For the Euro Area, we focus specifically on news related to gas imports. As discussed in the previous section, the vast majority of gas consumed in the region is imported, making import-related news both the most prevalent and the most relevant. This focus is also motivated to give a clear interpretation of the identified shocks, which can be viewed as exogenous disruptions to gas imports, whether realized or anticipated. Our news coverage includes key suppliers of both pipeline gas and LNG, highlighting factors that influence supply dynamics. This includes disruptions, announcements from major energy companies, labor strikes affecting gas fields, pipeline incidents (such as explosions, maintenance activities, or new investment projects), and legislative developments related to gas imports. The final sample comprises 72 supply-related news events, with 41 pertaining to Russian flows, 13 to Norwegian flows, and the remaining 18 to other suppliers.

An illustrative example of supply news for the EA is the unexpected drop in Norwegian gas flows that occurred on November 15, 2010 (see Figure 2). National Grid data showed that flows through the Langeled pipeline—which transports gas from the Nyhamna processing facility to the Easington terminal in the UK—were reduced by approximately 14 MCM (Million Cubic Meters) due to unforeseen tech-

[7] Prior to the invasion of Ukraine, Gazprom accounted for over 30% of Europe's total natural gas supply in 2021 (Milov, 2022), thus representing a key source of gas-related news due to its significant role in the market. However, relying solely on Gazprom is insufficient, as its announcements are released irregularly, and relevant developments often involve other major suppliers, geopolitical events, or policy actions. To ensure comprehensive coverage, it is necessary to incorporate news from multiple sources, capturing a broader spectrum of factors influencing gas prices.

nical issues.[8] This disruption left the British gas market undersupplied by around 4 MCM, which triggered an increase in European gas prices, with the TTF spot price rising by about 8% from the previous trading day.

An example of a price reduction is the one observed following the LNG Isle of Grain terminal expansion in October 2010. In contrast, an example of major news related to Russian gas supply is the price increase after Gazprom's announcement of reduced flows for Nord Stream 1 maintenance in June 2022. Both events are illustrated in Figures D27 and D28 in the Appendix.

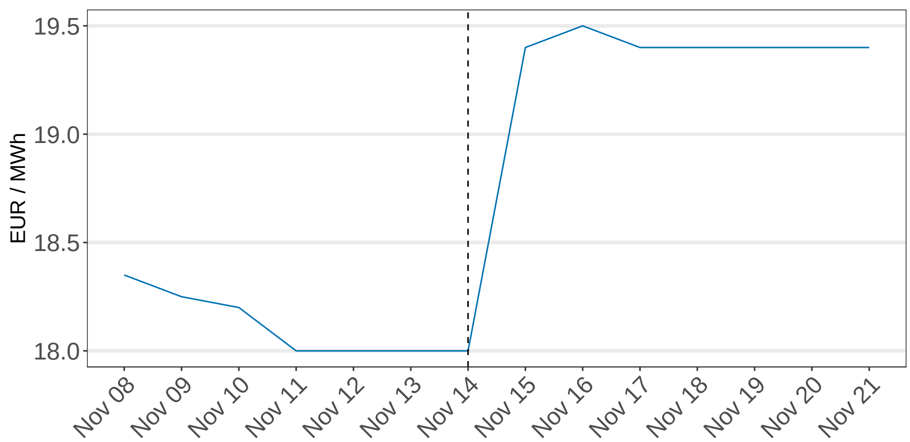


Figure 2: *Unexpected drop in gas flows from Norway through the Langeled pipeline*

Notes: The figure shows the surprise in the spot TTF gas price related to the news on November 15, 2010. The TTF spot price increased by more than 8% over the day, reflecting the market's reaction to the unexpected drop in gas flows. November 12, 13, 20, and 21 were non-trading days, and the close spot price is unavailable for these dates. The values shown in the figure for these dates correspond to the last available trading day's price.

For the United States, following the same logic of focusing on the most relevant and prevalent supply factors, we concentrate on news related to domestic production. Unlike the Euro Area, where gas imports constitute the majority of consumption, the U.S. benefits from substantial domestic production, making production-related news the most relevant for identifying supply shocks. Our dataset includes 27 supply-related news events, covering disruptions such as gas platform outages, maintenance activities, and explosions. This focus allows for a clear interpretation of the identified shocks as exogenous disruptions to domestic gas supply. The impact of such supply-related news on the Henry Hub (HH) price is illustrated by the event of June 15, 2009, when Kinder Morgan announced maintenance on the Natural Gas Pipeline Co.

[8] While Langeled does not directly connect to mainland Europe, the UK is part of the interconnected European gas market through which gas can be transferred to continental Europe. Therefore, disruptions in this pipeline can affect European supply and typically move European gas prices.

of America's mainline at Compressor Station 198 in Marion County, Iowa, resulting in a 75% reduction in capacity in that area. Following the announcement, the HH spot price rose by approximately 7%. This episode is illustrated in Figure D29 in the Appendix. A selected illustrative sample of our news collection is presented in Table D8.

It is important to note that, for the Euro Area, the relevant news items include both realized supply disruptions and announcements about anticipated future supply changes. For example, on December 24, 2021, President Putin's statement regarding the launch of Nord Stream 2 signaled a prospective increase in gas exports from Russia. Although such announcements do not necessarily lead to actual changes in supply, they are closely monitored by market participants. In this case, the announcement was followed by a decline in gas prices of approximately 15%. In Section 5, we characterize this distinction and show that, although the overall effects of these two types of shocks are broadly similar, certain variables exhibit distinct dynamics. This pattern suggests that supply news shocks may operate through expectation channels, leading to increased financial uncertainty and a higher demand for gas inventories. In contrast, the relevant gas-market news for the United States consist predominantly of realized supply disruptions.

Construction of gas surprises. Using the collected gas-related news, we construct a series of gas surprises by computing the (log) difference between the closing futures price on the day of the news release and the closing price on the last trading day before the news. This approach effectively captures the percentage change in price, isolating the market reaction to supply-related information:

$$GasSurprise_d^h = F_d^h - F_{d-1}^h \tag{1}$$

where d represents the day of the news event, and F_d^h denotes the (log) price of the gas futures contract with a maturity of h months ahead on date d.[9]

A crucial choice when constructing the surprises is the width of the event window. Following Känzig (2021a), we opt for a daily window. This differs from the monetary policy literature, where it is customary to use shorter windows. In the gas market, there is no major news source with regularly scheduled press releases that the market closely follows, as is the case with central banks. Furthermore, gas-related announcements lack the clarity of monetary policy statements, necessitating traders to invest more time in identifying and processing the information. Therefore, intraday windows would miss much of the response to the news. By contrast, using multi-day windows could introduce background noise that confounds the price reaction. This concern is particularly relevant for the latter part of our sample, which has been marked by an extraordinary series of events, particularly in Europe. Another important factor to consider is the selection of the futures contract maturity. Since disruptions and supply adjustments in the gas market can have both short-term and longer-term consequences, considering futures contracts with maturities

[9] We use Dutch TTF gas futures for the Euro Area and the Henry Hub futures for the United States.

ranging from one month to one year is a natural choice. Thus, we take the first principal component of the gas surprises spanning the first year of the gas futures term structure,[10] which is then rescaled to match the standard deviation of the underlying surprises.[11] To obtain a monthly series, we aggregate daily surprises within each month by summing them. In instances where there is no gas-related news, the monthly surprise is set to zero. Figure 3 shows the resulting monthly surprise series for the Euro Area.

Note that we use this series to instrument the settlement price rather than the average monthly natural gas price. This aligns with the critique of the standard proxy-SVAR practice in the oil literature by Kilian (2024), who emphasizes that relying on the average can result in the misattribution of effects driven by other factors to supply news events.

To evaluate the adequacy of the gas surprise series, we further perform a comprehensive series of checks. First, we assess the explanatory power of the principal components. The first principal component accounts for 67.6% of the total variance, while the second drops to 12.7%. The fact that the first component explains a large share of the variation is important not only because it ensures a high signal-to-noise ratio, but also because it suggests the presence of a common underlying factor driving movements across the futures curve. Moreover, the loadings on the first component are relatively homogeneous across maturities,[12] indicating that market participants revise their expectations broadly and consistently across different time horizons. As further discussed in Section 5, this supports the interpretation that gas supply shocks operate, at least in part, through revisions in expectations about future supply conditions.

One potential concern regarding our high-frequency approach is that non-gas-supply-related news might affect the gas price within the one-day event window. Furthermore, as discussed in Section 2, the recent disruptions of the gas market have heightened the sensitivity of gas prices to a diverse array of news, which can impact gas prices through various mechanisms, not limited to supply disruptions. To assess the relevance of background noise within the surprise series, we compare the daily changes in gas futures prices on gas-related news with the price changes on a sample of control days. Control days are chosen at random among days that do not contain gas supply news.

As shown in the left panel of Figure 4, the price changes on news days and control days are considerably different. Specifically, news days display significantly higher volatility and noticeable spikes in prices, contrary to the surprises observed in the control sample. Similarly, the estimated probability density function shows

[10] For the EA, we use the 1M, 2M, 3M, 4M, 6M, 9M, and 12M TTF futures contracts, while for the US, we include all monthly maturities from 1M to 12M, as these have fewer missing observations.

[11] The average price revision following a surprise is 7% for the EA and 2.6% for the US when calculated using the rescaled principal component. For front-month futures, these revisions increase to 9.7% and 4%, respectively. This difference reflects the generally lower volatility of HH prices compared to TTF prices, a consistent pattern observed throughout the sample.

[12] The loadings on the first principal component range from 0.29 to 0.44 across maturities: 0.44 for the 1-month contract, 0.43 for the 2-month, 0.41 for the 3-month, 0.29 for the 4-month, 0.40 for the 2-quarter, 0.29 for the 3-quarter, and 0.34 for the 1-year contract.

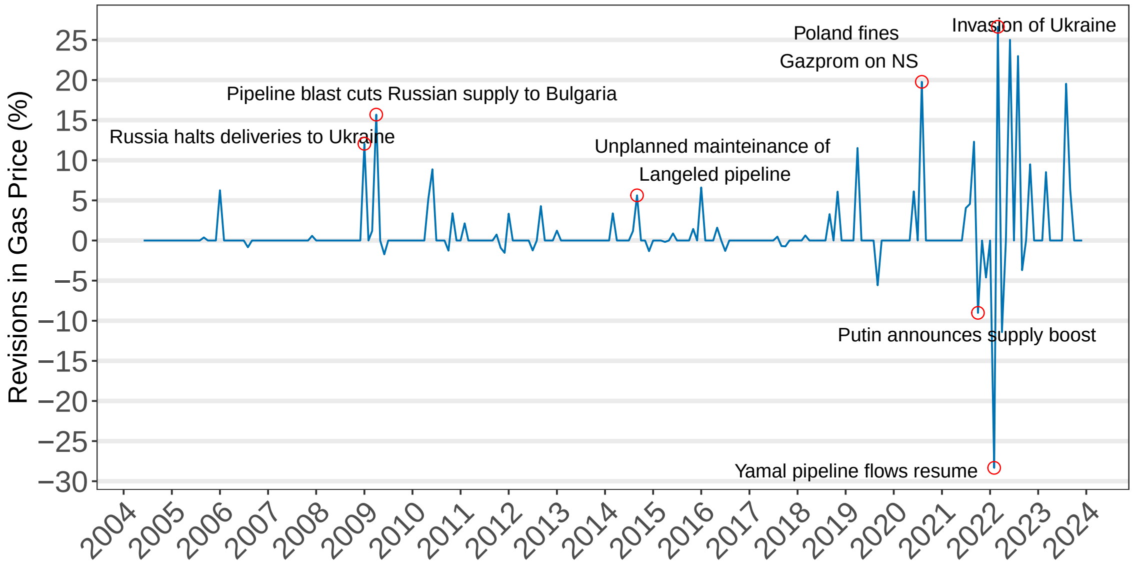
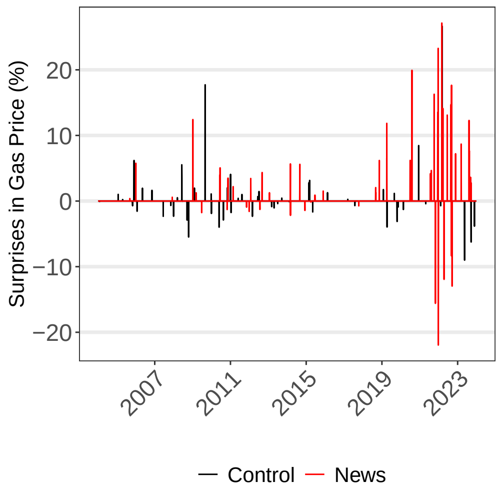


Figure 3: *Euro Area gas supply surprise series*

Notes: This figure shows the gas surprise series, which is constructed as the first principal component from changes in gas futures prices. We use TTF natural gas future contracts spanning the first-year term structure around important announcements in the gas market. The principal component is scaled to match the average volatility of the underlying price surprises so that the y-axis can be interpreted as percentage deviations in futures prices. Red circles highlight important supply events. In 2009M1 Russia halted its gas deliveries to Ukraine over a gas supply dispute. In 2009M4 a pipeline blast reduced Russian supplies to Bulgaria by 60%. In 2014M9 unplanned maintenance on the Langeled pipeline disrupted Norwegian gas imports. In 2020M8 Poland fined Gazprom over Nord Stream 2. In 2021M10 Putin announced that Gazprom would increase gas supplies to Europe. In 2022M2 flows resumed from the Yamal pipeline. In 2022M3 gas prices surged following the invasion of Ukraine.

that surprises on news days display higher variance and fatter tails (right panel). This suggests that the presence of background noise is limited. Appendix D.3 reports additional checks on the gas surprise series, including tests on autocorrelation, correlations with other macroeconomic shocks from the literature, and Granger's causality tests.

Nonetheless, the presence of confounding factors could still bias the results and compromise the reliability of inference, as demonstrated by Nakamura and Steinsson (2018) in the context of monetary policy. To address this concern, we explicitly account for potential confounding events and construct an informationally robust surprise series, which we show produces results that are virtually identical to the baseline series. Following the approach of Miranda-Agrippino and Ricco (2021), we refine the gas supply series by removing its own lagged effects as well as the contemporaneous and lagged effects of potential confounding factors. More specifically, we obtain the informationally robust surprises, IRS_t, as the residuals from the following



Daily surprises

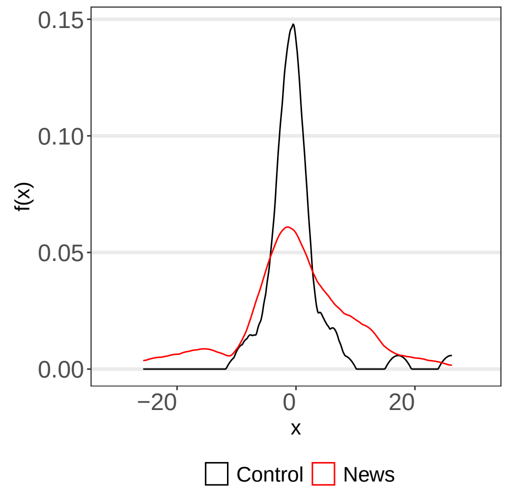


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Figure 4: *Gas news days versus control days*

Notes: The left panel displays the daily changes in gas futures prices on news and control days. The right panel shows the empirical probability density function, estimated by using the Epanechnikov kernel. The ratio of the news variance over the control variance is 3.11, and a Brown-Forsythe test for the equality of group variances confirms that this difference is highly statistically significant (F-statistic: 12.93).

regression:

$$GasSurprise_t^h = \alpha_0 + \sum_{j=1}^{l} \phi_j \, GasSurprise_{t-j}^h + \sum_{j=0}^{l} \mathbf{x}_{t-j}\Gamma_j + IRS_t \tag{2}$$

where $GasSurprise_t^h$ denotes the gas supply surprise in month t for the futures contract h, constructed as detailed previously, $\mathbf{x}_t$ is a vector of potentially confounding series and l is the number of lags. We consider surprises in food prices constructed around the same daily window used for gas-related news, as well as several relevant macroeconomic shocks studied in the literature. Additional details, including a plot of the informationally robust series and the related impulse responses are provided in Appendix I.1.

3.1.2 Temperatures and heating demand

We exploit a second source of exogenous variation in the real price of natural gas to identify gas demand shocks. Specifically, we construct a proxy for heating demand based on temperature deviations from seasonal averages. A positive temperature spell reduces heating demand, leading to lower energy prices, whereas a negative shock increases demand and raises prices (see, e.g., Colombo and Ferrara, 2023 for temperature effects on energy production and Pisa et al., 2022 on energy prices).

To capture demand-driven fluctuations in natural gas prices, we construct a montly proxy based on temperature deviations from seasonal averages as follows. First, we compute deviations from average temperature by subtracting, for each calendar day, the mean monthly average temperature (computed across all years in the sample) corresponding to the month in which the day is located. The resulting daily series is then aggregated to the monthly frequency by taking averages across time. Next, we apply a threshold to filter out minor fluctuations and retain only months with substantial temperature deviations, reducing noise by setting to zero any observation within a standard deviation. Finally, we exclude the summer months (April to September), as the relationship between temperatures and gas prices during warmer months is ambiguous: higher temperatures may either increase electricity demand for air conditioning or reduce heating demand.[13] Additionally, we exclude specific months affected by major confounding factors, such as the COVID-19 pandemic. Appendix E.1 further details the computation of the series and provides robustness checks.

An important requirement for this instrument is that, unlike typical seasonal temperature fluctuations, large deviations from average temperatures are unanticipated by economic agents. As a result, these deviations are not incorporated into trading decisions and affect gas prices only through the heating demand channel, ensuring the validity of the instrument.[14]

Since gas traded at the TTF serves multiple countries, for Europe, we construct an aggregate temperature measure based on the average temperatures of Belgium, Germany, France, Luxembourg, and the Netherlands—countries that predominantly rely on TTF gas. These averages are weighted by each country's gas consumption.[15] The resulting series is presented in Figure 5.[16] Positive spikes in the series tend to coincide with unexplained negative spikes in the price of gas, and vice versa. Indeed, the series exhibits a strong negative correlation with the real price of gas, even after controlling for relevant macroeconomic variables. This finding aligns with the proposed demand channel and supports the relevance of the instrument. If the primary mechanism through which temperature fluctuations affect natural gas prices is heating demand, we would expect the strongest correlations to occur during months when absolute temperatures necessitate heating. To support this claim, we provide additional evidence of this relationship. Specifically, unexpectedly cold temperatures

[13] An argument can be made that this choice is more relevant in the case of the United States, where cooling demand during the summer months constitutes an important driver of electricity consumption (Sailor & Pavlova, 2003; Bartos et al., 2016). However, as demonstrated in Appendix I, this decision does not materially affect our results.

[14] Temperature forecasts deteriorate significantly as the forecast horizon extends, remaining relatively unreliable even with the most advanced prediction methods. See, for example, Lopez-Gomez et al. (2023). In Figure E35 in the Appendix we provide evidence suggesting that anticipation effects are likely limited both in magnitude and in how far ahead they occur, reinforcing the suitability of our approach within a monthly estimation framework.

[15] At the country level, temperature is computed as a population-weighted average of grid-level temperatures. However, when aggregating temperatures across countries, we use gas consumption as weights, as grid-level consumption data is not available. See Gortan et al. (2024) for the weights used.

[16] Similarly, we construct the corresponding series for the United States by averaging temperatures across states. See Figure E38 in the Appendix.

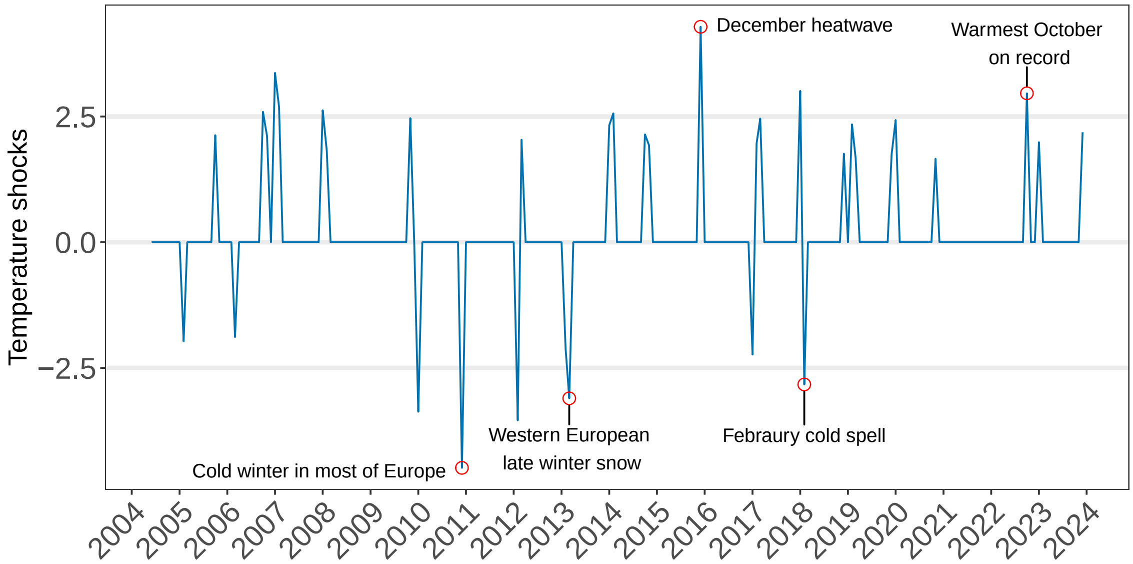

Figure 5: *Temperature proxy series for Europe*

Notes: This figure displays the temperature index, constructed as a proxy for gas demand. Red circles highlight significant temperature-related events in the gas market: 2010M12 was the coldest December in 100 years and the coldest winter month since February 1986; 2013M3 witnessed a late-season snow event that impacted Western Europe; 2015M12 was the warmest December on record for several countries; 2018M2 saw a cold spell, commonly referred to as "The Beast from the East", characterized by cold winds and low temperatures; 2022M10 was the warmest October on record in Europe.

in typically warm days should have a minimal impact on gas prices, as absolute temperatures would remain too high to justify widespread heating use. To assess this, we examine *cooling degree days* (CDD) and *heating degree days* (HDD).[17][18] When restricting the sample to months with low HDD, the correlation between the temperature series and the residual gas price is significantly weaker compared to months with high HDD. This indicates that temperature fluctuations primarily affect gas prices when they lead to the activation or deactivation of heating systems. Conversely, when the sample is limited to months with high CDD, the correlation remains lower than in months with low CDD, suggesting that cooling-related energy demand has a relatively smaller impact on natural gas prices. A similar pattern emerges when the sample is restricted to only winter or only summer months, motivating the deci-

[17] CDD and HDD serve as proxies for the energy required to heat and cool buildings. For the precise definitions, see https://ec.europa.eu/eurostat/statistics-explained/SEPDF/cache/92378.pdf. The data is available at https://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx.

[18] Figure E36 in the Appendix presents the average values of Cooling Degree Days (CDD) and Heating Degree Days (HDD) for the same set of European countries used in the construction of the temperature series. To ensure consistency with the temperature measure, we compute weighted averages of CDD and HDD using country-level gas consumption as weights.

sion to focus on temperature deviations during winter months when constructing the instrument. This approach helps reduce noise and enhances the instrument's relevance. As shown in Appendix I, however, the results remain qualitatively unchanged when including all months.

Finally, the supply and the demand instruments never exhibit simultaneous spikes within the same month. This temporal separation ensures that demand and supply effects are not misattributed, preserving the integrity of the identification strategy. This is illustrated in Figure D32 in the Appendix.

4 Econometric Framework

Consider the following structural VAR(p) model:

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{w}_t, \tag{3}$$

where $\mathbf{y}_t$ is a $K \times 1$ vector of endogenous variables, assumed to have zero mean without loss of generality. The vector $\mathbf{w}_t$ is a $K \times 1$ vector of structural shocks, assumed to be serially uncorrelated with full-rank variance-covariance matrix $\mathbb{E}(\mathbf{w}_t\mathbf{w}_t') = \mathbf{\Sigma}_w$. This model is "structural" because the elements of $\mathbf{w}_t$ are serially and mutually uncorrelated, that is:

$$\mathbb{E}(\mathbf{w}_t\mathbf{w}_s') = \begin{cases} \mathbf{\Sigma_w} & \text{for } t = s \\ \mathbf{0} & \text{for } t \neq s \end{cases}$$

Since the matrices $\mathbf{B}_0$ and $\mathbf{w}_t$ are generally unobserved, we rely on the reduced-form representation to estimate the model:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{B}_0^{-1}\mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_0^{-1}\mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{B}_0^{-1}\mathbf{w}_t \\ &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \end{aligned} \tag{4}$$

where $\mathbf{A}_i = \mathbf{B}_0^{-1}\mathbf{B}_i$ for $i = 1, \ldots, p$, and $\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t$. We estimate the reduced-form parameters $\mathbf{A}_1, \ldots, \mathbf{A}_p, \mathbf{\Sigma}_u$,[19] and the reduced-form residuals $\mathbf{u}_t$ using Bayesian methods. We implement standard Minnesota, sum-of-coefficients, and dummy-initial-observations priors. Details are provided in Appendix A.4.

The key equation linking the reduced-form innovations to the structural shocks is:

$$\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t. \tag{5}$$

Our objective is to identify the impact of a structural shock on the system. This corresponds to identifying one column of the impact matrix $\mathbf{B}_0^{-1}$. The instruments that we construct as detailed in section 3 enables us to do so, where we identify a gas supply shock when using the high-frequency instrument and a gas demand shock when using the temperature-based instrument to instrument the real price of gas in an external instrument setting.

[19] $\mathbb{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbb{E}(\mathbf{B}_0^{-1}\mathbf{w}_t\mathbf{w}_t'(\mathbf{B}_0^{-1})') = \mathbf{B}_0^{-1}\mathbb{E}(\mathbf{w}_t\mathbf{w}_t')(\mathbf{B}_0^{-1})' = \mathbf{B}_0^{-1}\mathbf{\Sigma_w}(\mathbf{B}_0^{-1})' = \mathbf{\Sigma}_{\boldsymbol{u}}$.

4.1 Identification via external instrument: proxy-VAR

In recent years, the instrumental variables (IV) approach, traditionally employed in microeconomics, has been adapted to the time series context to recover elements of $\mathbf{B}_0^{-1}$, giving rise to the proxy-VAR identification method. In settings where the regression of a dependent variable y on an explanatory variable x suffers from endogeneity, an external instrument z can be used to isolate exogenous variation in x. For z to be a valid instrument, it must be correlated with x (instrument relevance), but uncorrelated with the error term in the equation for y conditional on x (instrument exogeneity or the exclusion restriction). This ensures that z influences y only through its effect on x.

Denote the relevant column of the $\mathbf{B}_0^{-1}$ matrix as $\mathbf{b}_k$, with $k \in \{1, \ldots, K\}$, which represents the effect of the structural shock of interest, which we denote as $w_{k,t}$, on all the K variables of the system. For expository purposes, we here set $k = 1$ without loss of generality. Further, let z_t denote an instrument, which satisfies the relevance and exogeneity conditions:

$$\mathbb{E}[z_t w_{1,t}] \neq \mathbf{0} \tag{6}$$

$$\mathbb{E}[z_t \mathbf{w}_{2:K,t}] = \mathbf{0} \tag{7}$$

where $\mathbf{w}_t = (w_{1,t}, \mathbf{w}'_{2:K,t})'$. Given these moments conditions,[20] and using the partitions $\mathbf{b}_1 = (b_{1,1}, \mathbf{b}'_{2:K,1})'$ and $\mathbf{u}_t = (u_{1,t}, \mathbf{u}'_{2:K,t})'$, and the fact that $\mathbf{u}_t = \mathbf{b}_1 w_{1,t} + \mathbf{b}'_{2:K,1}\mathbf{w}_{2:K,t}$, we have

$$\mathbb{E}[z_t \mathbf{u}_t] = \mathbf{b}_1 \cdot \mathbb{E}[z_t w_{1,t}]$$

which can be rewritten as

$$\mathbb{E}[z_t u_{1,t}] = b_{1,1} \cdot \mathbb{E}[z_t w_{1,t}]$$
$$\mathbb{E}[z_t \mathbf{u}_{2:K,t}] = \mathbf{b}_{2:K,1} \cdot \mathbb{E}[z_t w_{1,t}]$$

Taking the ratio of these two expressions we obtain:

$$\frac{\mathbb{E}[z_t \mathbf{u}_{2:K,t}]}{\mathbb{E}[z_t u_{1,t}]} = \frac{\mathbf{b}_{2:K,1}}{b_{1,1}}$$

Finally, normalizing $b_{1,1} = 1$, which fixes the sign and scale of the shock, yields:

$$\mathbf{b}_{2:K,1} = \frac{\mathbb{E}[z_t \mathbf{u}_{2:K,t}]}{\mathbb{E}[z_t u_{1,t}]}$$

$\mathbf{b}_{2:K,1}$ can be estimated via the standard two-stage least square procedure as follows:

1. First stage:[21]

$$\hat{\pi}_1 = \left(\frac{1}{T} \sum_{t=1}^{T} z_t z_t' \right)^{-1} \left(\frac{1}{T} \sum_{t=1}^{T} z_t u_{1,t} \right)$$

[20] We also require $\mathbb{E}[z_t u_{1,t}]$ full column rank and $\mathbb{E}[z_t z_t'] < \infty$.

[21] An intercept is generally also included in this regression.

2. Second stage:

$$\hat{b}_{2:K} = \left(\frac{1}{T}\sum_{t=1}^{T}\hat{u}_{1,t}\hat{u}_{1,t}\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T}\hat{u}_{1,t}\mathbf{u}'_{2:K,t},\right)$$

With $\hat{u}_{1,t} = \hat{\pi}_1' z_t$ for $t = 1, \ldots, T$.

Normalisation. The scale $b_{1,1}$ can be set via any normalization subject to $\mathbf{\Sigma}_u = \mathbf{B}_0^{-1}\mathbf{\Sigma}_w(\mathbf{B}_0^{-1})'$. One common approach is to rescale the structural shocks to have unit variance: $\mathbf{\Sigma}_{\tilde{\boldsymbol{w}}} = \mathbf{I}_K$, which implies that a unit positive value of the structural shock $w_{1,t}$ corresponds to a one standard deviation positive effect on $y_{1,t}$. This leads to the unit-variance representation of the model in (2):

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \tilde{\mathbf{B}}_0^{-1}\tilde{\mathbf{w}}_t \tag{8}$$

$$\tilde{\mathbf{w}}_t = \mathbf{\Sigma}_w^{-1/2}\mathbf{w}_t \tag{9}$$

$$\tilde{\mathbf{B}}_0^{-1} = \mathbf{B}_0^{-1}\mathbf{\Sigma}_w^{1/2} \tag{10}$$

Alternatively, one may use $\mathbf{\Sigma}_{\boldsymbol{w}} = \mathrm{diag}(\sigma^2_{w_1}, \ldots, \sigma^2_{w_n})$ and normalize by setting $b_{1,1} = c$, which implies that a unit value of $w_{1,t}$ has a positive effect of magnitude c on $y_{1,t}$. When presenting the IRFs we use the latter normalization and set c such that the shock corresponds to a 10% increase in the real price of natural gas.

4.2 Estimating demand and supply elasticities

Consider dynamic demand and supply equations of the form:

$$q_t^d = \alpha_{qp}^d p_t + \mathbf{x}'\boldsymbol{\beta}_d + w_t^d, \tag{11}$$

$$q_t^s = \alpha_{qp}^s p_t + \mathbf{x}'\boldsymbol{\beta}_s + w_t^s, \tag{12}$$

where, p_t denotes the logarithm of the real price of natural gas, while q_t^d and q_t^s represent the logarithms of the quantity demanded and supplied, respectively. The parameters α_{qp}^d and α_{qp}^s denote the price elasticities of demand and supply. The terms w_t^d and w_t^s are the structural shocks to demand and supply, and $\mathbf{x}$ is a vector of control variables that includes a constant, contemporaneous values of other endogenous variables, as well as p lags of all endogenous variables in the system.[22]

[22] We define total demand Q_t^d as the sum of domestic consumption (C_t) and exports (X_t), and total supply Q_t^s as the sum of domestic production (DP_t) and imports (M_t) minus exports:

$$Q_t^d = C_t + X_t, \quad Q_t^s = DP_t + M_t - X_t.$$

This choice is motivated by the aim of ensuring that the demand measure captures the total quantity withdrawn from the domestic market, whether for domestic consumption or external demand, and that the supply measure reflects the total quantity of gas available for domestic use. Our definition of supply differs from some alternative approaches that do not net out exports (see, for example, Farag, 2024). In contrast, our measure excludes exports, capturing the quantity of natural gas available

Given the demand and supply instruments constructed as described in Section 3, we are able to estimate the key parameters of interest, α^d_{qp} and α^s_{qp}. These elasticities, however, are not directly represented by the coefficients of the impact matrix $\mathbf{B}_0^{-1}$, which is recovered using the external instrument identification strategy. As noted by Baumeister and Hamilton (2024), the elements of $\mathbf{B}_0^{-1}$ reflect the contemporaneous interactions among all variables and are thus suitable for computing impulse response functions. Nevertheless, they do not satisfy the *ceteris paribus* assumption inherent in the definition of structural elasticities. The elasticities of interest correspond instead to the relevant entries of the matrix $\mathbf{B}_0$.

Since the identification strategy recovers only a single column of $\mathbf{B}_0^{-1}$, the full inverse matrix cannot be directly computed. Despite this limitation, it is still possible to retrieve the corresponding row of $\mathbf{B}_0$ as follows. Consider the unit-variance representation of the model, defined in equations (8) through (10). It follows that[23]

$$\tilde{\mathbf{B}}_0 = (\tilde{\mathbf{B}}_0^{-1})'\mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1}, \tag{13}$$

and the j-th row of this matrix is given by

$$\tilde{\mathbf{b}}'_{0,j} = \left[(\tilde{\mathbf{B}}_0^{-1})_{:,j}\right]' \mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1}.$$

This expression shows that the relevant row of $\tilde{\mathbf{B}}_0$ can be obtained simply by multiplying the estimated column of the impact matrix by the inverse of the variance-covariance matrix of the reduced-form residuals. Using the unit-variance normalisation is without loss of generality, as shown by

$$\mathbf{b}'_{0,j} := \frac{\tilde{\mathbf{b}}'_{0,j}}{\lambda_j} = \left[(\mathbf{B_0}^{-1})_{:,j}\right]' \mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1},$$

where λ_j is the j-th entry on the diagonal of $\mathbf{\Sigma}_{\mathbf{w}}{}^{1/2}$.[24] Finally, since $\mathbf{b}'_{0,j}$ is identified only up to sign and scale, we normalize it such that the coefficient on quantity is equal to unity,[25] so that the α_{qp} coefficients correspond to the percentage change in quantity resulting from a 1% increase in price.

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for domestic use. This distinction is especially important in the case of the United States, where exports are significant and energy producers often allocate natural gas to international markets to capitalize on higher foreign prices (Medlock III, 2025), thereby effectively reducing the volume available for domestic consumption. Using an accounting identity, domestic consumption C_t can be expressed in terms of production, exports, and changes in inventories, $C_t = DP_t - X_t - \Delta I_t$ where $\Delta I_t = I_t - I_{t-1}$ denotes the inventory change from period $t-1$ to t. Therefore, we have the following relationship between demand and supply:

$$Q^d_t = Q^s_t - M_t + X_t - \Delta I_t$$

Finally, $q^s_t = \log(Q^s_t)$ and $q^d_t = \log\big(Q^d_t\big)$.

[23] Note that $\mathbf{\Sigma}_{\boldsymbol{u}} = \mathbf{B}_0^{-1}\mathbf{\Sigma}_{\mathbf{w}}(\mathbf{B}_0^{-1})' = \tilde{\mathbf{B}}_0^{-1}(\tilde{\mathbf{B}}_0^{-1})' =$, which implies $(\tilde{\mathbf{B}}_0^{-1})'\mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1} = (\tilde{\mathbf{B}}_0^{-1})^{-1} = \tilde{\mathbf{B}}_0$.

[24] Note that $\tilde{\mathbf{b}}'_{0,j} = \left[(\tilde{\mathbf{B}}_0^{-1})_{:,j}\right]' \mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1} = \left[(\mathbf{B_0}^{-1}\mathbf{\Sigma}_{\mathbf{w}}{}^{1/2})_{:,j}\right]' \mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1} = \lambda_j \left[(\mathbf{B_0}^{-1})_{:,j}\right]' \mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1}$.

[25] In practice, the demand and supply equations are estimated in their inverse form: $p_t = \frac{q^d_t}{\alpha^d_{qp}} +$

To the best of our knowledge, this study is the first empirical application of the strategy proposed by Baumeister and Hamilton (2024) in the context of external instrument identification.

Recovering the structural shocks. Similarly, when we only have knowledge of a single column of $\tilde{\mathbf{B}}_0^{-1}$, Stock and Watson (2018) showed that it is still possible to recover the corresponding structural shock as follows:

$$\left[(\tilde{\mathbf{B}}_0^{-1})_{:,j}\right]' \boldsymbol{\Sigma_u}^{-1}\mathbf{u}_t = \tilde{\mathbf{b}}_{0,j}'\mathbf{u}_t = \mathbf{e}_j'\tilde{\mathbf{B}}_0\mathbf{u}_t = \mathbf{e}_j'\tilde{\mathbf{B}}_0\mathbf{B}_0^{-1}\mathbf{w}_t$$
$$= \mathbf{e}_j'\tilde{\mathbf{B}}_0\tilde{\mathbf{B}}_0^{-1}\boldsymbol{\Sigma}_w^{-1/2}\boldsymbol{\Sigma}_w^{-1/2}\tilde{\mathbf{w}}_t = \mathbf{e}_j'\tilde{\mathbf{w}}_t = \tilde{w}_{j,t},$$

where $\mathbf{e}_j$ denotes the j-th standard basis vector. The unit-variance representation is adopted here purely for notational convenience and does not restrict generality.

5 Results

This section presents the results for the Euro Area and the United States, examining the macroeconomic effects of gas price shocks and the key transmission mechanisms that account for differences across shock types and regions. The second part of the section examines the sectoral impact of gas supply shocks on both prices and quantities in the Euro Area. For all specifications, the estimation sample spans from 2004M1 to 2023M12.[26]

The VAR models are estimated using a Bayesian approach (Bańbura et al., 2007), following the hierarchical framework of Giannone et al. (2015). Technical details on the estimation methodology are provided in Appendix A.

Our main specification includes seven variables: the real price of natural gas, gas quantity (supply or demand depending on the type of shock), gas inventories, the headline consumer price index, industrial production, financial volatility, and the real price of crude oil.[27] This specification allows us to study the dynamics specific to the natural gas market while also assessing the broader macroeconomic effects of gas price shocks. We estimate the VAR in log levels, meaning that all impulse responses can be understood as elasticities.[28] Importantly, the definition of gas quantity depends on the type of shock being analyzed. When estimating the effects of a gas demand shock, we define gas quantity as gas supply, which enables us to measure the causal reaction of supply. Conversely, when analyzing the effects of a

$\mathbf{x}'\check{\boldsymbol{\beta}}_d + \check{w}_t^d$ and $p_t = \frac{q_t^s}{\alpha_{qp}^s} + \mathbf{x}'\check{\boldsymbol{\beta}}_s + \check{w}_t^s$. Rescaling the coefficient on quantity to unity is equivalent to rescaling the coefficient on price to unity and then inverting the resulting coefficient.

[26] Our estimation sample begins in January 2004, the earliest date for which TTF data are available. To ensure comparability, we use the same sample period for the United States specification, although data for Henry Hub are available as early as 1997. However, as demonstrated in the Appendix, extending the sample period does not materially affect our results.

[27] We use monthly settlement spot prices, in line with Kilian (2024).

[28] That is, the responses represent percentage changes resulting from a percentage shock. However, these elasticities are not "structural," as discussed in Section 4.2.

gas supply shock, we define gas quantity as gas demand, allowing us to estimate the reaction of quantity demanded.[29] All responses are normalized to a one-time 10% increase in the spot price of natural gas. A detailed overview on the data and their sources can be found in Appendix C.1.

Figures 7 to 11 display the impulse response functions derived from our main specification. For better comparison, the left panels depict the effects of a gas demand shock, while the right panels illustrate the responses to a gas supply shock. The same responses, grouped together, are provided in Appendix G. Figures 13 to 15 augment the baseline specification for the Euro Area with sectoral variables. Black lines represent the responses for the Euro Area, while orange lines correspond to the United States. Shaded areas indicate the 68%, 80%, and 90% confidence intervals.[30] We first discuss our estimates of the short-run gas market elasticities.

Gas supply and demand elasticities and implications for price volatility. Following the strategy outlined in Section 4.2, we estimate the short-run elasticities of gas as follows: for the Euro Area, demand elasticity is -0.10 and supply elasticity is 0.75; for the United States, demand elasticity is -0.05 and supply elasticity is 0.24. The implied demand and supply curves are depicted in Figure 6.

Gas supply is more elastic than gas demand in both regions. This implies that supply shocks lead to comparatively larger price fluctuations. Table 1 shows the contribution of gas demand and supply shocks to the forecast error variance decomposition of gas price, confirming that supply shocks explain a larger share of price fluctuation. When we compare the elasticities across regions, we have that supply is more elastic in the Euro Area, which reflects the quicker adjustment of imports in the Euro Area compared to domestic production in the United States. In contrast, demand is slightly more rigid in the United States, and, in line with the insight of Caldara et al. (2019), we have that even relatively small differences in elasticity estimates can result in important differences in price dynamics.

These structural elasticities are identified by holding all other variables in the system constant, in contrast to the impulse response functions. As the next subsection demonstrates, IRFs exhibit a more muted response of gas supply and demand, primarily due to the buffering role of gas inventories. Inventories mitigate the impact of both supply and, more notably, demand shocks.

[29] We construct gas demand as the sum of domestic consumption and exports, and we define gas supply as domestic production plus imports.

[30] In Bayesian frameworks, instrument strength is typically assessed by examining the posterior distributions(Caldara et al., 2019; Giacomini et al., 2022). In our case, the posterior distributions of the impact coefficients are well-behaved and tightly centered around their median values, indicating that the instruments are sufficiently strong (see Figure D33 in Appendix D.3). Nonetheless, we also report the first-stage F-statistics that would result from estimating the same specification using a frequentist approach. For the Euro Area, the F-statistic and robust F-statistic are 16.74 and 10.90 for supply, and 30.13 and 12.56 for demand, respectively. For the United States, the corresponding values are 11.33 and 22.25 for supply, and 10.00 and 11.04 for demand. These statistics suggest that the instruments are sufficiently strong and do not raise concerns about weak identification (see, e.g., Montiel-Olea et al., 2016).

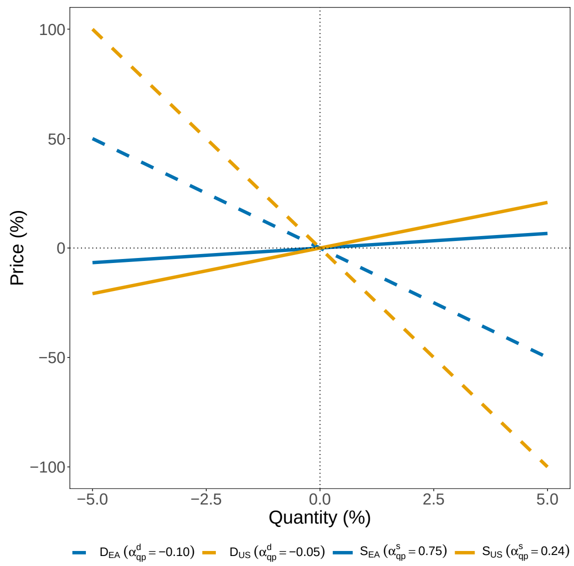


Figure 6: *Short-run gas demand and supply curves*

Notes: This figure depicts the short-run gas supply and demand curves for the Euro Area (blue) and the United States (orange). Dashed lines correspond to demand curves, while solid lines represent supply curves. Gas demand is defined as the sum of consumption and exports; gas supply is defined as production plus imports minus exports. For simplicity, supply and demand are equated in the figure, which does not affect the estimation of slope coefficients.

Region	Shock	$h = 1$	$h = 6$	$h = 12$	$h = 18$	$h = 24$
Euro Area	Gas supply	46.00	32.50	28.40	26.00	24.80
	Gas demand	17.96	22.10	19.80	18.90	18.50
United States	Gas supply	66.66	51.30	45.20	41.00	38.50
	Gas demand	14.50	19.00	17.60	16.50	15.80

Table 1: *FEVD of gas price at multiple horizons: contributions of gas supply and gas demand shocks*

Most previous studies that have tried to estimate short-run elasticities of gas demand and supply have adopted the identification strategy developed by Baumeister and Hamilton (2019) for the crude oil market. Other estimates that rely on autoregressive models are reported in Table 2. Our estimates, which leverage external exogenous variation, are generally consistent with the existing literature. However, we find somewhat lower demand elasticities and higher supply elasticities compared to prior studies.

Authors (year)	Region	Demand Quantity	Demand Estimate	Supply Quantity	Supply Estimate	Identification	Sample period
Casoli et al. (2022)	Europe	Consumption	-0.47	Production	0.34	Priors and sign restrictions*	2010M1–2022M7
Wiggins and Etienne (2017)	United States	Production	[-0.08; -0.18]**	Production	[0.15; 0.3]**	Sign restrictions	1976Q1–2015Q2
Rubaszek et al. (2021)	United States	Consumption	-0.42	Production	0.01	Priors and sign restrictions*	1978Q1–2020Q3
Farag (2024)	United States	Consumption	-0.177	Production + Imports	0.019	Priors and sign restrictions*	1992M1–2023M10

Table 2: *Previous estimates of short-run gas market elasticities*

* Baumeister and Hamilton (2019) identification strategy.
** Wiggins and Etienne (2017) report a range from a time-varying parameter model.

Response of gas supply and demand quantities. Figure 7 presents the estimated dynamic response of quantities supplied and demanded. In the United States, the reaction of supply to a one-time 10% increase price is estimated to be zero on impact, gradually increasing to approximately 1% after about a year. In contrast, in the Euro Area, the response of supply is estimated at around 2%. This difference in timing can be attributed to the different composition of supply. In the United States, supply adjustments occur mainly through domestic production, which requires more time to respond, whereas in the Euro Area, supply is primarily driven by imports, which can adjust more quickly. Indeed, when we replace total supply with domestic production for the United States, and net imports for the Euro Area we find very similar responses. Furthermore, in line with this trade channel, we find that the euro depreciates (see Figure H43 in the Appendix).

Gas Demand Shock

Gas Supply Shock

Figure 7: *Responses of quantities supplied and demanded*

Notes: Impulse responses of gas supply and demand to a gas demand shock (left panel) and a gas supply shock (right panel), respectively. The black solid lines with blue shaded confidence bands represent the Euro Area, while the orange solid lines with dashed and shaded orange confidence bands represent the United States.

We estimate that the response of demand in the Euro Area is zero on impact, with adjustments of up to -0.5% only after more than a year. In contrast, demand in the United States adjusts more rapidly, reaching a peak elasticity of approximately -0.5% after five months. This discrepancy in the timing of adjustments can be attributed to differences in gas demand elasticity across sectors, as well as variations in the sectoral composition of gas usage between the two regions.

The existing literature suggests that the power sector demonstrates relatively high short-run price elasticity compared to other sectors. This is primarily due to the ability of dual- and multi-fuel power plants to rapidly switch between energy sources in response to price changes (Pettersson et al., 2012). In contrast, the residential sector, while generally found to be the most responsive to price fluctuations—based on end-user rather than spot prices—tends to adjust more slowly. The manufacturing sector, on the other hand, displays the lowest degree of price elasticity.[31] As discussed in Section 2, gas consumption in the Euro Area is primarily concentrated in the residential sector, with the highly inelastic industrial sector as the second-largest consumer. In contrast, power generation constitutes the largest share of natural gas consumption in the United States, making interfuel substitution a key mechanism underlying aggregate adjustments in gas demand. To verify this, we estimate an alternative specification in which total gas demand is replaced with gas, coal and oil demand from the power sector. The impulse response functions presented in Figure H44 in the Appendix confirm significant interfuel substitution in the United States following a gas supply shock, with oil emerging as the primary alternative. In contrast, the Euro Area exhibits a more limited degree of interfuel substitution, with coal serving as the main substitute.[32]

Differences in taxation regimes also help explain the disparities in the gas demand elasticities that we estimate. In the United States, taxes account for a relatively small portion of gas prices, whereas in the Euro Area, they represent a significant share. A substantial portion of these taxes consists of specific (quantity-based) levies, such as excise duties, which constitute the largest component of gas taxation (European Commission, 2017). Additionally, carbon pricing mechanisms, which impose a per-unit tax on emissions, play a relatively minor role in shaping gas prices in the United

[31] Asche et al. (2008) estimate an elasticity of -0.23 for residential gas demand for a panel of European countries, while Auffhammer and Rubin (2018) find elasticities between -0.17 and -0.23 for the residential sector in California. For the power generation sector, Serletis et al. (2010) estimate a value of -0.14 using U.S. data. Finally, Andersen et al. (2011) estimate an average own-price elasticity of -0.1 for industrial gas consumption for a different panel of European countries. However, except for Auffhammer and Rubin (2018) that use monthly data, these estimates are based on annual data, which reflects a different adjustment timeline than our analysis. Additionally, the gas prices used in these studies are end-user prices rather than spot prices, which are the prices residential consumers are more directly responsive to. Individual contracts and government regulations can delay the transmission of spot price fluctuations to end consumers (Baget et al., 2024).

[32] The power generation sector in the United States is comparatively more flexible, with approximately 20% of natural gas-fired combined-cycle capacity capable of switching to alternative fuels—primarily oil, and to a lesser extent, coal (EIA, 2022). In contrast, most gas turbines in Europe are not designed for dual-fuel operation, which significantly constrains short-term interfuel substitution. Around 2000, only about 8% of European power generation capacity could switch between natural gas and oil (IEA, 2002), and this share has declined further in recent years (Reuters, 2022). Coal, however, has remained a key substitute for gas: although physical fuel switching within individual plants is limited, many European utilities operate mixed portfolios that include both gas- and coal-fired units, enabling them to adjust the fuel mix in response to relative price changes (Reuters, 2024). During the 2022 energy crisis, for example, utilities increased coal-fired output not only by reallocating generation within their active fleets, but also by reactivating decommissioned or reserve coal plants and ramping up production at older facilities (IEA, 2022).

States (OECD, 2019). The greater prevalence of specific taxes in the Euro Area partly insulates end-users from fluctuations in spot prices, thereby further dampening demand responsiveness to price shocks. Overall, the results closely align with the estimated structural elasticities. The main distinction is that, *ceteris paribus*, demand in the United States appears less elastic than in the Euro Area, while the overall response of quantity demanded is greater in the United States. This pattern reflects a comparatively stronger negative reaction of industrial production to gas price increases in the United States. As a result, when accounting for contemporaneous movements in other variables, the demand response is amplified relative to that observed in the Euro Area.

Inventories, volatility and uncertainty channel. As shown in the top-left panel of Figure 8, a gas demand shock leads to a significant decline in gas inventories in both regions. This response is more pronounced in the United States, both in percentage terms and absolute magnitude (see Table C6 in the Appendix for magnitudes), reflecting the region's greater capacity to absorb such shocks. In contrast, following a gas supply shock (top-right panel), gas inventories show a significantly weaker response, particularly in the Euro Area, where they exhibit a slight long-run increase. This asymmetry can be explained by two key factors.

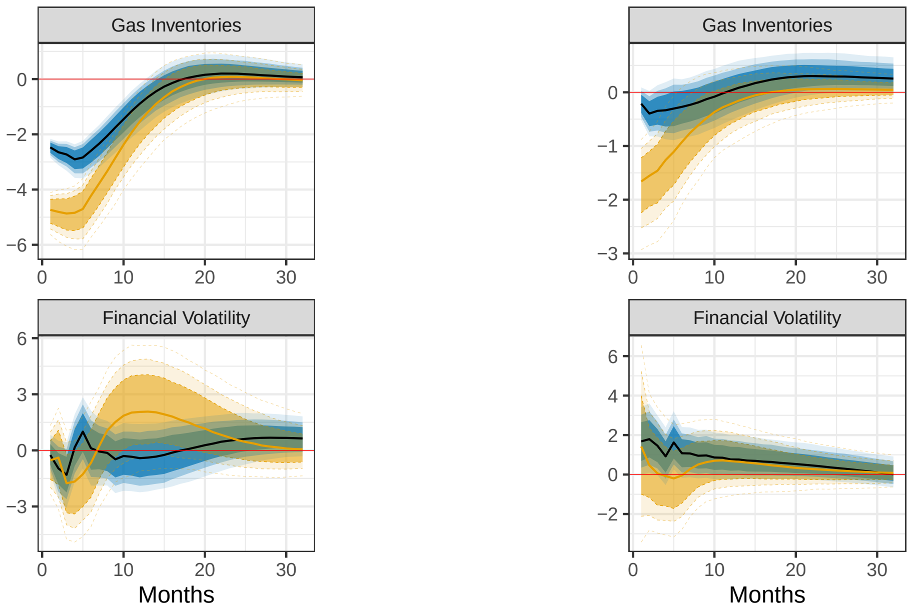
First, by construction, gas demand shocks primarily occur during winter, when gas inventories are deliberately accumulated to accommodate seasonal fluctuations in demand. In contrast, supply shocks can occur at any time of the year, meaning that inventories are not necessarily positioned to absorb these disruptions effectively (European Council, 2022).

Second, we find evidence suggestive of an expectations-driven mechanism. When a supply disruption occurs, any expectation that future gas demand will exceed supply leads to an increase in demand for inventories and a rise in the real price of gas. This effect may stem, for example, from revised expectations about market fundamentals, anticipation of other participants' actions, or precautionary motives. As a result, inventories do not decline as they do in the case of a demand shock. This finding aligns with the evidence documented by Kilian and Murphy (2014) in the crude oil market. Indeed, the type of supply news we consider, particularly in the Euro Area, where we look at disruptions to imports, is consistent with increased uncertainty about future availability, leading to expectations of shortages and rising prices.[33] Supporting this interpretation, we find that gas supply shocks in the Euro Area are associated with a rise in financial volatility, whereas demand shocks do not exhibit this effect.[34] Consequently, gas inventories tend to increase in the long run, reflecting strategic inventory adjustments in response to anticipated price pressures (top-right panel of Figure 8). Similarly, Känzig (2021a) documents an increase in crude oil inventories following a negative supply news shock but finds no significant impact on financial volatility. This discrepancy can be attributed to the nature

[33] Chiţu et al. (2024) document increased speculation on gas prices, particularly in Europe following the invasion of Ukraine

[34] This result can be seen more clearly (but is not statistically any different) when using the informationally robust version of the supply instruments (see Figure I49 in the Appendix).

of the news analyzed in his study, which does not generate heightened uncertainty but instead stabilizes expectations regarding future supply around the quantities announced by OPEC.



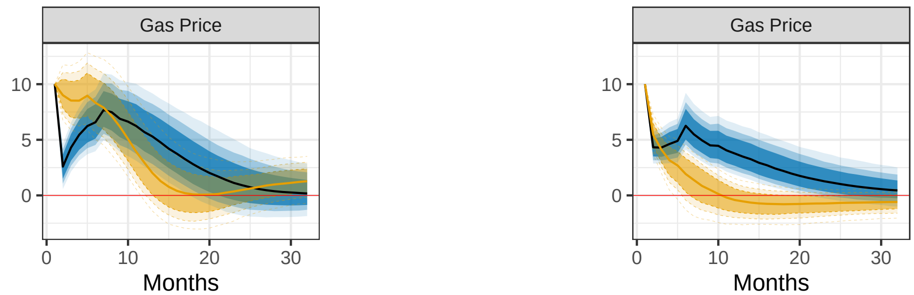
Gas Demand Shock

Gas Supply Shock

Figure 8: *Impact on gas inventories and financial volatility*

Figure H45 in the Appendix presents an alternative specification in which the European gas supply instrument is constructed using only news related to events that, at the time of the release, had not yet materialized but were only expected to occur in the future. Consistent with our interpretation, we find that the response of gas inventories is notably larger, indicating a stronger precautionary storage motive in anticipation of future supply disruptions. Financial market volatility also shows a heightened response relative to the baseline specification. In contrast, the responses of the remaining variables remain broadly unchanged.

Gas price shock persistence. Figure 9 illustrates the dynamics of the spot price following a one-time 10% increase. The results indicate that, in the United States, both demand and supply shocks exhibit lower persistence compared to the Euro Area. The degree of persistence reflects the interplay between adjustments in gas inventories and demand responses. As previously shown, gas inventories respond more strongly to offset demand shocks, with a larger adjustment observed in the United States than in the Euro Area. Moreover, gas demand in the United States declines earlier following a supply shock, whereas in the Euro Area, the adjustment occurs only after several months. As a result, in the Euro Area—particularly in response to supply shocks—the spot price remains elevated for a more prolonged period. This highlights the region's greater vulnerability to supply disruptions: inventories remain unresponsive due to increased precautionary demand amid heightened uncertainty, while gas demand adjusts slowly, limiting the system's capacity to absorb shocks effectively.



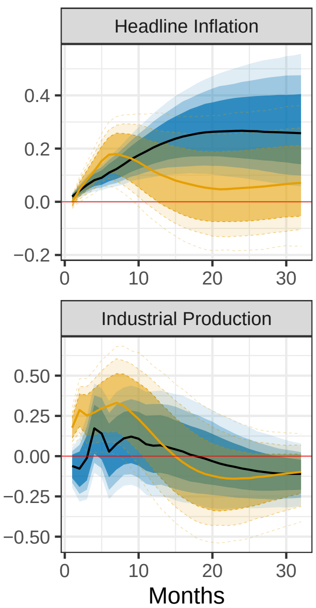
Gas Demand Shock

Gas Supply Shock

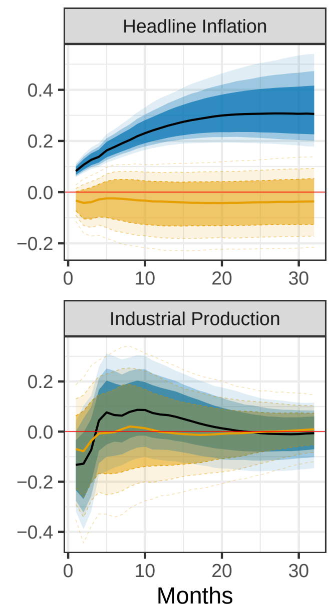
Figure 9: *Persistence of spot price responses*

Macroeconomic impact. Figure 10 illustrates the impact of gas price shocks on headline inflation and industrial production. In the Euro Area, both demand and supply shocks are largely inflationary, while real effects are limited, though more pronounced in the case of a supply shock. In contrast, in the United States, supply shocks have no significant impact, whereas gas demand shocks lead to peak increases of approximately 0.3% in industrial production and 0.2% in inflation, following a 10% increase in the real price of gas. The increase in industrial production in the United States is likely driven by higher activity in energy-related sectors, reflecting the rise in domestic gas production previously discussed.[35] In the Euro Area, demand shocks result in a persistent inflationary pass-through, reaching approximately 2.5% after more than a year. Supply shocks exhibit even larger effects, with inflation peaking at around 3%. These inflationary effects largely mirror spot price dynamics, which show more persistence in the Euro Area—particularly for supply shocks—than in the United States, where only demand shocks have a lasting impact (see again Figure 9).

[35] The energy sector is comparatively much larger in the United States, where it accounted for 5.2% of total employment in 2023 (U.S. Department of Energy, 2024).



Gas Demand Shock



Gas Supply Shock

Figure 10: *Propagation to the macroeconomy*

A notable finding is the strong inflationary effect of gas supply shocks in the Euro Area, contrasted with their muted negative impact on industrial production. This result aligns with recent studies suggesting that the economic consequences of the Russian-Ukrainian crisis would be limited (Bachmann et al., 2022; Gunnella et al., 2022; Di Bella et al., 2024). We also find that gas supply shocks have only a modest effect on aggregate spending (see Figure 16). However, since much of the discussion around the impact of Russian gas supply disruptions has focused on Germany in particular (Bundesbank, 2022; Sinn, 2022; Auclert et al., 2023; Moll et al., 2023), we estimate a Germany-specific version of our baseline model, augmented with national expenditure variables (see Figure H46 in the Appendix). The results indicate that while the direction of the responses is consistent with those observed for the Euro Area as a whole, the real effects are more pronounced in Germany. We find that, while investment declines, national expenditure remains relatively stable, suggesting that the contraction in output is primarily driven by reduced investment alongside higher production costs. These results should be interpreted with caution, however, as national expenditure data are only available at quarterly frequency and have been interpolated to monthly values. Nonetheless, the more pronounced impact on production may help explain the relatively slower post-pandemic recovery in German output.

While substitution in demand can help explain the relatively muted impact of gas supply shocks on aggregate production, and heightened volatility may contribute to increased inflationary persistence (Boeck et al., 2023), these factors alone do not fully account for the transmission of gas price shocks to broader inflation dynamics or their heterogeneous effects across sectors. To shed light on these transmission channels, the next subsection presents a sectoral analysis. We briefly preview some of the key findings here to contextualize the aggregate results. One prominent channel driving inflation in the Euro Area is the pass-through from gas prices to electricity prices. Our results suggest an almost one-to-one pass-through, consistent with the notion that the merit order principle in the European electricity market amplifies upstream energy price shocks (Baget et al., 2024). This transmission channel is illustrated in Figure 13. Another factor that would contribute to the limited real effects and the strong inflationary response is market power. If firms have pricing power, they can pass cost increases downstream, raising prices quickly without significantly reducing output. This effect is stronger to the extent that demand is inelastic. Figure H47 in the Appendix illustrates the response of the producer price index to a gas supply shock, demonstrating that a significant share of cost increases is transmitted through the supply chain. Similarly, Figure 10 shows that a considerable portion of these cost increases is immediately passed on to consumers. Moreover, consumer prices remain elevated even after intermediate goods prices begin to decline, as indicated by the greater persistence of the HICP impulse response functions compared to those of the PPI. Importantly, the inverted-U shape of price responses further indicates the presence of indirect effects (see Figures 13 and 14). This interpretation suggests that only sectors facing major cost increases from rising gas prices, without the ability to fully pass on these costs in the short-term, experience significant output declines. Indeed, we find that the negative impact on aggregate production is largely driven by industries such as electricity, gas, steam, and chemicals, where gas is a major input. In contrast, most other sectors exhibit only small or statistically insignificant effects (see Figure 15).

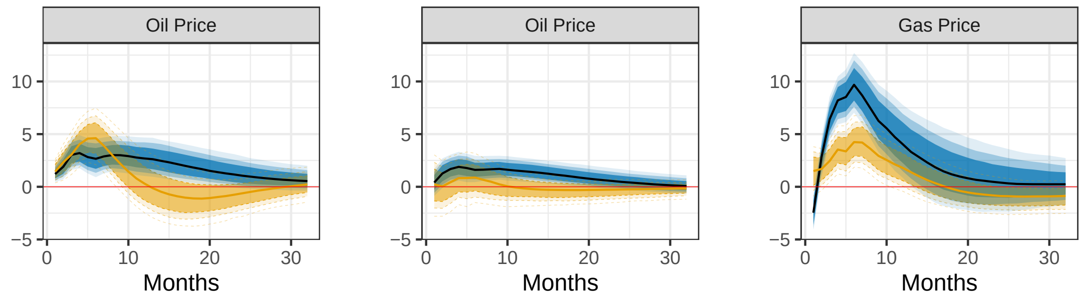
Gas and oil markets interrelation. Figure 11 compares how real gas and oil prices respond to shocks in the oil and gas markets respectively.[36] Given their substitutability, shocks to one commodity influence the other. However, this substitution is imperfect: oil prices react more mutedly but significantly to gas price shocks, while gas prices respond more strongly to oil price shocks than vice-versa. As the oil market is more globalized, an increase in domestic gas demand has a milder impact on oil prices.[37] In the Euro Area, gas price changes pass through to oil prices by approximately 25% at peak, with a slightly lower impact in the case of supply shocks. Conversely, the pass-through from oil prices to gas prices is significantly stronger, reaching near full pass-through at peak. In the United States, by contrast, pass-through effects are generally weaker for both gas and oil.

Recent evidence suggests that as the LNG market has become more integrated, European and Asian gas prices have become more closely linked, whereas the North

[36] To identify the oil price shock, we employ the instrument developed by Känzig (2021a), within the same external instrument framework described in Section 4.1, where two columns of $\mathbf{B}_0^{-1}$ are identified using two separate instruments.

[37] Note, for example, that the dynamics of the Brent (reference for Euro Area) and WTI (reference for United States) crude oil prices are very similar.

American market remains only partially integrated.[38] As a result, when a demand shock raises gas prices in the Euro Area, prices in Asia and other LNG-importing countries also increase, prompting interfuel substitution in these regions. This, in turn, generates a larger fluctuation in the global price of oil compared to a demand shock originating in the United States.



Gas demand shock　　Gas supply shock　　Oil supply shock

Figure 11: *Interrelation of natural gas and crude oil markets*

Notes: Responses of real gas and oil prices to a 10% increase in their respective prices. The left panel shows the responses to gas demand shocks in the Euro Area (in black) and the United States (in orange). The central panel details the responses to gas supply shocks, while the right panel examines responses to oil price shocks as identified in Känzig (2021a). The oil supply shocks series is displayed in Figure F39 in the Appendix.

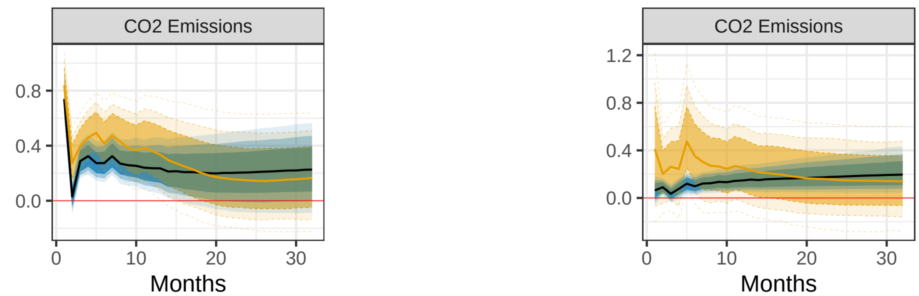
Some previous studies have explored the relationship between crude oil and natural gas markets, particularly in the U.S. context. Some of these studies find no significant long-run relationship between the prices of these commodities (Bachmeier & Griffin, 2006), while others focus primarily on the influence of oil on the gas market. For instance, Jadidzadeh and Serletis (2017) extend the model of Kilian (2009) to incorporate the real price of natural gas, which they assume to be predetermined relative to the oil market. Their findings suggest that approximately 45% of the variation in the real price of natural gas can be attributed to structural supply and aggregate demand shocks in the global crude oil market, whereas shocks within the natural gas market explain about 55% of the long-run variability in its real price. We find that although the impact of gas shocks on the oil market is limited, it is significant, particularly in the Euro Area.

Environmental impact of gas price shocks. When examining inter-fuel substitution patterns in the power generation sector—a major source of global carbon emissions (IPCC, 2022)—we found that the primary substitutes for natural gas are other, more polluting, fossil fuels. To assess the environmental impact of gas price

[38]Infrastructure constraints, particularly the limited capacity of LNG export terminals, restrict the volume of gas that can be shipped abroad (Albrizio et al., 2023).

shocks more specifically, we use CO_2 emissions data from the EDGAR (Global Greenhouse Gas Emissions) database.

Figure 12 shows the response of CO_2 emissions to natural gas price shocks. A gas demand shock that raises the price of natural gas by 10% leads to an immediate increase in emissions of about 0.8% in both the Euro Area and the United States, as more carbon-intensive fossil fuels are burned to satisfy demand. Following a gas supply shock, emissions rise by up to 0.2% in the Euro Area and 0.4% in the United States. As natural gas becomes more expensive, it is increasingly substituted with higher-emission fuels (see Figure H44).



Gas Demand Shock

Gas Supply Shock

Figure 12: *CO_2 emissions*

Notes: Impulse responses of CO_2 emissions to natural gas shocks, estimated using the baseline specification augmented with the CO_2 emissions series. The sample period ends in 2022M12 due to data availability constraints.

In the short to medium run, gas price shocks tend to increase carbon emissions. However, long-term effects may differ. For example, Stock and Zaragoza-Watkins (2024) show that sustained increases in gas prices—such as those resulting from LNG exports—can act similarly to a carbon tax by accelerating the transition to cleaner energy sources and lowering emissions over time. These dynamics underscore the intertemporal trade-offs associated with taxing natural gas. As Harstad and Holtsmark (2024) argue, expanding gas production can initially reduce emissions by displacing coal through price-driven substitution. Nonetheless, such policies may also deter long-term investment in renewables—a dilemma they describe as the "gas trap" (see also Acemoglu et al., 2023). This time-inconsistency problem suggests that taxing more carbon-intensive fuels, such as oil and coal, may offer a more effective strategy for long-term emissions reduction.

5.1 Sectoral effects of a gas supply shock in the EA

In this section, we provide a detailed sectoral analysis of the effects of a gas supply shock in the Euro Area. The Russia-Ukraine crisis has sparked extensive debate over the region's vulnerability to energy supply disruptions, particularly due to its reliance on Russian gas (Draghi, 2024). This study seeks to isolate the specific impacts of such shocks on the Euro Area's economic dynamics, first examining their transmission to power and utility prices before assessing their broader effects on sectoral prices and output.

Transmission to broader energy prices. We first examine the transmission to gas and power prices, shown in Figure 13. This is obtained by expanding the baseline specification with the electricity, gas and fuel prices of interest. The response of the electricity spot price mirrors that of the gas spot price (see Figure 9), with a near-full pass-through on impact. This relationship can be attributed to the merit-order principle and marginal electricity pricing, which dictate that when natural gas is the most expensive power source in use, it sets the price for electricity production (Baget et al., 2024; Segarra et al., 2024). Both households and businesses experience increases in gas and electricity prices; however, firms generally face more substantial price hikes due to their direct exposure to market rates and the relative absence of protective measures available to households (the effects on PPI are stronger than the ones on HICP). Government interventions, primarily aimed at shielding consumers (Sgaravatti et al., 2023), mitigate the impact on household energy bills, while businesses absorb the higher costs. We find that consumer prices for gas and electricity, which are largely composed of utility costs, exhibit similar pass-through dynamics, with gas experiencing a slightly stronger impact, peaking at approximately 12% after 12 months. The inverted U-shape of these responses highlights the gradual adjust-

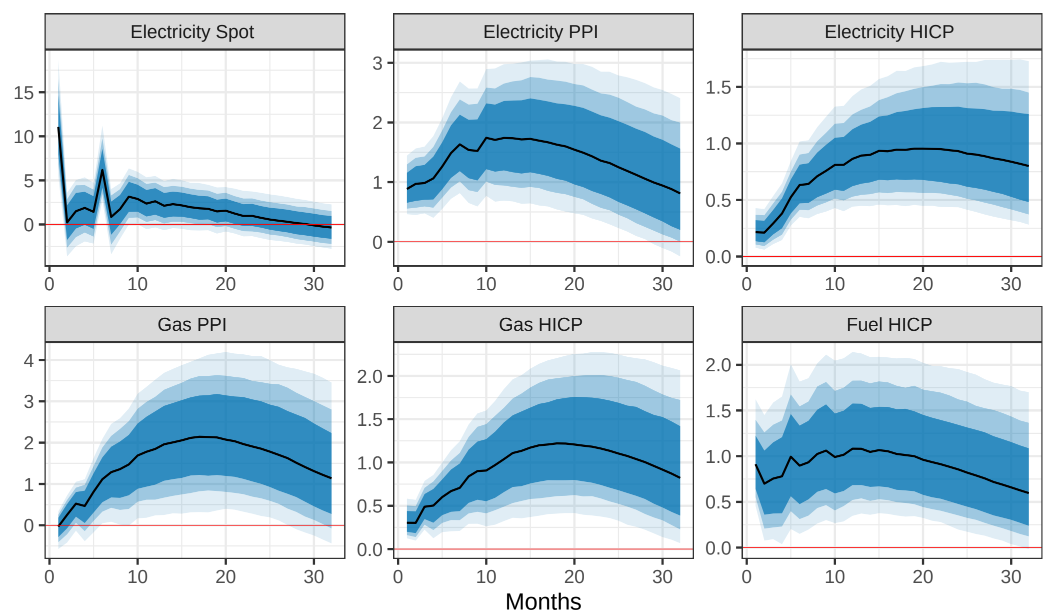


Figure 13: *Euro Area: Energy prices responses to a gas supply shock*

Notes: Impulse responses to a gas supply shock in the Euro Area on electricity prices, gas prices and fuel prices.

ment of these prices, shaped by contractual rigidities in both the wholesale (Ason,

2022) and retail sectors (Baget et al., 2024). These rigidities delay the immediate pass-through of cost changes, leading to a slower initial response and a more gradual return to equilibrium. This phenomenon aligns with a broader literature explaining price stickiness in spot transactions, where mechanisms such as menu costs, information imperfections, and long-term agreements prevent quick price adjustments despite changes in market-clearing prices (e.g. Rotemberg, 1982; Mankiw, 1985; Borenstein and Shepard, 2002). Finally, fuel consumer prices show a pass-through of around 10% on impact. Fuel prices, particularly for transportation, are more directly linked to fluctuations in wholesale energy markets, especially crude oil and refined petroleum products. Retail fuel prices tend to adjust rapidly to changes in spot market prices, leading to a faster pass-through effect (see for example Meyler, 2009, who finds that oil price shocks in the Euro Area pass through very rapidly to consumer fuel prices, with 90% of price changes transmitted within three to six weeks). Conversely, the gas and power sectors exhibit a delayed and gradual price adjustment due to long-term contracting, regulatory frameworks, and less direct exposure to spot market fluctuations.

Sectoral effects on inflation. Figure 14 presents broader responses of consumer prices, including core inflation and a selection of goods and services (2-digit ECOICOP sectors) that enter the headline inflation index. Core inflation remains unaffected initially but gradually increases, reaching its peak after 20 months with a pass-through of approximately 1%—about half of the headline inflation peak depicted in Figure 10. This lagged response indicates indirect effects and gradual price adjustments, suggesting that the impact on headline inflation extends beyond the direct effect of energy prices.

The sectoral analysis reveals that while gas supply shocks generally lead to inflationary pressures across most sectors, the impact varies significantly. Goods, such as food and clothing, display an inverted U-shaped response, characterized by an initial increase followed by a gradual decline. The impact tends to be stronger compared to services, such as education, healthcare, and, to some extent, restaurants and hotels. In contrast, the effects on services are generally more subdued and emerge gradually over several months.

The clothing sector is particularly sensitive to gas price shocks because energy is one of the main cost factors in the textile industry. Moreover, since synthetic fibers like polyester are derived from petrochemicals, their production costs are directly influenced by fossil fuel prices, including natural gas (Hasanbeigi & Price, 2012). Additionally, energy-intensive processes such as dyeing, washing, and finishing contribute to higher operational costs, which are rapidly reflected in retail prices. This explains the significant effect on impact.

Overall, two primary mechanisms account for these sectoral impacts. First, direct effects occur in sectors where energy constitutes a significant cost factor, such as clothing and transport (see Figure 13, Fuel HICP), where the impact of higher gas prices is felt quickly. Second, lagged effects occur in sectors where indirect effects play a role. For example, natural gas is used as a key input in fertilizer production, which in turn raises input costs in the food sector (American Gas Association,

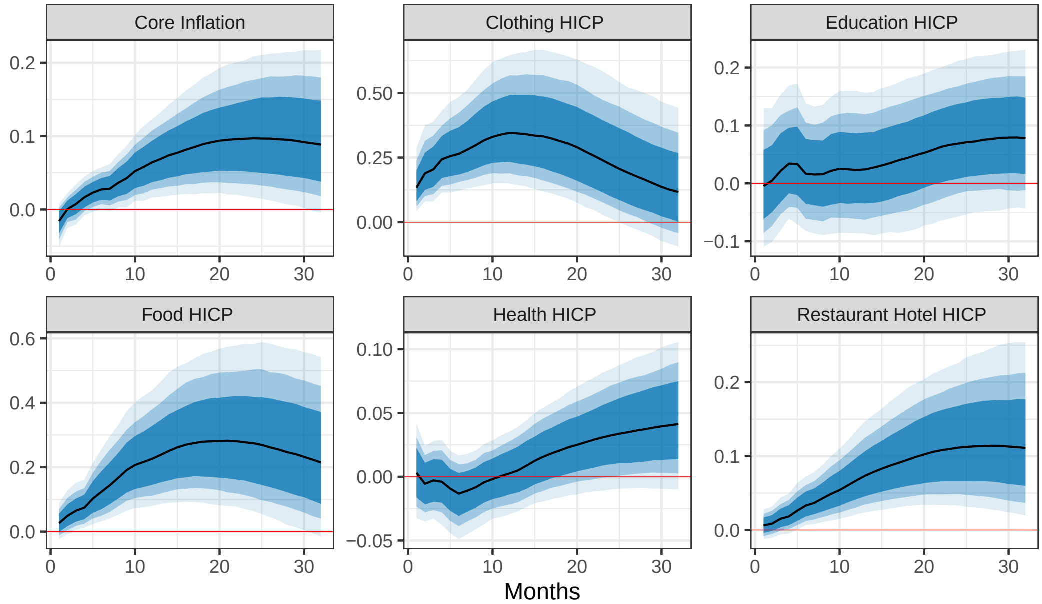


Figure 14: *Euro Area: Responses of core inflation and HICP 2-digit sectors to a gas supply shock*

2023). This results in a more gradual price adjustment. Finally, service sectors tend to experience only mild effects after an extended period, driven primarily by broader inflationary pressures.

Sectoral effects on output. In Figure 10, we demonstrated that the macroeconomic impact of gas supply shocks is primarily inflationary, with effects on real economic activity limited to the first months. Figure 15 provides a more detailed analysis of how different sub-sectors of industrial production are impacted, ordered by value added. The Electricity, Gas, and Steam sector, along with the Machinery and the Vehicles sector, are the main drivers of the immediate aggregate impact, while industries such as chemicals and paper experience lagged effects. The negative response in the Electricity, Gas, and Steam sector, the largest in terms of value added, can be attributed to the central role of natural gas as a key input, which directly transmits gas price shocks to production costs.[39] Within manufacturing, Level 2 sub-sectors are impacted unevenly, with gas-intensive industries, such as chemicals and paper, experiencing lagged but significant negative responses, while others, such as fabricated metals and textiles, show no substantial impact. When considered alongside the results on sectoral HICP, the responses reflect the classic dynamics of cost-push shocks in energy-dependent sectors. Output typically exhibits a U-shaped or inverted J-shaped trajectory, characterized by an initial decline followed by a gradual recovery. In contrast, inflation responses follow an inverted U-shaped pattern, driven by higher production costs being passed on to consumers. Inflation rises sharply at first, peaks, and then gradually declines over time as the shock dissipates.

[39]See Gunnella et al. (2022) for sectoral gas intensity statistics in the Euro Area.

Another characteristic of these types of shocks is the sectoral heterogeneity of their impacts (Davis & Haltiwanger, 2001), which is also evident in our findings. However, not all sectors are significantly affected, which explains the limited aggregate effect on production.

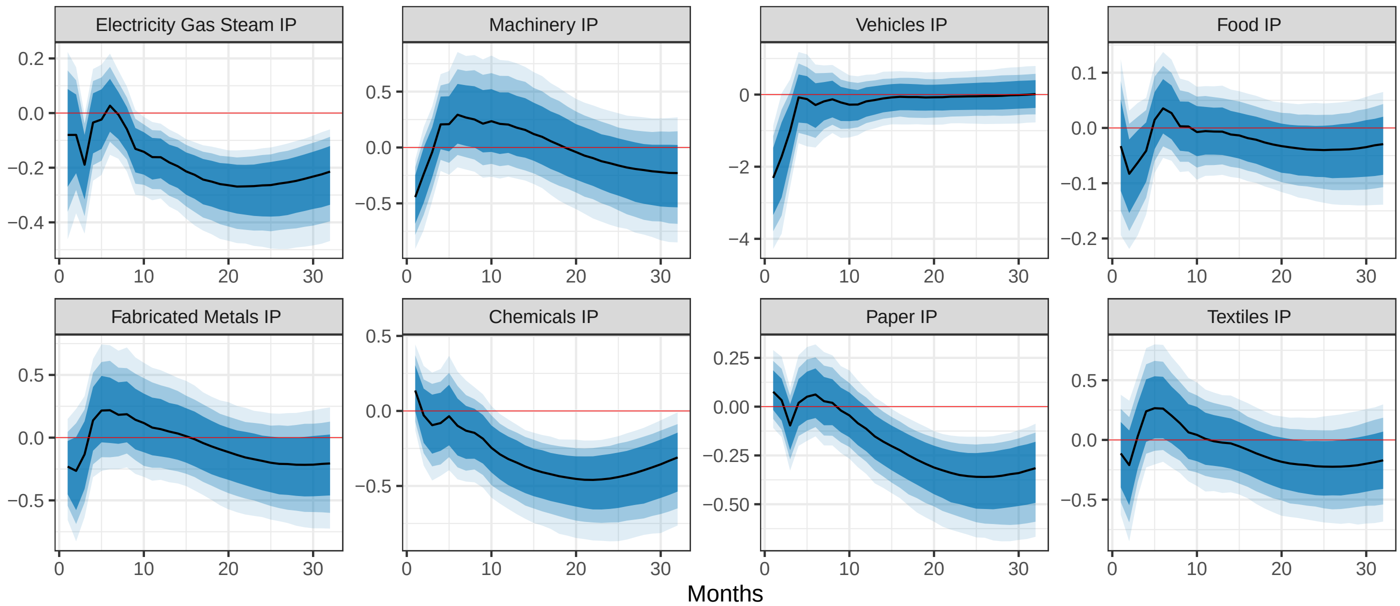


Figure 15: *Euro Area: Responses of IP sectors to a gas supply shock*

Notes: Impulse responses to a gas supply shock in the Euro Area on selected subsectors, ordered by value added. Electricity, gas, steam and air conditioning supply represents 10.0% of total industrial production, measured by value added; Manufacture of machinery and equipment 9.8%; Manufacture of motor vehicles, trailers and semi-trailers 9.5%; Manufacture of food products 8.6%; Manufacture of fabricated metal products 8.0%; Manufacture of chemicals and chemical products 6.1%; Manufacture of paper and paper products 2.1%; Manufacture of textiles 1.0% (Eurostat, 2024).[a]

[a]The figures refer to 2017, the latest year for which the value added for Europe is available for all sectors.

Aggregate demand channel. Gas supply price shocks appear to have limited and short-lived real effects, as discussed. This conclusion is further supported by additional economic indicators. Figure 16 shows that neither real Gross National Expenditure (GNE) nor the unemployment rate exhibit significant responses. In contrast, consumer spending and investment experience a modest decline, as households and firms reallocate expenditures in response to rising energy prices (Hamilton, 2023). One interpretation is that these effects remain relatively contained and do not trigger substantial cascading impacts at the aggregate level. However, these results should be interpreted with caution, as national expenditure data are available only at the quarterly frequency and have been interpolated to monthly values. In comparison, oil price shocks tend to have a more pronounced effect on aggregate demand (Hamilton, 2009; Känzig, 2021a). This difference is likely attributable to the relatively lower share of natural gas in overall energy expenditures, which amounts to roughly one-quarter of spending on petroleum products (Moll et al., 2023).

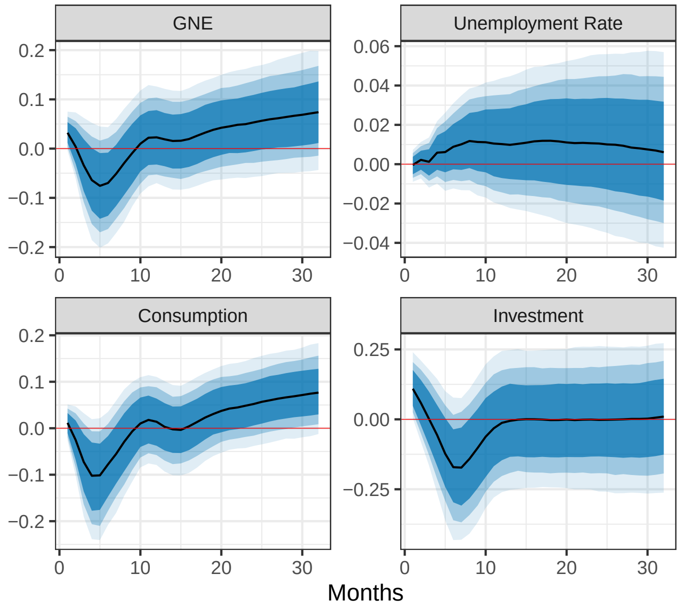


Figure 16: *Euro Area: Responses of key economic activity indicators to a gas supply shock*

Notes: Impulse responses of Gross National Expenditure (GNE), the unemployment rate, consumption, and investment to a gas supply shock in the Euro Area. The results are derived from the baseline model, augmented with the four variables shown. GNE, consumption, and investment are quarterly variables interpolated to monthly using a cubic spline interpolation.

Discussion. The analysis presented in this section reveals significant regional differences in the effects and transmission of gas price shocks between the Euro Area and the United States, driven by structural differences in supply composition, demand elasticities, and transmission mechanisms.

The timing and magnitude of supply adjustments differ markedly between the two regions. In the United States, where domestic production is the primary driver of supply, we estimate a short-run elasticity of zero that gradually increases over time, reaching approximately 0.1 after one year. In contrast, in the Euro Area, where supply is largely dependent on imports, adjustments occur more quickly, resulting in a higher short-run supply elasticity of approximately 0.2. However, this reliance on imports inherently limits the region's ability to mitigate supply shocks such as import disruptions. In the Euro Area, gas demand is inelastic on impact and adjusts only after several months. This rigidity stems at least in part from the composition of demand, with a larger share of gas consumption in the Euro Area concentrated in the residential and industrial sectors, where price pass-throughs are slower and consumption is less responsive. In contrast, in the United States, power generation accounts for a larger share of gas consumption, allowing for greater interfuel substitution and a faster demand adjustment, with an estimated elasticity of approximately -0.05 after a couple of months.

The inflationary impact of gas price shocks is more pronounced in the Euro Area than in the United States. Demand shocks in the Euro Area lead to a persistent pass-through to headline inflation, reaching approximately 2.5% after more than a year, while supply shocks exhibit even greater persistence, with inflation peaking at around 3%. In contrast, in the United States, supply shocks have no significant effect on inflation, while demand shocks result in a smaller and less persistent increase, peaking at approximately 2% within six months before quickly declining. These inflationary dynamics largely reflect spot price movements, which are shaped by adjustments in demand and gas inventories. In the Euro Area, in addition to the slower adjustment of demand, gas inventories do not offset price increases following gas supply shocks but instead rise in the long run, accompanied by increased financial volatility. This suggests an expectation-driven mechanism, where heightened uncertainty prompts stockpiling and precautionary demand, further amplifying inflationary pressures. Moreover, the near one-to-one pass-through of gas prices to electricity prices, driven by the merit-order principle, reinforces the persistence of inflation.

Aggregate real effects are limited in both regions. In the United States, gas demand shocks lead to a temporary increase in industrial production, as a result of heightened activity in energy production. In contrast, in the Euro Area, supply shocks have a negative but muted impact on industrial production, with significant sectoral heterogeneity. Sectoral analysis indicates that industries heavily reliant on gas—such as the electricity, gas, and steam sector, as well as chemicals—experience the largest negative output effects. However, over time industries are able to pass cost increases downstream, limiting the aggregate impact on industrial production. Instead, inflationary pressures are widespread but stronger in goods as opposed to services, with consumer price increases reaching up to 3% in sectors such as clothing and food following a 10% rise in natural gas prices.

5.2 Contributions to inflation surge

We now undertake a more detailed analysis of the impact of gas shocks on European inflation, comparing this with the influence of other factors that have been central to the macroeconomic debate surrounding the inflation surge that began in 2021. Specifically, we consider supply chain bottlenecks, which emerged prominently during the COVID-19 pandemic and intensified with subsequent disruptions; oil price shocks, driven by global supply imbalances and heightened geopolitical tensions; and monetary policy shocks, as central banks responded to rising inflationary pressures with sharp shifts in interest rates. The analysis presented in this section aims to disentangle the relative contributions of these factors to the inflationary environment during this period.

We therefore estimate a small-scale VAR model that includes the Global Supply Chain Pressure Index (GSCPI), the real price of gas, the real price of oil, core inflation, and the 1-year ECB rate. Following the approach of Benigno et al. (2022), we identify the effects of supply chain bottleneck shocks using short-run restrictions, assuming that the GSCPI is predetermined with respect to the other variables. Oil price shocks and monetary policy shocks are identified using external instruments, following Känzig (2021a) and Ricco et al. (2024), respectively. Further details on the identification of these shocks are provided in Appendix B. The residuals of inflation are left unidentified and therefore capture unexplained variation in prices attributable to other factors, such as unmodeled aggregate demand or the impact of food prices (ECB Blog, 2023).

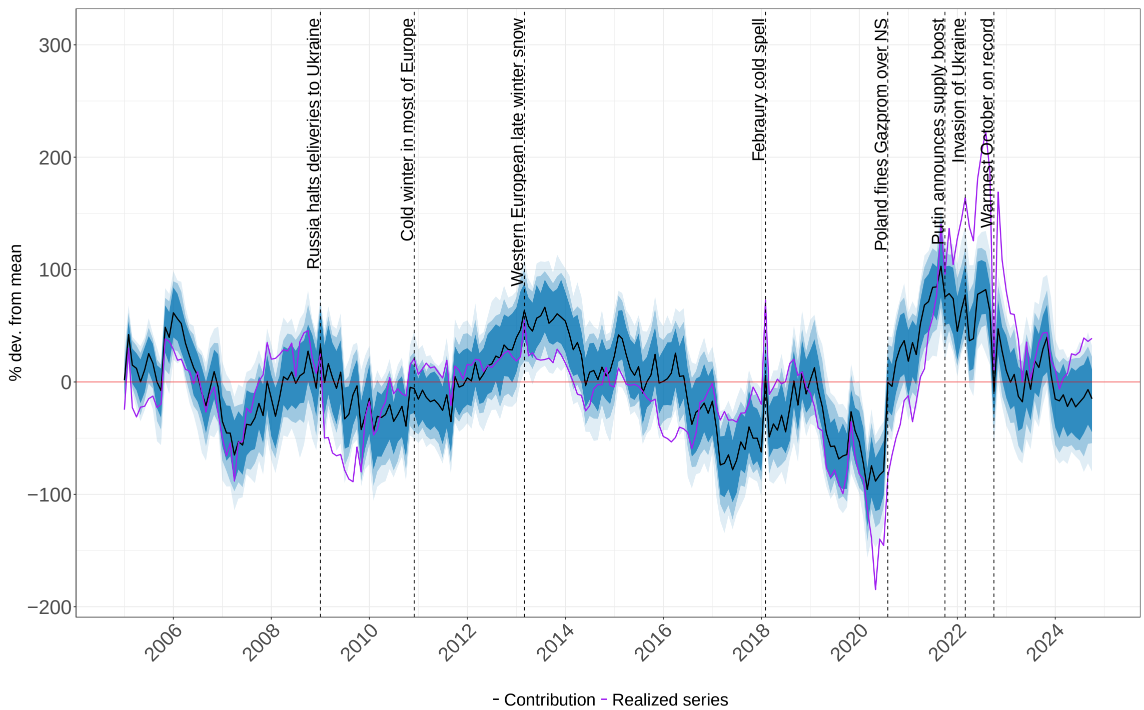


Figure 17: *Euro Area: Historical decomposition of the real price of gas*

Notes: The figure illustrates the estimated contributions of gas shocks to the real price of gas, alongside the realized gas price series (expressed as percent deviations from the mean). Both demand and supply instruments are used. Vertical dashed bars mark significant events in the gas markets: the Russian halt of all gas deliveries to Ukraine for 13 days in 2009M1; an abnormally cold winter in Europe in 2010M12; a late snow event in Western Europe in 2013M3; cold spell in 2018M2; Poland's imposition of fines on Gazprom in 2020M8; Putin's announcement of gas supply increases in 2021M10; supply fears in 2022M3 following the invasion of Ukraine; and the warmest October on record in 2023M10.

Before turning to the impacts on inflation, we first assess the contribution of our gas shocks to the real gas price series. Figure 17 shows the cumulative historical contribution of gas shocks to the real price of gas, together with the observed realized real gas price for the period 2004M1-2024M10. This is obtained by combining both our demand and supply instruments. We can see that our identified shocks have contributed substantially to the historical variation of the price of gas. For example, when in January 2009 Russia halted gas deliveries to Ukraine for 13 days following a Gazprom and Naftogaz dispute over the latter's accumulating debts, prices hiked. Prices then quickly returned to the usual levels after the dispute was resolved on January 18, when Russian Prime Minister Vladimir Putin and his Ukrainian counterpart, Yulia Tymoshenko, negotiated a new contract. In addition, unexpected temperature swings contributed to temporary spikes in the price of gas, as during the March 2013 storm in the West of Europe, or the cold February of 2018, which caused a very large hike in the price of gas. However, gas price shocks would have led to a higher gas price during the 2015-2017 period, but this was moderated by declining oil prices following OPEC announcements, as shown in Känzig (2021a). Similarly, the record-low prices in 2020 reflected broader pandemic-related disruptions rather than solely gas-specific shocks, as further discussed below.

Having evaluated the extent to which our identified shocks account for the variability in the real gas price series, we now focus on the primary objective of this section: quantifying the contributions of inflationary drivers to price dynamics. To provide a clearer understanding of inflation dynamics over time, we first categorize the period from February 2020 to October 2024 into three distinct chronological phases:[40]

- Phase I: *COVID-19 Pandemic* (February 2020 to December 2020): Inflation declines sharply as the pandemic disrupts economic activity.
- Phase II: *Inflation Surge* (January 2021 to March 2023): Inflation accelerates significantly, reaching historically high levels.
- Phase III: *Disinflation* (April 2023 onwards): Inflation starts to decline, going back to target.

Figure 18 presents the historical decompositions derived from the VAR model and compares them to the realized series of inflation. Historical decompositions provide a quantitative assessment of how much each series of structural shocks contributes to the observed fluctuations in the variables included in the VAR model (see Appendix A.2 for additional technical details). In this context, these decompositions help identify the relative importance of different inflation drivers over time, offering valuable insights into their changing relevance during the analyzed period.

First, we observe that the sum of the four identified shocks—out of the five variables included—(dashed line) closely matches the realized inflation series. This indicates that the residual unexplained variation in inflation is small, suggesting that the identified shocks represented the most significant drivers of inflation over the considered sample. Furthermore, this result confirms that the quality of the historical decomposition approximation is adequate and effectively captures the recent rise in inflation.

At the onset of the COVID-19 pandemic, oil and gas price shocks had a significant and comparable impact on inflation, as pandemic-related lockdowns triggered a collapse in economic activity and global energy demand. The role of energy shocks

[40] See, for example, Ascari et al. (2023) for a similar categorization.

remained critical during the inflation surge observed in Phase II. Gas price shocks, in particular, emerged as the dominant driver of core consumer prices, playing a key role in the rapid price increases. This impact was further exacerbated by the adverse supply shocks following the invasion of Ukraine. In addition to energy shocks, supply chain bottlenecks became a critical inflationary factor. With the post-pandemic reopening, the economy was exposed to severe disruptions, including shortages of semiconductors and memory chips, the global misallocation of shipping containers, and port delays due to pandemic-related restrictions (Stiglitz & Regmi, 2023). These supply chain bottlenecks, characterized by lagged and persistent effects, continued to influence inflation well into late 2023, as also found by De Santis (2024). Throughout the period of elevated inflation, monetary policy responded with sharp interest rate hikes. However, we find that its effectiveness in mitigating rising prices has been limited. Finally, Phase III was marked by a gradual normalization of inflation driven by the easing of energy price pressures and the resolution of pandemic-induced supply chain interruptions.

We now quantify these qualitative observations and assess the contribution of each historical decomposition to the series of inflation. To this aim, we introduce a metric that quantifies how much a series of shocks has contributed in percentage terms to the variation of inflation between two time periods. We denote

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

the approximation implied by equation (A.2). This allows us to define

$$\hat{y}_{kt}^{(j)} = \sum_{s=0}^{t-1} \theta_{kj,s} w_{t-s} \tag{14}$$

the historical decomposition representing the contribution of the series of the j^{th} structural shocks to the realization of the k^{th} variable at time t. By construction, it holds that

$$\hat{y}_{kt} = \sum_{j=1}^{K} \hat{y}_{kt}^{(j)}$$

Therefore, to quantify how much the series of the j^{th} shock has contributed in percentage terms to the variation of the k^{th} variable between time q and time r, we can compute the quantity

$$\frac{\sum_{t=q}^{r} |\hat{y}_{kt}^{(j)}|}{\sum_{k=1}^{K} \sum_{t=q}^{r} |\hat{y}_{kt}^{(j)}|} \tag{15}$$

It is important to note that this measure does not account for the sign of the historical decomposition contributions and should be interpreted accordingly. Specifically, it provides only a quantitative assessment of the extent to which each series of shocks has influenced the inflation series. Table 3 quantifies the contributions of each series of shocks to inflation by applying the proposed metric to different time periods.

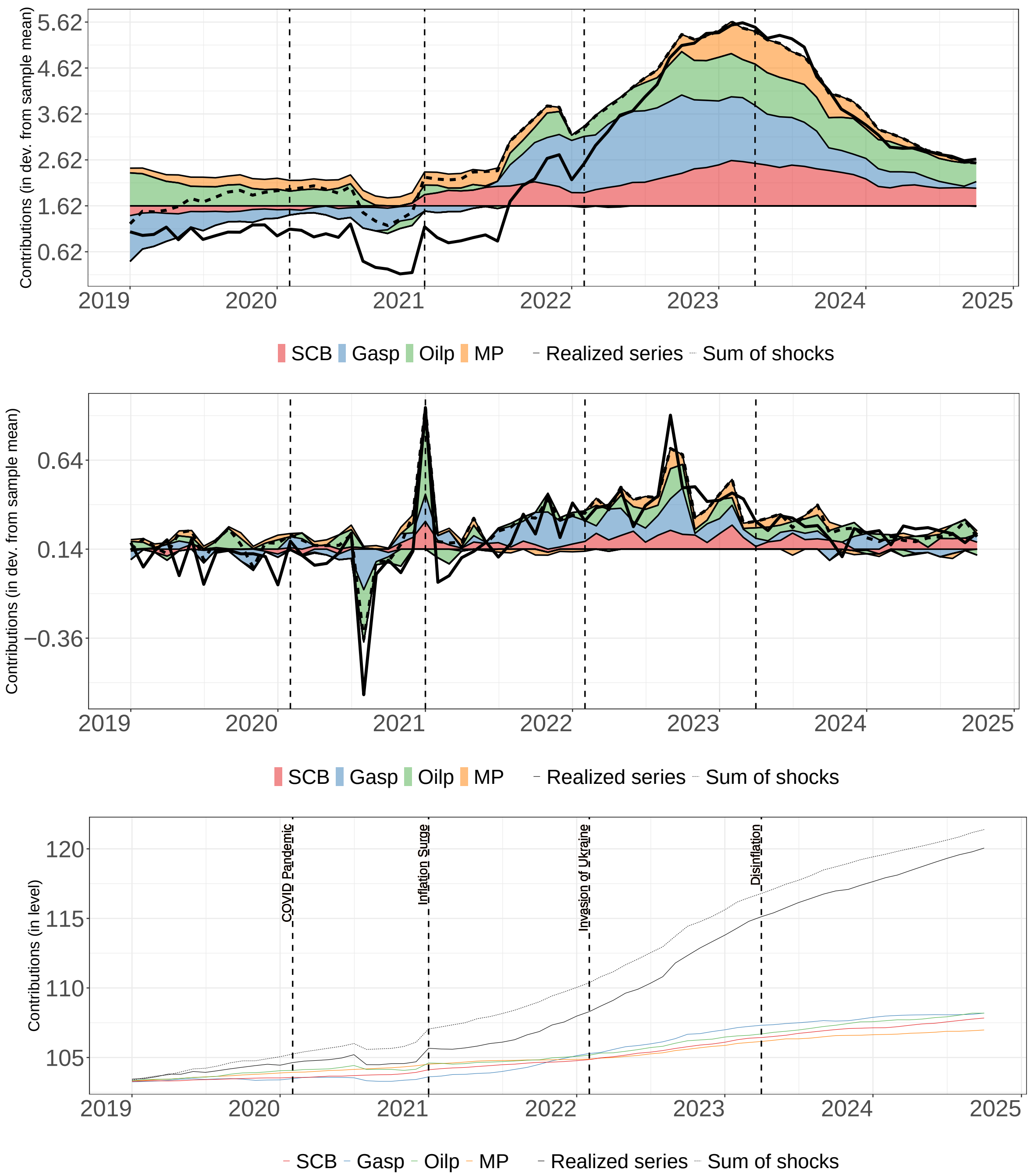


Figure 18: *Euro Area: Historical decompositions of YoY and MoM inflation selected sample*

Notes: The top panel shows the contributions of supply chain bottlenecks, gas price, oil price, and monetary policy shocks on the realized series of YoY inflation, relative to the unconditional mean (horizontal line). The central panel illustrates the contributions to MoM inflation. The bottom panel shows the implied contributions on the price level. Throughout all panels, the dashed line represents the total contribution of all shocks considered.

Shock contribution		SCB	Gasp	Oilp	MP	Residual
Pre-COVID	*2019M01* *2020M01*	6%	15%	17%	8%	54%
Phase I	*2020M02* *2020M12*	8%	22%	24%	8%	38%
Phase II	*2021M01* *2023M03*	18%	33%	21%	12%	16%
Phase III	*2023M04* *2024M10*	24%	19%	30%	14%	13%
All phases	*2020M02* *2024M10*	18%	27%	24%	12%	19%

Table 3: *Percentage contributions of the structural shocks to the realized series of inflation.*

In the pre-COVID period (January 2019-January 2020), inflation was relatively low, supported by low demand and strong supply (Binici et al., 2022). In this environment of price stability, energy price shocks played a relatively modest role in inflation dynamics, with gas and oil prices explaining 15% and 17% of inflation variation, respectively. During the COVID-19 crisis (Phase I), energy price shocks gained relevance, while supply chain bottlenecks had a minimal influence. Notably, in this period, the residual component contributed a substantial share of inflation volatility, possibly reflecting demand forces not captured in our analysis. In Phase II, marked by the Russian invasion of Ukraine, gas price shocks emerged as the primary driver of inflation, primarily due to gas supply disruptions. Gas price shocks explained 33% of the overall inflation variation, significantly outpacing the contribution of oil price shocks at 21%. Concurrently, the significance of supply chain bottleneck shocks increased to 18%, underscoring the growing relevance of the disruptions originated during the pandemic. The disinflation period (Phase III) saw a marked moderation in the impact of energy prices. The contribution of gas price shocks declined to 19%, reflecting the normalization of gas markets following the unprecedented price surges of 2021 and 2022. In contrast, supply chain bottlenecks persisted as a significant driver of inflation, reflecting their long-lasting effects.

Overall, energy shocks have consistently been important drivers of inflation from January 2020 onwards (explaining half of the variation in inflation), overshadowing the effects of monetary policy, which appeared relatively subdued despite a marked increase in interest rates.

To complement the information provided by the metric in Eq.(15), we assess the contribution of each historical decomposition on the price level, via the measure proposed by Kilian and Lütkepohl (2017), chapter 4. We measure the cumulative change in y_{kt} between time q and r attributed to the j^{th} structural shock as follows:

$$\hat{y}^{(j)}_{kr} - \hat{y}^{(j)}_{kq} \tag{16}$$

where $\hat{y}^{(j)}_{kt}$ denote the cumulative contribution of shock j to variable y_{kt} at time t, in line with Eq.(14). In addition to the previously proposed measure, this metric informs on the sign of the cumulative change in the variable of interest given by the j^{th} shock.

Table 4 reports this metric for the three time periods of interest. In Phase I, the price level remained relatively unchanged. The initial negative effects at the onset of the pandemic, driven by a slowdown in economic activity, were offset by the positive effects that followed the reopening of the economy, as illustrated in Figure 18. Additionally, the residual term contributed to a reduction of 0.8 points, likely reflecting an unmeasured reduction in aggregate demand. In Phase II, gas price shocks became the major driver of inflation, contributing over 3.8 points to price level increase. Supply chain bottlenecks and oil price shocks also played substantial roles, each contributing approximately 2.5 points. Energy price shocks, which collectively accounted for 50% of the variation in inflation during the surge, led to a cumulative effect of 6 points on the price level. Lastly, during the disinflation period, while all of the factors considered moderated, the influence of gas price shocks saw the greatest reduction.

Shock contribution to the price level	*Date and price level*		**SCB**	**Gasp**	**Oilp**	**MP**	**Residual**
Phase I	*2020M02* *2020M12*	104.63 104,69	0.37	-0.06	0.08	0.47	-0.80
Phase II	*2021M01* *2023M03*	104.69 114.79	2.44	3.83	2.42	1.65	-0.24
Phase III	*2023M3* *2024M10*	114.79 120.06	1.56	0.99	1.64	0.92	0.16

Table 4: *Cumulated contributions of the structural shocks to the realized series of price levels.*

Our analysis reveals that the surge and subsequent reversal of energy prices, alongside the persistent effects of supply chain bottlenecks, explain the bulk in the rise and subsequent fall in the Euro Area prices during the last few years. These results offer valuable insight into the sources of the inflation dynamics, suggesting that supply-side drivers had been key determinants of the post-pandemic inflation surge in the Euro Area (Bańbura et al., 2023; De Santis, 2024). Crucially, gas significantly outpaced the contribution of oil—particularly following the Russian invasion of Ukraine—accounting for one-third of inflation volatility between January 2021 and March 2023. Our conclusions align with Casoli et al. (2022), who, adopting an alternative identification strategy based on sign restrictions, find that gas price shocks have been the major contributing factor to the inflation surge. These findings are further supported by recent studies investigating the drivers of the inflation surge in the Euro Area. For example, similarly to Benigno et al. (2022), we show that mainly accounting for this surge was a combination of energy shocks and supply chain bottlenecks. However, by explicitly disentangling the impact of gas price shocks from that of oil, we increase the explanatory power of the historical decomposition and underscore the distinct contribution of gas to inflation volatility. Moreover, in the same vein of Bańbura et al. (2023), we showcase the importance of supply-side drivers for the inflation surge, but, in contrast to their findings, our results suggest that gas shocks had a greater influence than oil shocks.

6 Conclusions

In this paper we proposed a novel identification strategy to separately identify demand shocks and supply news shocks to the price of natural gas. Using exogenous variation in temperatures, we identified a gas demand shock, and using variation in futures prices around a tight window around gas market-relevant news, we identified a gas supply news shock. This approach enabled us to estimate gas demand and supply elasticities for both the United States and the Euro Area. Additionally, we presented detailed evidence on the macroeconomic and sectoral impacts of gas price shocks, offering new insights into their transmission mechanisms and effects.

Our analysis reveals that gas shocks have significant macroeconomic effects in both the Euro Area and the United States, with notable regional differences driven by structural disparities in supply composition, demand elasticity, and market dynamics. In the United States, greater flexibility in fuel substitution allows for a more responsive demand adjustment, whereas in the Euro Area, demand adjusts more gradually, contributing to the persistence of inflationary effects. Inflationary pressures in the Euro Area are further amplified by an expectation-driven mechanism linked to uncertainty, as reflected in increased inventory accumulation and heightened financial volatility following supply shocks. Although the aggregate real effects of gas price shocks remain limited, their impact varies across sectors. Energy-intensive industries are most affected by supply shocks, but cost increases are largely passed downstream over time, mitigating direct output losses while sustaining inflationary pressures, which are more pronounced for goods than for services.

This analysis highlights important policy considerations. First, strengthening energy security remains a key priority for the Euro Area. In the short term, fostering partnerships with reliable and diverse trade partners and supporting joint procurement initiatives can enhance resilience. Additionally, diversifying suppliers and expanding strategic reserves would further improve the region's ability to offset both supply and demand shocks. Reforming the electricity market in the Euro Area also warrants attention, as adjustments that reduce the disproportionate influence of marginal pricing by the most expensive energy sources could help mitigate overall energy price volatility. Finally, our estimates of consumption elasticities suggest that price-based mechanisms may be insufficient to achieve a meaningful shift away from fossil fuels. In the short to medium term, gas price shocks tend to induce substitution toward more carbon-intensive fuels such as coal and oil, rather than renewables—ultimately increasing CO_2 emissions.

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Online Appendix

Contents

A Econometric models

Consider the structural VAR(p) model:

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{w}_t, \tag{1}$$

where $\mathbf{y}_t$ is a $K \times 1$ vector of endogenous variables, assumed to have zero mean without loss of generality. The vector $\mathbf{w}_t$ is a $K \times 1$ vector of structural shocks, assumed to be serially uncorrelated with full-rank variance-covariance matrix $\mathbb{E}(\mathbf{w}_t\mathbf{w}_t') = \mathbf{\Sigma}_w$. This model is "structural" because the elements of $\mathbf{w}_t$ are mutually uncorrelated, that is, $\mathbf{\Sigma}_w$ is diagonal.

Since the matrices $\mathbf{B}_0$ and $\mathbf{w}_t$ are generally unobserved, we rely on the reduced-form representation to estimate the model:

$$\begin{aligned}\mathbf{y}_t &= \mathbf{B}_0^{-1}\mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_0^{-1}\mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{B}_0^{-1}\mathbf{w}_t \\ &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t,\end{aligned} \tag{2}$$

where $\mathbf{A}_i = \mathbf{B}_0^{-1}\mathbf{B}_i$ for $i = 1, \ldots, p$, and $\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t$. We estimate the reduced-form parameters $\mathbf{A}_1, \ldots, \mathbf{A}_p$, $\mathbf{\Sigma}_u = \mathbb{E}(\mathbf{u}_t\mathbf{u}_t')$, and the reduced-form residuals $\mathbf{u}_t$ using Bayesian methods (see below).

The key equation linking the reduced-form innovations to the structural shocks is:

$$\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t, \tag{3}$$

where the matrix $\mathbf{B}_0^{-1}$ has to be retrieved. For now, we assume $\mathbf{B}_0^{-1}$ to be known, and our strategy to recover such matrix will be presented in section A.3.

A.1 Structural impulse response functions

Given $\mathbf{B}_0$ and $\mathbf{u}_t$, it is straightforward to recover $\mathbf{w}_t$, which can be used to compute the impulse response functions (IRFs), that is, the responses of each element of $\mathbf{y}_t = (y_{1t}, \ldots, y_{Kt})'$ to a one-time impulse in each element of $\mathbf{w}_t = (w_{1t}, \ldots, w_{Kt})'$:

$$\frac{\partial \mathbf{y}_{t+i}}{\partial \mathbf{w}_t'} = \mathbf{\Theta}_i, \quad i = 0, 1, 2, \ldots, H \tag{4}$$

This is a $(K \times K)$ matrix whose elements are given by

$$\theta_{jk,i} = \frac{\partial y_{j,t+i}}{\partial w_{kt}}.$$

In order to recover the IRFs, we first resort to the VAR(1) representation of the VAR(p) process:

$$\mathbf{Y}_t = \mathbf{A}\mathbf{Y}_{t-1} + \mathbf{U}_t, \tag{5}$$

with

$$
\mathbf{Y}_t \equiv \begin{bmatrix} \mathbf{y}_t \\ \vdots \\ \mathbf{y}_{t-p+1} \end{bmatrix} \quad \mathbf{A} \equiv \begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \dots & \mathbf{A}_{p-1} & \mathbf{A}_p \\ \mathbf{I}_K & \mathbf{0} & & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_K & & \mathbf{0} & \mathbf{0} \\ \vdots & & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{I}_K & \mathbf{0} \end{bmatrix} \quad \mathbf{U}_t \equiv \begin{bmatrix} \mathbf{u}_t \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}.
$$

By recursive substitution, it can be shown that the response of the variable $j = 1, \dots, K$ to a unit shock u_{kt}, i periods in the past, for $k = 1, \dots, K$, is given by $\mathbf{\Phi}_i = \left[\phi_{jk,i}\right] \equiv \mathbf{J}\mathbf{A}^i\mathbf{J}'$, where $\mathbf{J} \equiv \left[\mathbf{I}_K \quad \mathbf{0}_{K \times K(p-1)}\right]$ is a selector matrix. These are sometimes called dynamic multipliers or reduced-form impulse responses.

Under covariance stationarity of $\mathbf{y}_t$, the system can be expressed as a weighted average of current and past shocks (multivariate MA(∞) representation), with weights $\mathbf{\Phi}_i$:

$$
\mathbf{y}_t = \sum_{i=0}^{\infty} \mathbf{\Phi}_i \mathbf{u}_{t-i} = \sum_{i=0}^{\infty} \mathbf{\Phi}_i \mathbf{B}_0^{-1} \mathbf{B}_0 \mathbf{u}_{t-i} = \sum_{i=0}^{\infty} \mathbf{\Theta}_i \mathbf{w}_{t-i}, \tag{6}
$$

where we define $\mathbf{\Theta}_i \mathbf{w}_{t-i} \equiv \mathbf{\Phi}_i \mathbf{B}_0^{-1}$. It follows that:

$$
\frac{\partial \mathbf{y}_t}{\partial \mathbf{w}'_{t-i}} = \frac{\partial \mathbf{y}_{t+i}}{\partial \mathbf{w}'_t} = \mathbf{\Theta}_i, \quad i = 0, 1, 2, \dots, H
$$

These structural impulse responses can be obtained simply by post-multiplying $\mathbf{\Phi}_i$ by $\mathbf{B}_0^{-1}$.

A.2 Historical decomposition

Structural impulse responses describe average movements in the data. However, we are often interested in quantifying how much a given identified structural shock contributes to the historically observed fluctuations of the variables in the VAR. For covariance stationary VAR models, such contributions—known as historical decompositions—can be computed by rewriting equation (6) as:

$$
\mathbf{y}_t = \sum_{s=0}^{t-1} \mathbf{\Theta}_s \mathbf{w}_{t-s} + \sum_{s=t}^{\infty} \mathbf{\Theta}_s \mathbf{w}_{t-s}.
$$

Since under covariance stationarity the MA coefficients decay over time, it holds that

$$
\mathbf{y}_t \approx \sum_{s=0}^{t-1} \mathbf{\Theta}_s \mathbf{w}_{t-s}. \tag{7}
$$

This approximation can only be computed from $t = p + 1$ onward and is more accurate for periods toward the end of the sample. The quality of the approximation also depends on the persistence of the roots of the VAR process.

A.3 Identification

As presented above, in the VAR context, the identification problem refers to the problem of recovering the $\mathbf{B}_0^{-1}$ matrix. We here briefly present the recursive identification scheme, used in the small-scale VAR of section 5.2, and the instrumental variable approach, our main identification strategy.

The recursive identification scheme. A common approach to solve the identification problem is to impose a sufficient number of restrictions to the entries of $\mathbf{B}_0$ in order to recover the unconstrained ones from the estimate of $\hat{\mathbf{\Sigma}}_u$. In particular, it is customary to assume that the simultaneous relationships between the variables are *acyclic*. This assumption imposes that there are no contemporary feedbacks in the system and that there exists a precise causal ordering of the variables. In practice, this is equivalent to imposing that $\mathbf{B}_0$ is lower triangular, given a particular ordering of the variables. By doing so, $\mathbf{B}_0^{-1}$ can be unambiguously identified through the Cholesky factorization of $\hat{\mathbf{\Sigma}}_u$ and the particular contemporaneous ordering is usually chosen by relying on prior economic knowledge. This technique has perhaps been the most popular way to identify structural VAR models, as the Cholesky factorization of the variance-covariance matrix of reduced-form residuals is an efficient and straightforwardly implementable way to "orthogonalize" the reduced-form errors, that is, to disentangle $\mathbf{w}_t$ from the reduced-form shocks $\mathbf{u}_t$. However, it must be stressed that this identification scheme is built upon the a priori imposition of a whole causal chain with a rigid, recursive causation order, deriving from the computational restriction imposed by the Cholesky factorization.

Since the Cholesky identification scheme can correctly retrieve the matrix $\mathbf{B}_0$ only if the true structure is indeed recursive and the ordering of the variables is specified correctly, this approach is problematic for a number of reasons. As Kilian and Lütkepohl (2017) put it, the credibility of an approach that imposes a recursive causal architecture without any clear order of the variables in mind is undermined in the first place. Furthermore, this is aggravated by the fact that the number of possible orderings grows with the factorial of the number of variables, and, finally, even if all the permutations lead to the same impulse responses, this does not prove that every identification strategy is bound to lead to the same results. It simply shows that all recursive identifications provide the same results, but it gives no evidence that the model should be recursive in the first place. This is why this approach has inspired a series of critic contributions to the literature that take explicit aim at the fact that it seems to be built on the (often quite misled) confidence in the data's ability to speak for themselves but which in practice relies on a set of assumptions that are extremely difficult to justify within real-world applications (Cooley & LeRoy, 1985).

Identification via external instrument: proxy-VAR. In recent years, the instrumental variables (IV) approach, traditionally employed in microeconomics, has been adapted to the time series context to recover elements of $\mathbf{B}_0^{-1}$, giving rise to the proxy-VAR identification method. In settings where the regression of a dependent variable y on an explanatory variable x suffers from endogeneity, an external instrument z can be used to isolate exogenous variation in x. For z to be a valid instrument, it must be correlated with x (instrument relevance), but uncorrelated with the error term in the equation for y conditional on x (instrument exogeneity or the exclusion restriction). This ensures that z influences y only through its effect on x.

Denote the column of interest of the $\mathbf{B}_0^{-1}$ matrix as $\mathbf{b}_k$, with $k \in \{1, \ldots, K\}$, which represents the effect of the structural shock of interest, which we denote as $w_{k,t}$, on all the K variables of the system. For expository purposes, we here set $k = 1$ without loss of generality. Further, let z_t denote an instrument, which satisfies the relevance and exogeneity conditions:

$$\mathbb{E}[z_t w_{1,t}] \neq \mathbf{0} \tag{8}$$

$$\mathbb{E}[z_t \mathbf{w}_{2:K,t}] = \mathbf{0} \tag{9}$$

Given these moments conditions,[41] we have

$$\mathbf{b}_{2:K,1} = \frac{\mathbb{E}[z_t \mathbf{u}_{2:K,t}]}{\mathbb{E}[z_t u_{1,t}]}. \tag{10}$$

The structural impact vector $\mathbf{b}_1$ is defined as $\mathbf{b}_1 = (b_{1,1}, \mathbf{b}'_{2:K,1})'$ and is identified up to sign and scale. The scale $b_{1,1}$ is set through a normalization, subject to $\mathbf{\Sigma}_u = \mathbf{B}_0^{-1}\mathbf{\Sigma}_w(\mathbf{B}_0^{-1})'$. One common approach is to set $\mathbf{\Sigma}_{\boldsymbol{w}} = \mathbf{I}_K$, which implies that a unit positive value of the structural shock $\varepsilon_{1,t}$ corresponds to a one standard deviation positive effect on $y_{1,t}$. Alternatively, one may use $\mathbf{\Sigma}_{\boldsymbol{w}} = \text{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$ and normalize by setting $b_{1,1} = x$, which implies that a unit value of $\varepsilon_{1,t}$ has a positive effect of magnitude x on $y_{1,t}$. We use the latter normalization and set x such that the shock corresponds to a 10% increase in the real price of natural gas.

In practice, $\mathbf{b}_{2:K,1}$ can be estimated via the standard two-stage least square procedure as follows:

1. First stage:

$$\hat{\beta}_1 = \left(\frac{1}{T}\sum_{t=1}^{T} z_t z_t'\right)^{-1} \left(\frac{1}{T}\sum_{t=1}^{T} z_t u_{1,t}\right)$$ [42]

2. Second stage:

$$\hat{b}_{2:K} = \left(\frac{1}{T}\sum_{t=1}^{T} \hat{u}_{1,t}\hat{u}_{1,t}\right)^{-1} \left(\frac{1}{T}\sum_{t=1}^{T} \hat{u}_{1,t}\mathbf{u}'_{2:K,t},\right)$$

With $\hat{u}_{1,t} = \hat{\beta}_1' z_t$ for $t = 1, \ldots, T$. Note that when we identify a shock via the proxy-VAR, in general only a column of $\mathbf{B}_0^{-1}$ is identified, so that it will not be possible to

[41] We also require $\mathbb{E}[z_t u_{1,t}]$ full column rank and $\mathbb{E}[z_t z_t'] < \infty$.

[42] An intercept is generally also included in this regression.

invert this matrix to obtain the structural shocks via $\mathbf{w}_t = \mathbf{B}_0\mathbf{u}_t$. However, following Stock and Watson (2018), the structural shocks can still be recovered as follows:

$$\mathbf{b}_1'\mathbf{\Sigma}^{-1}\mathbf{u}_t = \mathbf{b}_1'(\mathbf{B}_0\mathbf{B}_0')\mathbf{u}_t = \mathbf{b}_1'\mathbf{B}_0'\mathbf{B}_0\mathbf{B}_0^{-1}\mathbf{w}_t = \mathbf{e}_1'\mathbf{w}_t = w_{1,t}, \quad \text{where } \mathbf{B}_0\mathbf{b}_1 = \mathbf{e}_1,$$

under the $\mathbf{\Omega} = \mathbf{I}_K$ normalization, and where $\mathbf{e}_1$ is the first standard basis vector. To assess the validity of the instruments, a test relying on the F-statistic[43] can be implemented (see Stock and Yogo, 2002).

In the VAR context, this instrumental variable approach has been used mostly to identify a monetary policy shock (see for example Gertler and Karadi, 2015; Miranda-Agrippino, 2016; Nakamura and Steinsson, 2018), but not exclusively (see for example Känzig, 2021a for an oil price shock or Känzig, 2021b for a carbon price shock). The idea is to rely on short-term movements of financial variables around certain events. By looking at the movements of rates or yields during relatively narrow windows around policy announcements, it is possible to infer whether the monetary policy is more expansionary or more contractionary than anticipated. The underlying assumption is that before the start of the observation window, the market has priced in expectations of how the policy rate should move, given the state of the economy. Therefore, if during the window yields move in an unanticipated way, this surprise is exogenous, and can be used in the proxy-VAR framework. Since the observation windows are typically tight, this approach is often referred to as "high-frequency" approach.

As a final note of this section, when in the recursive identification scheme a variable is ordered first, this is equivalent to assuming that the regression of the other variables on the first does not present endogeneity problems. In other words, the first variable does not need to be instrumented for.

A.4 Bayesian estimation

The Bayesian estimation we implement uses Minnesota (Doan et al., 1984), sum-of-coefficients (see also Sims and Zha, 1998; Robertson and Tallman, 1999), and dummy-initial-observation (Sims, 1993) priors. These priors are implemented using dummy observations, where the choice of the informativeness of the prior distribution is determined by the marginal likelihood of the observed data, following the procedure proposed by Bańbura et al. (2007). The optimal choice of the informativeness of these priors, is picked following the hierarchical approach of Giannone et al. (2015). The estimation of the parameters is achieved via a standard Gibbs sampling algorithm. Some parts of this section are reworked and use notation mainly from Bańbura et al. (2007), Giannone et al. (2015), and Bini (n.d.).

Prior distribution. Following Kadiyala and Karlsson (1997), we specify the prior distributions as

[43] In this case the F-statistics takes the form $F = \frac{1}{q}\left(R\hat{\beta}\right)'\left[\hat{\sigma}^2 R(X'X)^{-1}R'\right]^{-1}\left(R\hat{\beta}\right)$, where R is a $q \times k$ matrix that defines the tested linear restrictions. q is the number of restrictions, while X is the $n \times k$ matrix of explanatory variables.

$$\text{vec}(\beta) \mid \Psi \sim \mathcal{N}(\text{vec}(\beta_0), \Psi \otimes \Omega_0) \quad \text{and} \quad \Psi \sim \mathcal{IW}(S_0, \alpha_0)$$

where $\beta = [\mathbf{A_1}, \ldots, \mathbf{A_p}, \mathbf{c}]$, with $\mathbf{c}$ an intercept and Ψ denotes the prior for the covariance matrix of reduced form residuals Σ_u from (2). The prior parameters β_0, Ω_0, S_0 and α_0 are chosen so that prior expectations and variances coincide with those implied by Minnesota, sum-of-coefficients and dummy-initial observation priors (more below). We implement the prior by adding dummy observations: Bańbura et al. (2007) have shown that adding T_d dummy observations $\mathbf{y}_d$ and $\mathbf{x}_d$ to the VAR(p) induces the Normal-Inverted Wishart priors:

$$\begin{aligned}
\beta_0 &= (\mathbf{x}_d'\mathbf{x}_d)^{-1}(\mathbf{x}_d'\mathbf{y}_d); \\
\Omega_0 &= (\mathbf{x}_d'\mathbf{x}_d)^{-1}; \\
S_0 &= (\mathbf{y}_d - \mathbf{x}_d\beta_0)'(\mathbf{y}_d - \mathbf{x}_d\beta_0); \\
\alpha_0 &= T_d - k.
\end{aligned}$$

where S_0 is a $(k \times k)$ scale matrix and α_0 are the degrees of freedom of the Inverted Wishart distribution. Conveniently, this prior distribution is conjugate, which implies that the posterior distribution is known.

Minnesota prior. The Minnesota (Doan et al., 1984; Litterman, 1986), formalizes the idea that, ex ante, all the individual variables are expected to follow random walk with drift processes: $y_t = c + y_{t-1} + u_t$. The prior reflects the belief that recent lags carry more informative value than older ones, and that a variable's past values are more useful for explaining its current behavior than the past values of other variables in the system. This amounts to shrinking the diagonal elements of $\mathbf{A}_1$ toward one and the remaining coefficients in $\mathbf{A}_1, \ldots, \mathbf{A}_p$ toward zero. The mean of the prior distribution is given by:

$$\mathbb{E}[(\mathbf{A}_s)_{ij}] = \begin{cases} \delta_i & \text{if } i = j \text{ and } s = 1 \\ 0 & \text{otherwise} \end{cases}$$

Originally, $\delta_i = 1$ was imposed for all i, based on the notion that most variables exhibit strong persistence. However, this prior is not suitable for variables that display substantial mean reversion. In such cases, we adopt the belief that the variable behaves like white noise by setting $\delta_i = 0$. The prior variance of the parameters is

$$\mathbb{V}[(A_s)_{ij}] = \begin{cases} \frac{\lambda^2}{s^2} & \text{if } i = j \\ \vartheta \frac{\lambda^2}{s^2} \cdot \frac{\sigma_i^2}{\sigma_j^2} & \text{otherwise} \end{cases}$$

where λ is the main hyperparameter and it controls the relative importance of prior and data (that is, the variance associated to the prior, in other words, the degree of confidence attributed to the prior). When $\lambda \to 0$, no weight is given to the data and vice versa for $\lambda \to \infty$. The factor $1/s^2$ is the rate at which prior variance decreases with increasing lag length, and σ_i^2/σ_j^2 accounts for the different scale and variability of the data. The coefficient $\vartheta \in (0,1)$ governs the extent to which the lags of other variables are "less important" than the own lags.

The original formulation of the Minnesota prior assumed the covariance matrix of the residuals diagonal and known: $\Sigma_u = \text{diag}(\sigma_1^2, \ldots, \sigma_n^2)$. However, for structural analysis, we must account for possible correlations among residuals across equations. To address this, we adopt the approach of Kadiyala and Karlsson (1997) and Robertson and Tallman (1999), who propose a Normal-inverted Wishart prior that preserves the key features of the Minnesota prior (more below). This is valid under $\vartheta = 1$, which we impose. The prior on the intercept c is taken to be diffuse.

These priors are implemented by adding the following dummy observations at the start of the sample:

$$\underset{(kp+k+1)\times k}{\mathbf{y}^+} = \left[\begin{array}{c} \frac{\text{diag}(\delta_1\sigma_1,\ldots,\delta_k\sigma_k)}{\lambda} \\ \mathbf{0}_{k(p-1)\times k} \\ \hline \text{diag}(\sigma_1,\ldots,\sigma_k) \\ \hline \mathbf{0}_{1\times k} \end{array}\right] \qquad \underset{(kp+k+1)\times(kp+1)}{\mathbf{x}^+} = \left[\begin{array}{cc} J_p \otimes \frac{\text{diag}(\sigma_1,\ldots,\sigma_k)}{\lambda} & \mathbf{0}_{kp\times 1} \\ \hline \mathbf{0}_{k\times kp} & \mathbf{0}_{k\times 1} \\ \hline \mathbf{0}_{1\times kp} & \underset{k\times 1}{\mathbf{1}}\,\varepsilon \end{array}\right]$$

where the the first block of dummies imposes prior beliefs on the autoregressive coefficients, the second block implements the prior for the covariance matrix, the third block reflects the uninformative prior for the intercept (ε is a very small number).

Refinements of the Minnesota prior have been proposed in order to favour unit roots and cointegration, grounded on the common practices of many applied works. These take the form of additional priors that try to reduce the importance of the deterministic component of the VAR model.

Sum-of-coefficients prior. This prior contrasts the presence of explosive roots by shrinking the sum of coefficients so that the draws obtained from the posterior are characterized by a unit root rather than by explosive behavior. We can rewrite the VAR of equation (2) in its error correction form:

$$\Delta\mathbf{y}_t = \mathbf{c} - (\mathbf{I}_n - \mathbf{A}_1 - \cdots - \mathbf{A}_p)\mathbf{y}_{t-1} + \tilde{\mathbf{A}}_1\Delta\mathbf{y}_{t-1} + \cdots + \tilde{\mathbf{A}}_{p-1}\Delta\mathbf{y}_{t-p+1} + \mathbf{u}_t$$

The term $\tilde{\mathbf{A}}_1\Delta\mathbf{y}_{t-1} + \cdots + \tilde{\mathbf{A}}_{p-1}\Delta\mathbf{y}_{t-p+1}$ is made of stationary terms and hence does not impact the stationarity of the model. It follows that if $\Pi := \mathbf{I}_n - \mathbf{A}_1 - \cdots - \mathbf{A}_p = 0$ (which is implied by a VAR in first differences) the model is stationary. The sum-of-coefficients prior imposes "inexact differencing" by shrinking the term towards 0 in the limit ($\Pi \to 0$). The prior states that a no-change forecast for all variables is a good forecast at the beginning of the sample. Then, either all the variables are at their unconditional mean, which implies that the model is stationary despite the unit roots in the variables (implying cointegration), or the dynamic of the system is characterized by an unspecified number of unit roots, and the variables share a common stochastic trend. It is implemented by adding at the beginning of the sample dummy observations constructed in the following way:

$$\underset{k\times k}{\mathbf{y}^{++}} = \begin{bmatrix} \frac{\mu_1\delta_1}{\tau} & 0 & \cdots & 0 \\ 0 & \frac{\mu_2\delta_2}{\tau} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \frac{\mu_k\delta_k}{\tau} \end{bmatrix} \quad \underset{k\times(kp+1)}{\mathbf{x}^{++}} = \left[\mathbf{y}^{++}, \cdots, \mathbf{y}^{++}, \underset{k\times 1}{\mathbf{0}}\right],$$

where μ_i captures the unconditional mean of variable y_{it}, δ_i is the term previously defined, and the hyperparameter τ controls the variance of these prior beliefs: as $\tau \to \infty$, the prior becomes uninformative, while $\tau \to 0$ enforces the presence of a unit root in each equation and rules out cointegration entirely. This is because we can have cointegration (individual series display unit-roots but some linear combination of the series is stationary) only if Π has reduced rank but is not zero, otherwise the VAR becomes a purely differenced system.

Dummy-initial-observation Since in the limit the sum-of-coefficients prior does not allow for cointegration, dummy initial observation prior can be implemented to push the variables towards the presence of cointegration. This is designed to remove the bias of the sum-of-coefficients prior against cointegration, while still addressing the overfitting of the deterministic component issue. It is implemented by adding dummy observations at the beginning of the sample constructed as follows:

$$\mathbf{y}^{+++}_{k\times k} = \begin{bmatrix} \frac{\mu_1}{\gamma} & 0 & \cdots & 0 \\ 0 & \frac{\mu_2}{\gamma} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \frac{\mu_k}{\gamma} \end{bmatrix}, \quad \underset{k\times(kp+1)}{\mathbf{x}^{+++}} = \left[\mathbf{y}^{+++}, \cdots, \mathbf{y}^{+++}, \underset{k\times 1}{\mathbf{1}}/\gamma\right],$$

The hyperparameter γ controls the tightness of the prior implied by this artificial observation. As $\gamma \to \infty$, the prior becomes uninformative. As $\gamma \to 0$, the model tends to a form in which either all variables are stationary with means equal to the sample averages of the initial conditions, or there are unit root components without drift terms.

Posterior distribution. When we augment the data with the dummy observations

$$\mathbf{y}_* = \begin{bmatrix} \mathbf{y} \\ \mathbf{y}^{+} \\ \mathbf{y}^{++} \\ \mathbf{y}^{+++} \end{bmatrix}, \quad \mathbf{x}_* = \begin{bmatrix} \mathbf{x} \\ \mathbf{x}^{+} \\ \mathbf{x}^{++} \\ \mathbf{x}^{+++} \end{bmatrix}$$

we can rewrite the VAR(p) as

$$\mathbf{y}_* = \mathbf{x}_*\beta + \mathbf{u}_*$$

and it can be shown that the posterior distribution has the form

$$\mathrm{vec}(\beta) \mid \Psi, \mathbf{y} \sim \mathcal{N}(\mathrm{vec}(\tilde{\beta}), \Psi \otimes (\mathbf{x}_*'\mathbf{x}_*)^{-1}) \quad \text{and} \quad \Psi \mid \mathbf{y} \sim \mathcal{IW}(\tilde{\Sigma}, T_d + T + 2 - n),$$

where the posterior expectations of the coefficients correspond to the OLS estimates of the regression model based on the appended data, with:

$$\tilde{\beta} = (\mathbf{x}_*'\mathbf{x}_*)^{-1}(\mathbf{x}_*'\mathbf{y}_*) \qquad \tilde{\Sigma}_u = (\mathbf{y}_* - \mathbf{x}_*\tilde{\beta})'(\mathbf{y}_* - \mathbf{x}_*\tilde{\beta})$$

Choosing the informativeness of the priors. As explained, the prior distribution of our Bayesian VAR is governed by a set of hyperparameters (or hyperpriors), which control the strength and structure of the imposed beliefs. δ_i is an indicator that takes the value 1 or 0, reflecting whether the i^{th} variable is assumed to follow a highly persistent process (random walk, $\delta_i = 1$) or a stationary process (white noise, $\delta_i = 0$). σ_i is the standard deviation of the residuals for variable i under the prior, used to scale the variance and account for differences in variable volatility. λ controls controls the overall tightness of the prior distribution. When $\lambda \to 0$, the prior dominates and the posterior shrinks heavily toward the prior mean. When $\lambda \to \infty$, the data dominate and the posterior approaches the OLS estimate. τ governs the strength of the sum-of-coefficients prior. γ controls the tightness of the dummy initial observation prior. The objective is to chose these hyperparameters to ensure that the prior structure is neither too tight nor too loose relative to the data. When well-calibrated, they help regularize the estimation in high-dimensional settings, improve forecast performance, and mitigate overfitting.

Following the hierarchical approach of Giannone et al. (2015), we select the hyperparameters that maximize the marginal likelihood of the data. From a Bayesian standpoint, selecting the informativeness of the prior distribution is conceptually analogous to conducting inference on any other unknown parameter of the model. Consider, for example, a model defined by a likelihood function $p(y \mid \theta)$ and a prior distribution $p_\gamma(\theta)$, where θ denotes the vector of VAR(p) parameters and γ represents the set of hyperparameters (or hyperpriors) that govern the specification of the prior. Although these hyperparameters do not directly influence the likelihood, they shape the prior distribution. Consequently, it is natural to treat them within a hierarchical modeling framework by substituting $p_\gamma(\theta)$ with $p(\theta \mid \gamma)$ and performing inference on γ evaluating their posterior.

B Identification of additional macroeconomic shocks

Supply chain bottleneck (SCB) shocks. The supply chain factors related to the disruptions induced by COVID-19 lockdowns and subsequent re-openings have been one of the main drivers of the recent increase in prices. In general, supply-chain pressures are correlated to higher inflation, and this can happen via several channels, such as import prices, costs of intermediate inputs, and inflation expectations (Liu & Nguyen, 2023). However, shocks to SCB have been studied relatively little in the literature, mainly due to the difficulty of measuring SCB. Some recent papers include Binici et al. (2022) and Kim et al. (2023), which identify a SCB shock by relying on sign-restrictions.

We build on this new strand of literature and identify the supply chain bottleneck (SCB) shocks by short-term restrictions. We measure SCB via the novel Global Supply Chain Pressure Index (Benigno et al., 2022), which integrates various indices of delivery times, backlogs, and inventories to quantify supply chain bottlenecks.[44] We argue that this variable is unlikely affected by the other shocks of the system within the same month (it is a "slow-moving" variable) and that we can therefore use the standard short-term restrictions / recursive identification scheme to identify this shock, where GSCPI is ordered first. We are therefore assuming that other shocks in the system do not impact SCB within the same month. This is supported by the fact that the GSCPI is constructed as the first principal component of several monthly indicators of transportation costs such as the Baltic Dry Index, the Harpex index, and the Bureau of Labor Statistics airfreight cost indexes and supply chain-related components from the Purchasing Managers' Index surveys for manufacturing firms. The principal component effectively smooths out idiosyncratic variability, helping to isolate the "slow-moving" component. Furthermore, the GSCPI is a global index, and despite the EA being a sizable fraction of the world's economy, several shocks in the GSCPI are likely to originate outside of it. Finally, we obtain that the reduced-form residuals of GSCPI are almost uncorrelated with the other residuals, supporting our contemporaneous exogeneity assumption.

Oil price shocks. We also emphasize the importance of oil prices, which exhibited a dramatic increase starting from mid-2021 and further acceleration in early 2022 due to the war in Ukraine (see Guerrieri et al., 2023). To instrument crude oil prices, we construct high-frequency oil price shocks by computing daily surprises in oil futures prices around OPEC announcements, closely following Känzig (2021a) and extending the sample. The core idea is that these announcements can provide exogenous variation in oil prices by revealing unexpected information about oil production plans, thereby surprising financial market operators. Specifically, we

[44] The Global Supply Chain Pressure Index (GSCPI) is maintained by the Federal Reserve Bank of New York and is not specific for the Euro Area, as it focuses on manufacturing firms across seven interconnected economies: China, the Euro Area, Japan, South Korea, Taiwan, the United Kingdom, and the United States. However, given the interconnections of the Euro Area supply chain and the global nature of the inflation surge, it is also a good indicator of supply chain disruptions that affect inflation in the Euro Area.

compute daily surprises in Brent futures around OPEC press releases, as described in Eq (1), considering future contracts from a one-month to a one-year horizon. Subsequently, we capture the daily oil supply shock by extracting the first principal component of these surprises. To aggregate the shocks into a monthly series, we sum the daily surprises within the respective month. Figure F39 shows the oil supply surprise series, and the corresponding West Texas Intermediate (WTI) oil surprise series can be found in Appendix Figure F40.

Monetary policy shocks. We also identify monetary policy shocks via an external high-frequency instrument approach. For monetary policy surprises, we use the shocks to conventional monetary policy using as instruments surprises as computed by Altavilla et al. (2019). We then follow Ricco et al. (2024) and correct for non-linear information effects. The general idea is to consider that part of the monetary policy surprise that is orthogonal to both the central bank's economic projections and to past market surprises.

C Data and descriptive statistics

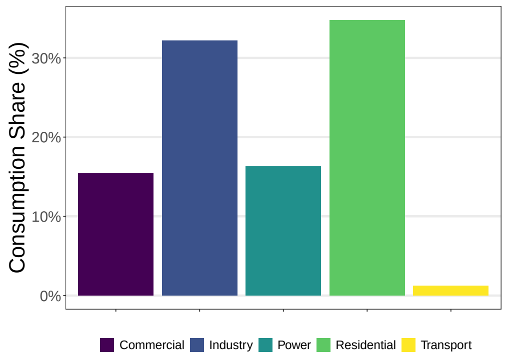
C.1 Data sources

Table C5 provides details on the data used, including information on the data sources, the time coverage, and the transformations applied.

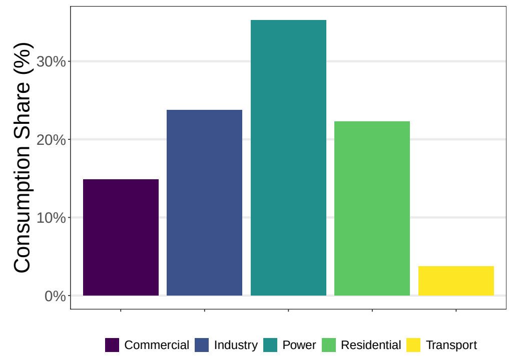
Variable	Description	Source	Time Coverage	Trans.
Instruments EA				
TRNLTTFc-h (RIC)	TTF natural gas futures h-month contracts from 1M to 12M (settlement price)	Datastream	2004M1-2024M1	100Δ log
LCOc-h (RIC)	Brent crude oil futures h-month contract (settlement price)	Datastream	1988M6-2024M1	100Δ log
OIS-h	OIS futures h-period contract	ECB website	1999M1-2024M1	100Δ log
EA Variables (baseline)				
Gas Price	Dutch TTF spot price at close (TRNLTTD1) in Euro per MWh and deflated by EA HICP all-items index	Datastream	2004M1-2024M1	$100 * \log$
Oil Price	Brent spot price at close (DCOILBRENTEU) in Euro per barrel and deflated by EA HICP all-items index	FRED	1987M3-2024M1	$100 * \log$
Gas Supply	EA dry marketable production (INDPROD) plus gas imports from RoW (IMPORTS), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Demand	EA gas consumption (GDINCTROAD) plus gas exports to RoW (EXPORTS), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Inventories	EA Closing stock levels (CSNATTER), SA	IEA	1984M1-2024M1	$100 * \log$
Financial Volatility	Euro Stoxx 50 Volatility Index (VSTOXX)	STOXX	1999M1-2024M1	$100 * \log$
Headline Inflation	HICP all-items index seasonally adjusted (OOOOOO)	EUROSTAT	2000M12-2024M1	$100 * \log$
Industrial Production	Total industry excluding construction (B-D), SA	EUROSTAT	1995M1-2024M1	$100 * \log$
Instruments US				
NGc-h (RIC)	NYMEX HH natural gas futures h-month contracts from 1M to 12M (settlement price)	Datastream	1990M4-2024M1	100Δ log
CLc-h (RIC)	WTI crude oil futures h-month contract from 1M to 12M (settlement price)	Datastream	1975M1-2024M1	100Δ log
US Variables (baseline)				
Gas Price	NYMEX HH spot price at close (MHHNGSP) in Dollar per Million BTU and deflated by CPI all-items index	FRED	1997M1-2024M1	$100 * \log$
Oil Price	WTI spot price at close (WTISLC) in Dollar per barrel and deflated by EA HICP all-items index	FRED	1974M1-2024M1	$100 * \log$
Gas Supply	U.S. Dry Gas Production (N9070US1) plus Gas Imports (N9100US2) as defined in EIA NG reports, SA	EIA	1984M1-2024M1	$100 * \log$
Gas Demand	U.S. Gas Total Consumption (N9140US1) plus Gas Exports (N9130US2) as defined in EIA NG reports, SA	EIA	2001M1-2024M1	$100 * \log$
Gas Inventories	U.S. Total Natural Gas in Underground Storage Working Gas (N5020US2), SA	EIA	1975M9-2024M1	$100 * \log$
Financial Volatility	CBOE Volatility Index (VIXCLS)	FRED	1990M1-2024M1	$100 * \log$
Headline Inflation	Headline CPI (CPIAUCSL) index, SA	FRED	1960M1-2024M1	$100 * \log$
Industrial Production	Total index (INDPRO), SA	FRED	1974M1-2024M1	$100 * \log$
Additional Variables				
Gas production (EA)	EA Dry marketable production (INDPROD), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Imports (EA)	EA Gas imports from RoW (IMPORTS), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Exports (EA)	EA Gas exports to RoW (EXPORTS), SA	IEA	1984M1-2024M1	$100 * \log$
Core Inflation (EA)	HICP index excluding energy and food seasonally adjusted (TOT_X_NRG_FOOD)	EUROSTAT	2000M12-2024M1	$100 * \log$
Nominal Exchange Rate (EA)	Nominal Broad Effective Exchange Rate for EA (NBXMBIS)	FRED	1994M1-2024M1	$100 * \log$
Interest Rate (EA)	Money market EURIBOR rate, 12-month rate (IRT_ST_M)	EUROSTAT	1994M1-2024M1	None
IP B-D (EA)	NACE2 1-digit level Industrial Production indexes, SA	EUROSTAT	1991M1-2024M1	$100 * \log$
IP C10-C33 (EA)	NACE2 2-digit level Manufacturing Industrial Production indexes, SA	EUROSTAT	1991M1-2024M1	$100 * \log$
PPI D35-10/20 (EA)	NACE2 4-digit level Electricity and Gas Producer Price indexes, SA	EUROSTAT	2000M1-2024M1	$100 * \log$
HICP CP01-CP12 (EA)	ECOICOP 1-digit level indexes, SA	EUROSTAT	2000M1-2024M1	$100 * \log$
Unemployment Rate (US)	Unemployment rate (UNRATE), SA	FRED	1974M1-2024M1	None
Gas Production (US)	U.S. Dry Natural Gas Production (N9070US1) in Bcf, SA	EIA	1973M1-2024M1	$100 * \log$
Gas Consumption (US)	U.S. Natural Gas Total Consumption (N9140US1) in Bcf, SA	EIA	2001M1-2024M1	$100 * \log$
Gas Imports (US)	U.S. Gas Imports (N9100US2), SA	EIA	1984M1-2024M1	$100 * \log$
Gas Exports (US)	U.S. Gas Exports (N9130US2), SA	EIA	1984M1-2024M1	$100 * \log$
Nominal Exchange Rate (US)	Nominal Broad Effective Exchange Rate for US (NBUSBIS)	FRED	1994M1-2024M1	$100 * \log$
Interest Rate (US)	Effective federal funds rate	FRED	1974M1-2024M1	None
SCB	GSCPI index of supply chain pressures (constructed as a latent factor)	NY FED	1997M1-2024M1	$100 * \log$
CO2 Emissions	Total CO_2 emissions from fossil fuel combustion and industrial processes, measured in gigagrams	EDGAR CO2	1970M1-2022M12	$100 * \log$

Table C5: *Data description, sources, and coverage.*

C.2 Euro Area and United States energy statistics



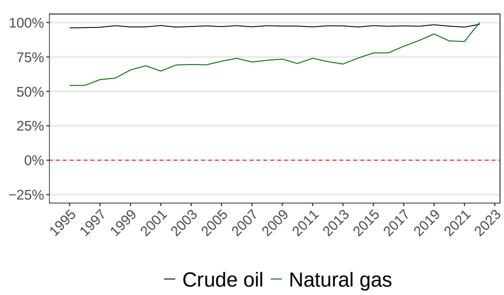
Euro Area



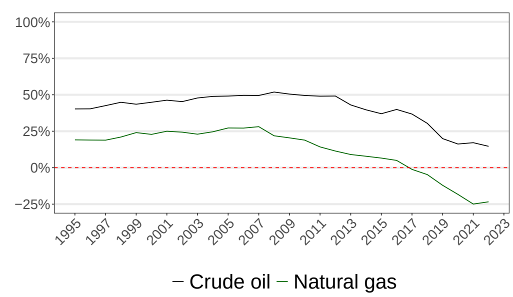
United States

Figure C19: *Natural gas consumption share by sector*

Notes: The left panel illustrates the sectoral distribution of natural gas consumption in the Euro Area (EA), while the right panel presents the corresponding breakdown for the United States (US). Both figures represent average consumption patterns over the period 2004–2022. Total consumption encompasses deliveries to the power generation, industrial, commercial, residential, and transportation sectors. Source: International Energy Agency.



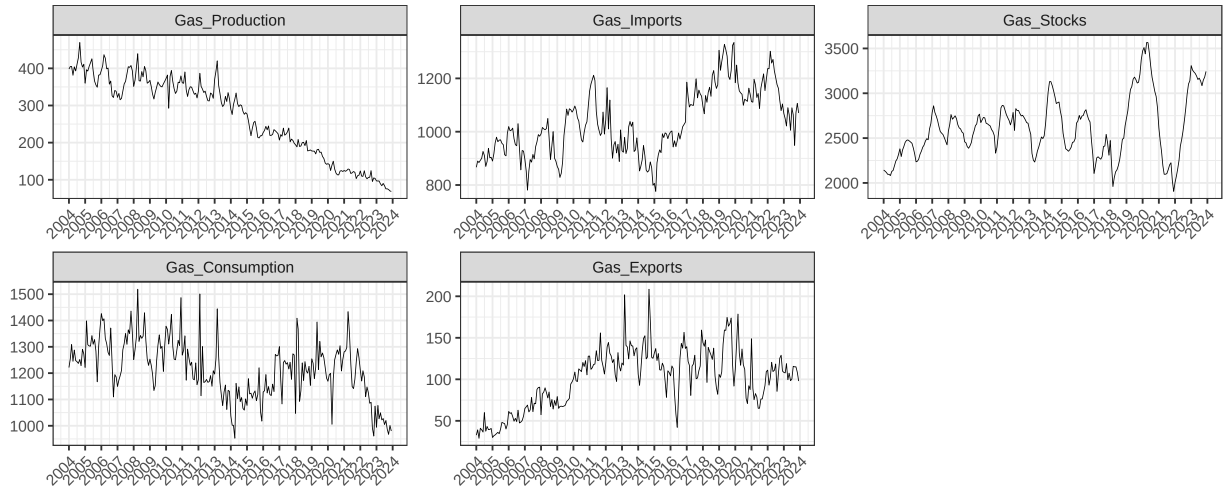
European Union



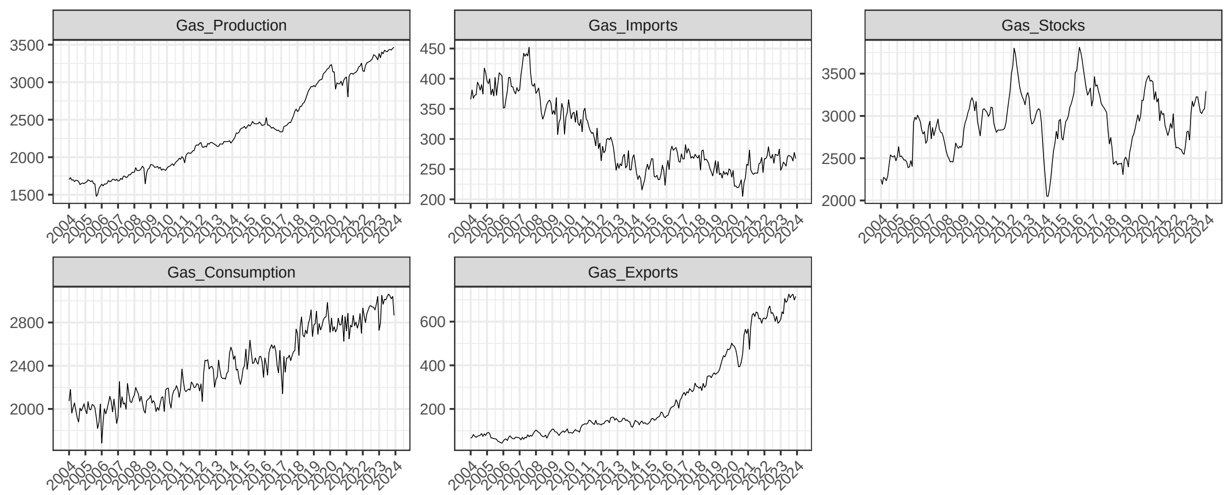
United States

Figure C20: *Energy import dependency*

Notes: The left panel shows the EU import dependency on gas and oil (1990-2020), and the right panel shows the US import dependency (1990-2021). Import dependency is calculated as the share of net imports over total consumption of each energy product. Sources: Eurostat, EIA, Energy Institute.



Euro Area



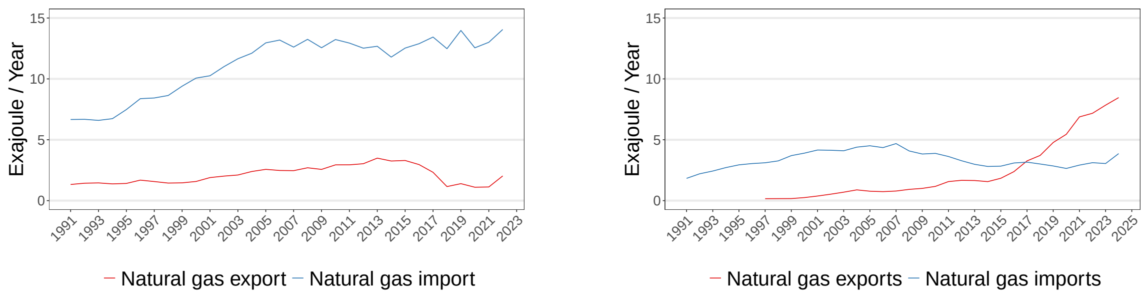
United States

Figure C21: *Gas Balances for the Euro Area and United States*

Notes: All figures are expressed in Petajoules and seasonally adjusted. Sources: International Energy Agency (IEA) and the Energy Information Administration (EIA).

Region	Prod.	Cons.	Imports	Exports	Stocks	Supply	Demand
Euro Area	271	1216	1033	100	2616	1204	1317
United States	2354	2400	301	246	2896	2586	2564

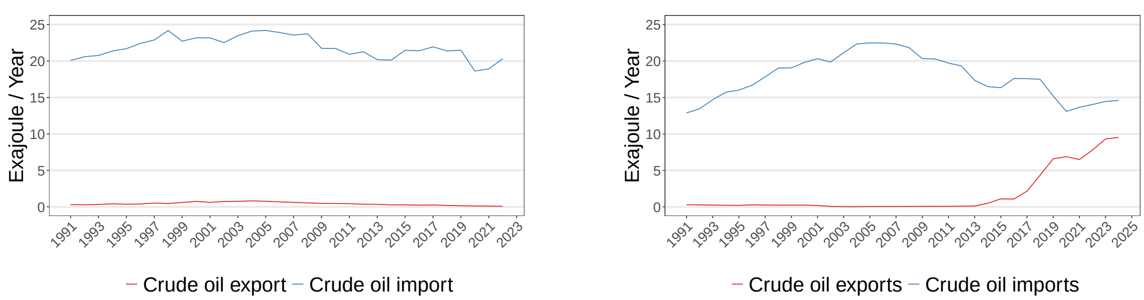
Table C6: *Gas balances for the Euro Area and United States, monthly averages (in Petajoules) over the sample. Supply = Production + Imports - Exports; Demand = Consumption + Exports.*



European Union United States

Figure C22: *Natural gas imports and exports*

Notes: The left panel shows natural gas imports and exports for the EU (1990-2022), and the right panel for the US (1990-2024). Values are in exajoules. Sources: Eurostat and EIA.



European Union United States

Figure C23: *Crude oil imports and exports*

Notes: The left panel shows crude oil imports and exports for the EU (1990-2022), and the right panel for the US (1990-2024). Values are in exajoules. Sources: Eurostat and EIA.

C.3 Correlation of TTF and other European gas prices

This Appendix provides evidence demonstrating that the Dutch TTF spot price is reflective of the overall dynamics of natural gas prices in Europe.

Figure C24 shows the natural gas spot prices at selected EA trading hubs: the Italian European Gas Network (EGN), the British Greater Buchan Area (GBA), the Spanish *Mercado Ibérico del GAS*(MIBGAS), the British National Balancing Point (NBP), the German NetConnect Germany (NCG), the French *Point d'échange de Gaz* (PEG), the Italian *Punto di Scambio Virtuale* (PSV), the Austrian Virtual Trading Point (VTP), and the Belgian Zeebrugge Trade Point (ZTP). These prices closely followed the TTF not only in the period before the pandemic but also amidst the subsequent market disruptions. Exceptions to this trend are exceedingly rare but significant, as seen in the spikes recorded at the end of 2017 and the beginning of 2018 in the PSV price, which did not correspond to movements in the TTF series.

Table C7 quantifies the comovement between TTF and these gas prices. The correlations are very high, ranging from 0.934 for the British NBP to 0.998 for NCG.

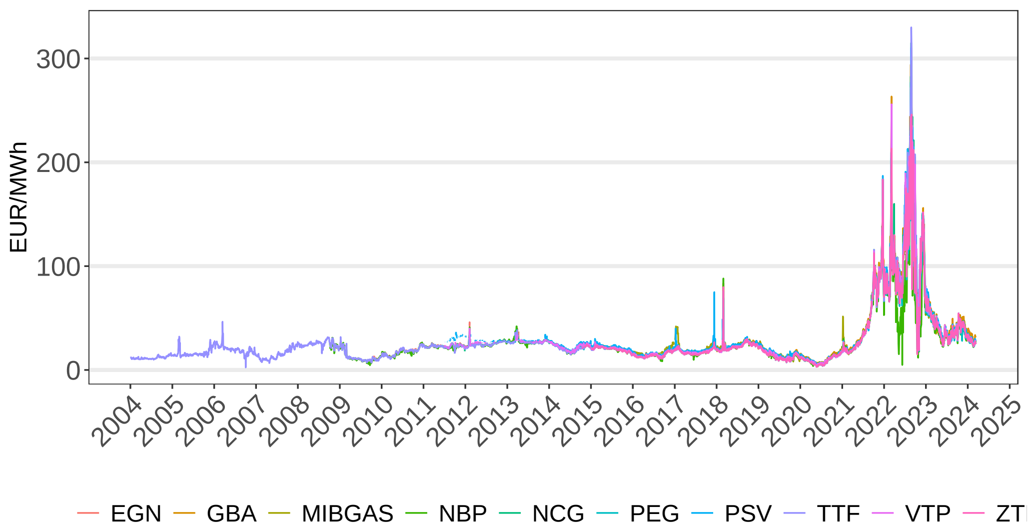


Figure C24: *TTF and other European gas prices.*

Notes: This figure displays the daily Dutch TTF spot price alongside spot prices at other European trading hubs.

Finally, we show that as LNG became more relevant in the EA over the past few years, its price almost matched the dynamics of the TTF price. This can be observed in Figure C25, while Figure C26 displays a sliding window correlation of the global LNG price with the TTF.

Hub price	TTF
NCG	1.00
VTP	1.00
PSV	1.00
ZTP	0.97
EGN	0.98
NBP	0.93
GBA	1.00
PEG	0.97
MIBGAS	0.97

Table C7: *Correlation between TTF and other EA gas prices.*

Notes: This table reports the correlation between the Dutch TTF spot price and spot prices of natural gas at various European trading hubs.

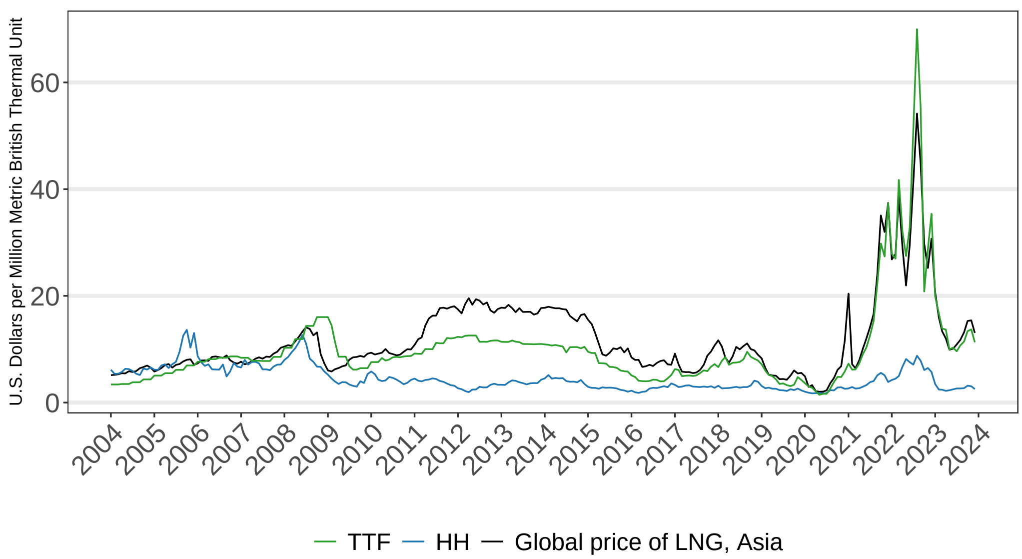


Figure C25: *TTF, HH, and Global LNG gas prices comparison*

Notes: The figure displays the monthly spot price of TTF alongside the Henry Hub (HH) and the global LNG benchmark price.

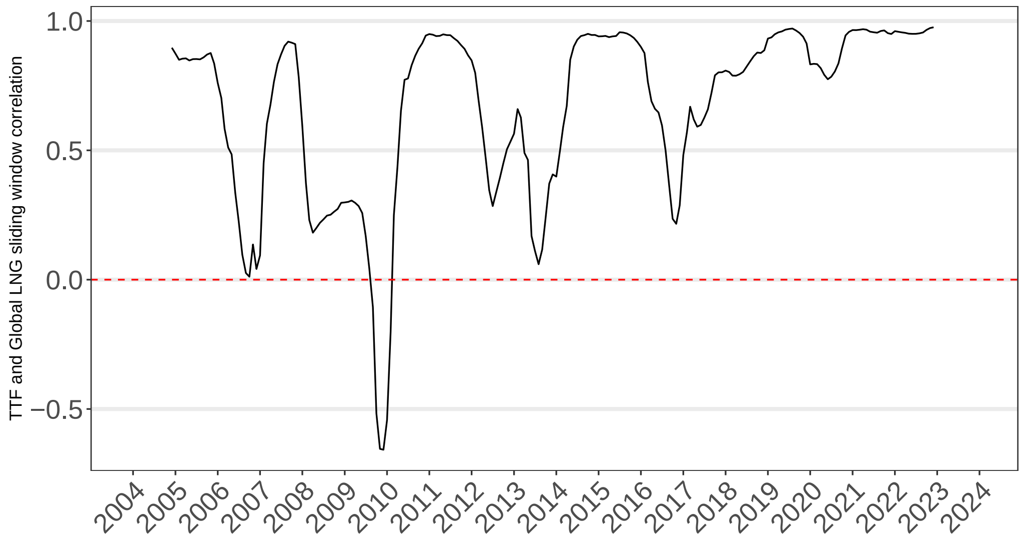


Figure C26: *TTF and Global LNG gas prices correlation*

Notes: The Figure displays the sliding window correlation of the TTF and the Global LNG gas prices. Sliding window of 24 months.

D Additional details on gas supply instruments

D.1 Market-relevant gas supply news

This Appendix presents some illustrative examples of news events used to construct gas supply surprises, as detailed in Section 3.1.1.

Date	**Event**	**daily %Δ (PC)**
EA		
2009-01-06	Russia halts gas deliveries to Ukraine amid escalating gas dispute.	12.1
2010-10-28	UK expands LNG Capacity at the Isle of Grain terminal.	-1.3
2010-11-15	Unexpected drop in flows from Norway through Langeled pipeline.	3.4
2014-03-03	Gazprom threatens to cut gas exports amid the Crimea crisis.	5.7
2019-04-05	Pipeline blast reduces Russian gas supplies to Bulgaria by 60%	11.5
2020-08-03	Polish anti-monopoly UOKiK fines Gazprom over Nord Stream.	19.8
2021-10-28	Putin announces Gazprom ready to start pumping natural gas into European gas storage.	-9.9
2022-02-25	Auction result shows flows might resume via Yamal pipeline.	-28.3
2022-03-02	Supply fears peak amid Russia-Germany dispute over NS2, following invasion of Ukraine.	26.6
2022-06-14	Gazprom announces reduced supply through Nord Stream 1 due to repair works.	12.8
2022-06-15	Gazprom announces further reduction in gas flows through Nord Stream 1.	12.2
US		
2009-06-15	Kinder Morgan announces maintenance on natural gas Pipeline Co. of America Mainline.	4.6
2012-07-24	Pipeline constraints limit supply in the Gulf Coast.	2.1
2012-09-21	Force Majeure at Julesburg compressor station.	3.2
2013-11-01	Transco begins full service on Northeast Supply Link project.	-2.0
2014-02-13	Columbia Gulf transmission pipeline shuts following explosion in Kentucky.	1.7
2014-09-15	Explosion at Chevron gas pipeline.	2.1
2017-05-10	FERC bans new drilling along Rover pipeline.	1.6
2022-06-08	Blast hits Freeport LNG plant, disrupting operations.	-4.5
2023-03-08	Unexpected flows drop at Freeport LNG related to outages.	-3.1
2023-06-30	Restrictions at Oxford and Stony Point compressors amid maintenance.	2.6

Table D8: *Selected gas supply news for the Euro Area and the US.*

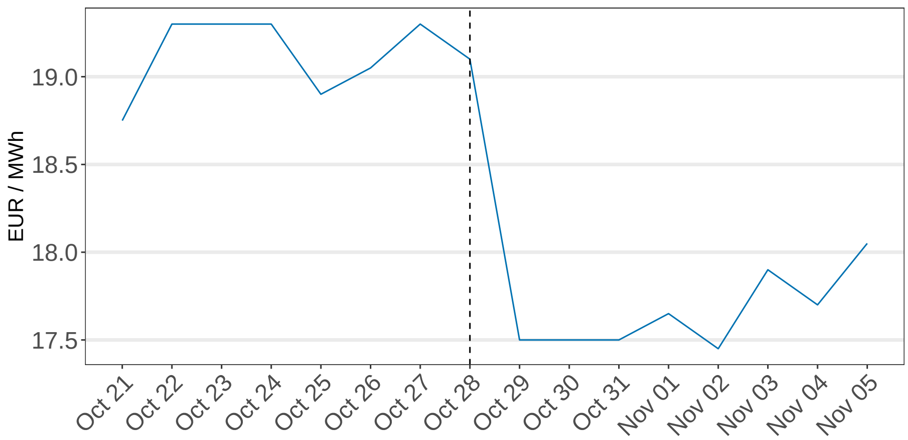


Figure D27: *UK expands LNG capacity at the Isle of Grain terminal*

Notes: The figure shows the surprise in the TTF spot gas price following the expansion of the LNG capacity at the Isle of Grain in the UK on October 28, 2010. October 23, 24, 30, and 31 were non-trading days for which the close spot price is not available. The values shown for these dates correspond to the last available trading day.

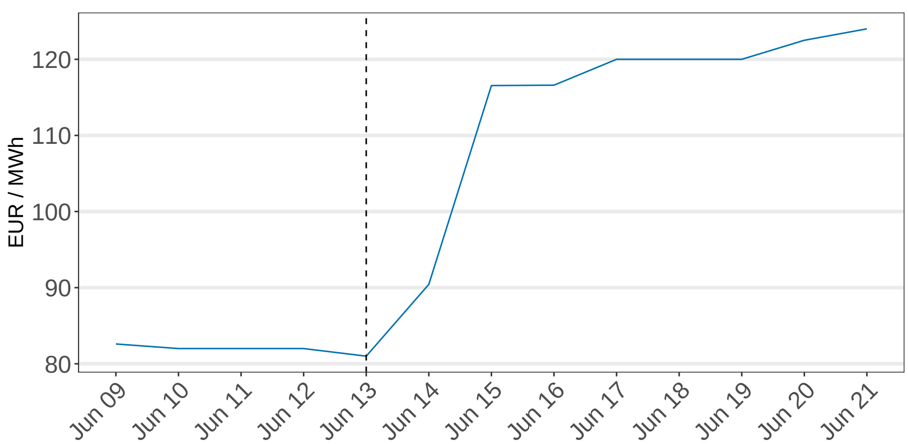


Figure D28: *Gazprom announces reduced supply through Nord Stream 1 due to repair works*

Notes: The figure shows the surprise in the TTF spot gas price related to the announcement by Gazprom of reduced flows through NS1 on June 14, 2022. In this case, two related announcements were made on consecutive days, with Gazprom announcing a further reduction on the second day. June 11, 12, 18, and 19 were non-trading days for which the close spot price is not available. The values shown for these dates correspond to the last available trading day.

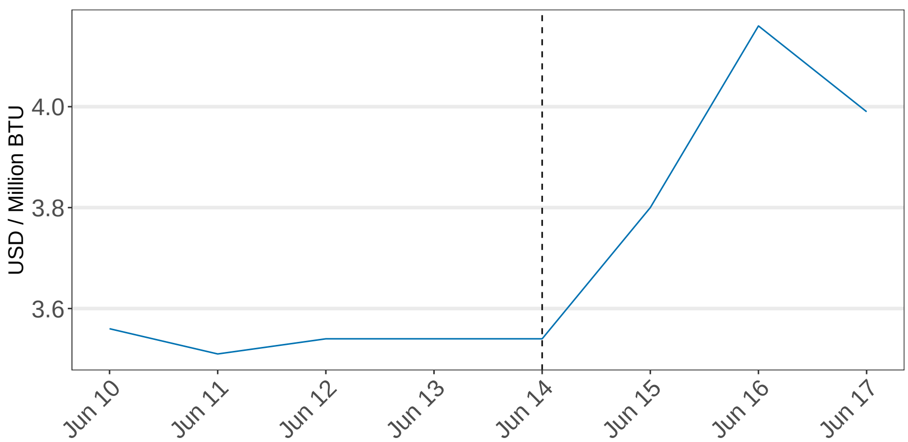


Figure D29: *Kinder Morgan announces maintenance*

Notes: The figure shows the surprise in the HH spot gas price related to maintenance on the Natural Gas Pipeline Co. of America's mainline at Compressor Station 198 in Marion County, Iowa. This maintenance resulted in a 75% reduction in capacity in the area on June 15, 2009. June 13 and 14 were non-trading days for which the close spot price is not available. The values shown for these dates correspond to the last available trading day.

D.2 Gas supply instrument for the United States

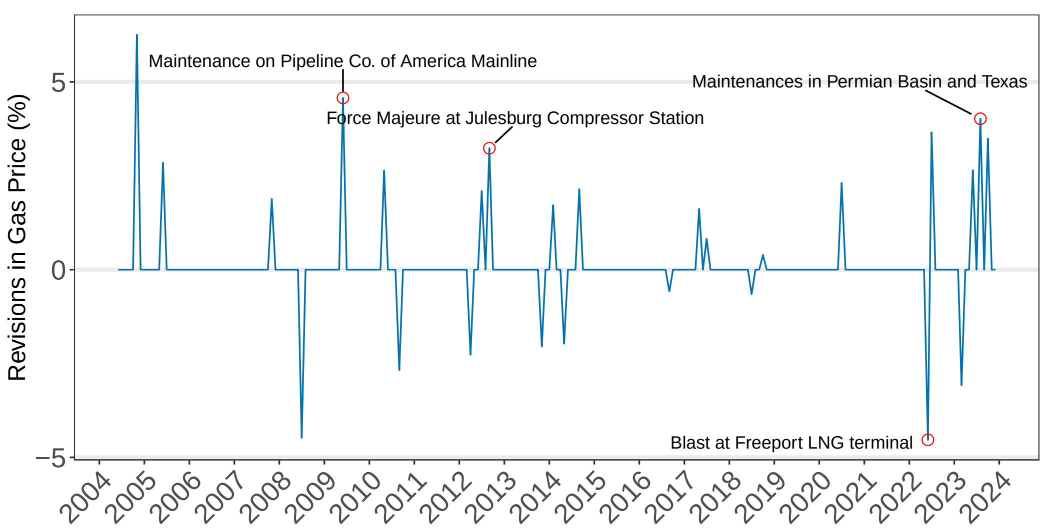
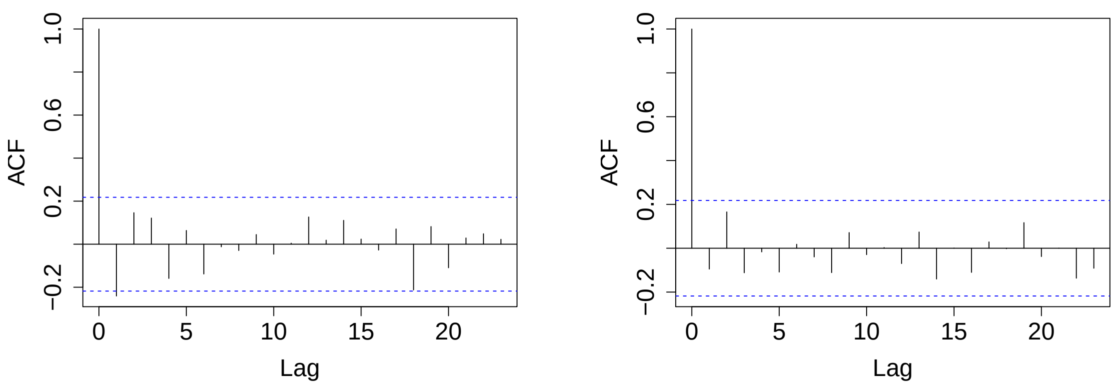


Figure D30: *Gas supply surprises series for the US*

D.3 Diagnostics of the gas surprise series

In this Appendix, we perform additional validity checks on the gas supply surprise series.

Figure D31 shows that the series exhibits no significant autocorrelation. We then assess its predictability using Granger causality tests. As reported in Table D9, the results indicate that the series cannot be predicted by past macroeconomic or financial variables. Similarly, it shows no forecastability when gas demand and gas inventories are included as predictors. In addition, we examine the correlation between the gas surprise series and a set of well-established shocks from the literature, as shown in Table D10. Notably, the series is not significantly correlated with oil-specific shocks, measures of uncertainty, or global demand shocks.



EA US

Figure D31: *Sample Autocorrelation Function of the gas surprise series*

Variable	p-value EA	p-value US
Instrument Lags	0.22	0.92
Gas price	0.45	0.71
Oil price	0.38	0.95
Gas demand	0.60	0.89
Gas inventories	0.32	0.83
Headline inflation	0.77	0.81
Industrial production	0.13	0.90
Financial volatility	0.25	0.86
Interest rate	0.69	0.97
Nominal exchange rate	0.66	0.98
Stock market (STOXX50E/SP500)	0.11	0.59
Supply Chain Bottlenecks (GSCPI)	0.22	0.85
Real economic activity	0.51	0.98
Joint Test	0.14	0.99

Table D9: *Granger causality tests.*

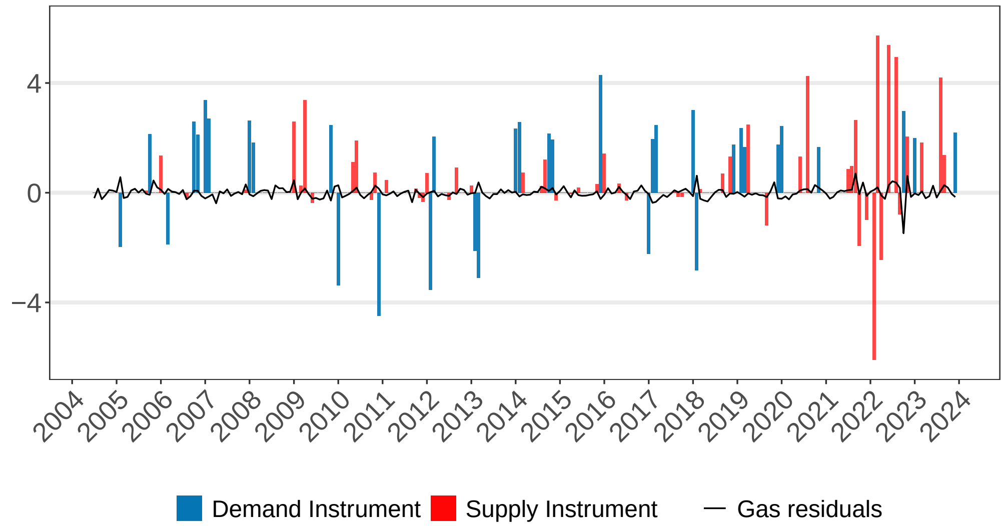
Notes: The table presents the p-values obtained from Granger's causality tests of the gas supply surprise series using the set of variables included in our baseline specification, expanded with financial and real activity variables. To conduct standard inference, the series are rendered stationary by taking first or second differences as required. The analysis includes 12 lags and a constant term.

Source	Shock	Europe supply		Europe demand		US supply		US demand		n
		ρ	p-value	ρ	p-value	ρ	p-value	ρ	p-value	
Kilian (2009)**	Oil supply	-0.02	0.79	-0.01	0.87	0.04	0.56	0.04	0.52	240
Kilian (2009)**	Aggregate demand	-0.07	0.31	0.01	0.83	0.02	0.77	-0.07	0.29	240
Kilian (2009)**	Oil-specific demand	0.05	0.42	-0.08	0.25	0.01	0.84	-0.05	0.44	240
Baumeister and Hamilton (2019)*	Oil supply	-0.06	0.36	0.03	0.67	-0.04	0.57	0.02	0.73	240
Baumeister and Hamilton (2019)*	Oil demand	0.00	0.99	-0.05	0.45	0.09	0.16	-0.04	0.51	240
Känzig (2021a)**	Oil supply expectations	-0.08	0.20	-0.03	0.70	0.02	0.82	0.12	0.07	240
Caldara et al. (2019)*	CCI oil supply	0.02	0.77	0.01	0.87	0.01	0.87	0.01	0.88	144
Miranda-Agrippino and Nenova (2022)	Target monetary policy (EA)	0.07	0.33	0.03	0.63	-0.05	0.51	0.02	0.73	207
Jarociński and Karadi (2020)	Information median monetary policy (EA)	-0.01	0.89	0.07	0.30	0.02	0.70	0.08	0.24	234
Gertler and Karadi (2015)	FF4 monetary policy (US)	-0.13	0.20	-0.14	0.15	-0.01	0.97	0.02	0.87	102
Miranda-Agrippino and Nenova (2022)	Target monetary policy (US)	0.02	0.74	-0.02	0.75	0.01	0.88	0.02	0.82	186
Bloom (2009)**	VXO-VIX	-0.03	0.70	0.03	0.60	0.00	0.99	0.06	0.38	240
Gilchrist and Zakrajšek (2012)*	Corporate credit spread index	0.05	0.49	-0.05	0.43	-0.04	0.60	-0.06	0.33	240
Caldara and Iacoviello (2022)*	Geopolitical risk index	0.05	0.40	0.05	0.46	0.04	0.51	0.06	0.38	240

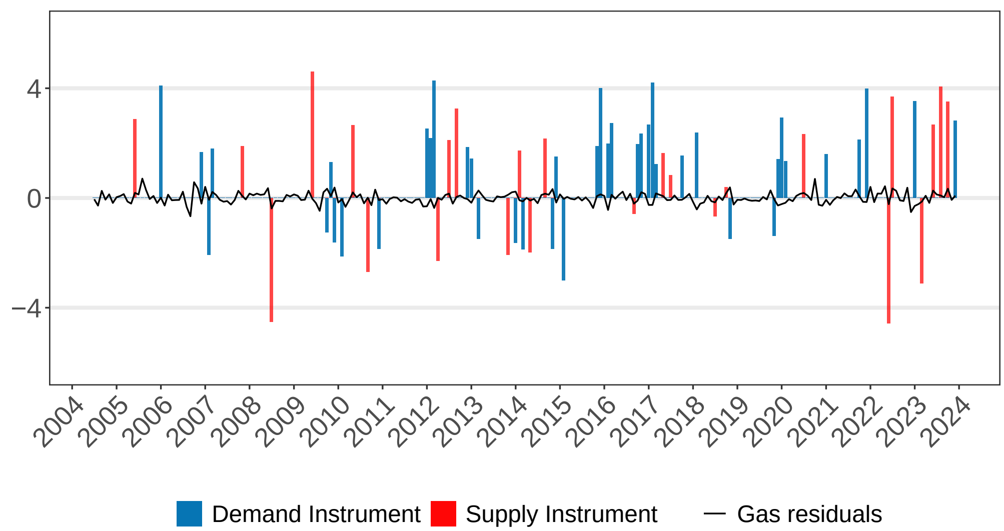
Table D10: *Correlation of instruments with other macroeconomic indicators.*

Notes: This table presents the correlation coefficients (ρ) and p-values for the EA and US supply and demand instruments in relation to a variety of economic shocks from the literature. The p-values correspond to two-sided tests for the null hypothesis of no correlation. The sample size (n) varies across shocks, as some are unavailable or not easily extendable to our full sample (2004-2023).

*Extended by the original authors beyond the original sample used in the published paper.
**Extended by the authors of this study.



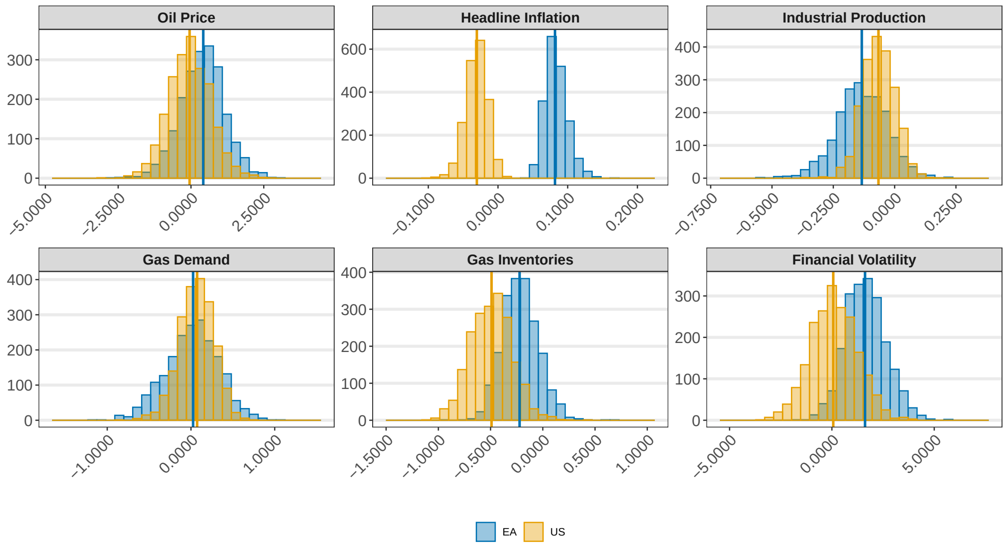
Europe



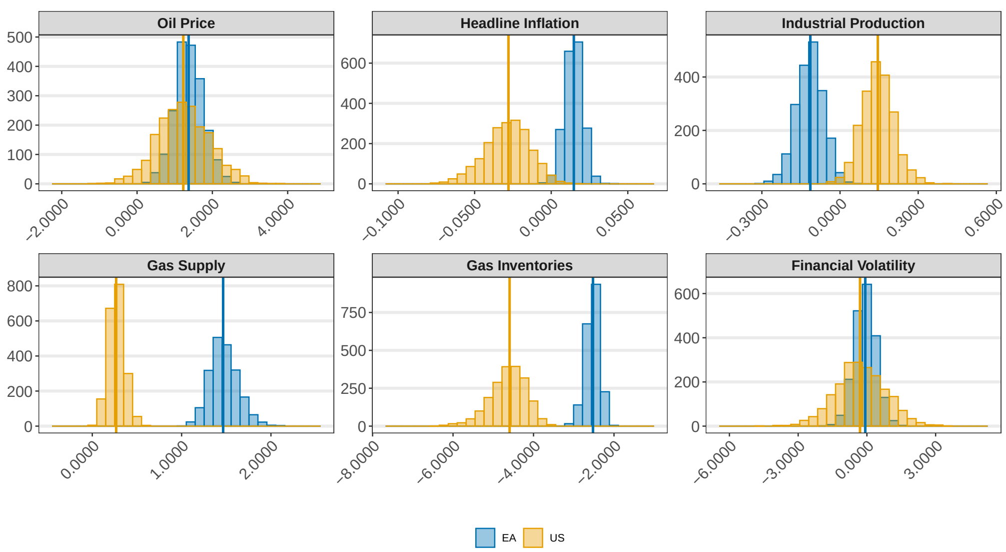
USA

Figure D32: *Supply and demand instruments strength*

Notes: The figure shows how the gas and demand instruments are related to the reduced form residuals of our baseline specification. All three series are rescaled to have unit variance for comparability. The top panel corresponds to Europe, and the bottom panel corresponds to the USA.



Supply



Demand

Figure D33: *Posterior distributions of impact coefficients*

Notes: This figure presents the posterior distributions of the impact coefficients identified for gas demand and supply shocks. Vertical lines indicate the median of each distribution. The top panel shows results for the gas demand shock, while the bottom panel pertains to the gas supply shock.

E Additional details on gas demand instruments

E.1 Construction of the temperature demand instrument

ERA5 surface temperature data. The daily temperature data are taken from ERA5's single levels dataset, the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts. Weather data from ERA5 (Hersbach et al., 2020) at a regular latitude-longitude grid of 0.25 is taken from the *reanalysis era5 single levels* dataset. Average daily temperature corresponds to the *2m temperature* (daily mean) variable. To aggregate the grid-level data to the country level we employ the Database of Global Administrative Areas (GADM), using the first level of resolution GADM0.[45][46]

Temperature shock series computation. The monthly temperature shock is computed as described in Equation (11). First, daily average temperatures are seasonally adjusted by subtracting to every calendar day the mean monthly average temperature (across all years in the sample) corresponding to the month where the calendar day is located. Figure E34 shows the seasonally adjusted series for the Netherlands as an example. The resulting series is aggregated from daily to monthly by taking temporal averages. Finally, the series is thresholded to isolate only months with large temperature deviations by setting to zero any observation within a standard deviation.

$$TS_{m,y} = \begin{cases} {}^{SA}K^{stat}_{m,y}, & \text{if } {}^{SA}K^{stat}_{m,y} \notin [\mu_{K^{SA}} - \sigma_{K^{SA}}; \mu_{K^{SA}} + \sigma_{K^{SA}}] \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

where

- $K_{h,d,m,y}$ denotes hourly temperature, where $h \in \{1, 2, \ldots, 24\}$ indexes hours, $d \in \{1, 2, \ldots, D_m\}$ indexes days (with D_m being the index of the last day in month m), $m \in \{1, 2, \ldots, 12\}$ indexes months, and $y \in \{y_0, y_1, \ldots, Y\}$ indexes years;

- $K^{stat}_{d,m,y} \equiv f(\{K_{h,d,m,y}\}^{24}_{h=1})$ is a daily statistic computed on hourly observations. In our baseline exercise, we consider $K^{Avg}_{d,m,y} = \sum\limits_{h=1}^{24} K_{h,d,m,y}/24$: daily average temperatures. Other options available in the ERA5 dataset include $K^{Min}_{d,m,y} = min(\{K_{h,d,m,y}\}^{24}_{h=1})$ and $K^{Max}_{d,m,y} = max(\{K_{h,d,m,y}\}^{24}_{h=1})$: daily minimum and daily maximum temperatures, respectively;

- $\overline{K^{stat}}_{d,m}$ denotes averages across years of $K^{stat}_{d,m,y}$. We consider $\overline{K^{stat}}_m = \frac{\sum\limits_{y=y_0}^{Y}\sum\limits_{d=1}^{D_m} K^{stat}_{d,m,y}}{(Y-y_0)D_m}$, the calendar month average.

[45] https://gadm.org/.

[46] When using U.S. temperature data we average across all U.S. states and aggregate at the second resolution level GADM1.

- ${}^{SA}K^{stat}_{d,m,y} = K^{stat}_{d,m,y} - \overline{K^{stat}}_m$ is the daily temperature statistic seasonally adjusted by subtracting the calendar month average;

- ${}^{SA}K^{stat}_{m,y} = \frac{\sum_{d=1}^{D_m} {}^{SA}K^{Avg}_{d,m,y}}{D_m}$ is the daily seasonally adjusted statistic aggregated to monthly by taking averages across all days in the month;

- $\mu_{K^{SA}} = \frac{\sum_{y=y_0}^{Y}\sum_{m=1}^{12} {}^{SA}K^{stat}_{m,y}}{(Y-y_0)12}$ and $\sigma_{K^{SA}} = \sqrt{\frac{\sum_{y=y_0}^{Y}\sum_{m=1}^{12}\left({}^{SA}K^{stat}_{m,y} - \mu_{K^{SA}}\right)}{(Y-y_0)12-1}}$ are the mean and the standard deviation of monthly the seasonally adjusted temperature statistic, respectively.

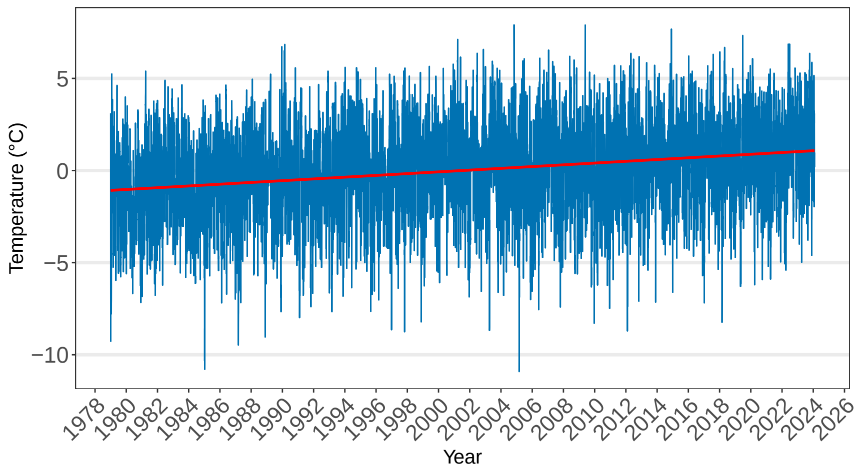


Figure E34: *Daily temperatures for the Netherlands, seasonally adjusted by subtracting the long-term calendar month averages, not detrended*

We have explored several alternative methods for computing the temperature shock series, all of which yield very similar temperature shock series to which our findings are robust. These robustness checks are available upon request. One approach involves removing a linear trend from the temperature series before applying seasonal adjustments. Another method adjusts for seasonality by subtracting the mean temperature for each calendar day, computed across all years in the sample, rather than using calendar month averages, though this tends to introduce more noise. Additionally, the index can be constructed using daily maximum or minimum temperatures instead of daily averages. An alternative weighting scheme incorporates demographic or geographic factors, such as night lights (Gortan et al., 2024), to refine the temperature series. Finally, a rolling seasonal adjustment can be implemented, where the reference means for adjustment are computed based on a moving window of preceding years.

The months excluded from the demand instrument due to confounding factors are the following. For Europe: 2006M1 (Russia cut gas supplies to Ukraine, following negotiations between Gazprom and Naftogaz), 2009M1 (Russia cut gas deliveries to

Europe amid escalating Russia-Ukraine gas dispute), 2011M12 (Turkey-Russia deal over South Stream pipeline), 2014M3 (Crimea crisis), 2015M11 (Gazprom halts gas supplies to Ukraine), 2020M2 (COVID-19 pandemic), 2022M2 (Invasion of Ukraine), 2022M8 (Turbine maintenance at Nord Stream 1), 2022M11 (Outages in Norway and delays in restart of Freeport LNG), and 2023M10 (Conflict in the Middle East). For the United States: 2005M11 (Gas production and transport resumes after Hurricane Katrina), 2007M10 (Tropical Storms), 2014M2 (Major pipeline explosion), 2020M3 (COVID-19 pandemic), 2020M11 (Hurricane Eta), 2021M2, M3, and 2023M2(Storm-related disruptions to natural gas pipelines and oil refineries), and 2023M10 (Reopening of major LNG terminal).

Figure E35 demonstrates that the anticipation effects of temperature fluctuations on natural gas prices are likely minimal. The top-left panel illustrates the correlation between daily temperatures and daily natural gas prices, revealing that the strongest (negative) correlation occurs contemporaneously. This indicates that price movements are primarily driven by actual temperature realizations rather than expectations about future temperatures. Additionally, the temporal correlation of daily temperatures can explain the presence of some correlations in lead terms without necessarily implying anticipation effects. In practice, forecasting average temperatures over a period may be more common than predicting daily temperatures with precision. However, the other panels show that even when considering the average temperature over several subsequent days, the strongest correlations remain contemporaneous. Overall, this analysis suggests that anticipation effects on natural gas prices, if present, are quite limited.

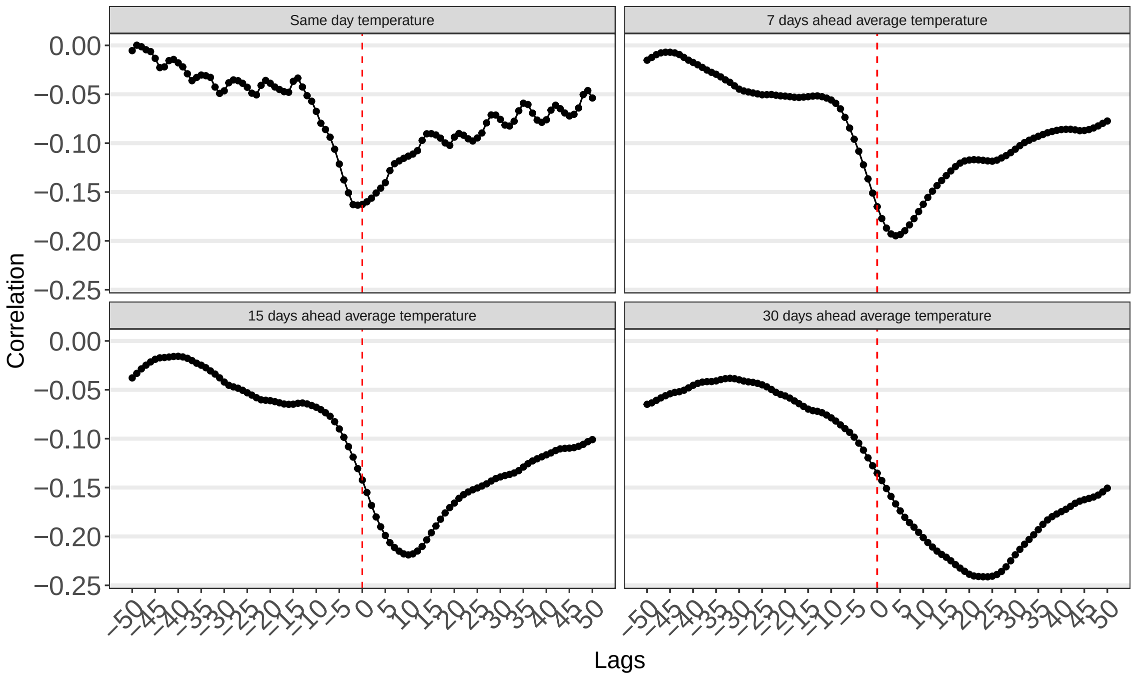


Figure E35: *Temperatures and gas price correlations*

Notes: The Figure plots the correlations at several leads and lags of the TTF spot price of natural gas and average temperatures. The different panels plot temperature averages of different temporal spans.

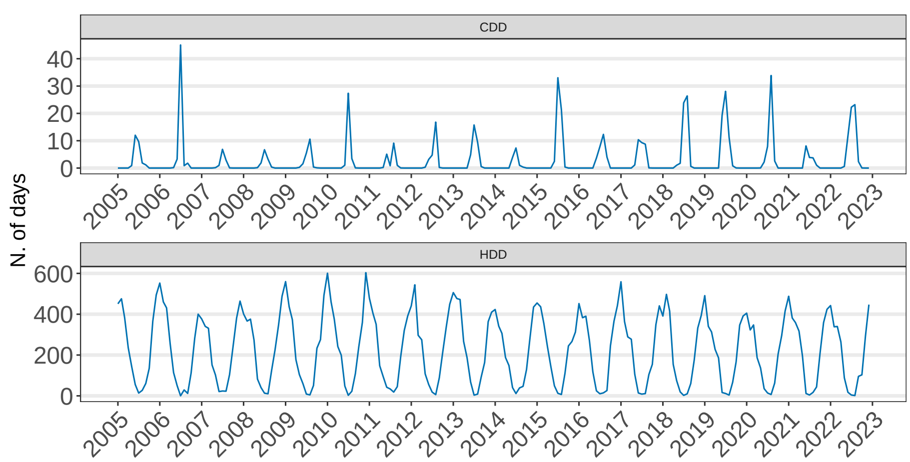
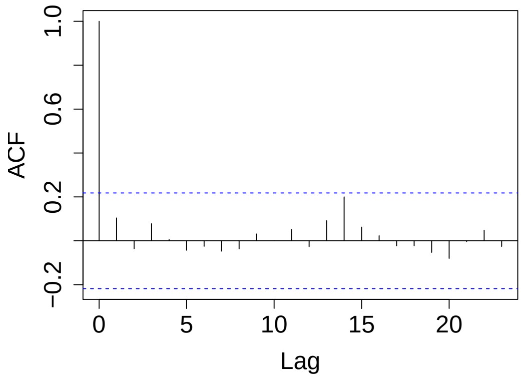
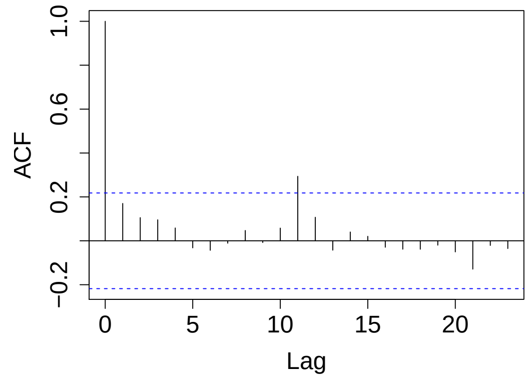


Figure E36: *Cooling degree days and heating degree days, average across selected European countries*



EA



US

Figure E37: *Sample Autocorrelation Function of the Temperature Shocks*

E.2 Gas demand instrument for the United States

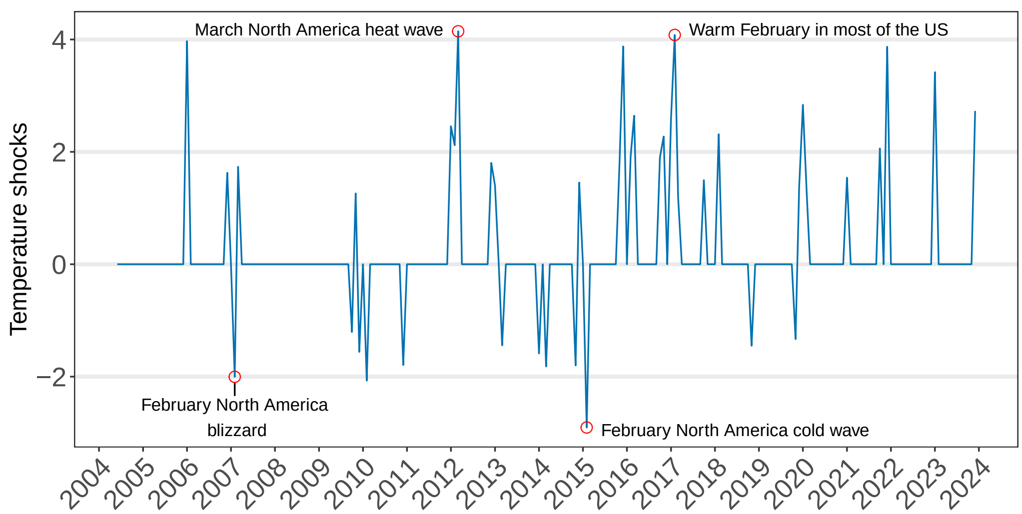


Figure E38: *Temperature shocks series for the US*

F Brent and WTI oil surprises

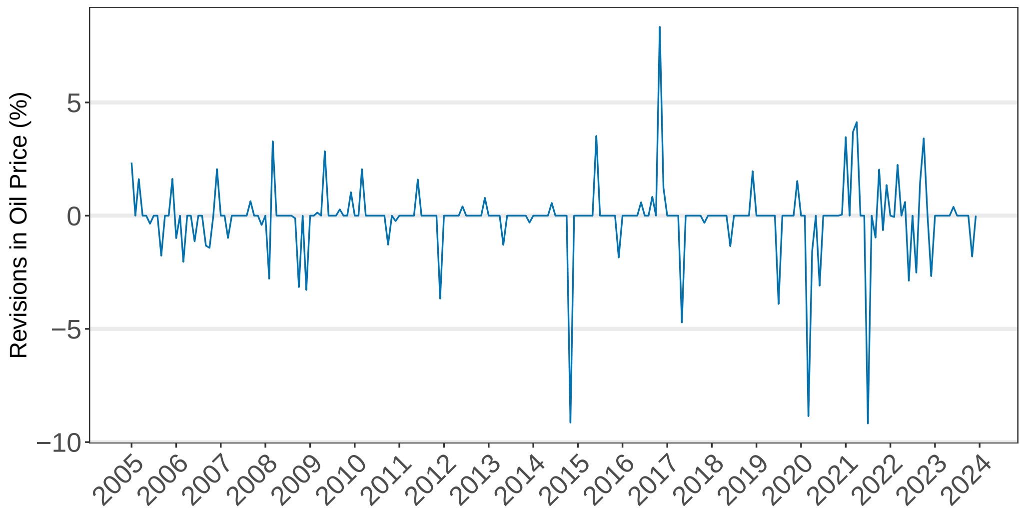


Figure F39: *The Brent oil supply surprises series*

Notes: This figure shows the oil surprise series, which is constructed as the first principal component from changes in oil futures prices. We use Brent crude oil future contracts spanning the first-year term structure around OPEC announcements. The series is scaled to match the average volatility of the underlying price surprises. See Känzig (2021a).

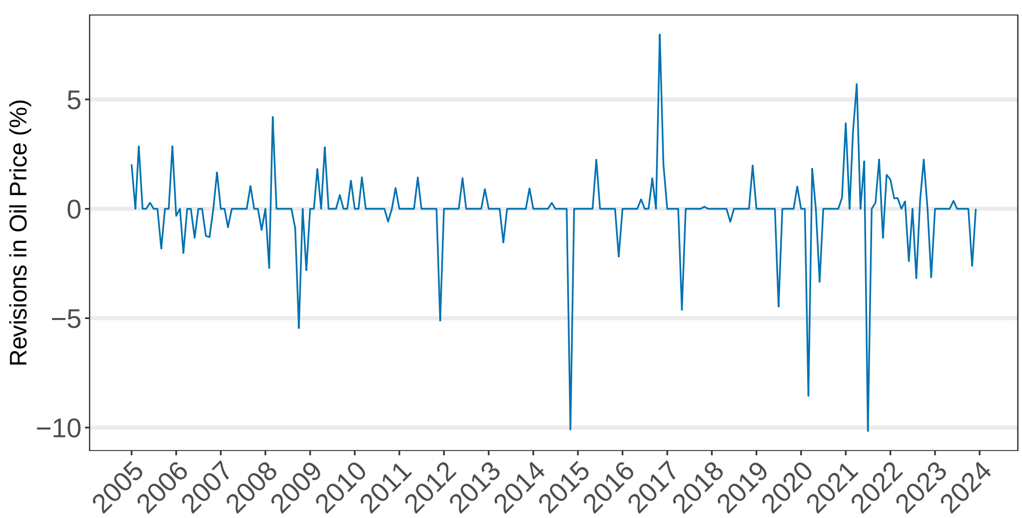


Figure F40: *The WTI oil supply surprises series*

Notes: This figure shows the oil surprise series constructed as the first principal component from changes in WTI gas futures prices.

G Baseline responses presented jointly

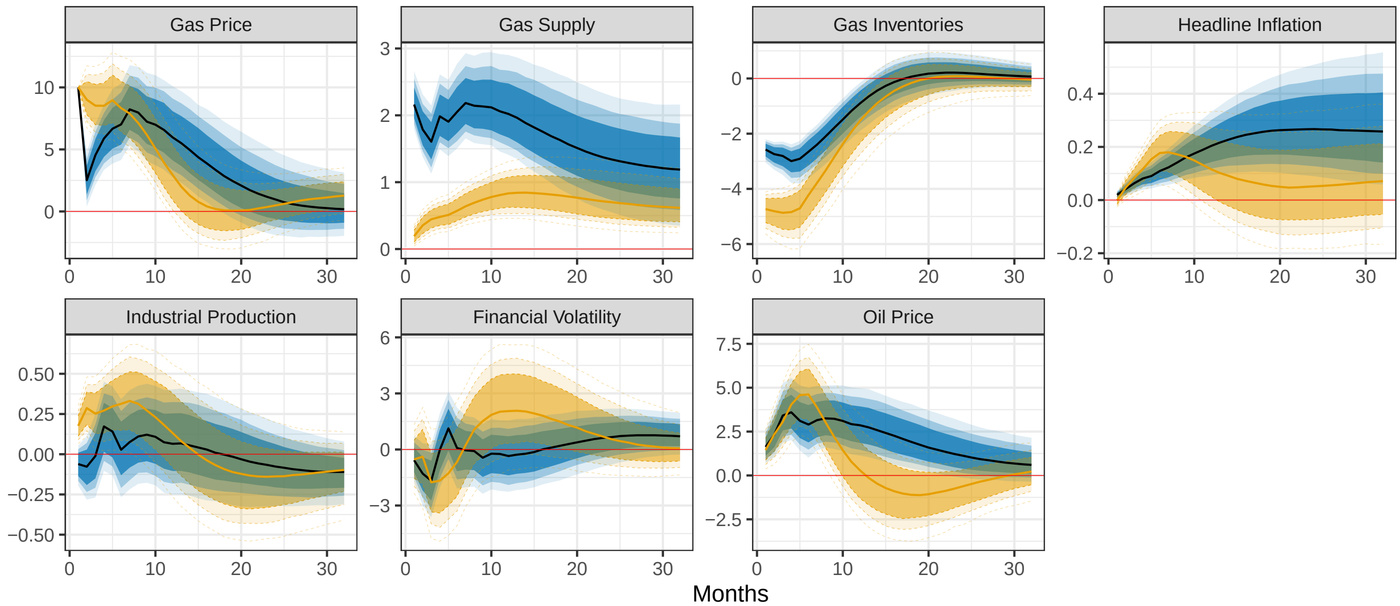


Figure G41: *Full responses to a gas demand shock. Left panels of Figures 7 to 10 grouped together.*

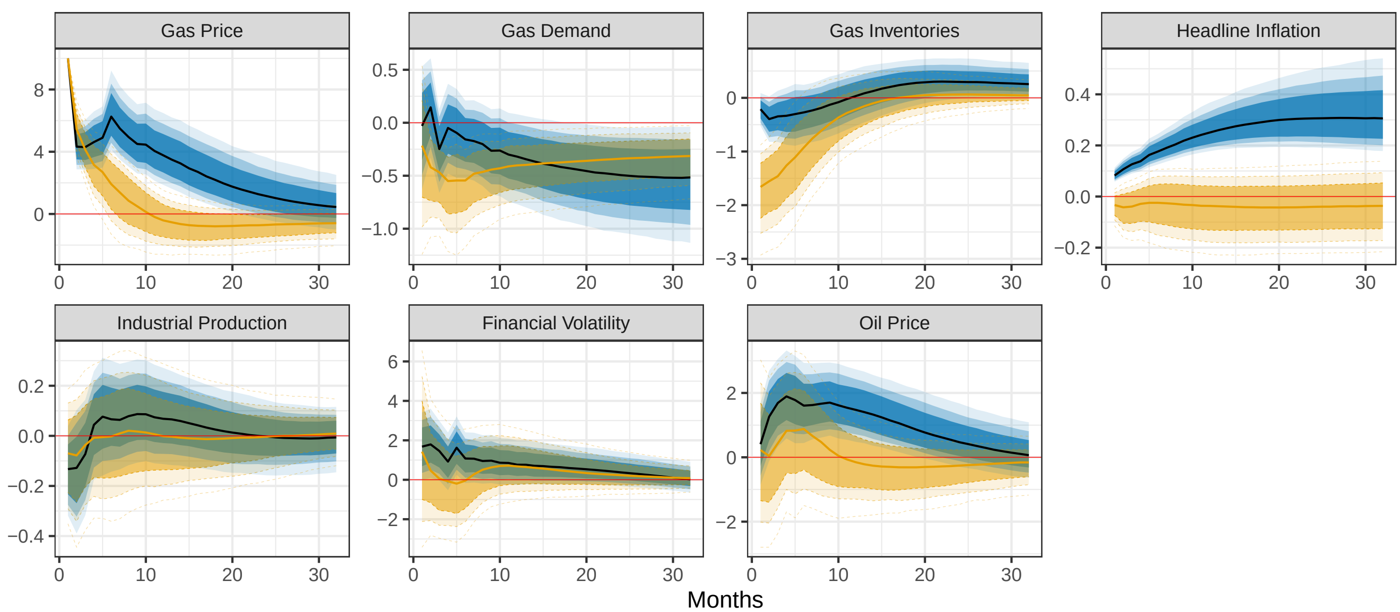


Figure G42: *Full responses to a gas supply shock. Right panels of Figures 7 to 10 grouped together.*

H Additional results

H.1 Drivers of demand and supply elasticities

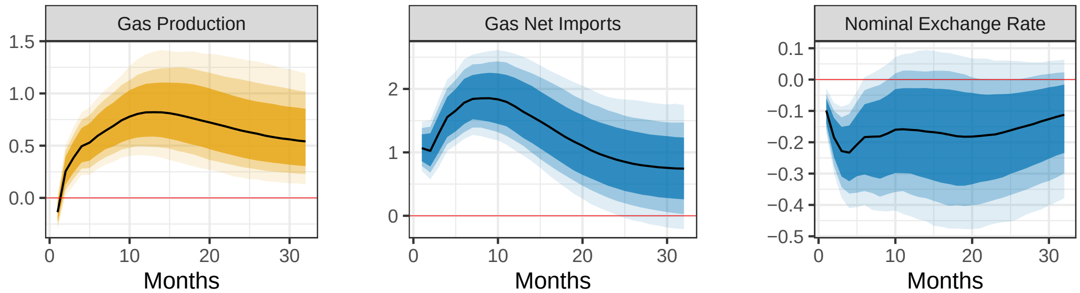
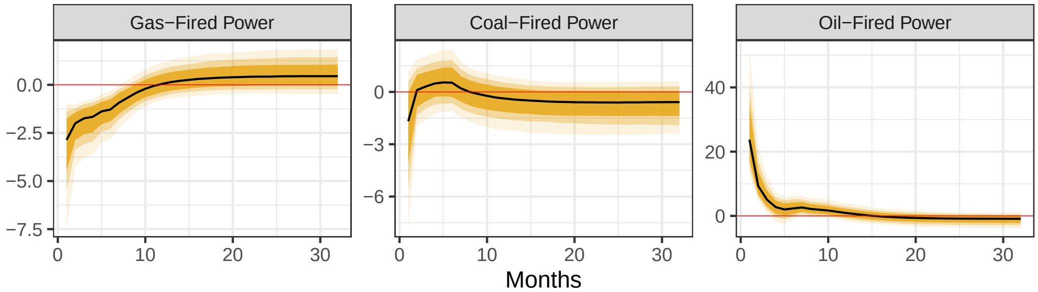
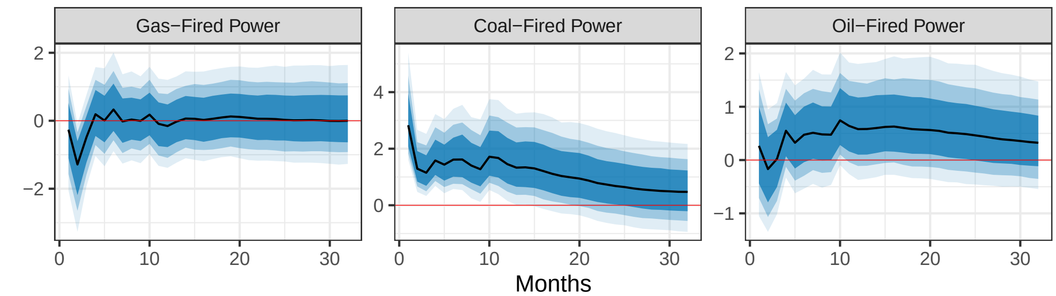


Figure H43: *Drivers of gas supply*

Notes: Impulse responses of gas production in the United States, as well as net imports and the nominal exchange rate in the Euro Area, following a gas demand shock. These results are derived from the baseline specification, replacing total supply with gas production for the United States, and with gas net imports and the nominal exchange rate for the Euro Area. A decrease in the exchange rate indicates a depreciation in nominal terms.



US



EA

Figure H44: *Interfuel substitution in the power sector*

Notes: Impulse responses of power generation from natural gas, crude oil, and coal to a natural gas supply shock. Estimates are based on the baseline specification, augmented to include fuel-specific power generation series. The sample for the Euro Area begins in 2010 due to data availability constraints.

H.2 Europe supply shock constructed only with expected events

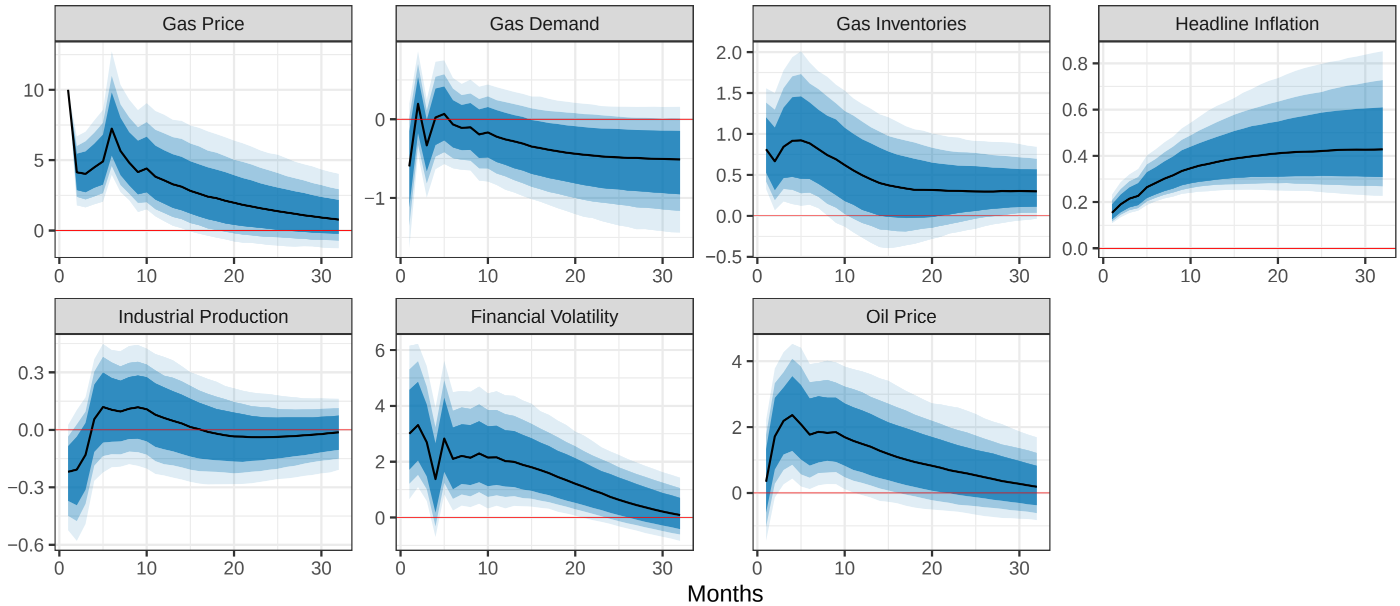


Figure H45: *Full responses to a gas supply shock for Europe, constructed using only news related to expected—but not yet realized—disruptions. The responses of gas inventories and financial volatility differ from those in the baseline specification.*

H.3 Effects of a gas supply shock in Germany

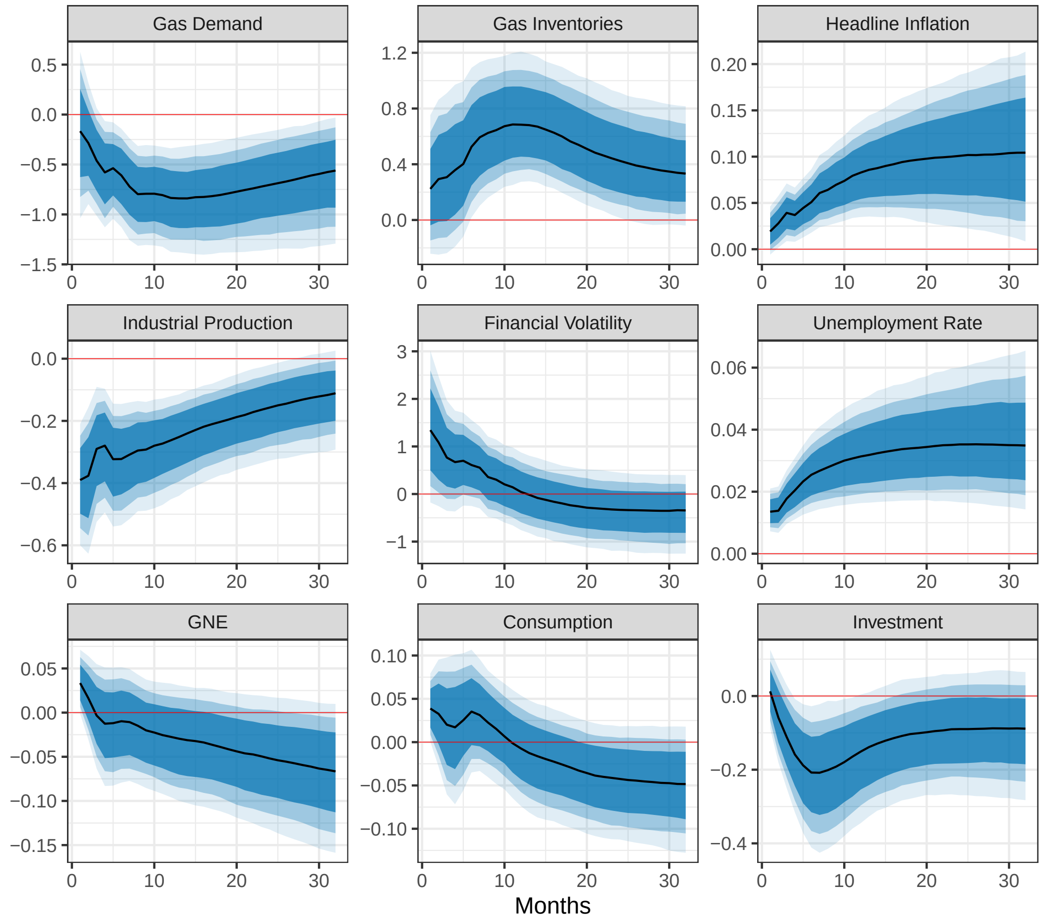


Figure H46: *Impulse responses to a gas supply shock: German economy*

Notes: GNE, consumption, and investment are quarterly variables interpolated to monthly using a cubic spline interpolation.

H.4 PPI inflation in Europe

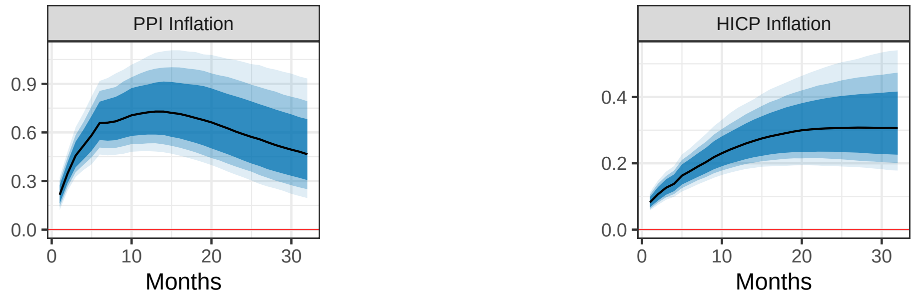


Figure H47: *Responses of producer price and consumer price inflation*

Notes: Impulse responses of producer price inflation and headline consumer price inflation to a gas supply shock in the Euro Area. These results are derived from the baseline specification augmented with the PPI series.

I Sensitivity analysis

In this Appendix, we provide evidence that our results are robust along multiple dimensions. First, we develop an informationally robust gas supply instrument by accounting for a variety of potential confounding factors, and show that the main findings are robust under this specification. We also offer an alternative estimation for the United States, where the estimation sample period begins earlier. Finally, we show that our findings remain qualitatively consistent when estimating the same specifications by VAR-OLS, indicating that the results are not sensitive to the choice of Bayesian priors.

I.1 Informationally robust supply surprises

To interpret the surprise series as an exogenous supply shock, it is crucial to ensure that these events do not simultaneously convey new information about confounding factors, as this would compromise the exogeneity of the instrument. One potential such confounder is food prices, which, in the context of the Russia-Ukraine conflict, rose alongside natural gas prices (Ben Hassen and El Bilali, 2022; Alexander et al., 2023). Given their broader macroeconomic implications, food price fluctuations could introduce an alternative transmission channel unrelated to gas supply shocks. More generally, some gas market-specific news events used to construct the surprise series may have broader economic consequences, potentially influencing endogenous variables through channels beyond natural gas prices. If such alternative transmission mechanisms are present, the exclusion restriction could be violated.

To address these concerns, we construct an informationally robust gas supply series, drawing from a strategy typically applied in the monetary policy literature that isolates the informational component of the surprises in gas futures by directly controlling for potential confounding factors (e.g. Romer and Romer, 2004; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2021). Following this approach, we refine the gas supply series by removing its own lagged effects as well as the contemporaneous and lagged effects of potential confounding factors. More specifically, we recover the informationally robust surprises, IRS_t, as the residuals of the following regression:

$$GasSurprise_t^h = \alpha_0 + \sum_{j=1}^{2} \phi_j \, GasSurprise_{t-j}^h + \sum_{j=0}^{2} \theta_j \, FoodSurprise_{t-j}^h + \sum_{j=0}^{2} \mathbf{x}_{t-j} \Gamma_j + IRS_t$$

where $GasSurprise_t^h$ denotes the gas supply surprise in month t for the futures contract h, constructed as detailed previously. Similarly, $FoodSurprise_t^h$ represents the surprise in food prices constructed around the same gas-related news. To construct food surprises, we use the price of wheat as a proxy for overall food prices, as this was the main export from Russia (OECD, 2022), and it is the most actively traded food commodity (CME, 2024).[47]

[47] We use Matif wheat futures for the Euro Area and Hard Red Winter wheat futures for the

Finally, $\mathbf{x}_t$ is a vector of monthly macroeconomic shocks sourced from the literature. These include the global oil supply shock proposed by Kilian (2009), which captures disruptions in the physical availability of crude oil worldwide, as well as the oil-specific demand shock and aggregate demand shock from the same study. Additionally, we incorporate oil supply and demand shocks from Baumeister and Hamilton (2019) and supply surprises in oil prices identified by Känzig (2021a). The uncertainty indicators considered span multiple domains, including geopolitical and financial market conditions. Specifically, we include the policy uncertainty index developed by Baker et al. (2016), the geopolitical risk index introduced by Caldara and Iacoviello (2022), the stock market volatility index from Bloom (2009), and the excess bond premium constructed by Gilchrist and Zakrajšek (2012).[48]

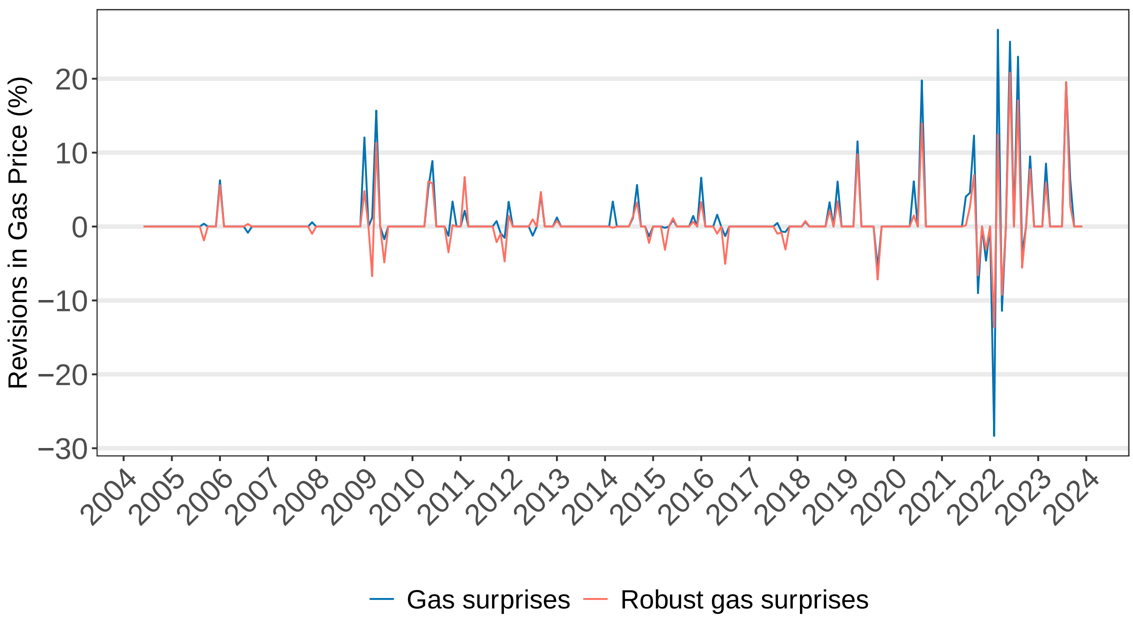


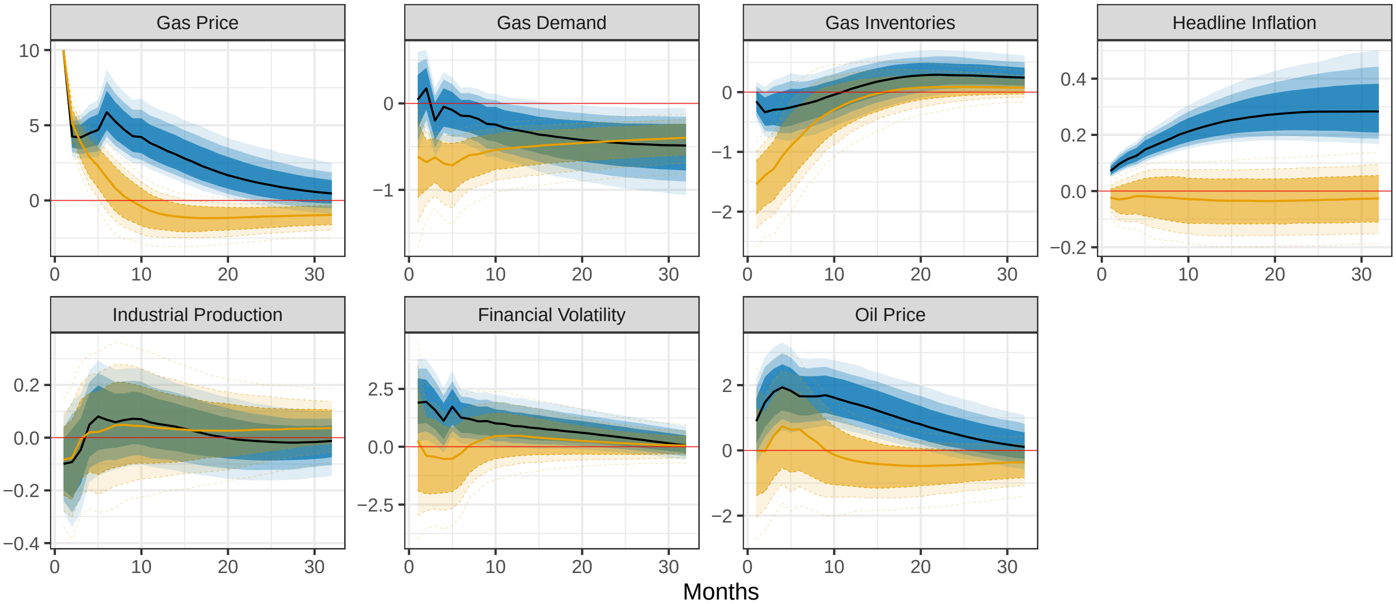
Figure I48: *Informationally robust gas surprises series for the Euro Area*

Notes: This figure shows the gas surprise series (blue line) alongside the informationally robust surprises, residual to Eq. (I.1) IRS_t (yellow line).

Figure I48 plots the gas surprise series at the monthly frequency ($GasSurprise_t$) and the corresponding informationally robust instrument (IRS_t). The two series are qualitatively similar and yield quantitatively similar results. Figure I49 presents the IRFs from the baseline specification using the informationally robust instrument. The responses closely align with those reported in the main analysis, exhibiting only minor and statistically insignificant differences. This suggests that informational confounding does not significantly impact our high-frequency gas surprises.

United States.

[48]These shock series are either taken directly from the original studies or extended where necessary, adhering closely to the methodologies outlined in the original papers.

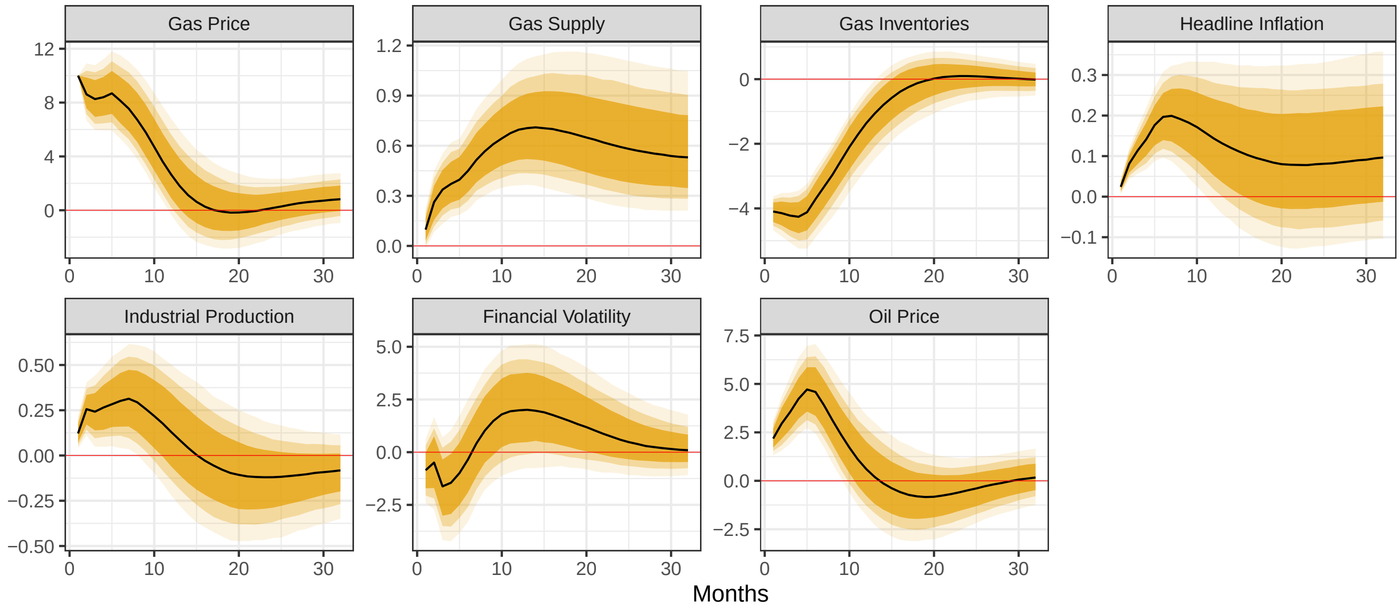


First stage regressions: EA F: 13.28, Robust F: 15.75; US F: 8.96, Robust F: 18.11

Figure I49: *Impulse responses to a gas supply shock, informationally robust refinement. Equivalent of right panels of Figures 7 to 10.*

Notes: Impulse responses to a gas supply shock in the Euro Area and the United States informationally robust refinement. The black solid lines with blue shaded confidence bands represent the EA, while the orange solid lines with dashed and shaded orange confidence bands represent the US.

I.2 Demand instrument including summer months (US)



First stage regressions: US F: 10.38 , Robust F: 12.43

Figure I50: *Impulse responses to a gas demand shock, estimated using an instrument constructed without excluding summer months. Results correspond to the left panels of Figures 7 to 10.*

Notes: For the summer months, the sign of the spikes in the instrument is inverted to account for the seasonal variation in the relationship between temperature and natural gas demand. While colder temperatures increase heating demand in winter, higher temperatures in summer raise cooling-related gas consumption. To maintain consistency and preserve a negative correlation between temperature and gas prices, the sign of the instrument is reversed during summer months. This adjustment results in a slightly higher F-statistic compared to the baseline instrument.

I.3 Extended estimation sample for the United States (1997-2023)

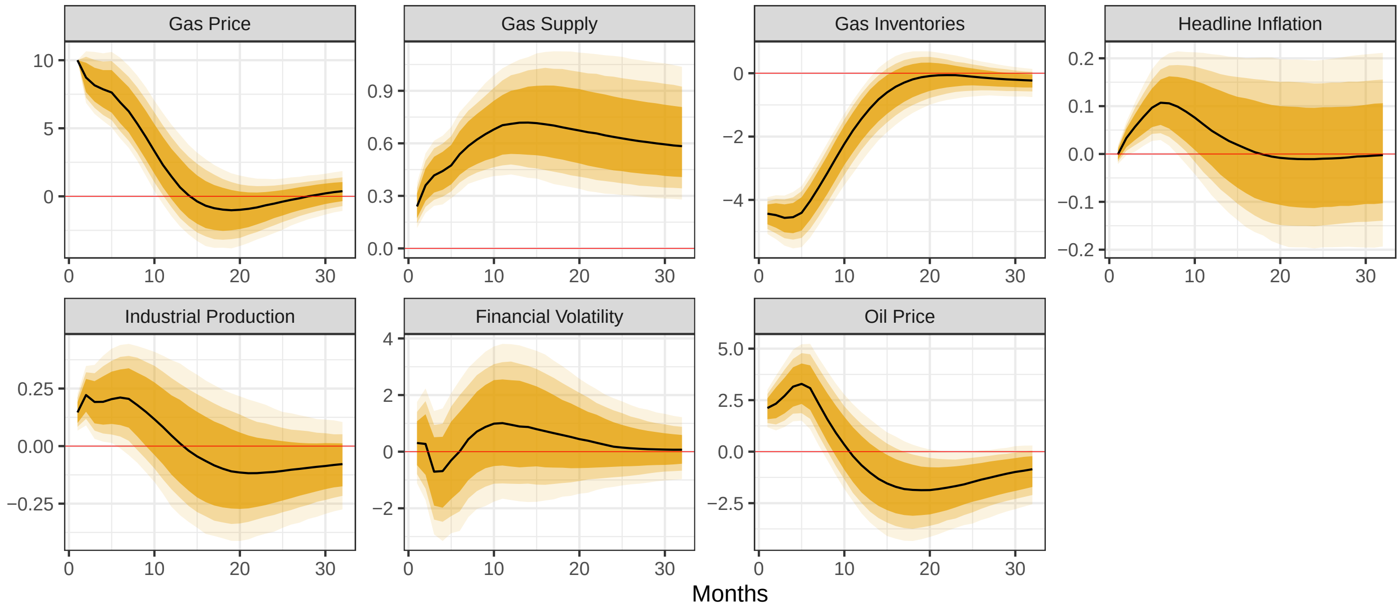


Figure I51: *Full responses to a gas demand shock in the US, extended sample. Corresponds to the right panels of Figures 7 to 10.*

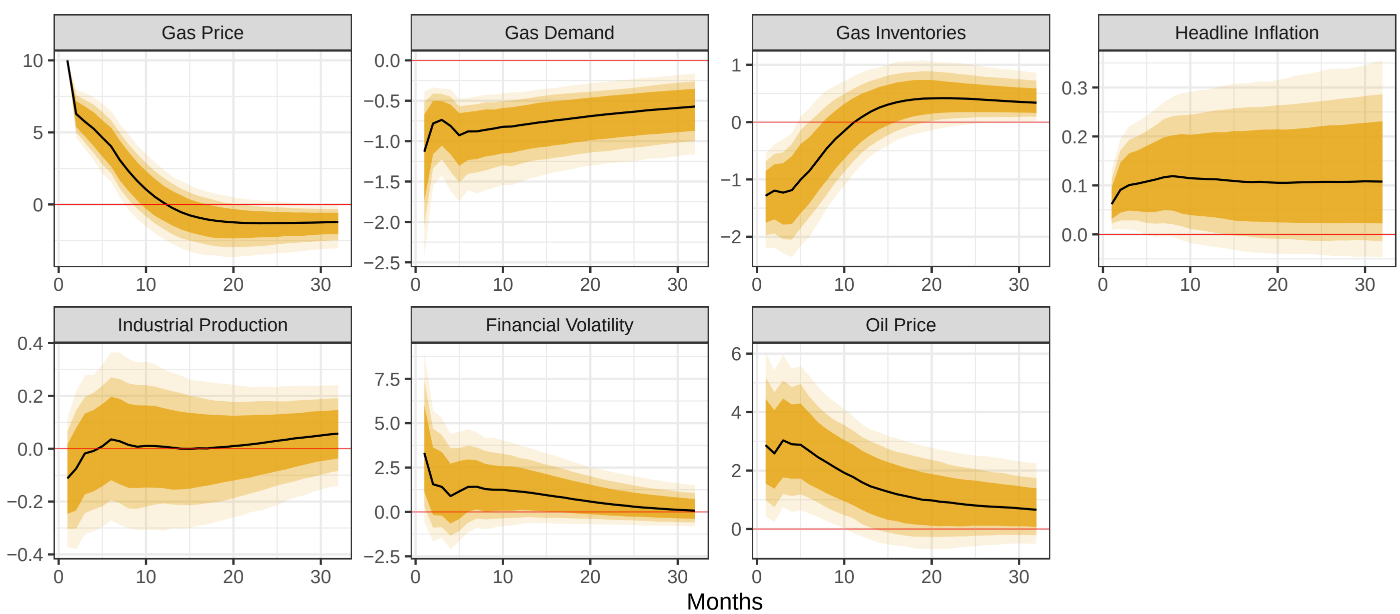


Figure I52: *Full responses to a gas supply shock in the US, extended sample. Corresponds to the left panels of Figures 7 to 10.*

I.4 Estimation by VAR-OLS

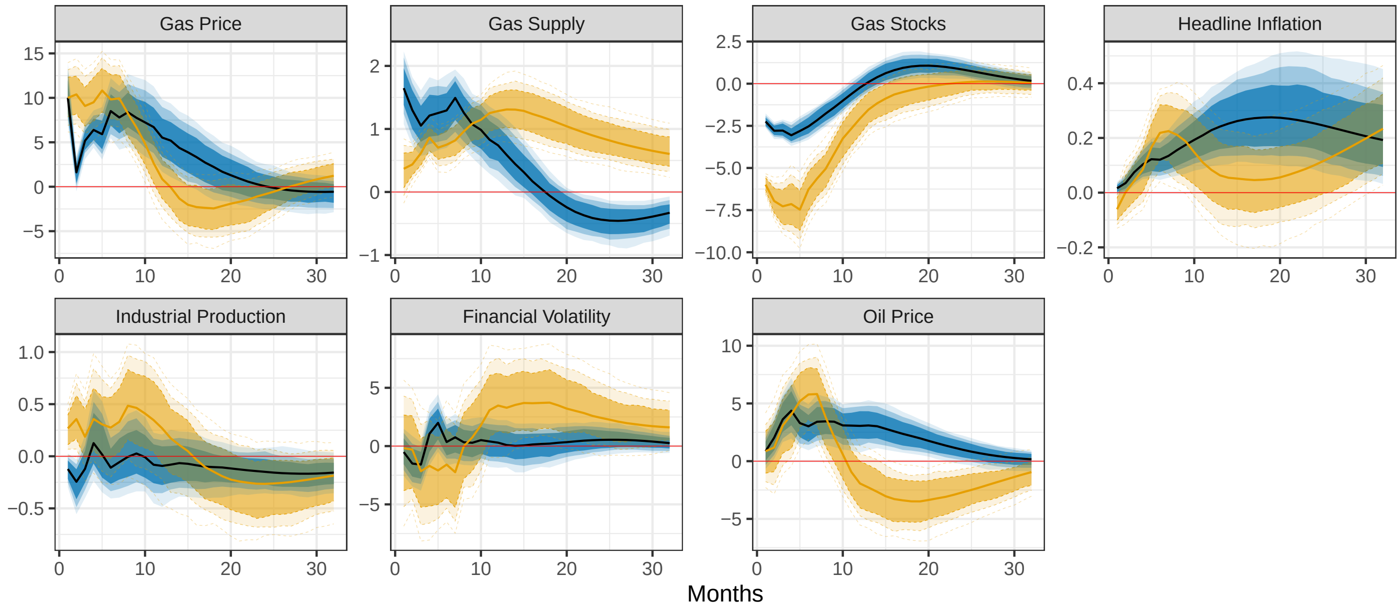


Figure I53: *Responses to a gas demand shock, estimated by VAR-OLS. Equivalent of left panels of Figures 7 to 10.*

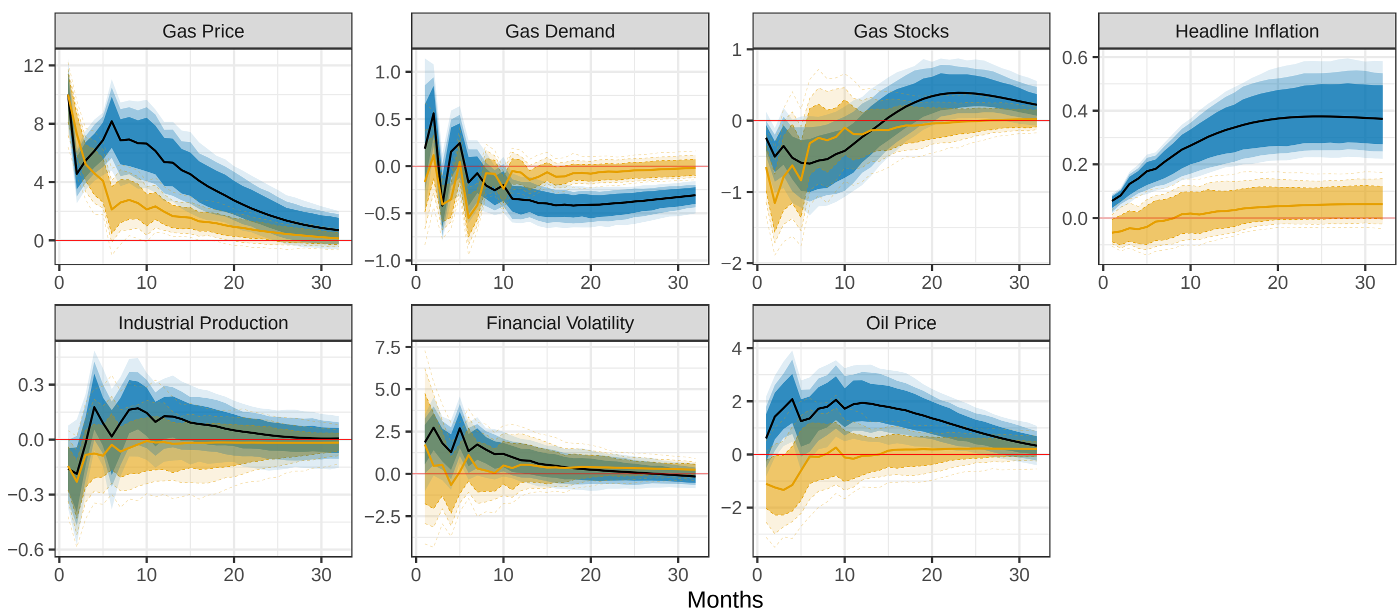


Figure I54: *Responses to a gas supply shock, estimated by VAR-OLS. Equivalent of right panels of Figures 7 to 10.*

J Comparison with an alternative gas supply instrument for Europe

Alessandri and Gazzani (2025) recently proposed an instrument for identifying gas supply shocks in Europe, employing a high-frequency approach similar to the one used in this paper. In this Appendix, we discuss both the technical and substantive differences between their instrument and ours.

A first distinction lies in the data source: their instrument is based on the ENDEX futures series, whereas we rely on TRPC continuation values. Although the two series are highly correlated, the TRPC data covers a longer time span, enabling us to construct an instrument over an extended sample. Specifically, their instrument spans the period from 2010M1 to 2022M11, while their estimation sample extends from 2000M1 to 2022M11. By contrast, our instrument covers our full estimation sample, from 2004M1 to 2023M12.

Another important difference concerns the treatment of futures contracts. Alessandri and Gazzani (2025) focus exclusively on surprises in the front-month contract. In contrast, we follow the standard approach in the literature (see e.g. Känzig, 2021a) and extract the first principal component from surprises across multiple maturities, up to one year. While Alessandri and Gazzani (2025) include a robustness check in which they incorporate 1-, 2-, 3-, and 12-month futures, their baseline specification does not. We argue that including longer-dated contracts is important, as gas supply shocks are also transmitted via expectations about future supply conditions, as we have shown. Moreover, as discussed in Section 3.1.1, using the principal component allows us to isolate a cleaner signal, especially in cases where futures with different maturities respond heterogeneously to market-relevant news.

Figure J55 compares the two gas supply shock measures. Despite some overlap, the correlation between the two instruments is relatively modest, at 0.30.

Perhaps the most substantial difference between the two instruments emerges when comparing the results they produce. When we use the instrument proposed by Alessandri and Gazzani (2025) in our baseline specification, we obtain the impulse responses shown in Figure J56. Unlike the responses generated using our instrument, the results indicate a positive impact on gas demand and a significant decline in inventories for up to one year, which suggests a drawdown in gas stocks to accommodate increased demand. This finding is somewhat puzzling, as the instrument is intended to capture purely supply-side news. In our specification, the first-stage F statistic associated with their instrument is also notably large: 49.6.

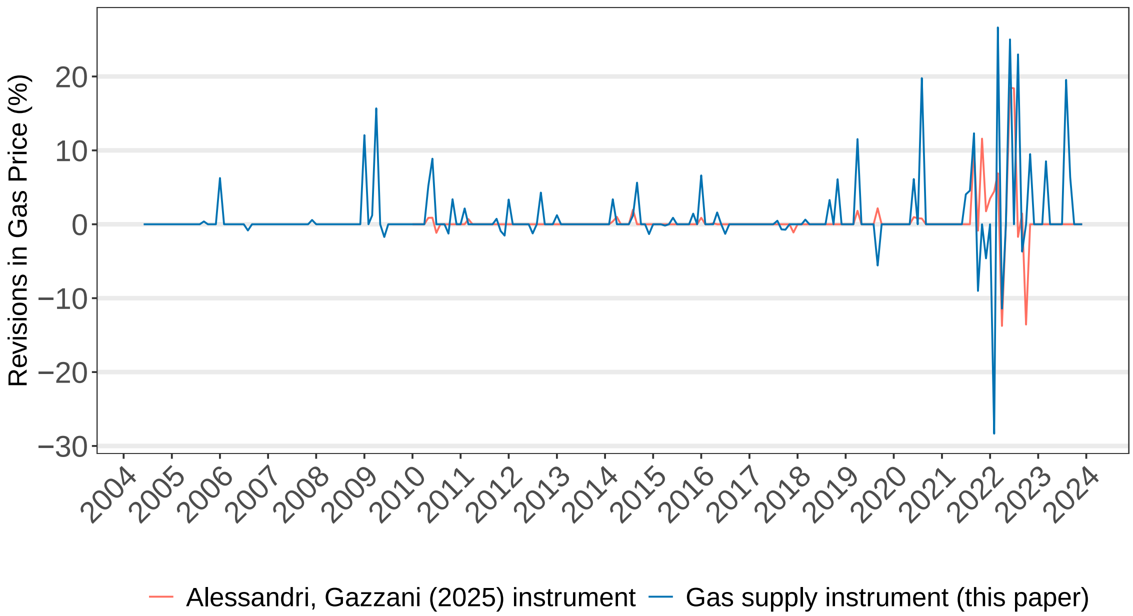


Figure J55: *Comparison of the two supply instruments for Europe.*

Notes: The correlation between the two instruments is 0.30.

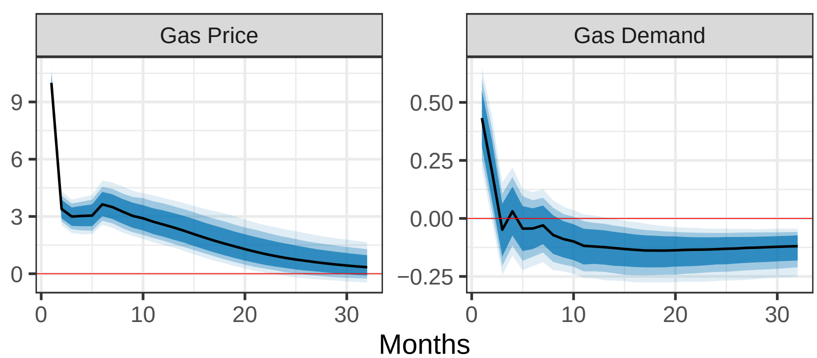


Figure J56: *Impulse responses of gas price and gas demand obtained by using the Alessandri and Gazzani (2025) gas supply instrument in our baseline specification.*

Notes: The Fstat is 49.6 and the Robust F is 7.8.

To further investigate the source of these results, we examine the correlation between their instrument and a range of established shocks from the literature (see Table J11), following a similar diagnostic approach to that used for our instrument in Appendix D.3. The analysis reveals that their instrument is primarily correlated with demand-side indicators, including the oil demand shock identified by Baumeister and Hamilton (2019), the FF4 monetary policy shock from Gertler and Karadi (2015)—with which the correlation is highly significant—and our own temperature-based gas demand shock.

In addition, Table J12 indicates that, while we can reject the null hypothesis that their instrument is Granger-caused by a broader set of macroeconomic variables, there is evidence of Granger causality from its own lags and the real spot price of gas.

Source	Shock	ρ	p-value	n
This study	Temperature demand shock	-0.10	0.23	155
Kilian (2009)**	Oil supply	-0.04	0.61	155
Kilian (2009)**	Aggregate demand	-0.09	0.24	155
Kilian (2009)**	Oil-specific demand	0.01	0.92	155
Baumeister and Hamilton (2019)*	Oil supply	-0.02	0.80	155
Baumeister and Hamilton (2019)*	Oil demand	0.13	0.11	155
Känzig (2021a)**	Oil supply expectations	-0.11	0.17	155
Caldara et al. (2019)*	CCI oil supply	-0.23	0.05	72
Altavilla et al. (2019)*	Target monetary policy (EA)	0.01	0.88	155
Miranda-Agrippino and Nenova (2022)	Target monetary policy (EA)	0.01	0.90	135
Jarociński and Karadi (2020)	Information median monetary policy (EA)	0.19	0.02	155
Gertler and Karadi (2015)	FF4 monetary policy (US)	-0.19	0.31	30
Miranda-Agrippino and Nenova (2022)	Target monetary policy (US)	-0.04	0.71	114
Bloom (2009)**	VXO-VIX	0.03	0.75	155
Gilchrist and Zakrajšek (2012)*	Corporate credit spread index	-0.09	0.27	155
Caldara and Iacoviello (2022)*	Geopolitical risk index	0.08	0.33	155

Table J11: *Correlation of Alessandri and Gazzani (2025) instrument with other shocks.*

Notes: This table presents the correlation coefficients (ρ) and p-values for the gas supply instrument in relation to a variety of economic shocks from the literature. The p-values correspond to two-sided tests for the null hypothesis of no correlation.

*Extended by the original authors beyond the original sample used in the published paper.
**Extended by the authors of this study.

Variable	p-value
Instrument Lags	0.00
Gas price	0.01
Oil price	0.78
Gas demand	0.80
Gas inventories	0.35
Headline inflation	0.53
Industrial production	0.45
Financial volatility	0.16
Interest rate	0.99
Nominal exchange rate	0.74
Stock market (STOXX50E/SP500)	0.29
Supply Chain Bottlenecks (GSCPI)	0.71
Real economic activity	0.64
Joint Test	0.33

Table J12: *Granger causality tests*

Notes: The table presents the p-values obtained from Granger's causality tests of the gas supply surprise series using the set of variables included in our baseline specification, expanded with financial and real activity variables. To conduct standard inference, the series are rendered stationary by taking first or second differences as required. The analysis includes 6 lags and a constant term.

These findings suggest that the instrument proposed by Alessandri and Gazzani (2025) may reflect some demand-side components of gas price variability, rather than isolating a purely supply-driven shock. This could arise from the selection of gas-market news used to construct the instrument, some of which may be directly related to demand developments or confounded by concurrent demand-side factors.

For instance, news from October 21, 2022, refers to Italy's approval of a new LNG terminal and the start of LNG exports from Mozambique to the EU. This coincided with an unseasonal heatwave in Europe. Further analysis of gas-market news around that date suggests that price movements were primarily driven by changes in demand due to weather conditions.

Another example the news item from May 16, 2022, reporting on Norway's potential to expand gas exports to the EU and the approval of new LNG projects in the United States. In our view, this news lacks clear evidence of exogeneity and may instead reflect supply responses to rising demand, rather than an exogenous movement in supply.

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