Gas Price Shocks and the Inflation Surge in Europe

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Abstract

We identify a supply shock to the gas price in the Euro Area using market-relevant news and high-frequency data, as well as a demand shock exploiting exogenous variation induced in the price of gas by surface temperatures. These shocks have economically significant effects. Gas demand and supply shocks exert significant impacts on both headline and core inflation. However, while gas supply shocks have a less pronounced effect overall, they elicit a stronger response in interest rates. Moreover, there exists a notable interdependence between the gas and oil markets, where shocks in gas and oil prices mutually influence both commodities. We then quantify the contribution of the gas price shocks, together with oil price, global supply chain bottlenecks and monetary policy shocks on the realized series of inflation, focusing on the recent inflation surge period. We document that gas and supply chain bottlenecks shocks have been among the major drivers of the recent inflation surge in the Euro Area. Finally, we identify the corresponding gas price shocks in the US and show that their macroeconomic effects are less severe compared to those in the Euro Area.

Keywords: Gas price shocks, inflation surge, extreme temperatures, global supply chain, proxy-VAR.

JEL classification: C32, E31, Q43.

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1 Introduction

The recent disruptions in the energy market, particularly following Russia's invasion of Ukraine, have sparked interest in the macroeconomic effects of energy price shocks. While extensive research has examined the macroeconomic impacts of oil price shocks (see Hamilton (1993), Kilian, 2009, and Känzig, 2021a), there is a conspicuous absence of empirical evidence regarding the effects of gas price shocks. This scarcity of empirical analyses likely stems from the historical integration between oil and gas markets, leading to the common practice of using oil as a proxy for energy prices as a whole. Similarly, New-Keynesian macroeconomic models often treat energy as a single homogeneous good (see for example Gagliardone and Gertler, 2023's work on the recent inflation surge). However, recent disruptions in the energy market have led to a decoupling between natural gas prices and crude oil prices (Szafranek & Rubaszek, 2023), particularly pronounced in the European market. This divergence has been under scrutiny even before the recent conflict, as evidenced by studies such as Zhang and Ji (2018). In this paper, we investigate the effects of gas price shocks, disentangling the effects of supply shocks and demand shocks. We achieve the first by leveraging relevant gas supply news and information contained in high-frequency data. We exploit exogenous variation in gas prices around relevant announcements involving major gas suppliers of the Euro Area, such as the Russian energy giant Gazprom. Given Europe's heavy reliance on gas imports, disruptions in the supply of gas can have a significant impact on gas prices. On the demand side, we consider variations in gas prices induced by exogenous abnormal temperatures. These weather anomalies provide exogenous variation in the price of gas through their impact on consumer demand. For example, an unexpected warm spell during a typically cold month leads to a reduced consumption for heating and lower gas prices.

This paper contributes to the empirical literature on the role of energy markets in the inflation surge. Numerous studies have delved into the relationship between energy prices and inflation. Boeck et al. (2023) develop a structural VAR model and identify a natural gas price shock using a combination of sign and zero restrictions, and they find that gas price shocks have strong effects on inflation in the Euro Area. Similarly, Pallara et al. (2023) explore the pass-through of energy price shocks to core inflation through a VAR model and find that the effect was negligible in the US but large and persistent in the Euro Area. Compared to these studies, our approach based on external instruments allows us to avoid imposing prior restrictions on the impact of gas price shocks. Moreover, by using a supply instrument alongside temperature anomalies, we can discern differences in the effects of supply and demand shocks.

We show that gas shocks have significant macroeconomic effects, and more so in the Euro Area than in the United States. In particular, in the EA the gas and oil markets appear significantly interdependent and core inflation is more persistently impacted by gas shocks. We also document a differentiated effect on interest rates. Monetary policy exhibits a swifter response to gas supply shocks, transitioning to a restrictive stance with a lag of a few months in the case of demand shocks.

Furthermore, this paper contributes to the ongoing debate on the drivers of the recent inflation surge. Over the last two years, the world experienced the highest levels of inflation in more than three decades. The Harmonised Index of Consumer Prices (HICP) of the Euro Area peaked at 10.6% in October 2022, while the US Consumer Price Index (CPI) stood at 9.1% in June 2022 (Koester et al., 2022). The recent inflation surge has sparked a debate on its causes, with some scholars claiming that it is demand driven, and due to excessive spending in response to the COVID-19 pandemic combined with a loose monetary policy (Bordo et al., 2023). Others emphasize pandemic-induced supply bottlenecks, shifts in sectoral demand, and exacerbated market power (Stiglitz and Regmi, 2023). Labor market tightness, another factor discussed in the literature, was initially seen to have made only a modest contribution to inflation. However, according to authors like Bernanke and Blanchard (2023), its significance grew over time, suggesting that balancing the labor market should be a primary concern for central banks. While all these factors likely played a role in the inflation surge, crafting effective policy responses necessitates identifying and addressing the primary drivers of inflation. In 2021 many regarded the initial upswing in inflation as a transitory phenomenon, while the central banks substantially underestimated the surge in inflation (including the Federal Reserve[1] and the European Central Bank[2]). However, possibly as a consequence of supply chain disruptions induced by shutdowns and reopenings related to the pandemic, restrictions of energy supply from Russia due to the outburst of the war in Ukraine, sectoral demand shifts, and increased mark-ups, high inflation has persisted through 2023. Given the slow decline in inflation, some claim that we could even be entering "a new era of high inflation" (Bordo et al., 2023). With high prices continuing to deteriorate living standards worldwide, taming inflation should be among the main priorities for policymakers. High and volatile inflation has huge costs for the economy. First and foremost, the increase in energy and food prices depresses consumption. Furthermore, unstable inflation makes economic planning more difficult and increases the resources devoted to hedging inflation risks (see amongst others Lucas, 2000). More broadly, in a context already characterized by radical uncertainty in the aftermath of the COVID-19 crisis, volatile inflation generates further uncertainty and reduces confidence.

Our study enriches the ongoing discourse regarding the drivers of inflation by investigating an additional supply-side factor: disruptions in global value chains. An emerging body of literature empirically studies the impact of supply chain disruptions on inflation. For example, Celasun et al. (2022) uses a sign restriction VAR and estimates that supply bottlenecks accounted for approximately half of manufacturing producer price inflation in the Euro Area in 2021. Mućk and Postek (2023) propose a measure of supply chain disruptions based on business surveys and, through panel local projections, find that supply chain disruptions had prolonged effects on inflation. We use the FED of New York's Global Supply Pressure Index

[1] See FOMC projections of March 2021.

[2] See ECB economic bulletin, issue 3/2022.

(GSCPI) (Benigno et al., 2022) to estimate the effect of supply chain pressures on the dynamics of inflation. 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, which are both persistent, and that the latter propagates with a significant lag.

The rest of this work is structured as follows. Section 2 outlines our empirical strategy, with a focus on the identification of a shock to the price of gas. Section 3 presents the main results. Finally, section 4 concludes. Several appendices follow with additional details on the data we use, the econometric models we implement and further empirical results.

2 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 hence assess the impact of gas shocks via a VAR that includes several commonly used macroeconomic variables.

Next, we examine how inflation is affected, specifically comparing the influence of a gas shock with other significant factors such as supply chain bottlenecks, oil prices, and monetary policy shocks. We achieve this by estimating a smaller VAR model and identifying four different series of shocks. Through a historical decomposition exercise, we can untangle the significance of each factor 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 the small VAR specification, we allow for a single residual variable that accounts for the remaining variability in the time series of inflation.[3]

All the technical details on the econometric modelling are given in Appendix A, and the results are presented in section 3. The next three subsections detail our identification strategy.

2.1 Gas price shocks

Following the outbreak of the war in Ukraine in February 2022, restrictions on gas supply to Europe generated a major disruption in the energy market and consequently a steep increase in energy prices. Alongside the economic effects induced by

[3]We therefore estimate a VAR of five variables and identify four shocks. As we touched on 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.

the Covid-19 pandemic, energy prices have played a crucial role in the recent inflation. Moreover, this upheaval induced a dynamics in the price of gas, more unbound to the price of oil that it had been for decades (see Figure 1). Historically, the dy-

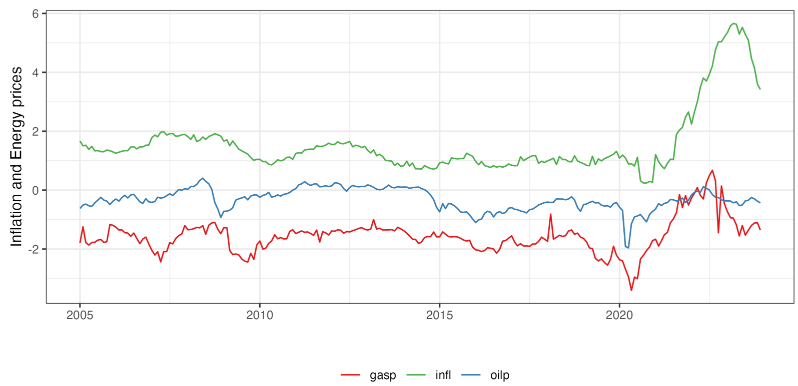

Figure 1: *Inflation and energy prices*

Note: The figure shows the YoY core inflation in Europe alongside the real prices of TTF natural gas and Brent crude oil, benchmarks prices for gas and oil in Europe.

namics of natural gas and global crude oil have been closely intertwined, resulting in a predominant focus in the literature on identifying energy shocks through variations in oil prices (*e.g.* Kilian, 2009 and Känzig, 2021a), rather than to the price of gas. However, recent events have underscored the need to also examine the dynamics of gas prices.

We identify a shock to the gas price in Europe using market-relevant news and high-frequency data on natural gas futures. Additionally, we consider variations in gas prices induced by extreme surface temperatures. To do this, we use the gas surprises series and the extreme temperature shocks. The construction of these series is discussed in detail in Sections 2.1.2 and 2.1.3, respectively. Extreme temperature shocks capture 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. Conversely, the gas surprises, given by the high-frequency fluctuations in prices induced by market-relevant news, primarily reflect variations in gas prices driven by supply factors. We are therefore able to construct an instrument using high-frequency techniques developed in the monetary policy literature and more recently applied to oil prices by Känzig (2021a). The announcements related to the war and the statements made by suppliers, such as Gazprom, serve as illustrative examples of supply-side surprises.

2.1.1 Institutional Background

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. The consequences of this fragmentation were evident during Russia's invasion of Ukraine when pipeline flows to Europe from Russia decreased. This caused European gas prices to surge 14-fold to a record level in August 2022, while Liquefied Natural Gas (LNG) prices in the United States remained considerably lower than in Europe and Asia (IMF Blog, 2023).

The Euro Area is a substantial consumer of natural gas, ranking as the second-largest energy source and accounting for around 15% of the total available energy. In the European Union, gas is mainly used for power generation, residential heating, and industrial activities. In contrast to other fossil fuels, notably oil, a substantial portion of gas consumption occurs in private households, accounting for 24% of total consumption in 2021 according to Eurostat statistics. The natural gas used in the Euro Area comes from a mix of domestic production, pipeline imports, and LNG sources. In Europe, countries like the United Kingdom and the Netherlands have notable domestic gas production, while many others rely more on gas imports, such as Spain and Italy. The region as a whole heavily relies on imports from a select group of major suppliers, including Russia, Norway, the United States, and Qatar. Over the past decade, the European Union's dependence on Russian natural gas has increased (see Figure C13, panel (a)), 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 (see Figure C13, panel (b)). In 2021, the EU's natural gas imports constituted over 80%, with approximately half of this supply coming from Russia (European Council, 2023). In contrast, 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.[4] The US has progressively become an LNG exporter, with a focus on the European and Asian markets.

The European gas market is regulated by the European Union, which aims to establish a unified market for natural gas. 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. Historically, the pricing of natural gas in Europe has been predominantly linked to oil products, such as fuel oil, in contrast to the gas-on-gas pricing model adopted in North America since the 1980s. This liberalization effort prompted the establishment of European gas hubs, which serve as market points where participants can freely trade both spot and futures gas contracts. Currently, the European gas market features 11 distinct trading hubs, varying significantly in terms of liquidity and gas infrastructure.[5] Despite the

[4] 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.

[5] While there are approximately 30 gas trading hubs in Europe, it's important to note that not all of them are actively operational, as reported by the Oxford Institute for Energy Studies (Heather, 2021).

heterogeneous nature of the European gas market and the absence of a unified market with a single price, the Dutch TTF gas hub, recognized as the most liquid trading hub, serves as the European gas price benchmark (Jotanovic and D'Ecclesia, 2021). 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. This market has a more mature structure compared to its European counterpart. In the United States, most natural gas transactions involve pricing mechanisms linked to the price of gas quoted at the Henry Hub.

2.1.2 Market-relevant news and high-frequency data

We construct daily surprises in the futures prices of gas in correspondence of 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.

The main challenge in collecting relevant gas-related news stems from the absence of a single source that systematically triggers significant price reactions, akin to OPEC in the oil market (Känzig, 2021a) and the Central Bank for monetary policy (see for example Kuttner, 2001 for the US and Altavilla et al., 2019 for the Euro Area). One potential candidate for our study is the Gazprom energy corporation, which accounts for over 10% of global natural gas production. However, Gazprom is predominantly state-owned, with substantial government oversight. Consequently, focusing solely on Gazprom's announcements may not suffice to capture all relevant news. Therefore, we gather news from multiple sources related to gas supply, including Gazprom, the Russian government, and other major suppliers. In addition to supply-related news, we also consider European Union regulations regarding natural gas storage and price caps on Russian gas imports, focusing on press releases from the European Council. As an illustrative example, 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 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 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, 24$^{\text{th}}$ 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 estimates 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.

Gas futures market. Natural gas is an internationally traded commodity with highly liquid future markets. The Henry Hub Natural Gas (HH) futures contract is the most actively traded worldwide (CME Group, 2021). In Europe, the Dutch Title Transfer Facility (TTF) stands as the largest and most liquid hub for natural gas trading. Henry Hub and TTF serve as benchmarks for pricing natural gas in the United States and Europe, respectively. Notably, the Henry Hub natural gas futures, introduced at the New York Mercantile Exchange (NYMEX) in 1990, have the longest available history, thus making it the natural choice for the US analysis. The TTF, exchanged at the Dutch Gas hub, was founded only in 2003, whereas the first European gas hub, the National Balancing Point (NBP), was created in the United Kingdom in 1996. However, for the Euro Area, we focus on the TTF for several reasons. First, TTF overtook NBP as the most liquid gas hub in 2017, accounting for approximately 75% of the total European gas trade in Q4 2022 (European Commission, 2022). Second, the Dutch hub TTF is widely recognized as the referencing trading hub in the European gas market (Jotanovic and D'Ecclesia, 2021). Moreover, our study pays special attention to the recent disruptions in the gas market, including their impact on energy prices and the decoupling of gas and oil prices.

Construction of gas surprises. To construct a time series of gas surprises, we look at 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:

$$Surprise_d^h = F_d^h - F_{d-1}^h \tag{2.1.1}$$

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.

A crucial choice when constructing the surprises is the width of the event window. We opt for a daily window, in contrast to the monetary policy literature where it is customary to use a 30-minute window. This choice is motivated by the fact that, 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. Moreover, gas-relevant announcements are not as clear as monetary policy announcements, requiring traders more time to identify them and to process the information contained 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 long-term consequences, futures contracts with maturities ranging from one month to one year are reasonable choices. Thus, we take the first principal component of the gas surprises spanning the first year of the gas futures term structure. To create 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 recorded as zero. Figure 2 shows the resulting monthly surprises series.

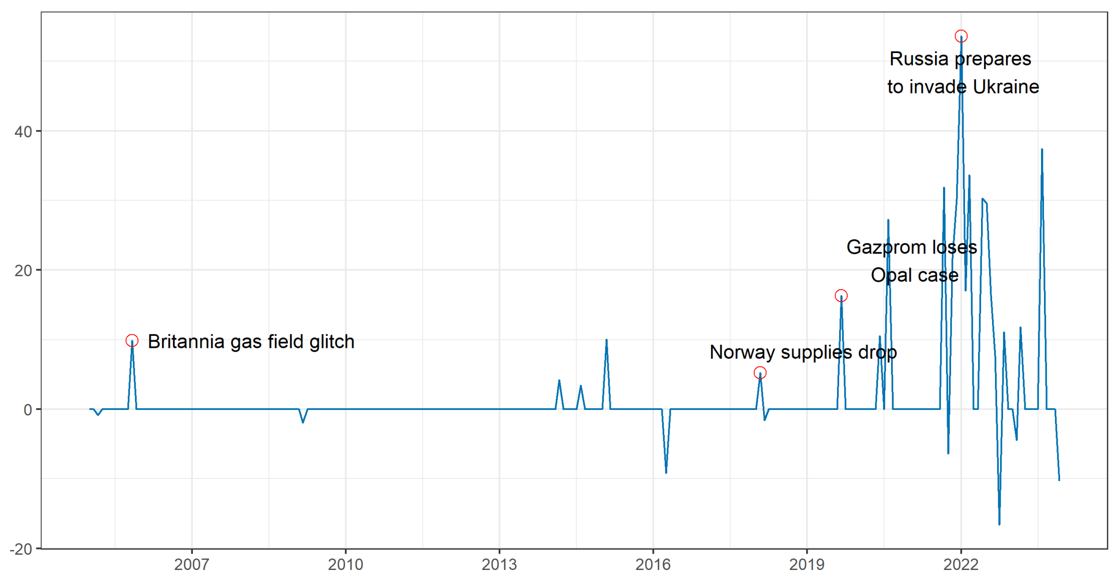

Figure 2: *The gas supply surprises series*

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 series is scaled to match the average volatility of the underlying price surprises. Red circles highlight important events for the gas market: in 2005M11 there was an important glitch in the Britannia field in the North Sea, in 2018M2 an earthquake in Norway led to a decrease in gas exports, in 2019M9 the EU court judgement to limit Gazprom's dominance, and in 2022M2 the invasion of Ukraine started.

2.1.3 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 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,[6] but moves the price of gas via the demand for heating channel, therefore constituting a valid and relevant instrument. 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 B.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.[7] Figure 3 shows the resulting ETI for the considered sample of countries.

[6] 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).

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

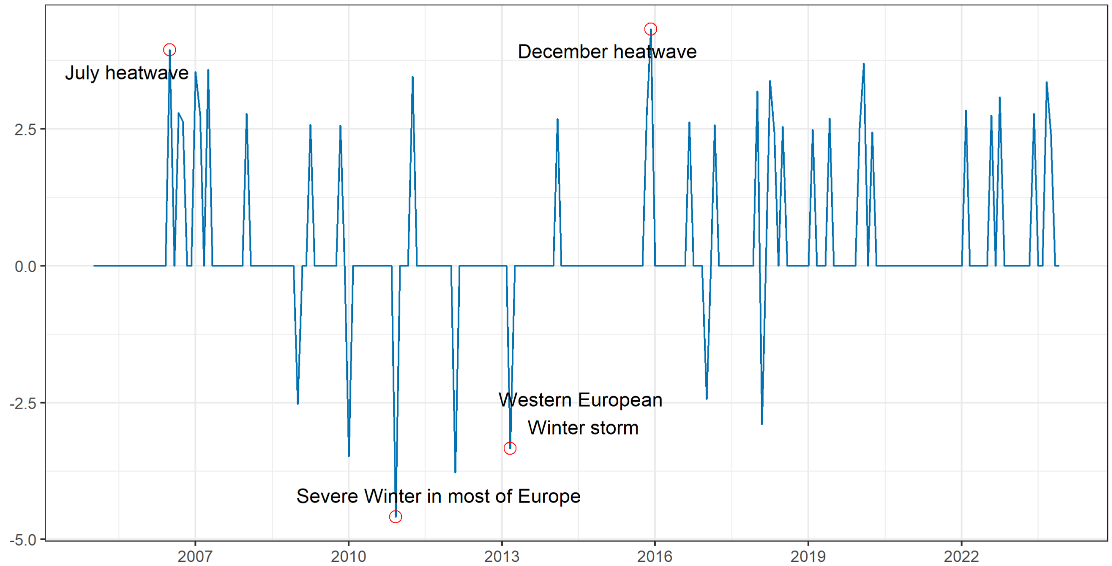

Figure 3: *Extreme temperatures index (ETI) for Europe.*

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). In the remainder of this section, we argue why this correlation stems mainly from the demand-for-heating channel.

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).[8] Figure C14 shows the averaged CCD and HHD for the same sample of countries:[9]

When we restrict the sample to months when the HDD is low,[10] 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 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

[8]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.

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

[10]We choose 70 as a threshold.

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,[11] 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.[12] Conveniently, we have that most of the spikes in the ETI (both positive or negative) shown in Figure 3 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 C15 shows the cross-correlation function of the reduced-form residuals of the price of gas and the ETI, indicating that the correlation between the two series is not very persistent, which is consistent with the gas demand channel.

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.

2.2 Identification of additional macroeconomic shocks

Supply chain bottlenecks 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.[13] We argue that this variable is unlikely affected by the other shocks of the

[11]We choose 5 as a threshold.

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

[13]The Global Supply Chain Pressure Index (GSCPI) is maintained by the Federal Reserve Bank of New York and is not specific for the Euro Area, as it focuses on manufacturing firms across seven interconnected economies: China, the Euro Area, Japan, South Korea, Taiwan, the United

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; Känzig, 2021a; Kilian, 2009; 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 2.1.1, 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 C18 shows the oil supply surprise series, and the corresponding WTI oil surprise series can be found in Appendix Figure C19.

Differing from Känzig (2021a), we use Brent oil futures traded at the Intercontinental Exchange (ICE) as they constitute the relevant benchmark for oil pricing in the Euro Area, the primary focus of this study. Additionally, ICE Brent is the

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.

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 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.[14]

3 Results

We first focus on the Euro Area and show that gas price shocks have important macroeconomic effects and that there are small but significant differences between gas demand and supply news shocks. We then compare the effect of gas shocks with the effect of oil shocks, also showing that the two markets are asymmetrically interrelated. We then focus on the determinants of core inflation in the EA, and show that gas price shocks and supply chain bottlenecks have been the main drivers of the recent inflation surge. Finally, we run the same analysis with US data and show that the macroeconomic effects of gas price shocks are less severe compared to those in the Euro Area.

3.1 Macroeconomic effects of gas shocks in the EA

We first present the results from a large VAR estimated on Euro Area data, where we include a broad set of macroeconomic variables. Figure 4 shows the impulse

[14] 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.

responses to the identified gas demand and gas supply news shocks, normalized to increase the real gas price by 1 standard deviation.[15] In this figure and the following, the solid black lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands based on 1000 bootstrap iterations.[16]

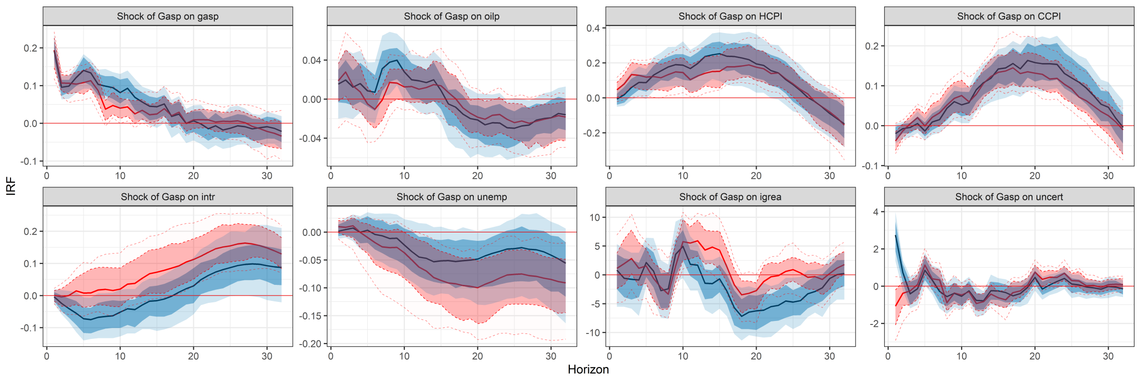

Figure 4: *Macroeconomic Effects of Gas Price shocks in the Euro Area*

Notes: Impulse responses of macroeconomic variables to demand (blue) and supply news (red) shocks to the real price of gas. The solid lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands, respectively.[a]

[a]When estimating this specification we get a first-stage F-stat of 18.07 (p-value: 3.13e-5) and Frobust of 6.19 (p-value: 0.014) for the supply shock. For the demand shock we get an F-stat of 17.06 (p-value 5.10e-05) and Frobust of 14.36 (p-value 1.94e-4).

A negative gas supply and a positive gas demand shocks both lead to a significant immediate increase in the price of gas. However, a demand shock is more persistent, and bears significant effects up to 14 months after impact. The real price of oil is not impacted significantly but shows a mild increase. Further details on responses of gas and oil prices are given below in this section. Coherently with standard macroeconomic theory, headline and core Y-to-Y inflation both respond positively and persistently. Core inflation lags headline and bears a longer lasting effect, peaking after 20 months and increasing by about 1.5pp. This is consistent with the typical pass-through mechanism on prices, wherein higher energy costs increase firms' costs, subsequently leading to price hikes (see Boeck et al., 2023). Note that this initial effect on prices, often referred to as the "first-round effect", manifests more swiftly in response to supply shocks compared to demand shocks. The energy and food components of inflation naturally respond earlier to a gas price shock, but more so after a supply news shock. In response, the monetary authority reacts more to supply news shocks, albeit with a significant lag. The responses of gas and supply shocks on interest rates differ considerably. While supply shocks increase interest

[15]Where explicitly noted, figures show responses normalized to a 10% increase in the price of gas. The real price of gas is logged, so that its displayed impulse can be interpreted as percentage deviation.

[16]Confidence bands are computed using a block bootstrap, as proposed by Jentsch and Lunsford (2019), where the block size is optimally set to 20.

rates throughout the response, demand shocks lead to a negative effect on interest rates initially, which then turns positive after 15 months. Finally, real economic activity as measured by the IGREA Kilian (2019) responds negatively after 18 to a demand shock, and the Equity Market Volatility tracker Baker et al. (2019) responds only on impact after gas demand shocks.

Comparison with oil shocks. We now compare the previous results with Figure 5, which shows the responses to a supply news shock in the real price of oil, identified as in Känzig (2021a).

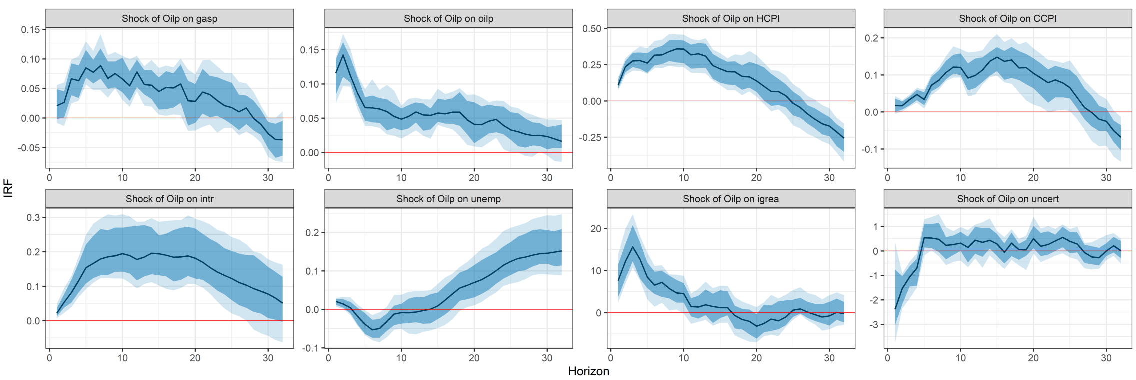

Figure 5: *Macroeconomic Effects of Oil Price shocks in the Euro Area*

Notes: Impulse responses of macroeconomic variables to news supply shocks to the real price of oil. The first-stage F statistic is 27.28 with an associated p-value of 4.00e-07. The robust F is 4.01.

Similarly to gas shocks, oil shocks exhibit a persistent and positive impact on both headline and core inflation. Nevertheless, we find noticeable differences between gas shocks and oil shocks. Oil shocks tend to produce virtually immediate effects, whereas gas shocks require more time to manifest.

Regarding the relationship between the oil market and the gas market, we have that the gas price responds significantly with a 5% increase after a 10% increase in the oil price. This is shown in greater detail in Figure C20, which shows that in the Euro Area oil price shocks are more persistent than gas price shock and that the oil price only responds mildly (about 2%) after 8 months to a gas price shock. 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 as a result the price of gas also increases. However, the opposite effect is not as strong because the oil market is much more globalized and an increase in oil demand in the EA does not move significantly the global price of oil.[17] In contrast, when the demand for gas in the EA increases, the TTF gas price increases significantly, given that the global market for gas is fragmented and the EA crucially depends on neighbouring countries as a net importer of gas.

[17]Note for example that the dynamics of the Brent and WTI crude oil prices are very similar.

Gas shock contribution to the gas price series. We now address the question of how important gas demand and gas news supply shocks are in explaining historical episodes in the gas market.

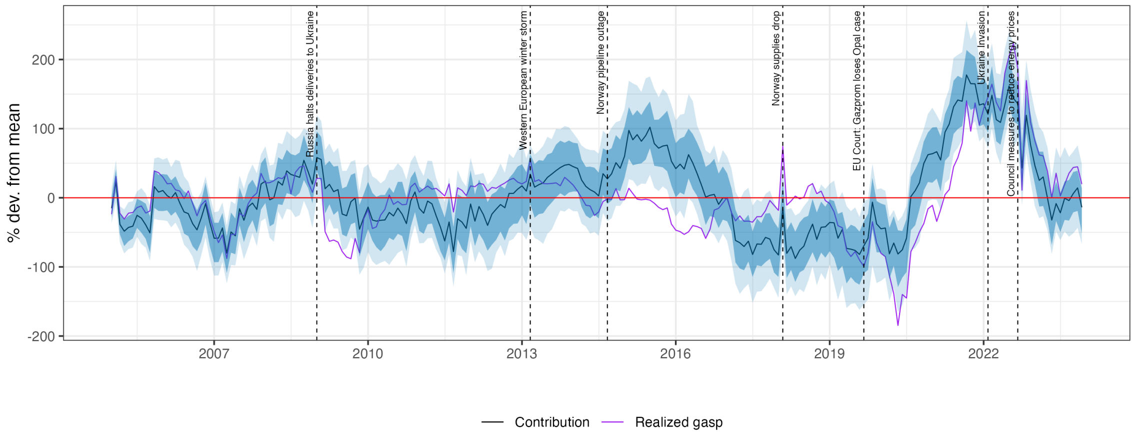

Figure 6: *EA: Historical decomposition of the real price of gas*

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.

Figure 6 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 immediately see that our identified shocks have contributed substantially to the historical variation of the price of gas. For example, when in January 2009 Russia halted gas deliveries to Ukraine for 13 days following a Gazprom and Naftogaz dispute over the latter's accumulating debts, prices hiked. Prices then quickly returned to the usual levels after the dispute was resolved on January 18 when Russian Prime Minister Vladimir Putin and his Ukrainian counterpart Yulia Tymoshenko negotiated a new contract.

In addition, unexpected 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 thanks 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.

3.2 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. We therefore estimate a smaller VAR model where we include the GSCPI, the real price of gas, the real price of oil, Y-to-Y inflation, and the 1Y ECB rate. As descibed in section 2.2, we identify supply chain bottlenecks shocks by short-run restrictions, as well as oil price (Känzig, 2021a) and monetary policy (Miranda-Agrippino & Ricco, 2021) shocks which we take from the proxy-VAR literature and of which we extend the respective instruments to January 2024. The resulting impulse responses are shown in Figure 7.

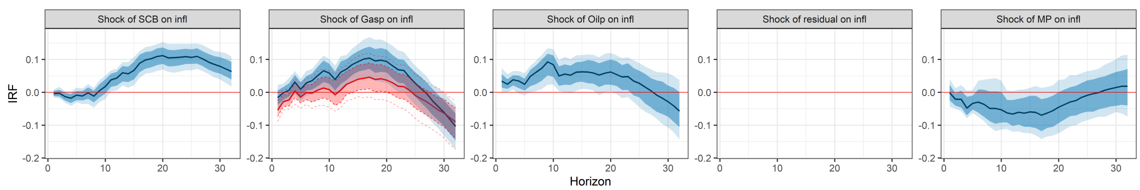

Figure 7: *Responses of Y-to-Y inflation to macroeconomic shocks*

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 7 shows the identified responses of inflation to a standard deviation in each of the four shocks. Supply chain bottlenecks shocks impact after 10 months and they have a strongly positive and persistent effect on inflation. Gas and oil price shocks show a similar dynamics, as they both increase inflation up to about 20 months. However, gas price shocks have a more significant effect, but only when they are demand shocks. Gas supply shocks have a milder and less significant effect on inflation. Finally, as the standard macroeconomic theory predicts, monetary policy shocks reduce inflation, but we estimate this response to be only mildly significant.

We now turn to a more in depth analysis of the recent inflation surge episode. To better characterize the iflation 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.

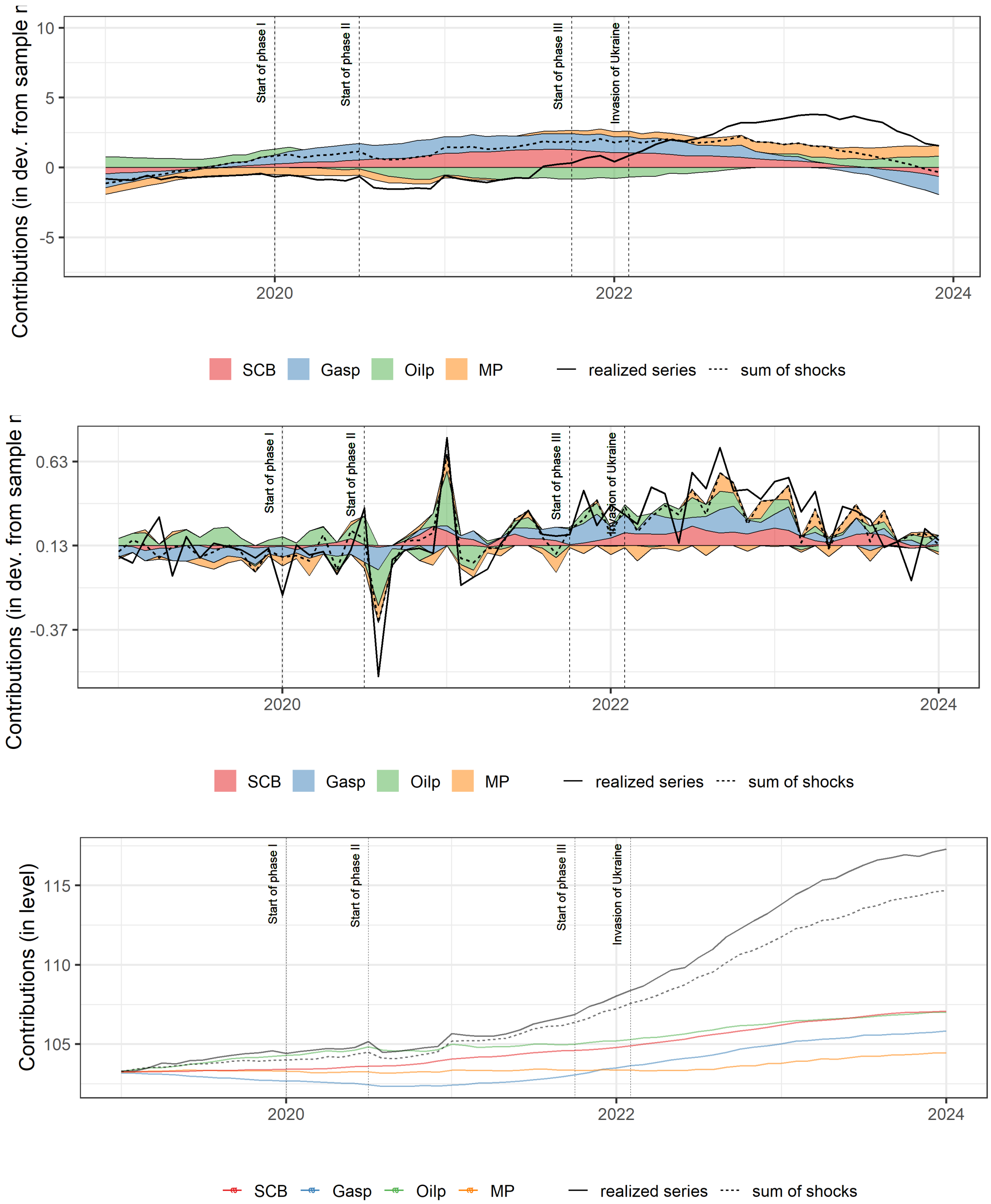

Figure 8: *Historical decompositions of Y-to-Y, M-to-M inflation and price level, selected sample.*

Notes: The top panel shows the contributions of supply chain bottlenecks, oil price, gas price, and monetary policy shocks on the realized series of Y-to-Y inflation, relative to the unconditional mean (horizontal line). The central panel shows the contributions on M-to-M 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).

Figure 8 shows the obtained historical decompositions and compares them to the realized series of inflation. From the Y-to-Y decompositions we can recover the implied M-to-M 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.

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 tell us that the quality of the historical decomposition approximation is adequate and that it is able to 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 8, 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).[18]

3.3 Comparing EA and US

We now run the same analysis as in section 3.1 on US data. The identification strategy is unchanged but instruments are adapted using US temperatures (see Appendix B) for the gas demand instrument, the Henry Hub futures for the gas supply instrument, and the WTI futures for the oil supply news shocks.

[18]See the ECB blog at this link.

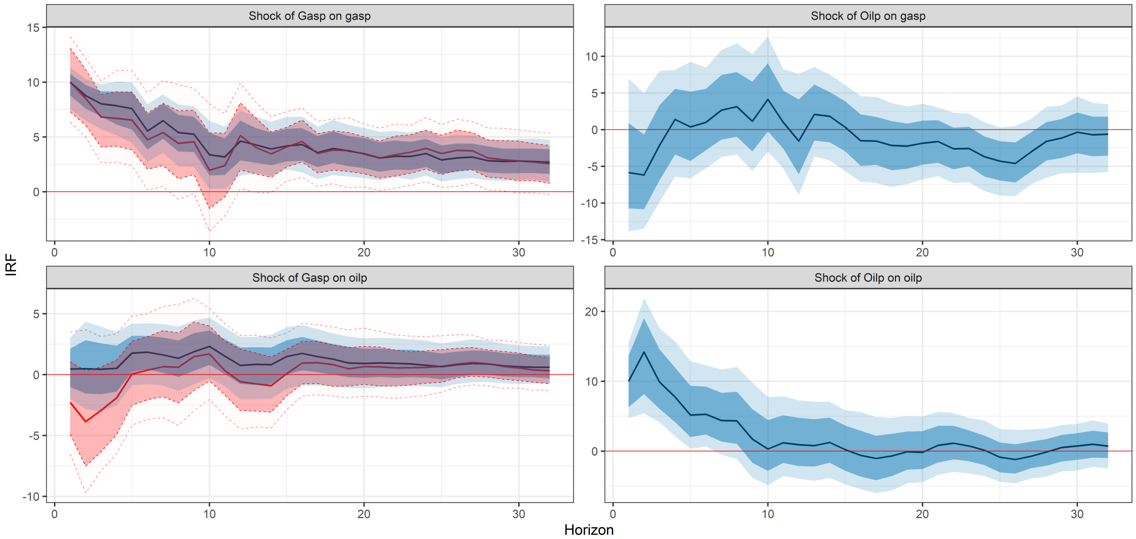

Figure 9: *Interrelation of Gas and Oil markets in the US*

Notes: the responses are normalized to correspond to a 10% increase in the price of oil and in the price of gas.

Figure 9 is the analogous for the US of Figure C20 and shows the responses of gas and oil prices to their respective shocks. The energy market in the US appears to be less interdependent than in the EA, as neither oil shocks impact gas prices significantly, nor gas shocks impact oil prices. However, with respect to the EA, in the US gas price shocks have a more persistent effect on the price of gas, while oil price shocks impact the price of oil only up to 9 months. Figure 10 shows that headline and core inflation are less impacted by gas price shocks in the US than in the EA. In contrast, oil price shocks bear a similar impact on both EA and US inflation, although the responses in the EA are more persistent.

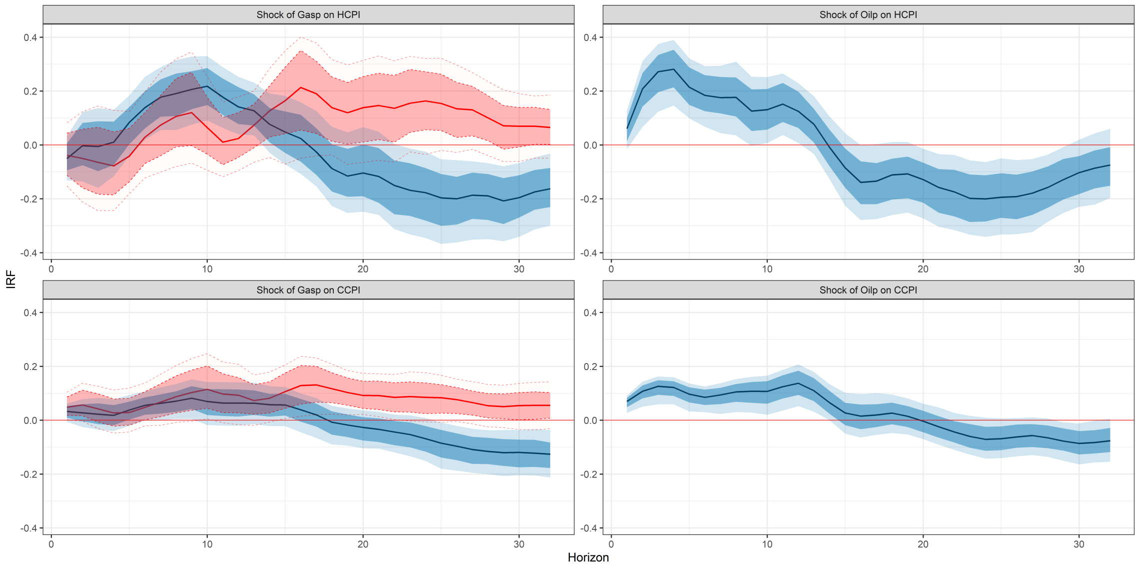

Figure 10: *Inflation IRFs in the US*

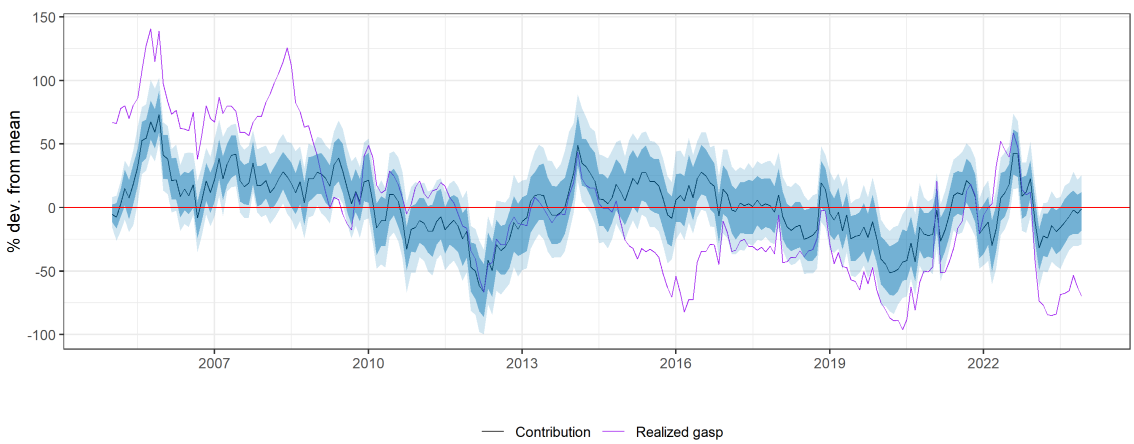

Figure 11: *US: Historical decomposition of the real price of gas*

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 mean).

Figure 11 shows the equivalent historical decomposition of Figure 6 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 market in the US is less dependent from domestic demand as the US are a net exporter of gas.

4 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, and more so in the Euro Area than in the United States. In particular, in the EA the gas and oil markets appear significantly interdependent and core inflation is more persistently impacted by gas shocks. Via the identified gas supply and gas demand shocks, we can distinguish between the effects of demand and supply disruptions, shedding light on the transmission of gas price shocks. Notably, we document a differentiated effect on interest rates. Monetary policy exhibits a swifter response to gas supply shocks, transitioning to a restrictive stance with a lag of a few months in the case of demand shocks. 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. Using this strategy, we show that the recent inflation surge in the EA was mainly driven by gas and supply chain bottlenecks shocks, which are both persistent, and the latter propagates with a significant lag.

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Appendix A Econometric models

This appendix is mostly based on Kilian and Lütkepohl (2017), chapter 4. 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

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

By recursive substitution, it can be shown that the response of the variable $j = 1, \ldots, K$ to a unit shock u_{kt}, i periods in the past, for $k = 1, \ldots, K$ 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

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

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,[19] 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:

$$\hat{\beta}_1 = \left(\frac{1}{T}\sum_{t=1}^{T} z_t z_t'\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T} z_t u_{1,t}\right)^{20}$$

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

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:

$$\mathbf{s}_1'\mathbf{\Sigma}^{-1}\mathbf{u}_t = \mathbf{s}_1'(B_0^{-1}B_0^{-1\prime})^{-1}u_t = \mathbf{s}_1'B_0'B_0B_0^{-1}\mathbf{w}_t = \mathbf{e}_1'\mathbf{w}_t = w_{1,t},^{21}$$

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[22] (including the constant). can be implemented (see Stock and Yogo, 2002).
In the VAR context, this instrumental variable approach has been used mostly to identify a monetary policy shock (see for example Gertler and Karadi, 2015; Miranda-Agrippino, 2016; Nakamura and Steinsson, 2018), but not exclusively (see for example Känzig, 2021a for an oil price shock or Känzig, 2021b for a carbon price shock). The idea is to rely on short-term movements of financial variables around certain

[19] We also need $\mathbb{E}[\mathbf{z}_t u_{1,t}]$ full column rank and $\mathbb{E}[\mathbf{z}_t\mathbf{z}_t'] < \infty$.
[20] An intercept is generally also included in this regression.
[21] Note that $B_0\mathbf{s}_1 = \mathbf{e}_1$.
[22] 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

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 form.

Appendix B Data sources

B.1 Temperatures 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.[23]

Extreme temperatures index. The monthly ETI is computed as described in Equation B.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 B12 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.

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

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

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

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

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

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

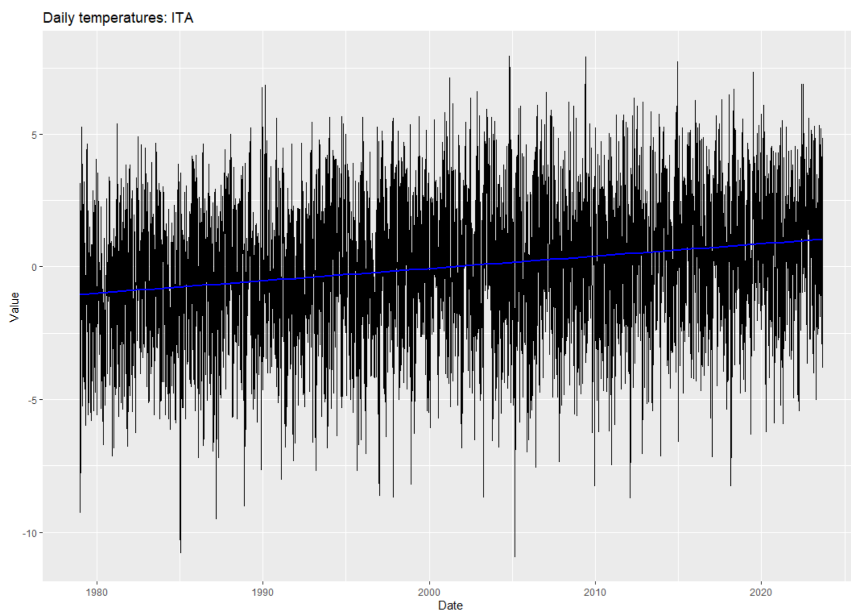


Figure B12: *Daily seasonally adjusted temperatures for Italy, not detrended.*

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;

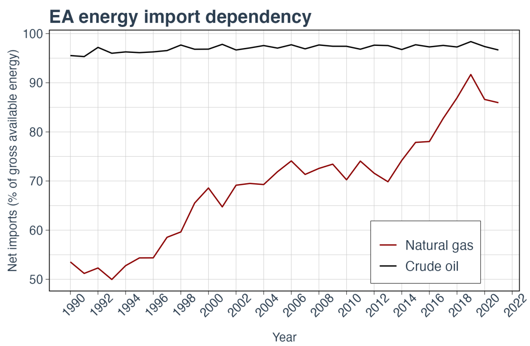
- weighting the daily temperature series using (2015) population or (2015) night lights;

- 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.

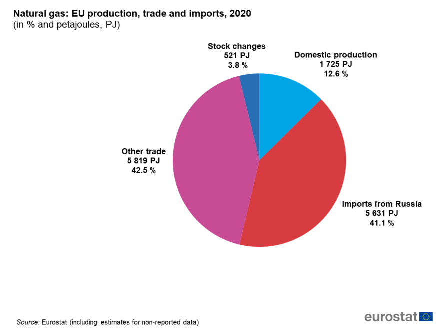
Appendix C Additional figures

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

C.1 Descriptive Statistics



(a) Natural Gas import dependency



(b) Import from Russia

Figure C13: *Euro Area imports of natural gas.*

Notes: The left panel displays the EA import dependency of gas and oil over the period 1990-2020. The right panel shows the imports from Russia as a share of gross available energy derived from natural gas. Source: Eurostat.

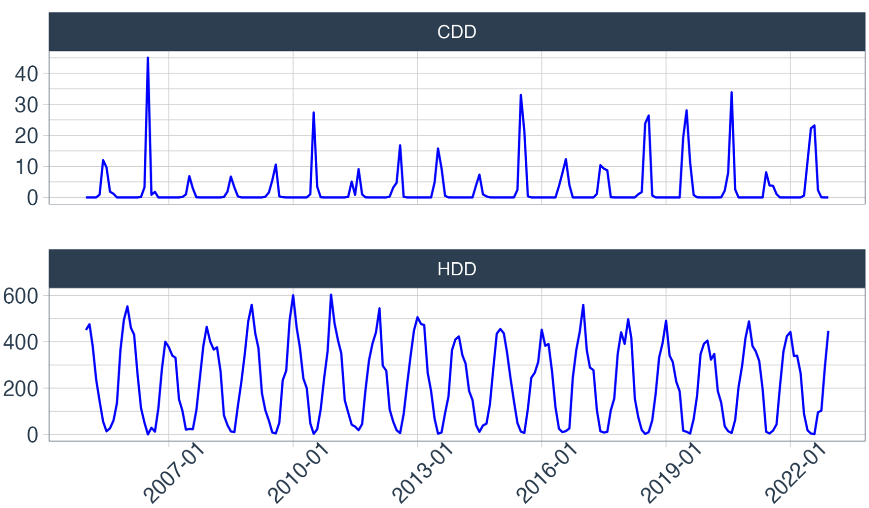


Figure C14: *Cooling degree days and heating degree days, average across selected European countries.*

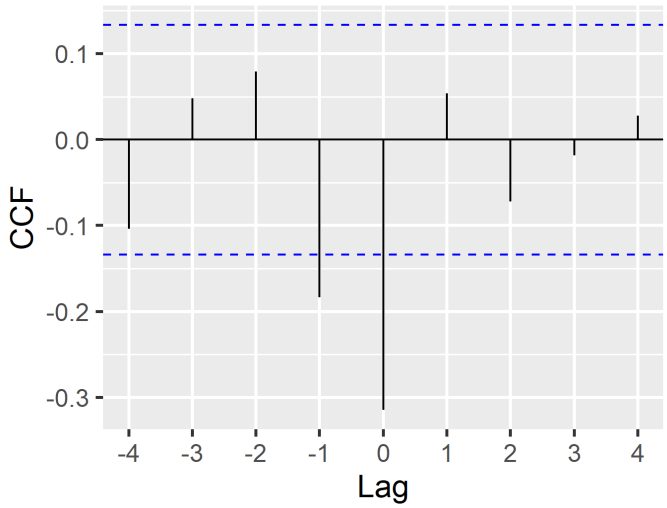


Figure C15: *Cross-correlation function of the reduced-form residuals of the price of gas (at time t) and the extreme temperatures index (at time $t + Lag$).*

C.2 Data used in the VAR models

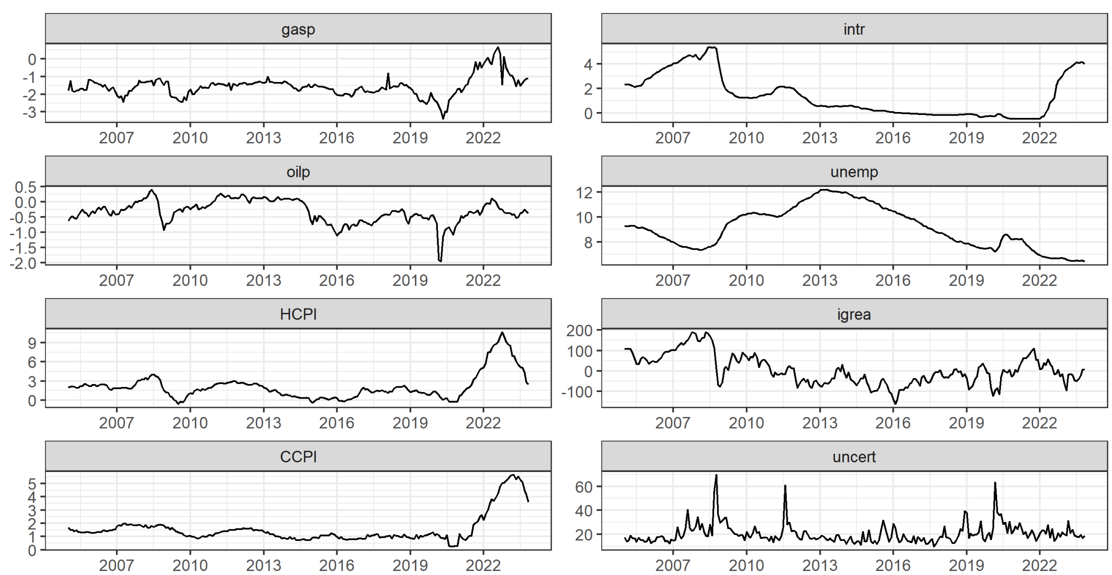


Figure C16: *Data used in the main specification.*

Notes: Gasp and oil prices are deflated using the headline price level, headline and core inflation are Y-to-Y growth rates of the respective seasonally adjusted price levels, the interest rate is the 1Y ECB rate, unemployment is seasonally adjusted, and the IGREA and the EM volatility indices are left untransformed.

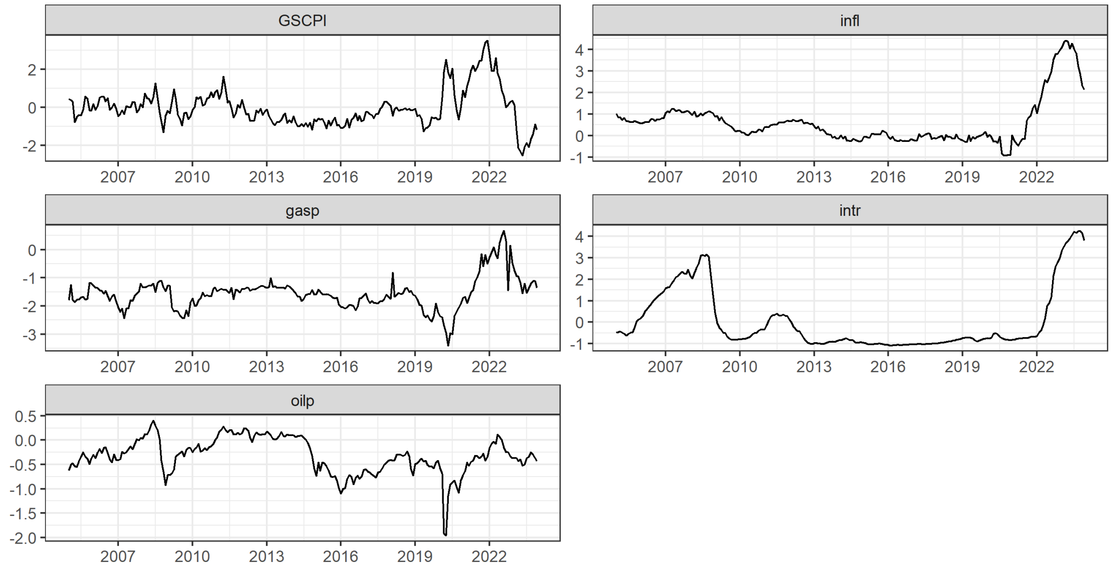


Figure C17: *Data used in the smaller specification*

Notes: In this specification the GSCPI index is included, and left untransformed. Gasp and oil prices are deflated using the headline price level, inflation is Y-to-Y core inflation seasonally adjusted, and the interest rate is the 1Y ECB rate.

C.3 Brent and WTI oil surprises

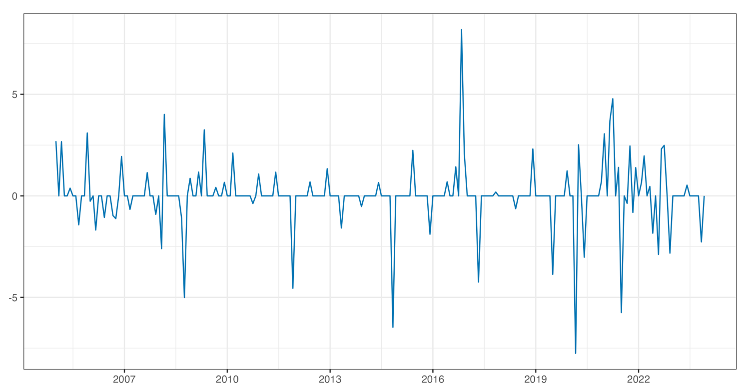


Figure C18: *The oil supply surprises series*

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.

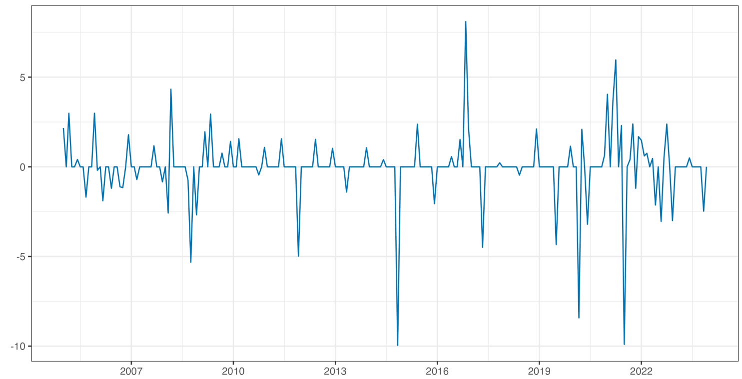


Figure C19: *The WTI oil supply surprises series*

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

C.4 EA: Gas and oil markets interrelation

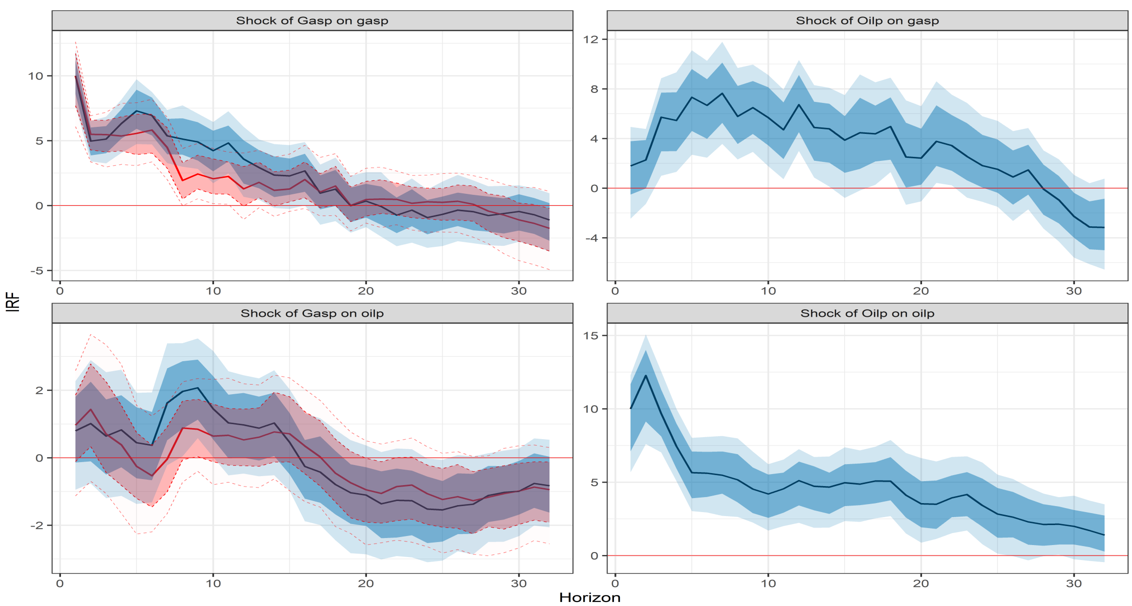


Figure C20: *Interrelation of Gas and Oil markets in the Euro Area*

Notes: Responses of the real price of gas and the real price of oil to 10 % increases in the gas price and oil price. In the left panel, red lines indicate responses to supply shocks blue lines indicate responses to demand shocks.