Gas Price Shocks and the Inflation Surge in Europe

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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 *anomalous* temperatures. These shocks have economically significant effects. We show that in the Euro Area gas supply and demand shocks exert significant impacts on both headline and core inflation (1% pass-through), whereas in the US, these shocks are less inflationary, with the effect being felt mostly through production in the energy sector. Gas demand and supply shocks have distinct macroeconomic impacts. Demand shocks stimulate real activity, particularly in the energy sector, whereas supply shocks dampen industrial production via supply constraints and increased input costs. In particular, supply shocks can be interpreted as disruptions to domestic production in the US and to gas imports in the EA. Overall, we show that the EA is more vulnerable to supply constraints, given that its gas balances have a limited capacity to offset these shocks. We also document an important interdependence of the gas and oil markets, where shocks in gas and oil prices mutually influence both commodities. Crucially, gas price shocks have more persistent effects on macro variables with respect to the corresponding oil price shocks. Finally, we provide comparable estimates of the pass-through of gas and oil price shocks to several components of inflation across both regions.

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

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 often treat energy as a single homogeneous good (oil), as in the framework by Blanchard and Gali (2007) and also in some more recent works, such as Gagliardone and Gertler (2023). However, the outbreak of the Ukraine war in February 2022, which led to restrictions on gas supply to Europe, caused major disruptions in the energy market and steep price increases, thus highlighting the relevance of gas shocks. Furthermore, Szafranek and Rubaszek (2023) provide evidence that these events have accelerated the decoupling of natural gas prices from oil prices, a trend already attributable to the shift from oil price indexation to gas-on-gas competition. This decoupling is particularly evident in European spot gas prices, which reached unprecedented levels in the third quarter of 2022.[1]

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 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 necessitates identifying and addressing the primary drivers of inflation, of which energy prices are a key component. This raises concerns that focusing solely on oil prices may understate the inflationary impact of energy shocks, especially given the unprecedented surge in natural gas prices in recent years, as argued by Kilian and Zhou (2023).

In this paper, we investigate the effects of gas price shocks in the Euro Area and the United States, disentangling the impacts of gas supply shocks and gas demand shocks. We achieve the first by leveraging relevant supply-related news and information contained in high-frequency data. We exploit exogenous variations in gas prices surrounding these supply-related events. For the EA, these events predominantly involve disruptions to gas imports from suppliers such as the Russian energy corporation Gazprom. In contrast, for the US, the events more frequently

[1] In August 2022, prices hit a record high, increasing approximately 30-fold compared to August 2019.

relate to disruptions in domestic production, such as outages at gas platforms. To identify shocks to the demand of gas, we employ variations in the gas price induced by *abnormal* temperatures. These weather anomalies provide exogenous variation in gas prices through their impact on consumer demand. For example, an unexpected warm spell during a typically cold month leads to reduced consumption for heating and lowers gas prices. Comparing the effects of gas price shocks in the EA vis-à-vis the US allows us to appreciate the structural differences between a net importer of natural gas and the world's largest gas producer. The EA is inherently more vulnerable to gas shocks, with its fragility potentially arising from a combination of low supply elasticity, high import dependency on a select group of suppliers, and specific market design features. For example, Baget et al. (2024) and Segarra et al. (2024) suggest that one such feature could be the merit order principle in electricity pricing, which would amplify the impact of gas price shocks on overall energy prices.

Related Literature. This work relates to a long literature studying the economic effects of commodity price shocks, which has typically focused on oil price shocks in the US (e.g. Hamilton, 2003; Kilian, 2009; Baumeister and Kilian, 2016; Caldara et al., 2019; and Känzig, 2021a). While the literature on the economic impact of gas shocks is more recent and limited, the Russian invasion of Ukraine in 2022 heightened concerns about the potentially drastic economic effects of gas supply shocks, particularly in the EA, prompting a wave of studies on this topic. 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. Their research underscores the importance of sectoral interdependencies and substitution effects when assessing the real effects of gas price shocks. 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 can mitigate economic losses, explaining why actual outcomes were less severe than initially feared.

More closely related to our work, Adolfsen et al. (2024) using sign restrictions 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. Our findings, based on the use of external instruments, indicate instead that gas supply shocks have tangible real effects, as evidenced by a modest but significant decline in industrial production in response to these disruptions. Similarly, Boeck et al. (2023) examine the effects of natural gas prices using a Bayesian VAR 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. Additionally, they conduct a counterfactual exercise, assuming no response in inflation expectations, which reveals a more muted inflation reaction without second-round effects, suggesting that the expectation channel plays a more prominent role than the cost channel. We contribute to this literature by offering a fresh approach to identify gas price shocks using external instruments (Lunsford, 2015; Stock and Watson, 2018). We separately identify supply and demand gas price shocks. Moreover, we present, to the best of our knowledge, the first comprehensive comparison of the impacts of both oil and gas shocks in the EA and the US. While previous studies have analyzed the effects of gas supply-related announcements on gas prices using event study techniques (Bartelet & Mulder, 2020; Goodell et al., 2023), by using a VAR framework we are able to investigate the structural macroeconomic effects of this type of announcement over a large time period.

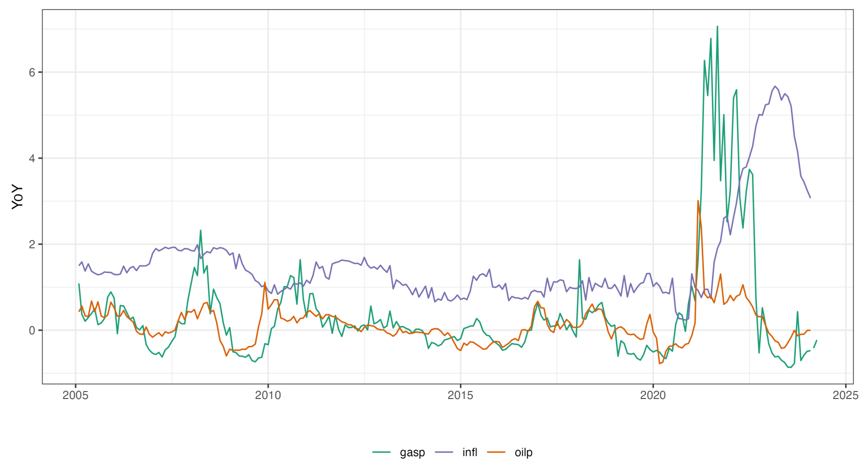
When estimating the energy pass-through to inflation, the empirical literature has again predominantly focused on oil price shocks. For example, Gao et al. (2014) estimate via a VAR a 7% pass-through on headline inflation and 40% on the energy component of headline. More recently, Känzig (2021a) via 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, only few studies have tried to estimate the pass-through of gas shocks to inflation in 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 developing a framework that can provide comparable estimates of both gas and oil shocks pass-through to (components of) inflation. For the EA, we estimate a pass-through up to 0.8% for core and 1-2% for headline inflation, depending on the nature of the shock. Individual sectors are affected unevenly in both magnitude and timing, depending on their respective gas-intensity.

Immediate pass-throughs reach up to 15% for the transportation sector, while delayed pass-throughs range from 10% to 20% for food and service-related sectors. In the US we only find mildly significant evidence of pass-through to headline after gas demand shocks.

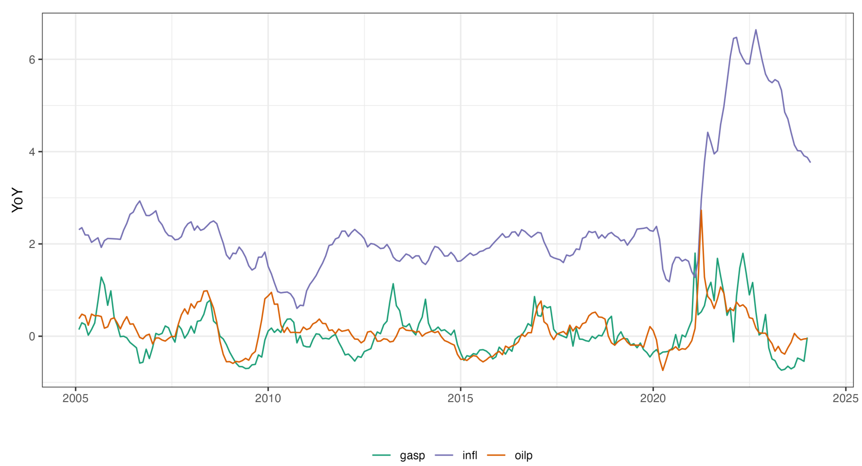
Preview of main results. The gas demand and supply instruments that we construct contribute meaningfully to historical variations in the gas price. Moreover, these gas price shocks have significant effects in both the EA and the US, with notable differences in their nature and impact. In the EA, gas supply shocks primarily involve disruptions to imports, while in the US, they are predominantly related to domestic production disruptions. We find that gas supply shocks have notable real effects in both regions, though through distinct mechanisms. In the EA, these effects arise from increased production costs and supply constraints, while in the US, they operate primarily through disruptions to the domestic energy production sector. Importantly, the inflationary impact of gas supply shocks appears to be more pronounced in the EA, whereas in the US, it is less significant. We observe similar patterns in the impact of demand shocks across both regions, with the key exception being their limited inflationary effect in the US. Unlike supply shocks, gas demand shocks have a positive effect on production, as they tend to stimulate the energy sector in both the EA and the US. Moreover, we provide evidence on the interrelation between gas and oil markets, showing that they act as imperfect substitutes. This relationship differs between the EA and the US due to their distinct energy market structures. In the EA, gas and oil prices mutually influence each other, while in the US, oil prices affect gas prices, but not vice versa. Lastly, via a historical decomposition exercise, we show that the recent inflation surge in the EA was mainly driven by gas shocks and supply chain bottlenecks shocks, both of which have persistent effects.

A comprehensive series of sensitivity checks indicates that the results are robust across several dimensions, including the estimation approach, model specification, and accounting for background noise over event windows (for the gas supply instrument). We also demonstrate that the results are robust when estimating the responses to the identified shocks using a frequentist VAR-OLS instead of Bayesian estimation and when constructing an informationally-robust gas supply instrument that controls for several potential confounding factors.

Layout. The rest of this work is structured as follows. Section 2 details important background of 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 5 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 shows the Year-on-Year (YoY) core inflation rate in the Euro Area alongside the YoY inflation rates of Title Transfer Facility natural gas and Brent crude oil prices, benchmark prices for the gas and oil markets in Europe. The bottom panel shows the corresponding series for the US, where the benchmark price for gas is the NYMEX Henry Hub and the benchmark price for oil is the WTI.

2 Gas market background

This section describes some important characteristics of the natural gas market in the Euro Area and the United States, emphasizing notable distinctions across the two regions and from the crude oil market, which is more integrated globally. This motivates a distinct analysis of gas price shocks in the EA and in the US.

The global natural gas market exhibits partial fragmentation, with prices of the same commodity varying significantly across regions. This is in contrast to the crude oil market, which tends to be more integrated, trading at a relatively uniform price in most places.[2] The consequences of this fragmentation were evident during Russia's invasion of Ukraine, that caused pipeline flows to Europe to decrease. As a consequence, European gas prices surged 14-fold to a record level in August 2022, while gas prices in the United States remained considerably lower than in Europe.

These differences in price reactions can likely be attributed to the distinct characteristics of gas balances in the two regions, particularly the energy self-sufficiency of the United States (IMF Blog, 2023). The Euro Area is a substantial consumer of natural gas, which ranks as the second-largest energy source and accounts for around 23% of the total available energy. Europe heavily relies on gas imports, with import dependence increasing rapidly from about half of total available energy derived from gas in the early 1990s to a record 90% in 2019 (see Figure F27). Europe sources gas from a select group of major suppliers, including Russia, Norway, the United States, and Qatar. Prior to the war in Ukraine, the Euro Area was particularly reliant on Russia, positioning it as the dominant player in the EU gas market and thereby capable of significantly influencing gas prices. Over the past decade, the European Union's dependence on Russian natural gas has increased, reaching 41.1% of gross available energy derived from natural gas in 2020, making it the fuel with the highest exposure to imports from Russia. In 2021, over 80% of the natural gas energy used in the EU was imported, with approximately half of this supply coming from Russia (European Council, 2023). Due to the dependence on imports from a limited number of suppliers, disruptions to gas flows—whether actual or merely perceived as potential—are closely monitored by financial markets and can result in significant price fluctuations. These price fluctuations that occur after market-relevant events can be leveraged to study the effects of gas price shocks using high-frequency identification techniques.

On the other hand, the United States stands as one of the world's largest natural gas producers, experiencing substantial growth in production, driven primarily by shale gas exploration and extraction.[3] The US has progressively become an LNG exporter, with a focus on the 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 F25). Turning to crude oil, although exports have almost reached the level of imports, the US remains a net importer despite being a major crude oil exporter (see Figure F26).

A second difference is that the U.S. market has a more mature structure compared

[2]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). However, there have been a few instances of limited and temporary decoupling (Baumeister & Kilian, 2016). See also Mastroeni et al. (2021) for a more recent examination of the integration of the crude oil price benchmarks.

[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.

to its European counterpart.[4] The European Union, which regulates the European gas market, aims to establish a unified market for natural gas via the "Gas Regulation" for a single energy market.[5] Historically, natural gas pricing in Europe has been predominantly linked to oil products, such as fuel oil, unlike the gas-on-gas pricing model adopted in North America since the 1980s. The process of deregulating the European gas market began in the late 1990s, leading to the issuance of three European Packages designed to create a single market for natural gas. This initiative sought to foster competition and liberalization within the gas sector. Consequently, European gas hubs were established, providing market points where participants can freely trade both spot and futures gas contracts. In 2021, the European gas market featured 11 main distinct active trading hubs, varying significantly in terms of liquidity and gas infrastructure, as reported by the Oxford Institute for Energy Studies (Heather, 2021).[6] In contrast, in the US the liberalization of the gas market started in the 1970s and the Henry Hub (HH) has been the benchmark gas hub since 1990.

Although a unified European gas market with a single price does not exist, the 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, 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] This development enables the analysis of the economic effects of gas price variations through the study 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., 2022). 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 D20 and D22 and Table D6 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 D, Figure D21 and Table D6.

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

[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.

[7]European Commission (2022).

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).

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 (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 VAR that includes several commonly studied macroeconomic variables.

Next, we examine how inflation is affected, comparing the impact of gas shocks with that of other significant factors such as supply chain bottlenecks, oil prices, and monetary policy shocks. We achieve this by estimating a more parsimonious VAR model and identifying four different series of shocks. Through a historical decomposition exercise, we untangle the significance of each of these shocks in the recent surge of inflation. The gas price, oil price, and monetary policy shocks are identified relying on exogenous variation (instruments), while the supply chain bottlenecks shock is identified by short-run restrictions. In this smaller VAR specification, we allow for a single residual variable that accounts for the remaining variability in the time series of inflation.[8]

All the technical details on the econometric modelling are given in Appendix A, and the results are presented in section 4. The next three subsections detail our identification strategy.

3.1 Gas price shocks

We identify a supply shock to the gas price in Europe using market-relevant news and high-frequency data on natural gas futures prices. We also identify a demand shock exploiting exogenous variation induced by extreme surface temperatures. Gas surprises, given by high-frequency changes in the price of gas around market-relevant news reflect variations driven by supply factors. Conversely, extreme temperature provide exogenous variations in gas prices through their impact on consumer demand. For example, an unexpected warm spell during a typically cold month leads to reduced gas consumption for heating. The construction of these instruments is detailed in the next two subsections.

[8]We therefore estimate a VAR of five variables and identify four shocks. As touched upon in Section 1, potential additional drivers of inflation might include demand shifts, inflation expectations, labor market tightness, and mark-ups. However, we will show that these factors, captured by the residual, are less relevant in explaining the recent dynamics of inflation.

3.1.1 Market-relevant news and high-frequency data

We construct daily surprises in the futures prices of gas corresponding to market-relevant news. These constitute an exogenous variation in the price of gas and, once aggregated to monthly, can be used to instrument the spot price of gas in a proxy-VAR setting.

Collecting relevant gas-related news presents a significant challenge due to the lack of a single authoritative source capable of consistently influencing price movements, analogous to OPEC in the oil market (Känzig, 2021a), or central banks for monetary policy (e.g., Kuttner, 2001 and Nakamura and Steinsson, 2018, for the US, and Altavilla et al., 2019, for the Euro Area). We gather news from multiple sources related to gas supply for both the EA and the US, using Reuters.

While Gazprom, a major energy corporation responsible for over 10% of global natural gas production, emerges as a potential focus for constructing the instrument for the EA, several factors complicate its use as a primary source. The irregular release of announcements and Gazprom's predominantly state-owned status pose challenges. Furthermore, statements regarding Gazprom's supply are often issued by the Russian government, blurring direct source attribution. Our collection extends beyond Gazprom and the Russian government to include other major suppliers. Our collection includes 89 supply news, of which 52% are related to flows from Russia, 15% from Norway, and 13% to LNG imports from countries like the US, Qatar, and Australia. The news spans from geopolitical events, such as the conflict in Ukraine, to announcements by major energy corporations, occurrences related to pipelines (e.g., explosions, unforeseen maintenance, or investment projects), and legislative actions by the EU, like the endorsement of gas infrastructure projects. The resulting set of news for the EA predominantly involves gas import disruptions, a selection of which is reported in the first panel of Table B3, underscoring the EA's dependence on gas importers. For the US, we collect 41 supply news, which primarily involve disruptions in domestic production, such as gas platform outages, maintenance works, and explosions, as detailed in the second panel of Table B3. The focus on domestic production events in US news, as opposed to the import-related news in the EA, reflects the structural difference between the EA as a substantial gas importer and the US as a significant producer of natural gas.

As an illustrative example of supply news for the EA, we report the announcement made by President Putin on February 24, 2022. This announcement, which declared a "special military operation" in the Donbas region, marked the beginning of the war in Ukraine.

> "We have been left no other option to protect Russia and our people, but for the one that we will be forced to use today. The situation requires us to take decisive and immediate action. The People's Republics of Donbas turned to Russia with a request for help. [. . .]
> In this regard, in accordance with Article 51 of Part 7 of the UN Charter, with the approval of the Federation Council of Russia and in pursuance of the treaties of friendship and mutual assistance ratified by the Duma on

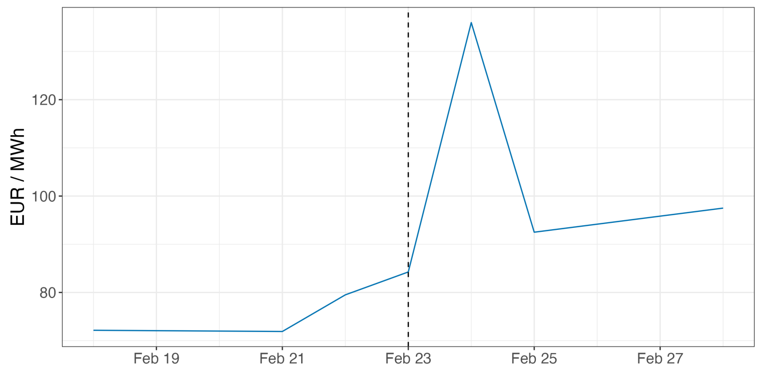


Figure 2: *Putin announces Ukraine invasion*

Notes: The figure shows the surprise in the spot TTF gas price related to announcement of the invasion of Ukraine in February 2022.

> February 22 with the Donetsk People's Republic and the Luhansk People's Republic, I have decided to conduct a special military operation."
>
> BBC News, 24th February 2022

Notably, even though the announcement made no explicit reference to the potential consequences of the conflict on the supply of natural gas, traders paid close attention to it. Their heightened interest was driven by the clear understanding that the Russian invasion of Ukraine posed a serious threat to the European supply of natural gas, given that a substantial volume of Russian gas flowed through the Ukrainian pipeline system. The resulting panic within the natural gas market triggered a spike in gas prices, with the TTF spot price surging by approximately 33% (own calculations based on the TTF spot price). Indeed, on the same day, European Union leaders urged the Commission to propose contingency measures aimed at addressing the unfolding challenges in the energy market.

Construction of gas surprises. To construct a time series of gas surprises, we take changes in gas futures prices following gas-related news. Gas futures prices serve as a market-based indicator of gas price expectations, making them well-suited for assessing the impact of natural gas news.

Using the gas-related news, we construct a series of gas surprises by taking the (log) difference between the futures price on the day of the gas news and the price on the last trading day preceding the news release:

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

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.[9]

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

A crucial choice when constructing the surprises is the width of the event window. Following Känzig (2021a), we opt for a daily window. This is in contrast to 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 announcements, necessitating traders to invest more time in identifying and processing the information conveyed in the news.

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. 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.

To evaluate the adequacy of the gas surprise series, we perform a comprehensive series of checks. One potential concern regarding our high-frequency approach is that non-gas-related news might affect the gas price during the event window. This can be relevant as we use a one-day event window as opposed to a narrower intra-day 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, and geopolitical events, notably those associated with the conflict in Ukraine. 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.

States.

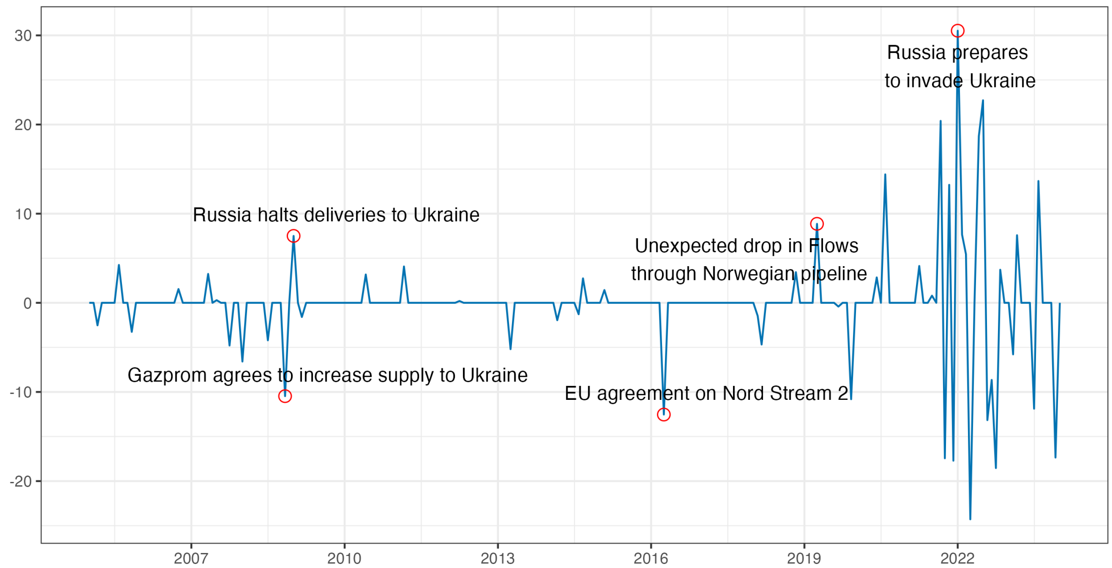
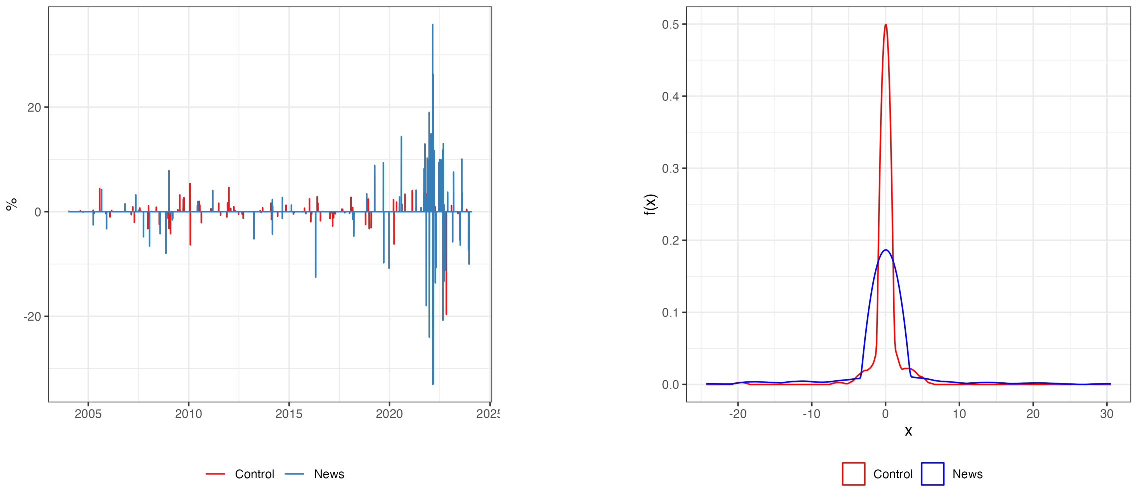


Figure 3: *The gas supply surprises series*

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 2008M11 Gazprom announced an increase in its gas supply to Ukraine following a provisional agreement with Naftogaz. However, the situation deteriorated, leading to an escalation of the gas supply dispute, and in 2009M1 Russia halted its gas deliveries to Ukraine. In 2016M4 EU leaders reached an agreement on the Nord Stream 2 project. On the 5th of 2019M4, there was a noticeable and unexpected decrease in the gas supply from Norway via the Langeled pipeline, dropping more than 50% compared to the previous day. In 2022M2 the invasion of Ukraine started.



(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.

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. However, the presence of noise could still could bias the results and lead to unreliable inference, as shown by Nakamura and Steinsson (2018) in the context of monetary policy. To further address these concerns, we evaluate the sensitivity of our results to background noise, by constructing informationally robust surprises (see next paragraph).

Appendix C reports additional checks on the gas surprise series, including tests on autocorrelation, correlations with other shocks, and Granger's causality tests.

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 news related to geopolitical events, such as 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 of oil and gas markets, another concern is that the changes in the gas price may be confounded by additional information released in the event window but related to the oil market. 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, adopting a strategy typically applied in the monetary policy literature (e.g. Romer and Romer, 2004; Miranda-Agrippino and Ricco, 2021). Following this approach, we refine the gas supply series by purging the gas supply series from confounding factors such as food and oil price surprises arising from the same gas-related news, as well as prior gas supply surprises. Finally, we also control for other relevant shocks documented in the literature.

More specifically, we recover the informationally-robust surprises, IRS_t, as the residuals of the following regression:

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

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, and $OilSurprise_t^h$ is the monthly oil price surprise around gas news. 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).[10]

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. Specifically, these include the global oil supply shock proposed by Kilian (2009), which reflects disruptions in the physical availability of crude oil worldwide, along with oil supply and oil demand shocks from Baumeister and Hamilton (2019), and supply surprises in the price of oil identified by Känzig (2021a). Additionally, we include the oil-specific demand shock and the aggregate demand shock from Kilian (2009). The uncertainty indicators considered encompass various domains, ranging from geopolitical to financial uncertainty. Namely, these include the stock market volatility index as in Bloom (2009), the policy uncertainty index developed by Baker et al. (2016), and the geopolitical risk index introduced by

[10] We use Matif wheat futures and Brent oil futures for the analysis of the Euro Area.

Caldara and Iacoviello (2022).[11] We run the regression specified in Eq. 3.1.2 using the complete sample for which *GasSurprises* are available, including the months that do not contain gas news. In months without news, we then assign IRS_t a value of 0.

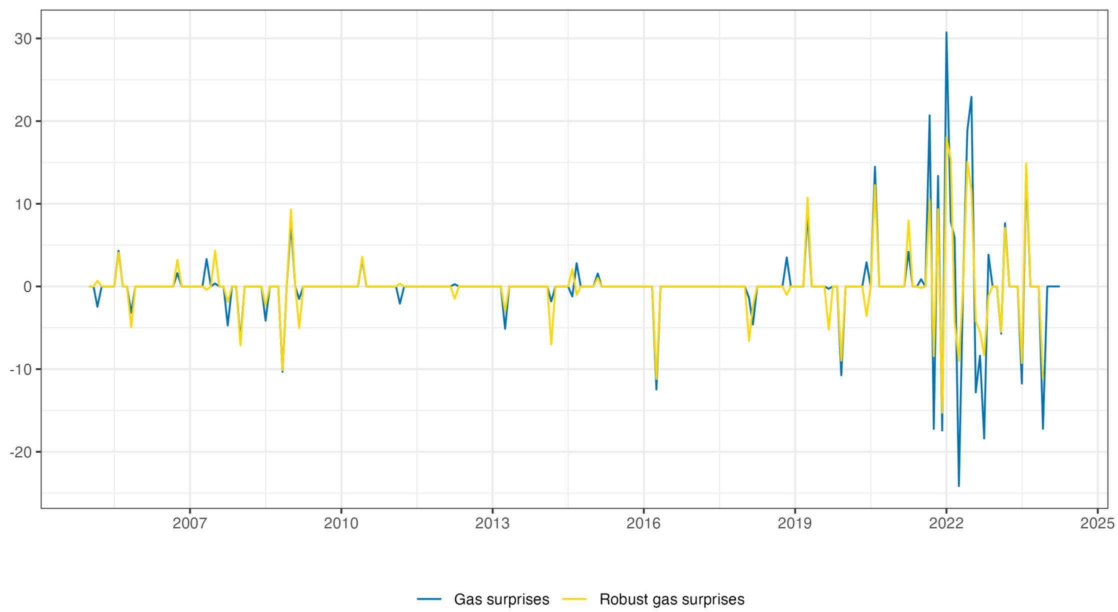


Figure 5: *Informationally-robust gas surprises series*

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).

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, with some notable differences in the last part of the sample.

Appendix H, Figure H36, presents the results obtained using the informationally-robust instrument. The responses are largely similar, with only minor, statistically insignificant differences. This suggests that there is no strong informational channel confounding the high-frequency gas surprises. In Appendix C, Table C5 reports the correlation between gas surprises and other shocks from existing literature. We find that the gas surprise series does not inadvertently capture global demand, uncertainty, financial, or monetary policy shocks that influence gas prices.

3.1.2 Extreme temperatures

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

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

We construct a monthly extreme temperatures index (ETI) which we argue to be exogenous to the price of gas. The idea is that at any given month, unlike average seasonal temperature fluctuations, an extreme deviation from the average temperatures is not anticipated by economic agents, and, importantly, not incorporated in trading decisions, but moves the price of gas via the demand for heating channel, therefore constituting a valid and relevant instrument.[12] To construct the ETI, we first isolate deviations from historical temperatures and then consider only the largest among these. The computation is 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 extreme temperature deviations by setting to zero any observation within 2 standard deviations. Appendix E.1 further details the computation of the extreme temperatures index.

Since the gas traded at the TTF is supplied to several countries, 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.[13] Figure 6 shows the resulting ETI for the considered sample of countries.[14]

Positive spikes in the ETI tend to be associated with unexplained negative spikes in the price of gas and vice-versa. Indeed, the series show a negative correlation of -0.31 with the reduced form residuals, leading to an F-statistic of 20.93, indicating that this is not a weak instrument (see e.g. Montiel-Olea et al., 2016).[15] In the remainder of this section, we argue why this correlation stems mainly from the demand-for-heating channel.

[12]Temperature forecasts typically drop in accuracy as the horizon increases, quickly becoming relatively unreliable, even when the most advanced forecasting methods are employed. See for example Lopez-Gomez et al. (2023). In Figure E24 we show that there is almost no anticipation effect, at most limited to 2-3 days.

[13]Note that at the country level temperature is a weighted-by-population average of grid-level temperatures (see Appendix E.1). 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.

[14]Similarly, we construct the ETI for the United States, using U.S. temperatures, as detailed in Appendix E.1

[15]These correlations and F-statistics refer to the smaller VAR specification (see section 4) but are robust to different specifications.

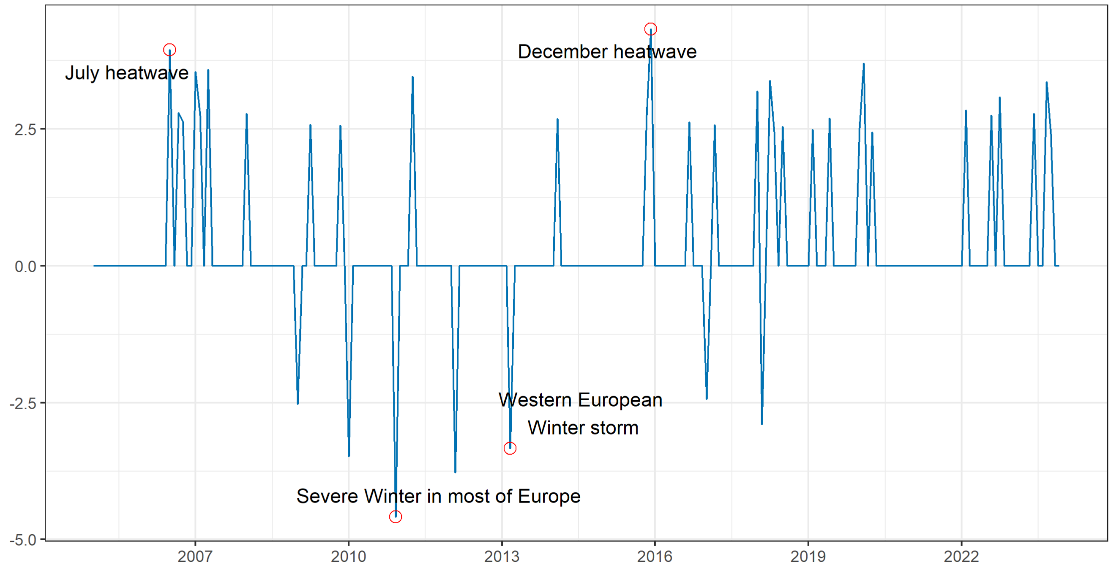


Figure 6: *Extreme temperatures index (ETI) for Europe.*

Notes: This figure shows the extreme temperatures index, which we construct to proxy gas demand. Red circles highlight important temperature-related events for the gas market: 2006M7 was a record-breaking month for heat in many Western European countries, coming in as the hottest July on record in several countries, 2010M12 was the coldest December in 100 years, and the coldest of any winter month since February 1986, 2013M3 saw a late season snow event that affected Western Europe, and 2015M12 was the warmest December on record for many countries worldwide.

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).[16] Figure F28 shows the averaged CCD and HHD for the same sample of countries that we use to construct the ETI.[17]

When we restrict the sample to months when the HDD is low,[18] the correlation between the ETI and the reduced form residuals drops to -0.11 (which would lead to an F-statistic of 0.52, but note that the sample size is smaller than before, see Section A.4 for details on the F-statistic). In contrast, when we restrict the sample to months

[16]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.

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

[18]We choose 70 as a threshold.

when the HDD is high, the correlation is maintained, and slightly increases: we get -0.36 (F-statistic of 21.5). 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,[19] 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.[20] Conveniently, we have that most of the spikes in the ETI (both positive or negative), as shown in Figure 6, occur during Winter months. Nonetheless, we could extract even more correlation by setting to zero any spikes in the ETI 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 F29 shows the cross-correlation function of the reduced-form residuals of the price of gas and the ETI.

As a final note of this section, even though we have argued that the variation in the price of gas induced by extreme 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 ETI is uncorrelated with the revisions in gas price expectations: correlation of -0.02, further supporting the argument that extreme temperatures operate via a demand for gas channel and do not co-vary with supply-related news.

3.2 Identification of additional macroeconomic shocks

Supply chain bottleneck 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 always correlated to higher inflation, and this can happen via several channels, such as inflation expectations, import prices, and costs of intermediate inputs (Liu & Nguyen, 2023). However, shocks to SCB have been studied relatively little in the literature, mainly due to the difficulty of measuring SCB. Some recent papers include Binici et al. (2022) and Kim et al. (2023), which identify a shock by relying on sign-restrictions.

We contribute 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.[21] We argue that this variable is unlikely affected by the other shocks of the

[19] We choose 5 as a threshold.

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

[21] 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

system within the same month (it is a "slow-moving" variable, due to its supply-side nature) 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). By considering both gas and oil price shocks, we aim to compare the two and investigate potential differences in the pass-through from these energy shocks to inflation. While existing literature has traditionally focused on the oil market (Hamilton, 1983; Kilian, 2009; Känzig, 2021a; Kilian and Zhou, 2022 among others), only a limited number of recent studies have delved into the macroeconomic impact of gas shocks (Boeck et al., 2023; Casoli et al., 2022). Furthermore, to the best of our knowledge, no prior work has thoroughly examined the similarities and differences between oil and gas shocks, disentangling the two while considering the interrelations between the oil and gas markets by using a high-frequency approach.

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). The core idea is that these announcements can provide exogenous variation in oil prices by revealing unexpected information about oil production plans, thereby surprising financial market operators. Specifically, we 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 F33 shows the oil supply surprise series, and the corresponding West Texas Intermediate (WTI) oil surprise series can be found in Appendix Figure F34.

Differing from Känzig (2021a), we use Brent oil futures traded at the Intercontinental Exchange (ICE) as they constitute the relevant benchmark for oil pricing

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.

in the Euro Area, the primary focus of this study. Additionally, ICE Brent is the most liquid and largest market for crude oil in the Atlantic basin crude oils (ICE, 2020). For the analysis of the United States, we adhere to the aforementioned study by using the West Texas Intermediate (WTI) crude.

Monetary policy shocks. We also identify monetary policy shocks via an external high-frequency instrument approach. We instrument the OIS 3 months ahead future with a monetary policy surprise series constructed by looking at unexpected movements in OIS futures around the ECB press releases and press conferences. First, we construct monthly surprises series, following closely Altavilla et al. (2019) and considering a window of thirty minutes around the monetary policy event. We aggregate the monetary policy surprises at the monthly frequency by summing the daily surprises. Then, we build an informationally robust instrument that is orthogonal to both past market surprises and to the Central Bank's economic projections. We do this by applying the methodology proposed by Miranda-Agrippino and Ricco (2021), which projects market-based monetary policy surprises onto their own lags and forecasts for real output growth.[22]

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 few but important differences 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. For all specifications, our estimation sample is 2004M1-2023M12.[23] We first address the question of how important gas demand and gas news supply shocks are in explaining historical episodes in the gas market.

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).

[22]The typical policy communication structure during a day of Governing Council policy meeting at the ECB consists of a press release at 13.45 CET (lasting about 15 minutes) and a press conference at 14.30 CET (lasting about 60 minutes). It follows that the policy surprises can be measured via a high-frequency approach during two distinct windows around the two conferences. Altavilla et al. (2019) consider changes in the Euro Area Overnight Index Swap (OIS) contracts with different maturities, from one week to 20 years, to build a dataset of surprises in each OIS for each of the two windows. Further, by extracting the common components of the surprises relative to each window, the authors show that during the press release the rates react prevalently to the information on the decisions on "conventional" monetary policy (key interest rates), while the press conference mainly delivers information on "unconventional" monetary policy (such as quantitative easing and forward guidance). Since in our analysis, we do not distinguish between conventional and unconventional monetary policy, we consider the surprises measured over the whole monetary event.

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

Technical details on the estimation technique are given in Appendix A. However, in Appendix H we show that our results can be qualitatively replicated using a standard frequentist approach.

Gas shock contribution to the real gas price series. Figure 7 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 Jan2004-Dec2023. 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.

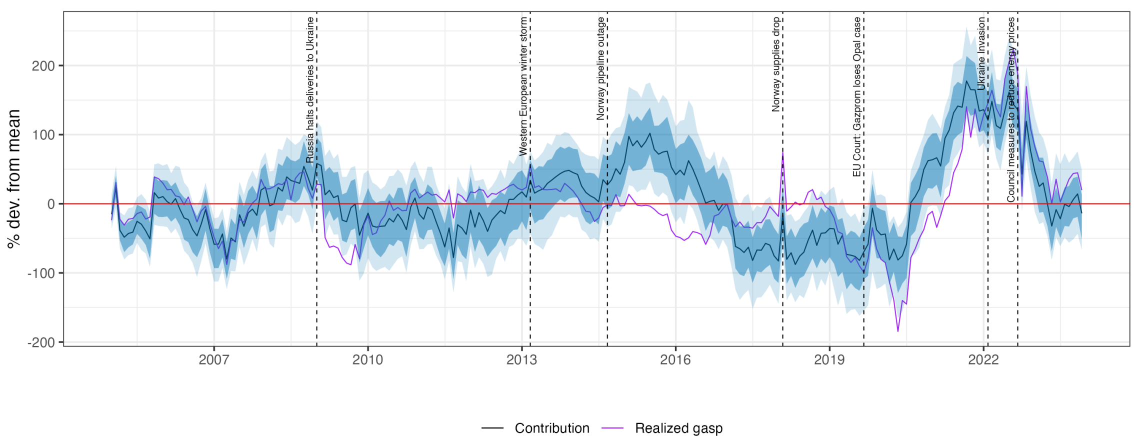


Figure 7: *EA: Historical decomposition of the real price of gas*

Notes: The figure shows the estimated contributions of gas shocks to the real price of gas and the 68 and 90 percent confidence bands together with the realized gas price series (in percent deviation from the mean). Both demand and supply instruments are used. The vertical dashed bars indicate major events in the gas markets: the Russian halt of all gas deliveries to Ukraine for 13 days in 2009M1, the Western European storm in 2013M3, the Norwegian Langeled pipeline halt in 2014M9, the earthquake in Norway that led to a decrease in exports in 2018M2, the EU court judgement to limit Gazprom's dominance in 2019M9, the invasion of Ukraine in 2022M2, and the Council measures to reduce energy prices in 2022M9.

In addition, unexpected severe temperatures 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, combined with the temporary halt of the Norwegian Langeled pipeline due to maintenance, caused a very large hike in the price of gas. However, gas price shocks would have led to a much higher gas price during the 2015-2017 period but this was not the case owing to the low oil prices caused by OPEC announcements as shown in Känzig (2021a). Similarly, the record-low prices of 2020 are to be attributed to the COVID19 pandemic and not solely to gas shocks.

Gas shock in the EA. Figure 8 shows the responses of a gas supply shock in the Euro Area on gas and oil prices, gas balances, and selected macro variables. A negative gas supply shock results in a sharp, immediate spike in gas prices, followed by a rapid correction within the first month and a gradual decline back to baseline over the course of a year. Gas net imports, the primary source of natural gas for the EA (see Section 2), experience a significant decline within a few months. In line with the nature of the market-relevant news used to construct the supply instrument, these shocks can be interpreted as disruptions to natural gas imports, as discussed in Section 3.1.1. As a consequence, the euro depreciates *vis-à-vis* the rest of the world. Gas production shows no significant response, given its limited role in the EA. Gas stocks decline to offset the supply shortfall. Due to substitution effects, the real price of crude oil rises, with a pass-through of 15% (further discussed later in this section).

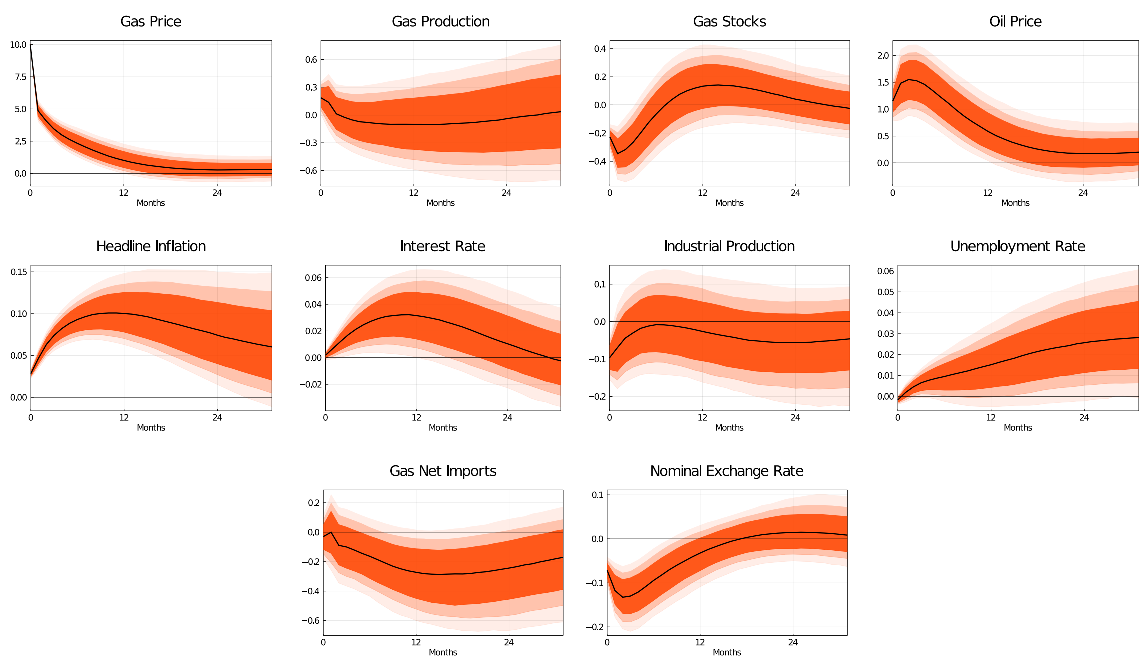


Figure 8: *EA: Responses to a gas supply shock. F-stat: 30.63, Robust F-stat: 9.33.*

The second row presents the responses of the macro variables. There is a significant immediate increase in inflation following a gas supply news shock, which reaches the peak after 9 months (10% pass-through), with a consequent response of the central bank that increases interest rates. Industrial production decreases on impact but quickly recovers, so that the real effect is limited. Unemployment increases persistently but the magnitude of the increase is small: 0.02% increase after a 10% increase in the real gas price. These findings align with the predictions of multi-sector macro models by Bachmann et al. (2022) for the German economy and Di Bella et al. (2024) for the broader European context. Both studies argue that substitution effects helped maintain an integrated European gas market, thereby mitigating economic losses. This can explain why the magnitude of the drop in economic activity was less severe than initially feared by many (Bundesbank, 2022; Gunnella et al., 2022).

We therefore have that the macroeconomic impact of gas supply shocks is primarily inflationary, with limited effects on real economic activity. Figure 9 provides a more detailed breakdown of how different sub-sectors of industrial production are affected. The left panel shows the response of the three Level 1 sub-sectors that comprise industrial production. It reveals that the overall decline in industrial production is largely driven by manufacturing, while electricity, gas, and steam production increases, reflecting the rise in gas output. Within manufacturing, Level 2 sub-sectors are impacted unevenly, with gas-intensive industries, such as pharmaceuticals, experiencing significant negative responses, while others, such as fabricated metals, show no substantial impact. This heterogeneity is illustrated in the right panel.

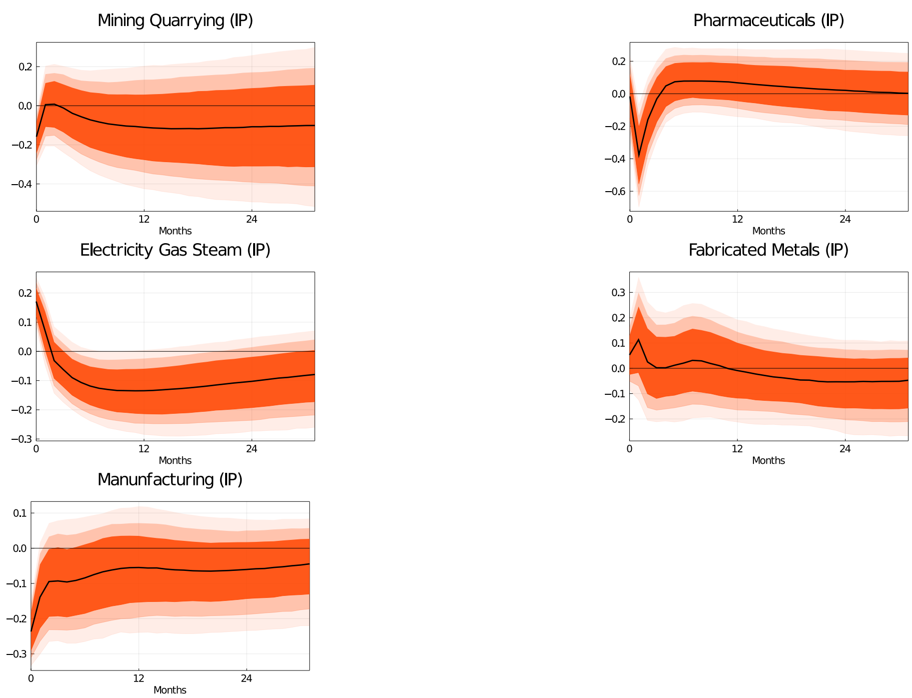


Figure 9: *EA: Responses of Level 2 NACE sectors (left column) and selected Level 2 NACE sectors (right column) to a gas supply shock.*

Figure 10 presents the responses of eleven 2-digit (ECOICOP) sectors that contribute to the headline inflation index, alongside the response of core inflation. While core inflation remains unaffected initially, it steadily increases and reaches its peak after more than 20 months, with a pass-through of approximately 0.8% at the peak. This gradual response suggests the presence of second-round effects, indicating that the impact on headline inflation is not solely driven by energy prices.

We find that different sectors are affected asymmetrically by gas supply shocks, although they generally exhibit an inflationary trend. The food sector is among the most impacted, largely due to the use of gas as an input in fertilizer production, which drives up costs. Similarly, the clothing sector experiences significant inflationary pressures, likely due to the use of synthetic fibers and chemical products, which are gas-intensive inputs. The transportation sector's response closely mirrors the trajectory of gas prices, with the impact becoming insignificant after approximately 12 months. This pattern is driven by the rise in both gas and oil prices, which contribute to increased transportation costs. Overall, two primary mechanisms explain these sectoral impacts. First, direct effects are observed in sectors that consume energy intensively, such as transport and clothing, where the effects are felt early. Second, indirect effects arise in sectors where the cost of inputs, like food, increases due to higher gas prices. For example, food price increases also affect the restaurant sector through higher input costs.

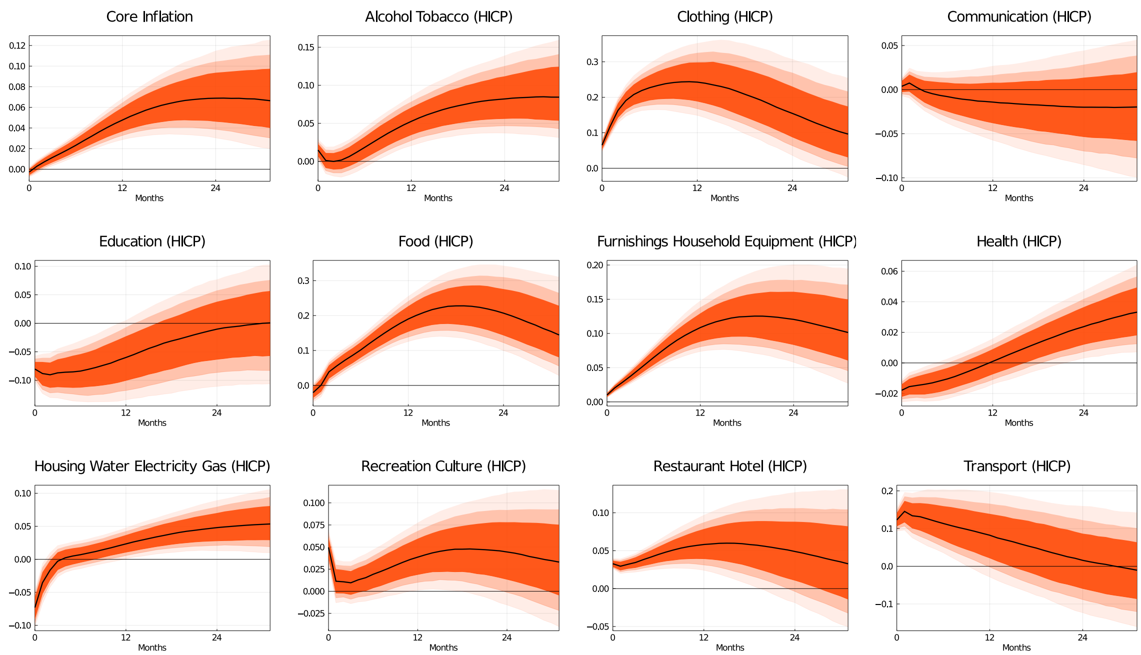


Figure 10: *EA: Responses of HICP 2-digit sectors and core inflation to a gas supply shock.*

Next, we examine the responses following a gas demand shock in the EA, as depicted in Figure 11. Unlike the supply shock scenario, there are no constraints on gas imports, which rise significantly in response to the increased demand. Gas stocks, the real oil price, and headline inflation exhibit patterns similar to those observed in the supply shock case. However, a key distinction is the positive reaction of industrial production. This increase is largely driven by activities related to the production, processing, and refinement of imported gas, as evidenced by the positive response of gas production.[24]

[24]Gas production in this context includes not only extraction but also the infrastructure supporting the processing and distribution of imported gas.

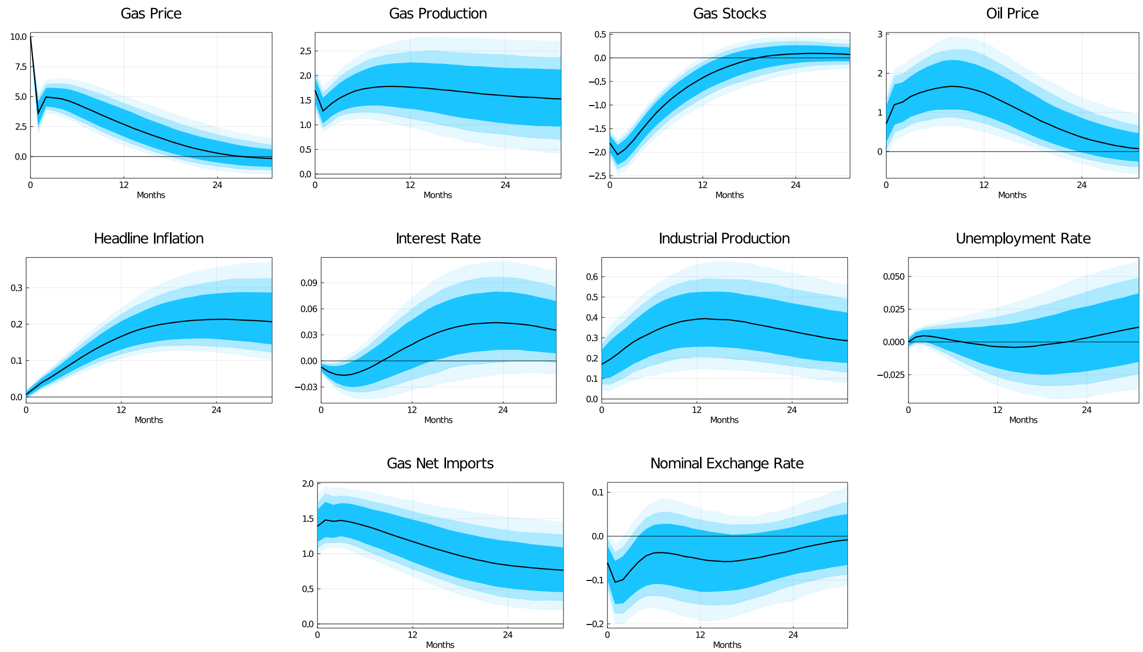


Figure 11: *EA: Responses to a gas demand shock. F-stat: 20.24, Robust F-stat: 12.66.*

Gas shock in the U.S. Figure 12 illustrates the responses to a gas supply shock in the U.S., where this shock is best interpreted as a disruption to domestic production, given that the U.S. is a major producer and net exporter of natural gas, unlike the EA. The negative response of gas production supports this interpretation, while net imports increase to compensate for the reduced domestic supply. This adjustment is driven by both a reduction in exports and an increase in imports. Unlike in the EA, the real effects in the U.S. are substantial, largely due to the significant role of the oil and natural gas industry, which accounts for 5.6% of total U.S. employment.[25] Industrial production declines sharply, and unemployment rises in response to the shock. Overall, the gas supply disruption leads to a contractionary shock that also exerts modest deflationary pressure.

[25] PwC.

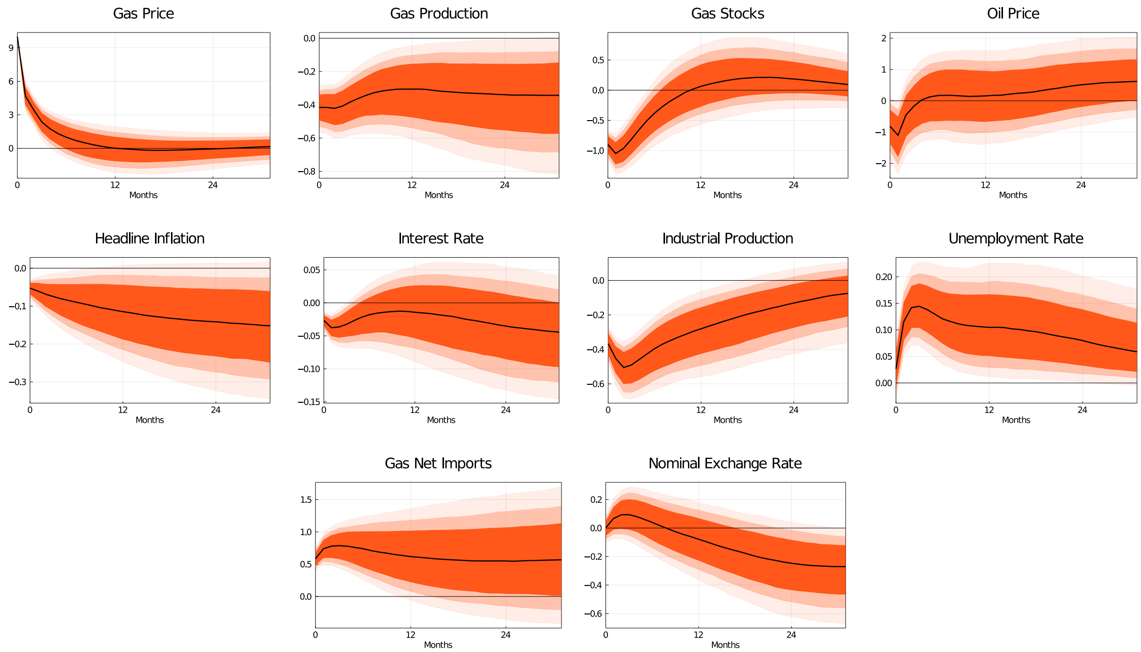


Figure 12: *US: Responses to a gas supply shock. F-stat: 14.37, Robust F-stat: 2.67.*

Finally, Figure 13 presents the responses to a gas demand shock in the U.S. These responses closely resemble those observed in the EA, with the key distinction being the much milder and less significant inflationary response in the U.S. 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 absorb demand shocks, mitigating the inflationary pressure typically seen in the EA.

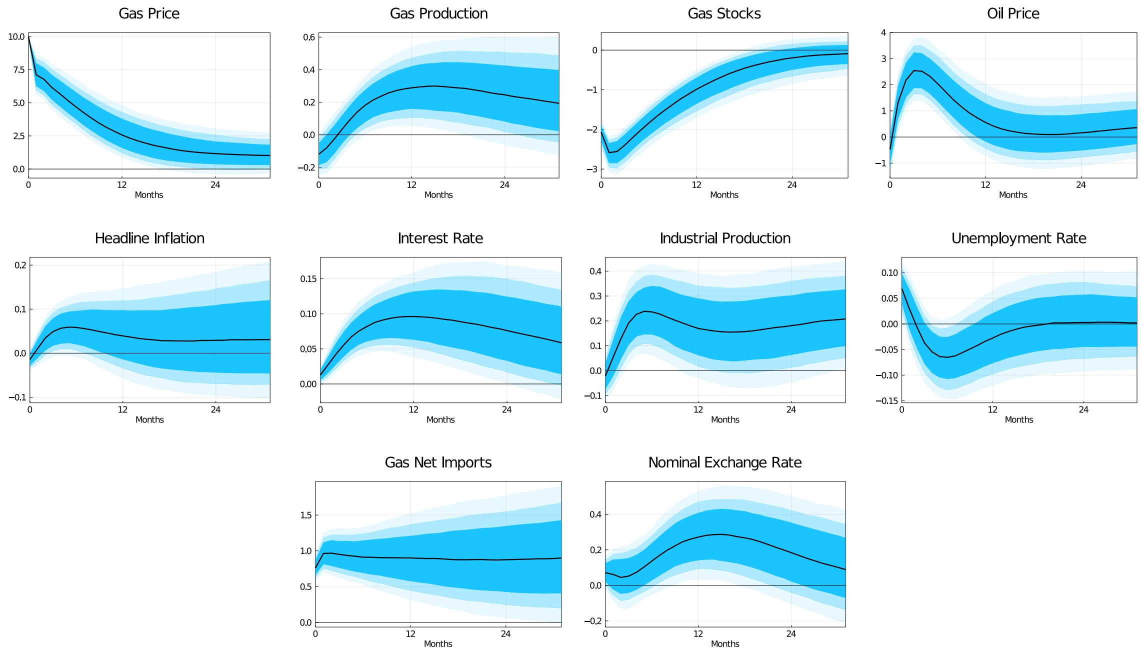
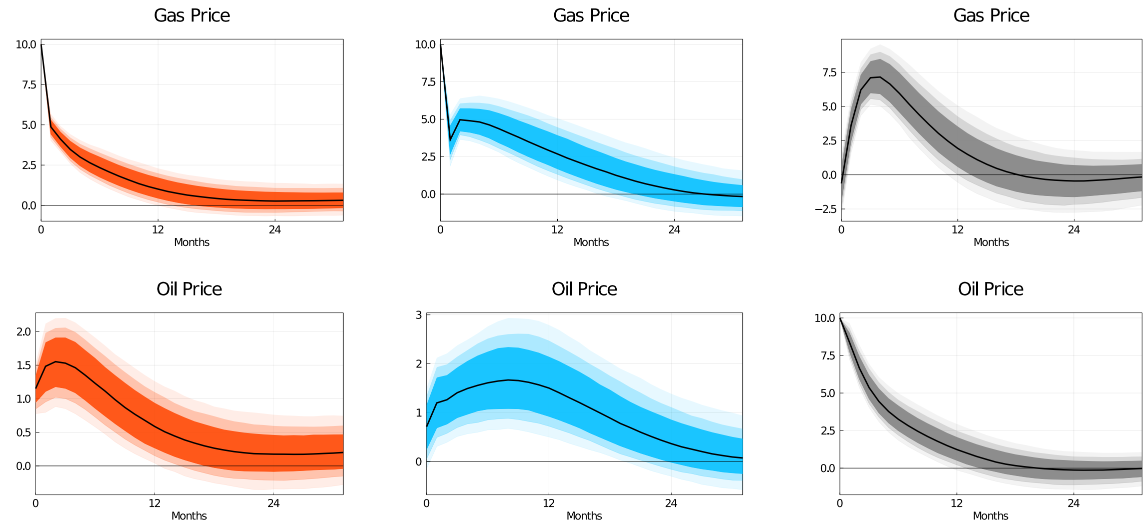


Figure 13: *US: Responses to a gas demand shock. F-stat: 40.14, Robust F-stat: 30.91*

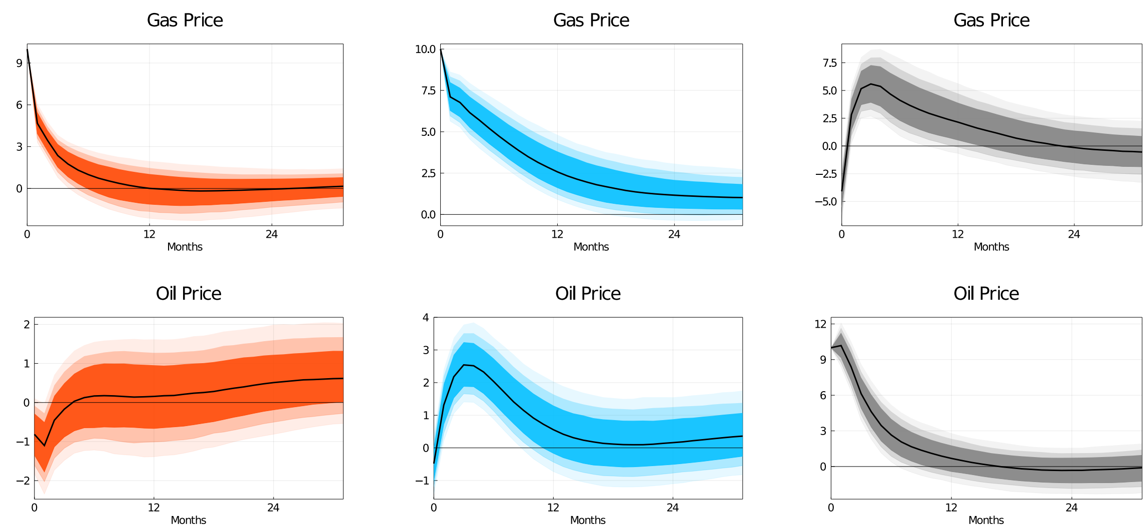
Gas and oil markets interrelation. Figure 14 compares the responses of real gas and oil prices to the respective shocks in both regions. In the EA, there is a pass-through from gas prices to oil prices of approximately 20%, with a quicker adjustment observed in the case of supply shocks. On the other hand, the pass-through from oil prices to gas prices is significantly stronger, reaching up to 70%. 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 a more limited effect on oil prices.

In the US the two markets appear to be less interdependent than in the EA, as gas supply shocks do not impact oil prices as much in the supply case. 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, we note that oil price respond comparatively mildly to gas price shocks, in both regions. This finding 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 oil demand does not significantly move the global price of oil.[26] In contrast, when the demand for gas increases, the gas price increases significantly, given that the global market for gas is fragmented and the EA depends heavily on neighboring countries as a net importer of gas.

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



(a) Euro Area



(b) United States

Figure 14: *Interrelation of Gas and Oil markets*

Notes: Responses of the real price of gas and the real price of oil to 10% increases in gas and oil prices. Panel (a) shows the responses in the Euro Area, where gas demand shocks are shown in blue, and gas supply shocks are shown in orange. Responses to oil shocks identified as in Känzig (2021a) are shown in grey. Panel (b) illustrates the same responses for the United States.

4.1 Contributions to inflation surge

We now explore in greater depth the impacts on inflation of the gas shocks and the other macroeconomic shocks that we identify. To do this we estimate a smaller VAR model where we include the GSCPI, the real price of gas, the real price of oil, YoY inflation, and the 1Y ECB rate. As described in section 3.2, we identify supply chain bottlenecks shocks by short-run restrictions, as well as oil price (following Känzig, 2021a) and monetary policy (following Miranda-Agrippino and Ricco, 2021) shocks which we take from the proxy-VAR literature and of which we extend the respective instruments to December 2023. The resulting impulse responses are shown in Figure 15.

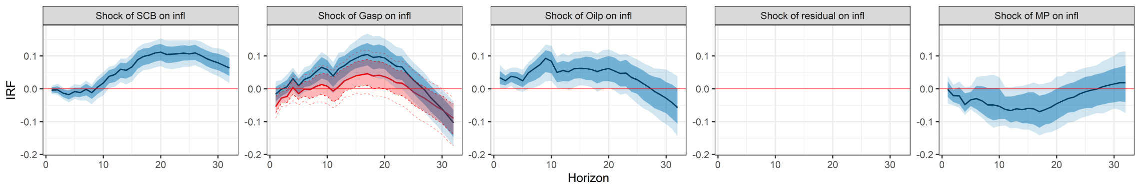


Figure 15: *Responses of YoY inflation to macroeconomic shocks*

Notes: The figure shows the impulses responses of inflation stemming from a VAR with five variables where four are identified: supply chain bottlenecks, gas price demand (blue) and supply (red), oil price, and monetary policy. The fourth panel is empty as the residuals of inflation are not identified.

Figure 15 shows the identified responses of inflation to a standard deviation in each of the four shocks. Supply chain bottleneck shocks exhibit their impact after 10 months, exerting a strongly positive and persistent effect on inflation. Gas and oil price shocks demonstrate a similar dynamic, leading to increased inflation for approximately 20 months. However, gas price shocks have a stronger effect than oil shocks, particularly when they manifest as demand shocks. Conversely, gas supply shocks produce a milder and less substantial impact on inflation. Additionally, in line with standard macroeconomic theory predictions, monetary policy shocks decrease inflation, though we estimate this response to be only moderately significant.

We now turn to a more in depth analysis of the recent inflation surge episode. To better characterize the inflation dynamics, we adopt the chronological categorization of the COVID-19 pandemic period proposed by Ascari et al. (2023):

- Phase I: COVID-19 initial diffusion (January 2020 to June 2020), inflation drops.
- Phase II: the re-opening of the economy (July 2020 to September 2021), inflation starts to increase as economic activity resumes.
- Phase III: the post reopening (October 2021 onwards), inflation experiences a severe surge.

Figure 16 shows the obtained historical decompositions and compares them to the realized series of inflation. From the YoY decompositions we can recover the implied MoM and the contributions to the price level. Historical decompositions allow to quantify how much a given series of structural shocks explains of the historically observed fluctuation of the variables included in the VAR (see Appendix A.2 for additional technical details). In our setting, this device can shed light on which drivers of inflation have been more relevant at each point in time.

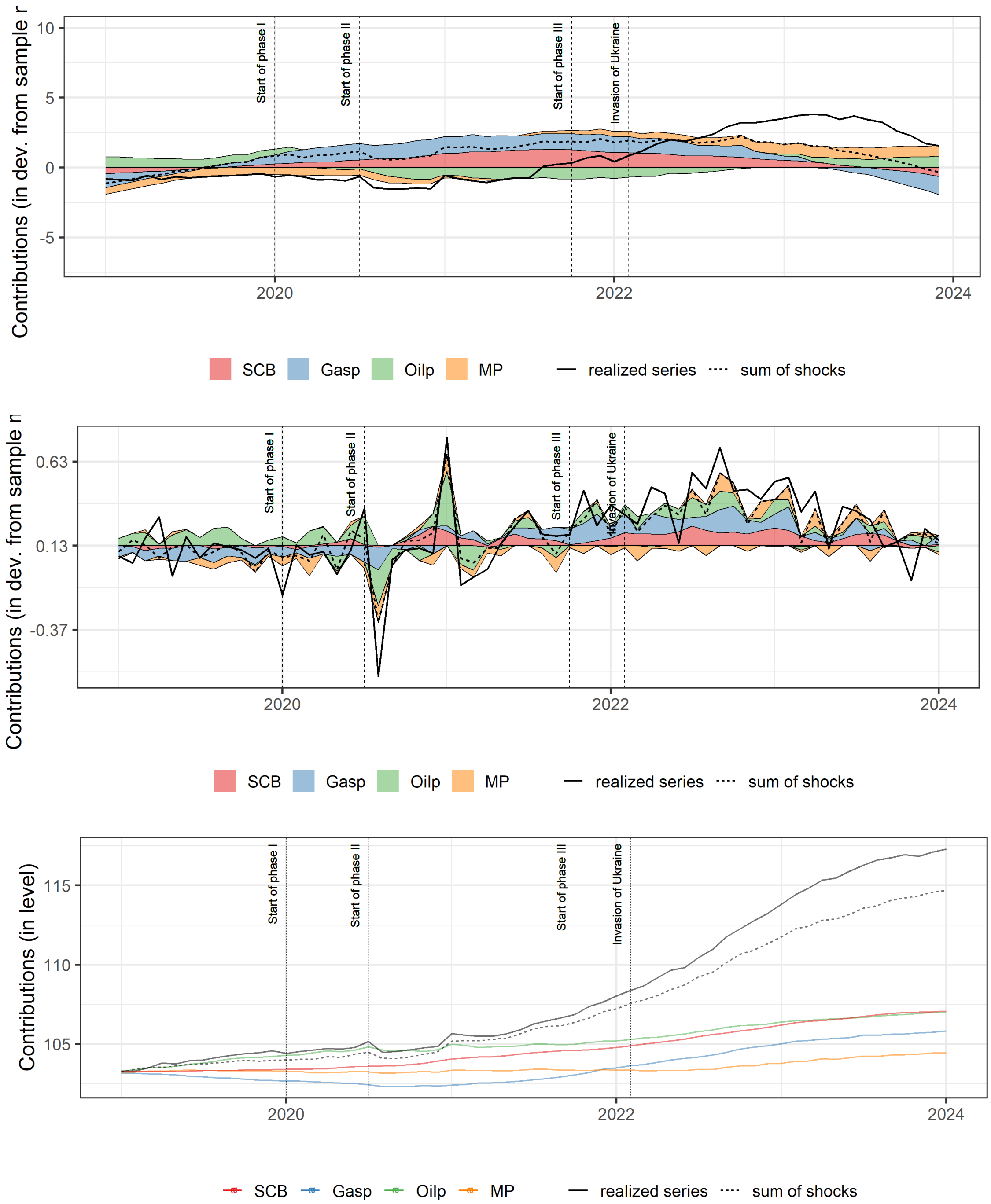


Figure 16: *Historical decompositions of YoY, MoM inflation and price level, selected sample.*

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 central panel shows the contributions on MoM inflation. The bottom panel shows the implied contributions on the price level. The dashed line represents the total contribution of all shocks. We adopt the phases categorization of the inflation surge proposed by Ascari et al. (2023).

First, we have that the sum of the four shocks - out of five variables - that we identify (dashed line) explains very well the realization of the inflation series. This means that the residual of the unexplained variation in inflation is small, or that the shocks that we identify are the most relevant drivers of inflation. This also tells us that the quality of the historical decomposition approximation is adequate and that it can explain well the recent rise in inflation.

Oil price shocks have been relevant during phase I when the drop in energy prices lowered inflation substantially, but have not been as important in phases II and III. Perhaps more easily from the central and bottom panels of figure 16, we can see that oil prices have been a main driver of inflation up to 2021, and were instead less relevant in the rest of the sample. In particular, oil price shocks had a key role in the 2020 sharp fall of inflation related to the COVID19 pandemic. With the reopening, supply chain bottlenecks, which we have seen impact inflation with a significant lag, led to a significant increase in prices, which has been felt up to late 2023. At the same time, during and after phase III, gas prices played a key role and contributed to the fast inflation increase. This effect of gas price shocks started before but was felt especially after the invasion of Ukraine. Throughout the high inflation period, monetary policy has counteracted rising prices only modestly, despite the sharp increase in interest rates.

However, in the last part of the sample, a larger part of the variation in inflation is not captured by our empirical exercise. Russia's invasion of Ukraine may well have been at the origin of additional inflation that we are not capturing. For example, food prices, which have been argued to have contributed to the inflationary pressures due to the invasion of Ukraine, are not taken into account in our empirical model (see among others Arce, Koester, and Nickel, 2023).[27]

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

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

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

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

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

[27] See the ECB blog at this link.

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 take it into account the sign of the historical decomposition contribution, and should be interpreted in such terms. That is, it only gives a quantitative assessment of how much each series of shocks has shaped the series of inflation. Table 1 quantifies the contributions of each series of shocks on MoM inflation by computing the proposed metric for different time periods.

Shock contribution		**SCB**	**Gasp**	**Oilp**	**MP**	**Residual**
Pre-COVID	*2007M01* *2019M12*	14%	21%	26%	14%	24%
Phase I	*2020M01* *2020M06*	7%	20%	29%	15%	29%
Phase II	*2020M07* *2021M09*	13%	14%	30%	12%	31%
Phase III	*2021M10* *2023M02*	18%	23%	16%	12%	31%
All phases	*2020M01* *2023M02*	15%	19%	23%	13%	31%

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

During the pre-COVID period (January 2007-December 2019)[28] the identified energy price shocks had a significant contribution, with gas price explaining 21% and oil price explaining 26% of the variation in inflation, respectively. During the COVID-19 pandemic (Phase I), the impact of energy price shocks became even more pronounced, primarily due to a substantial decrease in global energy demand triggered by pandemic-related lockdowns. Conversely, during this period, the influence of supply chain bottlenecks on inflation was minimal. As the global economy began to reopen (Phase II), supply chain bottlenecks emerged as a more significant factor, explaining 13% of inflation, indicating that these effects tend to operate with a delay. Regarding energy price shocks, gas shocks contribute less than oil shocks during the reopening. During the subsequent period (Phase III), characterized by the Russian invasion of Ukraine, gas price shocks emerged as the primary driver of

[28] We discard 12 months - from the beginning of the sample up to December 2006 - as the initial transient period in which the historical decomposition approximation is not accurate.

inflation, surpassing the influence of oil price shocks, primarily due to disruptions in gas supply. Additionally, the significance of supply chain bottleneck shocks increased to 18%, highlighting the growing importance of supply chain dynamics in inflationary pressures.

Overall, we have that energy shocks have consistently been important drivers of the variation in inflation, overshadowing the effects of monetary policy, which appeared relatively subdued despite a marked increase in interest rates. Notably, while oil prices have traditionally played a pivotal role in driving inflation, the outbreak of the Russian war against Ukraine has shifted this dynamic, making gas prices a more significant factor due to disruptions in the gas supply. During the COVID-19 crisis, the impact of supply chain bottlenecks on inflation was minimal. However, as the global economy began to recover and reopen, these bottlenecks emerged as a more prominent factor contributing to inflationary pressures.

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:

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

where $\hat{y}^{(j)}_{kt}$ 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. As shown in Figure 16, the cut in interest rates increased the price level during Phase I only slightly. Yet, this increase was more than counterbalanced by the large drop in energy prices and the negative impact of supply chain shocks.

In phase II SCB shocks, which operate with a lag, became the major driver of inflation, increasing the price level by over 1 point, while each of the other shocks had a contribution lower than a half point. Specifically, energy price shocks (which accounted for over 40% of the variation in inflation) contributed to a change in the price level of only 0.72 points. Although energy - in particular oil - prices shocks co-moved with inflation throughout the period (see bottom panel of Figure 16), in cumulative terms their contribution to the price level was more modest. This is because they exerted a negative effect initially (still related to the pandemic-induced fall in energy prices) but a positive effect after the re-opening of the economies, with the two contributions offsetting each other.

Lastly, in the post reopening, all the shocks contributed to the increase on the price level, including monetary policy shocks. This suggests that the restrictive monetary policy stance was unable to fully slow down inflation. Gas prices have been the major driver of the price level in phase III.

Shock contribution to the price level / *Date and price level*			**SCB**	**Gasp**	**Oilp**	**MP**	**Residual**
Phase I	*2020M01* *2020M06*	104,58 104,80	0,17	-0,15	0,38	-0,01	0,17
Phase II	*2020M07* *2021M09*	104,80 106,67	1,03	0,46	0,26	0,14	-0,02
Phase III	*2021M10* *2023M02*	106,67 114,43	1,76	2,16	1,65	0,57	1,50

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

5 Conclusions

This paper proposes a novel identification strategy to separately identify demand shocks and supply news shocks to the price of gas. Using exogenous variation in temperatures, we identify a gas demand shock, and using variation in futures prices in a tight window around gas market-relevant news, we identify a gas supply news shock. Gas shocks have significant macroeconomic effects, both in the Euro Area and in the United States. However, they are strongly inflationary only in the Euro Area, while the US is mostly affected through production in its energy sector. Moreover, in the Euro Area, the gas and oil markets appear significantly interdependent. Our separate identification strategy allows us to distinguish between the effects of demand and supply disruptions in the gas market. Our findings reveal that, in contrast to a gas supply shock, the response to a gas demand shock does not constrain domestic production—significant for the U.S.—or imports, which are crucial for Europe. Consequently, economic activity is not negatively affected following a gas demand shock. To our knowledge, this paper is the first to offer a framework capable of delivering comparable estimates of the pass-through effects of gas and oil price shocks on various components of inflation across both regions.

To further investigate the effects of macroeconomic shocks on inflation, we propose 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 show 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.

Our analysis shows that there are important policy implications in addressing the adverse economic effects induced by gas price shocks. First and foremost, it is essential for the Euro Area to prioritize energy security procurement. The considerable reliance of the region on gas imports underscores the need for policies that promote energy diversification strategies. Building strategic reserves can serve as a buffer against potential supply disruptions, ensuring that the economy remains resilient in the face of external shocks. In tandem with these efforts, both the EA and the US must accelerate the transition towards renewable energy sources. This shift is not only imperative for reducing dependence on fossil fuels but also plays a role in mitigating the adverse effects of future gas supply shocks. Investing in renewable energy infrastructure can pave the way for a more sustainable and stable energy mix, reducing vulnerability to gas price fluctuations. 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.

References

Adolfsen, J. F., Minesso, M. F., Mork, J. E., & Robays, I. V. (2024). Gas price shocks and euro area inflation.

Alexander, P., Arneth, A., Henry, R., Maire, J., Rabin, S., & Rounsevell, M. D. (2023). High energy and fertilizer prices are more damaging than food export curtailment from ukraine and russia for food prices, health and the environment. *Nature food*, *4*(1), 84–95.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., & Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, *108*, 162–179.

Ascari, G., Trezzi, R., thank Olaf, W., & Sleijpen, N. G. (2023). The euro area great inflation surge. *SUERF Policy Brief, No 548*.

Bachmann, R., Baqaee, D., Bayer, C., Kuhn, M., Löschel, A., Moll, B., Peichl, A., Pittel, K., & Schularick, M. (2022). *What if? the economic effects for germany of a stop of energy imports from russia* (tech. rep.). ECONtribute Policy Brief.

Baget, C., Gaulier, G., Carluccio, J., Stalla-Bourdillon, A., Gossé, J.-B., Gallo, F. L., & Schneider, A. (2024). The gas price shock: Never again? *Bulletin de la Banque de France*, (252).

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593–1636.

Banbura, M., Giannone, D., & Reichlin, L. (2007). Bayesian vars with large panels.

Bartelet, H., & Mulder, M. (2020). Natural gas markets in the european union. *Economics of Energy & Environmental Policy*, *9*(1), 185–206.

Baumeister, C., & Hamilton, J. D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review*, *109*(5), 1873–1910.

Baumeister, C., & Kilian, L. (2016). Forty years of oil price fluctuations: Why the price of oil may still surprise us. *Journal of Economic Perspectives*, *30*(1), 139–160.

Ben Hassen, T., & El Bilali, H. (2022). Impacts of the russia-ukraine war on global food security: Towards more sustainable and resilient food systems? *Foods*, *11*(15), 2301.

Benigno, G., Di Giovanni, J., Groen, J. J., & Noble, A. I. (2022). The gscpi: A new barometer of global supply chain pressures. *FRB of New York Staff Report*, (1017).

Bernanke, B., & Blanchard, O. (2023). 23-4 what caused the us pandemic-era inflation?

Binici, M., Centorrino, S., Cevik, S., & Gwon, G. (2022). Here comes the change: The role of global and domestic factors in post-pandemic inflation in europe.

Blanchard, O., & Gali, J. (2007). Real wage rigidities and the new keynesian model. *Journal of money, credit and banking*, *39*, 35–65.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, *77*(3), 623–685.

Boeck, M., Zörner, T. O., & Nationalbank, O. (2023). Natural gas prices and unnatural propagation effects: The role of inflation expectations in the euro area.

Bordo, M. D., Taylor, J. B., & Cochrane, J. H. (2023). *How monetary policy got behind the curve—and how to get back*. Hoover Press.
Bundesbank, D. (2022). Outlook for the german economy for 2022 to 2024. *Bundesbank*, *1*.
Caldara, D., Cavallo, M., & Iacoviello, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics*, *103*, 1–20.
Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, *112*(4), 1194–1225.
Casoli, C., Manera, M., & Valenti, D. (2022). Energy shocks in the euro area: Disentangling the pass-through from oil and gas prices to inflation.
CME Group. (2021). *Henry hub natural gas futures: Global benchmark*. Retrieved October 10, 2023, from https://www.cmegroup.com/education/articles-and-reports/henry-hub-natural-gas-futures-global-benchmark.html
Colombo, D., & Ferrara, L. (2023). Dynamic effects of weather shocks on production in european economies. *Available at SSRN...*
Cooley, T. F., & LeRoy, S. F. (1985). Atheoretical macroeconometrics: A critique. *Journal of Monetary Economics*, *16*(3), 283–308.
Di Bella, G., Flanagan, M., Foda, K., Maslova, S., Pienkowski, A., Stuermer, M., & Toscani, F. (2024). Natural gas in europe: The potential impact of disruptions to supply. *Energy Economics*, *138*, 107777.
Doan, T., Litterman, R., & Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric reviews*, *3*(1), 1–100.
European Commission. (2022). *Quarterly report on european gas markets*. Retrieved October 10, 2023, from https://energy.ec.europa.eu/system/files/2023-05/Quarterly%20Report%20on%20European%20Gas%20Markets%20report%20Q4%202022.pdf
European Council. (2023). *Infographic - where does the eu's gas come from?* Retrieved October 10, 2023, from https://www.consilium.europa.eu/en/infographics/eu-gas-supply/
Gagliardone, L., & Gertler, M. (2023). Oil prices, monetary policy and inflation surges. *Available at SSRN*.
Gao, L., Kim, H., & Saba, R. (2014). How do oil price shocks affect consumer prices? *Energy Economics*, *45*, 313–323.
Gertler, M., & Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, *7*(1), 44–76.
Giannone, D., Lenza, M., & Primiceri, G. E. (2015). Prior selection for vector autoregressions. *Review of Economics and Statistics*, *97*(2), 436–451.
Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review*, *102*(4), 1692–1720.
Goodell, J. W., Gurdgiev, C., Paltrinieri, A., & Piserà, S. (2023). Global energy supply risk: Evidence from the reactions of european natural gas futures to nord stream announcements. *Energy Economics*, *125*, 106838.
Guerrieri, V., Marcussen, M., Reichlin, L., & Tenreyro, S. (2023). Geneva report: The art and science of patience: Relative prices and inflation.

Gunnella, V., Jarvis, V., Morris, R., & Tóth, M. (2022). Natural gas dependence and risks to activity in the euro area. *Economic Bulletin Boxes*, *1*.

Hamilton, J. D. (1983). Oil and the macroeconomy since world war ii. *Journal of political economy*, *91*(2), 228–248.

Hamilton, J. D. (2003). What is an oil shock? *Journal of econometrics*, *113*(2), 363–398.

Heather, P. (2021). *European traded gas hubs: German hubs about to merge* (tech. rep. No. 170). OIES Paper: NG.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049.

ICE. (2020). *Brent: The world's crude benchmark*. Retrieved October 10, 2023, from https://www.ice.com/insights/market-pulse/brent-the-worlds-crude-benchmark

ICE. (2023). *Ice announces record traded volumes in ttf natural gas*. Retrieved May 18, 2024, from https://ir.theice.com/press/news-details/2023/ICE-Announces-Record-Traded-Volumes-in-TTF-Natural-Gas/default.aspx

IMF Blog. (2023). *How natural gas market integration can help increase energy security*. Retrieved October 10, 2023, from https://www.imf.org/en/Blogs/Articles/2023/05/23/how-natural-gas-market-integration-can-help-increase-energy-security

Jarociński, M., & Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, *12*(2), 1–43.

Jotanovic, V., & D'Ecclesia, R. L. (2021). The european gas market: New evidences. *Annals of Operations Research*, *299*(1-2), 963–999.

Joussier, R. L., Martin, J., & Mejean, I. (2023). Energy cost pass-through and the rise of inflation: Evidence from french manufacturing firms.

Känzig, D. R. (2021a). The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, *111*(4), 1092–1125.

Känzig, D. R. (2021b). The unequal economic consequences of carbon pricing. *Available at SSRN 3786030*.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053–1069.

Kilian, L., & Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press.

Kilian, L., & Zhou, X. (2022). The impact of rising oil prices on us inflation and inflation expectations in 2020–23. *Energy Economics*, *113*, 106228.

Kilian, L., & Zhou, X. (2023). A broader perspective on the inflationary effects of energy price shocks. *Energy Economics*, *125*, 106893.

Kim, I., Li, Q., & Noh, S. (2023). Global supply chain pressure, uncertainty, and prices. *Uncertainty, and Prices*.

Koester, G., Gonçalves, E., Gomez-Salvador, R., Doleschel, J., Andersson, M., Pardo, B. G., & Lebastard, L. (2022). Inflation developments in the euro area and the united states. *ECB Economic Bulletin, issue 8/2022*.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of monetary economics*, *47*(3), 523–544.

Liu, Z., & Nguyen, T. L. (2023). Global supply chain pressures and us inflation. *FRBSF Economic Letter*, *2023*(14), 1–6.

López, L., Párraga Rodrıguez, S., & Santabárbara Garcıa, D. (2022). Box 4. the pass-through of higher natural gas prices to inflation in the euro area and in spain. *Economic Bulletin/Banco de España, 3/2022, p. 49-52*.

Lopez-Gomez, I., McGovern, A., Agrawal, S., & Hickey, J. (2023). Global extreme heat forecasting using neural weather models. *Artificial Intelligence for the Earth Systems*, *2*(1), e220035.

Lunsford, K. G. (2015). Identifying structural vars with a proxy variable and a test for a weak proxy.

Mastroeni, L., Mazzoccoli, A., Quaresima, G., & Vellucci, P. (2021). Decoupling and recoupling in the crude oil price benchmarks: An investigation of similarity patterns. *Energy Economics*, *94*, 105036.

Miranda-Agrippino, S. (2016). Unsurprising shocks: Information, premia, and the monetary transmission.

Miranda-Agrippino, S., & Nenova, T. (2022). A tale of two global monetary policies. *Journal of International Economics*, *136*, 103606.

Miranda-Agrippino, S., & Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, *13*(3), 74–107.

Montiel-Olea, J. L., Stock, J. H., & Watson, M. W. (2016). Uniform inference in svars identified with external instruments. *Harvard Manuscript*.

Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, *133*(3), 1283–1330.

Pisa, M. M., Lucidi, F. S., & Tancioni, M. (2022). The macroeconomic effects of temperature shocks in europe. *Available at SSRN 4109417*.

Reboredo, J. C. (2011). How do crude oil prices co-move?: A copula approach. *Energy Economics*, *33*(5), 948–955.

Romer, C. D., & Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American economic review*, *94*(4), 1055–1084.

Segarra, I., Atanasova, C., & Figuerola-Ferretti, I. (2024). Electricity markets regulations: The financial impact of the global energy crisis. *Journal of International Financial Markets, Institutions and Money*, *93*, 102008.

Sims, C. A. (1993). A nine-variable probabilistic macroeconomic forecasting model. In *Business cycles, indicators, and forecasting* (pp. 179–212). University of Chicago press.

Stiglitz, J. E., & Regmi, I. (2023). The causes of and responses to today's inflation. *Industrial and Corporate Change*, *32*(2), 336–385.

Stock, J. H., & Watson, M. W. (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal*, *128*(610), 917–948.

Stock, J. H., & Yogo, M. (2002). Testing for weak instruments in linear iv regression.

Szafranek, K., & Rubaszek, M. (2023). Have european natural gas prices decoupled from crude oil prices? evidence from tvp-var analysis. *Studies in Nonlinear Dynamics & Econometrics*, (0).

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 $k = 1, \ldots, K$ 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 $j = 1, \ldots, K$.
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,[29] 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:

$$\hat{\beta}_1 = \left(\frac{1}{T}\sum_{t=1}^{T} z_t z_t'\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T} z_t u_{1,t}\right)$$ [30]

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

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:

$$\mathbf{s}_1'\mathbf{\Sigma}^{-1}\mathbf{u}_t = \mathbf{s}_1'(B_0^{-1}B_0^{-1\prime})^{-1}u_t = \mathbf{s}_1'B_0'B_0B_0^{-1}\mathbf{w}_t = \mathbf{e}_1'\mathbf{w}_t = w_{1,t},$$ [31]

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[32] (including the constant). can be implemented (see Stock and Yogo, 2002).

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

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

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

[32] 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:

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

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

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 Market-relevant gas supply news

Date	News
EA	
2005-11-29	The UK Britannia gas field restarts after a power glitch.
2008-11-11	Gazprom announces an increase in gas supplies to Ukraine.
2009-01-06	Russia halts gas deliveries to Ukraine.
2010-06-08	QatarGas cuts LNG exports due to maintenance shutdowns.
2014-03-03	Gazprom announces reduced gas exports amid the Crimea crisis.
2019-04-05	Unexpected decrease in gas flows from Norway via Langeled.
2022-02-24	Putin announces the invasion of Ukraine.
US	
2008-04-28	Gas platform outages in the Gulf of Mexico.
2009-08-06	Positive drilling results from a well with Houston Energy.
2010-08-06	Baker Hughes reports gas drilling rigs rise to a 17-month high.
2014-02-13	Pipeline explosion in Kentucky.
2015-05-08	Transco upgrades and force majeure on Destin pipelines.
2018-02-05	Record high gas production after pipe in Ohio returns on service.
2018-12-03	U.S. LNG developers see potential from the US-China trade agreement.

Table B3: *Selected gas supply news for EA and US.*

Appendix C 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 C4, 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 C5). Notably, we find that the series is not significantly correlated with oil-specific, uncertainty, and global demand shocks.

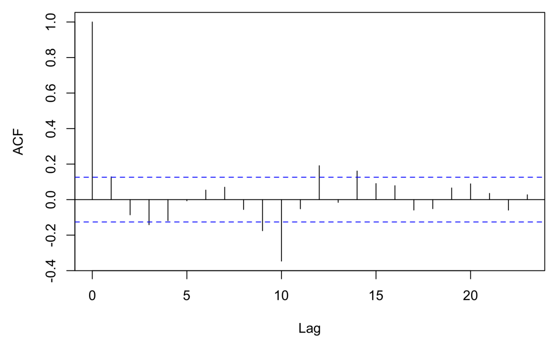


Figure C17: *Sample Autocorrelation Function of the gas surprise series.*

X	p-value
EU Gas consumption	0.89
EU Gas stock changes	0.89
SP500	0.11
World economic activity	0.68
Brent spot	0.17

Table C4: *Granger causality tests*

Notes: The table presents the p-values obtained from Granger's causality tests of the gas supply surprise series using a set of macroeconomic and financial 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	ρ_{gas}	p-value gas	ρ_{temp}	p-value temp	n
Kilian (2009)**	Oil supply	-0.00	0.96	-0.05	0.29	241
Kilian (2009)**	Aggregate demand	-0.05	0.44	-0.02	0.57	241
Kilian (2009)**	Oil-specific demand	0.08	0.21	-0.02	0.61	241
Caldara et al. (2019)	Oil supply	0.05	0.52	0.02	0.65	144
Baumeister and Hamilton (2019)*	Oil supply	-0.07	0.25	0.08	0.08	240
Baumeister and Hamilton (2019)*	Oil demand	0.07	0.30	-0.01	0.80	240
Känzig (2021a)**	Oil supply expectations	-0.10	0.12	-0.01	0.86	244
Gertler and Karadi (2015)	FF4 monetary policy (US)	0.07	0.50	0.14	0.02	102
Altavilla et al. (2019)*	Target monetary policy (EA)	0.02	0.77	0.06	0.29	234
Jarociński and Karadi (2020)	"Poor man" monetary policy	-0.03	0.68	0.01	0.91	234
Miranda-Agrippino and Nenova (2022)	Target monetary policy (EA)	-0.19	0.01	0.03	0.58	207
Bloom (2009)**	VXO-VIX	0.01	0.90	-0.03	0.48	243
Gilchrist and Zakrajšek (2012)*	Corporate credit spread index	-0.04	0.49	0.05	0.21	243
Baker et al. (2016)*	Global Economic Policy Uncertainty Index	0.03	0.63	0.08	0.17	240
Caldara and Iacoviello (2022)*	Geopolitical risk index	-0.01	0.83	0.04	0.41	243

Table C5: *Correlation with other shocks*

Notes: The table reports the correlation of the gas surprise series with a wide range of different shocks from the literature. ρ is the Pearson correlation coefficient, the p-value corresponds to the two-sided test with null hypothesis of zero correlation, and n denotes the sample size.

*Extended by the authors with respect to the original paper.
**Extended by us.

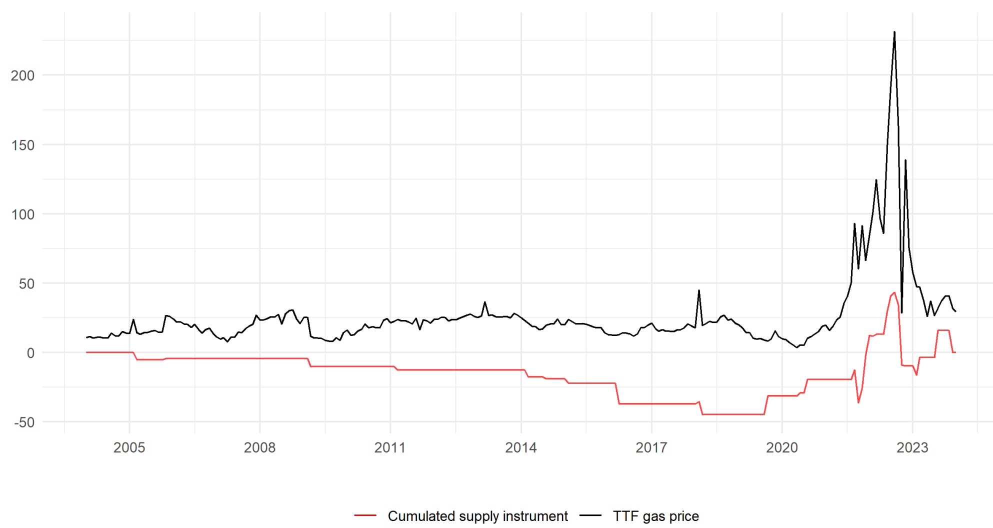


Figure C18: *TTF price and cumulated gas surprises.*

Notes: This figure illustrates a comparison between the spot TTF gas price and the cumulated surprises in 1-month TTF futures.

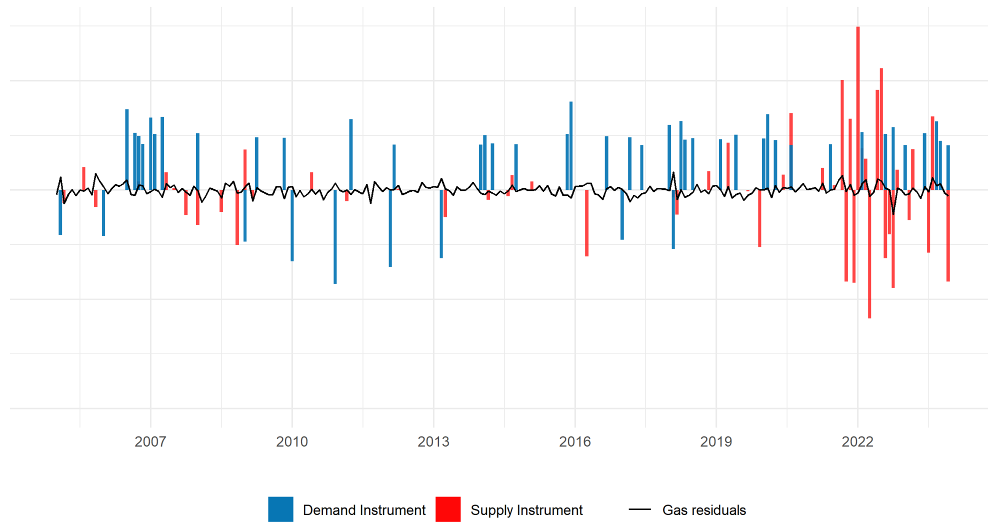


Figure C19: *Supply and demand instruments strength.*

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.

Appendix D TTF and other 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 D20 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 D6 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.

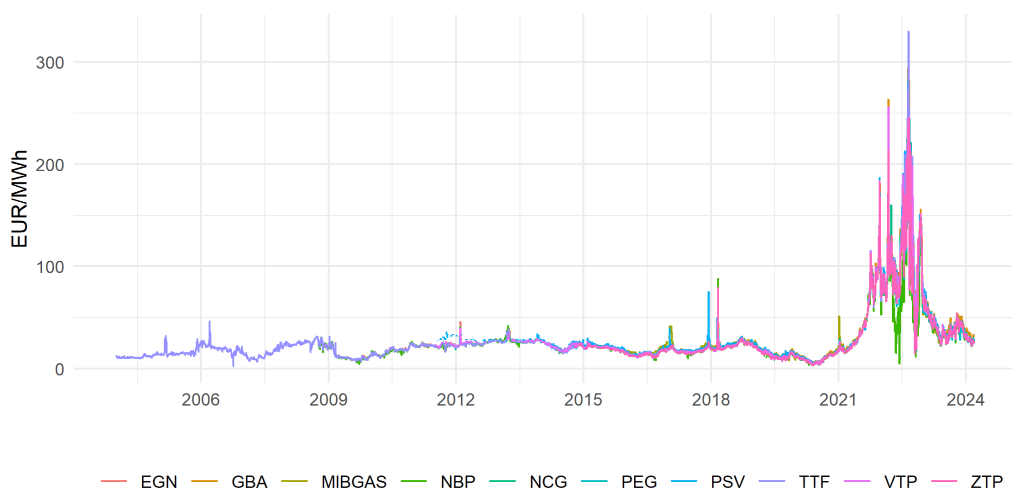


Figure D20: *TTF and other European gas prices.*

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

Finally, we show that as LNG became more relevant in the EA over the past few years, its price almost matched the TTF price. This can be observed in Figure D21 , while Figure D22 displays a sliding window correlation of the global LNG price with the TTF.

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

Table D6: *Correlation between TTF and other EA gas prices.*

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

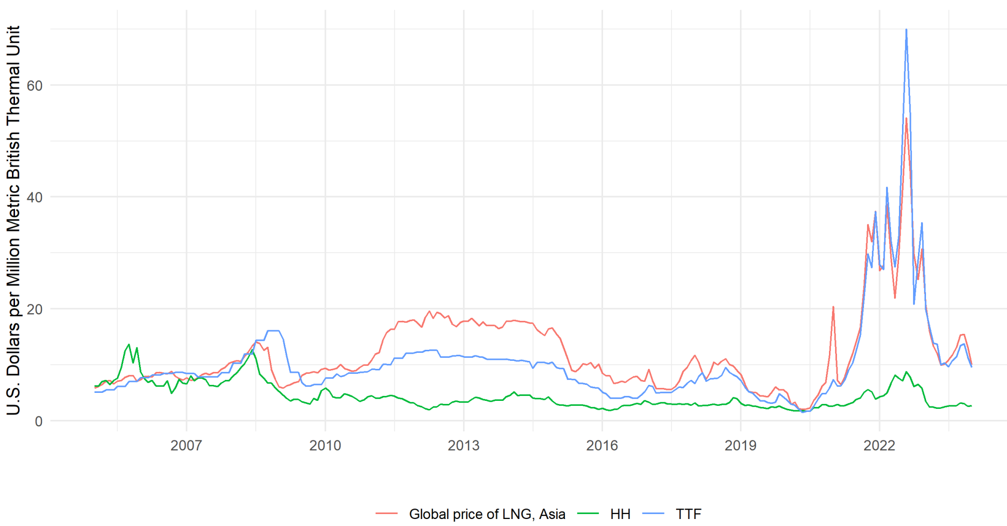


Figure D21: *TTF, HH and Global LNG prices.*

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

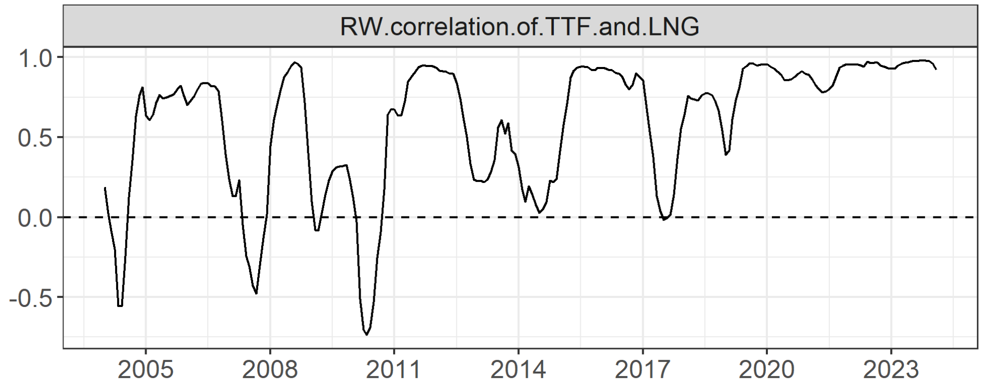


Figure D22: *TTF and Global LNG gas prices correlation.*

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

Appendix E Data sources

Table E7 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 (RIC)	TTF natural gas futures month contracts (settlement price)	Datastream	2004M1-2024M1	100Δ log
LCOc (RIC)	Brent crude oil futures hh-month contract (settlement price)	Datastream	1988M6-2024M1	100Δ log
OIS.hh	OIS futures hh-period contract	ECB website	1999M1-2024M1	100Δ log
EA Variables (baseline)				
Gas Price	Dutch TTF spot natural gas price (TRNLTTD1) in Euro per MWh and deflated by EA HICP all-items index	Datastream	2004M1-2024M1	$100 * \log$
Oil Price	Brent spot crude oil price (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 (ICP.M.U2.Y.XEF000.3.INX)	EUROSTAT	2001M1-2024M1	$100 * \log$
Headline Inflation	HICP index excluding energy and food seasonally adjusted (ICP.M.U2.Y.XEF000.3.INX)	EUROSTAT	2001M1-2024M1	$100 * \log$
Industrial Production	Total industry excluding construction (STS.M.I8.Y.PROD.NS0020.4.000), 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 - Gas exports to RoW, 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 (RIC)	NYMEX natural gas futures month contracts (settlement price)	Datastream	1990M4-2024M1	100Δ log
CLc (RIC)	WTI crude oil futures hh-month contract (settlement price)	Datastream	1975M1-2024M1	100Δ log
US Variables (baseline)				
Gas Price	NYMEX Henry Hub spot natural gas price (MHHNGSP) in Dollar per Million BTU and deflated by CPI all-items index	FRED	1997M1-2024M1	$100 * \log$
Oil Price	WTI spot crude oil price (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 marketable production (INDPROD), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Stocks	U.S. Closing stock levels (CSNATTER), SA	IEA	1984M1-2024M1	$100 * \log$
Gas Net Imports	U.S. Gas imports from RoW - U.S. Gas exports to RoW, SA	IEA	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	$100 * \log$

Table E7: *Data description and sources*

E.1 Temperature data

ERA5 surface temperature data. The daily weather 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.[33][34]

Extreme temperatures index. The monthly ETI is computed as described in Equation E.1.1. 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 E23 shows the seasonally adjusted series for Italy. The resulting series is aggregated to monthly by taking temporal averages. Finally, the series is then thresholded to isolate only months with extreme temperatures by setting to zero any observation within 2 standard deviations.

$$ETI_{m,y} = \begin{cases} {}^{SA}K^{stat}_{m,y}, & \text{if } {}^{SA}K^{stat}_{m,y} \notin [\mu_{K^{SA}} - 2\sigma_{K^{SA}}; \mu_{K^{SA}} + 2\sigma_{K^{SA}}] \\ 0, & \text{otherwise} \end{cases} \tag{E.1.1}$$

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 $K^{Avg}_{d,m,y} = \sum\limits_{h=1}^{24} K_{h,d,m,y}/24$: 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 $K^{stat}_{d,m,y}$. In our baseline exercise we consider $\overline{K^{stat}}_{m} = \frac{\sum\limits_{y=y_0}^{Y} \sum\limits_{d=1}^{D_m} K^{stat}_{d,m,y}}{(Y - y_0) D_m}$, the calendar month average. Another option is $\overline{K^{stat}}_{d,m} = \frac{\sum\limits_{y=y_0}^{Y} K^{stat}_{d,m,y}}{Y - y_0}$, the calendar day average;

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

[34] 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 mothly the seasonally adjusted temperature statistic, respectively.

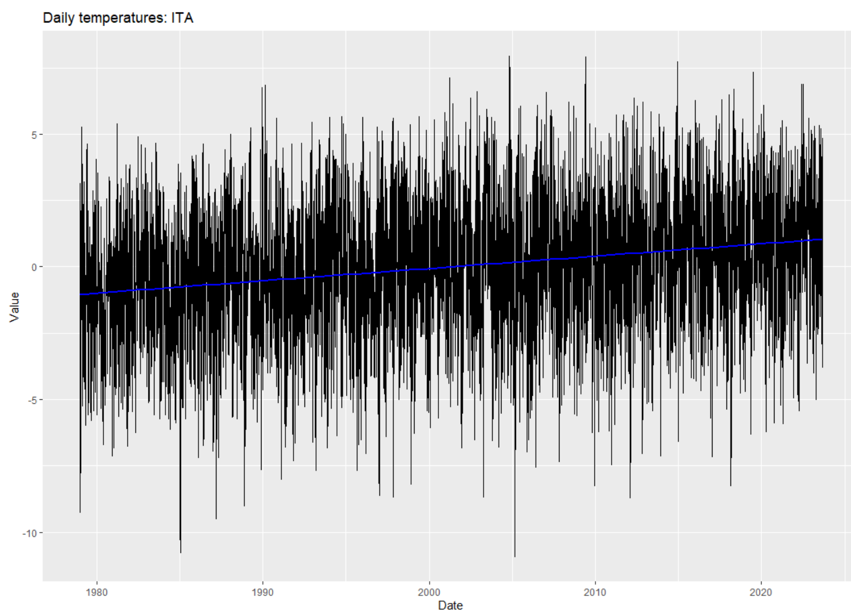


Figure E23: *Daily seasonally adjusted temperatures for Italy, not detrended.*

Alternative computations include:

- subtracting a linear trend to the temperature series previously to seasonally adjusting the series;

- performing the seasonal adjustment subtracting the mean calendar day temperature (across all years in the sample) corresponding to each calendar day, instead of subtracting the mean monthly temperature;

- using the series of daily maximum temperatures or of daily minimum temperatures instead of daily average temperatures;

- weighting the daily temperature series using (2015) population or (2015) night lights;

- performing the seasonal adjustment in a rolling way: once a window (number of years) is specified, the means to subtract during the seasonal adjustment are computed only across the previous years.

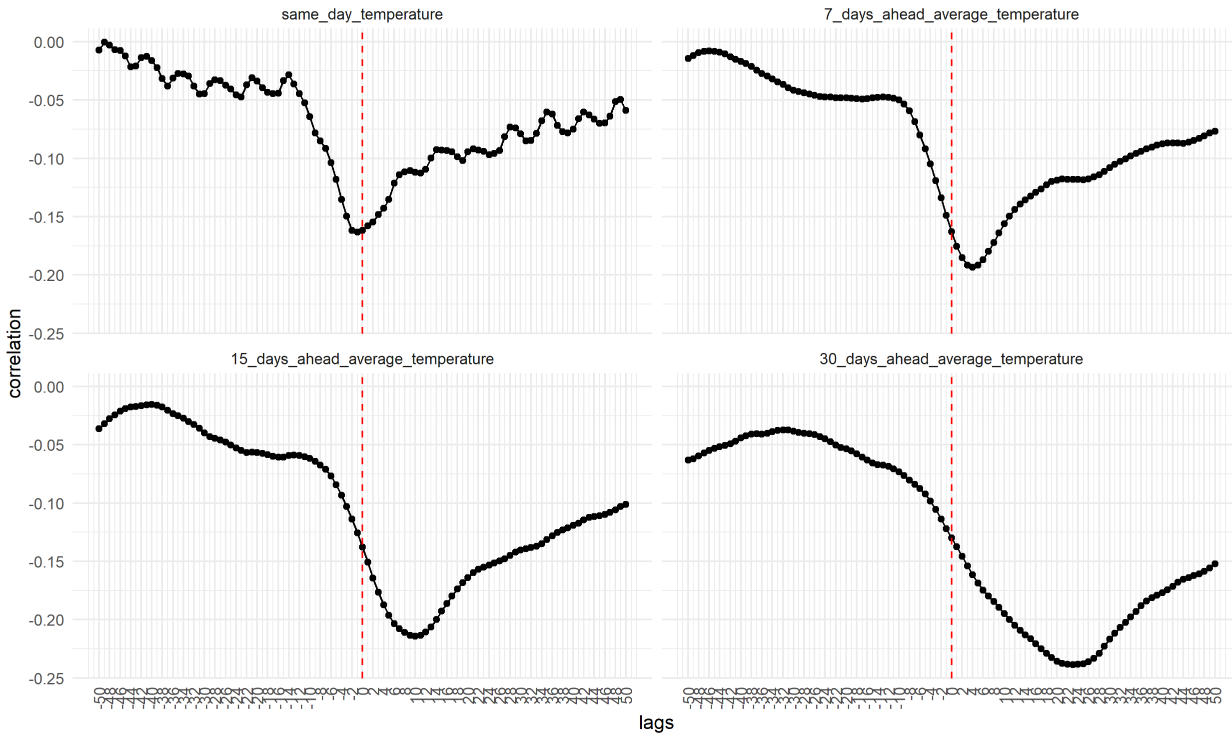


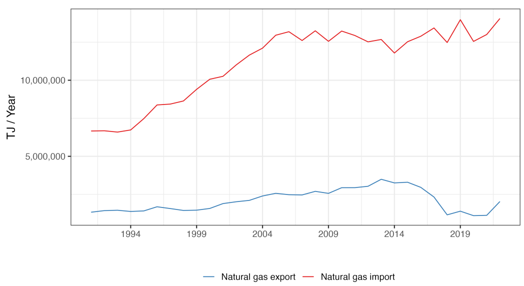
Figure E24: *Temperatures and gas price correlations.*

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.

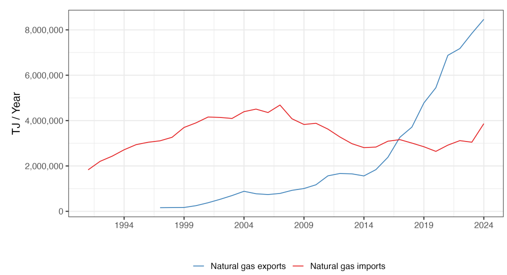
Appendix F Additional figures

In this Appendix, we present additional figures that are not featured in the main body of the paper.

F.1 Descriptive Statistics



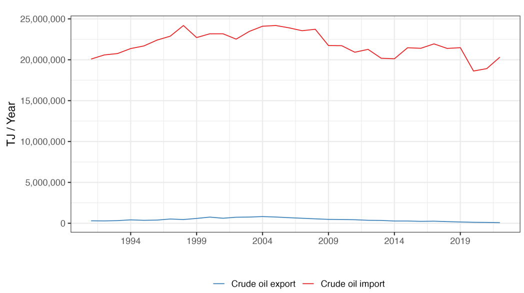
(a) European Union



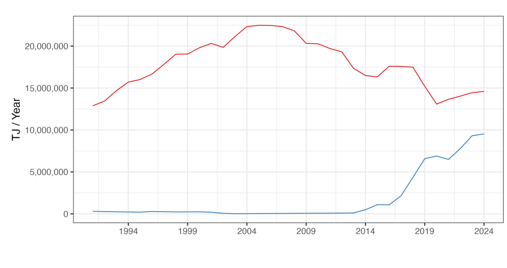
(b) United States

Figure F25: *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 terajoules. Sources: Eurostat and EIA.



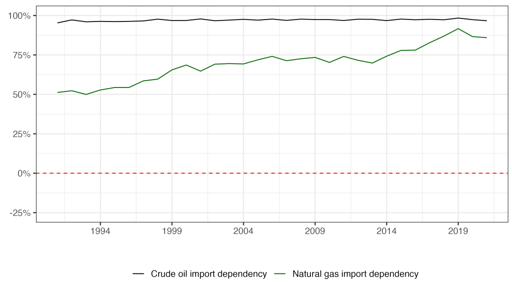
(a) European Union



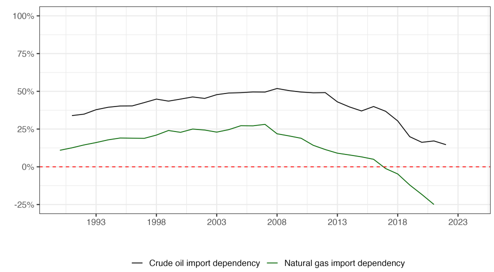
(b) United States

Figure F26: *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 terajoules. Sources: Eurostat and EIA.



(a) European Union



(b) United States

Figure F27: *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.

Figure F28: *Cooling degree days and heating degree days, average across selected European countries.*

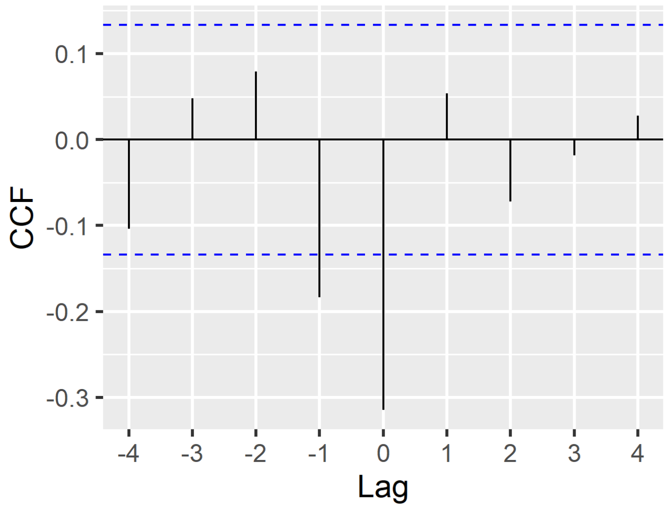


Figure F29: *Cross-correlation function of the reduced-form residuals of the price of gas (at time t) and the extreme temperatures index (at time $t + Lag$).*

F.2 Data used in the VAR models

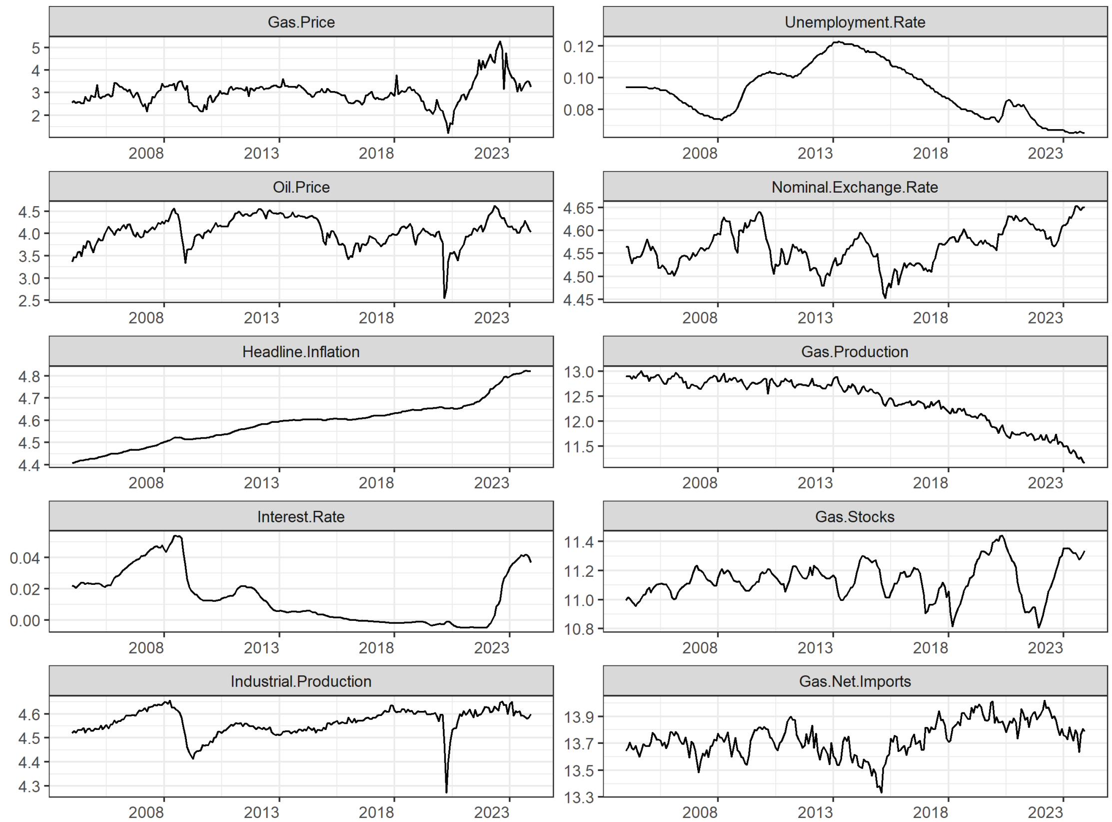


Figure F30: *EU: Data used in the main specification.*

Notes: Gas and oil prices are deflated using the headline price level. Gas price, oil price, headline inflation, industrial production, nominal exchange rate, gas production, gas stocks and gas net imports are logged. Interest rate and unemployment rate are left untransformed in hundredths. Headline inflation, industrial production, unemployment rate, gas production, gas stocks, gas net imports are seasonally adjusted. The interest rate is the 1Y ECB rate, the nominal exchange rate is the NBXMBIS.

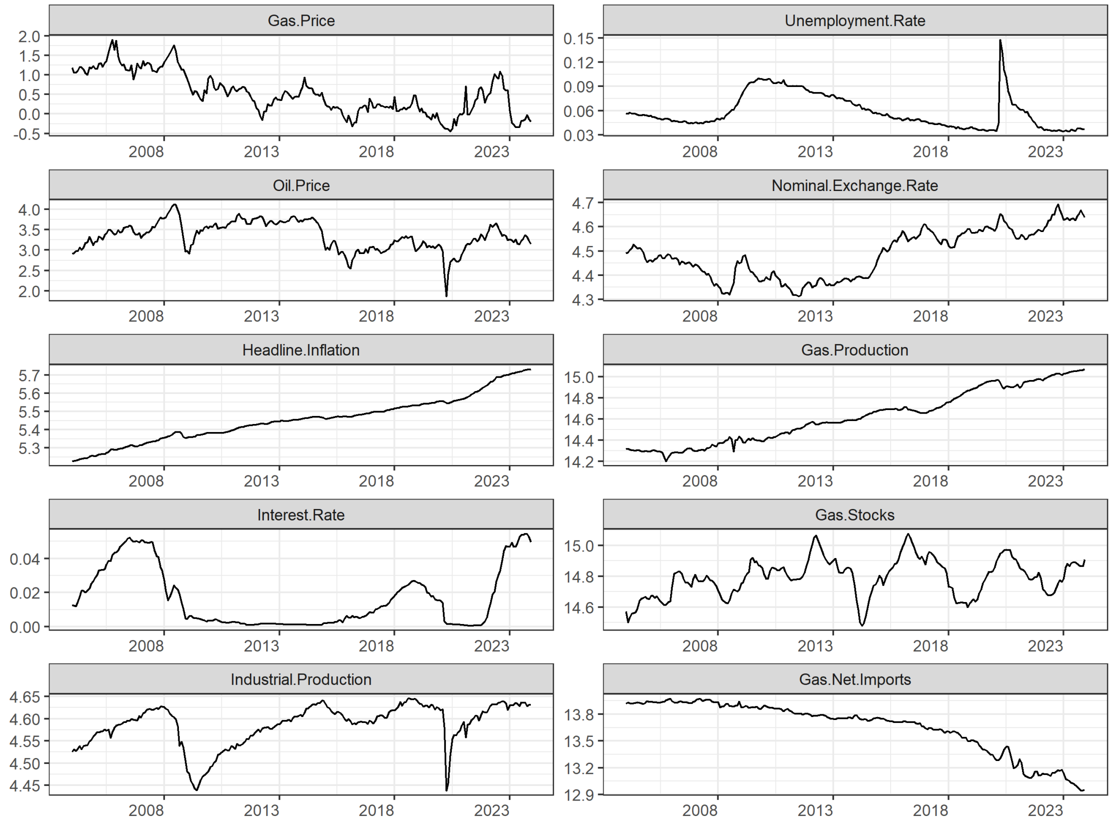


Figure F31: *US: Data used in the main specification.*

Notes: Gas and oil prices are deflated using the headline price level. Gas price, oil price, headline inflation, industrial production, nominal exchange rate, gas production, gas stocks and gas net imports are logged. Interest rate and unemployment rate are left untransformed in hundredths. Headline inflation, industrial production, unemployment rate, gas production, gas stocks, gas net imports are seasonally adjusted. The interest rate is the market yield at 1 year constant maturity (GS1), the nominal exchange rate is the NBUSBIS.

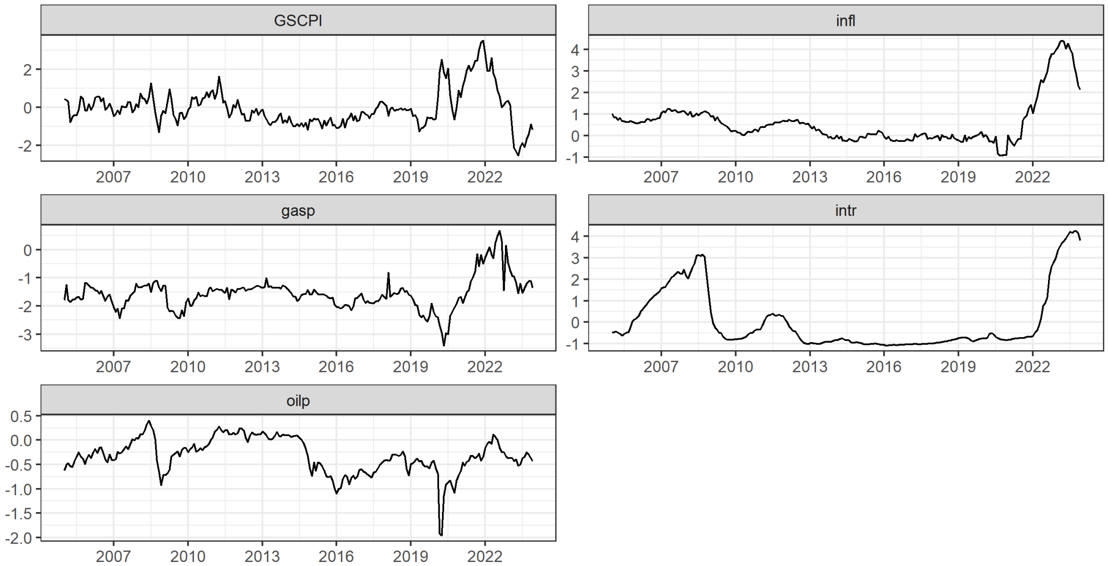


Figure F32: *Data used in the smaller specification*

Notes: In this specification the GSCPI index is included, and left untransformed. Inflation is YoY core inflation seasonally adjusted, and the interest rate is the 1Y ECB rate.

F.3 Brent and WTI oil surprises

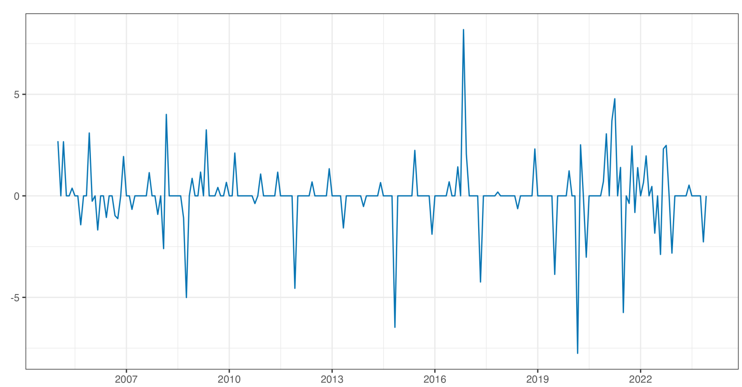


Figure F33: *The Brent oil supply surprises series*

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.

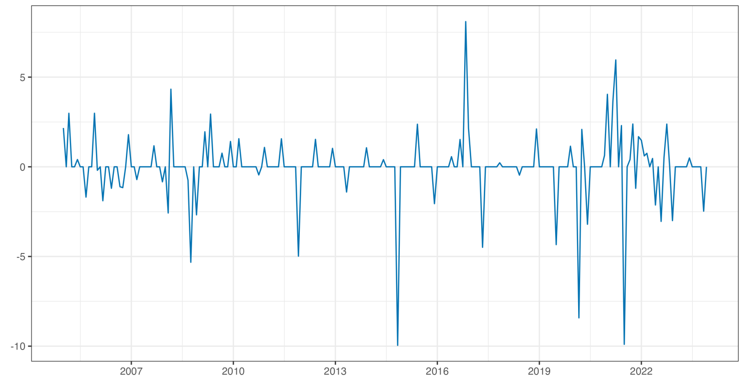


Figure F34: *The WTI oil supply surprises series*

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

Appendix G Additional results

G.1 Historical decomposition of gas price in the US

Figure G35 shows the equivalent historical decomposition of Figure 7 for the US. Our identified gas shocks explain a significant share of variation in the real price of gas but less so than in the EA. This is again consistent with the fact that the gas price in the US is less dependent from domestic demand as the US are a net exporter of gas. Furthermore, as a major gas producer, the US are likely to be able to better absorb both supply and demand gas shocks.

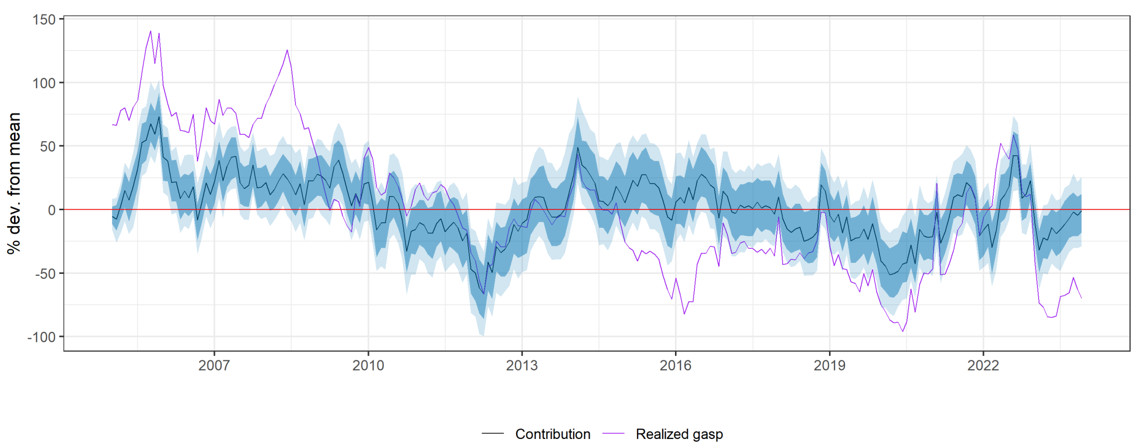


Figure G35: *US: Historical decomposition of the real price of gas*

Notes: the figure shows the historical decomposition of gas shocks to the real price of gas and the 68 and 90 percent confidence bands together with the real price of gas (in percent deviation from the mean).

Appendix H Additional 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.

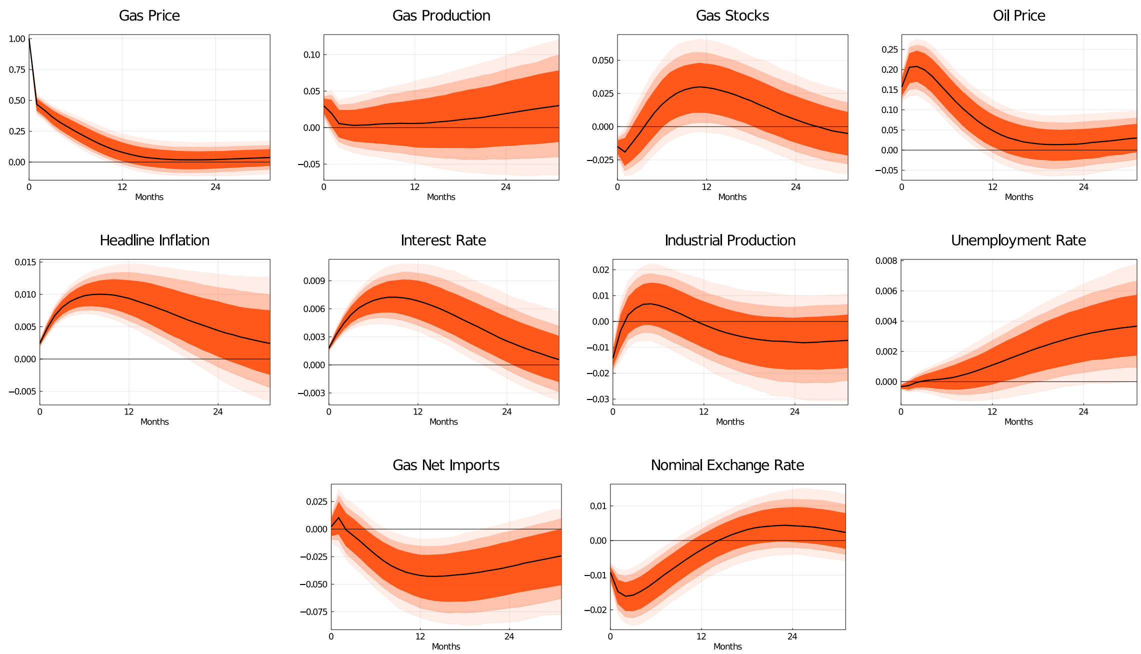


Figure H36: *EA: Informationally-robust responses to a gas supply shock. Equivalent of Figure 8.*

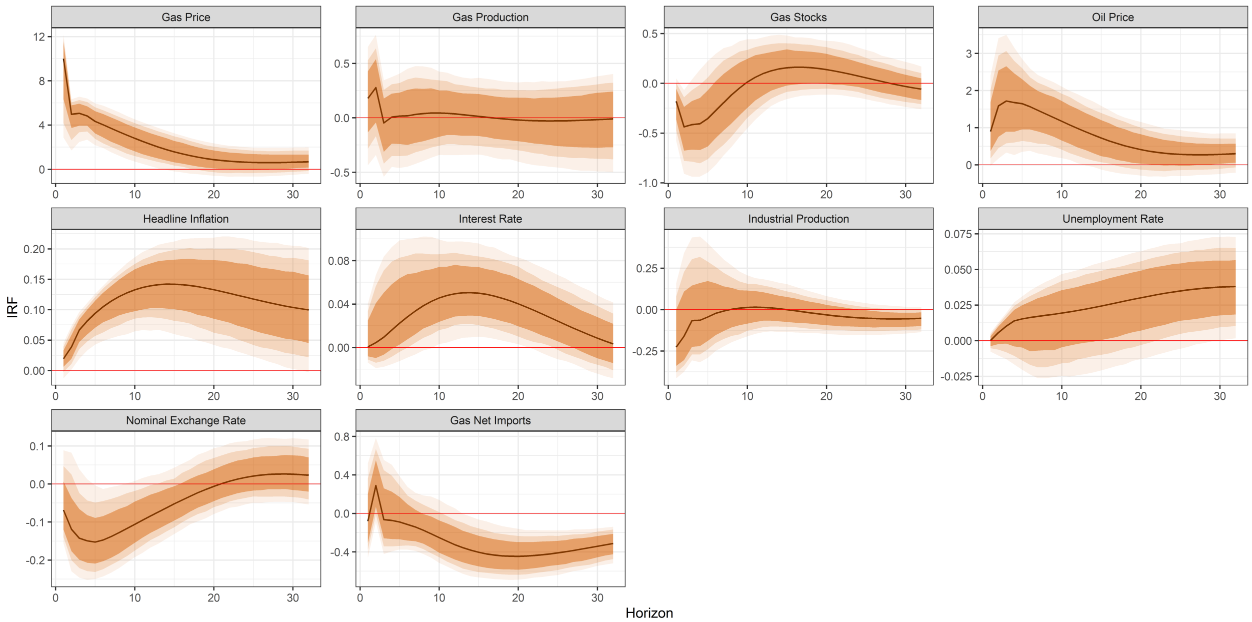


Figure H37: *EA: Responses to a gas supply shock, estimated by VAR-OLS. Equivalent of Figure 8.*

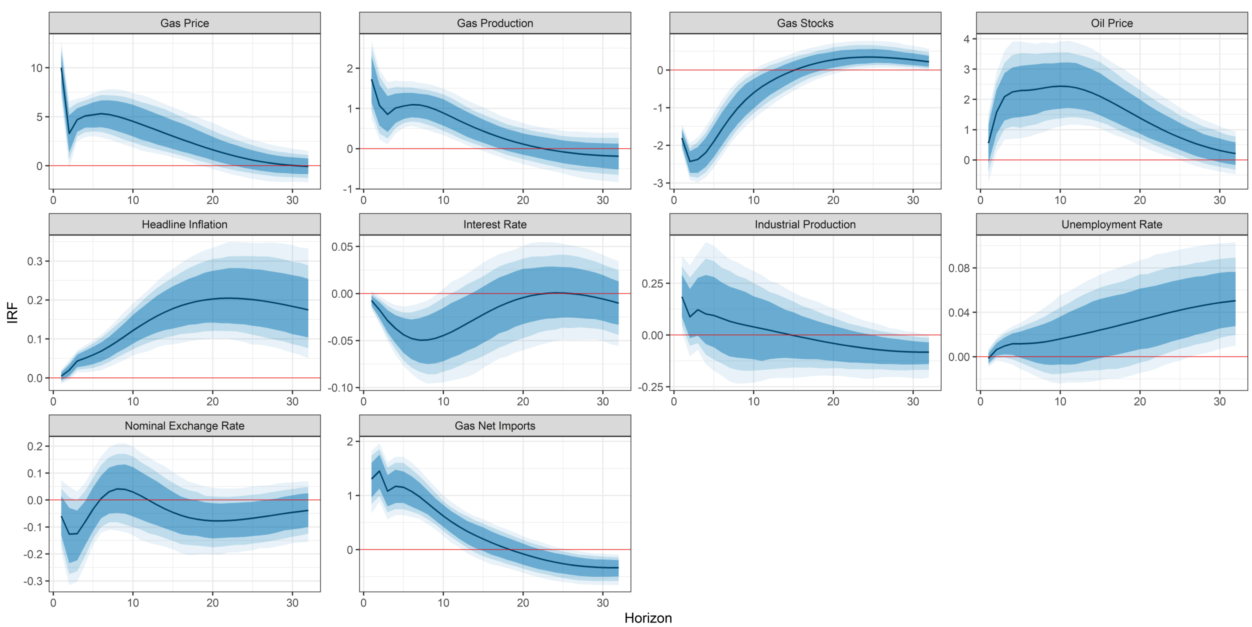


Figure H38: *EA: Responses to a gas demand shock, estimated by VAR-OLS. Equivalent of Figure 11.*