Gas Price Shocks and the Inflation Surge

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December 17, 2024

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Abstract

We identify a supply shock to the gas price using market-relevant news and high-frequency data, as well as a demand shock leveraging exogenous variation induced in the price of gas by large temperature deviations. These shocks have economically significant effects. We show that in the Euro Area gas supply and demand shocks significantly impact both headline and core inflation, with a pass-through of 1.7–3%. This underscores the role of second-round effects, where the initial price increases feed into broader inflationary pressures. By contrast, in the United States, these shocks are less inflationary. The US economy adjusts more quickly through short-term consumption and stock responses, as well as longer-term production adjustments, mitigating the overall inflationary impact of gas price shocks. To illustrate these dynamics, we provide the first estimates of gas consumption and supply elasticities for both regions using an instrumental variable approach. In the Euro Area, we estimate a short-run demand elasticity that is statistically zero, while supply elasticity is approximately 0.15, reflecting the region's reliance on imports. In the United States, demand adjusts more rapidly, with an elasticity of approximately -0.1, and supply elasticity is lower at 0.05, driven primarily by domestic production, which adjusts more gradually. However, the Euro Area's reliance on imports inherently limits its ability to mitigate gas price shocks caused by supply disruptions. We further examine several other macroeconomic effects of gas price shocks, highlighting significant sectoral heterogeneity in their transmission. Finally, our analysis shows that gas price shocks and supply chain bottlenecks accounted for the majority of the variation in inflation dynamics during the recent inflation surge.

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

JEL classification: C32, E31, Q41, Q43.

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1 Introduction

Historically, energy price shocks have been analyzed primarily through variations in crude oil prices. This focus on oil markets in macroeconomic research is due to the role of oil as the primary energy input and can be justified by the fact that other commodity prices, notably natural gas, have closely followed the price of crude oil for a long time. Similarly, New-Keynesian macroeconomic models frequently represent energy as a single homogeneous good, typically oil, as exemplified in the framework proposed by Blanchard and Gali (2007) and in more recent studies, such as Gagliardone and Gertler (2023). However, the outbreak of the Ukraine war in February 2022 caused major disruptions in the energy market and steep price increases, thus highlighting the relevance of gas shocks. These events also accelerated the decoupling of natural gas prices from oil prices, a trend already underway due to the transition from oil price indexation to gas-on-gas competition (Szafranek & Rubaszek, 2023). This decoupling is particularly evident in European spot gas prices, which reached unprecedented levels in the third quarter of 2022,but a similar trend is also observable in U.S. gas prices, driven not only by recent developments but also by longer-term dynamics initiated by the shale gas revolution (Acemoglu et al., 2023).

The increase in energy prices, particularly in the Euro Area (EA), has also been associated with the recent inflation surge, as illustrated in Figure 1. Over the past three years, the world experienced the highest levels of inflation in more than three decades. The Harmonised Index of Consumer Prices (HICP) in the Euro Area peaked at 10.6% in October 2022, while the U.S. Consumer Price Index (CPI) reached 9.1% in June 2022 (Koester et al., 2022). This inflation surge has sparked a debate on its causes, with some scholars arguing that it was mostly demand-driven, resulting from excessive pandemic-related spending and loose monetary policy (Bordo et al., 2023). Others emphasize pandemic-induced supply bottlenecks, shifts in sectoral demand, and exacerbated market power (Stiglitz & Regmi, 2023). Labor market tightness, initially seen to have made only a modest contribution to inflation, has gained significance over time according to Bernanke and Blanchard (2023), suggesting that balancing the labor market should be a primary concern for central banks. While these factors likely all played a role in the inflation surge, crafting effective policy responses necessitate identifying and addressing the primary drivers of inflation, of which energy prices have been a key component. This highlights concerns that an exclusive focus on oil prices may underestimate the inflationary impact of energy shocks, particularly in light of the unprecedented surge in natural gas prices in recent years, as noted by Kilian and Zhou (2023).

In this paper, we investigate the effects of gas price shocks in the Euro Area and the United States in a proxy-SVAR, separately identifying the impacts of gas supply and gas demand shocks. We identify supply shocks to the gas price using market-relevant news and high-frequency data, and demand shocks leveraging exogenous variation induced in the price of gas by large temperature deviations. This methodology allows us to provide the first estimates of gas consumption and supply elasticities for both regions using an instrumental variable approach. Our findings highlight structural differences between the two regions and help understanding how these shocks propagate across a range of macroeconomic and sectoral variables, with a particular focus on their impact on inflation and output.

Studying the transmission of gas price shocks is highly relevant for policy. Recent events have underscored the greater vulnerabilities of the Euro Area's energy system compared to that of the United States, primarily due to its heavy dependence on external energy sources. Understanding these transmission mechanisms is crucial for designing effective energy diversification strategies and enhancing energy security (Draghi, 2024). In addition, estimates of the pass-through from gas prices to the electricity market and subsequently to other sectors and overall consumer prices can provide valuable insights into how electricity market design may amplify inflationary pressures driven by fossil fuels (Baget et al., 2024). This analysis can inform potential reforms while also shedding light on both direct and second-round effects on sectoral inflation. Moreover, estimating the elasticities of gas supply and demand is essential for assessing the effectiveness of price-based measures in reducing reliance on natural gas. Looking ahead, both the Euro Area and the United States will need to accelerate their transition to renewable energy sources. This shift will not only mitigate carbon emissions from fossil fuels but also strengthen energy security by reducing vulnerabilities to future external shocks.

Preview of main results. Our analysis reveals significant regional differences in the impacts and dynamics of gas shocks between the Euro Area and the United States, reflecting structural disparities in their energy market structures and consumption patterns. In the EA, gas shocks are more persistent, reflecting a heavy reliance on imports and slower consumption adjustments. By contrast, the US is better able to mitigate demand shocks through adjustments in domestic production and stock levels, while supply shocks are smoothed by immediate reductions in consumption and responsive stock management. In the EA, we estimate a short-run demand elasticity of zero, indicating that consumption does not respond immediately to price changes, while supply elasticity is higher at around 0.15, reflecting the role of imports. However, this reliance on imports limits the region's ability to counteract price shocks caused by import disruptions. In the US, demand adjusts more quickly, with an elasticity of approximately -0.1, and supply elasticity is lower at 0.05, driven by domestic production that adjusts more gradually. The inflationary effects of gas shocks are more pronounced in the EA than in the US. In the EA, demand shocks pass-through up to 3% to headline inflation after one year, while supply shocks to around 2.5%. In contrast, in the US, demand shocks produce smaller and shorter-lived inflationary effects, peaking at approximately 1% within six months before dissipating. Supply shocks, however, have no observable inflationary impact. In both regions, stock responses to supply shocks reflect evidence of precautionary demand and speculative behavior, with adjustments to gas stock levels being lower than in the case of demand shocks, particularly in the Euro Area. Sectoral analysis reveals significant heterogeneity in the transmission of gas shocks across industries. In the EA, supply shocks have an immediate and pronounced impact on power spot prices, with a nearly one-to-one pass-through. The pass-through to gas and electricity utilities is substantial, reaching up to 20%, initiating on impact, and persisting over time. Gas supply shocks exert broadly inflationary effects across all sectors, with clear evidence of second-round effects amplifying their impact. While the aggregate real effects are limited, they exhibit considerable variation across sectors. These sectoral responses are consistent with the dynamics typically associated with cost-push shocks. Overall, our findings emphasize the inflationary nature of gas supply shocks, particularly in the EA, and underscore the sectoral heterogeneity in their transmission. Moreover, through a historical decomposition exercise, we show that the gas demand and supply instruments we construct significantly account for historical variations in gas prices. Our analysis further reveals that the recent inflation surge in the Euro Area was primarily driven by gas shocks and supply chain bottleneck shocks, both of which exhibit persistent effects.

A comprehensive series of sensitivity checks indicates that the results are robust across several dimensions, including the model specification, and that the instruments that we construct do not capture unintended mechanisms. We demonstrate that the results are qualitatively robust when estimating the responses to the identified shocks using a frequentist VAR-OLS instead of Bayesian estimation and quantitatively unchanged when constructing an informationally-robust gas supply instrument that controls for several potential confounding factors as well as background information over event windows.

Related Literature. This work relates to a long literature studying the economic effects of commodity price shocks, which has typically focused on the effects of oil price shocks in the US (e.g. Hamilton, 2003; Kilian, 2009; Kilian and Park, 2009; Baumeister and Hamilton, 2019; Caldara et al., 2019; Känzig, 2021a), while the literature on the economic impact of gas shocks is more recent and limited. Nonetheless, the Russian invasion of Ukraine in 2022 intensified concerns about the potentially severe economic impacts of gas supply shocks, prompting an initial number of studies to explore their macroeconomic effects in the Euro Area. Among the theoretical works, Bachmann et al. (2022) employ a theoretical multi-sector macro model with production networks to examine the impact of halting Russian gas imports on the German economy. They estimate a GDP decline ranging from 0.5% to 3%, emphasizing the role of substitution and reallocation of energy imports across sectors in mitigating the shock's impact. Di Bella et al. (2024) expand this line of inquiry to the broader European context using a dynamic general equilibrium multi-sector country model. They find that a severe gas supply shock could lead to GDP contractions ranging from 0.4% to 2.7% for the EU, with individual country impacts varying based on the energy mix and industrial sector energy-switching protocols. The central insight is that greater gas market integration could mitigate economic losses, explaining why actual outcomes were less severe than initially feared.

A few empirical studies using VAR techniques have started to examine the macroeconomic effects of gas shocks in the Euro Area. Adolfsen et al. (2024) use sign restrictions to identify three structural shocks: supply, demand (economic activity), and inventory shocks. They find that both supply and demand shocks significantly impact inflation, while inventory shocks are short-lived and do not influence aggregate prices. Regarding real effects, the impact on industrial production is significant only in response to demand shocks and lasts for a few months, whereas supply and inventory shocks (where the variable is not restricted) do not have significant effects. Similarly, Boeck et al. (2023) examine the effects of natural gas prices using a Bayesian VAR also identified via sign-restrictions, but focus on how inflation expectations influence the pass-through to prices. They find that both inflation and inflation expectations react positively to natural gas price shocks. López et al. (2024) employ narrative sign restrictions to analyze the pass-through of gas and oil supply shocks in the Euro Area. They find that gas price shocks exhibit a pass-through to headline inflation that is approximately one-third smaller than that of oil price shocks, with significant variation in responses across countries.

We contribute to this literature in several key ways. First, we introduce a novel approach to identifying gas price shocks using external instruments (Lunsford, 2015; Stock & Watson, 2018). By leveraging exogenous variation in temperatures and gas prices following market-relevant announcements, we construct instruments for both gas supply and demand shocks. Second, we employ a unified framework to compare the macroeconomic effects of gas shocks in the Euro Area and the United States. This allows us to estimate the elasticities of gas supply and demand and to study the broader propagation of gas shocks throughout the economy. Our findings produce responses of gas balances that are consistent with, but not restricted by, common predictions on prices and quantities. They also provide important insights into how, and to what extent, each region can mitigate these shocks, shedding light on their nominal and real impacts. Third, we conduct a detailed sectoral analysis for the Euro Area, revealing that gas shocks exhibit heterogeneous effects across sectors, which include both direct and second-round effects. Finally, we compare the inflationary effects of gas price shocks with those of oil price shocks, supply chain bottlenecks, and monetary policy shocks to assess the primary drivers of the recent inflation surge in Europe.

This paper is not the first to analyze high-frequency reactions to gas market news or the relationship between gas prices and temperatures. A substantial body of literature employs event-study techniques to examine various types of announcements, including EIA's Weekly Natural Gas Storage Reports (Bjursell et al., 2010; Gay et al., 2009; 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). Several works have also identified temperature as a key determinant of natural gas prices by using various measures. Most studies employ measures of heating degree day and cooling degree day (Mu, 2007; Nick & Thoenes, 2014; Wang et al., 2019), while others use extreme temperature indexes (Baumeister et al., 2024; Chen et al., 2023; Dubin & Gamponia, 2007). While previous studies have explored the relationship between supply events and high-frequency price reactions, as well as the effect of temperature variations on gas demand, this is, to the best of our knowledge, the first work to integrate these elements into a proxy-SVAR framework to analyze their macroeconomic impacts.

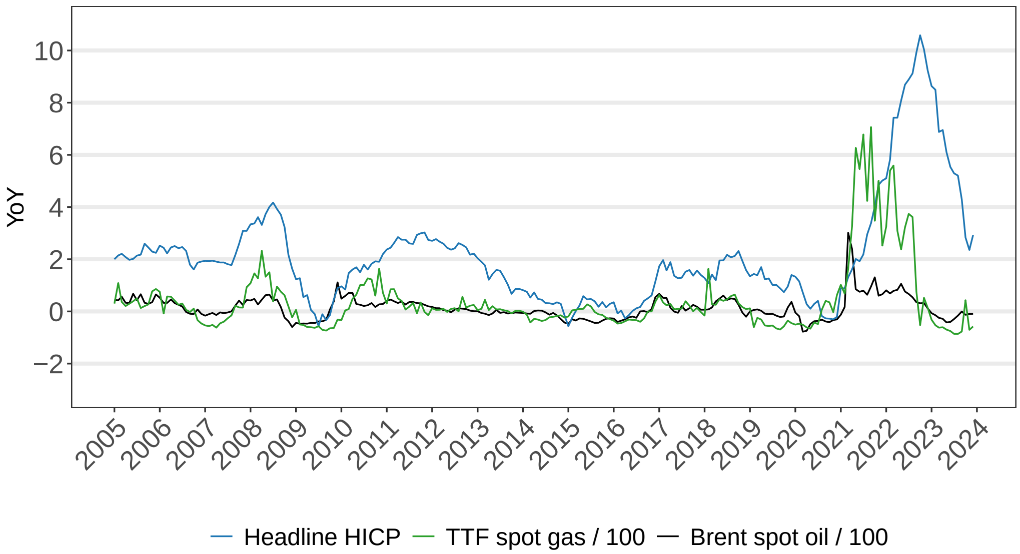
Among the relatively few studies available, the most recent and methodologically advanced estimates of price elasticities in the natural gas market rely on the framework developed by Baumeister and Hamilton (2023) for the U.S. oil market.

This approach integrates zero and magnitude restrictions with prior information derived from earlier estimates and employs a Bayesian estimation strategy. Rubaszek et al. (2021) adapt this framework to estimate short-run elasticities for the U.S. natural gas market, finding a supply elasticity of 0.01 and a demand elasticity of -0.42. Similarly, Casoli et al. (2022) extend the strategy to the European natural gas market, reporting a short-run price elasticity of gas supply of 0.34 and a demand elasticity of -0.47. These studies represent a significant methodological advancement over traditional recursively identified VARs (e.g., Hou and Nguyen, 2018; Nguyen and Okimoto, 2019; Rubaszek and Uddin, 2020; Wiggins and Etienne, 2017), which largely draw from the foundational contributions of Kilian (2009) and Kilian and Murphy (2014). Specifically, this newer approach relaxes the assumption of a zero short-run supply elasticity. Nonetheless, we argue that our framework improves upon these studies in two key aspects. First, by leveraging exogenous variation through external instruments, we eliminate the need for sign or zero restrictions in identifying the contemporaneous effects. Second, we are able to distinguish between the responses of gas production, gas consumption, and gas imports. This contrasts with prior work, where supply is proxied solely by production (Rubaszek et al., 2021) or calculated as the aggregate of imports and domestic production (Casoli et al., 2022). This distinction is particularly relevant for the European natural gas market, where imports play a dominant role in supply dynamics, as discussed further in Section 2. Moreover, prior studies typically estimate demand elasticities indirectly, identifying them from residuals of gas price equations. Unless, all the possible determinants of gas prices are controlled for, this approach risks misattributing other determinants of gas price variation to demand shocks. By employing two distinct instruments for demand and supply, we address these limitations directly. We estimate a short-run price elasticity of gas production in the U.S. of zero, which increases marginally to 0.05 after a few months. In contrast, the European market, where supply predominantly hinges on imports, exhibits a short-run elasticity of 0.15. These supply-side estimates align broadly with previous literature. However, we find notable differences in demand elasticities. Specifically, we estimate a short-run elasticity of gas consumption in the U.S. of -0.1, whereas in the European market, gas consumption appears rigid in the short run, only beginning to decline after several months.

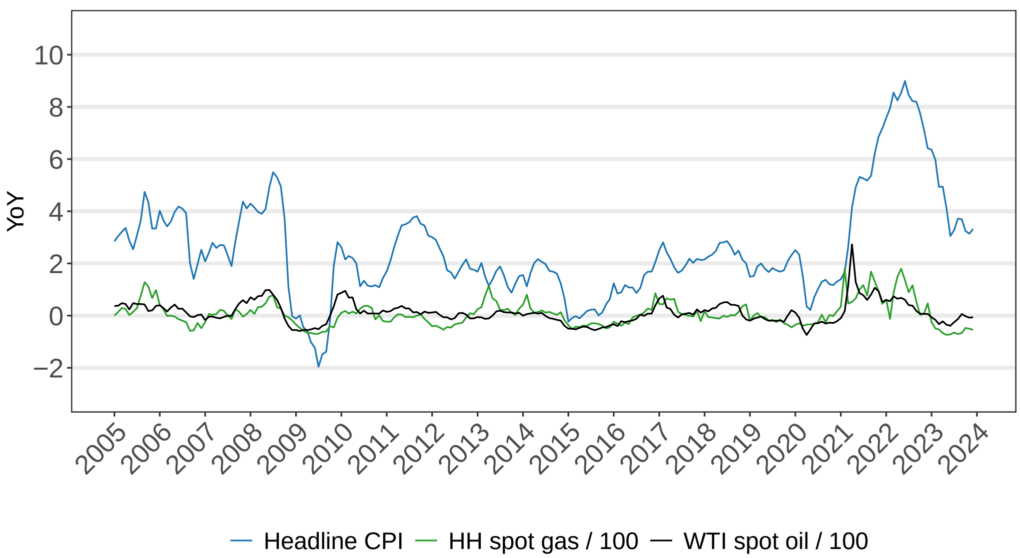
When estimating the pass-through to inflation of energy shocks, the empirical literature has again predominantly focused on oil price shocks. For example, Gao et al. (2014) estimate via a VAR a 7% pass-through on headline inflation and 40% on the energy component of headline. More recently, Känzig (2021a) via an instrumented-VAR estimated on U.S. data found a pass-through of 4.5% on headline, of 35% on the energy component of headline, and on core a non-significant effect of 1.9%. Kilian and Zhou (2022) recursively identify a VAR to quantify the impact of shocks to several energy prices on headline and core inflation in the US. They find that in the U.S. gasoline price shocks are the most relevant, with a pass-through to headline of around 2%, while natural gas price shocks pass-through up to 1% and are not persistent. Neither has significant impact on core inflation. Over the last two years, few studies have tried to estimate the pass-through of gas shocks to inflation, focusing on the Euro Area. In a short report for the Bank of Spain, López et al. (2022)

run several trivariate VARs in reduced-form and document a total pass-through of gas price increases of up to 1.9% on headline inflation. By including the natural gas component or the electricity component in the model instead of total headline, they attribute this effect for 21% to the direct effect on the natural gas component, for 17% to indirect effects via electricity prices, and for the remaining 62% to other indirect effects. Boeck et al. (2023) find a low pass-through of 2-3% to headline and 1.1% to core inflation. Moreover, Adolfsen et al. (2024) find that supply shocks pass-through up to 8.5% to headline and 4.5% to core, demand shocks up to 6.6% to headline and 3.4% to core, while inventories shocks are not significant. They also document that supply shocks pass-through to the energy component of headline by 46% and demand shocks by 33%. Finally, by using a shift-share approach, Joussier et al. (2023) estimate a total pass-through of all energy shocks of 7.3% on inflation, using French firm data. We contribute to this literature by providing estimates of gas shocks pass-through to (components of) inflation obtained via external instruments. For the EA, we estimate a pass-through up to 1.7% for core and 2.5-3% for headline inflation. Individual sectors are affected unevenly in both magnitude and timing, depending on their respective gas-intensity. Immediate pass-throughs reach up to 7% for the transportation sector, while delayed pass-throughs range from 1% to 6% for health and food sectors. In the US we only find mildly significant evidence of pass-through to headline after gas demand shocks.

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



(a) EA



(b) US

Figure 1: *Inflation and energy prices*

Notes: The top panel displays the Year-on-Year (YoY) core 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). For comparability, gas and oil spot prices are scaled by dividing by 100.

2 Gas market background

This section outlines key characteristics of the natural gas market in the Euro Area and the United States, highlighting regional differences and contrasts with the more globally integrated crude oil market. These characteristics underscore the need for a distinct interpretation of gas price shocks in the EA and the US and form the foundation of our empirical strategy.

The global natural gas market features regional fragmentation, with prices for the same commodity differing markedly across areas. This contrasts with the crude oil market, which tends to be more integrated, trading at a relatively uniform price in most places.[1] The consequences of this fragmentation 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. These differences in price reactions are likely attributable to the distinct characteristics of gas balances in the two regions, particularly the energy self-sufficiency of the United States (IMF Blog, 2023).

Natural gas is a critical energy source in both the EA and the US, accounting for 23% of total energy consumption in the Euro Area and 32% in the United States. It plays a crucial role as a primary fuel in residential and commercial heating and it also serves as an important input for industrial activities and electricity generation. Residential consumption represents a substantial share of total demand — 24% in the EA and 18% in the US (Energy Information Administration, 2024b; Eurostat, 2024b) — primarily for heating purposes.[2] Gas demand is highly sensitive to temperature fluctuations during winter (Chen et al., 2023). Consequently, anomalous weather-driven variability can be exploited as a valuable source of exogenous variation to study the effects of gas demand shocks.

The supply structure of the gas market differs starkly between the two regions. In the Euro Area natural gas production has steadily declined over time, with monthly output falling to negligible levels below 100 PJ in recent years (see Figure C15). Correspondingly, import dependence has increased rapidly, from about half of its total available energy derived from gas in the early 1990s to a record 90% in 2019 (see Figure C18). The region sources gas from a select group of major suppliers, including Russia, Norway, Algeria, and the US. Prior to the war in Ukraine, Russia dominated the EU gas market, supplying 41% of gross available energy by 2020, making it the fuel with the highest exposure to Russian imports. This share further increased to approximately 50% of total imports by 2021, when imported gas accounted for over 80% of EU consumption (European Council, 2023). Due to the heavy dependence on imports from a limited number of suppliers, disruptions to gas flows—whether

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

[2] These figures refer to 2021.

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. Notably, the reliance of the EA on external energy sources is not confined to natural gas; nearly all crude oil consumed in the region is also imported (see Figure C18).

In contrast, the United States stands as the world's largest natural gas producers. Domestic production has grown substantially, doubling from approximately 2000 PJ per month in the early 2000s to 4000 PJ in 2023 (see Figure C15). This remarkable expansion has been largely driven by the shale gas revolution (Acemoglu et al., 2023).[3] The US has progressively become a natural gas exporter, particularly in the form of LNG to European and Asian markets. In the aftermath of Russia's invasion of Ukraine, the US became a net exporter of natural gas, with exports doubling imports in recent years (see Figure C15). Turning to crude oil, although exports have almost reached the level of imports, the US remains a net importer (see Figure C17).

A second key difference lies in market structure and maturity.[4] The US pioneered gas market liberalization in the 1970s, adopting a gas-on-gas pricing model, and the Henry Hub (HH) has served as the benchmark price since 1990. In contrast, historically, natural gas pricing in Europe has been predominantly linked to oil products. Over the last two decades, gas prices have moved away from oil indexation to spot pricing by means of 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.[5] 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).[6]

After more than two decades, full liberalization is not yet completed in Europe (Cardinale, 2019). Nevertheless, the gas market is regionally increasingly integrated. 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,

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

[4] The U.S. natural gas market is regulated at both the federal and state levels, with the Federal Energy Regulatory Commission (FERC) playing a prominent role.

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

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

whereas the first European gas hub, the National Balancing Point (NBP), was created in the United Kingdom in 1996. TTF overtook NBP as the largest gas hub in 2017, accounting for approximately 75% of the total European gas trade in 2022 Q4).[7]

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 (International Energy Agency, 2021). As part of this trend, oil-indexed contracts, which constituted over 90% of European gas imports in 2005, declined sharply to just 25% by 2019 (International Energy Agency, 2020). These developments enables 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. Adolfsen et al., 2024; Boeck et al., 2023; 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 Figures C19 and C21 and Table C4 we also show that the dynamics of the different hub prices are greatly correlated. However, a source of potential price divergence is given by the increasing role of LNG in the European market. We provide evidence that, while LNG prices historically have not closely followed the TTF price, the growing significance of LNG over time has led to a closer correlation between the two. This is shown in Appendix C.4, Figure C20 and Table C4.

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 infra-day changes in gas futures prices. The Henry Hub futures, introduced at the New York Mercantile Exchange (NYMEX) in 1990, are the most actively traded worldwide (CME Group, 2021). Moreover, these futures have the longest available history, thus making them a natural choice for analysis in the US. TTF is the most liquid and most widely traded future for natural gas in Europe, hitting a record of 5.7 million contracts per month in May 2023 (ICE, 2023).

These characteristics of gas markets in the Euro Area and the United States motivate our empirical strategy for analyzing the macroeconomic effects of gas price shocks. In the EA, the reliance on external natural gas sources and the frequent disruptions naturally motivate the construction of high-frequency supply shock series to capture import disruptions. Conversely, in the US, where domestic gas production is predominant, supply shocks are identified by focusing on disruptions to domestic production as an instrument for gas supply. On the demand side, the significant use of gas for heating and its high sensitivity to temperature fluctuations enable the use of temperature shocks to identify the effects of gas demand. Regarding which price best proxies overall natural gas market conditions, the Henry Hub price serves as an effective proxy for US natural gas prices due to its established role as the primary reference price. Similarly, in the EA, the Title Transfer Facility has become the benchmark for natural gas prices, owing to its status as the most liquid and widely

[7] European Commission (2022).

traded gas market. While LNG has gained importance, the TTF remains a reliable proxy for overall gas prices as the increased significance of LNG has strengthened its correlation with TTF spot prices. Furthermore, hub-based indexing has become the dominant pricing mechanism for natural gas in the EA, reinforcing the TTF's suitability as the reference price for the region.

3 Identification strategy

To study the impact of macroeconomic shocks on the Euro Area, 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 in the US and in the EA, as well as detailed sectoral responses for the EA. Finally, we examine in greater detail the impact of gas shocks on inflation in the EA via a historical decompositions exercise. We 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 4. 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 surface 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 consumer 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 (Altavilla et al., 2019; Cochrane & Piazzesi, 2002; Nakamura & Steinsson, 2018) and more recently adapted to the crude oil market (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.[8] To address this, we collect gas supply-related news from multiple sources, relying on Reuters for both the EA and the US, and carefully assess the exogeneity of each news item. 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 influenced 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 clearer interpretation of the identified shocks, which can be viewed as exogenous disruptions to gas imports, whether realized or anticipated. Our collection of news encompasses major suppliers of both pipeline gas and LNG, including events driven by geopolitical tensions and conflicts (such as disruptions related to the Ukraine war), announcements by major energy companies, gas field strikes, pipeline incidents (such as explosions, maintenance activities, or new investment projects), and EU legislative actions related to gas imports. The final sample includes 60 supply-related news events, with Russian flows accounting for 35 of the total, Norwegian sources for 12, and the remaining 13 attributed to other suppliers such as the United States and Qatar.

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 unforseen technical issues.[9] This disruption left the British gas market undersupplied by around 4 MCM, and the supply concerns triggered an increase in European gas prices, with the TTF

[8] 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.

[9] 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.

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 (Figure D27). 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 (Figure D28).

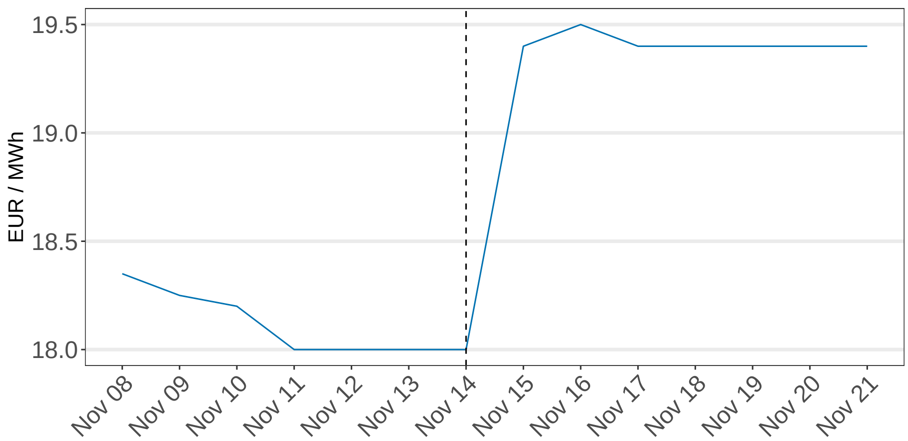


Figure 2: *Unexpected drop in gas flows from Norway through the Langeled pipeline.*

Notes: The figure shows the surprise in the spot TTF gas price related to the news. 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. For clarity, the values shown in the figure for these dates correspond to the last available trading day's price.

For the United States, applying the same logic of focusing on the most relevant and prevalent supply factors, we concentrate on news related to domestic production. Unlike the Euro Area, where gas imports dominate consumption, the U.S. benefits from substantial domestic production, making production-related news the most pertinent for identifying supply shocks. Our collection includes 24 supply-related news items, encompassing events such as gas platform outages, maintenance activities, and explosions. This focus provides a clear interpretation of the shocks as exogenous disruptions to domestic gas supply. The effect on the HH price of a supply-related news is illustrated in Figure D26. On November 8, 2006, the ANR Pipeline Company announced that engine repairs at the St. John and Bridgman compressor stations had reduced the capacity of the Michigan Leg South, which serves as a critical link between major interstate pipeline systems. As a result of this disruption, the HH spot price increased by about 12%. A selected sample of our collection of news is given in Table D5.

Construction of gas surprises. Using the gas-related news, we construct a series of gas surprises by calculating the (log) difference between the closing futures price on the day of the news and the closing price on the last trading day prior to the news release, effectively capturing the percentage change in price:

$$GasSurprise_d^h = F_d^h - F_{d-1}^h \tag{3.1.1}$$

where d denotes the day of the news, F_d^h is the (log) price of the h-months ahead gas futures contract in date d.[10]

A crucial choice when constructing the surprises is the width of the event window. Following Känzig (2021a), we opt for a daily window. This differs from the monetary policy literature where it is customary to use shorter windows. In the gas market, there is no major news source with regularly scheduled press releases that the market closely follows, as is the case with central banks. Furthermore, gas-related announcements lack the clarity of monetary policy statements, necessitating traders to invest more time in identifying and processing the information. Therefore, intraday windows would miss much of the response to the news. By contrast, using multi-day windows could introduce background noise that confounds the price reaction. This concern is particularly relevant for the latter part of our sample, which has been marked by an extraordinary series of events, particularly in Europe. Another important factor to consider is the selection of the futures contract maturity. Given that disruptions and supply adjustments in the gas market can have both short-term and longer-term consequences, futures contracts with maturities ranging from one month to one year are natural choices. Thus, we take the first principal component of the gas surprises spanning the first year of the gas futures term structure, which is then rescaled to match the standard deviation of the underlying surprises.[11] To obtain a monthly series, we aggregate daily surprises within each month by summing them. In instances where there is no gas-related news, the monthly surprise is set to zero. Figure 3 shows the resulting monthly surprises series.

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. In addition to using the settlement price, we also approach this issue from a different perspective, one that has so far been overlooked in the proxy-SVAR literature. In a monthly VAR, the residual for a month containing a news event reflects price changes driven by multiple forces within that month, including various intra-day fluctuations, and is not limited to the price shift caused by the specific news event being analyzed. As a result, when conducting the first-stage regression at the monthly frequency, there is a risk of inadvertently attributing cor-

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

[11] The average price revision following a surprise is 7% for the EA and 3% for the US when calculated using the rescaled principal component. On the front-month futures, these revisions increase to 10% and 5%, respectively. This discrepancy reflects the generally lower volatility of HH prices compared to TTF prices, a stylized fact that was also true in the period preceding the Ukraine crisis.

relations arising from other economic forces to the constructed proxy. Importantly, this concern is distinct from the question of whether the event itself is exogenous. For instance, consider the news on April 28, 2016, when Gazprom expressed optimism about Nord Stream 2 gaining approval from the European Commission without encountering the regulatory challenges faced by Nord Stream 1, used by Alessandri and Gazzani (2023) to construct their proxy. While the TTF price movements on April 28 were likely influenced by this news, the primary price fluctuations for the month were largely driven by gas demand changes due to temperature variations. Prices initially rose until April 27, before declining in response to a warmer weather outlook (European Commission, 2016). To address this concern, we conduct a detailed analysis of gas price dynamics over each month and exclude any supply news occurring in months where the identified supply events are not the primary drivers of price variation. This approach ensures that our results more accurately capture the influence of supply news while minimizing the risk of confounding effects. Figure E30 provides graphical evidence demonstrating the clear distinction between our demand and supply instruments. In addition, following standard practice, we ensure that the proxy is uncorrelated with its own lags and a wide range of potential confounding factors (see the next subsection).

To evaluate the adequacy of the gas surprise series, we further perform a comprehensive series of checks. 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. These includes institutional news, such as the energy measures implemented by the European Council as well as other events involved in broader geopolitical developments, notably those associated with the conflict in Ukraine (for example oil supply disruptions) . To assess the relevance of background noise within the surprise series, we compare the daily changes in gas future 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 feature higher variance and fatter tails (right panel of Figure 4). This suggests that the presence of background noise is limited. Appendix E 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.

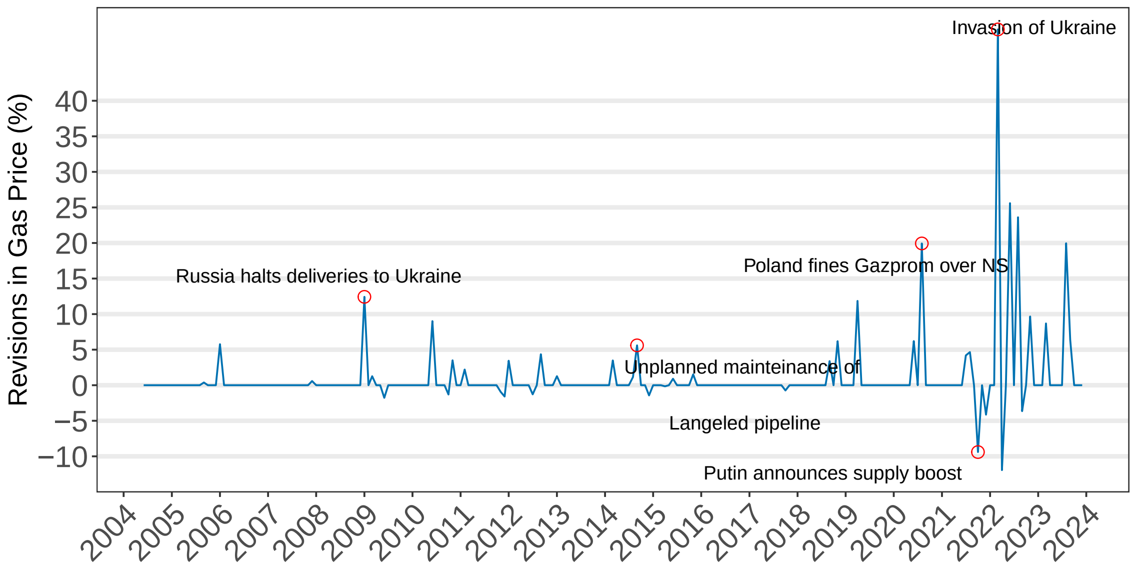
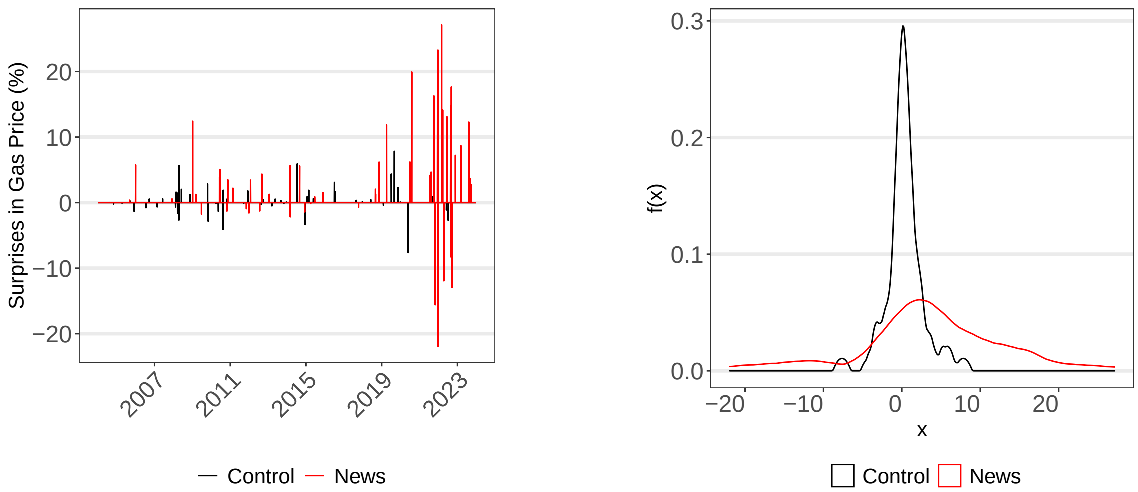


Figure 3: *The EA gas supply surprises series*

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 for the gas market. In 2009M1 Russia halted its gas deliveries to Ukraine over a gas supply dispute. In 2014M9 unplanned maintenance on the Langeled pipeline disrupted Norwegian gas imports. In 2020M8 Poland fined Gazprom, posing threaths to Europe's gas imports. On the 28th October 2021 Putin announced that Gazprom could increase gas supplies, while supply fears peaked in 2022M3 following the invasion of Ukraine.



(a) Daily surprises

(b) PDF

Figure 4: *Gas news days versus control days.*

Notes: The left panel displays the daily changes in gas future 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 15.71 and a a Brown-Forsythe test for the equality of group variances confirms that this difference is highly statistically significant (F-statistic: 35.26).

However, the presence of noise could still bias the results and compromise the reliability of inference, as demonstrated by Nakamura and Steinsson (2018) in the context of monetary policy. To address this concern, we explicitly account for potential confounding events and construct an informationally robust surprises series, which we show produces results that are virtually identical to the baseline series.

Informationally-robust surprises. To interpret the surprise series as an exogenous supply shock, it is important to ensure that these events do not also contain new information regarding confounding factors, as this would violate the exogeneity of our instrument. One such potential concern regards food prices, which, for example, can impact the overall price level. This consideration becomes particularly relevant when assessing gas supply news related to the conflict in Ukraine, which not only disrupted gas supplies and prices but also had a notable impact on the global food market, severely moving international food prices (Ben Hassen and El Bilali, 2022; Alexander et al., 2023). Moreover, given the integration between oil and gas markets, news affecting gas supplies might also impact oil market expectations. More broadly, some of the events included in the construction of the gas surprises, especially those concerning geopolitical tensions and war, could have far-reaching consequences that affect endogenous variables contemporaneously through channels other than the one of gas prices. All of which could imply a violation of the exclusion restriction.

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 purging the gas supply series from food price surprises arising from the same gas-related news, prior gas supply surprises, and other relevant shocks documented in the literature. More specifically, we recover the informationally-robust surprises, IRS_t, as the residuals of the following regression:

$$GasSurprise_t^h = \alpha_0 + \sum_{j=1}^{2} \phi_j \, GasSurprise_{t-j}^h + \sum_{j=0}^{2} \theta_j \, FoodSurprise_{t-j}^h + \sum_{j=0}^{2} \mathbf{x}_{t-j}\Gamma_j + IRS_t \tag{3.1.2}$$

where $GasSurprise_t^h$ denotes the gas supply surprise of month t in the future contract h, computed around the gas supply news as detailed previously. Similarly, $FoodSurprise_t^h$ represents surprise in food prices constructed around the same gas news and aggregated at the monthly frequency by summing the daily surprises but calculated using wheat futures prices. Note that 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).[12]

Finally, $\mathbf{x}_j$ is a vector of monthly shocks sourced from the literature. We incorporate several shocks to assess whether the observed changes in gas prices are influenced by other factors, such as oil shocks or the uncertainty induced by the geopolitical events considered. These are the global oil supply shock proposed by Kilian (2009), which reflects disruptions in the physical availability of crude oil worldwide, oil-specific demand shock and the aggregate demand shock from the same paper, oil supply and oil demand shocks from Baumeister and Hamilton (2019), and supply surprises in the price of oil identified by Känzig (2021a). The uncertainty indicators considered encompass various domains, ranging from geopolitical to financial market conditions: these 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 as in Bloom (2009) and the excess bond premium by Gilchrist and Zakrajšek (2012).[13]

Figure 5 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. Appendix H, Figure H36, presents the results obtained using the informationally-robust instrument. The responses are largely similar, with only minor, statistically insignificant differences, suggesting that informational confounding does not materially affect our high-frequency gas surprises. In Appendix E, Table E7 reports the correlation between gas surprises and other shocks from the existing literature. We find that the

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

[13] These measures are sourced directly from the authors' references or extended, following closely the methodologies outlined in the original papers.

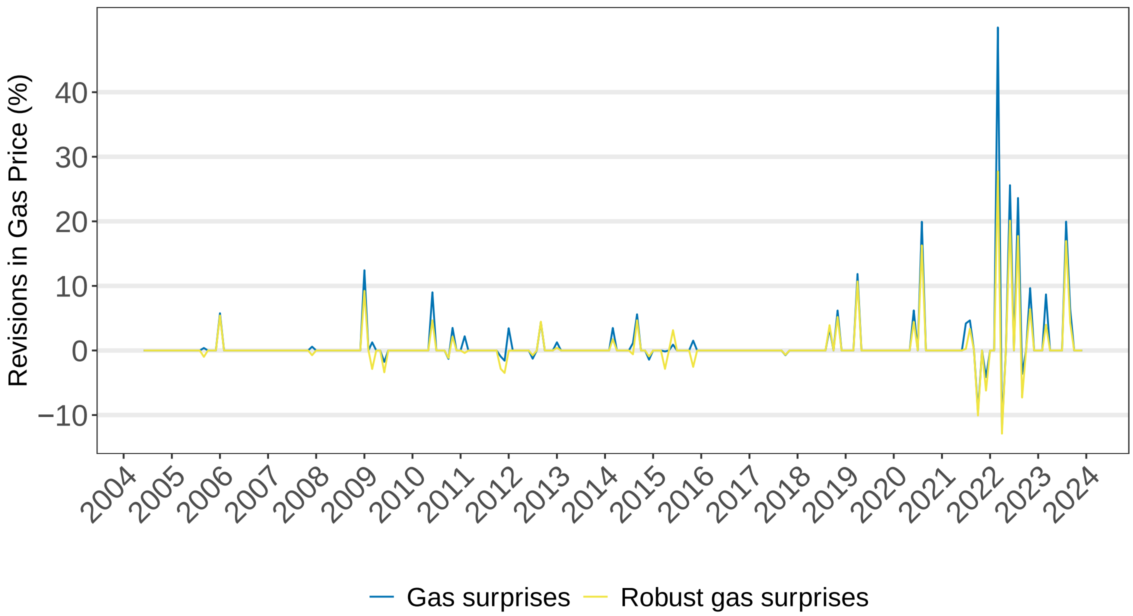


Figure 5: *Informationally-robust gas surprises series*

Notes: This figure shows the gas surprise series (blue line) alongside the informationally-robust surprises, residual to Eq. 3.1.2 IRS_t (yellow line).

gas surprise series does not inadvertently capture oil supply and demand, global demand, uncertainty, financial, or monetary policy shocks.

3.1.2 Temperatures and heating demand

In addition to unexpected market-related news, we exploit a second source of exogenous variation to identify the effects of shocks to the gas price: the unexpected demand of gas for heating due to anomalous temperatures. As highlighted in Colombo and Ferrara (2023) and Pisa et al. (2022), an important channel of transmission by which temperatures impact inflation is via energy demand. These papers argue that a positive "temperature shock" reduces the demand for heating, which leads to a fall in energy production and energy prices, while the opposite occurs with a negative temperature shock. Specifically, the former focus on the effect on production of energy while the latter focus on energy prices. We take advantage of this fact to construct an instrument for the price of gas that captures demand-induced variation.

We construct a monthly series of temperature shocks, which we argue are exogenous to the price of gas. The underlying premise is that, unlike typical seasonal temperature variations, large deviations from average temperatures in any given month are unanticipated by economic agents. Consequently, such deviations are not factored into trading decisions but instead influence gas prices through the demand-for-heating channel, making them a valid and relevant instrument.[14]

[14] Temperature forecasts generally decline in accuracy as the forecast horizon increases, becoming

To construct the series, we first isolate deviations from historical temperature norms and then select only the most significant deviations. The computation proceeds as follows. First, we consider deviations from average temperature by subtracting to daily average temperatures of each calendar day the mean monthly average temperature (across all years in the sample) corresponding to the month where the calendar day is located. The resulting series is then aggregated to the monthly frequency by taking averages across time. Finally, the series is thresholded to isolate only months with large temperature deviations by setting to zero any observation within 2 standard deviations. Appendix F further details the computation of the series.

Since the gas traded at the TTF is supplied to several countries, for Europe we consider the average temperature of the countries that mostly rely on the TTF, namely Belgium, Germany, France, Luxembourg, and The Netherlands, where we weight each country by its gas consumption.[15] Figure C22 presents the resulting series for the sample of averaged countries considered.[16] Positive spikes in the series are on average associated with unexplained negative spikes in the price of gas, and vice versa. Notably, the series exhibit a strong negative correlation with the real price of gas after controlling for relevant macroeconomic variables, consistently with the proposed channel, and providing evidence that this is not a weak instrument.[17]

In the remainder of this section, we provide additional evidence to support the claim that this correlation primarily arises from the demand-for-heating channel.

relatively unreliable even with the most advanced methods. See, for example, Lopez-Gomez et al. (2023). In Figure F32, we demonstrate that anticipation effects are negligible, at most limited to 2–3 days. This limited anticipation does not present a concern for our monthly estimation framework.

[15]Note that at the country level temperature is a weighted-by-population average of grid-level temperatures (see Appendix F). Instead, when we take weighted averages of temperatures across countries, we use the average gas consumption as weights, which is not available at the grid level.

[16]Similarly, we construct the corresponding series for the United States using U.S. temperatures, averaging across states.

[17]The relevant F-statistics is presented in the next section (see, e.g., Montiel-Olea et al., 2016).

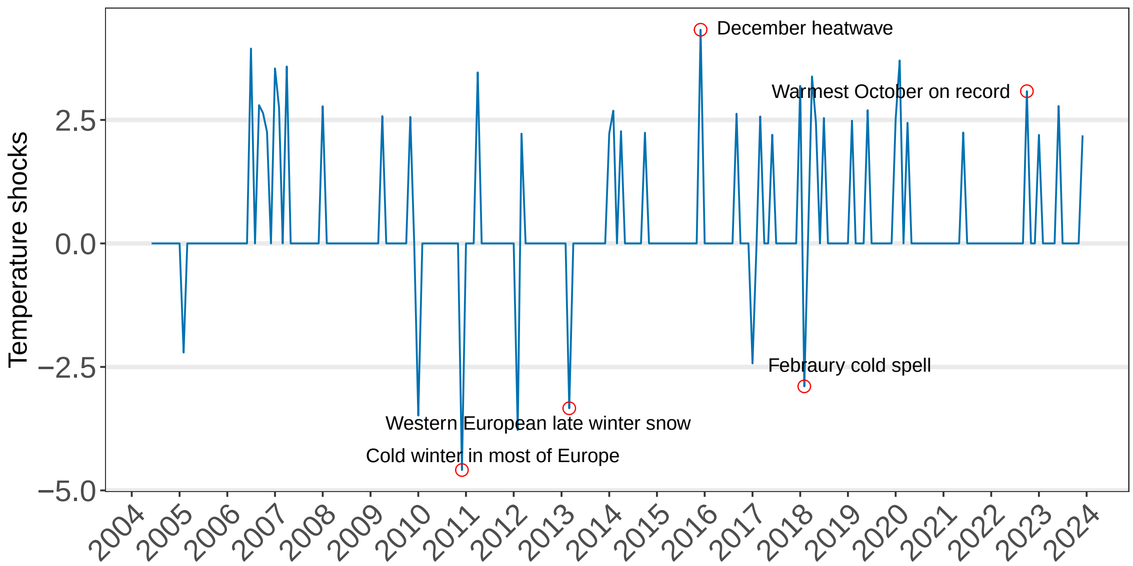


Figure 6: *Temperature shocks series for Europe.*

Notes: This figure shows the temperature shocks index, which we construct 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.

If the main channel via which temperatures impact the price of gas is demand for heating, we should find that most of this correlation takes place during months where absolute temperatures justify heating. In other words, unexpectedly cold temperatures during months such as July and August (typically the hottest months in Europe) should not move much the price of gas, as absolute temperatures would not be low enough to justify turning on heating. To study whether this is the case, we look at the *cooling degree days* (CDD) and *heating degree days* (HDD).[18] Figure F33 shows the averaged CCD and HHD for the same sample of countries that we use to construct the temperature series.[19]

When we restrict the sample to months when the HDD is low,[20] the correlation between the temperature series and the residual gas price drops to -0.11 In contrast, when we restrict the sample to months when the HDD is high, the correlation is

[18] CDD and HDD are proxies for the heating and cooling energy requirement of buildings. For the exact definition 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.

[19] We again use gas consumption at the country level as weights to compute the CDD and HDD weighted averages.

[20] We choose 70 as a threshold.

maintained, and slightly increases: we get -0.36. These results show that temperatures induce variation in the price of gas mostly when this is associated to months when such temperatures lead to the turning-on or -off of heating. Furthermore, when we restrict the sample to months when the CDD is high,[21] we get a correlation of -0.11, while when CDD is low we get a correlation of -0.34, showing that the energy required for cooling does not impact the price of natural gas. Since CDD and HDD naturally have a very strong seasonal component, similar results can be obtained by looking at the correlation only within the Winter or Summer seasons.[22] Conveniently, we have that most of the spikes in the temperature series (both positive or negative), occur during Winter months. Nonetheless, we could extract even more correlation by setting to zero any spikes in the temperature series that occur during Summer months (June, July, August, September), obtaining a correlation of -0.32. While if we set to zero all spikes that occur in other (non-Summer) months we get a correlation close to zero: -0.04. Finally, Figure F34 shows the auto-correlation function of the temperature series, consistent with a *shock* interpretation.

As a final note of this section, even though we have argued that the variation in the price of gas induced by temperatures acts predominantly via a demand channel, if important supply channels were also to be at play, this would not necessarily violate the exogeneity of the instrument. Nonetheless, we check that the temperature series is uncorrelated with the revisions in gas price expectations series: correlation of -0.02, further supporting the argument that temperatures operate via a demand for gas channel and do not co-vary with supply-related news. Note that we never have a spike in the same month for both series, as shown in Figure E30.

4 Results

In this section, we present results for the Euro Area and the United States, showing that gas price shocks have important macroeconomic effects and that there are important differences between the two regions and between gas demand and supply news shocks. We then compare the effects of gas shocks with those of oil shocks, showing that the two markets are asymmetrically interrelated. Finally, we examine the sectoral impacts of gas supply shock on both prices and quantities in the Euro Area. For all specifications, our estimation sample is 2004M1-2023M12.[23]

The impulse response functions (IRFs) are estimated in a Bayesian fashion (Banbura et al., 2007), and we follow the hierarchical approach by Giannone et al. (2015). Technical details on the estimation technique are given in Appendix A. Nonetheless, in Appendix H we show that our results can be qualitatively replicated using a standard frequentist approach.

Our main specification includes 10 variables: the real price of natural gas,[24] gas

[21]We choose 5 as a threshold.

[22]In this case we get -0.36 (Winter) vs -0.12 (Summer) correlation.

[23]We start from January 2004 as that is the earliest for which TTF natural gas futures are available.

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

quantity, gas stocks, gas net imports, the headline consumer price index, interest rate, industrial production, the nominal exchange rate and we also control for the real price of crude oil and unemployment rate. We are thus able to give a detailed description of the natural gas market as well as study in depth the macroeconomic effects of gas price shocks. The model is estimated in log levels so that all responses can be interpreted as elasticities. When estimating the effects of a gas demand shock we use gas production as gas quantity, which allows us to estimate the elasticity of domestic production. Conversely, when we estimate the effects of a gas supply shock, we use gas consumption as quantity, which gives the elasticity of demand. At the end of this section, we enrich our specification with sectoral production and price variables to study the sectoral effects of a gas supply shock in Europe. Specifically, we include sectoral industrial production and producer price indexes based on the statistical classification of economic activities NACE Rev. 2, as well as HICP consumer price series based on the classification of individual consumption by purpose ECOICOP. A detailed overview on the data and their sources can be found in Appendix C.1.

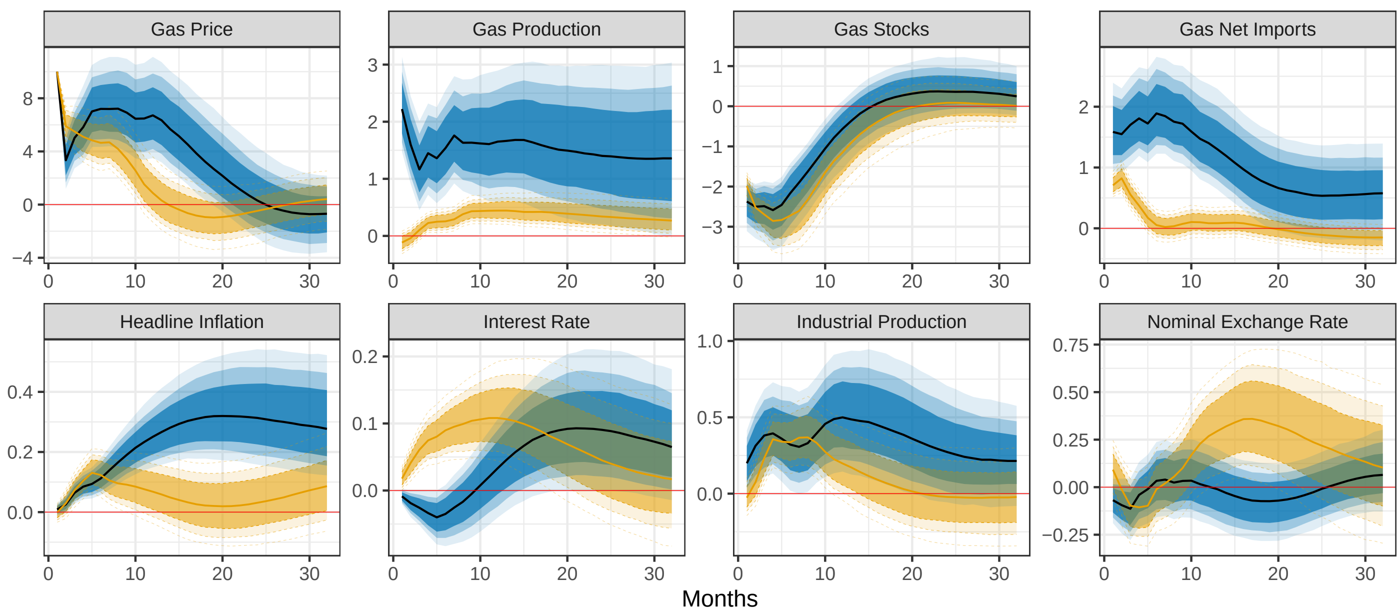
Effects of a gas demand shock. The effects of a gas-specific demand shock exhibit regional differences between the euro area and the United States. In the EA, the gas price response is more persistent compared to the US, where the effects dissipate after about one year. In response to an increase in gas demand, the EA primarily adjusts through changes in stocks and imports, as domestic gas production is negligible in this region (see Figure C15). Conversely, the US accommodates increased demand through a combination of production and stock adjustments, with imports playing only a minor role due to their relatively small share of the overall gas balance. The dynamic responses of gas production represent an estimate of the price elasticity of production. In the US, we estimate a short-run price elasticity of production of zero, which increases to approximately 0.05 after a few months. In contrast, for the EA, the estimated price elasticity of production is around 0.15. However, this finding is less meaningful in the EA context due to the minimal scale of gas production in the region. Instead the elasticity of imports is more relevant, which we estimate to be 0.15 on impact. Figure G35 (left panel) presents results from an alternative specification that considers total supply without distinguishing between domestic production and net imports. As anticipated, the elasticity of supply in the US approximately corresponds to the elasticity of production, while in the Euro Area, it aligns closely with the elasticity of imports.[25]

The inflationary impact of this shock is more pronounced in the Euro Area, where we estimate a peak pass-through to inflation of 3% approximately one year after the shock. In contrast, the response in the United States is less persistent, with a peak pass-through of 1% occurring about six months after the shock. This difference can be attributed to the reduction in gas exports, as well as the U.S.'s greater storage and production capacity compared to the EA. These factors allow the U.S. to better

[25] Following the standard convention in this literature, we define elasticities as the percentage change in quantity resulting from a 1% increase in price.

absorb demand shocks, mitigating the inflationary pressure typically seen in the EA. In addition the ECB look-through these shock, while the Fed appears more reactive

The real economic effects of the shock are mild but slightly positive in both regions, with industrial production increasing by about 0.3% at its peak. This rise is not indicative of a broader aggregate demand response but rather reflects increased activity in energy-related sectors, which benefit directly from the heightened demand for gas. Lastly, the euro experiences a slight depreciation against other currencies immediately following the shock, driven by the increased need for gas imports to satisfy higher demand. In contrast, the US dollar tends to appreciate. This finding is particularly noteworthy, as the negative correlation between the dollar and commodity prices is a well-established stylized fact (Obstfeld & Zhou, 2022). While this relationship holds true for both gas and oil in our sample, we observe that, conditional on a positive gas price shock, the dollar initially experiences a mild depreciation but subsequently appreciates after several months.



First stage regressions: EA F: 21.02, Robust F: 14.38; US F: 34.93, Robust F: 28.03

Figure 7: *Impulse responses to a gas demand shock.*

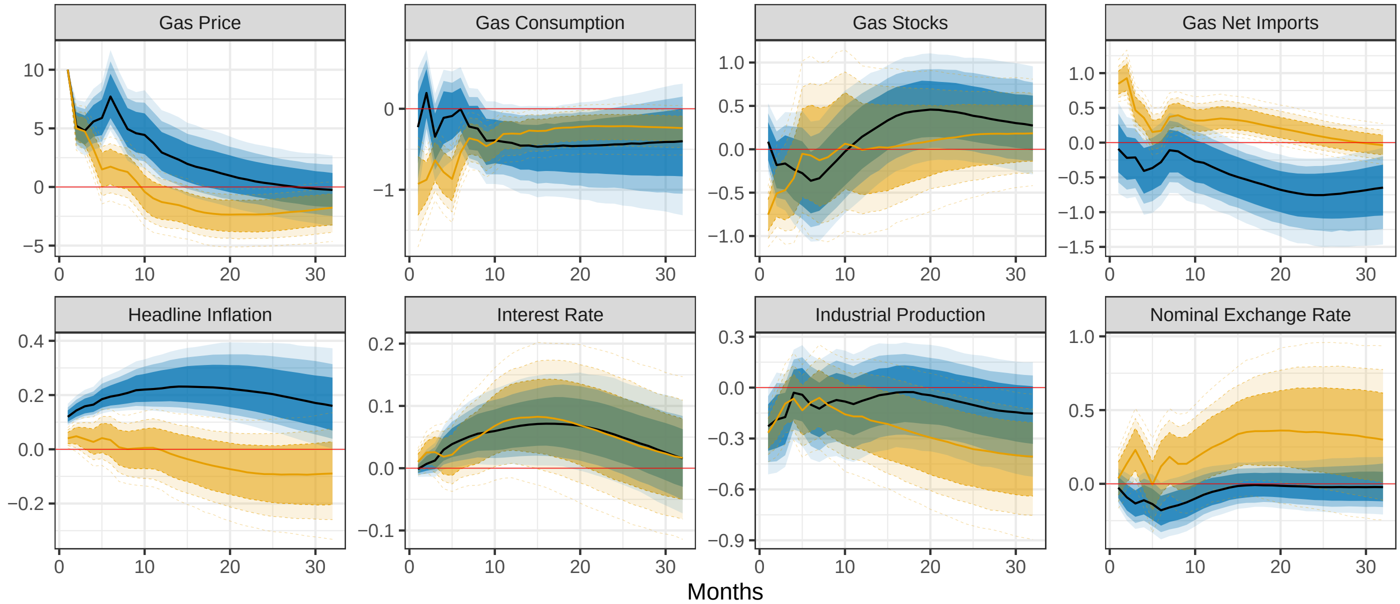
Notes: Impulse responses to a gas demand shock in the Euro Area and the United States. The black solid lines with blue shaded confidence bands represent the EA, while the orange solid lines with dashed and shaded orange confidence bands represent the US.

Effects of a gas supply shock. Figure 8 illustrates the effects of a gas supply shock on the real gas price, gas balances, and selected macroeconomic variables, highlighting notable regional differences between the euro area and the United States. As with gas demand shocks, supply shocks are more persistent in the EA, reflecting structural disparities in their energy markets. In the EA, gas consumption reacts only with a significant lag, contributing to the persistence of the price shock. By contrast, in the US, gas consumption adjusts more quickly, with an estimated short-run elasticity of -0.1. This estimate is in the ballpark of the results of Auffhammer and Rubin (2018), who, using a large panel of California bills, estimate that the elasticity of demand for (only residential) natural gas is between -0.23 and -0.17. The timing of the decline in gas consumption coincides with the start of a reduction in gas prices. The US also responds through a combination of reduced consumption, decreased gas stocks, and increased imports. In the EA, however, imports cannot rise due to the nature of the supply disruption, further explaining the prolonged price response.

The persistence of the supply shock in the EA translates into a stronger inflationary effect, with a pass-through to inflation peaking at over 2.5%. Unlike the response to demand shocks, central banks in both regions counteract supply shocks, highlighting their broader macroeconomic significance. Industrial production declines in both regions, with an estimated elasticity of -0.3% on impact. Industrial production initially declines but recovers relatively quickly, resulting in limited real effects. These findings align with predictions from multi-sector macroeconomic models by Bachmann et al. (2022) and Di Bella et al. (2024), which highlight substitution effects and market integration as mitigating factors during the European gas crisis. These dynamics likely explain why the economic fallout following the Russian–Ukrainian crisis was less severe than anticipated (Bundesbank, 2022; Gunnella et al., 2022). These real effects, though limited, combined with the strongly inflationary impact, highlight the economic importance of gas supply disruptions. Additionally, the euro depreciates slightly while the US dollar appreciates, likely reflecting changes in trade balances. The response of gas stocks varies notably between supply and demand shocks. Stocks exhibit a smaller reaction to supply shocks compared to demand shocks. This difference can be attributed to the dual factors at play during supply shocks: while stocks may be utilized to offset liquidity shortages, precautionary demand and speculative behavior—as documented by Kilian and Murphy (2014) and Känzig (2021a) for the crude oil market—can simultaneously drive stock levels higher. In the case of gas demand shocks, this dynamic partially offsets the decline in stocks, particularly in the Euro Area.

As discussed in section 3.1.1, in the US, gas supply shocks are to be interpreted as disruptions to domestic production, given the nature of the news used to construct the surprises and the country's position as a major producer and net exporter of natural gas. The negative response of gas production supports this interpretation, with net imports increasing to offset reduced domestic supply. This adjustment reflects both a reduction in exports and an increase in imports. The real effects are limited but significant, influenced by the substantial contribution of the oil and natural gas sector to the US economy, accounting for 5.6% of total employment.[26]

[26] PwC.



First stage regressions: EA F: 12.13, Robust F: 13.23; US F: 7.39, Robust F: 12.15

Figure 8: *Impulse responses to a gas supply shock.*

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

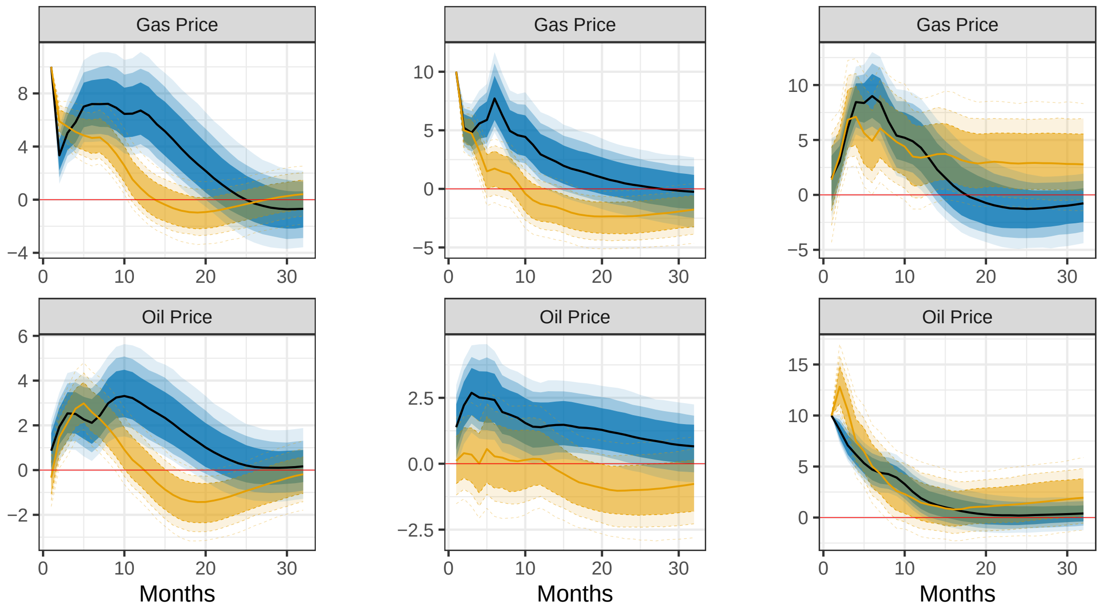
Gas and oil markets interrelation. Figure 9 compares the responses of real gas and oil prices to the respective shocks in both regions.[27] In the EA, there is a pass-through from gas prices to oil prices of approximately 25%, with a slightly lower persistence observed in the case of supply shocks. On the other hand, the pass-through from oil prices to gas prices is significantly stronger, reaching up to 85% at peak. In contrast, the pass-through effects in the US are smaller for both gas and oil. The two markets in the US appear less interdependent compared to the EA, as gas supply shocks have no statistically significant effect on oil prices.

The less persistent nature and the weaker effect of gas shocks in the US may be related to the capability of the US economy to quickly offset gas shocks by relying on domestic production of natural gas, as discussed above. Additionally, the finding that the oil price responds comparatively mildly to gas price shocks in both regions can be explained by the imperfect substitutability of oil and gas: when the price of oil increases, the demand for gas increases, and consequently, the price of gas also rises. Moreover, the oil market is more globalized and an increase in domestic gas demand does not move the global price of oil as much.[28] In contrast, when the demand for gas increases, the gas price increases significantly, given that the global

[27] We consider the real log real price of crude oil and natural gas, following the standard practice in the literature (Jadidzadeh & Serletis, 2017; Känzig, 2021a; Kilian, 2009).

[28] Note, for example, that the dynamics of the Brent (reference for EA) and WTI (reference for US) crude oil prices are very similar.

market for gas is fragmented and the EA depends heavily on neighboring countries as a net importer of gas.



(a) Gas Demand (b) Gas Supply (c) Oil Supply

Figure 9: *Interrelation of Gas and Oil markets.*

Notes: Responses of real gas and oil prices to a 10% increase in their respective prices. Panel (a) shows the responses to gas demand shocks in the Euro Area (in blue) and the United States (in orange). Panel (b) details the responses to gas supply shocks, while Panel (c) examines responses to oil price shocks as identified in Känzig (2021a).

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

Sectoral effects of a gas supply shock in the EA. In this and the following section, we examine in greater detail the effects of a gas supply shock in the Euro Area. Since the onset of the Russia-Ukraine crisis, there has been extensive debate regarding the vulnerabilities of the EA to energy supply disruptions, particularly concerning the region's dependence on Russian gas. This analysis aims to disentangle the specific impacts of such shocks on the Euro Area's economic dynamics, beginning with their transmission to power and utility prices and extending to broader effects on general prices and quantities. This contributes to the ongoing discourse on energy security and economic resilience.

We begin by examining the transmission to gas and power prices, shown in Figure 10. The response of the electricity spot price closely mirrors that of the gas spot price (see Figure 8), with a pass-through of nearly 100%. 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, 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 that the ones on HICP). Government interventions, primarily designed to shield consumers (Sgaravatti et al., 2023), mitigate the impact on household energy bills. In contrast, businesses absorb higher costs, resulting in operational and economic challenges. Naturally, the pass-through to gas utilities is higher than that to electricity utilities (20% vs. 15% at peak after 12 months), given the more direct link between gas prices and gas utilities. The inverted U-shape of these responses reflects the gradual adjustments of these prices, driven by the influence of long-term contracts in both the wholesale and retail sectors (Ason, 2022). These contracts delay the immediate pass-through of cost changes, leading to a slower initial response and a more gradual return to equilibrium. This phenomenon aligns with a broader literature explaining price stickiness in spot transactions, where mechanisms such as menu costs, information imperfections, and long-term agreements prevent quick price adjustments despite changes in market-clearing prices (e.g. Borenstein and Shepard, 2002; Mankiw, 1985; Rotemberg, 1982). Finally, fuel consumer prices show a pass-through of around 20% on impact. Fuel prices, particularly for transportation, are more directly linked to fluctuations in wholesale energy markets, especially crude oil and refined petroleum products. Retail fuel prices tend to adjust rapidly to changes in spot market prices, leading to a faster pass-through effect (see for example Meyler (2009), who finds that oil price shocks in the Euro Area pass through very rapidly to consumer fuel prices, with 90% of price changes transmitted within three to six weeks). Conversely, the gas and power sectors exhibit a delayed and gradual price adjustment due to long-term contracting, regulatory frameworks, and less direct exposure to spot market fluctuations.

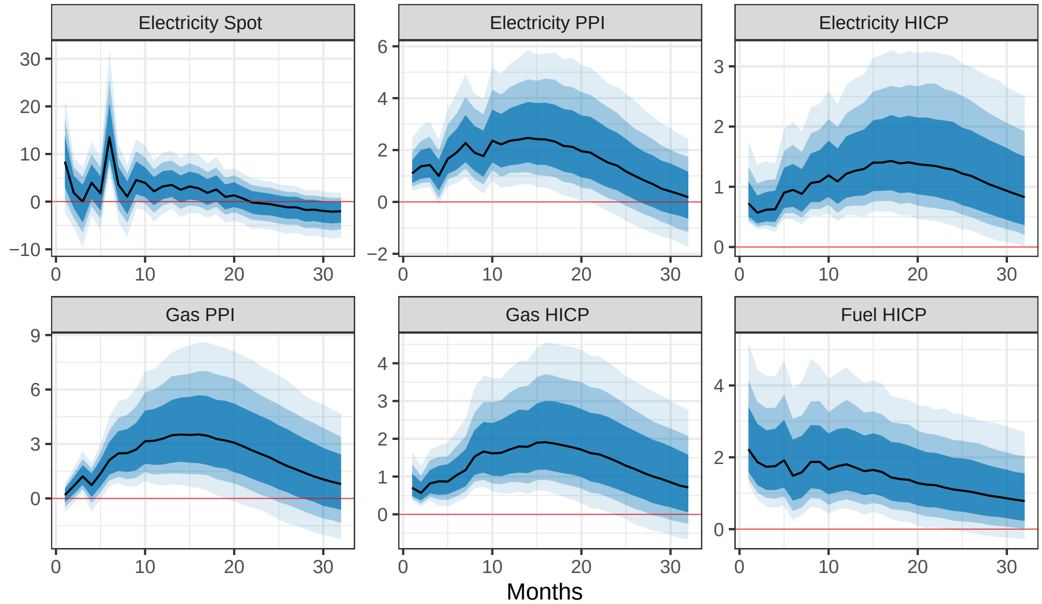


Figure 10: *Impulse responses to a gas supply shock.*

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

Figure 11 presents the broader responses of consumer prices, including core inflation and contributions from ten 2-digit ECOICOP sectors that make up the headline inflation index. Core inflation remains unaffected initially but gradually increases, reaching its peak after more than 20 months with a pass-through of approximately 1.7%—slightly lower than the headline inflation peak depicted in Figure 8. This delayed and measured response suggests the presence of second-round effects, implying that the impact on headline inflation extends beyond direct energy price changes.

Our analysis reveals that while gas supply shocks generally lead to inflationary pressures across sectors, their impacts vary significantly by sector. Many sectors, including food, alcohol and tobacco, furnishing and household equipment, restaurants and hotels, and recreation, exhibit an inverted U-shaped response, indicative of the influence of second-round effects. Among these, the food sector stands out as one of the most affected, with a pass-through of approximately 6% after 12 months. Other sectors, such as education, health, and communication, are less directly linked to gas prices and exhibit only a very mild impact, which emerges gradually after several months. In contrast, the clothing and transport sectors display distinct dynamics, with immediate pass-throughs of approximately 7% for both sectors. 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.

The transport sector, which encompasses vehicle purchases, the operation of personal transport equipment, and transport services, is significantly influenced by increases in fuel prices. This reflects the sector's heavy reliance on petroleum products, which represent a substantial component of transport expenses (Energy Information Administration, 2024a).

Overall, two primary mechanisms account for the sectoral impacts. First, direct effects occur in sectors where energy constitutes a significant cost factor, such as transport and clothing, where the impact of higher gas prices is felt quickly. Second, indirect and lagged effects occur in sectors where second-round 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, some sectors experience only mild effects after an extended period, driven primarily by broader inflationary pressures.

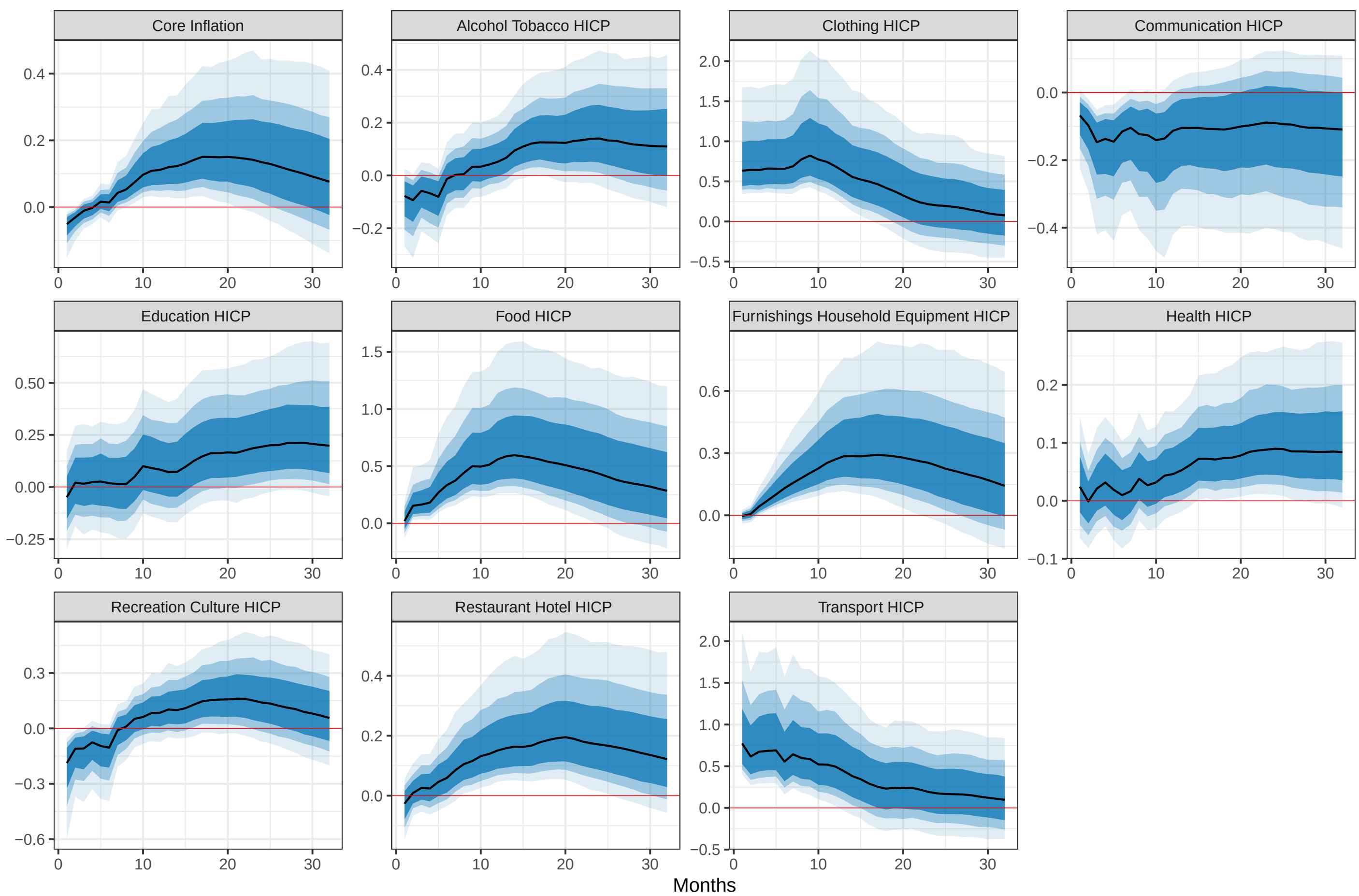


Figure 11: *EA: Responses of core inflation and HICP 2-digit sectors to a gas supply shock.*

In Figure 8, we demonstrated that the macroeconomic impact of gas supply shocks is primarily inflationary, with limited effects on real economic activity. Figure 12 provides a more detailed analysis of how different sub-sectors of industrial production are impacted. The primary contributors to the aggregate effect are the Electricity, Gas, and Steam sector and the Vehicles sector. The negative response in the Electricity, Gas, and Steam sector is expected, as gas is one of its primary inputs, directly linking gas price shocks to production costs. The response in the Vehicles sector aligns with the HICP response for transport (while the correspondence between the sectors is not exact, they are closely related), showing an immediate impact. This reflects the reliance of vehicle production and operation on energy and transport-related inputs, making it particularly sensitive to gas price fluctuations.

Within manufacturing, Level 2 sub-sectors are impacted unevenly, with gas-intensive industries, such as chemicals and paper, experiencing lagged but significant negative responses, while others, such as fabricated metals and textiles show no substantial impact. When considered alongside the results on sectoral HICP, the responses reflect the classic dynamics of cost-push shocks in energy-dependent sectors. Output typically exhibits a U-shaped or inverted J-shaped trajectory, characterized by an initial decline followed by a gradual recovery. In contrast, inflation responses follow an inverted U-shaped pattern, driven by higher production costs being passed on to consumers. Inflation rises sharply at first, peaks, and then gradually declines over time as the shock dissipates. Another characteristic of these types of shocks is the sectoral heterogeneity of their impacts (Davis & Haltiwanger, 2001), which is also evident in our findings. However, not all sectors are significantly affected, which helps explain the limited aggregate real effects, which are primarily inflationary. Notably, gas intensity does not appear to be the primary determinant of whether real effects are observed in a given sector.[29]

[29] Sectoral gas intensity statistics taken from Gunnella et al. (2022).

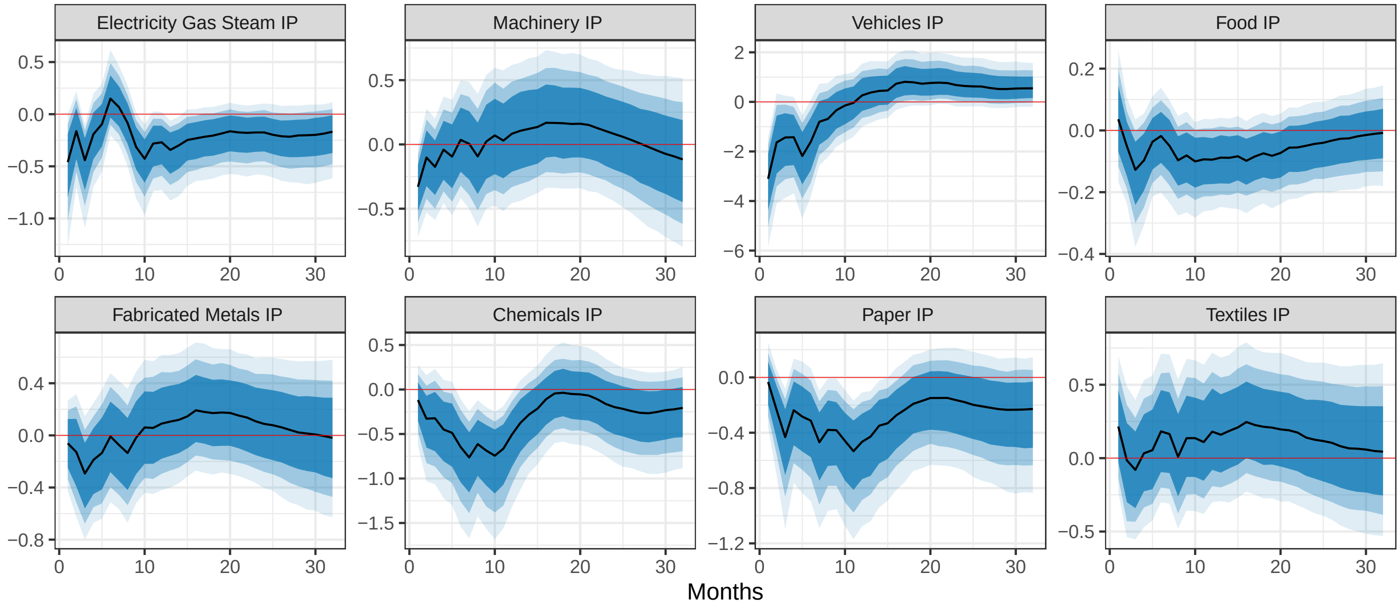


Figure 12: *Impulse responses of IP sectors to a gas supply shock.*

Notes: EA: 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, 2024a).[a]

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

In summary, our analysis reveals significant regional differences in the impacts and dynamics of gas shocks between the Euro Area and the United States. In the EA, gas shocks are generally more persistent than in the US, driven by structural differences in energy markets, reliance on imports, and slower adjustments in consumption behavior. In the US, demand shocks are mitigated primarily through adjustments in domestic production and stock levels. In the EA, by contrast, these shocks are offset by a combination of stock releases and increased imports. Supply shocks, on the other hand, are smoothed in the US through a combination of stock adjustments and more immediate reductions in consumption following price increases. In the EA, consumption adjusts more slowly, and stock responses are limited, amplifying the macroeconomic effects of these shocks. For the EA, we estimate a short-run demand elasticity of zero, indicating that consumption does not initially respond to price changes. In the US, demand adjusts on impact, with an estimated elasticity of approximately -0.1. On the supply side, the US exhibits a supply elasticity of approximately 0.05, dominated by domestic production, which adjusts gradually over time. In the EA, where imports constitute the primary source of supply, supply elasticity is estimated at around 0.15. However, this reliance on imports inherently limits the region's ability to counteract gas price shocks caused by import disruptions. As a consequence of these structural differences, the inflationary impacts of both demand and supply shocks are more pronounced in the EA than in the US. For demand shocks, the pass-through to headline inflation in the EA reaches approximately 3% after one year, while supply shocks result in a pass-through of about 2.5%. In the US, demand shocks lead to a smaller inflationary impact of around 1% within six months, which then fades, and supply shocks have no discernible inflationary effect. Stock responses to supply shocks provide evidence of precautionary demand and speculative behavior, consistent with findings by Kilian and Murphy (2014) and Känzig (2021a) for the crude oil market. This behavior is reflected in only modest adjustments in gas stock levels to offset supply disruptions. Additionally, there is evidence of imperfect substitution between crude oil and natural gas in both regions, with crude oil exhibiting a stronger pass-through to gas prices than vice versa.

Supply shocks have negative real effects, with an initial significant impact on output that is generally mild and short-lived. Sectoral analysis in the Euro Area reveals notable heterogeneity in these effects, emphasizing differences in the transmission and magnitude of shocks across industries. In the EA, supply shocks demonstrate an immediate and substantial transmission to power spot prices, with a nearly one-to-one pass-through. The pass-through to gas and electricity utilities reaches up to 20%, begins on impact, and remains persistent over time. Gas supply shocks are broadly inflationary across all sectors, with clear evidence of second-round effects. This is evident also in the delayed response of core inflation, which reflects the wider inflationary pressures that extend beyond energy prices. Sectoral pass-throughs to consumer prices vary significantly, reaching as high as 7% in sectors like clothing and transport. Coupled with the sectoral inflationary effects, the real output effects of gas supply shocks are consistent with the dynamics of a cost-push shock. Most sectors exhibit a U-shaped response, characterized by an initial decline in output followed by a gradual recovery. However, these real effects are confined to a limited number of sectors, resulting in a relatively modest aggregate impact on industrial production. Overall, these findings highlight the inflationary nature of gas supply shocks, particularly in the EA, and underscore the sectoral heterogeneity in their transmission and effects.

4.1 Contributions to inflation surge

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

We therefore estimate a small-scale VAR model that includes the Global Supply Chain Pressure Index (GSCPI), the real price of gas, the real price of oil, core inflation, and the 1-year ECB rate. Following the approach of Benigno et al. (2022), we identify the effects of supply chain bottleneck shocks using short-run restrictions, assuming that the GSCPI is predetermined with respect to the other variables. Oil price shocks and monetary policy shocks are identified using external instruments, following Känzig (2021a) and Ricco et al. (2024), respectively. Further details on the identification of these shocks are provided in Appendix B. The residuals of inflation are left unidentified and therefore capture unexplained variation in prices attributable to other factors, such as unmodeled aggregate demand or the impact of food prices.[30]

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

[30]See the ECB blog at this link.

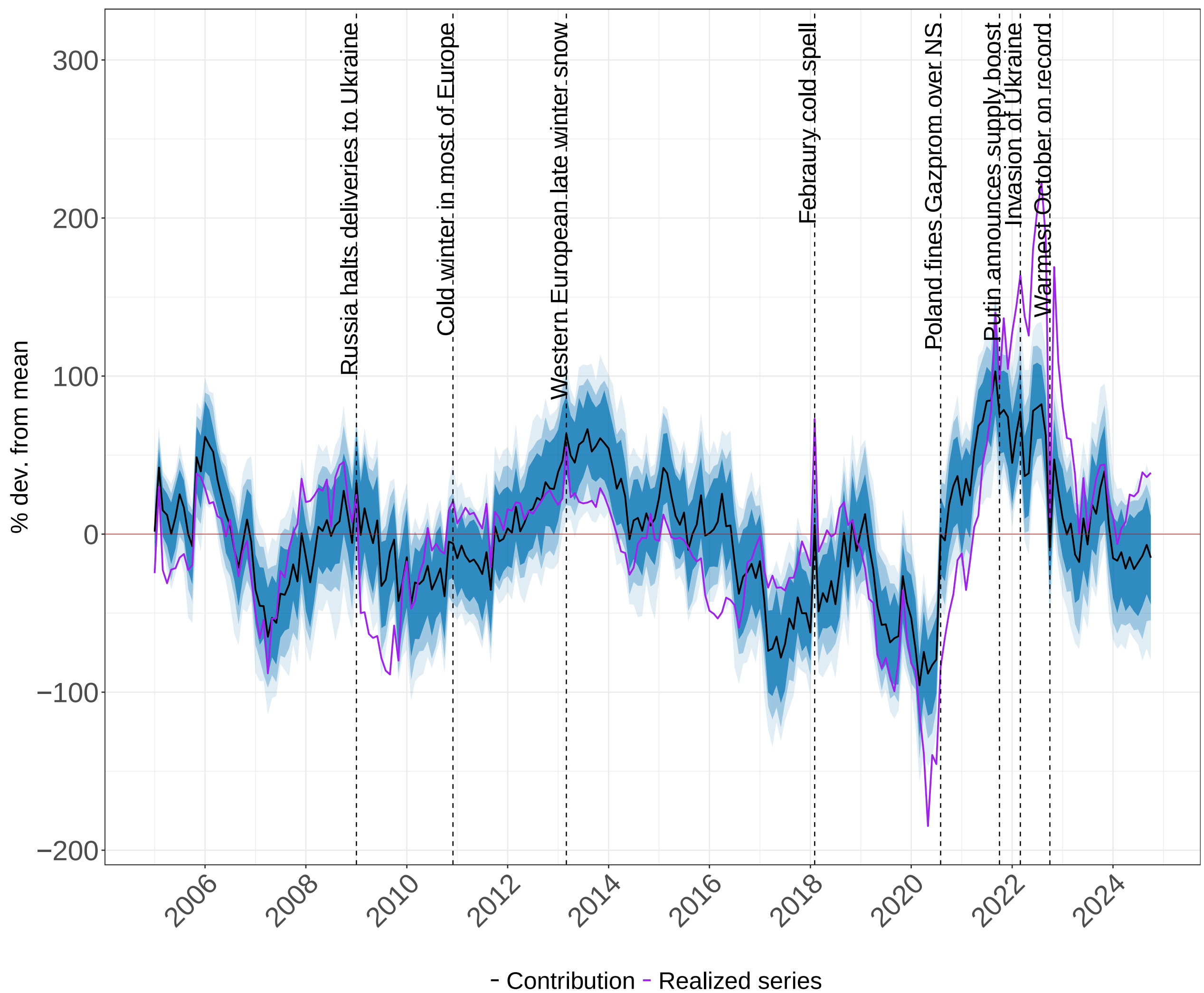


Figure 13: *EA: Historical decomposition of the real price of gas*

Notes: The figure illustrates the estimated contributions of gas shocks to the real price of gas, alongside the realized gas price series (expressed as percent deviations from the mean). Both demand and supply instruments are used. Vertical dashed bars mark significant events in the gas markets: the Russian halt of all gas deliveries to Ukraine for 13 days in 2009M1; an abnormally cold winter in Europe in 2010M12; a late snow event in Western Europe in 2013M3; a 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 2023.

Having evaluated the extent to which our identified shocks account for the variability in the real gas price series, we now focus on the primary objective of this section: quantifying the contributions of inflationary drivers to price dynamics. To provide a clearer understanding of inflation dynamics over time, we first categorize the period from February 2020 to October 2024 into three distinct chronological phases:[31]

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

Figure 14 presents the historical decompositions derived from the VAR model and compares them to the realized series of inflation. Historical decompositions provide a quantitative assessment of how much each series of structural shocks contributes to the observed fluctuations in the variables included in the VAR model (see Appendix A.2 for additional technical details). In this context, these decompositions help identify the relative importance of different inflation drivers over time, offering valuable insights into their changing relevance during the analyzed period.

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

At the onset of the COVID-19 pandemic, oil and gas price shocks had a significant and comparable impact on inflation, as pandemic-related lock-downs triggered a collapse in economic activity and global energy demand. The role of energy shocks, remained critical during the inflation surge observed in Phase II. Gas price shocks, in particular, emerged as the dominant driver of core consumer prices, playing a key role in the rapid price increases. This impact, was further exacerbated by the adverse supply shocks following the invasion of Ukraine. In addition to energy shocks, supply chain bottlenecks became a critical inflationary factor. With the post pandemic reopening, the economy was exposed to severe disruptions, including shortages of semiconductors and memory chips, the global misallocation of shipping containers, and port delays due to pandemic-related restrictions (Stiglitz & Regmi, 2023). These supply chain bottlenecks, characterized by lagged and persistent effects, continued to influence inflation well into late 2023, as also found by De Santis (2024). Throughout the period of elevated inflation, monetary policy responded with a sharp interest rate hikes. However, we find that its effectiveness in mitigating rising prices has been limited. Finally, Phase III was marked by a gradual normalization of inflation driven by the easing of energy price pressures and the resolution of pandemic-induced supply chain interruptions.

We now quantify these qualitative observations and assess the contribution of each historical decomposition to the series of inflation. To this aim, we introduce

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

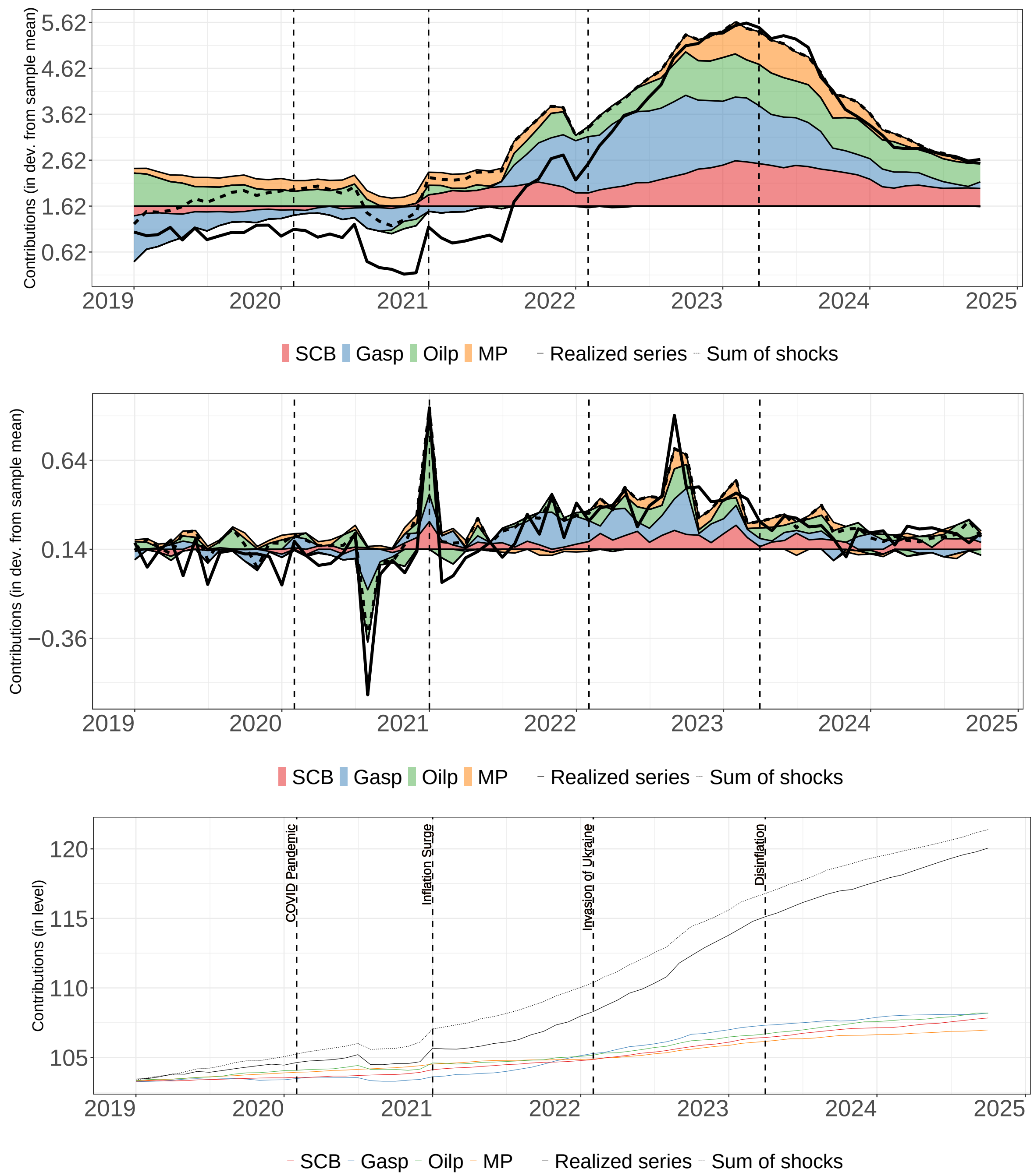


Figure 14: *Historical decompositions of YoY, MoM inflation and price level, selected sample.*

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

a metric that quantifies how much a series of shocks has contributed in percentage terms to the variation of inflation between two time periods. We denote

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

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

$$\hat{y}_{kt}^{(j)} = \sum_{s=0}^{t-1} \theta_{kj,s} w_{t-s} \tag{4.1.1}$$

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

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

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

$$\frac{\sum_{t=q}^{r} |\hat{y}_{kt}^{(j)}|}{\sum_{k=1}^{K} \sum_{t=q}^{r} |\hat{y}_{kt}^{(j)}|} \tag{4.1.2}$$

It is important to note that this measure does not account for the sign of the historical decomposition contributions and should be interpreted accordingly. Specifically, it provides only a quantitative assessment of the extent to which each series of shocks has influenced the inflation series. Table 1 quantifies the contributions of each series of shocks to inflation by applying the proposed metric to different time periods.

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

Table 1: *Percentage contributions of the structural shocks to the realized series of inflation.*

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

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

To complement the information provided by the metric in Eq.4.1.2, we assess the contribution of each historical decomposition on the price level, via the measure proposed by Kilian and Lütkepohl (2017), chapter 4. We measure the cumulative change in y_{kt} between time q and r attributed to the j^{th} structural shock as follows:

$$\hat{y}_{kr}^{(j)} - \hat{y}_{kq}^{(j)} \tag{4.1.3}$$

where $\hat{y}_{kt}^{(j)}$ denote the cumulative contribution of shock j to variable y_{kt} at time t, in line with Eq.4.1.1. In addition to the previously proposed measure, this metric informs on the sign of the cumulative change in the variable of interest given by the j^{th} shock.

Table 2 reports this metric for the three time periods of interest. In Phase I, the price level remained relatively unchanged. The initial negative effects at the onset of the pandemic, driven by a slowdown in economic activity, were offset by the positive effects that followed the reopening of the economy, as illustrated in Figure 14. Additionally, the residual term contributed to a reduction of 0.8 points, likely reflecting unmeasured reduction in aggregate demand. In Phase II, gas price shocks became the major driver of inflation, contributing over 3.8 points to price level increase. Supply chain bottlenecks and oil price shocks also played substantial roles, each contributing approximately 2.5 points. Energy price shocks, which collectively accounted for 50% of the variation in inflation during the surge, led to a cumulative effect of 6 points on the price level. Lastly, during the disinflation period, while all of the factors considered moderated, the influence of gas price shocks saw the greatest reduction.

Our analysis reveals that the surge and subsequent reversal of energy prices, alongside the persistent effects of supply chain bottlenecks explain the bulk in the

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

Table 2: *Cumulated contributions of the structural shocks to the realized series of price levels.*

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

5 Policy implications

Our analysis reveals critical vulnerabilities in the Euro Area energy system, showing that gas price shocks generate severe and persistent macroeconomic effects. The inflationary impacts of both supply and demand shocks are more pronounced and longer-lasting in the EA compared to the US.

This heightened vulnerability relates to structural characteristics of the European gas market. First, as detailed in Section 2, Europe's heavy dependence on external energy sources as a substantial net importer exposes the region to significant risks. The 2022 energy crisis following the invasion of Ukraine starkly illustrated that gas price shocks contributed to an unprecedented rise in prices, as our results show (see Section 4.1). The EA must strengthen its energy security through strategic diversification to address this vulnerability. This requires establishing partnerships with reliable and diversified trade partners, and supporting joint purchasing via procurement (Draghi, 2024). Diversifying suppliers while building strategic reserves can enhance the EA's resilience to both negative supply and demand shocks.

Second, institutional features amplify these vulnerabilities, particularly through the electricity pricing system. Under the merit order principle, when natural gas is the most expensive power source, it sets the price for all electricity production (Segarra et al., 2024). We find that gas price shocks are almost completely passed through to electricity prices, raising firms' energy costs that are ultimately transmitted to consumers. Altogether, this mechanism substantially amplifies the inflationary effects of gas price shocks. These findings suggest the need to reform the EA electricity market to prevent marginal pricing by the most expensive energy sources from disproportionately influencing overall energy prices, along the lines of the revision to the Electricity Market Design directive (Baget et al., 2024). Alternatively, a more sustainable solution would involve significantly increasing the supply of renewable energy sources, thereby reducing the reliance on natural gas for power generation, particularly on high-demand days.

Moreover, our analysis shows that gas consumption in the EA is highly inelastic, which has crucial implications for the effectiveness of price-based mechanisms in achieving the green transition. Specifically, we estimate a short-run demand elasticity of zero, indicating that consumption in the EA does not adjust immediately and responds only gradually, with noticeable changes occurring several months after the shock, in contrast to the quicker adjustments observed in the US. Building on the insights of Moll et al. (2023), the rigidities in the production structure not only can amplify the severity of short-run macroeconomic effects but also indicate that price mechanisms alone will not succeed in reducing natural gas dependence—unless gas prices remain elevated for an extended period. Instead, direct investment and command-and-control policies may prove more effective in achieving the transition to renewable energy. However, contrary to the argumentation presented in Moll et al. (2023), our results suggest that gas consumption across the EA exhibits limited substitutability in the short run, even under elevated gas prices, further emphasizing the need for targeted policy interventions to address this rigidity.

Looking ahead, both the EA and the US must accelerate their transition toward renewable energy sources through strategic investments (Draghi, 2024). This shift serves a dual purpose: reducing carbon emissions from fossil fuels and strengthening energy security against the risk of future external shocks. As shown by J. Kim et al. (2025), climate mitigation policies will reduce fossil fuel demand, thereby decreasing import dependence. Moreover, the increasing penetration of renewable energy in the electricity mix directly strengthens energy security by shifting production toward domestic sources. While the authors note that the green transition may temporarily increase market concentration among remaining fossil fuel suppliers as high-cost producers exit, they find that the overall effect on energy security is positive due to reduced reliance on imported fuels. These findings underscore the importance of coordinated policies that promote green innovation in the energy sector to make renewable technologies more affordable, while avoiding a "fossil-fuel trap" that could result from an overreliance on natural gas during this period of change. In this context, elevated gas prices could act as a catalyst, accelerating innovation in green technologies and advancing the shift toward renewable energy sources (Acemoglu et al., 2023).

6 Conclusions

In this paper we proposed a novel identification strategy to separately identify demand shocks and supply news shocks to the price of 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 provide the first estimates of gas consumption and supply elasticities for both the United States and the Euro Area using an instrumental variable framework. Additionally, we presented detailed evidence on the macroeconomic and sectoral impacts of gas price shocks, offering new insights into their transmission mechanisms and effects.

Our analysis revealed that gas shocks have substantial macroeconomic effects in both the Euro Area and the United States, albeit with notable regional differences in their impacts and dynamics. These variations are driven by structural disparities in energy markets and consumption behaviors. In the Euro Area, gas shocks are more persistent due to reliance on imports and slower consumption adjustments, whereas the United States mitigates these shocks more effectively through domestic production and stock management. Demand responds more quickly in the US, with a short-run elasticity of approximately -0.1, compared to zero in the Euro Area, where supply elasticity is higher at around 0.15 but limited by dependence on imports. Inflationary effects of gas shocks are more pronounced in the Euro Area, where demand shocks contribute up to 3% to headline inflation after one year, and supply shocks add around 2.5%. In the United States, demand shocks result in smaller, shorter-lived inflationary effects, peaking at 1% within six months before fading, while supply shocks have no observable impact. Stock responses to supply shocks in both regions indicate precautionary demand and speculative behavior, with gas stock adjustments particularly limited in the Euro Area. Sectoral analysis revealed notable heterogeneity in the transmission of gas shocks. Supply shocks have an immediate and significant impact on power spot prices in the Euro Area, with a nearly one-to-one pass-through. The pass-through to gas and electricity utilities reaches up to 20%, beginning on impact and persisting over time. Gas supply shocks are broadly inflationary across sectors, with strong evidence of second-round effects, as reflected in the delayed response of core inflation. Real effects on output are limited in aggregate but exhibit considerable sectoral variation, consistent with the dynamics of cost-push shocks. To further investigate the effects of macroeconomic shocks on inflation in the EA, we proposed an historical decomposition of inflation in which we compare the contributions of gas price, oil price, supply chain bottlenecks and monetary policy shocks to the variation of inflation. We showed that the recent inflation surge in the EA has mainly been driven by gas shocks and supply chain bottlenecks shocks, both of which have persistent effects. Additionally, our findings indicate that both types of shocks exhibit significant lags in the propagation, pointing to the presence of second-round effects.

This analysis highlights several policy considerations for addressing the adverse economic effects induced by gas price shocks. First, enhancing energy security remains a key priority for the Euro Area. In the short term, fostering partnerships with reliable and diversified trade partners and supporting joint procurement initiatives can improve resilience. Diversifying suppliers and building strategic reserves would further strengthen the region's capacity to manage both supply and demand shocks. Reforming the electricity market in the Euro Area also emerges as an important area of focus. Adjustments aimed at reducing the disproportionate influence of marginal pricing by the most expensive energy sources could mitigate overall energy price volatility. Such reforms would help avoid scenarios like the 2022 energy crisis, during which gas prices contributed significantly to the inflation surge. In parallel, accelerating the transition to renewable energy sources remains critical for both the Euro Area and the United States. Beyond the environmental benefits of reducing carbon emissions, such efforts can enhance energy security by lowering dependence on external supply shocks. However, our findings suggest that gas consumption in the Euro Area demonstrates limited substitutability in the short run. This indicates that price mechanisms alone may be insufficient to reduce reliance on natural gas unless prices remain elevated over an extended period. Direct investments and command-and-control policies may therefore offer other effective pathways to achieving a successful transition. Moreover, coordinated policies that promote green innovation in the energy sector can facilitate the adoption of renewable energy technologies. Such efforts would support the development of a more sustainable and stable energy mix, reducing vulnerability to fluctuations in gas prices and enhancing long-term energy security.

Finally, advancing research on the second-round effects of gas and oil price shocks can enhance our ability to address both the immediate and longer-term implications of these types of shocks. We leave this a significant avenue for future research.

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Appendix A Econometric models

This appendix is mostly based on Kilian and Lütkepohl (2017), chapter 4 for the frequentist part, and on Giannone et al. (2015) for the Bayesian part. We consider the structural VAR(p) model

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + w_t \tag{A.0.1}$$

with y_t a $(K \times 1)$ vector that is taken to have zero mean without loss of generality, where K is the number of variables included in the VAR, and where w_t is assumed to be white noise. This model is "structural" since the elements of w_t are uncorrelated. Furthermore, is is assumed that the model is driven by K distinct shocks, so that their variance-covariance matrix Σ_w is full-rank. However, since B_0 and w_t are in general unobserved, to estimate the model we resort to its reduced form representation

$$\begin{aligned} y_t &= B_0^{-1} B_1 y_{t-1} + \cdots + B_0^{-1} B_p y_{t-p} + B_0^{-1} w_t \\ &= A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \end{aligned} \tag{A.0.2}$$

where $A_1, \ldots, A_p, u_t$ can easily be estimated by OLS. Without loss of generality, the covariance matrix of the structural shocks can be normalized so that $\mathbb{E}(w_t w_t') \equiv \Sigma_w = I_K$. The key equation that characterizes the model is $u_t = B_0^{-1} w_t$, where the matrix B_0^{-1} has to be retrieved. For now, we assume B_0^{-1} to be known, and our strategy to recover such matrix will be presented in section A.4.

A.1 Structural Impulse Response Functions

Given B_0 and u_t, it is straightforward to recover w_t, which can be used to compute the impulse response functions (IRFs), that is, the responses of each element of $y_t = (y_{1t}, \ldots, y_{Kt})'$ to a one-time impulse in each element of $w_t = (w_{1t}, \ldots, w_{Kt})'$:

$$\frac{\partial y_{t+i}}{\partial w_t'} = \Theta_i, \quad i = 0, 1, 2, \ldots, H \tag{A.1.1}$$

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

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

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

$$Y_t = \mathbf{A} Y_{t-1} + U_t, \tag{A.1.2}$$

with

$$Y_t \equiv \begin{bmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix} \quad \mathbf{A0} \equiv \begin{bmatrix} A1 & A2 & \dots & A_{p-1} & A_p \\ I_K & 0 & & 0 & 0 \\ 0 & I_K & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_K & 0 \end{bmatrix} \quad U_t \equiv \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

By recursive substitution, it can be shown that the response of the variable $j = 1, \dots, K$ to a unit shock u_{kt}, i periods in the past, for $k = 1, \dots, K$ is given by $\Phi_i = \left[\phi_{jk,i}\right] \equiv J\mathbf{A}^i J$, where $J \equiv \left[I_K, 0_{K\times K(p-1)}\right]$ is a selector matrix. These are sometimes called dynamic multipliers of reduced form impulse responses.
Under covariance stationarity of y_t, it can be expressed as a weighted average of current and past shocks (multivariate MA(∞) representation), with weights Φ_i:

$$y_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i} = \sum_{i=0}^{\infty} \Phi_i B_0^{-1} B_0 u_{t-i} = \sum_{i=0}^{\infty} \Theta_i w_{t-1}, \tag{A.1.3}$$

where we define $\Theta_i w_{t-i} \equiv \Phi_i B_0^{-1}$. It follows that

$$\frac{\partial y_t}{\partial w'_{t-i}} = \frac{\partial y_{t+i}}{\partial w'_t} = \Theta_i, \quad i = 0, 1, 2, \dots, H$$

These structural impulse responses can be obtained simply by post-multiplying Ψ_i by B_0^{-1}.

A.2 Historical Decomposition

Structural impulse responses describe average movements in the data. However, we are often interested in quantifying how much a given identified structural shock explains of the historically observed fluctuation of the variables included in the VAR. For covariance stationary VAR models, it is possible to compute such contributions of the shocks to the empirical realization of the variables, called historical decompositions. We can rewrite equation A.1.3 as

$$y_t = \sum_{s=0}^{t-1} \Theta_s w_{t-s} + \sum_{s=t}^{\infty} \Theta_s w_{t-s}.$$

Since under covariance stationarity the MA coefficients will die out, it holds that

$$y_t \approx \sum_{s=0}^{t-1} \Theta_s w_{t-s}. \tag{A.2.1}$$

This approximation can be computed only from $t = p + 1$ to the end of the available sample and will be better for the time periods at the end of the sample, with the quality of the approximation also depending on the persistence of the roots of the

VAR process.

A.3 Forecast Error Variance Decomposition

Forecast Error Decompositions (FEVDs) are another tool that can help answering questions like "how much of the Prediction Mean Squared Error (PMSE) - or the forecast error variance, since the data is mean-zero - is accounted for by each of the structural shocks?"
The FEVD can be computed simply with the Θ_i matrices. It can be shown that for a VAR process the h-step ahead forecast error is

$$y_{t+h} - y_{t+h|t} = \sum_{i=0}^{h-1} \Phi_i u_{t+h-i} = \sum_{i=0}^{h-1} \Theta_i w_{t+h-i}$$

Therefore,

$$\text{MSPE}(h) \equiv \mathbb{E}\left[(y_{t+h} - y_{t+h|t})(y_{t+h} - y_{t+h|t})'\right] = \sum_{i=0}^{h-1} \Theta_i \Theta_i'$$

It follows that the contribution of shock j to the MPSE of y_{kt} for $k = 1, \dots, K$ at horizon h is

$$\text{MSPE}_j^k(h) = \theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2.$$

By reworking these expressions we get

$$1 = \frac{\text{MSPE}_1^k(h)}{\text{MSPE}^k(h)} + \frac{\text{MSPE}_2^k(h)}{\text{MSPE}^k(h)} + \cdots + \frac{\text{MSPE}_K^k(h)}{\text{MSPE}^k(h)} \tag{A.3.1}$$

where each ratio gives the fraction of the contribution of the j^{th} shock to the MSPE(h) of variable k, for $j = 1, \dots, K$.
Finally, for stationary systems, the forecast error variance decomposition converges to the actual variance decomposition, for $h \to \infty$.

A.4 Identification

As presented above, in the VAR context the identification problem refers to the problem of recovering the B_0^{-1} matrix. We here briefly present the recursive identification scheme - which we use as a benchmark - and the instrumental variable approach, our main identification strategy.

The recursive identification scheme. A common approach to solve the identification problem is to impose a sufficient number of restrictions to the entries of B_0 in order to recover the unconstrained ones from the estimate of $\hat{\Sigma}_u$. In particular, it is customary to assume that the simultaneous relationships between the variables are *acyclic*. This assumption imposes that there are no contemporary feedbacks in the system and that there exists a precise causal ordering of the variables. In practice, this is equivalent to imposing that B_0 is lower triangular, given a particular ordering of the variables. By doing so, B_0^{-1} can be unambiguously identified through the Cholesky factorization of $\hat{\Sigma}_u$ and the particular contemporaneous ordering is usually chosen by relying on prior economic knowledge. This technique has perhaps been the most popular way to identify a structural VAR models, as the Cholesky factorization of the variance-covariance matrix of reduced-form residuals is an efficient and straightforwardly implementable way to "orthogonalize" the reduced-form errors, that is, to disentangle w_t from the reduced-form shocks u_t. However, it must be stressed that this identification scheme is built upon the a priori imposition of a whole causal chain with a rigid, recursive causation order, deriving from the computational restriction imposed by the Cholesky factorization.

Since the Cholesky identification scheme can correctly retrieve the matrix B_0 only if the true structure is indeed recursive and the ordering of the variables is specified correctly, this approach is problematic for a number of reasons. As Kilian and Lütkepohl (2017) put it, the credibility of an approach that imposes a recursive causal architecture without any clear order of the variables in mind is undermined in the first place. Furthermore, this is aggravated by the fact that the number of possible orderings grows with the factorial of the number of variables, and, finally, even if all the permutations lead to the same impulse responses, this does not prove that every identification strategy is bound to lead to the same results. It simply shows that all recursive identifications provide the same results, but it gives no evidence that the model should be recursive in the first place. This is why this approach has inspired a series of critic contributions to the literature that take explicit aim at the fact that it seems to be built on the (often quite misled) confidence in the data's ability to speak for themselves but which in practice relies on a set of assumptions that are extremely difficult to justify within real-world applications (Cooley & LeRoy, 1985).

Identification via external instrument: proxy-VAR. In recent years, the instrumental variables approach typically used in microeconomics has been adapted to a time series context, leading to an identification method called proxy-VAR. In a situation where the regression of variable y on variable x presents an endogeneity problem, we can make use of the exogenous variation that an instrument z provides to identify the causal impact of x on y, where z is correlated to x (sometimes referred to as "validity" of the instrument) but not to $y|x$ (sometimes referred to as "exogeneity" of the instrument or as "exclusion restriction"), so that z affects y only through x.

In the VAR context, this approach allows to identify only one structural shock, or rather, at least one instrument is needed to identify each of the structural shocks to be instrumented for. We denote the column of interest of the B_0^{-1} matrix as $\mathbf{s}_k$, with $k \in (1, K)$, which has dimensions $(K \times 1)$, and 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. Therefore, we have

$$u_t = \mathbf{s}_1' w_{1,t}$$

Further, let $\mathbf{z}_t$ denote an instrument (or several), which satisfies:

$$\mathbb{E}[\mathbf{z}_t w_{1,t}] \neq \mathbf{0} \tag{A.4.1}$$

$$\mathbb{E}[\mathbf{z}_t \mathbf{w}_{2:K,t}] = \mathbf{0} \tag{A.4.2}$$

Given these moments conditions,[32] it can be shown that

$$\mathbf{s}_{2:K,1} = \left[\mathbb{E}[\mathbf{z}_t u_{1,t}]'\mathbb{E}[\mathbf{z}_t\mathbf{z}_t']^{-1}\mathbb{E}[\mathbf{z}_t u_{1,t}]\right]^{-1} \mathbb{E}\left[\mathbf{z}_t'\mathbb{E}[\mathbf{z}_t\mathbf{z}_t']^{-1}\mathbb{E}[\mathbf{z}_t u_{1,t}]\mathbf{u}_{2:K,t}\right], \tag{A.4.3}$$

which in the case of a single instrument (z_t scalar), collapses to

$$\mathbf{s}_{2:K,1} = \frac{\mathbb{E}[z_t u_{2:K,t}]}{\mathbb{E}[z_t u_{1,t}]} \tag{A.4.4}$$

Note that the vector $\mathbf{s}_{2:K,1}$ is estimated up to sign and scale, as we have implicitly assumed above that $s_{1,1} = 1$. The sign and scale of $\mathbf{s}_1$ are set subject to a normalization $\Sigma_u = B_0^{-1}\Omega B_0^{-1\prime}$. It is customary to set $\Omega = I_K$ so that a unit positive value of $w_{1,t}$ has a one standard deviation positive effect on $y_{1,t}$.
$\mathbf{s}_{2:K,1}$ can be estimated via the standard two-stage least square procedure as follows:

1. First stage:

$$\hat{\beta}_1 = \left(\frac{1}{T}\sum_{t=1}^{T} z_t z_t'\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T} z_t u_{1,t}\right)$$ [33]

$$\hat{u}_{1,t} = \hat{\beta}_1' z_t \quad \text{for } t = 1, \ldots, T$$

2. Second stage:

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

Note that when we identify a shock via the proxy-VAR, in general only a column of B_0^{-1} is identified, so that it will not be possible to invert this matrix to obtain the structural shocks via $w_t = B_0 u_t$. However, following Stock and Watson (2018) the structural shocks can still be recovered as follows:

$$\mathbf{s}_1'\boldsymbol{\Sigma}^{-1}\mathbf{u}_t = \mathbf{s}_1'(B_0^{-1}B_0^{-1\prime})^{-1}u_t = \mathbf{s}_1'B_0'B_0B_0^{-1}\mathbf{w}_t = \mathbf{e}_1'\mathbf{w}_t = w_{1,t},$$ [34]

under the $\Omega = I_K$ normalization, and where $\mathbf{e}_1$ is the first standard basis vector.
To assess the validity of the instruments, a test relying on the F-statistic[35] (including the constant). can be implemented (see Stock and Yogo, 2002).

[32] We also need $\mathbb{E}[\mathbf{z}_t u_{1,t}]$ full column rank and $\mathbb{E}[\mathbf{z}_t\mathbf{z}_t'] < \infty$.

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

[34] Note that $B_0\mathbf{s}_1 = \mathbf{e}_1$.

[35] In this case the F-statistics takes the form $F = \frac{(\sum_{t=1}^{T} u_{1,t}^2 - \sum_{t=1}^{T}(u_{1,t}-\hat{u}_{1,t})^2)/p}{\sum_{t=1}^{T}(u_{1,t}-\hat{u}_{1,t})^2/(T-p)}$, where p is the number of instruments

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

A.5 Bayesian estimation

The Bayesian VAR we estimate implements Minnesota and sum-of-coefficients priors following Banbura et al. (2007), expanded with dummy-initial-observations priors (Sims, 1993). Parameter estimation of the SVAR model is performed within a Bayesian framework in the spirit of Giannone et al. (2015). The priors for the SVAR coefficients are taken from the *Normal-Inverse-Wishart* family and are of the following form:

$$\beta|\Sigma \sim N(\mathbf{b}, \Sigma \otimes \Omega),$$

$$\Sigma \sim IW(\Psi, \mathbf{d}),$$

where $\mathbf{b}$, Ω, Ψ and $\mathbf{d}$ can be expressed as a function of the lower-dimensional vector of hyper-parameters γ. Here, β is the vector of listed coefficients of the A_j matrices. This class has two advantages: it includes the priors most commonly used in the literature and, since the priors are conjugate with respect to the likelihood function, the marginal likelihood is available in closed form. Giannone et al. (2015) set the degrees of freedom of the inverse-Wishart distribution to $d = n + 2$, where n is the number of variables included in the model, which is the minimum value that guarantees the existence of the mean of the IW distribution of Σ, given by $\frac{\Phi}{d-n-1}$. The matrix Φ is diagonal with the vector ϕ on the main diagonal.

Giannone et al. (2015) propose to use three priors pertaining to the normal-inverse-Wishart family. The Minnesota (Doan et al., 1984), formalizes the idea that, ex ante, all the individual variables are expected to follow random walk processes.

We specify it as follows. The conditional mean of the prior distribution is given by:

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

so that an impact on a given variable only affects that variable at the next period in time, without affecting any variable at different lags. The conditional covariance of the prior distribution is given by:

$$cov[(\mathbf{A}_s)_{ij}, (\mathbf{A}_r)_{kl}|\Sigma] = \begin{cases} \lambda^2 \frac{1}{s^\alpha} \frac{\Sigma_{ik}}{\psi_j/(d-n-1)} & \text{if } l = j \text{ and } r = s \\ 0 & \text{otherwise} \end{cases},$$

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 $\lambda \to \infty$. α is an hyperparameter that controls how fast this covariance should decrease with the number of lags and ψ_j is the j^{th} entry of ψ, which controls the variance associated to each variable. Some 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.

The sum-of-coefficients prior is based on the idea that a "no-change" forecast is a good forecast at the beginning of the period. It is implemented by adding at the beginning of the sample artificial data constructed in the following way:

$$\underset{n\times n}{y^+} = \text{diag}\left(\frac{\bar{y}_0}{\mu}\right) = \begin{bmatrix} \frac{\bar{y}_1}{\mu} & 0 & \cdots & 0 \\ 0 & \frac{\bar{y}_2}{\mu} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \frac{\bar{y}_n}{\mu} \end{bmatrix}$$

$$\underset{n\times(1+np)}{x^+} = \left[\underset{n\times 1}{0}, y^+, \cdots, y^+\right],$$

where $\bar{y}_j$ denotes the average of the first p observations for each variable $j = 1, \cdots, n$. This prior implies that the sum of the coefficients of each variable on its lags is 1 and that the sum of the coefficients of each variable on the other variables' lags is 0. It also introduces correlation among the coefficients of the same variable in that variable's equation. The hyperparameter μ controls the variance of these prior beliefs: as $\mu \to \infty$, the prior becomes uninformative, while $\mu \to 0$ implies the presence of a unit root in each equation and rules out cointegration.

Since in the limit this prior does not allow for cointegration, the single-unit-root (also called 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 one artificial data point at the beginning of the sample:

$$\underset{1\times n}{y^{++}} = \left(\frac{\bar{y_0}}{\delta}\right)' = \left[\frac{\bar{y_1}}{\delta}, \quad \cdots, \quad \frac{\bar{y_n}}{\delta}\right]$$

$$\underset{1\times(1+np)}{x^{++}} = \left[\frac{1}{\delta}, y^{++}, \cdots, y^{++}\right],$$

The hyperparameter δ controls the tightness of the prior implied by this artificial observation. As $\delta \to \infty$, the prior becomes uninformative. As $\delta \to 0$, 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.

The three priors illustrated depend on the hyperparameters λ (the tightness of the Minnesota prior), μ (the tightness of the sum-of-coefficients prior), δ (the tightness of the single-unit root prior) ψ (which specifies the prior variance associated with each variable) and α (which relates to the decay of the covariance of coefficients relative to more lagged variables). We use the following parametrization: $\lambda \sim \Gamma$ with mode equal to 0.2 and standard deviation equal to 0.4; , $\mu \sim \Gamma$ with mode equal to 1 and standard deviation equal to 1; $\delta \sim \Gamma$ with mode equal to 1 and standard deviation equal to 1; $\alpha \sim \Gamma$ with mode equal to 2 and stadard deviation equal to 0.25. The hyperprior for the elements in ψ is set to an inverse-Gamma with scale and shape equal to 0.0004. Note that these are not flat hyperpriors. This guarantees the tractability of the posterior and it helps to stabilize inference when the marginal likelihood happens to show little curvature with respect to some hyperparameters.

Appendix B Identification of additional macroeconomic shocks

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

We build on to this new strand of literature and identify the supply chain bottlenecks (SCB) shocks by short-term restrictions. We measure SCB via the novel Global Supply Chain Pressure Index (Benigno et al., 2022), which integrates various indices of delivery times, backlogs, and inventories to quantify supply chain bottlenecks.[36] We argue that this variable is unlikely affected by the other shocks of the system within the same month (it is a "slow-moving" variable) and that we can therefore use the standard short-term restrictions / recursive identification scheme to identify this shock, where GSCPI is ordered first. We are therefore assuming that other shocks in the system do not impact SCB within the same month. This is supported by the fact that the GSCPI is constructed as the first principal component of several monthly indicators of transportation costs such as the Baltic Dry Index, the Harpex index, and the Bureau of Labor Statistics airfreight cost indexes and supply chain-related components from the Purchasing Managers' Index surveys for manufacturing firms. The principal component effectively smooths out idiosyncratic variability, helping to isolate the "slow-moving" component. Furthermore, the GSCPI is a global index, and despite the EA being a sizable fraction of the world's economy, several shocks in the GSCPI are likely to originate outside of it. Finally, we obtain that the reduced-form residuals of GSCPI are almost uncorrelated with the other residuals, supporting our contemporaneous exogeneity assumption.

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

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

oil production plans, thereby surprising financial market operators. Specifically, we compute daily surprises in Brent futures around OPEC press releases, as described in Eq 3.1.1, considering future contracts spanning from a one-month to a one-year horizon. Subsequently, we capture the daily oil supply shock by extracting the first principal component of these surprises. To aggregate the shocks into a monthly series, we sum the daily surprises within the respective month. Figure C24 shows the oil supply surprise series, and the corresponding West Texas Intermediate (WTI) oil surprise series can be found in Appendix Figure C25.

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

Appendix C Data and descriptive statistics

C.1 Data sources

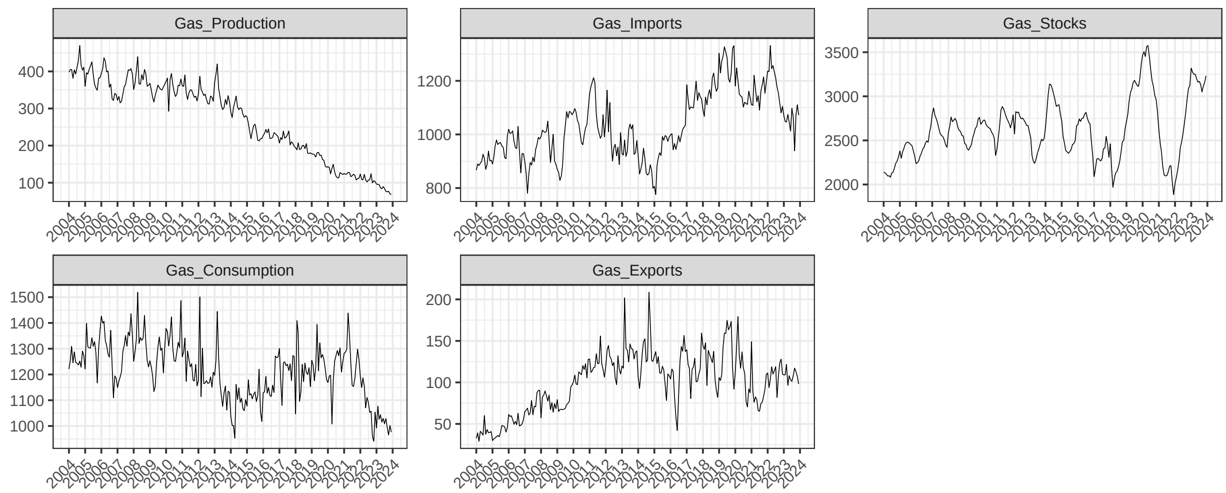
Table C3 provides details on the data used, including information on the data sources, the time coverage, and the transformations applied.

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	$100\Delta \log$
LCOc-h (RIC)	Brent crude oil futures h-month contract (settlement price)	Datastream	1988M6-2024M1	$100\Delta \log$
OIS-h	OIS futures h-period contract	ECB website	1999M1-2024M1	$100\Delta \log$
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	$100 * \log$
Core Inflation	HICP index excluding energy and food seasonally adjusted (TOT_X_NRG_FOOD)	EUROSTAT	2000M12-2024M1	$100 * \log$
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	$100 * \log$
Unemployment Rate	Unemployment Rate (UNE$_R T_M$), SA	EUROSTAT	2001M1-2024M1	None
Gas production	EA Dry marketable production (INDPROD), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Stocks	EA Closing stock levels (CSNATTER), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Net Imports	EA Gas imports from RoW (IMPORTS) - Gas exports to RoW (EXPORTS), SA	IEA	1984M1-2024M1	$100 * \log$
Nominal Exchange Rate	Nominal Broad Effective Exchange Rate for EA (NBXMBIS)	FRED	1994M1-2024M1	$100 * \log$
Interest Rate	Money market EURIBOR rate, 12-month rate (IRT_ST_M)	EUROSTAT	1994M1-2024M1	None
Instruments US				
NGc-h (RIC)	NYMEX HH natural gas futures h-month contracts from 1M to 12M (settlement price)	Datastream	1990M4-2024M1	$100\Delta \log$
CLc-h (RIC)	WTI crude oil futures h-month contract from 1M to 12M (settlement price)	Datastream	1975M1-2024M1	$100\Delta \log$
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	$100 * \log$
Core Inflation	Core CPI (CPILFESL) index, SA	FRED	1960M1-2024M1	$100 * \log$
Headline Inflation	Headline CPI (CPIAUCSL) index, SA	FRED	1960M1-2024M1	$100 * \log$
Industrial Production	Total index (INDPRO), SA	FRED	1974M1-2024M1	$100 * \log$
Unemployment Rate	Unemployment rate (UNRATE), SA	FRED	1974M1-2024M1	None
Gas Production	U.S. Dry Natural Gas Production (N9070US1) in Bcf, SA	EIA	1973M1-2024M1	$100 * \log$
Gas Consumption	U.S. Natural Gas Total Consumption (N9140US1) in Bcf, SA	EIA	2001M1-2024M1	$100 * \log$
Gas Stocks	U.S. Total Natural Gas in Underground Storage Working (N5020US2), SA	EIA	1975M9-2024M1	$100 * \log$
Gas Net Imports	U.S. Gas Imports (N9100US2) - U.S. Gas Exports (N9130US2), SA	EIA	1984M1-2024M1	$100 * \log$
Nominal Exchange Rate	Nominal Broad Effective Exchange Rate for US (NBUSBIS)	FRED	1994M1-2024M1	$100 * \log$
Interest Rate	Effective federal funds rate	FRED	1974M1-2024M1	None
Additional Variables				
SCB	GSCPI index of supply chain pressures (constructed as a latent factor)	NY FED	1997M1-2024M1	$100 * \log$
IP B-D	NACE2 1-digit level Industrial Production indexes, SA	EUROSTAT	1991M1-2024M1	$100 * \log$
IP C10-C33	NACE2 2-digit level Manufacturing Industrial Production indexes, SA	EUROSTAT	1991M1-2024M1	$100 * \log$
PPI D35-10/20	NACE2 4-digit level Electricity and Gas Producer Price indexes, SA	EUROSTAT	2000M1-2024M1	$100 * \log$
HICP CP01-CP12	ECOICOP 1-digit level indexes, SA	EUROSTAT	2000M1-2024M1	$100 * \log$

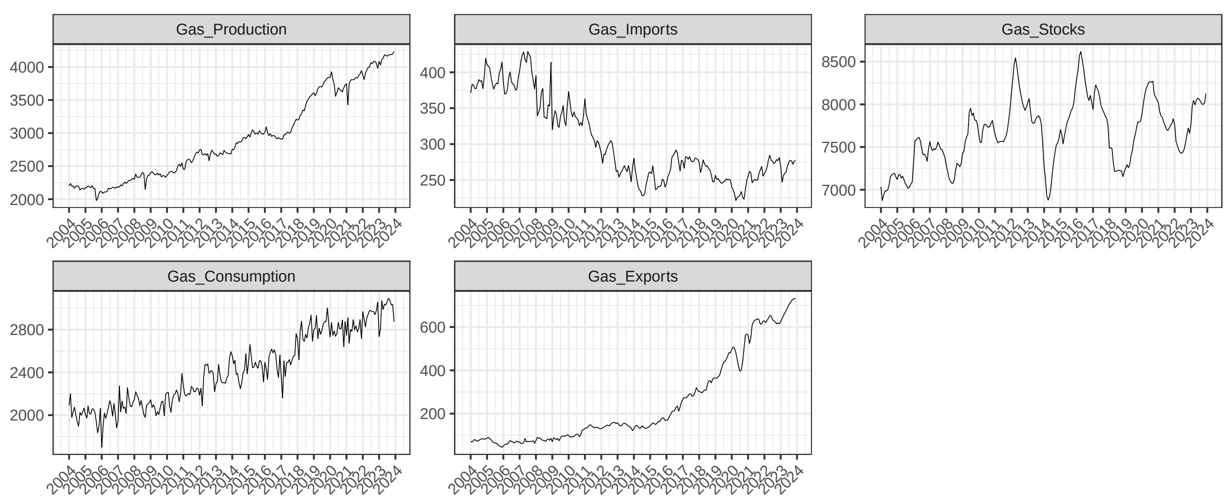
Table C3: *Data description and sources*

C.2 Gas Balances in the Euro Area and United States

This appendix presents data on the gas balances in both the Euro Area and the United States over time. It includes natural gas production, consumption, imports, exports, and storage levels.



(a) Euro Area

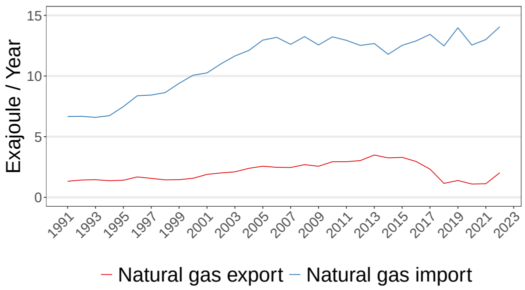


(b) United States

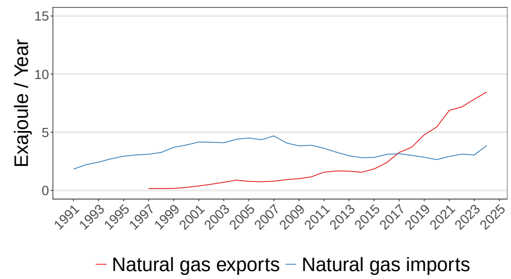
Figure C15: *Gas Balances for the Euro Area and United States*

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

C.3 Additional data not used in the analysis



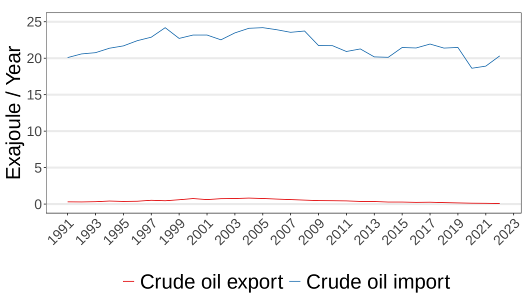
(c) European Union



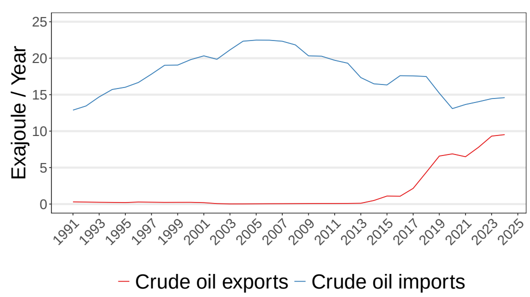
(d) United States

Figure C16: *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.



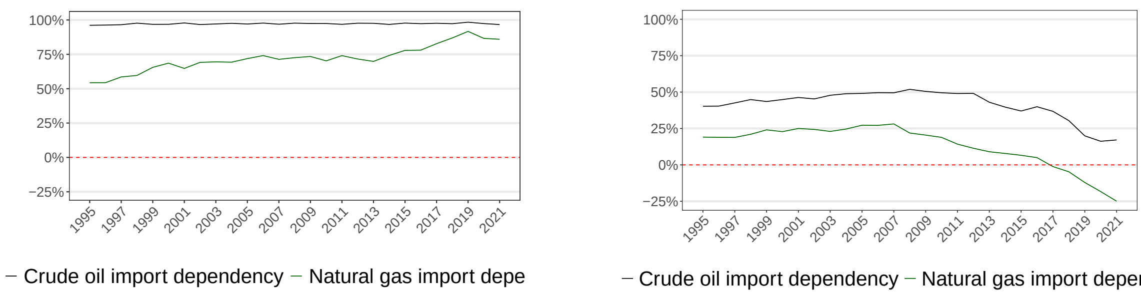
(a) European Union



(b) United States

Figure C17: *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.



(a) European Union

(b) United States

Figure C18: *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.

C.4 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 C19 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 C4 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.

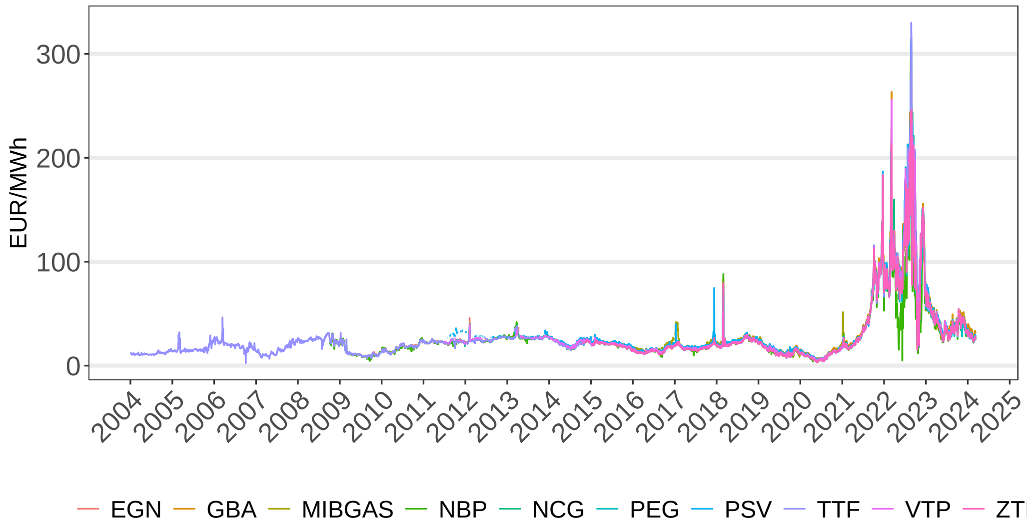


Figure C19: *TTF and other European gas prices.*

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

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 C4: *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.

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 C20 , while Figure C21 displays a sliding window correlation of the global LNG price with the TTF.

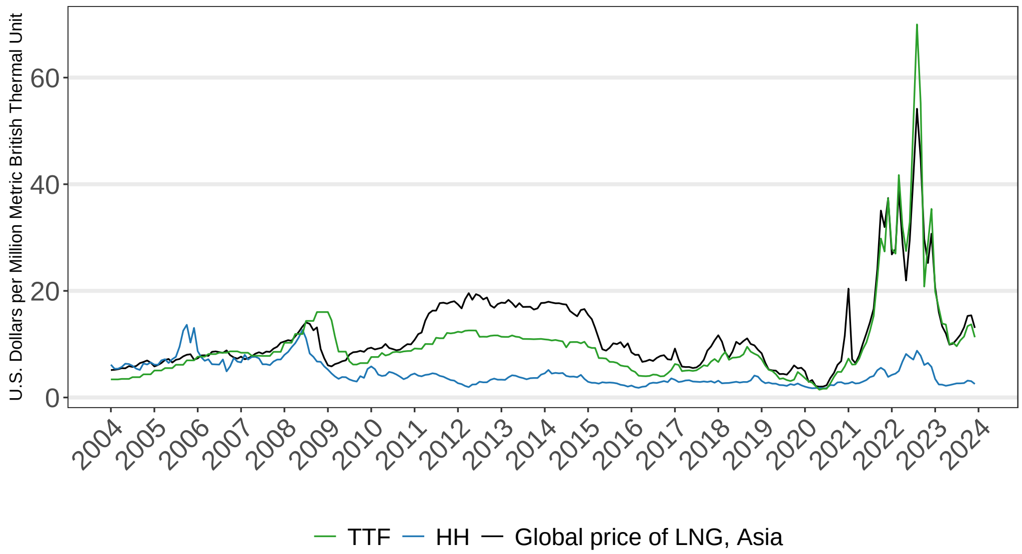


Figure C20: *TTF, HH and Global LNG prices.*

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

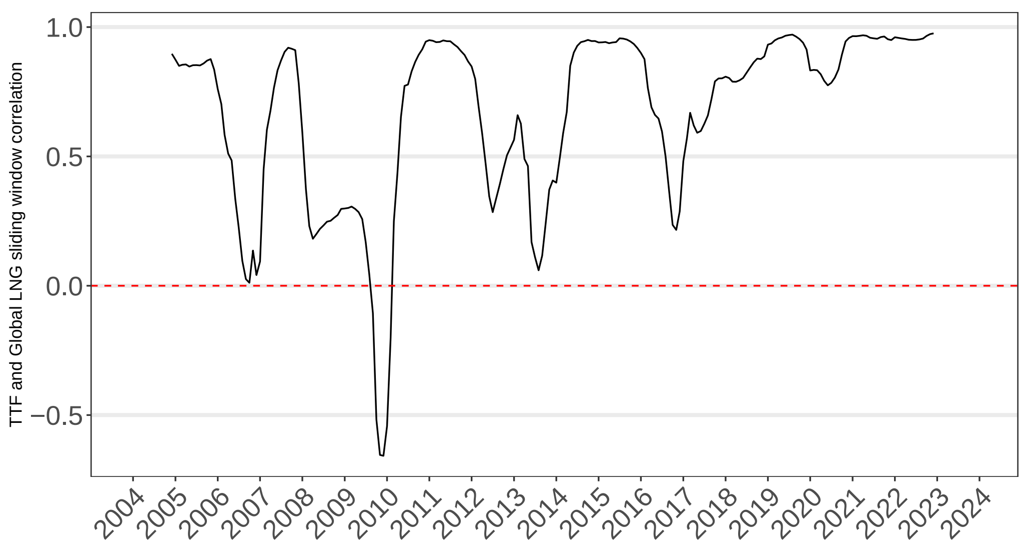


Figure C21: *TTF and Global LNG gas prices correlation.*

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

C.5 US instruments

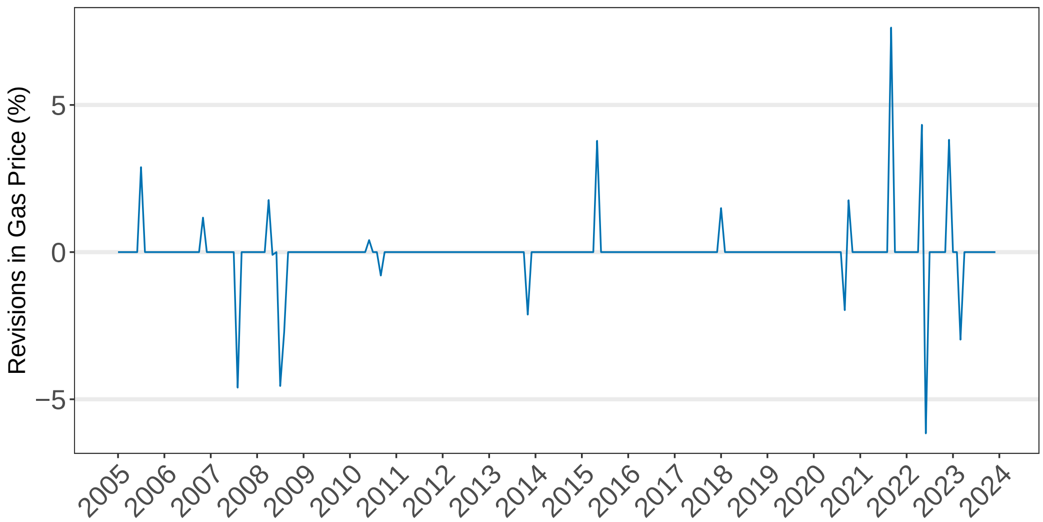


Figure C22: *The US gas supply surprises series.*

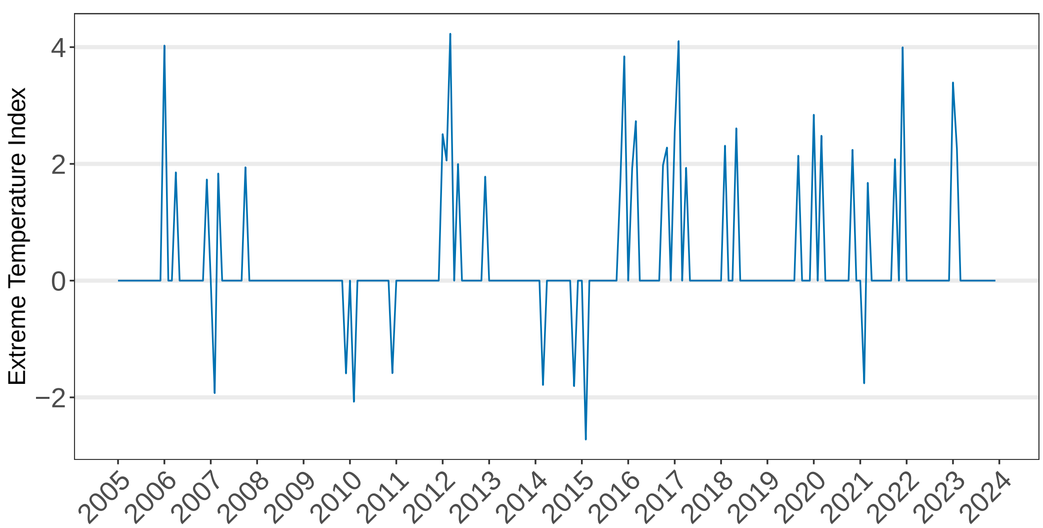


Figure C23: *Temperature shocks series for the US.*

C.6 Brent and WTI oil surprises

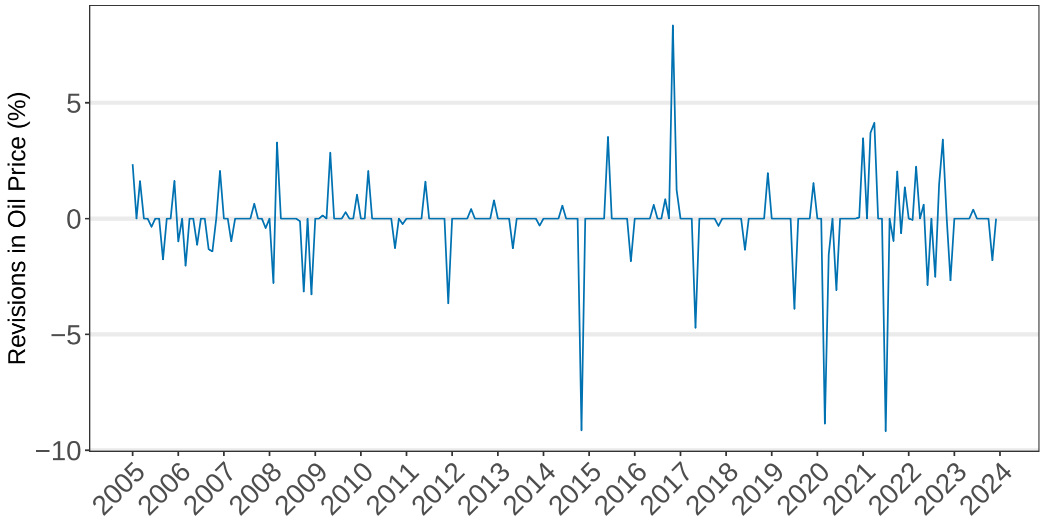


Figure C24: *The Brent oil supply surprises series*

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

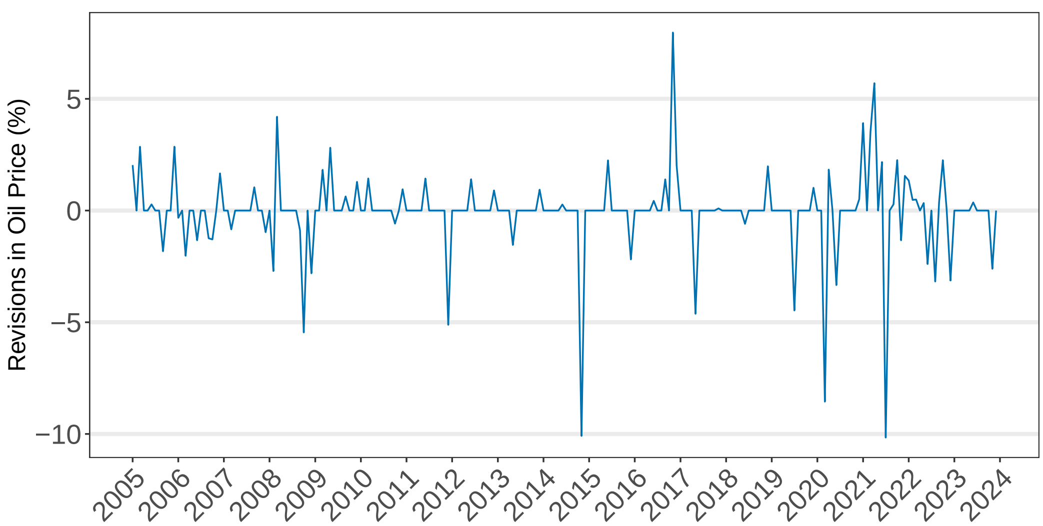


Figure C25: *The WTI oil supply surprises series*

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

Appendix D Market-relevant gas supply news

This appendix provides examples of news events used to construct gas supply surprises, as detailed in Section 3.1.1. Table D5 presents selected events for both the Euro Area and the United States, illustrating the different nature of supply news across the two regions. The set for the EA includes events related to import disruptions from major suppliers, including Russia, Norway, and Qatar. The US panel features news primarily concerning domestic production and infrastructure, such as platform operations, drilling activity, and pipeline incidents.

Date	**Event**	**daily %Δ (PC)**
EA		
2009-01-06	Russia halts gas deliveries to Ukraine amid escalating gas dispute.	12.4
2014-03-03	Gazprom threatens to cut gas exports amid the Crimea crisis.	5.7
2014-09-01	Unplanned mainteinance of Langeled pipeline announced.	5.6
2020-08-03	Polish anti-monopoly UOKiK fines Gazprom over Nord Stream	19.9
2021-07-26	Unplanned maintenance at Troll, Visund, Kvitebjørn Fields, and Kollsnes Plant.	4.2
2021-10-28	Putin announces Gazprom ready to start pumping natural gas into European gas storage.	-10.1
2022-06-14	Gazprom announces reduced supply through Nord Stream 1 due to repair works.	13.1
2022-06-15	Gazprom announces further reduction in gas flows through Nord Stream 1.	12.5
US		
2006-11-08	Engine Repairs lead to capacity reduction on Michigan Leg South.	1.2
2008-04-28	Outages at Independence Hub in the Gulf of Mexico.	1.8
2013-11-01	Transco begins full service on Northeast Supply Link project.	-2.1
2015-05-08	Transco upgrades and force majeure on Destin pipelines.	3.8
2022-05-10	Unexpected decline in gas production in Texas	4.3
2022-06-23	U.S. NatGas Falls to 11-Week Low Due to Freeport LNG outage.	-6.2
2023-03-08	Unexpected flows drop at Freeport LNG related to outages.	-3.0

Table D5: *Selected gas supply news for EA and US.*

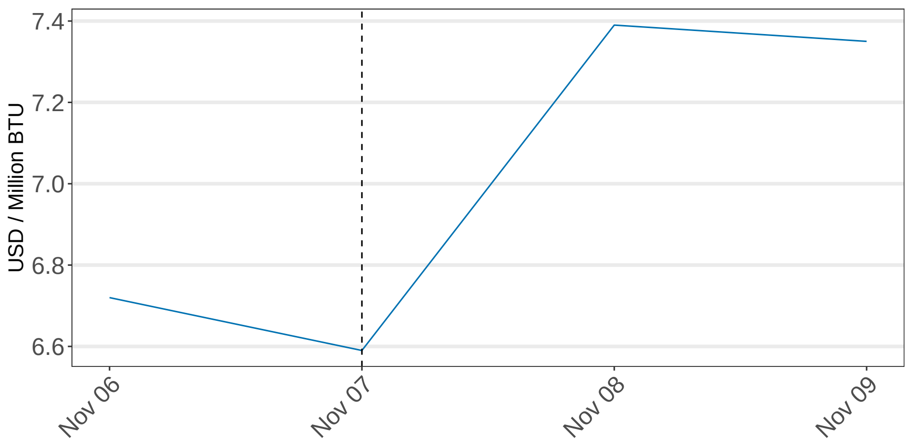


Figure D26: *Repairs at compressor stations lead to capacity reduction on Michigan Leg South.*

Notes: The figure shows the surprise in the HH spot gas price related to engine repairs at St. John and Bridgman compressor stations, which led to capacity reduction on the Michigan Leg South (which serves as a link between major interstate pipeline systems) on November 8, 2006.

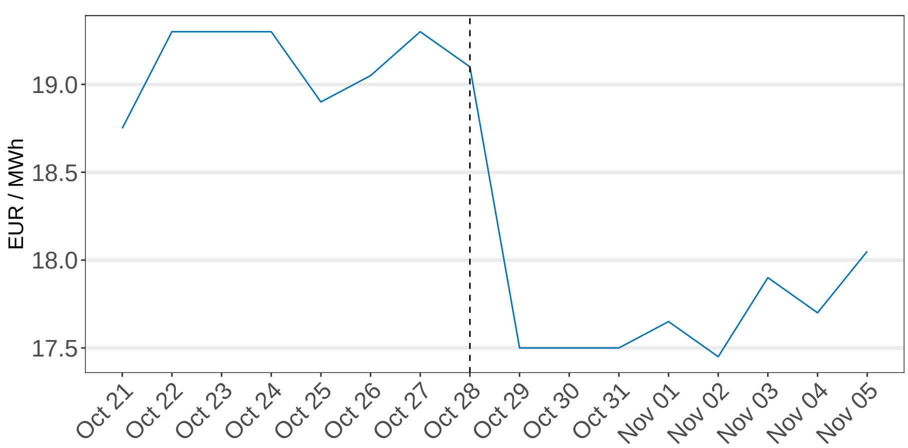


Figure D27: *UK expands LNG capacity at the Isle of Grain terminal.*

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

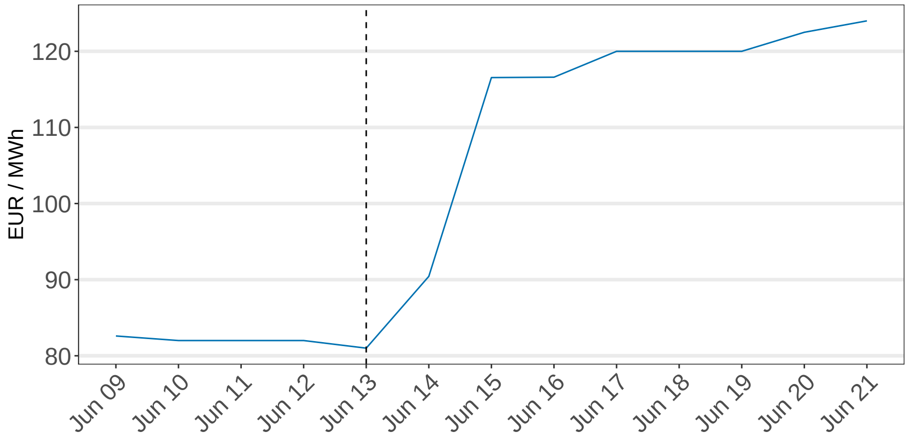


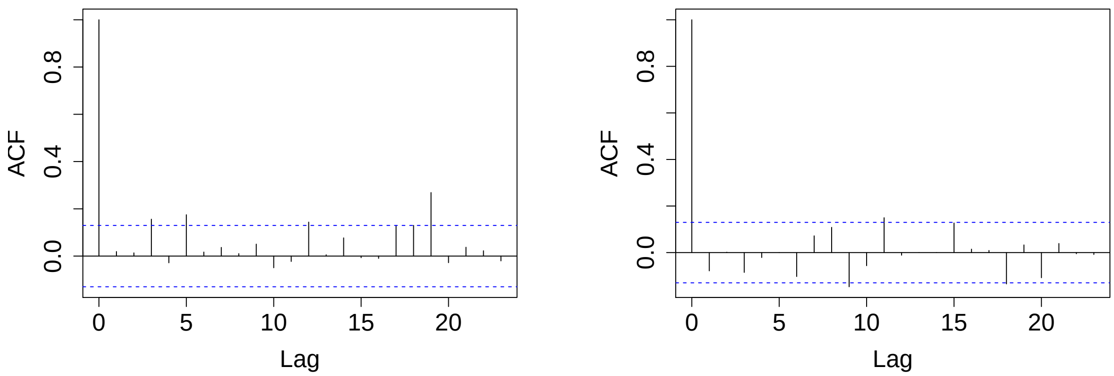
Figure D28: *Gazprom announces reduced supply through Nord Stream 1 due to repair works.*

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

Appendix E Diagnostics of the gas surprise series

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

We start by evaluating the predictability of the surprise series. As shown in Table E6, results from Granger's causality tests suggest that the series cannot be predicted by past macroeconomic or financial variables. Similarly, the series shows no forecastability when considering gas demand and gas inventories. Moreover, we look at the correlation between the series and other shocks from the literature (see Table E7). Notably, we find that the series is not significantly correlated with oil-specific, uncertainty, and global demand shocks.



(a) EA

(b) US

Figure E29: *Sample Autocorrelation Function of the gas surprise series.*

Variable	p-value EA	p-value US
Oil price	0.12	0.43
Headline inflation	0.03	0.95
Interest rate	0.96	0.09
Industrial production	0.21	0.86
Unemployment rate	0.03	0.52
Nominal exchange rate	0.99	0.93
Gas consumption	0.55	0.56
Gas stocks	0.74	0.78
Gas net imports	0.39	0.007
Stock market (STOXX50E/SP500)	0.08	0.004
World economic activity	0.02	0.34

Table E6: *Granger causality tests*

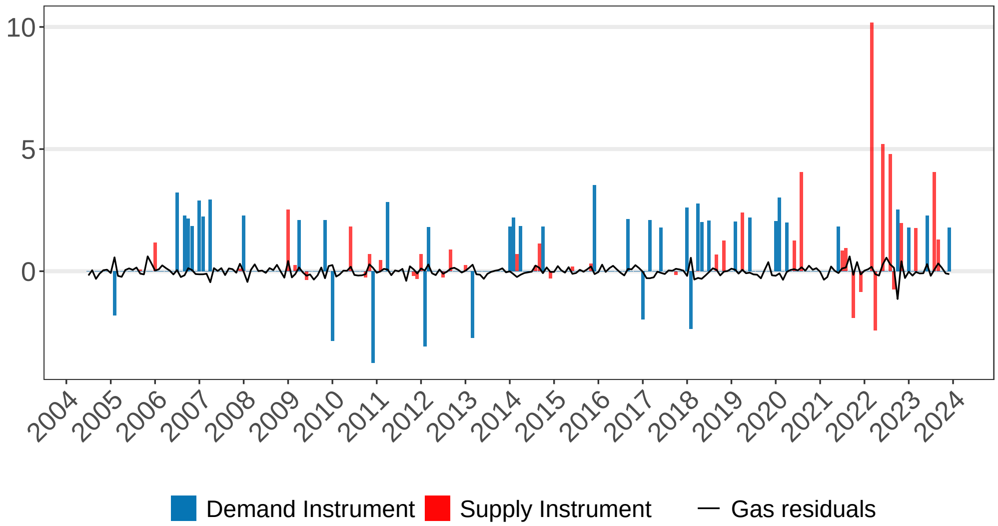
Notes: The table presents the p-values obtained from Granger's causality tests of the gas supply surprise series using the set of variables included in our baseline specification, expanded with a financial and real activity variables. To conduct standard inference, the series are rendered stationary 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	0.00	0.95	-0.00	0.97	-0.04	0.51	0.04	0.57	240
Kilian (2009)**	Aggregate demand	-0.01	0.93	-0.00	0.99	0.05	0.41	-0.07	0.30	240
Kilian (2009)**	Oil-specific demand	0.10	0.13	-0.08	0.19	0.11	0.09	-0.05	0.40	240
Baumeister and Hamilton (2019)*	Oil supply	-0.09	0.19	0.08	0.20	-0.06	0.34	0.05	0.42	240
Baumeister and Hamilton (2019)*	Oil demand	-0.04	0.53	-0.13	0.04	-0.01	0.86	-0.01	0.83	240
Känzig (2021a)**	Oil supply expectations	-0.05	0.48	0.01	0.91	0.02	0.80	0.06	0.34	240
Caldara et al. (2019)*	CCI oil supply	0.02	0.79	0.03	0.75	-0.01	0.94	0.02	0.81	144
Gertler and Karadi (2015)	FF4 monetary policy (US)	-0.17	0.09	-0.06	0.57	0.04	0.70	-0.03	0.80	102
Altavilla et al. (2019)*	Target monetary policy (EA)	-0.01	0.83	0.05	0.46	–	–	–	–	234
Jarociński and Karadi (2020)	Poor man monetary policy	0.00	0.99	0.04	0.53	–	–	–	–	234
Miranda-Agrippino and Nenova (2022)	Target monetary policy	-0.05	0.45	0.07	0.32	-0.10	0.18	0.02	0.79	207
Bloom (2009)**	VXO-VIX	-0.02	0.80	-0.02	0.71	0.01	0.89	0.07	0.28	240
Gilchrist and Zakrajšek (2012)*	Corporate credit spread index	-0.04	0.50	-0.09	0.19	-0.09	0.15	-0.05	0.44	240
Baker et al. (2016)*	Global Economic Policy Uncertainty Index	0.22	0.00	0.02	0.78	0.02	0.72	0.13	0.05	240
Caldara and Iacoviello (2022)*	Geopolitical risk index	0.41	0.00	0.15	0.02	0.02	0.77	0.04	0.54	240

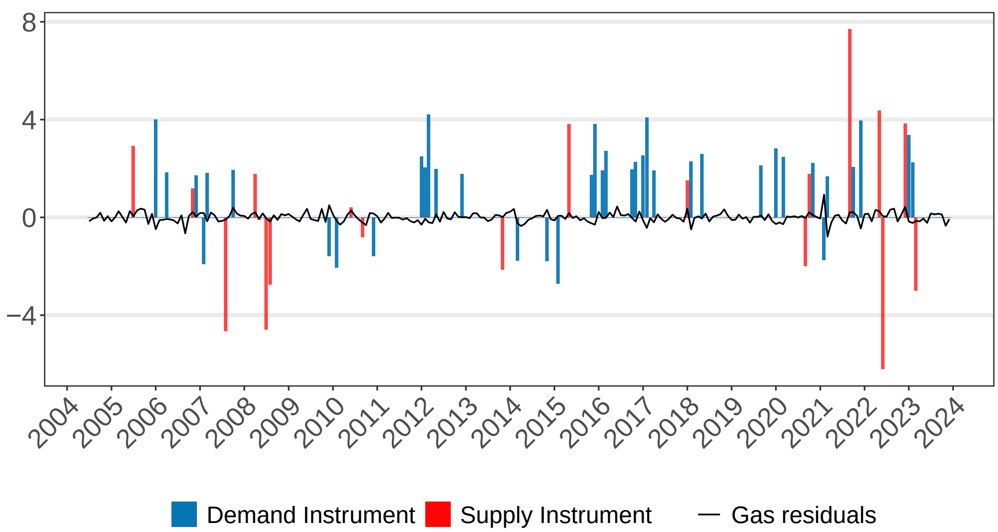
Table E7: *Correlation of instruments with other shocks.*

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 zero 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.



(a) Europe



(b) USA

Figure E30: *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.

Appendix F Construction of the Temperature Demand Instrument

ERA5 surface temperature data. The daily temeratures 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.[37][38]

Temperature shock series. The monthly temperature shock is computed as described in Equation F.0.1. 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 F31 shows the seasonally adjusted series for the Netherlands. The resulting series is aggregated to monthly by taking temporal averages. Finally, the series is then thresholded to isolate only months with large temperature deviations by setting to zero any observation within 2 standard deviations.

$$TS_{m,y} = \begin{cases} {}^{SA}K^{stat}_{m,y}, & \text{if } {}^{SA}K^{stat}_{m,y} \notin [\mu_{K^{SA}} - 2\sigma_{K^{SA}}; \mu_{K^{SA}} + 2\sigma_{K^{SA}}] \\ 0, & \text{otherwise} \end{cases} \tag{F.0.1}$$

where

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

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

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

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

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

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

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

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

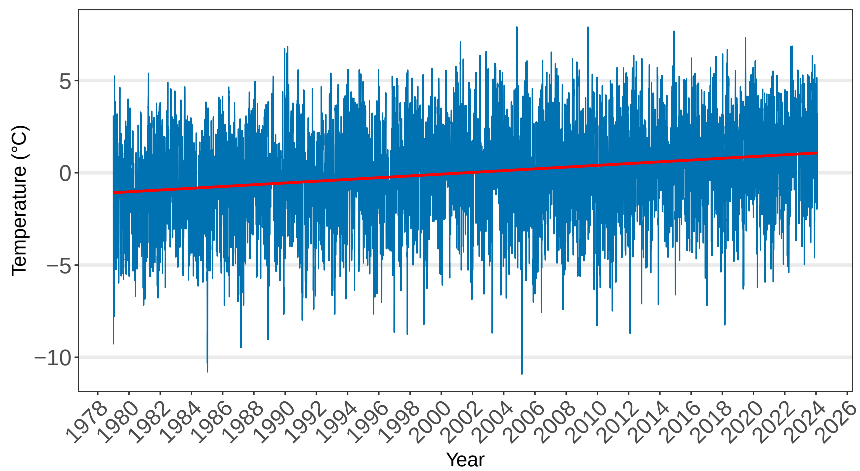


Figure F31: *Daily seasonally adjusted temperatures for the Netherlands, not detrended.*

Several alternative but equivalent methods can be used to construct a temperature index that serves the purpose of this analysis. One approach involves subtracting a linear trend from the temperature series before performing seasonal adjustments. Another option is to seasonally adjust the data by subtracting the mean temperature for each calendar day (calculated across all years in the sample) instead of using monthly averages. Additionally, the index can be based on daily maximum or minimum temperatures rather than daily averages. Weighting the daily temperature series using demographic or geographic factors, such as the 2015 population or night light data, is another viable alternative. Lastly, a rolling seasonal adjustment can be applied, where the means used for adjustment are computed based on data from a specified window of preceding years. These alternatives all yield equivalent temperature shock series to which the results are robust.

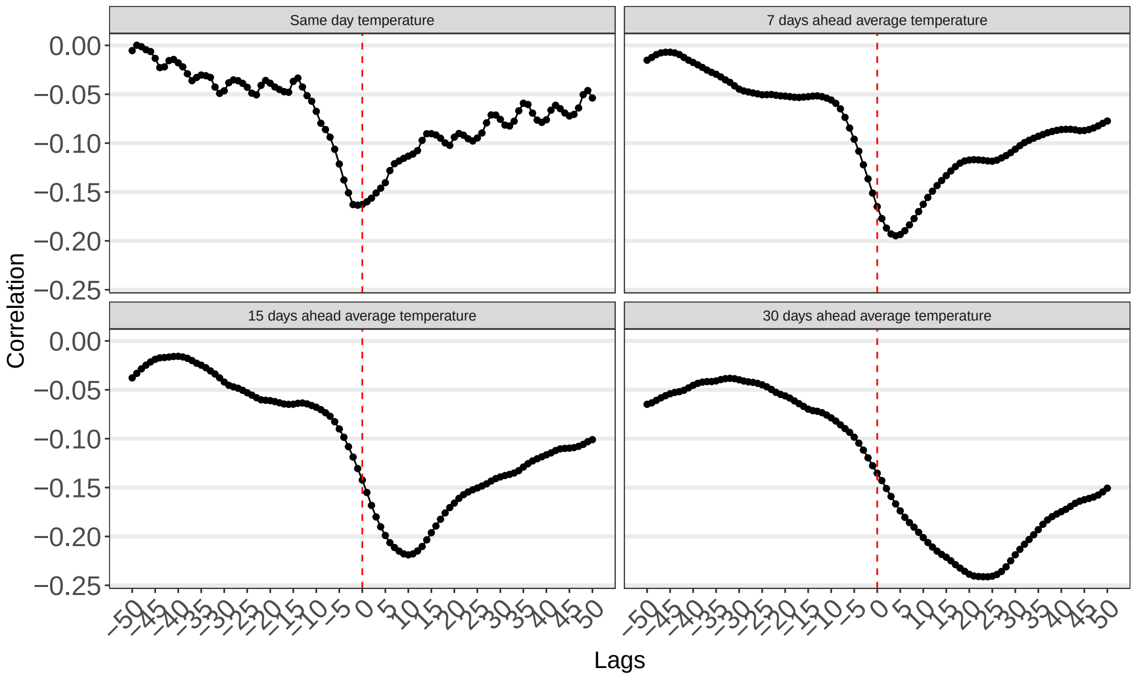


Figure F32: *Temperatures and gas price correlations.*

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 temperatures averages of different temporal span.

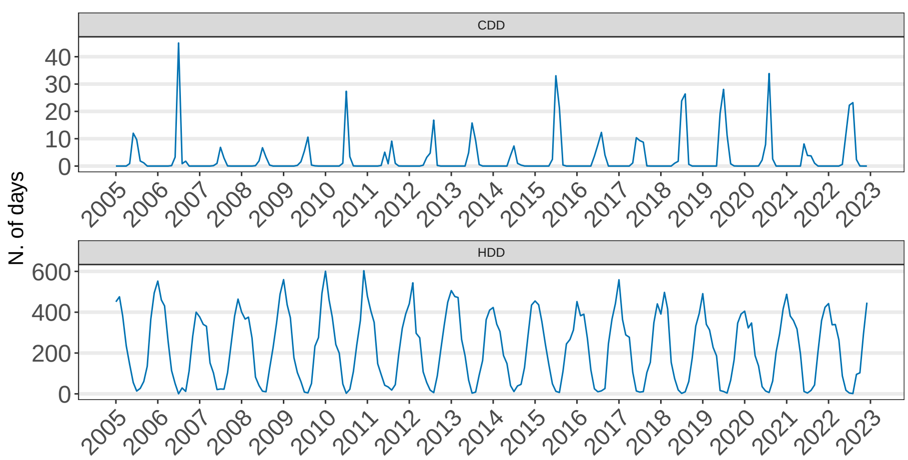
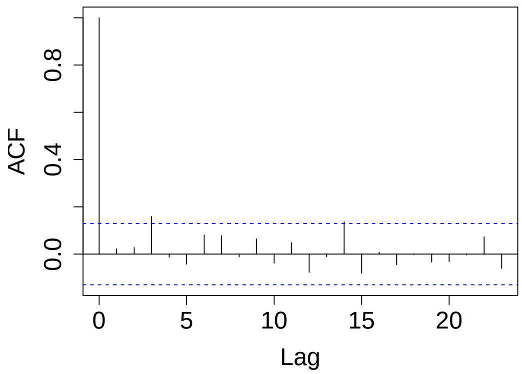
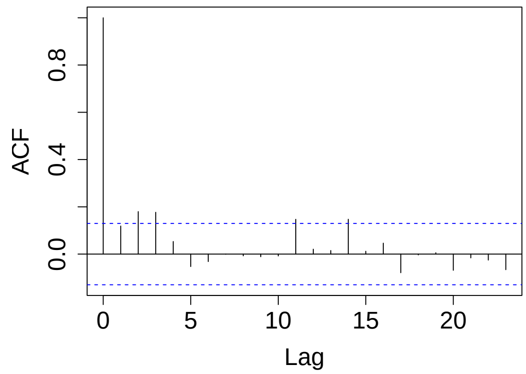


Figure F33: *Cooling degree days and heating degree days, average across selected European countries.*



(a) EA

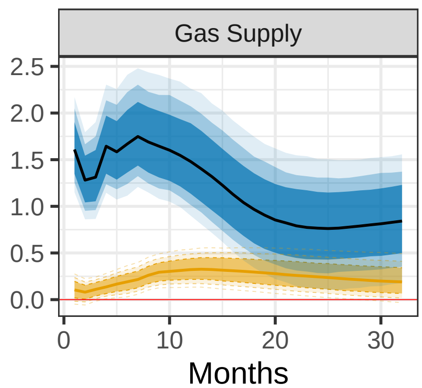


(b) US

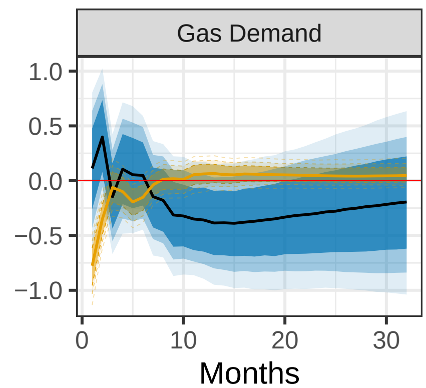
Figure F34: *Sample Autocorrelation Function of the Temperature Shocks.*

Appendix G Additional results

G.1 Demand and Supply elasticities



(a) Gas Demand Shock



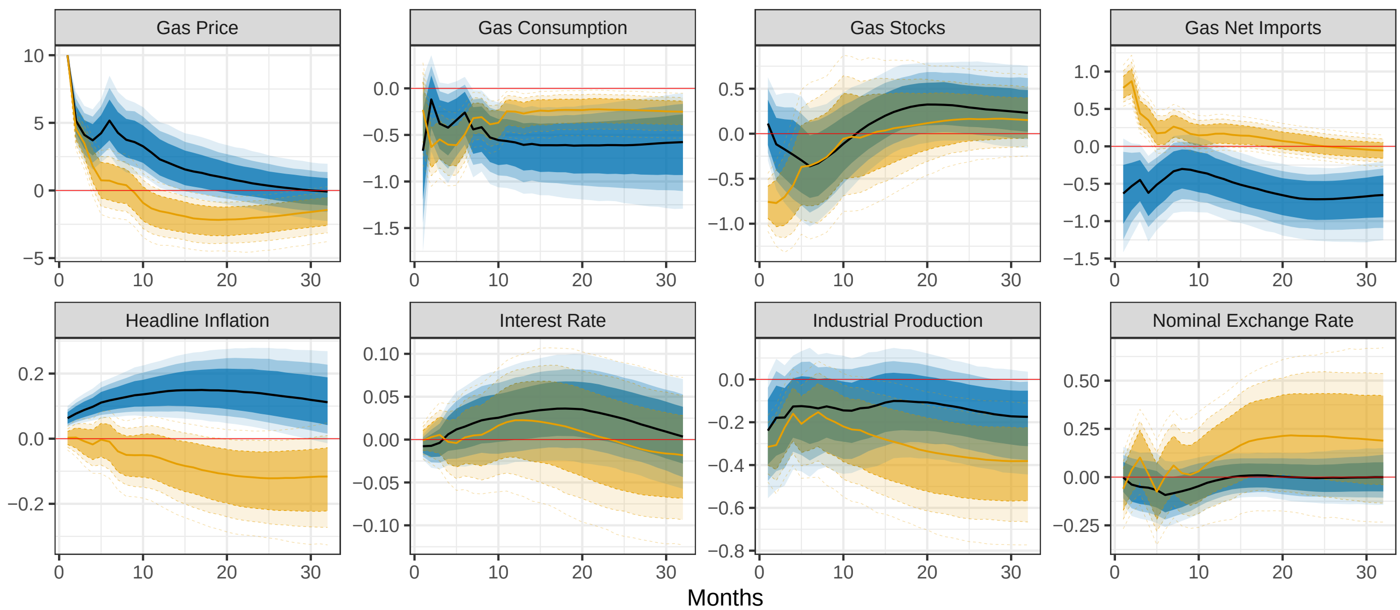
(b) Gas Supply Shock

Figure G35: *Supply and Demand price elasticities*

Notes: Responses of natural gas demand and supply to gas price shocks. The black solid lines with blue shaded confidence bands represent the EA, while the orange solid lines with dashed and shaded orange confidence bands represent the US. Gas demand is given by the sum of consumption plus exports, while gas supply is domestic production plus imports.

Appendix H Robustness checks

In this Appendix, we show that our results are robust to constructing an informationally robust gas supply instrument by controlling for several potential confounding factors. We also demonstrate that our findings remain qualitatively consistent regardless of the priors imposed. We show this by estimating the same specifications by VAR-OLS.



First stage regressions: EA F: 10.65, Robust F: 27.90; US F: 5.09, Robust F: 13.19

Figure H36: *Impulse responses to a gas supply shock, informationally-robust refinement. Equivalent of Figure 8.*

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

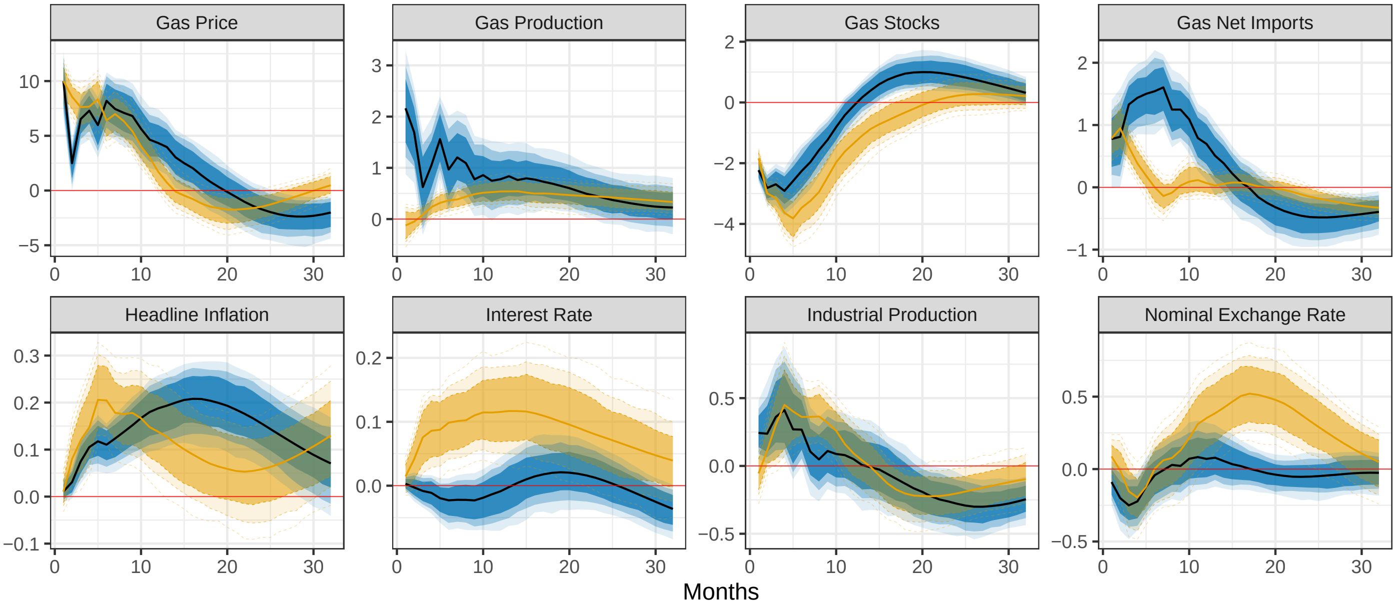


Figure H37: *Responses to a gas demand shock, estimated by VAR-OLS. Equivalent of Figure 7.*

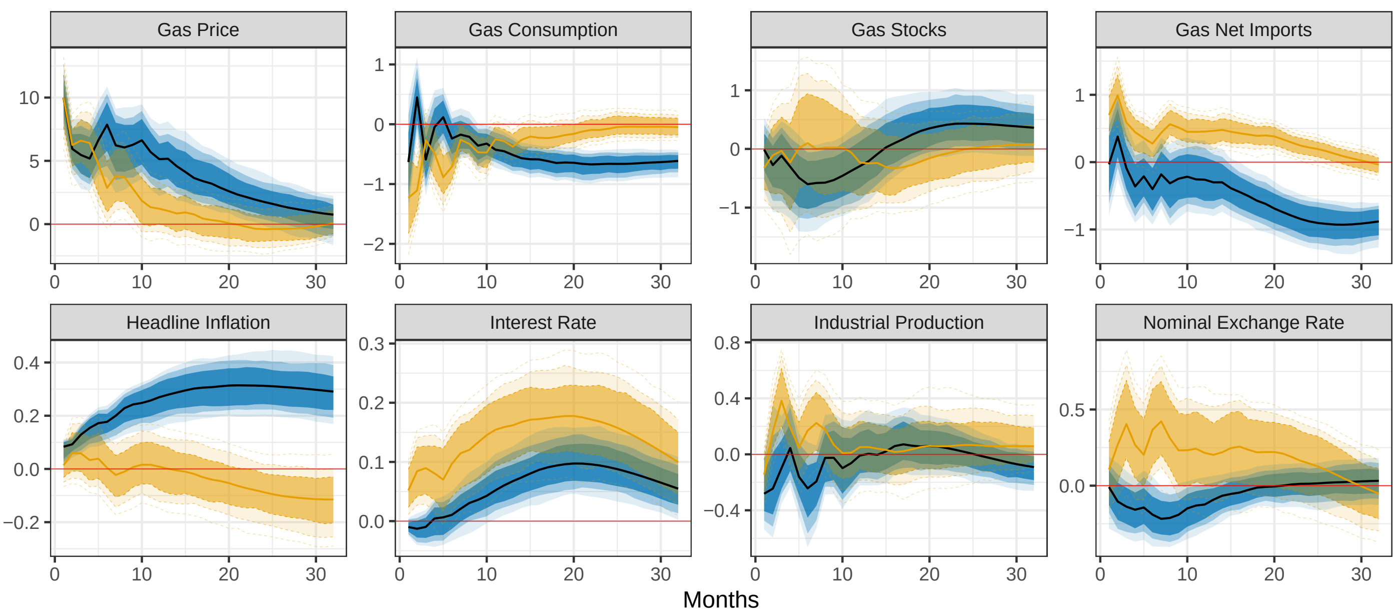


Figure H38: *Responses to a gas supply shock, estimated by VAR-OLS. Equivalent of Figure 8.*

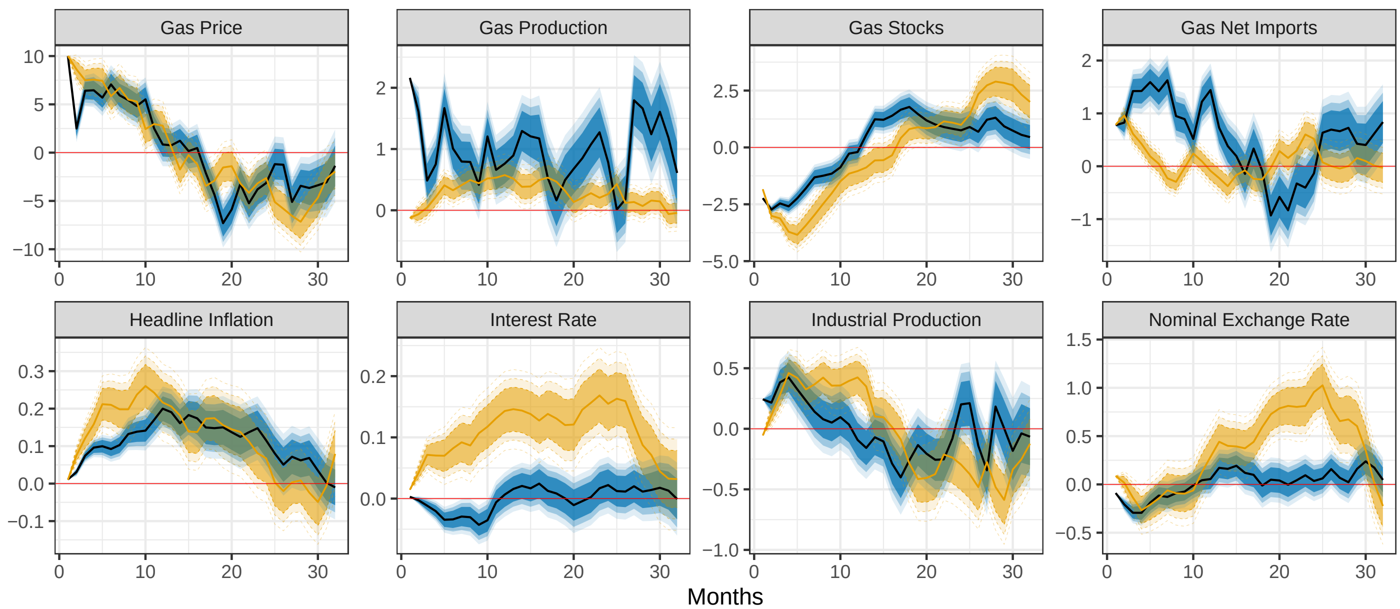


Figure H39: *Responses to a gas demand shock, estimated by VAR-LPs. Equivalent of Figure 7.*

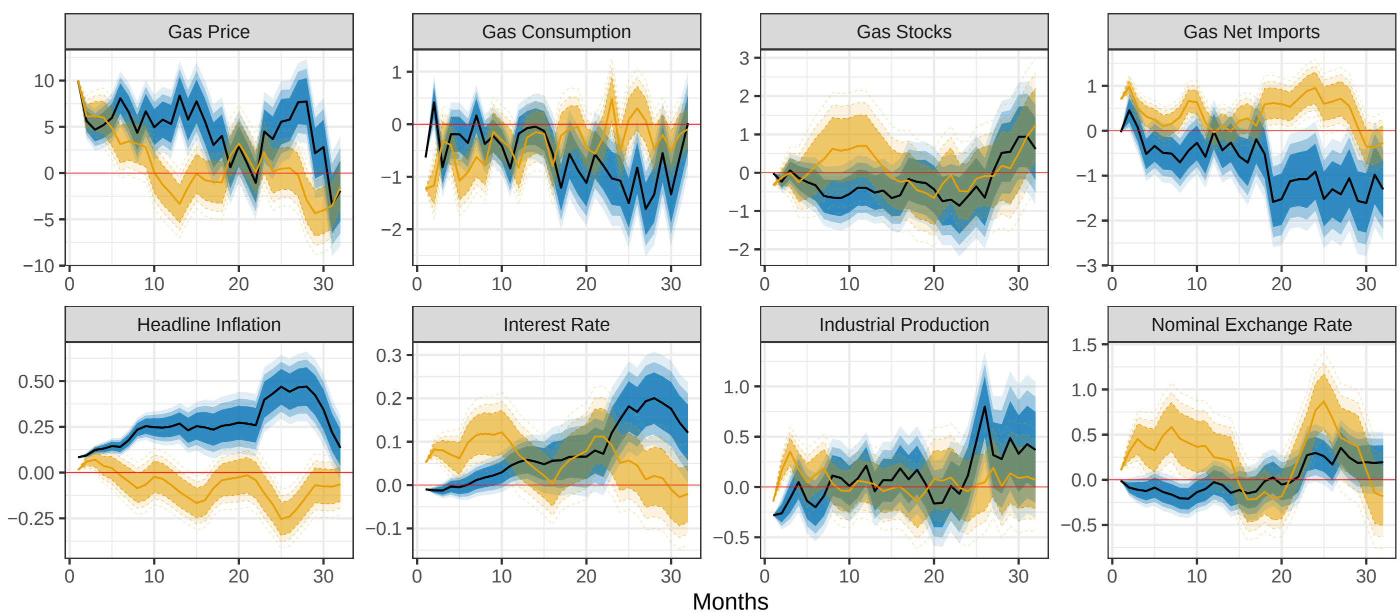


Figure H40: *Responses to a gas supply shock, estimated by VAR-LPs. Equivalent of Figure 8.*