Gas Prices and the Macroeconomy*

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Abstract

We identify supply and demand shocks to the real price of natural gas leveraging exogenous temperature variation and a high-frequency strategy based on an extensive collection of market-relevant news. Gas demand is less elastic than supply, resulting in larger price fluctuations following supply shocks. These shocks have notable macroeconomic effects: they are strongly inflationary in the Euro Area, with impacts amplified by inventory dynamics and financial market volatility, suggesting a transmission channel driven by expectations and uncertainty. As such, gas supply shocks have been a major driver of the recent inflation surge, while their impact has been more muted in the United States. Aggregate real effects appear short-lived, though we document substantial sectoral heterogeneity and a persistent decline in activity in Germany.

JEL classification: C32, E31, Q41, Q43.

Keywords: Business cycles, gas price shocks, gas supply, gas demand, elasticities, external instruments, temperature deviations, inflation.

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1 Introduction

The recent outbreak of war between Russia and Ukraine has driven natural gas prices to unprecedented levels, sparking significant interest in a commodity that had previously received relatively little attention in the literature. Notably, the surge in gas and broader energy prices coincided with a global rise in inflation (see Figure 1). These developments have raised several critical economic questions that have shaped both political and academic debates: To what extent, and how rapidly, can economies respond to supply disruptions through adjustments in consumption and substitution toward alternative gas suppliers or other energy sources (Moll et al., 2023)? Is the segmentation of natural gas markets relevant for the transmission of gas price shocks compared to the more integrated crude oil market? Moreover, to what degree do gas prices reflect fundamental supply and demand dynamics, as opposed to other factors such as speculative activity (Knittel & Pindyck, 2016)? Finally, how much of the recent inflation surge can be attributed to energy 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. Nevertheless, addressing these issues is crucial for understanding the macroeconomic transmission of gas price shocks and their role in shaping recent inflation and output dynamics.

This paper proposes a novel approach to identifying structural supply and demand shocks in the natural gas market. Demand shocks are identified leveraging variation in temperatures, while supply shocks are identified using market-relevant news and high-frequency data. Employing the resulting series as external instruments in a Bayesian VAR framework, we analyze gas market dynamics and their broader macroeconomic transmission in both the Euro Area and the United States. To the best of our knowledge, this provides the first macro-level estimates of gas market elasticities based on exogenous variation. 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 several of these differences reflect well-known disparities in gas balances and fundamental supply and demand dynamics, we also find evidence that supply shocks are amplified through an expectations and volatility channel, with varying strength across the two regions. We then evaluate the contribution of gas price shocks to the recent surge in inflation and investigate the channels through which they can generate aggregate real effects. Finally, we show that CO_2 emissions tend to rise in response to gas price increases in the short to medium term, as natural gas is substituted with more carbon-intensive fuels.

Preview of results. Gas price shocks have economically meaningful effects. 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 1% after one year, following a 10% 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 1.5% 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 rigid 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 -0.11 and the supply elasticity is 0.76; for the United States, the demand elasticity is -0.05 and the supply elasticity is 0.33.

Inflationary effects are more pronounced in the Euro Area, with both demand and supply shocks contributing up to a 3.5% pass-through to headline inflation, 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. Accordingly, we show that gas supply shocks have been a major contributor to the recent inflation surge in the Euro Area, whereas their impact has been more limited in the United States, where oil price shocks have played a more important role in driving the inflationary spike.

The aggregate real effects of gas price shocks appear limited; however, we document substantial variation across sectors. 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 and materialize more rapidly in goods-producing sectors than in services. In Germany, however, we find that supply shocks can generate a significant fall in economic activity, suggesting that the disruption of Russian gas flows has been a contributing factor to the country's recent economic stagnation.

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 analyses confirms the robustness of our results across multiple dimensions, including identification strategy, model specification, estimation sample, estimation method, and instrument construction. In particular, the findings are robust to the use of an informationally robust gas supply instrument that accounts for potential confounding factors and background information during the event window. We further show that the results remain consistent when impulse responses are estimated using local projections or frequentist instead of Bayesian methods. In addition, we demonstrate that the constructed instruments are not contaminated by unintended channels, as they show 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).

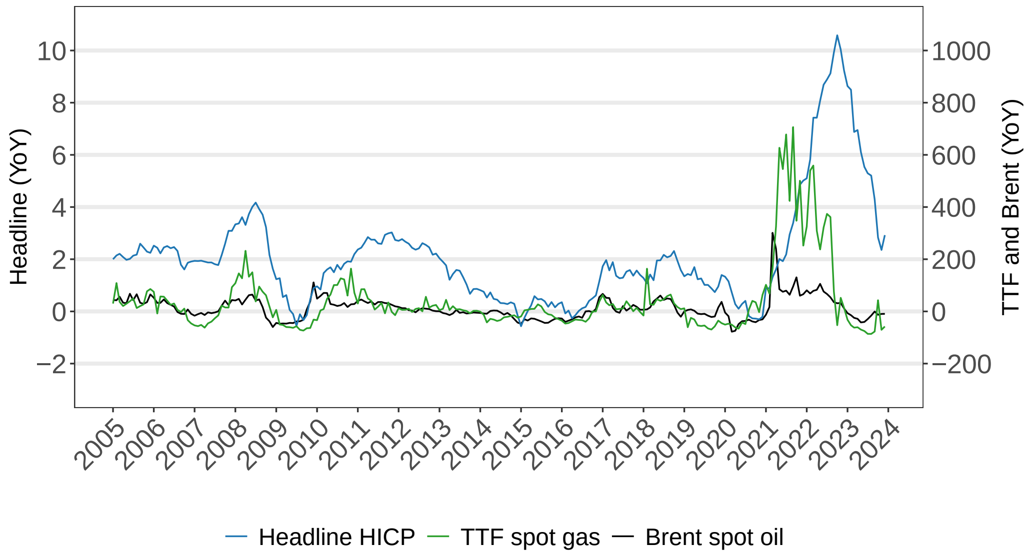
A key contribution of this study is the estimation of elasticities of gas demand and supply in both the United States and the Euro Area using external instruments. This analysis is related to a well-established body of research in the oil market literature, which seeks to estimate such elasticities and 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, giving rise to a heated policy debate and prompting an initial wave of theoretical studies on their macroeconomic effects (Bachmann et al., 2022; Bundesbank, 2022; Gunnella et al., 2022; Lan et al., 2022; Sinn, 2022; Albrizio et al., 2023; Auclert et al., 2023; Moll et al., 2023; Di Bella et al., 2024). 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 L. 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.

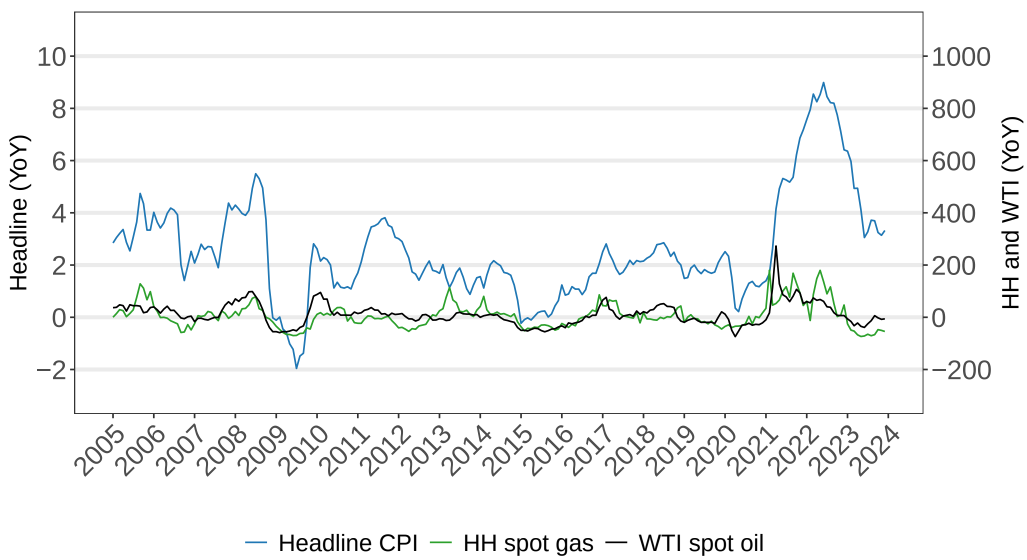
Moreover, this study also relates to the literature on the pass-through of energy shocks to inflation, which, once again, has primarily focused on oil price shocks in the United States. Existing estimates suggest that while energy price shocks have a strong impact on headline inflation, their effect 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 3% for both demand and supply shocks. Notably, supply shocks also affect core inflation, with a peak pass-through of almost 2%. Our findings indicate that gas price shocks, have played a central role in the post-pandemic inflation surge in the Euro Area, whereas oil price shocks have played a more prominent role in the United States. 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 remainder of the paper is structured as follows. Section 2 provides key background on the gas markets. Section 3 details our identification strategy for supply and demand shocks to the price of gas. Section 4 outlines the econometric framework and estimation approach. Section 5 discusses the main empirical findings. Finally, section 6 concludes. Several appendices follow, with additional details on the data, the Bayesian estimation framework, supplementary empirical results, and sensitivity analyses.



Euro Area



United States

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 key characteristics of the natural gas markets in the Euro Area and the United States, emphasizing important regional differences. These distinctions motivate the use of a region-specific approach to analyzing gas price shocks and provide the foundation for our empirical strategy. Additional supporting figures and tables are provided in Appendix B.

Natural gas is a critical energy source, accounting for about one quarter of total energy consumption in both the Euro Area and the United States (see Figures B19 and B20 in the Appendix). 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 natural gas demand — 35% in the Euro Area and 22% in the United States — primarily for heating purposes.[1] For a detailed breakdown of natural gas consumption by end use, see Figure B21 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.

While the demand side of the natural gas market is broadly comparable across the two regions, the supply side exhibits substantial differences. In the Euro Area, natural gas supply relies overwhelmingly on imports rather than domestic production. Monthly domestic output has fallen to negligible levels—below 100 petajoules (PJ) in recent years—reflecting a steady decline over time. As a result, import dependence has risen sharply, increasing from around 50% of total consumption in the early 1990s to a peak of 90% by 2019. Illustrative trends are shown in Figure B22 in the Appendix. The region sources gas from a select group of major suppliers, including Russia (at the time of writing), Norway, Algeria, and the United States (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).[2] The United States has progressively become a

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

[2] 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

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 B23 and in Figure B24 in the Appendix. As a result, natural gas prices in the United States display lower volatility compared to those in the Euro Area, but remain responsive to disruptions in domestic production. Exogenous domestic disturbances can be leveraged through high-frequency identification methods to examine the effects of supply shocks.

The global natural gas market remains regionally segmented, primarily due to supply-side constraints and limited fungibility. As a result, prices for the same commodity can diverge significantly across regions, even amid the expansion of global LNG trade. This stands in contrast to the crude oil market, which is more globally integrated and typically exhibits relatively uniform pricing across regions.[3] 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 differences in regional gas supply balances and limited fungibility arising from infrastructure dependencies, such as pipeline networks and terminal capacity. 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). This degree of market segmentation underscores the need for a region-specific analysis of gas price shocks, starting with the identification of the regionally relevant price benchmarks.

The United States 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]

from tight shale formations.

[3]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).

[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

While full liberalization of the European gas market remains incomplete (Cardinale, 2019; ACER, 2022), regional integration has nonetheless advanced significantly and has been a defining feature of the market for over two decades. 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 Point (NBP), was created in the United Kingdom in 1996.

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 B26 and Table B4 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 B27 and B28, as well as in Table B4 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 United States. 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 motivate a region-specific empirical strategy for analyzing the macroeconomic effects of gas price shocks. In the Euro Area, the heavy reliance on imports and the prevalence of supply disruptions justify identifying supply shocks through

operational.

high-frequency fluctuations in futures prices triggered by disruptions in import flows. In contrast, in the United States—where domestic production is the dominant source of supply—supply shocks can be identified based on disruptions to domestic production. On the demand side, the widespread use of natural gas for heating, coupled with its strong sensitivity to temperature variation, provides a basis for identifying shifts in demand. Taken together, the presence of different reference prices across regions, along with varying market structures, underscores the need for a region-specific approach to analyzing natural gas price shocks. Regarding the choice of price benchmarks, the Henry Hub price serves as an effective proxy for natural gas prices in the United States, reflecting its role as the primary reference point for domestic gas markets. Similarly, in the Euro Area, the Title Transfer Facility has become the key benchmark due to its high liquidity and prominence in trading activity. While LNG has grown in importance, the TTF remains a reliable proxy for overall gas prices in the Euro Area, as its increasing integration with LNG markets has strengthened the correlation between LNG and TTF spot prices. Moreover, the growing role of hub-based pricing mechanisms further supports the TTF's suitability as the region's benchmark 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.[6] 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

[6] 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.

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 technical issues.[7] 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 C29 and C30 in the Appendix.

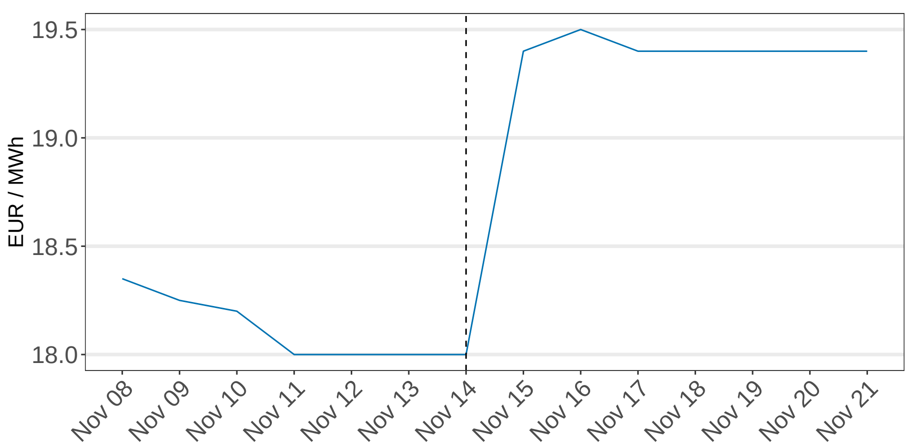


Figure 2: *Unexpected drop in gas flows from Norway through the Langeled pipeline*

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.

[7] 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.

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. 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 C31 in the Appendix. A selected illustrative sample of our news collection is presented in Table C5.

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.[8]

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

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

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 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,[9] which is then rescaled to match the standard deviation of the underlying surprises.[10] 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,[11] 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.

[9]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.

[10]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.

[11]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.

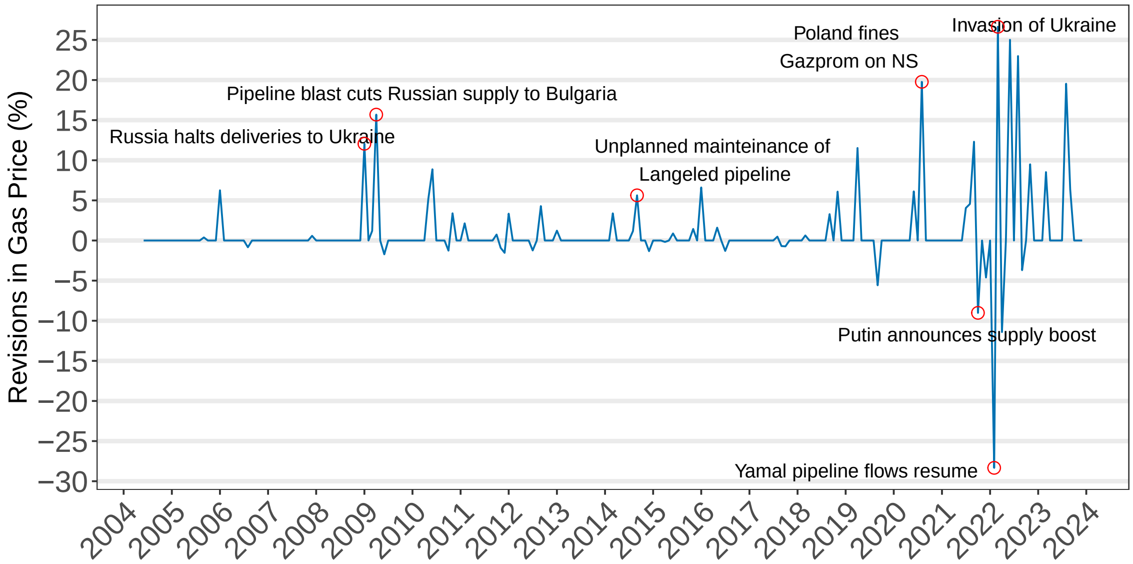


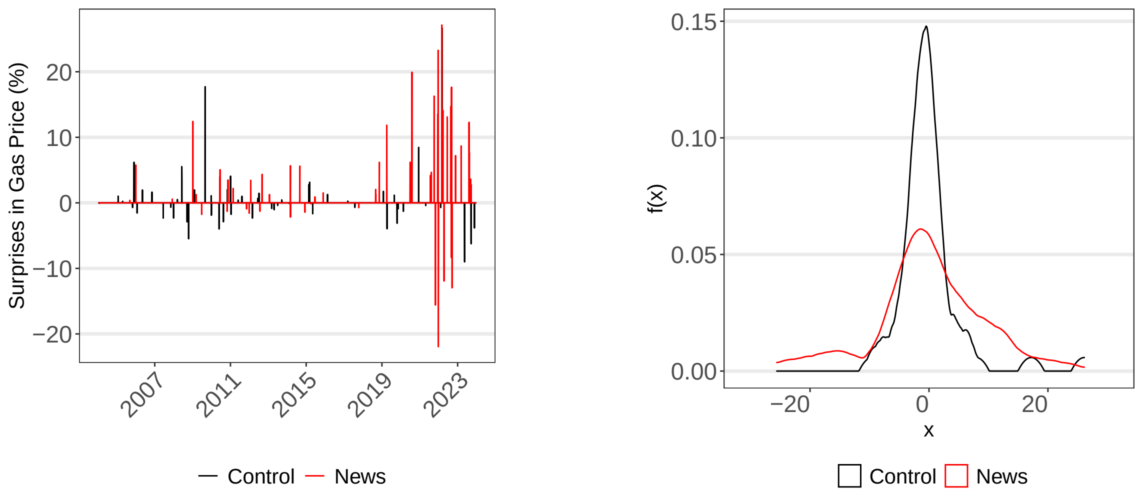
Figure 3: *Euro Area gas supply surprise series*

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.

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 that surprises on news days display higher variance and fatter tails (right panel). This suggests that the presence of background noise is limited. Appendix C.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



Daily surprises

PDF

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).

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 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 K.3.

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 monthly 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. Formally, this monthly temperature index $TI_{y,m}$ is computed as

$$TI_{y,m} = \begin{cases} 0, & \text{if } \left|\left(\mathcal{T}^{SA}_{y,m}\right) - \mu_{\mathcal{T}}\right| \leq \sigma_{\mathcal{T}} \\ \mathcal{T}^{SA}_{y,m}, & \text{otherwise} \end{cases} \tag{3}$$

with

$$\mathcal{T}^{SA}_{y,m} = \frac{1}{D_m} \sum_{d=1}^{D_m} \left(\mathcal{T}_{y,m,d} - \overline{\mathcal{T}}_m\right) \text{ [12]}$$

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 D.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]

[12] Here $\mathcal{T}_{y,m,d}$ denotes the average temperature on day d of month m and year y, and $\overline{\mathcal{T}}_m$ is the long-run average temperature for calendar month m, computed across all years in the sample. The number of days in month m is denoted by D_m. The terms $\mu_{\mathcal{T}}$ and $\sigma_{\mathcal{T}}$ represent the means and standard deviations of the monthly seasonally adjusted temperature series, computed across all years in the sample.

[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 K, this decision does not materially affect our results.

[14] Temperature forecasts deteriorate significantly as the forecast horizon extends, remaining rela-

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 pri-

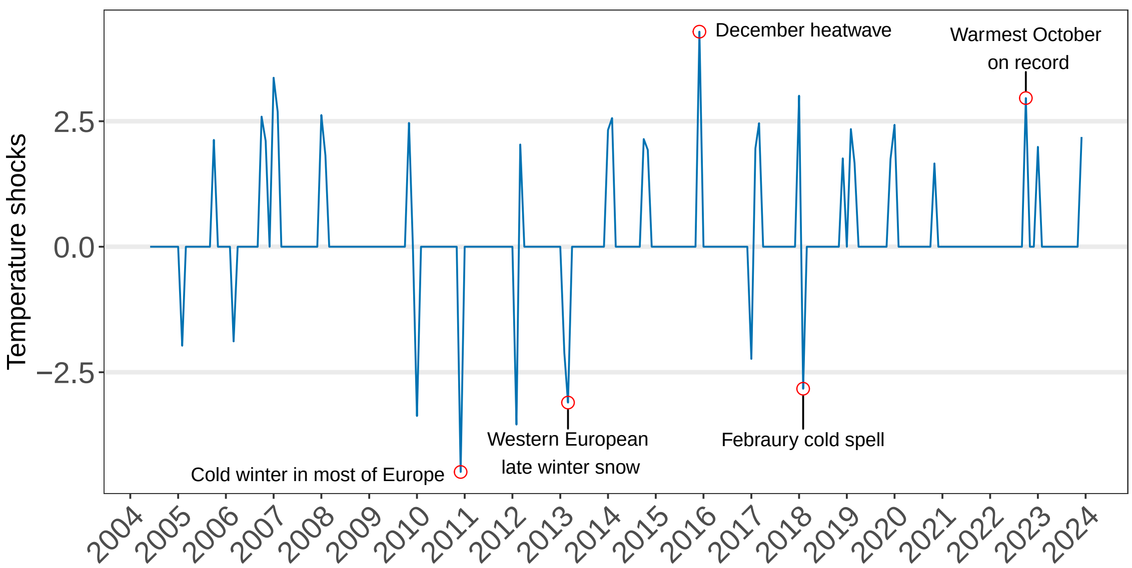


Figure 5: *Temperature proxy series for Europe*

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.

tively unreliable even with the most advanced prediction methods. See, for example, Lopez-Gomez et al. (2023). In Figure D37 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 D40 in the Appendix.

mary 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 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 decision 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 K, 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 C34 in the Appendix.

4 Econometric Framework

Consider the following structural VAR(p) model:

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{w}_t, \tag{4}$$

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:

[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 D38 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.

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

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

$$\begin{aligned} \mathbf{y}_t &= \mathbf{B}_0^{-1}\mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_0^{-1}\mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{B}_0^{-1}\mathbf{w}_t \\ &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \end{aligned} \tag{5}$$

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.5.

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

$$\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t. \tag{6}$$

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 using the high-frequency instrument and a gas demand shock using the temperature-based instrument.

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:

$$\mathbb{E}[z_t w_{1,t}] \neq \mathbf{0} \tag{7}$$

$$\mathbb{E}[z_t \mathbf{w}_{2:K,t}] = \mathbf{0} \tag{8}$$

where $\mathbf{w}_t = (w_{1,t}, \mathbf{w}_{2:K,t}')'$. Given these moments conditions,[20] and using the par-

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

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

titions $\mathbf{b}_1 = (b_{1,1}, \mathbf{b}'_{2:K,1})'$ 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

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

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 squares procedure as follows:

1. First stage:[21]

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

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 (16):

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \tilde{\mathbf{B}}_0^{-1}\tilde{\mathbf{w}}_t \tag{9}$$

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

$$\tilde{\mathbf{B}}_0^{-1} = \mathbf{B}_0^{-1}\mathbf{\Sigma}_w^{1/2} \tag{11}$$

Alternatively, one may use $\mathbf{\Sigma}_{\boldsymbol{w}} = \mathrm{diag}(\sigma^2_{w_1}, \ldots, \sigma^2_{w_k})$ and normalize by setting $b_{1,1} = c$, which implies that a unit value of $w_{1,t}$ has a positive effect of magnitude

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

c on $y_{1,t}$. In presenting the impulse response functions in Section 5, we adopt 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:

$$q_t^d = \alpha_{qp}^d p_t + \mathbf{x}'\boldsymbol{\beta}_d + w_t^d, \tag{12}$$
$$q_t^s = \alpha_{qp}^s p_t + \mathbf{x}'\boldsymbol{\beta}_s + w_t^s, \tag{13}$$

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]

Given the demand and supply instruments constructed as described in Section 3, we are able to estimate the key parameters of interest, α_{qp}^d and α_{qp}^s. 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

[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 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:

$$Q_t^d = Q_t^s - M_t + X_t - \Delta I_t$$

Finally, we define $q_t^s = \log(Q_t^s)$ and $q_t^d = \log(Q_t^d)$.

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 (9) through (11). It follows that[23]

$$\tilde{\mathbf{B}}_0 = (\tilde{\mathbf{B}}_0^{-1})' \mathbf{\Sigma}_{\boldsymbol{u}}{}^{-1}, \tag{14}$$

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 $\mathbf{\Sigma_w}{}^{1/2}$.[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, so that the α_{qp} coefficients correspond to the percentage change in quantity resulting from a 1% increase in price.

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 identification via instruments.

5 Results

This section presents the empirical results for the Euro Area and the United States. We begin by estimating the short-run elasticities of gas demand and supply. We then examine the impulse response functions, emphasizing the macroeconomic effects of gas price shocks and the key transmission channels that account for differences across shock types and regions. To inform the debate on the economic consequences of a disruption in Russian gas supply, we extend our baseline specification to assess the sectoral impact of gas supply shocks on both prices and quantities in the Euro Area and evaluate the extent to which gas price shocks can generate significant real effects. Finally, we quantify the contribution of gas price shocks to the recent post-pandemic surge in inflation.

For all specifications, the estimation sample spans from 2004M1 to 2023M12.[25]

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

[25] 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

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 eight variables: the real price of natural gas, gas quantity supplied, gas quantity demanded, gas inventories, the headline consumer price index, industrial production, financial volatility, and the real price of crude oil.[26][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 interpreted as percentage changes. 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 B.1.

Figures 8 to 12 present the impulse response functions derived from our main specification. Black lines correspond to responses for the Euro Area, while orange lines represent those for the United States. Shaded areas denote the 68%, 80%, and 90% confidence intervals. For ease of comparison, the left panels show the effects of a gas demand shock, while the right panels display the responses to a gas supply shock. The same set of responses, grouped together, is provided in Appendix H. Figures 14 to 16 extend this baseline specification for the Euro Area by incorporating sectoral variables. Appendix K demonstrates that our results are robust across several dimensions, including sample, instrument construction, and estimation strategy. Regarding instrument construction, we show that the supply instruments are informationally robust, that the high-frequency proxies constructed as proposed by Kilian (2024) yield similar results, and that excluding summer months from the demand instrument—particularly in the case of the United States—does not materially affect our findings. With respect to the estimation strategy, we confirm robustness to extending the sample period where possible, implementing an internal instrument approach (Ramey, 2011; Plagborg-Møller & Wolf, 2021), estimating using Local Projections (Jordà, 2005), and estimating without Bayesian priors. Standard diagnostic tests do not indicate a weak instrument problem.[28]

Appendix, extending the sample period for the United States does not materially affect our results.

[26] Gas demand is defined as the sum of domestic consumption and exports, capturing the total quantity of natural gas demanded within the region. Gas supply is defined as domestic production plus net imports, representing the total quantity available for use in a given month (see Section 4.2).

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

[28] 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 C35 in the Appendix). Nonetheless, we also report the first-stage F-statistics that would result from estimating the same specification using a frequentist approach, where the demand instrument instruments quantity demanded and the supply instrument instruments the real price of natural gas. For the Euro Area, the F-statistic and robust F-statistic are 16.16 and 11.50 for supply, and 105.45 and 88.42 for demand, respectively. For the United States, the corresponding values are 10.75 and 13.09 for supply, and 94.74 and 101.04 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).

5.1 Gas demand and supply elasticities and price volatility

Using the strategy described in Section 4.2, we estimate the short-run price elasticities of natural gas. For the Euro Area, the demand elasticity is -0.11 and the supply elasticity is 0.76; for the United States, the corresponding estimates are -0.05 and 0.33, respectively. Table F8 in the Appendix reports previous estimates of short-run elasticities of natural gas demand and supply based on autoregressive models. Most previous studies adopted the identification strategy developed by Baumeister and Hamilton (2019) for the crude oil market. Our estimates, which exploit external exogenous variation, are broadly consistent with the existing literature, though we find lower demand elasticities and higher supply elasticities relative to earlier studies. The implied demand and supply curves based on our estimates are illustrated in Figure 6.

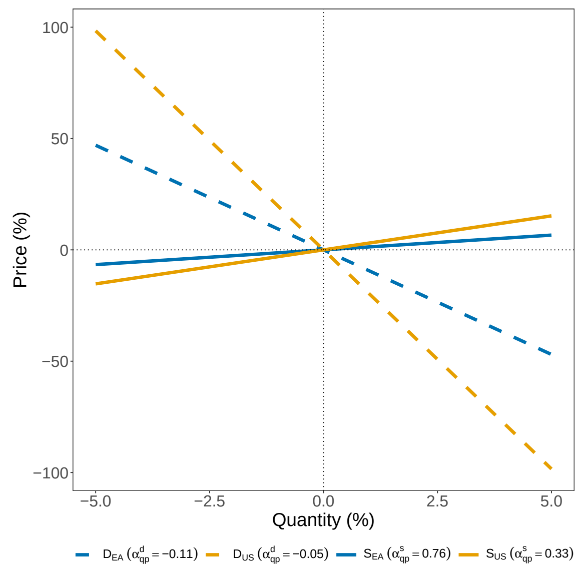


Figure 6: *Short-run gas demand and supply curves*

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 illustrative purposes, supply and demand quantities are equated in the figure; this simplification does not affect the estimated slope coefficients.

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 find 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 section demonstrates, the IRFs exhibit a more muted response of quantities after a 1% price increase, primarily due to the buffering role of gas inventories.

Region	Shock	$h = 1$	$h = 6$	$h = 12$	$h = 18$	$h = 24$
Euro Area	Gas supply	46.8	38.5	36.0	34.5	33.2
	Gas demand	19.0	19.1	23.4	24.2	24.2
United States	Gas supply	68.6	32.5	23.3	21.1	19.8
	Gas demand	14.5	23.3	22.9	21.8	22.2

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

Figure 7 presents the cumulative historical contributions of gas demand and supply shocks to the real price of natural gas, alongside the observed series. The identified shocks account for a substantial share of the observed price dynamics, with the combined contributions closely tracking the realized series. Consistent with the previous findings, gas supply shocks explain a larger portion of the variation in gas prices. 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. Nonetheless, unexpected temperature fluctuations have also played a role in driving price spikes, such as during the March 2013 late snow event in Western Europe and the exceptionally cold February of 2018, both of which were associated with sharp increases in gas prices. Figure G43 in the Appendix presents the corresponding historical decomposition for the United States. Similar conclusions hold, though with an important distinction: due to the lower supply elasticity, gas demand shocks account for a larger share of the realized price dynamics in the United States relative to the Euro Area. This pattern is also reflected in the forecast error variance decomposition at longer horizons.

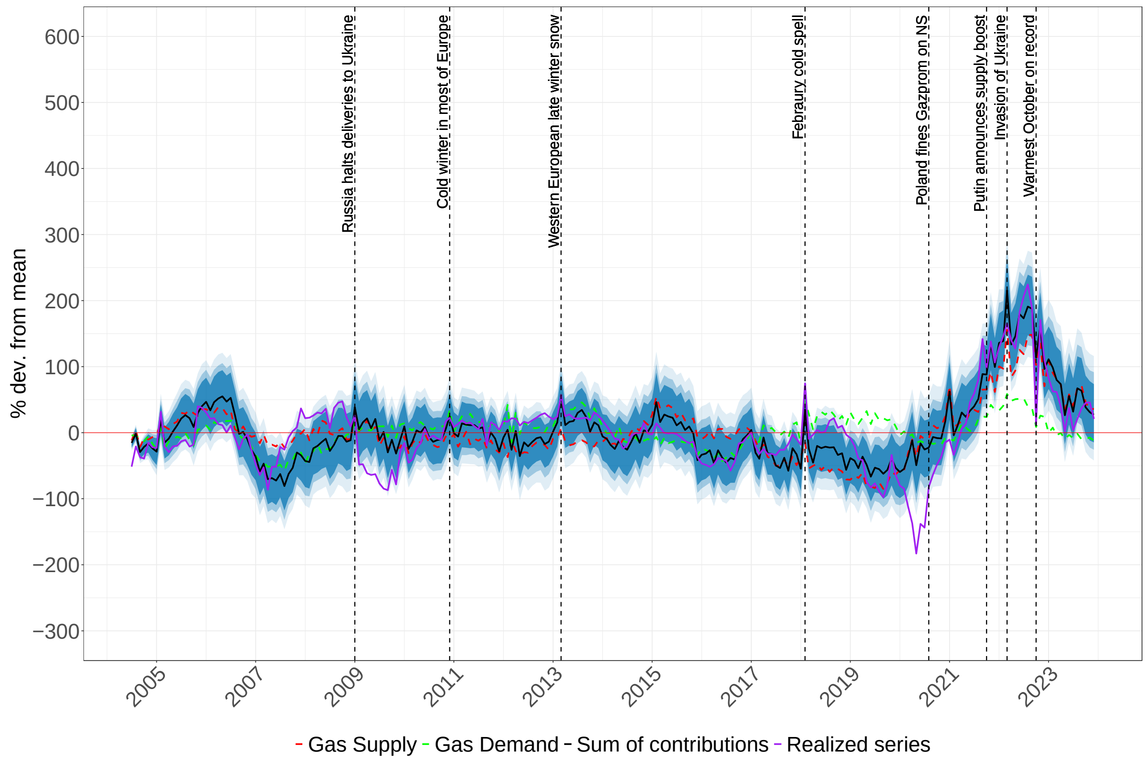


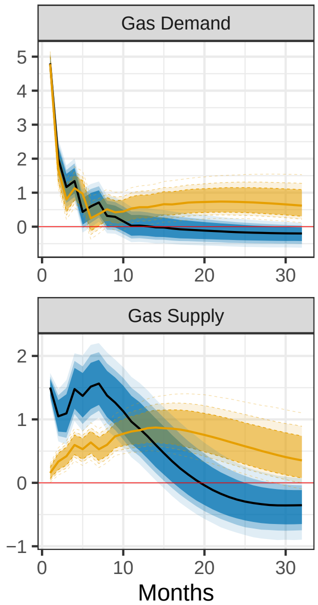
Figure 7: *Euro Area: historical decomposition of the real price of natural gas*

Notes: This figure illustrates the estimated contributions of gas supply shocks (red dashed line) and gas demand shocks (green dashed line) to the real price of natural gas, along with their combined contribution (solid black line with blue confidence bands). All contributions are expressed as percentage deviations from the mean. The realized real gas price series is shown in purple. 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 2022M10.

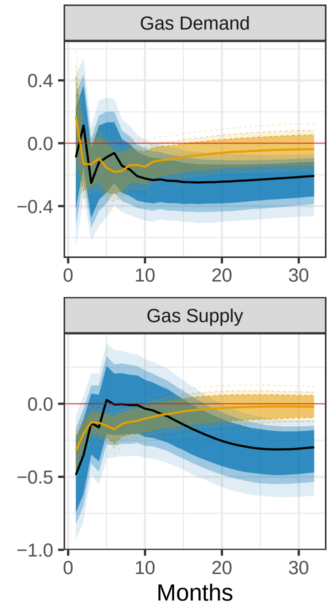
5.2 Impulse-response analysis

We now present the impulse-response functions resulting from the baseline specification, identified using the external instruments approach. All responses are normalized to a one-time 10% increase in the real price of natural gas.

Responses of gas quantities. Figure 8 presents the estimated dynamic response of quantities supplied and demanded. In both regions, a 10% increase in natural gas prices is triggered by a 5% rise in quantity demanded (top left panel), whereas a reduction in quantity supplied of just 0.5% is sufficient to generate the same price response (bottom right panel). This asymmetry is consistent with our estimated short-run elasticities, which indicate that demand is relatively more rigid to price changes than supply.



Gas Demand Shock



Gas Supply Shock

Figure 8: *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.

Following a 10% price increase induced by a demand shock, supply reacts sluggishly in the United States, with a dynamic response estimated to be just above zero on impact, gradually increasing to approximately 1% after about a year. In contrast, supply in the Euro Area responds faster, with an estimated increase of around 1.5% (see bottom left panel). 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 I46 in the Appendix).

In the Euro Area, the response of quantity demanded is estimated to be zero on impact, with statistically significant adjustments of up to -0.2% emerging only after approximately one year. In contrast, demand in the United States exhibits a faster adjustment, reaching a comparable magnitude within five months before returning to its baseline level within a year (see top right panel of Figure 8). 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 quantity adjustments 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.[29] 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 I47 in the Appendix confirm significant interfuel substitution in the United States following a gas supply shock, with oil as the primary alternative. In contrast, the Euro Area exhibits a more limited degree of interfuel substitution, with coal serving as the main substitute.[30] Differences in taxation regimes could also help explain the disparities in the timing of adjustment of gas quantity demanded. 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

[29] 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).

[30] 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).

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 States (OECD, 2019). The greater prevalence of specific taxes in the Euro Area partly insulates end-users from fluctuations in spot prices. These structural differences between the two regions help explain the relatively slower adjustment of quantity demanded in the Euro Area, both in its initial decline and in its return to baseline.

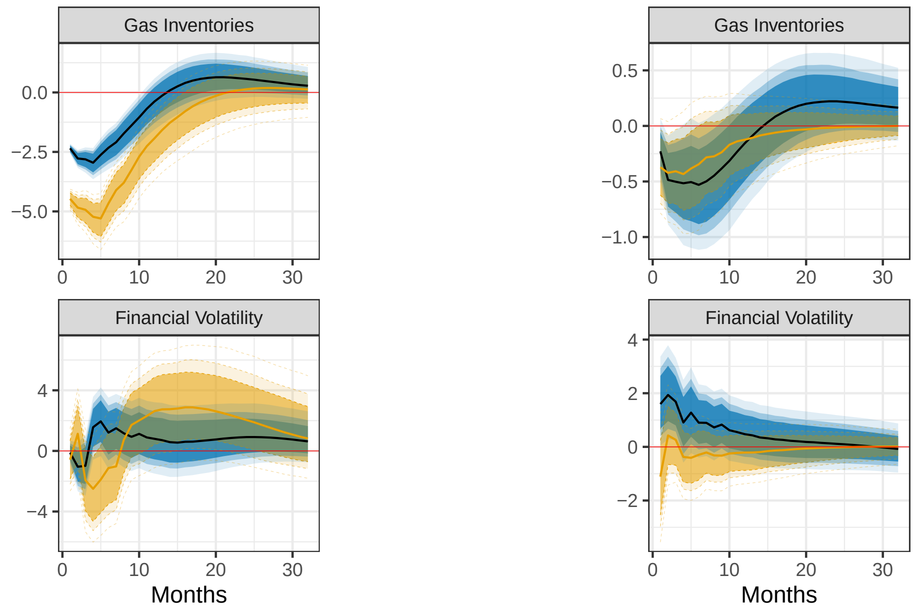
Overall, the impulse responses are broadly consistent with the estimated structural elasticities reported in the previous subsection. A notable difference, however, is that gas supply appears to react more under *ceteris paribus* conditions than observed in the dynamic responses. This discrepancy reflects the role of gas inventories, which act as a buffer in the presence of price shocks, thereby mitigating the need for large supply adjustments. In contrast, under *ceteris paribus*—where inventories are held fixed—supply must adjust more to accommodate the shock.

Inventories, volatility and uncertainty channel. As shown in the top-left panel of Figure 9, 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 B3 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.[31] 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. 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 9). Similarly, Känzig (2021a) documents

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

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 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

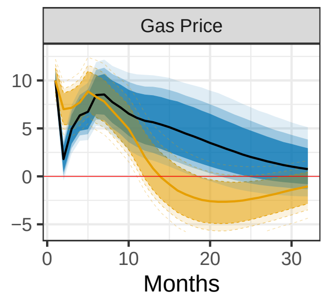
Gas Supply Shock

Figure 9: *Impact on gas inventories and financial volatility*

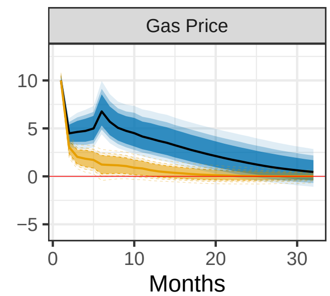
Figure I48 in the Appendix presents an alternative specification in which the European gas supply instrument is constructed using only news related to events that, at the time of the release, had not yet materialized but were only expected to occur in the future. As a result, quantity supplied does not decrease on impact but only after several months. Consistent with this 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 10 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 we discussed. 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 comparatively earlier following a supply shock. 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. Notably, the natural gas price remains elevated even after the impacted quantities return to their baseline levels: as shown in Figure 8, the responses of gas demand to a demand shock and gas supply to a supply shock exhibit limited persistence.



Gas Demand Shock



Gas Supply Shock

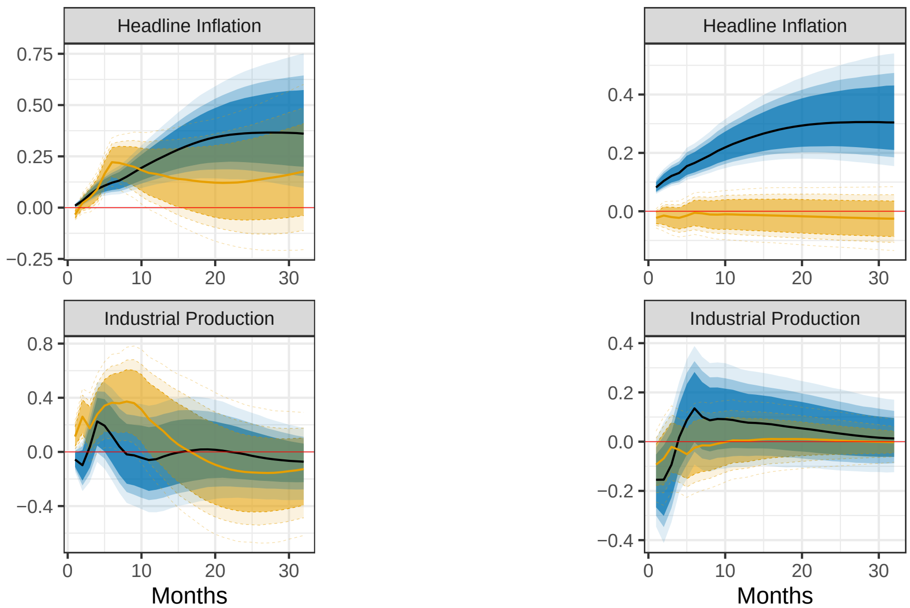
Figure 10: *Persistence of spot price responses*

Macroeconomic propagation. Figure 11 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 on impact. In contrast, in the United States, supply shocks have no significant impact, whereas gas demand shocks lead to peak increases of approximately 0.4% in industrial production and 0.25% 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.[32] In the Euro Area, demand shocks lead to a persistent inflationary pass-through, with effects reaching approximately 3.5% after nearly two years. In contrast, supply shocks generate a more rapid pass-through, though inflation similarly peaks at around 3.5%. These inflationary effects largely mirror spot price dynamics, which show more persistence in the Euro Area than in the United States, where only demand shocks have a lasting impact (see again Figure 10).

A notable finding is the strong inflationary effect of gas supply shocks in the Euro Area, which contrasts with their relatively muted and short-lived impact on industrial production. While the uncertainty and volatility channel discussed earlier contributes to greater inflation persistence (Boeck et al., 2023), we further examine how gas supply shocks propagate through the economy. The next subsection presents a sectoral analysis, and we briefly preview its key insights here to contextualize the

[32]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).

aggregate results. We find that the modest decline in aggregate output is primarily driven by a few energy-intensive industries, such as electricity, gas, steam, and chemicals, where natural gas constitutes a major input. In contrast, most other sectors exhibit only small or statistically insignificant responses, suggesting that cascading effects are limited. By contrast, the impact on prices is broad-based, with price responses generally occurring more rapidly for goods than for services.



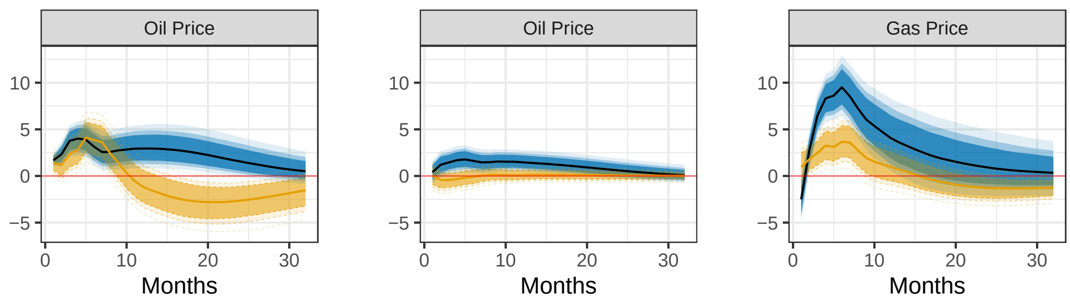
Gas Demand Shock

Gas Supply Shock

Figure 11: *Propagation to the macroeconomy*

One prominent channel behind the inflationary effects in the Euro Area is the pass-through from gas prices to electricity prices. Our results indicate an almost one-to-one pass-through, consistent with the view that the merit-order pricing mechanism in European electricity markets amplifies upstream energy price shocks (Baget et al., 2024). Another factor contributing to the limited real effects and pronounced inflationary response is the extent to which firms are able to pass cost increases downstream. When firms can adjust prices quickly in response to rising input costs, prices increase with minimal reductions in output—particularly when demand is relatively inelastic. Figure I49 in the Appendix shows the response of the producer price index to a gas supply shock. The figure illustrates that a substantial portion of cost increases is passed along the supply chain, although the pass-through is incomplete and occurs with a delay. Notably, consumer prices remain elevated even after prices for intermediate goods begin to decline. This pattern supports the interpretation that significant output losses are concentrated in sectors facing substantial cost increases but with limited ability to adjust prices in the short term.

Gas and oil markets interrelation. Figure 12 compares how real gas and oil prices respond to shocks in the oil and gas markets, respectively.[33] 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.[34] In the Euro Area, gas price changes pass through to oil prices by approximately 25-40% 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.



Gas demand shock | Gas supply shock | Oil supply shock

Figure 12: *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 E41 in the Appendix.

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 American market remains only partially integrated.[35] As a result, when a 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 shock originating in the United States.

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 &

[33] To identify the oil price shock, we employ the instrument developed by Känzig (2021a), within our baseline specification.

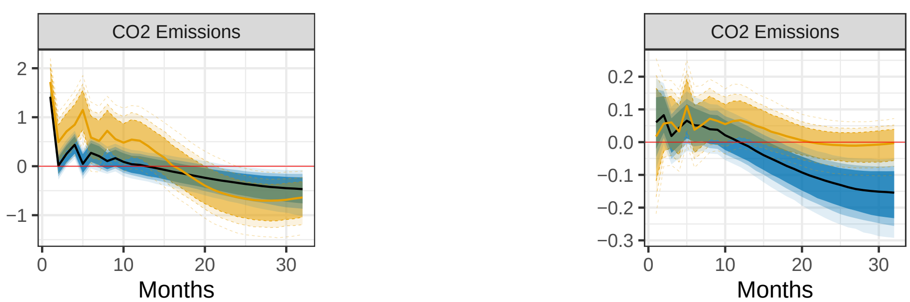
[34] Note, for example, that the dynamics of the Brent (reference for Euro Area) and WTI (reference for United States) crude oil prices are very similar.

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

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. In the context of inter-fuel substitution within the power generation sector—a major contributor to global carbon emissions (IPCC, 2022)—we showed that natural gas is primarily replaced by other, more polluting fossil fuels (see again Figure I47 in the Appendix). To more directly evaluate the environmental consequences of gas price shocks, we draw on CO_2 emissions data from the EDGAR (Global Greenhouse Gas Emissions) database.

Figure 13 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 1.5% 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 0.1% in both the Euro Area and the United States. As natural gas becomes more expensive, it is increasingly substituted with higher-emission fuels.



Gas Demand Shock

Gas Supply Shock

Figure 13: *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 are associated with increases in carbon emissions. Over the longer term, however, the effects may differ. For instance, Stock and Zaragoza-Watkins (2024) show that sustained increases in gas prices—such as those observed in the United States due to rising LNG exports—can have effects similar to those of a carbon tax by accelerating the transition to cleaner energy sources and reducing 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).

5.3 Sectoral effects of a gas supply shock in the Euro Area

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 14. 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 again Figure 10), 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 10% after 12 months. The inverted U-shape of these responses highlights the gradual adjustment 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 baseline levels. 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 8% 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

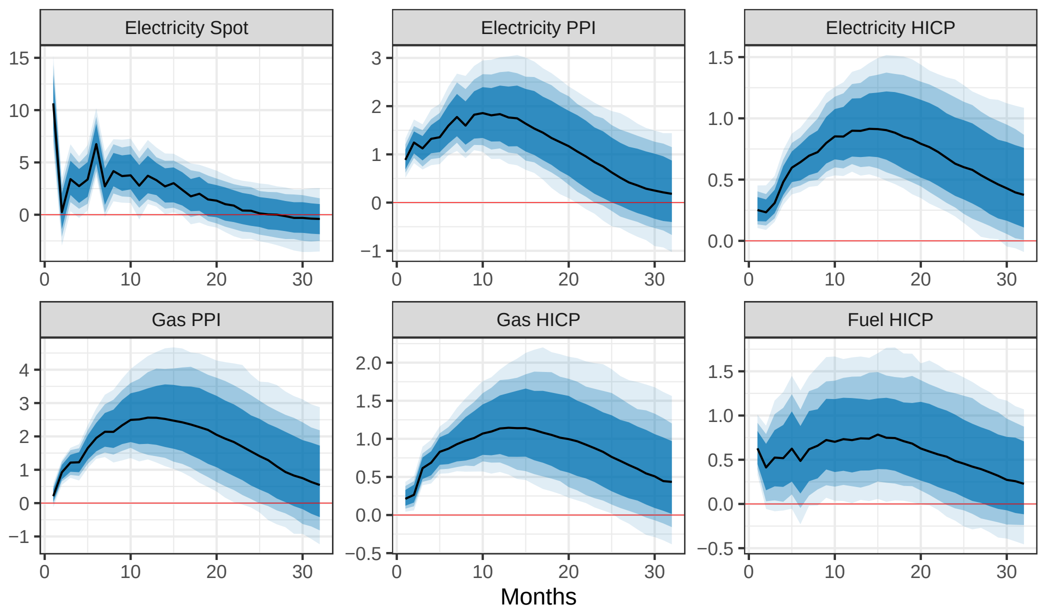


Figure 14: *Euro Area: Energy prices responses to a gas supply shock*

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

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 prices. Figure 15 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 1.8%—about half of the headline inflation peak depicted in Figure 11. 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 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. This impact tends to be stronger compared to the one observed for services, such as education, healthcare, and, to some extent, restaurants and hotels. The effects on services are generally more subdued and emerge gradually over several months.

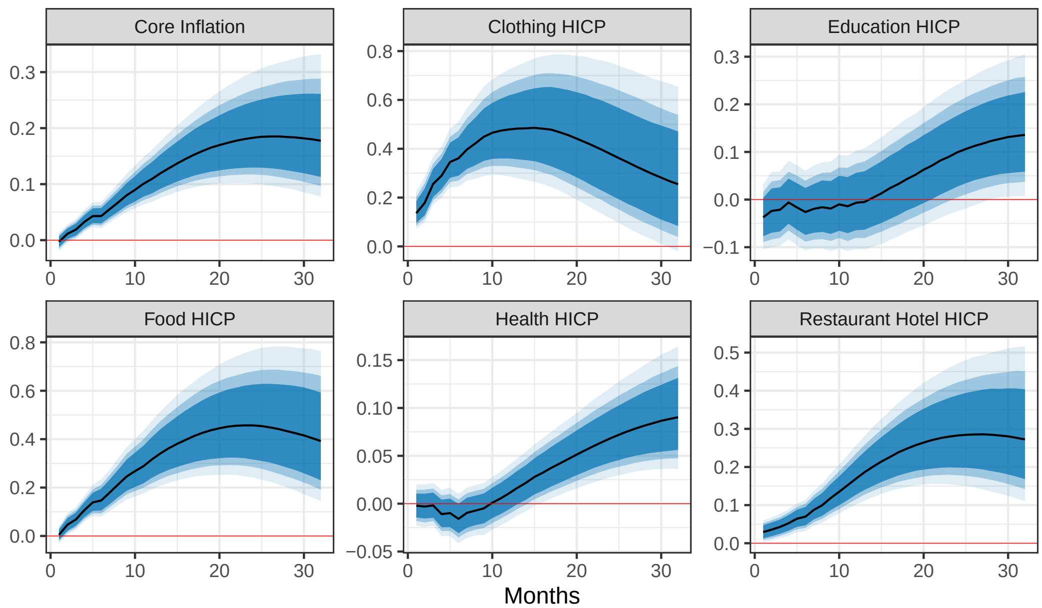


Figure 15: *Euro Area: Responses of core inflation and HICP 2-digit sectors to a gas supply shock.*

These sectoral impacts reflect both direct effects through energy costs and indirect effects through supply chain linkages. Direct effects occur in sectors where energy constitutes a significant cost factor, such as clothing and transport (see again Figure 14, Fuel HICP), where the impact of higher gas prices is felt quickly. 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, 2023). This results in a more gradual price adjustment. Finally, service sectors tend to experience only mild effects after an extended period, driven by broader inflationary pressures.

Sectoral effects on quantities. In Figure 11, we demonstrated that, in the Euro Area, the macroeconomic impact of gas supply shocks is primarily inflationary, while the effects on real economic activity are modest and largely concentrated in the initial months following the shock. Figure 16 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.[36] 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.

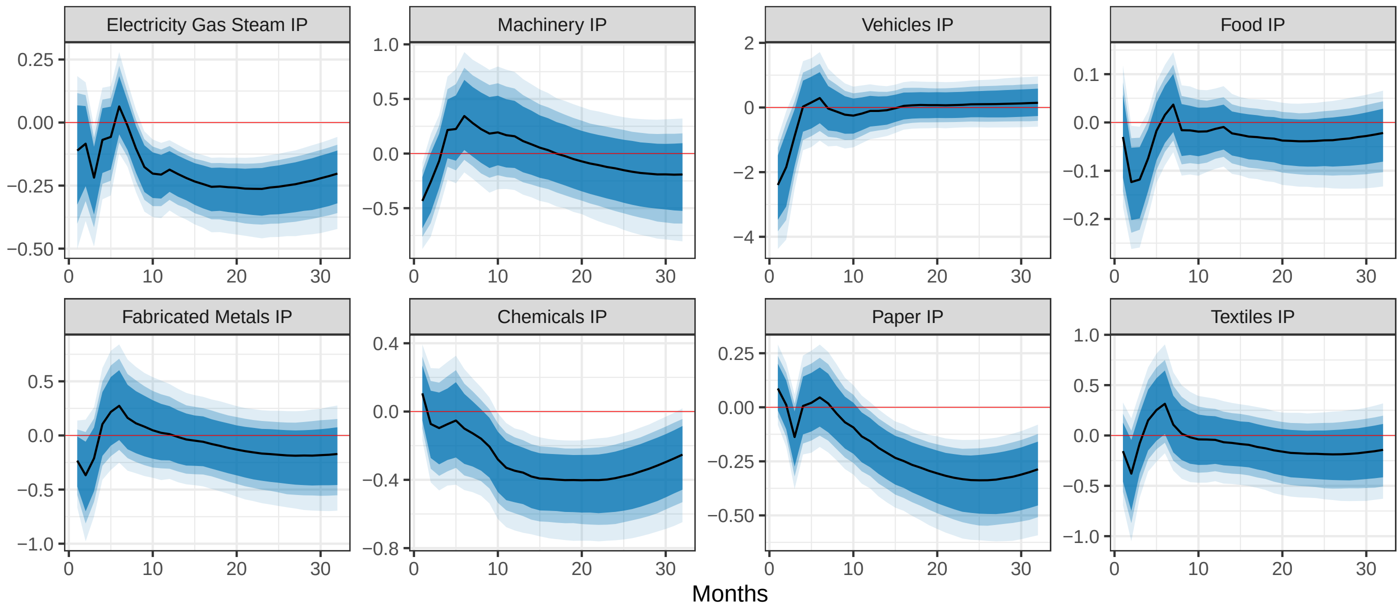


Figure 16: *Euro Area: Responses of IP sectors to a gas supply shock*

Notes: Impulse responses to a gas supply shock in the Euro Area on selected sub-sectors, 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.

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. Another characteristic of these types of shocks is the sectoral heterogeneity of their impacts (Davis & Haltiwanger, 2001), which is also

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

evident in our findings. However, the fact that not all sectors are significantly affected suggests the absence of meaningful cascading effects, helping to explain the limited aggregate impact on overall production.

Real effects of gas supply shocks, Euro Area and Germany. We now turn more directly to the question of whether gas supply shocks can generate significant aggregate real effects. The Russian invasion of Ukraine in February 2022 exposed Europe's reliance on Russian energy imports and sparked an intense debate over the potential economic costs of a disruption in gas supply (Bachmann et al., 2022; Bundesbank, 2022; Gunnella et al., 2022; Lan et al., 2022; Sinn, 2022; Albrizio et al., 2023; Auclert et al., 2023; Moll et al., 2023; Di Bella et al., 2024). To study this question, we augment our baseline specification with national expenditure variables (GNE,[37] consumption, investment, and the unemployment rate. Since much of the discussion around the impact of a cutoff of Russian gas has focused specifically on Germany, we also estimate a Germany-specific version of the model. Figure 17 reports the relevant impulse responses for Germany and the Euro Area.

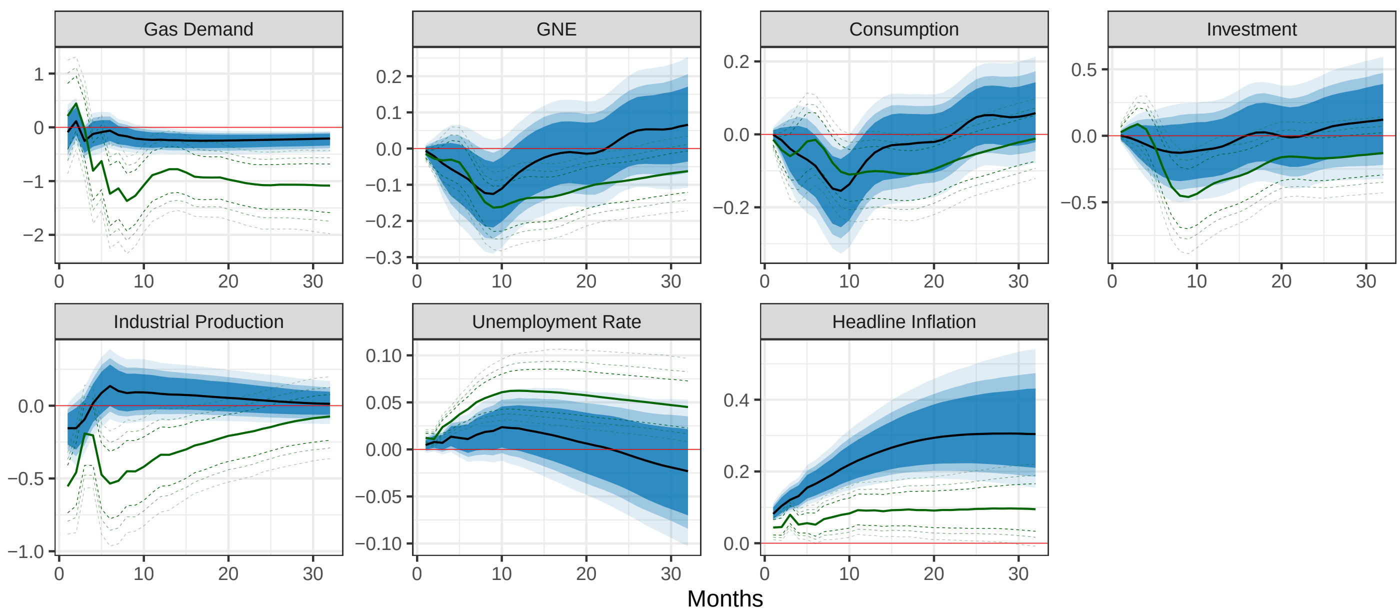


Figure 17: *Impulse responses to a gas supply shock: Euro Area (Black solid lines with blue shaded confidence bands) and Germany (green solid and dashed lines)*

Notes: GNE, consumption, and investment are originally measured at the quarterly frequency and interpolated to monthly using cubic spline interpolation. The estimated elasticity of gas demand is −0.20 for Germany and −0.11 for the Euro Area.

[37] As noted by Moll et al. (2023), Gross National Expenditure (GNE) is the welfare-relevant measure in this context, since GDP may not fully capture the terms-of-trade effects. However, the results for national expenditure should be interpreted with caution, as the data are originally available at a quarterly frequency and are interpolated to monthly values for the analysis.

Following a one-time increase in the real price of natural gas, the quantity demanded in Germany declines by up to 1%, with the response exhibiting strong persistence. In contrast, the reduction in demand for the Euro Area as a whole is smaller and less pronounced. Using the same identification strategy described in Section 4.2, we estimate a structural elasticity of demand of -0.20 for Germany, compared to -0.11 for the Euro Area. As shown by Moll et al. (2023), when the decline in natural gas consumption primarily reflects substitution toward alternative inputs or reductions in heating demand—without a substantial decrease in spending on other goods—real effects tend to be limited, and no significant cascading effects arise, as upstream energy-intensive industries do not transmit the shock downstream. In contrast, when substitution between natural gas and other domestic goods is limited, and the reduction in gas consumption reflects a decline in real income, knock-on effects can emerge through an aggregate demand channel, leading to significant output losses. This mechanism is amplified the more energy price increases result in a broader contraction in overall consumption (see, e.g., Auclert et al., 2023).

The responses observed for Germany are consistent with the latter mechanism, showing a lagged but significant reduction in expenditure, including sustained declines in both consumption and investment. These effects contribute to a contraction in industrial production and a rise in unemployment. This pattern helps explain why, despite experiencing only a relatively mild, one-quarter contraction during the winter of 2022–2023, Germany has since remained in a state of near-stagnation, with GDP growth hovering around zero. In comparison, the real effects for the Euro Area as a whole are similar in direction but more muted and short-lived, suggesting limited knock-on effects. In addition to the lagged effect, industrial production exhibits a short-lived decline on impact, observed in both Germany and the Euro Area. As shown in the previous subsection for the Euro Area, this immediate response reflects the heterogeneous supply-side impact across sectors, with energy-intensive industries reducing output due to their limited ability to pass through higher energy costs in the short term. However, the effect is not sufficiently pronounced to trigger broader cascading dynamics, and industrial production returns to baseline levels after a couple of months.

By contrast, existing literature finds that oil price shocks tend to exert a more pronounced effect on aggregate demand (see, e.g., Hamilton, 2009; Känzig, 2021a for the United States and Cai et al., 2022 for the Euro Area). This difference is likely due to the relatively smaller role of natural gas in total energy expenditures, which account for approximately one-quarter of spending on petroleum products (Moll et al., 2023).

5.4 Contribution of gas price shocks to the inflation surge

In the introduction, we noted that the surge in natural gas and broader energy prices coincided with rising inflation globally (see again Figure 1). This raises two related questions: To what extent did gas price shocks contribute to the post-pandemic inflation surge? And how can we reconcile the fact that inflation followed a similar path in the United States and the Euro Area, despite stark differences in the behavior of energy prices?

We provide a tentative answer to these questions through historical decompositions of headline inflation. Consistent with the evidence discussed in Section 5.2, Figure 18 shows that gas price shocks—particularly supply shocks—were a key driver of the 2021–2023 inflation surge in the Euro Area. In contrast, these shocks appear considerably less relevant in the United States. What, then, accounts for the inflationary pressures observed in the United States? A natural candidate, which we can evaluate within our baseline specification, is the role of oil price shocks—driven by global supply imbalances and heightened geopolitical uncertainty. Indeed, we find that oil shocks contributed more significantly to the inflation surge in the United States. Figure J50 in the Appendix presents the corresponding historical decomposition of headline inflation. At the same time, the greater contribution of gas supply shocks in the Euro Area helps explain why inflation peaked at higher levels there than in the United States.

Our findings suggest that energy-related supply shocks were a major contributor to the recent inflation surge, consistent with the conclusions of several recent studies (see, e.g., Benigno et al., 2022; Bańbura et al., 2023; De Santis, 2024). However, the fact that gas and oil shocks closely track the realized inflation series does not rule out the influence of other, potentially offsetting, factors. Other contributors to the inflation surge likely include persistent supply-chain disruptions—such as component shortages and logistical bottlenecks (Stiglitz & Regmi, 2023; De Santis, 2024)—as well as the surge in aggregate demand during the reopening phase (Giannone & Primiceri, 2024), and monetary policy shocks, as central banks responded to rising inflationary pressures through sharp adjustments in interest rates.

6 Conclusions

In this paper we proposed a novel identification strategy to separately identify demand and supply 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 and to present 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 price shocks exert significant macroeconomic effects in both the Euro Area and the United States, with notable regional differences driven by structural disparities in supply composition, demand elasticities, and market dynamics. Following a supply shock, 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. 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. In the case of Germany, however, our analysis shows that gas supply shocks have more significant real effects, which is consistent with the interpretation that the country's recent economic stagnation was, at least in part, a consequence of the disruption in Russian gas flows. Finally, we show that gas price shocks have been a major contributor to the recent inflation surge in the Euro Area, whereas their role has been considerably smaller in the United States.

Our findings highlight several important policy implications. First, strengthening energy security and enhancing the flexibility of energy use should remain central policy priorities. In the short term, resilience in the Euro Area can be improved by fostering partnerships with reliable and diversified trade partners, supporting joint procurement initiatives, and expanding strategic reserves. Another key takeaway is that, over the longer term, greater substitutability would allow economies to adjust more effectively in the face of future climate-related disruptions. Second, reforming electricity market design also warrants attention. Reducing the disproportionate influence of marginal pricing—where the most expensive energy sources set the market price—could help mitigate overall energy price volatility. Finally, our results suggest that price-based mechanisms alone may be insufficient to induce a sustained 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 toward renewables, thereby contributing to higher CO_2 emissions.

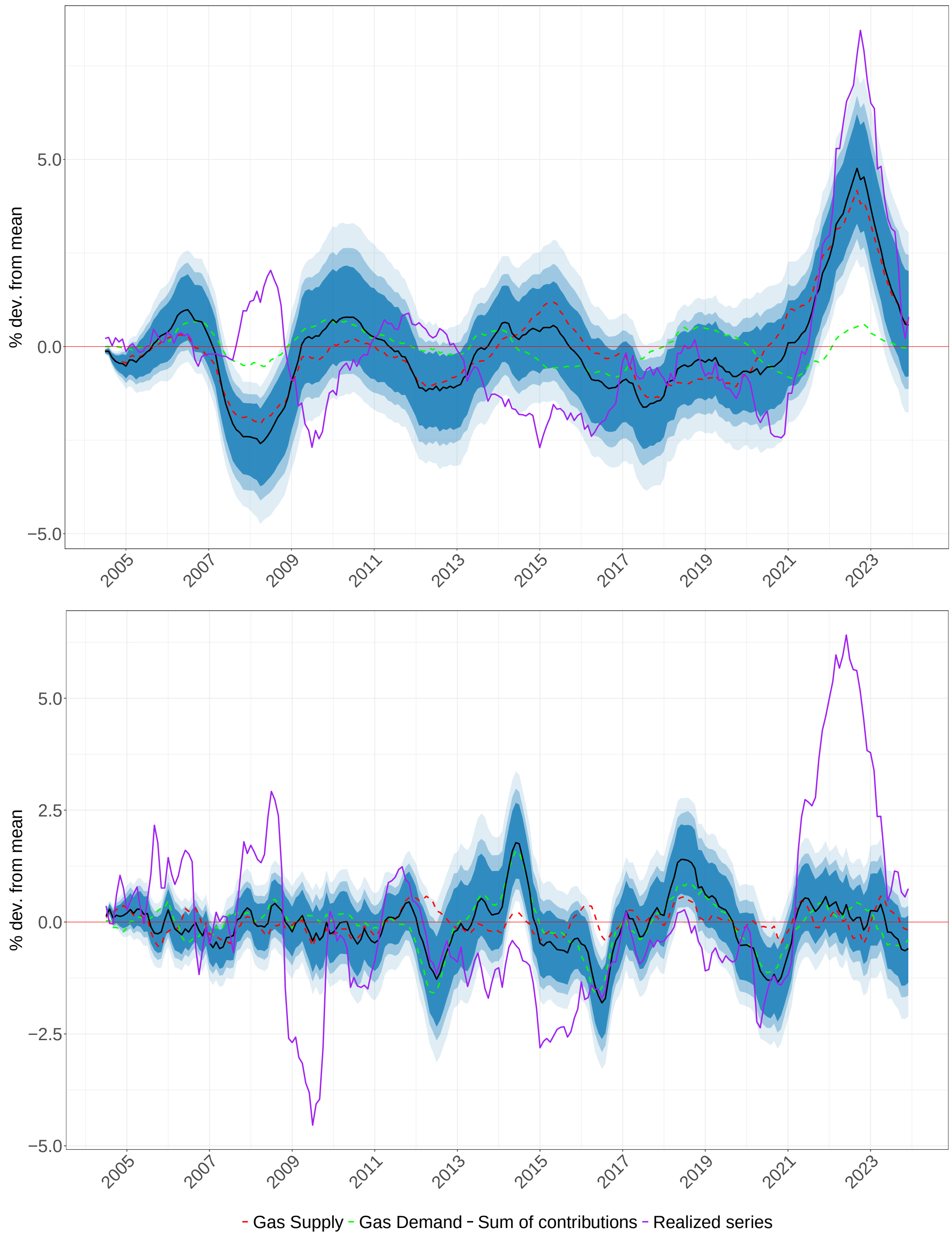


Figure 18: *Historical decomposition of headline inflation in the Euro Area (top panel) and the United States (bottom panel)*

Notes: This figure illustrates the estimated contributions of gas supply shocks (red dashed line) and gas demand shocks (green dashed line) to the year-on-year headline inflation rate, along with their combined contribution (solid black line with blue confidence bands). All contributions are expressed as percentage deviations from the mean. The realized headline inflation series is shown in purple.

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Online Appendix

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

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Contents

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A Econometric models

Consider the structural VAR(p) model:

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{w}_t, \tag{15}$$

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:

$$\begin{aligned}\mathbf{y}_t &= \mathbf{B}_0^{-1}\mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_0^{-1}\mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{B}_0^{-1}\mathbf{w}_t \\ &= \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t,\end{aligned} \tag{16}$$

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:

$$\mathbf{u}_t = \mathbf{B}_0^{-1}\mathbf{w}_t, \tag{17}$$

where the matrix $\mathbf{B}_0^{-1}$ has to be retrieved.

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 $\mathbf{w}_t = (w_{1t}, \ldots, w_{Kt})'$:

$$\frac{\partial \mathbf{y}_{t+h}}{\partial \mathbf{w}_t'} = \mathbf{\Theta}_h, \quad h = 0, 1, 2, \ldots, H \tag{18}$$

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

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

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

$$\mathbf{Y}_t = \mathbf{A}\mathbf{Y}_{t-1} + \mathbf{U}_t, \tag{19}$$

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}, h periods in the past, for $k = 1, \dots, K$, is given by $\mathbf{\Phi}_h = \left[\phi_{jk,h}\right] \equiv \mathbf{J}\mathbf{A}^h\mathbf{J}'$, 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 $\mathbf{\Phi}_h$:

$$\mathbf{y}_t = \sum_{h=0}^{\infty} \mathbf{\Phi}_h \mathbf{u}_{t-h} = \sum_{h=0}^{\infty} \mathbf{\Phi}_h \mathbf{B}_0^{-1}\mathbf{B}_0 \mathbf{u}_{t-h} = \sum_{h=0}^{\infty} \mathbf{\Theta}_h \mathbf{w}_{t-h}, \tag{20}$$

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

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

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

A.2 Forecast error variance decomposition

From equation (20), the h-step-ahead forecast error is given by

$$\mathbf{y}_{t+h} - \mathbb{E}_t[\mathbf{y}_{t+h}] = \sum_{s=0}^{h-1} \mathbf{\Theta}_s \mathbf{w}_{t+h-s},$$

with forecast error variance:

$$\mathbf{\Sigma}_h \equiv \mathbb{E}_t\left[(\mathbf{y}_{t+h} - \mathbb{E}_t[\mathbf{y}_{t+h}])(\mathbf{y}_{t+h} - \mathbb{E}_t[\mathbf{y}_{t+h}])'\right] = \sum_{s=0}^{h-1} \mathbf{\Theta}_s \mathbf{\Theta}'_s. \tag{21}$$

The j^{th} entry on the diagonal of $\mathbf{\Sigma}_h$ is therefore the variance of the forecast error of variable j due to all shocks $1, \dots, K$. This is:

$$[\mathbf{\Sigma}_h]_{j,j} = \sum_{s=0}^{h-1} \sum_{k=1}^{K} \left([\mathbf{\Theta}_s]_{j,k}\right)^2$$

while the contribution of a single shock k at horizon h is

$$\sum_{s=0}^{h-1} \left([\mathbf{\Theta}_s]_{j,k}\right)^2$$

It follows that the percentage contribution of shock k to the total error variance of variable j at horizon h is:

$$\text{FEVD}_{j,k}(h) = \frac{\sum_{s=0}^{h-1} \left([\mathbf{\Theta}_s]_{j,k}\right)^2}{\sum_{s=0}^{h-1} \sum_{k=1}^{K} \left([\mathbf{\Theta}_s]_{j,k}\right)^2} \tag{22}$$

Partially identified case. However, when not all columns of $\mathbf{\Theta}_h$ are identified, we cannot compute $\mathbf{\Sigma}_h$ directly using equation (21). Instead, leveraging the identity $\mathbf{\Theta}_h \mathbf{\Theta}'_h = \mathbf{\Phi}_h \mathbf{B}_0^{-1} (\mathbf{B}_0^{-1})' \mathbf{\Phi}'_h = \mathbf{\Phi}_h \mathbf{\Sigma}_u \mathbf{\Phi}'_h$, we compute:

$$\text{FEVD}_{j,k}(h) = \frac{\sum_{s=0}^{h-1} \left([\mathbf{\Theta}_s]_{j,k}\right)^2}{[\mathbf{\Phi}_h \mathbf{\Sigma}_u \mathbf{\Phi}'_h]_{j,j}}. \tag{23}$$

Note that this is derived without loss of generality under the unit-variance normalization of the structural shocks: $\mathbb{E}[\mathbf{w}_t \mathbf{w}'_t] = \mathbf{I}_K$.

A.3 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 (20) 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

$$\mathbf{y}_t \approx \sum_{s=0}^{t-1} \mathbf{\Theta}_s \mathbf{w}_{t-s}. \tag{24}$$

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.4 Structural shocks

In the partially identified case, where not all columns of $\mathbf{B}_0^{-1}$ are recovered, the matrix cannot be directly inverted to obtain the structural shocks via equation (17).

Nevertheless, Stock and Watson (2018) demonstrated that the corresponding structural shock can still be recovered using the following expression:

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

where $\mathbf{e}_j$ denotes the j-th standard basis vector and, without loss of generality, we adopted the the unit-variance representation of the model in (16), given by:

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

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

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

with $\boldsymbol{\Sigma}_{\tilde{\boldsymbol{w}}} = \mathbf{I}_K$.

A.5 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

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

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 (16). 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:

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

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 (16) 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:

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

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:

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

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

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

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 Data and descriptive statistics

B.1 Data sources

Table B2 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 B2: *Data description, sources, and coverage.*

B.2 Euro Area and United States energy statistics

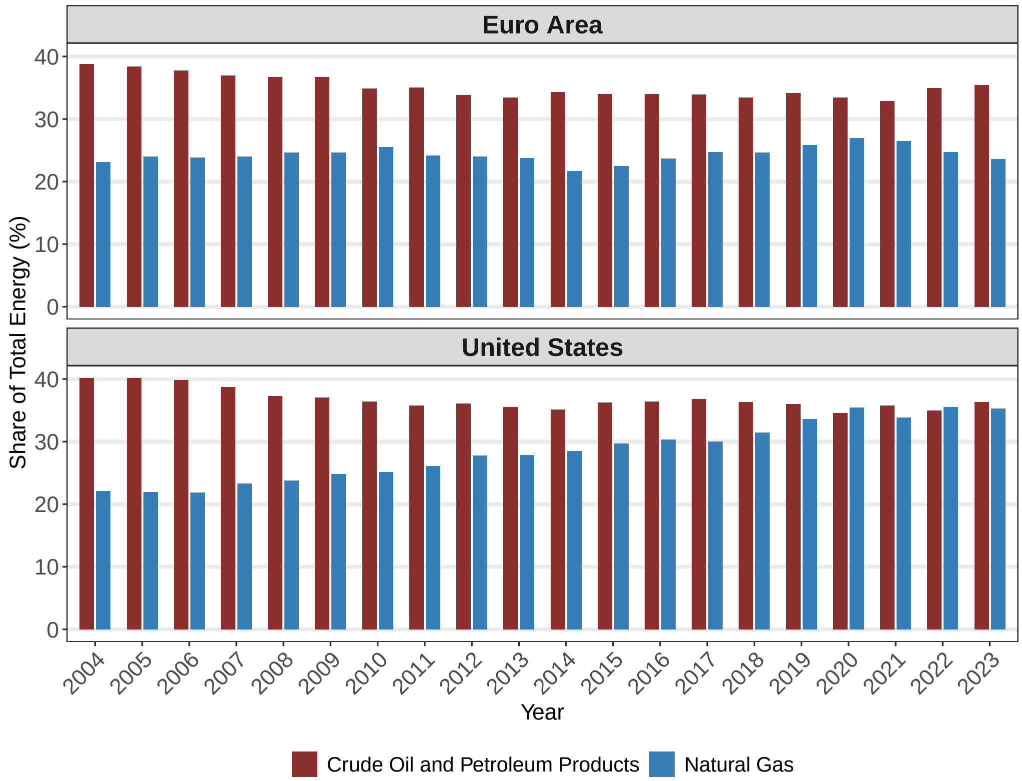
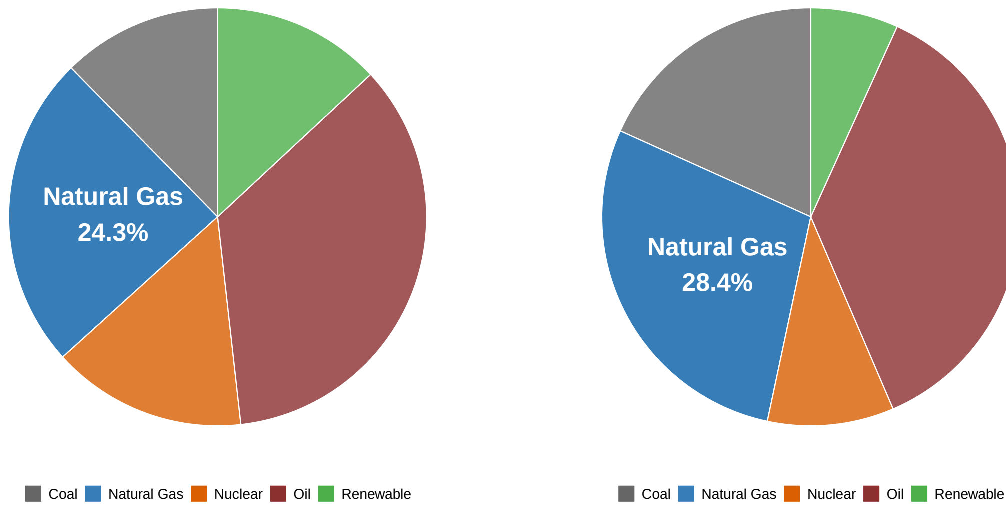


Figure B19: *crude oil and petroleum products and natural gas as a share of total energy supply*

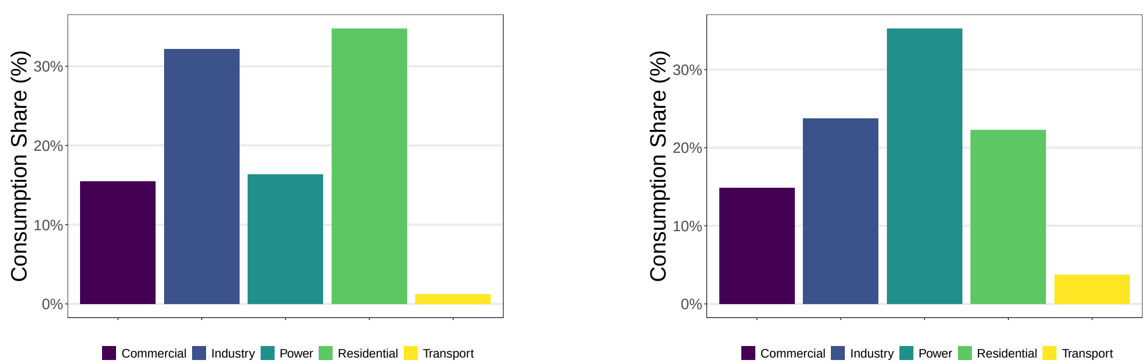
Notes: Share of natural gas and oil in total energy supply (2004-2023). The top panel reports the shares for the Euro Area, while the bottom panel presents the corresponding shares for the United States. Energy supply is defined as production plus imports minus exportsplus stock changes. Source: IEA.



Euro Area United States

Figure B20: *Energy supply by source*

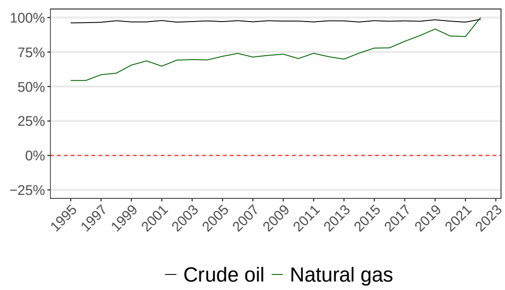
Notes: Composition of total energy supply by source, average over the period 2004-2023. The left panel displays the energy supply for the Euro Area, while the right panel shows the supply for the United States. Energy supply is defined as production plus imports minus exportsplus stock changes. Source: IEA.



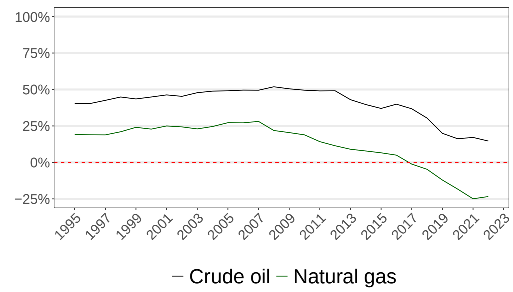
Euro Area United States

Figure B21: *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.



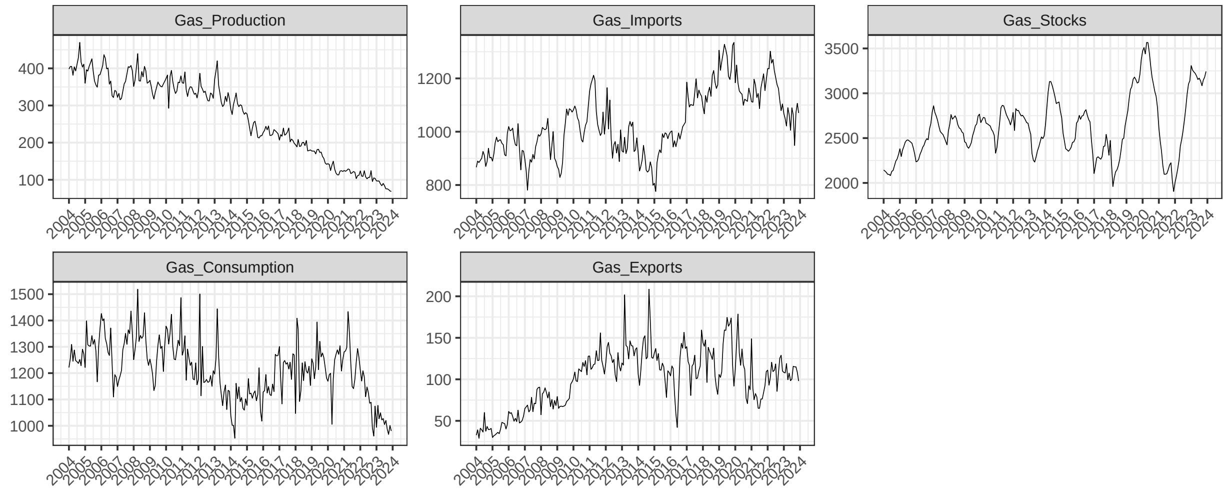
European Union



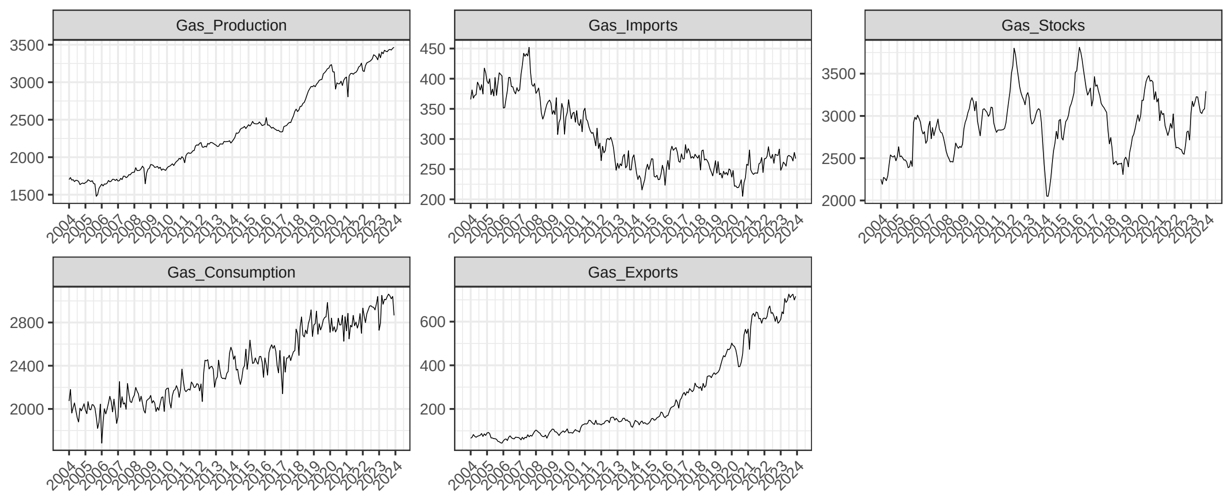
United States

Figure B22: *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



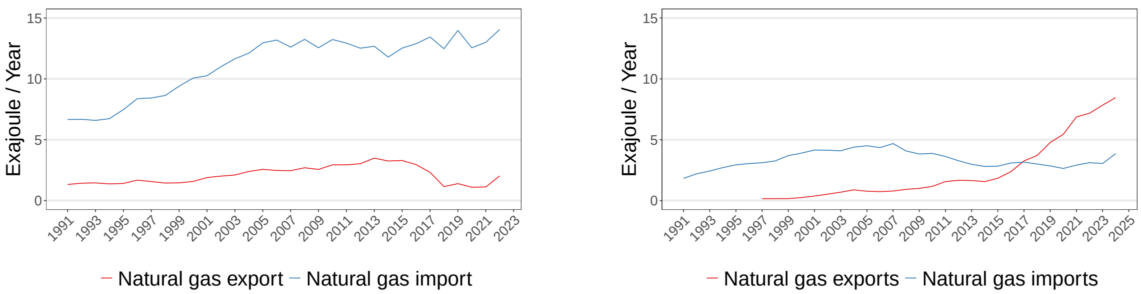
United States

Figure B23: *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 B3: *Gas balances for the Euro Area and United States, monthly averages (in Petajoules) over the sample. Supply = Production + Imports - Exports; Demand = Consumption + Exports.*

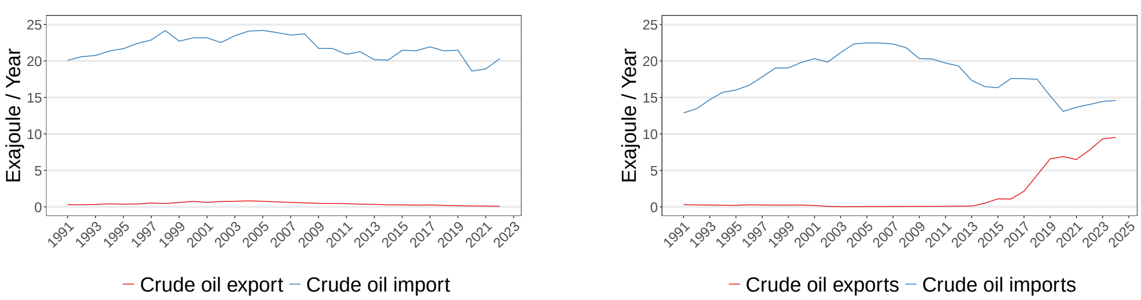


European Union

United States

Figure B24: *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 B25: *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.

B.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 B26 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 B4 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.

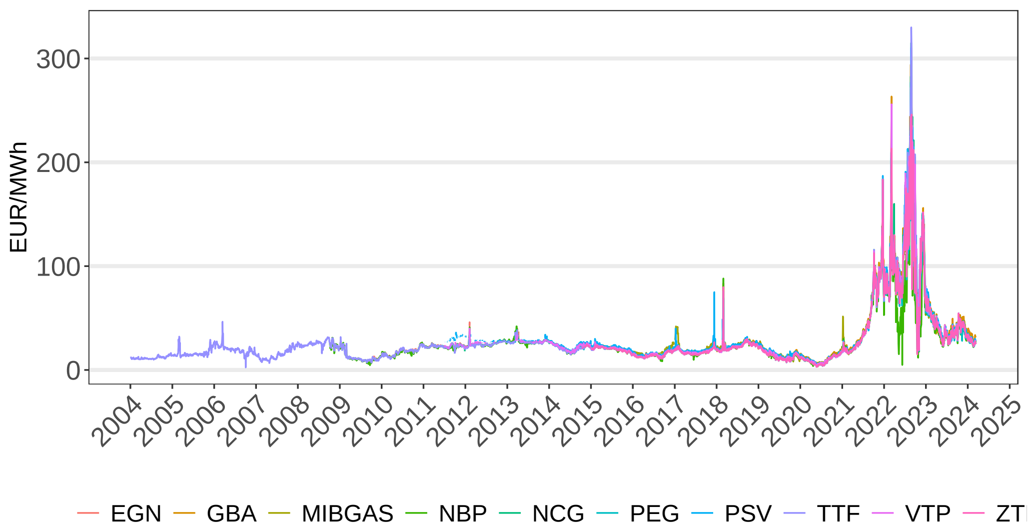


Figure B26: *TTF and other European gas prices.*

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 B27, while Figure B28 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 B4: *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.

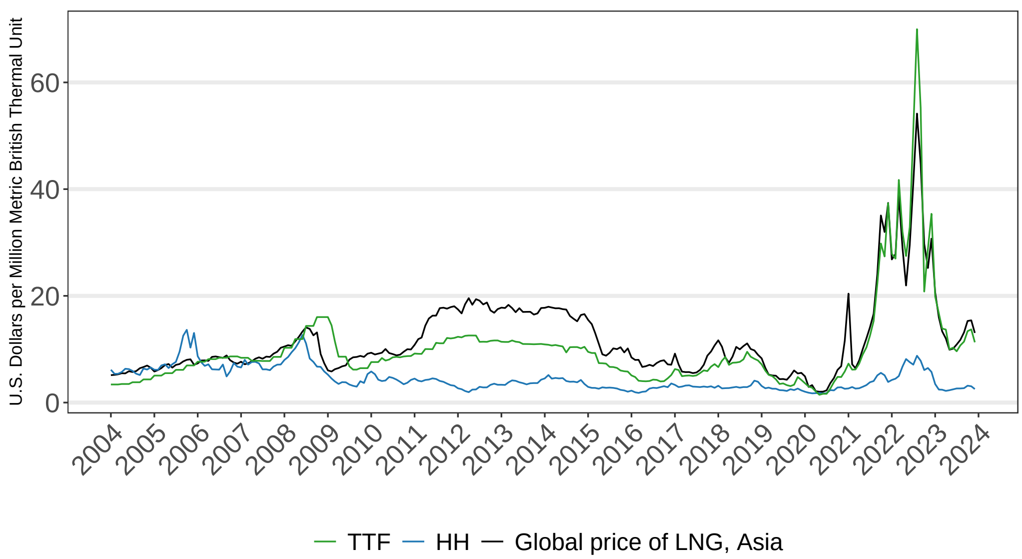


Figure B27: *TTF, HH, and Global LNG gas prices comparison*

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

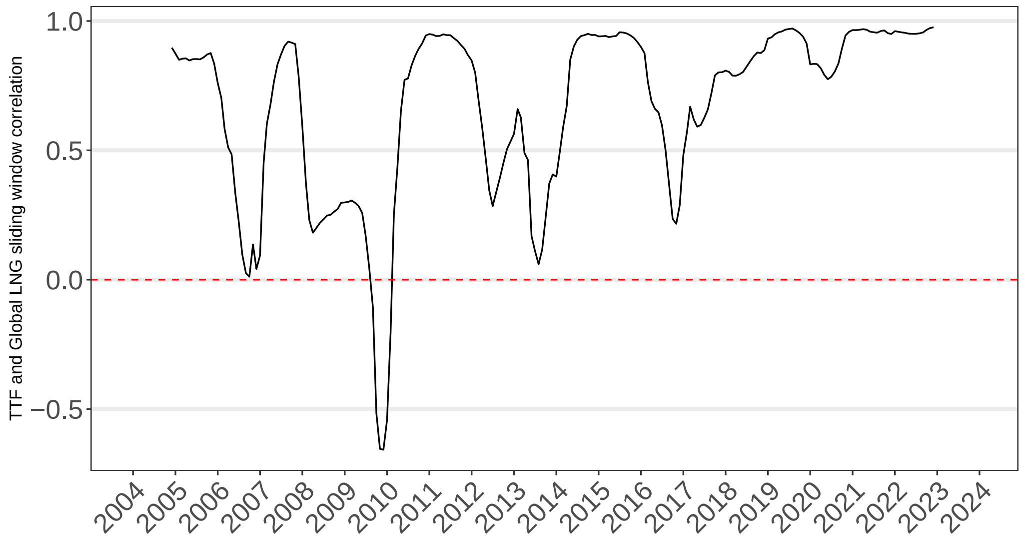


Figure B28: *TTF and Global LNG gas prices correlation*

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

C Additional details on gas supply instruments

C.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
2010-05-12	Gas outages across the South.	2.6
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 C5: *Selected gas supply news for the Euro Area and the US.*

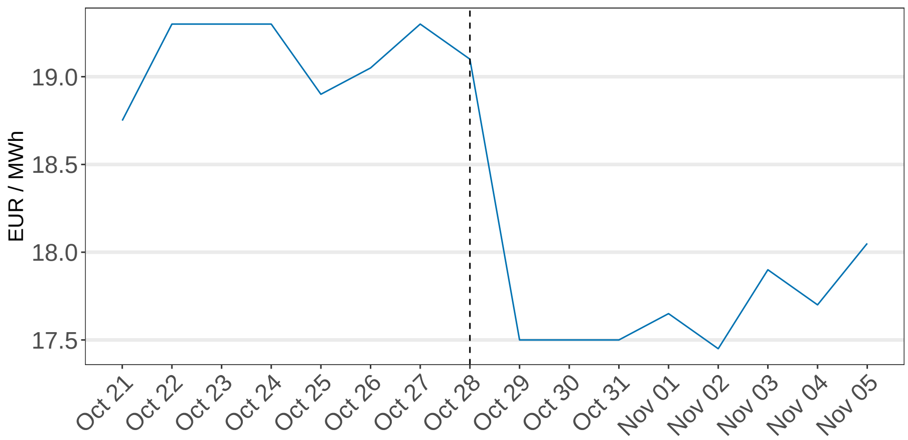


Figure C29: *UK expands LNG capacity at the Isle of Grain terminal*

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.

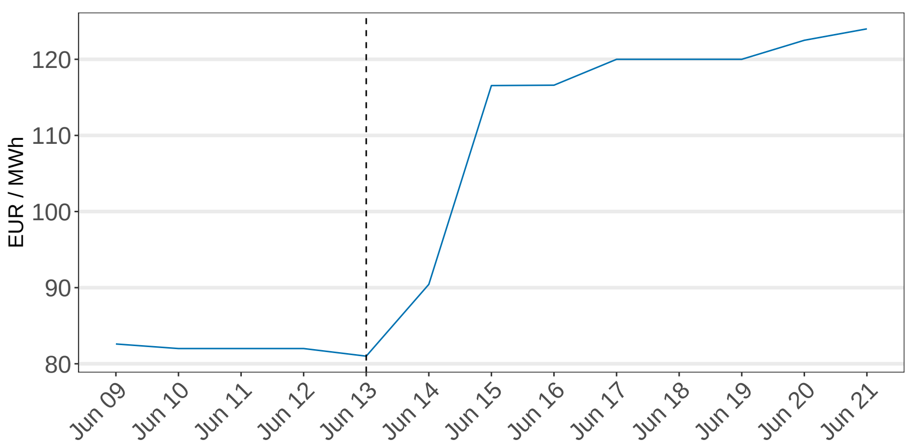


Figure C30: *Gazprom announces reduced supply through Nord Stream 1 due to repair works*

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.

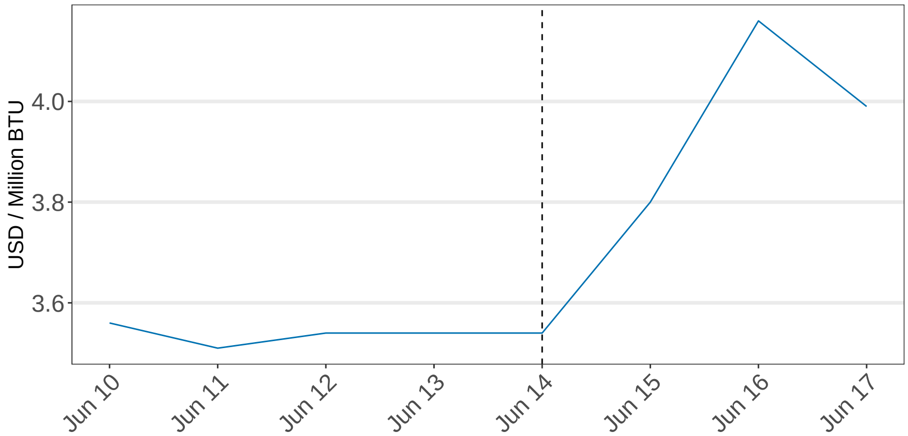


Figure C31: *Kinder Morgan announces maintenance*

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.

C.2 Gas supply instrument for the United States

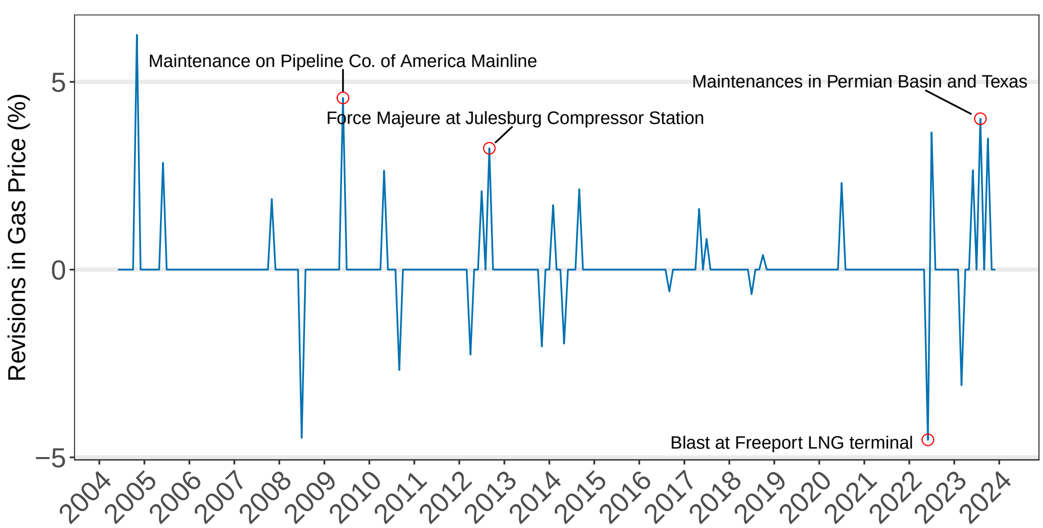
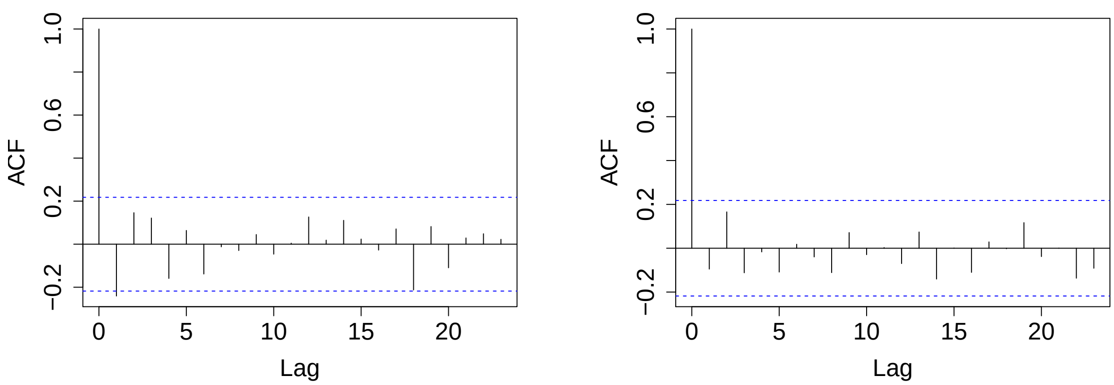


Figure C32: *Gas supply surprises series for the US*

C.3 Diagnostics of the gas surprise series

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

Figure C33 shows that the series exhibits no significant autocorrelation. We then assess its predictability using Granger causality tests. As reported in Table C6, 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 C7. Notably, the series is not significantly correlated with oil-specific shocks, measures of uncertainty, or global demand shocks.



EA

US

Figure C33: *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 C6: *Granger causality tests.*

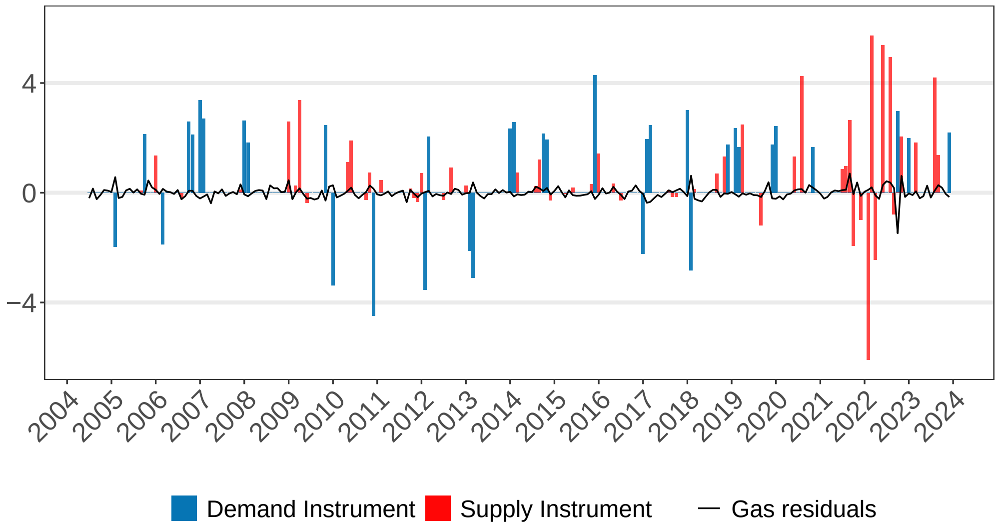
Notes: The table presents the p-values obtained from Granger's causality tests of the gas supply surprise series using the set of variables included in our baseline specification, expanded with financial and real activity variables. To conduct standard inference, the series are rendered stationary by 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 (2021)**	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

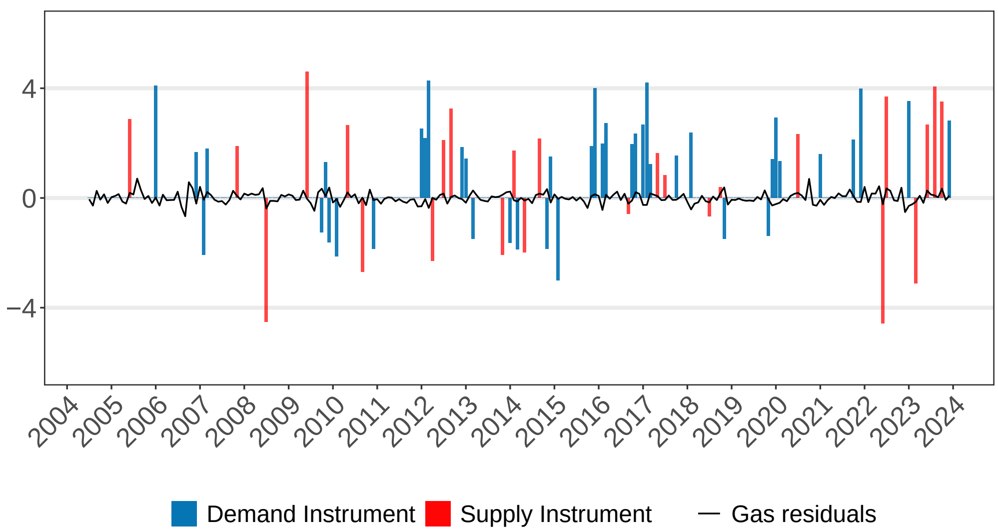
Table C7: *Correlation of instruments with other macroeconomic indicators.*

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.



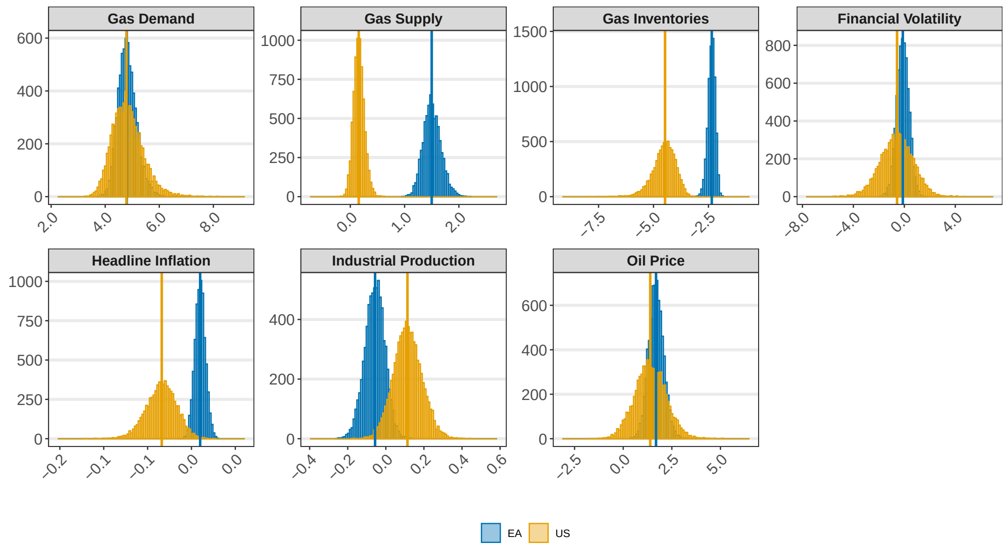
Europe



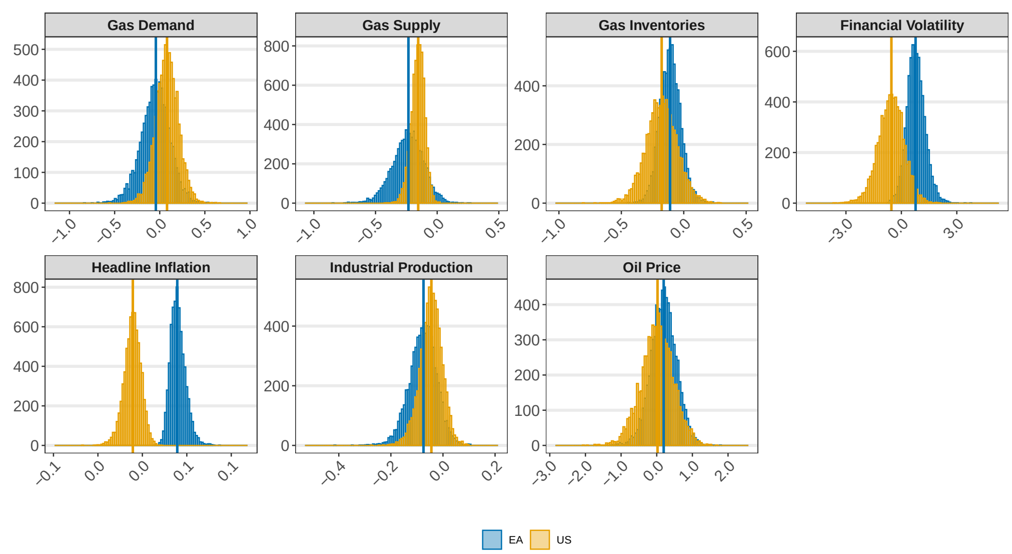
USA

Figure C34: *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.



Demand



Supply

Figure C35: *Posterior distributions of impact coefficients*

Notes: This figure shows 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 reports results for the gas demand shock, while the bottom panel corresponds to the gas supply shock. The coefficient for the gas price is omitted, as it is normalized to 10 in each Gibbs sampling iteration.

D Additional details on gas demand instruments

D.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.[38][39]

Temperature proxy for gas demand. The monthly temperature index is computed as described in Equation (25). 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 D36 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.

$$TI_{y,m} = \begin{cases} 0, & \text{if } \left|\mathcal{T}^{\text{SA}}_{y,m} - \mu_{\mathcal{T}}\right| \leq \sigma_{\mathcal{T}} \\ \mathcal{T}^{\text{SA}}_{y,m}, & \text{otherwise} \end{cases} \tag{25}$$

where:

- $\mathcal{T}_{y,m,d,h}$ 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;

- $\mathcal{T}^{\text{stat}}_{y,m,d} \equiv f(\{\mathcal{T}_{y,m,d,h}\}_{h=1}^{24})$ denotes a daily statistic computed over hourly temperature observations. In our baseline computation, we use the daily average, defined as $\mathcal{T}^{\text{Avg}}_{y,m,d} = \frac{1}{24}\sum_{h=1}^{24} \mathcal{T}_{y,m,d,h}$. As alternatives, the ERA5 dataset also provides daily minimum and maximum temperatures, given by $\mathcal{T}^{\text{Min}}_{y,m,d} = \min(\{\mathcal{T}_{y,m,d,h}\}_{h=1}^{24})$ and $\mathcal{T}^{\text{Max}}_{y,m,d} = \max(\{\mathcal{T}_{y,m,d,h}\}_{h=1}^{24})$, respectively.

- $\overline{\mathcal{T}}^{\text{stat}}_{m} = \frac{1}{(Y-y_0+1)D_m} \sum_{y=y_0}^{Y} \sum_{d=1}^{D_m} \mathcal{T}^{\text{stat}}_{y,m,d}$ is the long-run average of the statistic for calendar month m;

- $\mathcal{T}^{\text{SA}}_{y,m,d} = \mathcal{T}^{\text{stat}}_{y,m,d} - \overline{\mathcal{T}}^{\text{stat}}_{m}$ is the seasonally adjusted daily statistic;

[38] `https://gadm.org/`.

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

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

- $\mu_{\mathcal{T}}$ and $\sigma_{\mathcal{T}}$ are the mean and standard deviation of the seasonally adjusted monthly series, computed as:

$$\mu_{\mathcal{T}} = \frac{1}{12(Y - y_0 + 1)} \sum_{y=y_0}^{Y} \sum_{m=1}^{12} \mathcal{T}^{\text{SA}}_{y,m},$$

$$\sigma_{\mathcal{T}} = \sqrt{\frac{1}{12(Y - y_0 + 1) - 1} \sum_{y=y_0}^{Y} \sum_{m=1}^{12} \left(\mathcal{T}^{\text{SA}}_{y,m} - \mu_{\mathcal{T}}\right)^2}.$$

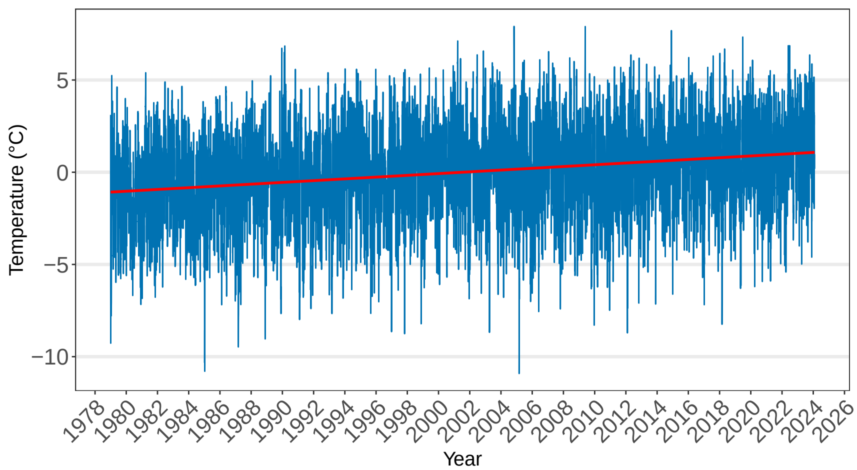


Figure D36: *Daily temperatures for the Netherlands, seasonally adjusted by subtracting the long-term calendar month averages, not detrended*

We have explored several alternative methods for computing the temperature index series, all of which yield very similar 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), 2007M1 (Gas and oil transit dispute between Russia and Belarus), 2008M2 (Gazprom threatens supply cuts over debt dispute with Ukraine), 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), 2020M11 (Second COVID-19 wave and renewed lockdowns), 2022M2 (Invasion of Ukraine), 2022M8 (Turbine maintenance at Nord Stream 1), 2022M11 (Outages in Norway and delays in the 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 D37 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.

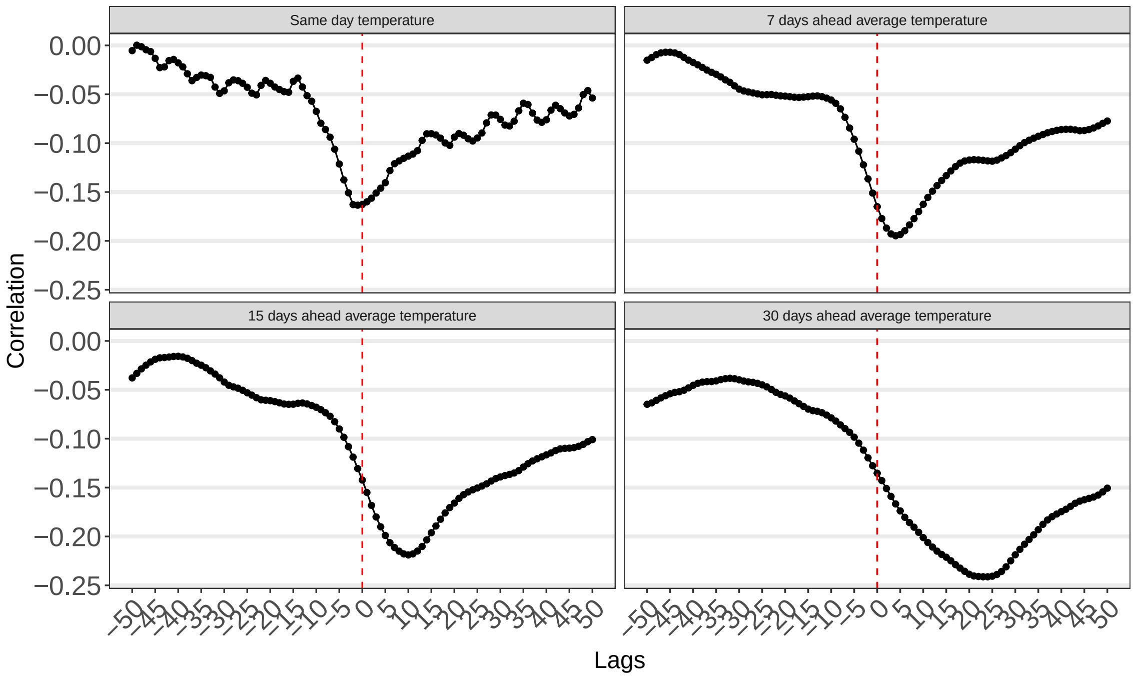


Figure D37: *Temperatures and gas price correlations*

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.

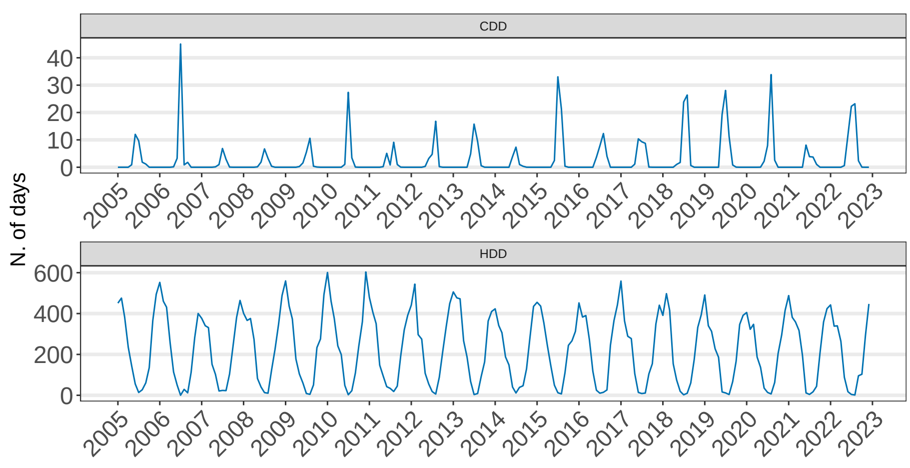
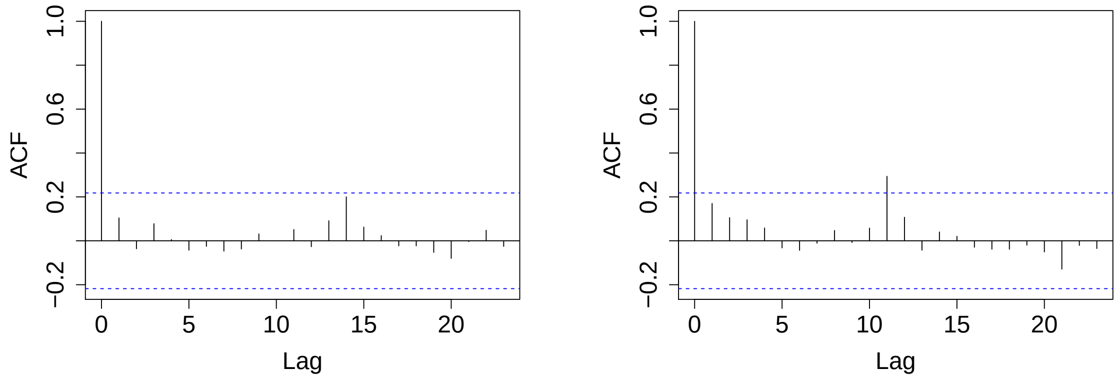


Figure D38: *Cooling degree days and heating degree days, average across selected European countries*



EA US

Figure D39: *Sample Autocorrelation Function of the Temperature Shocks*

D.2 Gas demand instrument for the United States

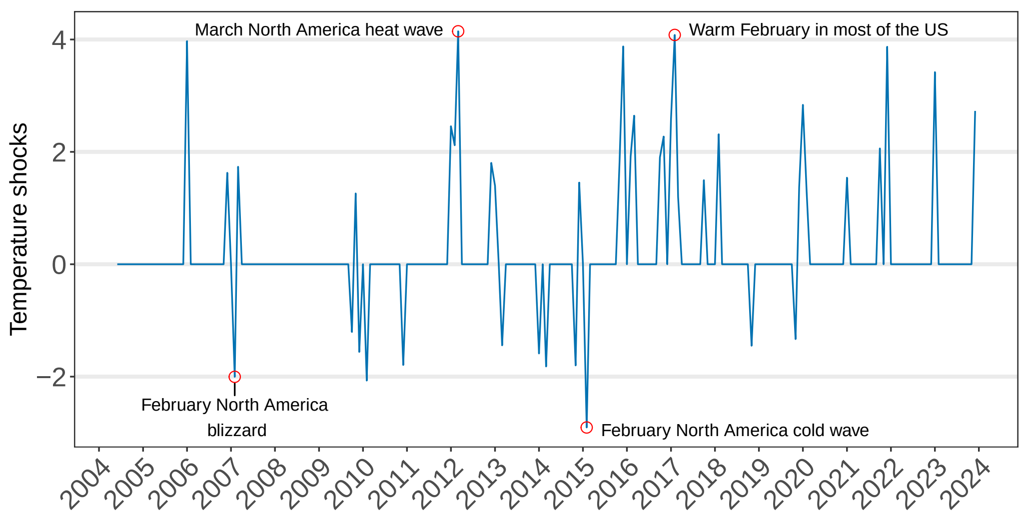


Figure D40: *Temperature shocks series for the United States*

E Brent and WTI oil surprises

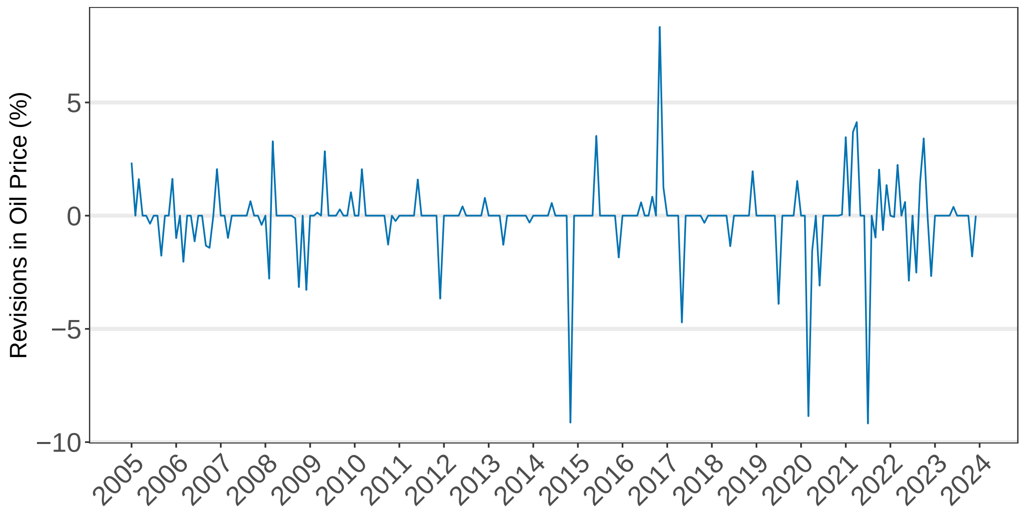


Figure E41: *The Brent oil supply surprises series*

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 (2021).

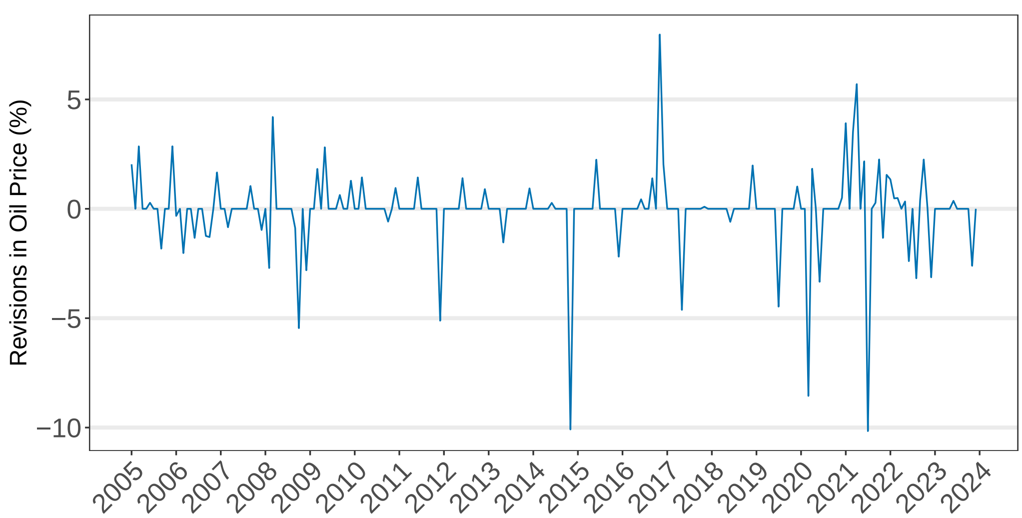


Figure E42: *The WTI oil supply surprises series*

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

F Previous estimates of short-run gas market elasticities

Authors (year)	Region	Demand		Supply		Identification	Sample period
		Quantity	Estimate	Quantity	Estimate		
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 F8: *Previous estimates of short-run gas market elasticities*

Notes: "Quantity" refers to the specific aggregate used in each study to evaluate the percentage response to increases in gas prices..

*Baumeister and Hamilton (2019) identification strategy.

**Wiggins and Etienne (2017) report a range from a time-varying parameter model.

G Historical decomposition of the real price of natural gas: United States

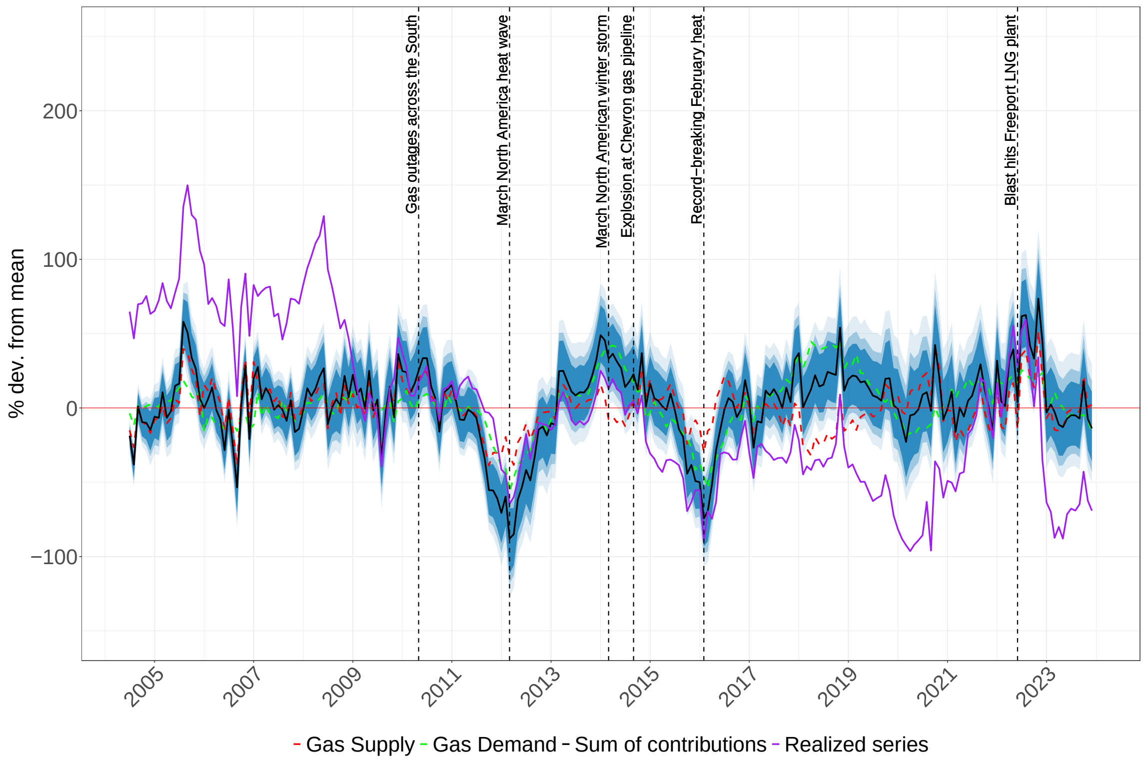


Figure G43: *United States: historical decomposition of the real price of natural gas*

Notes: This figure illustrates the estimated contributions of gas supply shocks (red dashed line) and gas demand shocks (green dashed line) to the real price of natural gas, along with their combined contribution (solid black line with blue confidence bands). All contributions are expressed as percentage deviations from the mean. Vertical dashed bars mark significant events in the gas markets: gas outages across the South in 2010M5; a heat wave across North America in 2012M3; a winter storm in North America in 2014M3; an explosion at the Chevron gas pipeline in Louisiana in 2014M9; record-breaking February warmth in the United States in 2016M2; and a blast at the Freeport LNG terminal that disrupted operations in 2022M6.

H Baseline responses presented jointly

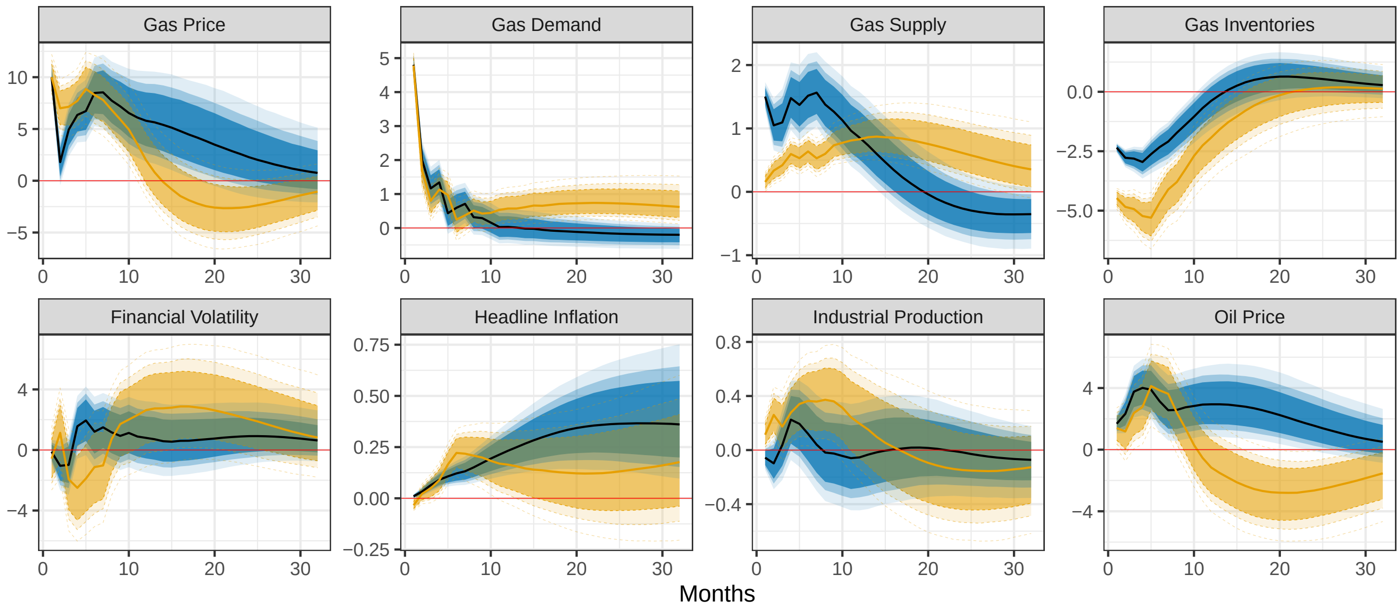


Figure H44: *Full responses to a gas demand shock. Left panels of Figures 8 to 12 grouped together.*

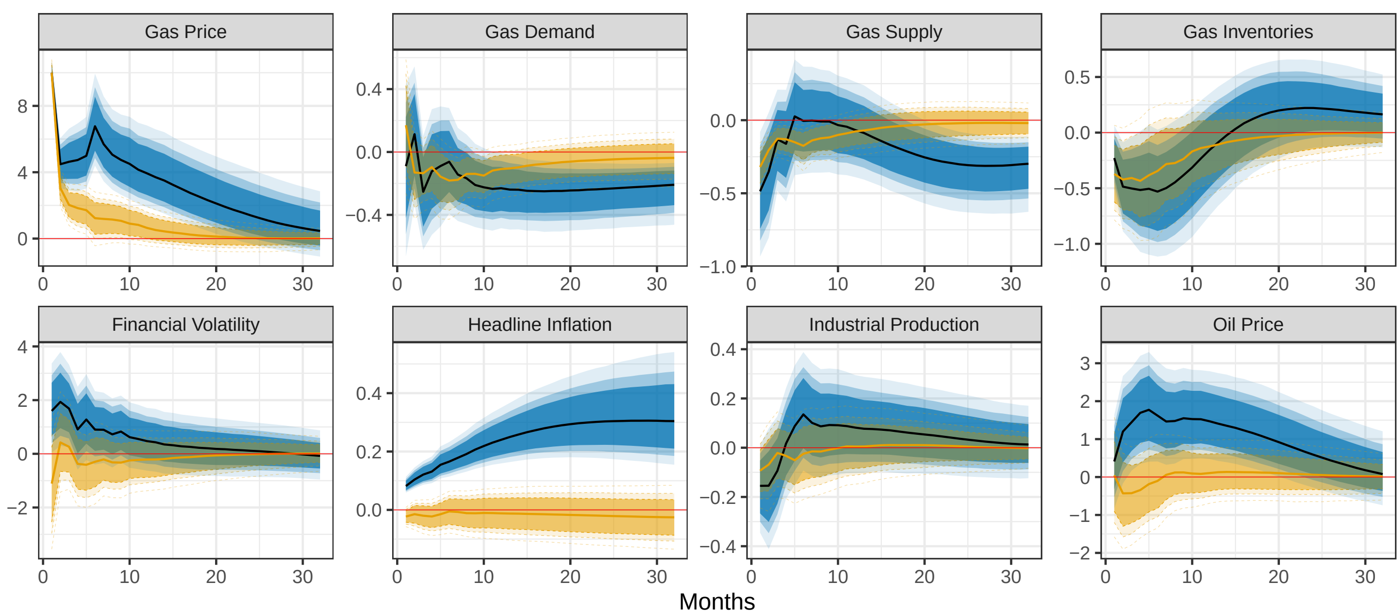


Figure H45: *Full responses to a gas supply shock. Right panels of Figures 8 to 12 grouped together.*

I Additional results

I.1 Drivers of demand and supply elasticities

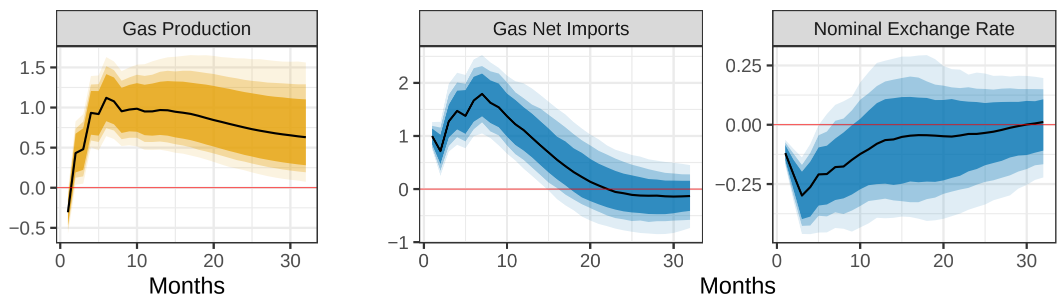


Figure I46: *Drivers of gas supply*

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.

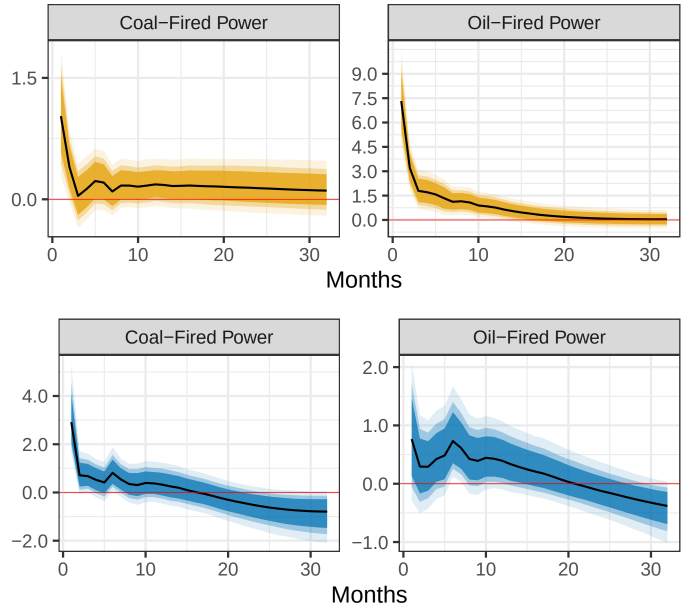


Figure I47: *Interfuel substitution in the power sector*

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.

I.2 Europe supply shock constructed only with expected events

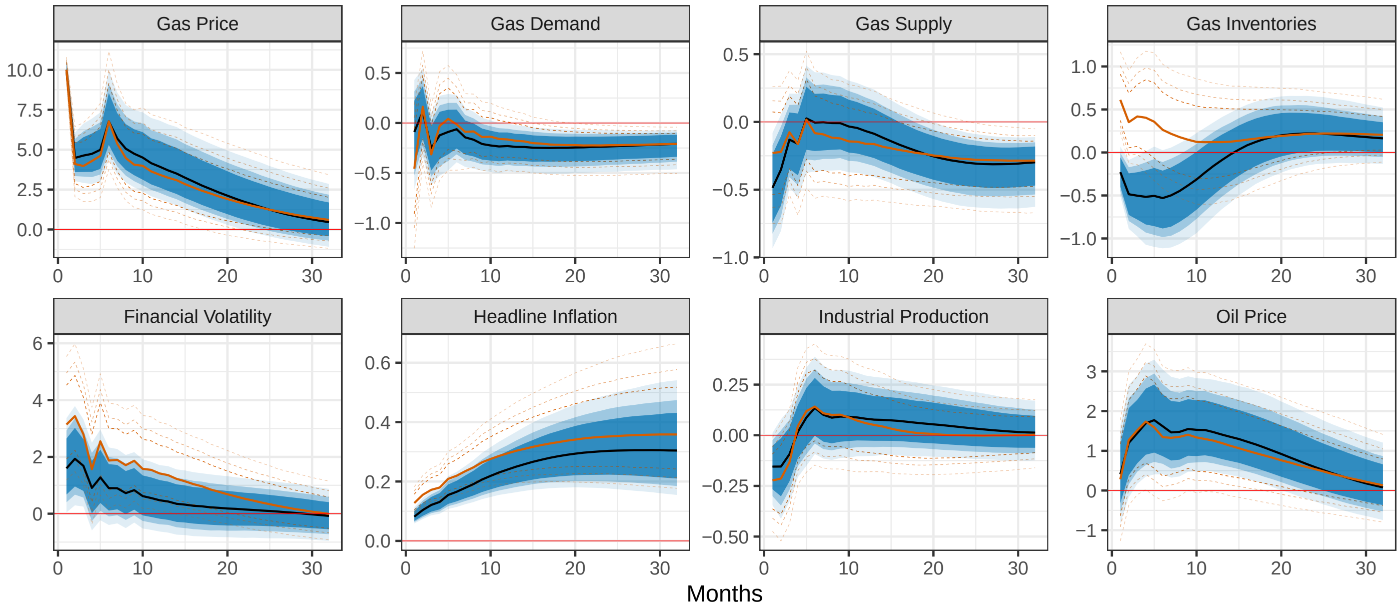


Figure I48: *Full impulse responses to a gas supply shock in Europe: comparison between the baseline specification (black solid line with blue shaded confidence bands) and an alternative specification using an instrument constructed solely from news about expected—but not yet realized—supply disruptions (red solid and dashed lines).*

I.3 PPI inflation in Europe

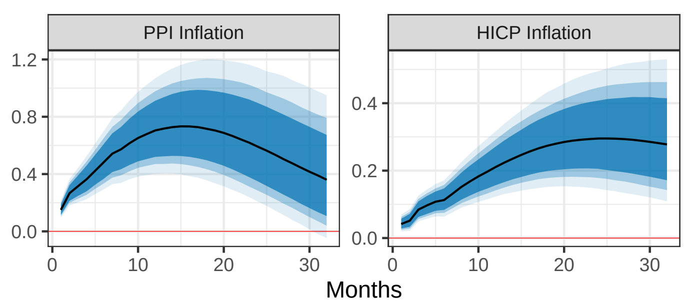


Figure I49: *Responses of producer price and consumer price inflation*

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.

J Contribution of oil supply shocks to the historical decomposition of headline inflation

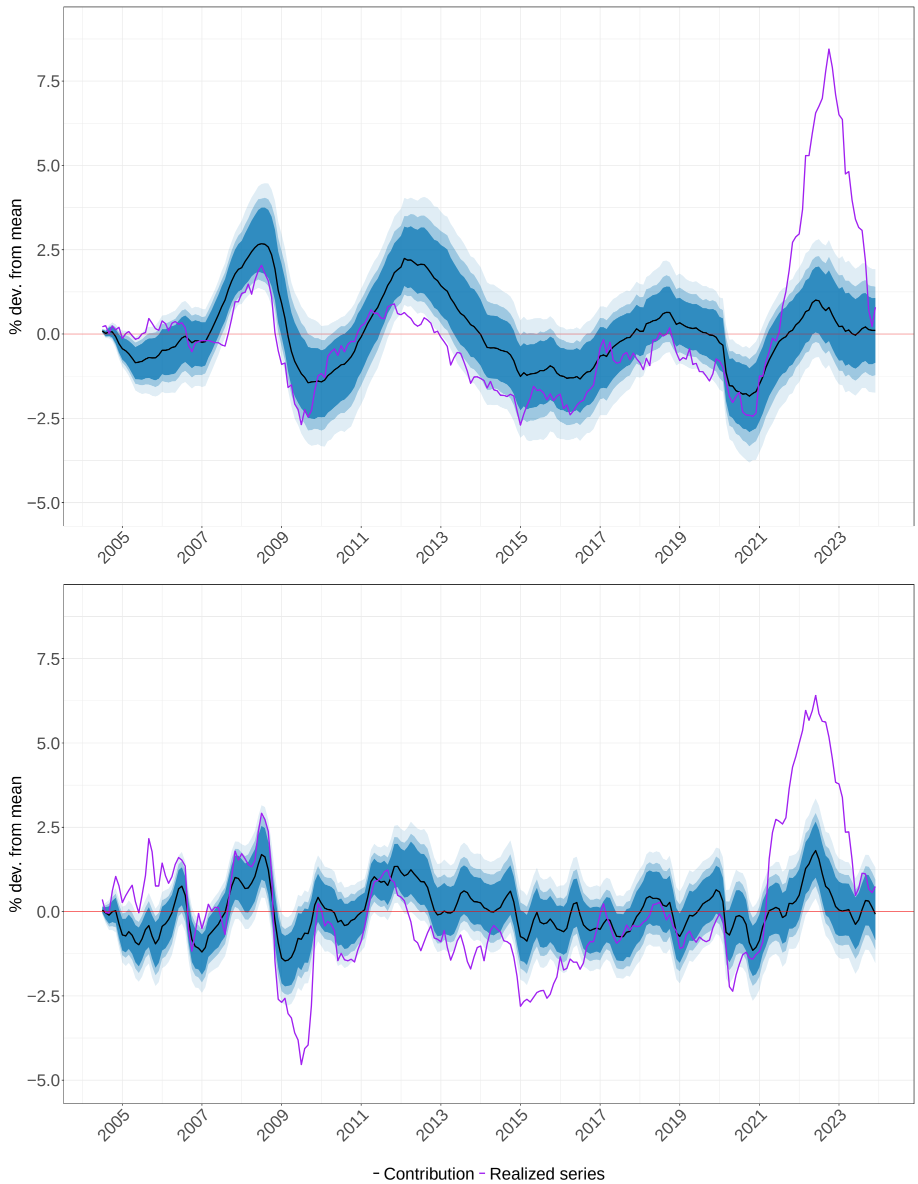


Figure J50: *Historical decomposition of headline inflation in the Euro Area (top panel) and the United States (bottom panel)*

Notes: This figure displays the estimated contributions of oil supply shocks (Känzig, 2021) to the year-on-year headline inflation rate. The contribution is represented by a solid line with shaded confidence bands and is expressed as a percentage deviation from the mean. The realized headline inflation series is shown in purple.

K Sensitivity analysis

In this Appendix, we provide evidence that our results are robust along multiple dimensions. We begin by extending the estimation sample for the United States to cover the period 1997–2023 and by including summer months in the construction of the demand instrument. We then construct an informationally robust gas supply instrument that accounts for potential confounding factors and background information over the event window, and we confirm that our main findings are unaffected.

We also validate our high-frequency proxy construction by applying the procedure proposed in Kilian (2024), and present an alternative identification approach based on an "internal instrument" strategy. To assess the sensitivity of our results to the estimation method, we replicate the analysis using a frequentist VAR-OLS and local projections, both of which yield similar results, though less precisely estimated. Finally, we verify that the orthogonalisation of structural shocks—implemented via a recursive ordering—does not materially affect our conclusions.

K.1 Demand instrument including summer months (US)

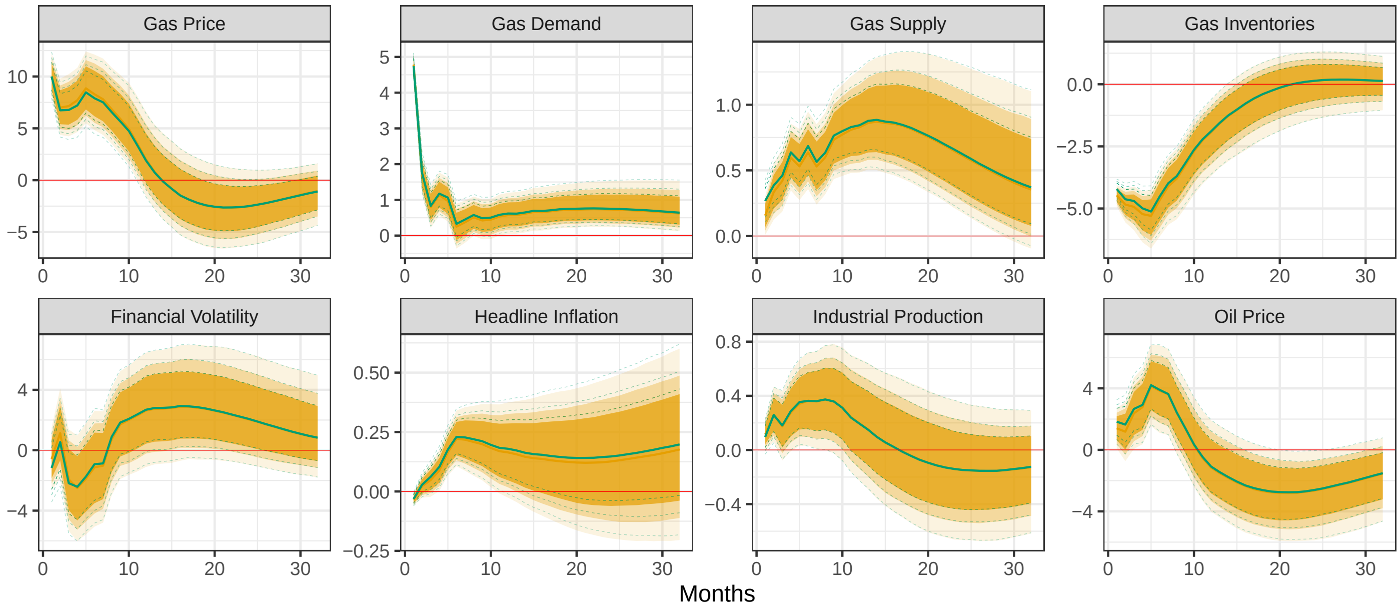


Figure K51: *Impulse responses to a gas demand shock in the United States, estimated using alternative instrument constructed without excluding summer months.*

Notes: Orange solid lines with dashed and shaded orange confidence bands represent the baseline responses, and green solid and dashed lines illustrate the results obtained with the alternative instrument. 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. In the United States, 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.

K.2 Extended estimation sample for the United States (1997-2023)

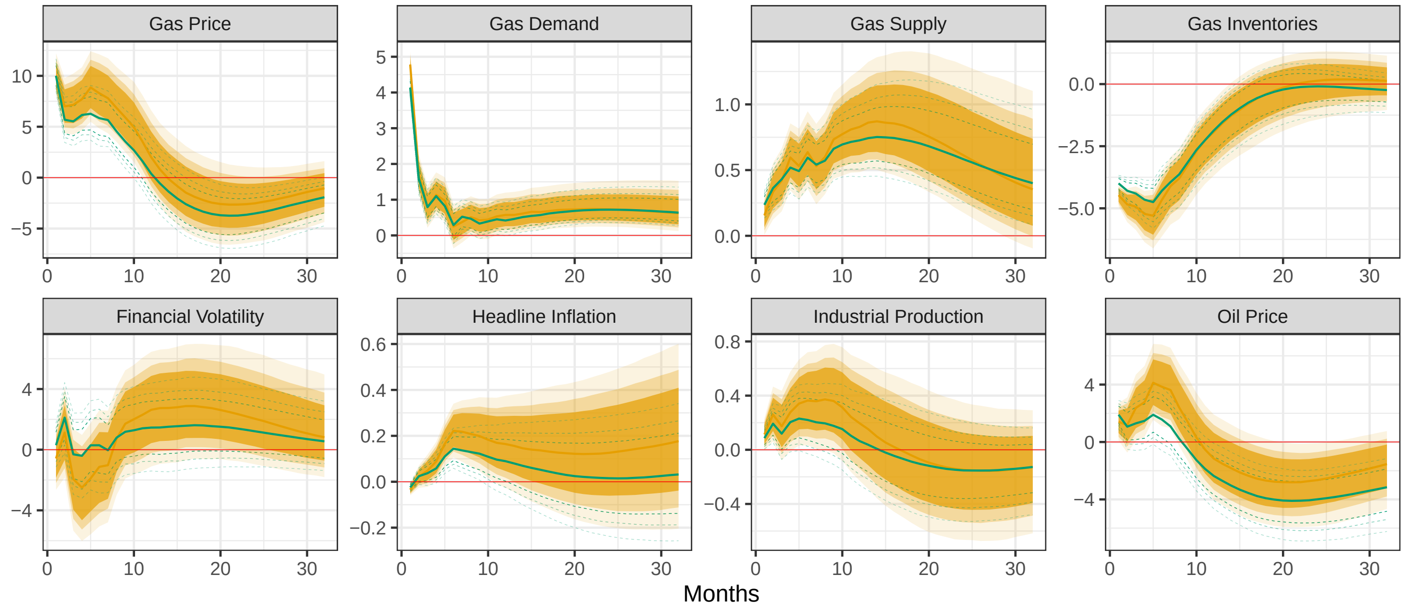


Figure K52: *Full responses to a gas demand shock in the US, extended sample.*

Notes: Orange solid lines with dashed and shaded orange confidence bands represent the baseline responses, and green solid and dashed lines illustrate the results obtained with the alternative instrument.

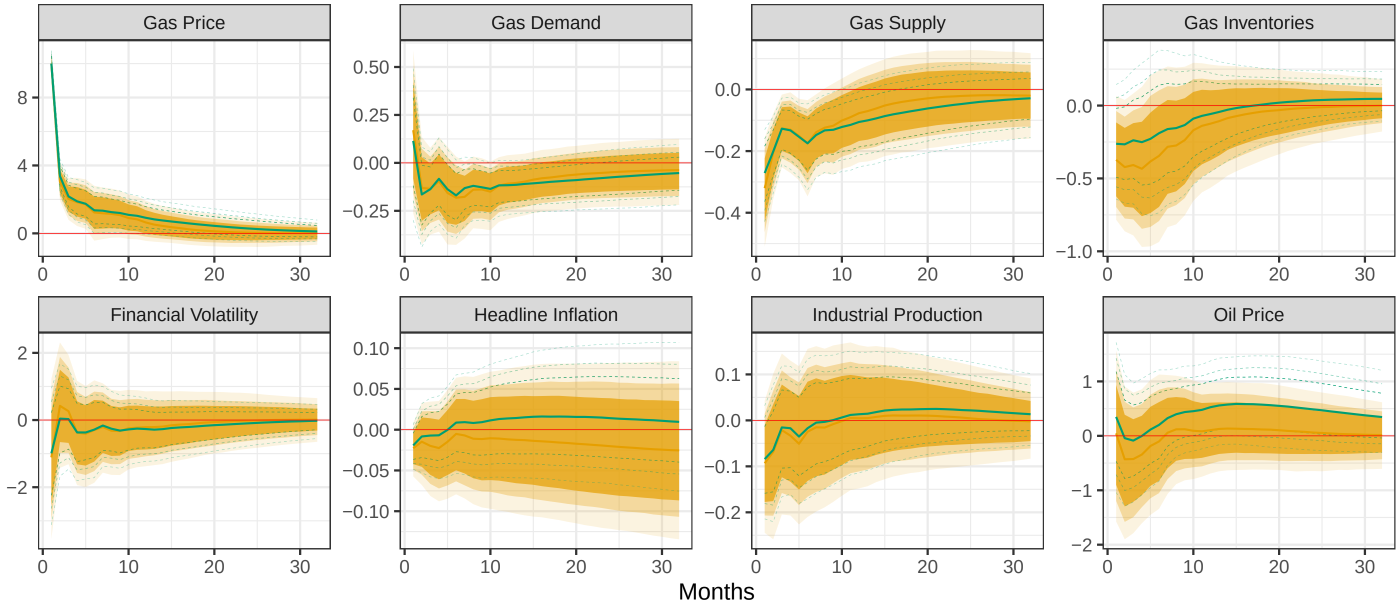


Figure K53: *Full responses to a gas supply shock in the US, extended sample.*

Notes: Orange solid lines with dashed and shaded orange confidence bands represent the baseline responses, and green solid and dashed lines illustrate the results obtained with the alternative instrument.

K.3 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).[40]

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 (2021). 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).[41]

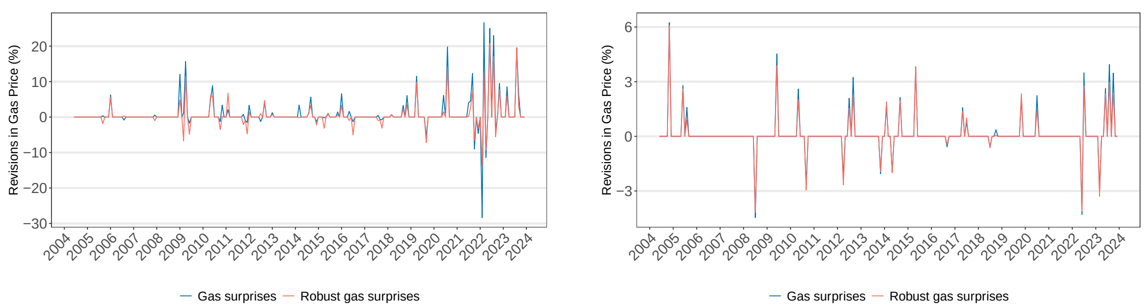


Figure K54: *Informationally robust gas surprises series*

Notes: This figure shows the gas surprise series (blue line) alongside the informationally robust surprises, residual to Eq. (K.3), IRS_t (red line). The left panel corresponds to the Euro Area, while the right panel presents the series for the United States.

Figure K54 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 K55 presents the IRFs from the baseline specification using the informationally robust instrument.

[40] We use Matif wheat futures for the Euro Area and Hard Red Winter wheat futures for the United States.

[41] 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.

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.

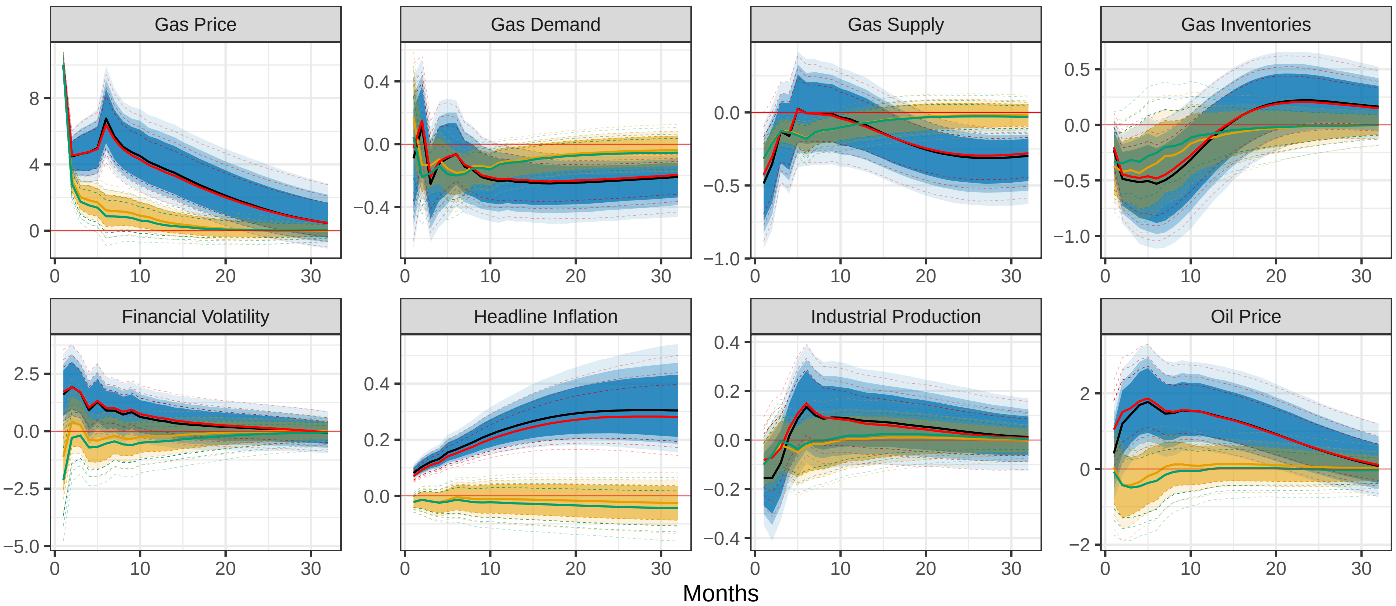


Figure K55: *Impulse responses to a gas supply shock, informationally robust refinement.*

Notes: Impulse responses to a gas supply shock in the Euro Area and the United States, informationally robust refinement. Black solid lines with blue shaded confidence bands show the baseline results for the Euro Area, while red solid and dotted lines depict the corresponding informationally robust refinement. For the United States, orange solid lines with dashed and shaded orange confidence bands represent the baseline responses, and green solid and dashed lines illustrate the informationally robust refinement.

K.4 Constructing the high-frequency proxies as in Kilian (2024)

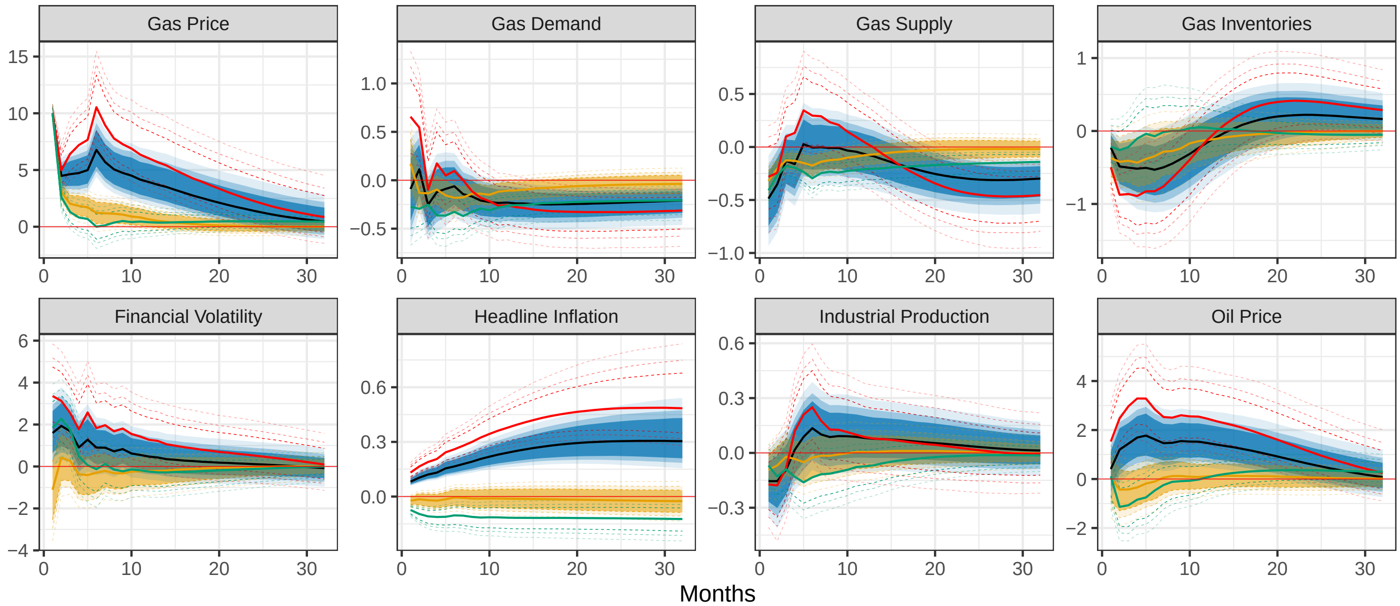


Figure K56: *Impulse responses to a gas supply shock, comparison of results obtained with baseline instrument and constructed using the temporal aggregation technique proposed by Kilian (2024).*

Notes: Black solid lines with blue shaded confidence bands show the baseline results for the Euro Area, while red solid and dotted lines depict the results obtained with the corresponding alternative instrument. For the United States, orange solid lines with dashed and shaded orange confidence bands represent the baseline responses, and green solid and dashed lines illustrate the results obtained with the alternative instrument.

K.5 Estimation via "internal instrument" strategy

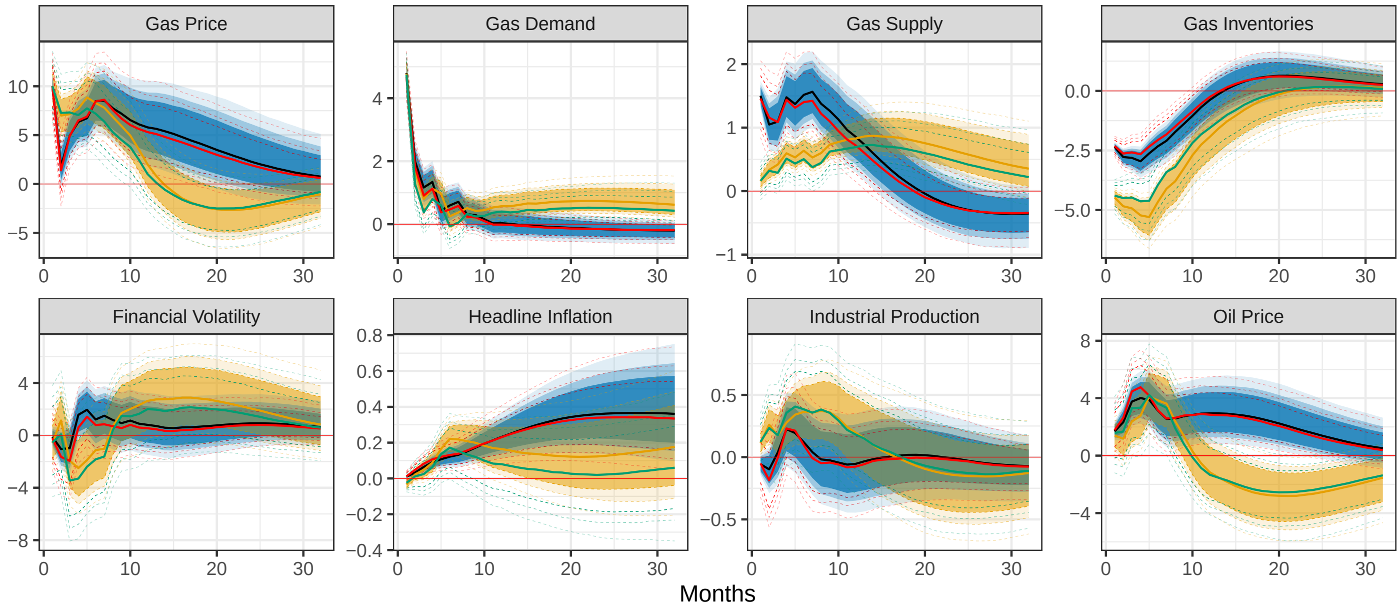


Figure K57: *Impulse responses to a gas demand shock, comparison of baseline and identified using the internal instruments approach by placing the demand instrument as the first variable in a recursive BVAR.*

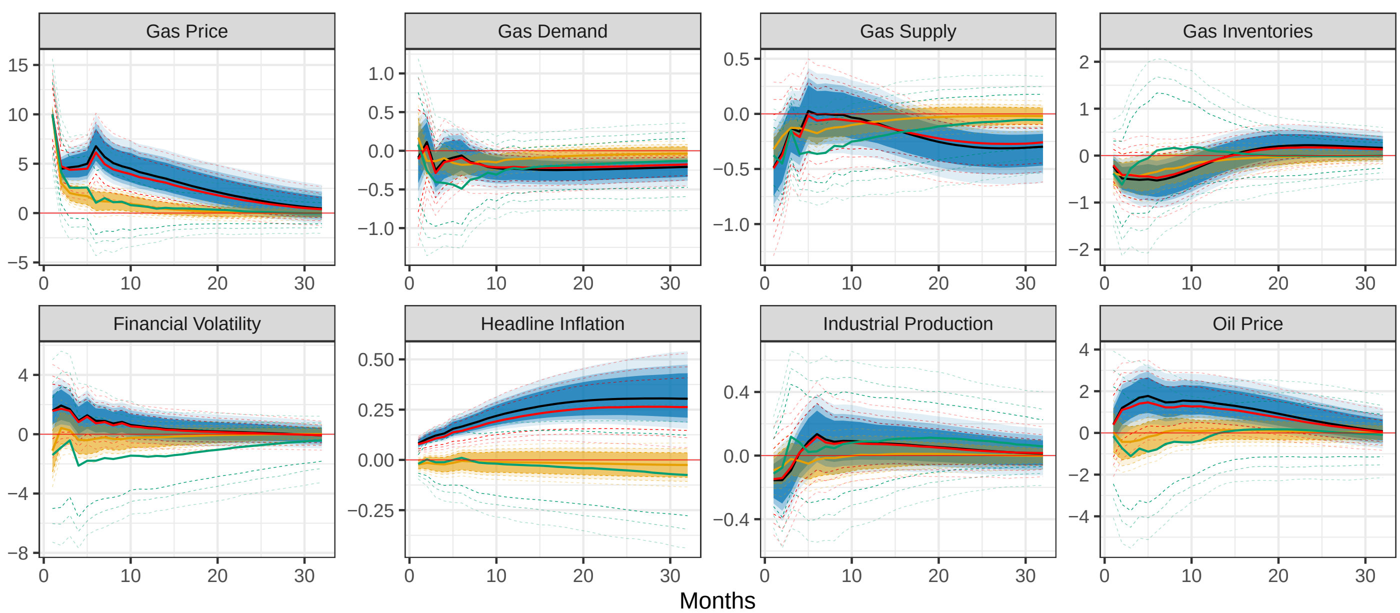


Figure K58: *Impulse responses to a gas supply shock, comparison of baseline and identified using the internal instruments approach by placing the supply instrument as the first variable in a recursive BVAR.*

K.6 Estimation by VAR-OLS

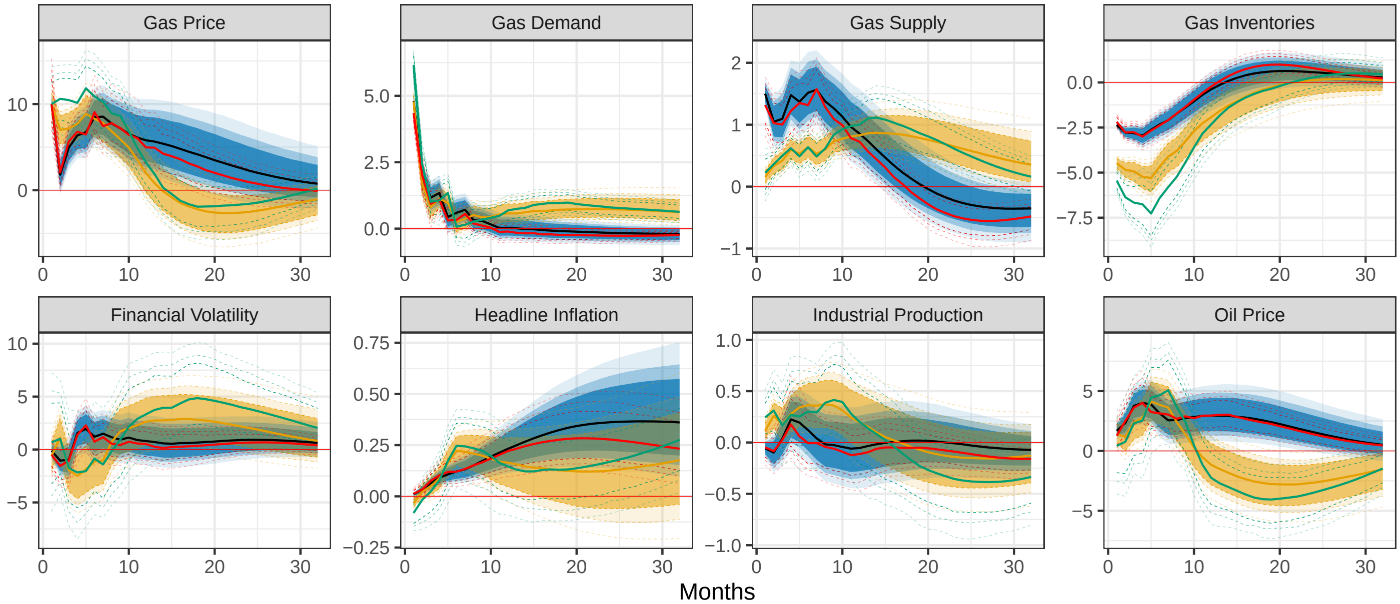


Figure K59: *Responses to a gas demand shock, comparison of baseline and estimated by VAR-OLS.*

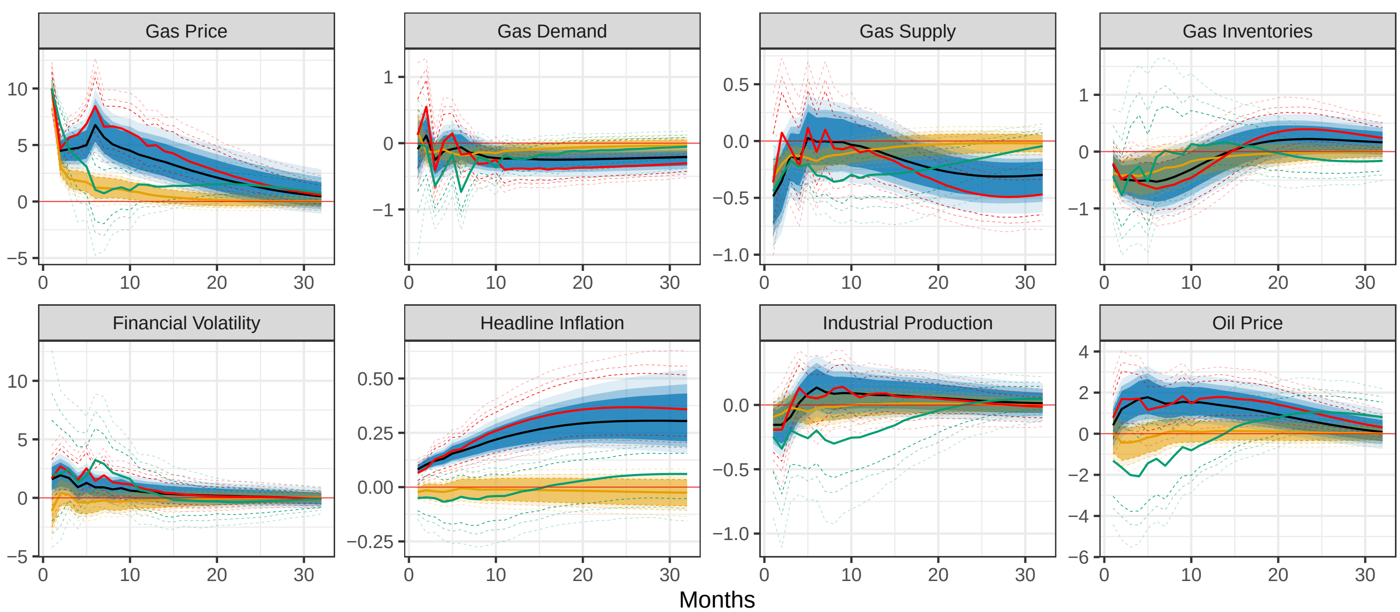


Figure K60: *Responses to a gas supply shock, comparison of baseline and estimated by VAR-OLS.*

K.7 Estimation by Local Projections (LP-IV)

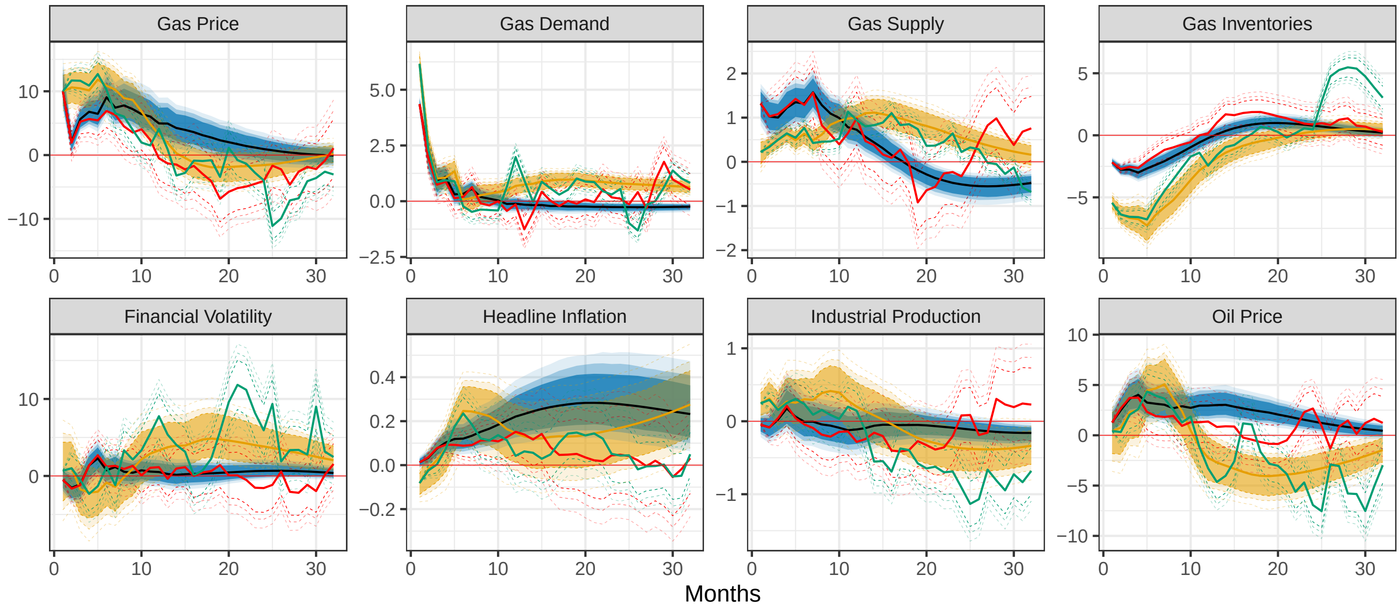


Figure K61: *Responses to a gas demand shock, comparison of responses estimated by VAR-OLS and LP-IV.*

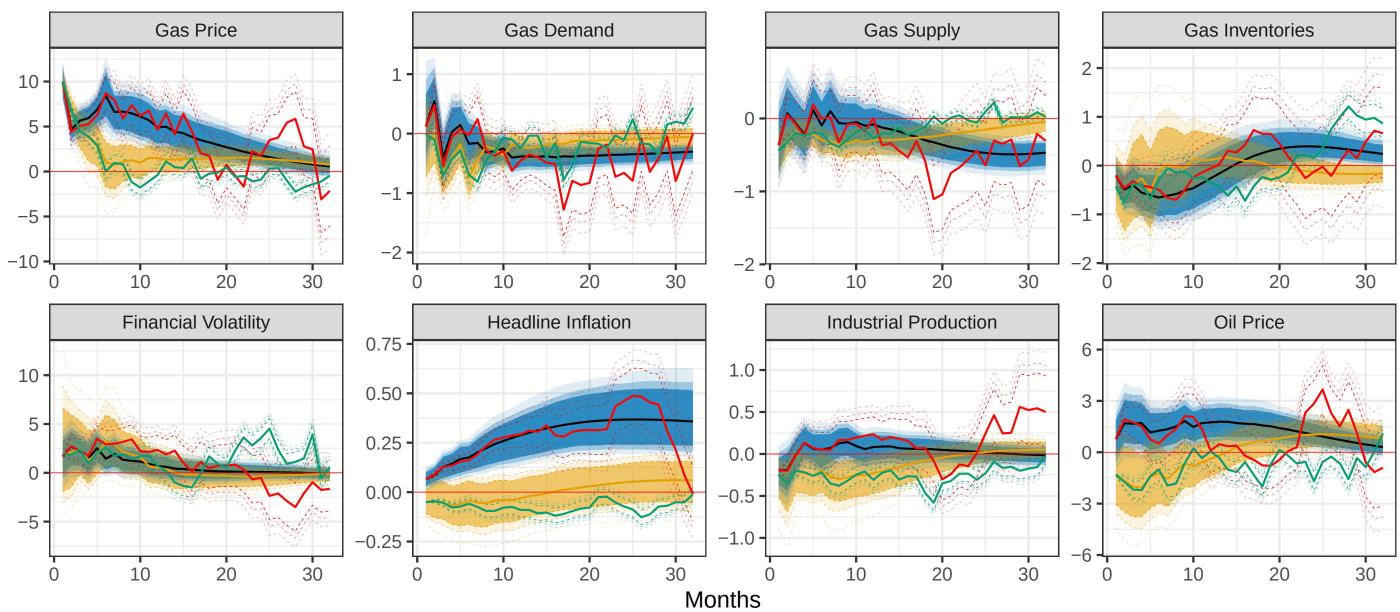


Figure K62: *Responses to a gas supply shock, comparison of responses estimated by VAR-OLS and LP-IV.*

K.8 Orthogonalising the structural shocks

When two structural shocks are identified using two instruments, the resulting shocks are not orthogonal in sample unless additional restrictions are imposed. Following the approach of Mertens and Ravn (2013), we impose a recursive ordering to orthogonalize the structural shocks. The results are broadly robust to the choice of ordering, with only minor deviations from the baseline arising when the shock is placed second in the recursive structure.

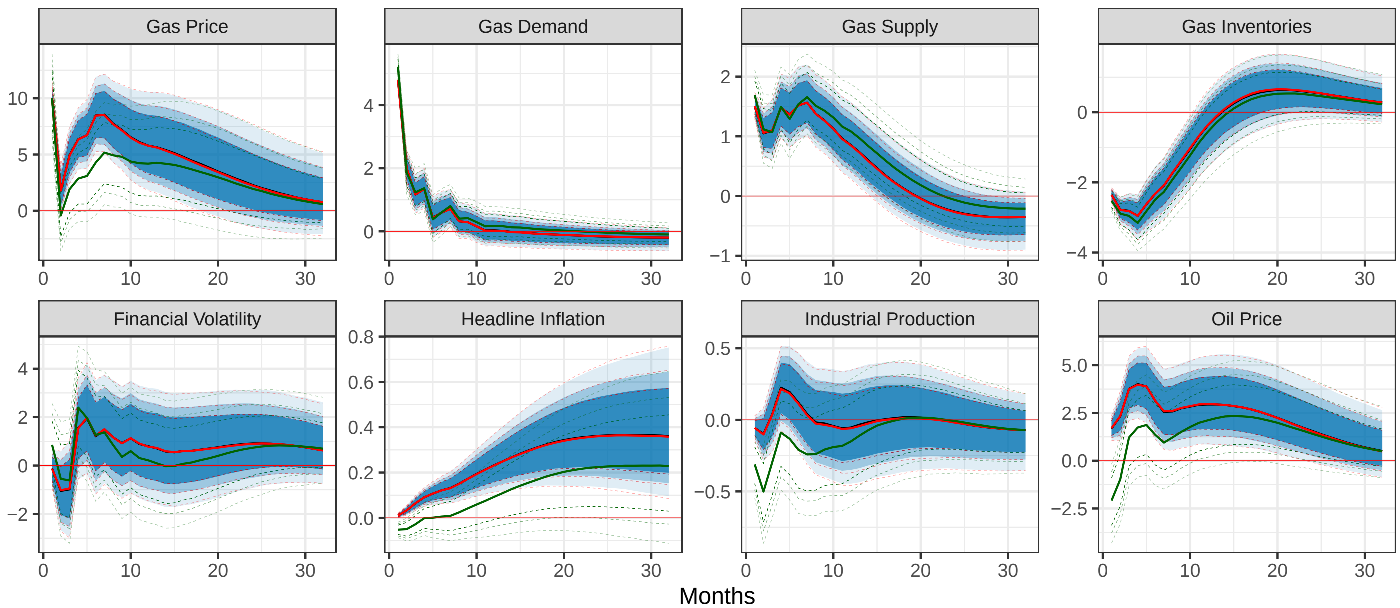


Figure K63: *Impulse responses to a gas demand shock, orthogonalised via recursive ordering. Baseline shown as black solid lines with blue shaded confidence bands; demand shock ordered first in red and second in green.*

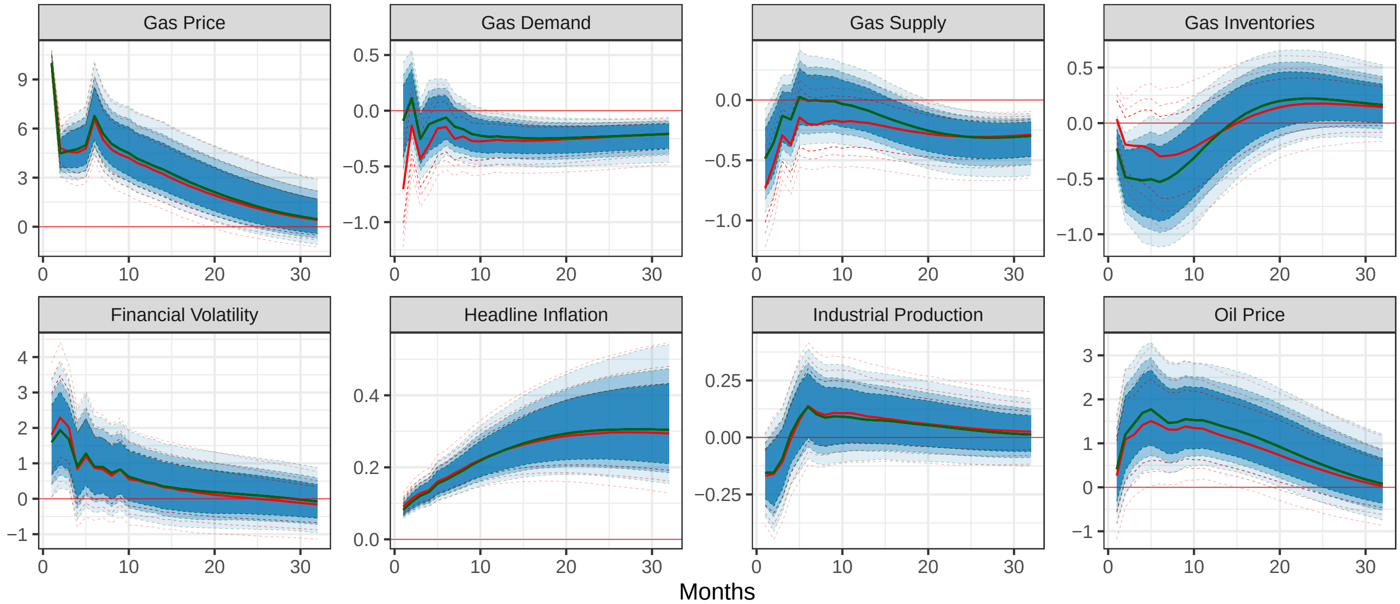


Figure K64: *Impulse responses to a gas supply shock, orthogonalised via recursive ordering. Baseline shown as black solid lines with blue shaded confidence bands; demand shock ordered first in red and second in green.*

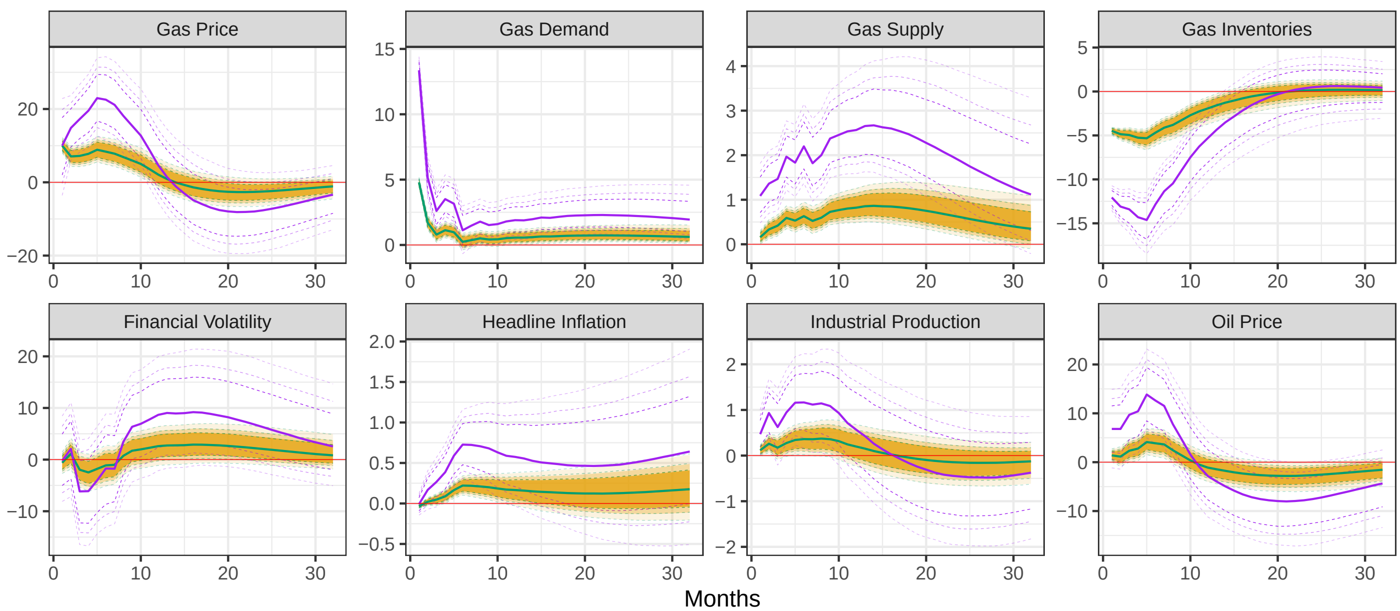


Figure K65: *Impulse responses to a gas demand shock, orthogonalised via recursive ordering. Baseline shown as orange solid lines with orange shaded confidence bands; demand shock ordered first in green and second in purple.*

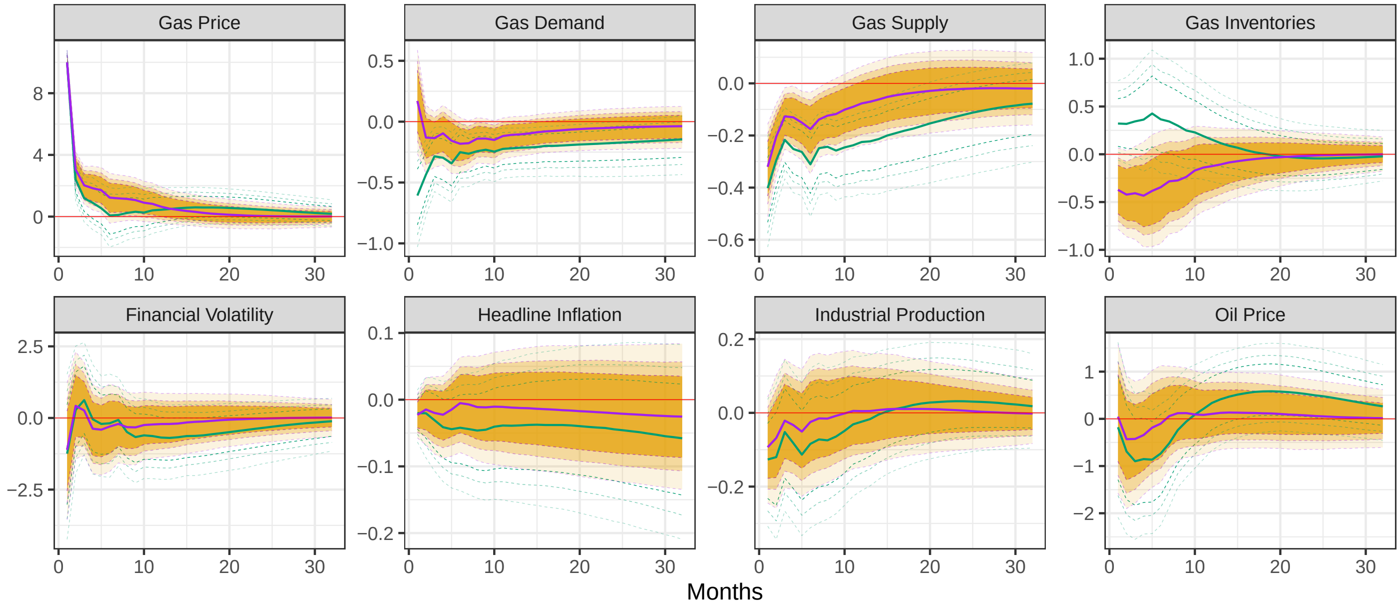


Figure K66: *Impulse responses to a gas supply shock, orthogonalised via recursive ordering. Baseline shown as orange solid lines with orange shaded confidence bands; demand shock ordered first in green and second in purple.*

L 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, 2021) 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 L67 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 response shown in Figure L68. Unlike the responses generated using our instrument, the results on quantities indicate a positive impact on gas demand and no decrease in gas supply up to at least a year. This finding is somewhat puzzling, as the instrument is intended to capture purely supply-side disruptions. In our specification, the first-stage F statistic associated with their instrument is also large, but falls below the conventional threshold of 10 when estimated robust to heteroskedasticity.

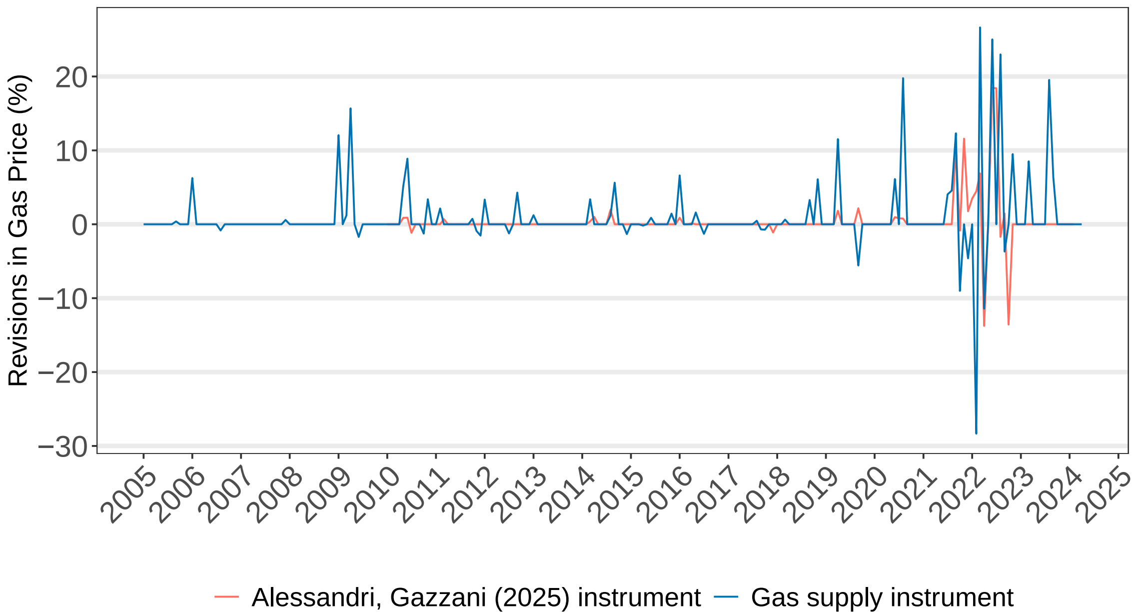


Figure L67: *Comparison of the two supply instruments for Europe.*

Notes: The correlation between the two instruments is 0.30.

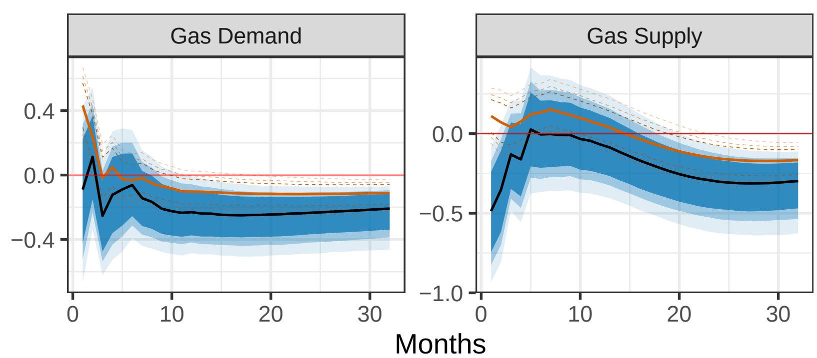


Figure L68: *Impulse responses of gas demand obtained by using the Alessandri and Gazzani (2025) gas supply instrument in our baseline specification.*

Notes: The Fstat is 50.8 and the Robust F is 7.9. Black solid line with blue shaded confidence bands represent our baseline responses and the red solid and dashed lines the results obtained with the alterantive instrument.

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 L9), following a similar diagnostic approach to that used for our instrument in Appendix C.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 L10 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 (2021)**	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 L9: *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 L10: *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 is the news 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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