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. We also document an important interdependence of 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. We find that gas and supply chain bottleneck 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, 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

The recent disruptions in the energy market, particularly following Russia's invasion of Ukraine, have sparked renewed interest in the macroeconomic effects of energy price shocks. While extensive research has examined the macroeconomic impacts of oil price shocks, 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 studying energy shocks through the global crude oil market (Hamilton, 1983; Kilian, 2009; Baumeister and Kilian, 2016; Caldara et al., 2019; Känzig, 2021a). 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 (Kilian & Zhou, 2022; Szafranek & Rubaszek, 2023), particularly pronounced in the European market. In this paper, we investigate the effects of gas price shocks, disentangling the effects of gas supply shocks and gas 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 (EA), 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 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 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 investigated 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 gas supply and gas 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 highlighted 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 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 outbreak of the war in Ukraine, and sectoral demand shifts, 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 exacerbated the existing uncertainty and diminished confidence.

Our study enriches the ongoing debate 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 infla-

[1] See FOMC projections of March 2021.

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

tion. We use the FED of New York's Global Supply Chain Pressure Index (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, both of which have persistent effects. Furthermore, we find that the latter shock propagates with a significant lag.

In our analysis of the EA, we find that, similarly to oil shocks, gas shocks also have an inflationary effect, causing a notable rise in both headline and core inflation. Distinctive characteristics among these energy shocks are evident, with gas shocks exerting more pronounced, albeit more deferred, impacts. While interest rates are quick to respond to the inflationary oil shocks, the reaction to gas shocks is noticeably subdued and occurs later. Additionally, we document different responses to gas supply versus gas demand shocks. Supply-induced shocks trigger a gradual increase in interest rates, in contrast to demand shocks, which initially dampen rates and only induce a rise after one year. Our findings suggest that the ECB exhibits varied responses to different types of energy shocks, with a tendency to underreact to gas demand shocks, despite their greater inflationary impact compared to gas supply shocks. This result could possibly be attributable to the ECB's closer monitoring of supply-related news, which may result in more immediate policy adjustments in response to supply shocks.

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, the econometric models we use and further empirical results.

2 Identification strategy

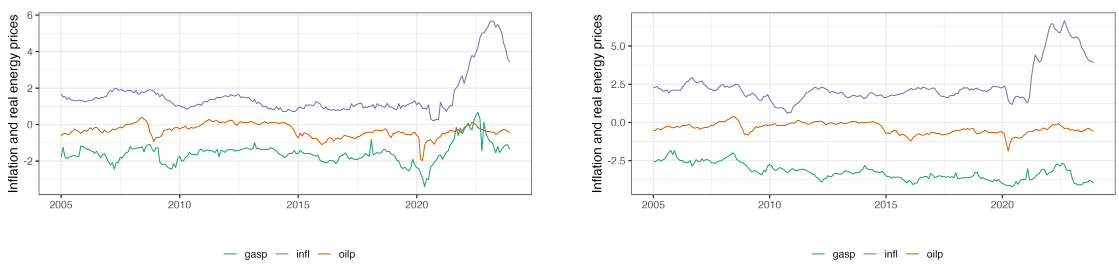
To study the impact of macroeconomic shocks on the Euro Area, our main model of choice is the literature-standard structural vector auto-regression (SVAR). We identify both demand and supply shocks to the price of gas, exploiting exogenous variation in temperatures and in futures prices in a tight window around gas market-relevant news, respectively. We then assess the responses to gas shocks in a VAR that includes several literature-standard 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 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.[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 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 than it had been for decades (see Figure 1).



(a) EA

(b) US

Figure 1: *Inflation and energy prices*

Notes: The left panel shows the YoY core inflation in the Euro Area alongside the real TTF natural gas and Brent crude oil prices, benchmark prices for the gas and oil markets in Europe. The right panel shows the corresponding series for the US, where the benchmark price of gas is the NYMEX Henry Hub and the benchmark price of oil is the WTI.

Historically, the dynamics of natural gas and global crude oil have been tightly linked, 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 developments have underscored the need to also examine the dynamics of gas prices, which have increasingly diverged from oil prices, as noted by Szafranek and Rubaszek (2023).[4] This shift implied a growing recognition of the natural gas markets, warranting a more focused analysis.

[3]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.

[4]This divergence has been highlighted only by few studies before the recent conflict (Zhang & Ji, 2018).

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.

We construct an instrument using high-frequency techniques developed in the monetary policy literature (Kuttner, 2001; Nakamura and Steinsson, 2018) and more recently applied to oil prices by Känzig (2021a). Gas surprises, given by high-frequency fluctuations in the price of gas around market-relevant news, primarily reflect variations driven by supply factors. The announcements related to the war and the statements from major suppliers, such as Gazprom, serve as illustrative examples of supply-side surprises. Conversely, 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. Before describing the construction of the two series in greater detail, we provide essential background information on the gas market.

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 23% of the total available energy (based on Eurostat data for 2021). 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 E21, 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 E21, 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.[5] 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. In 2021, the European gas market featured 11 main distinct trading hubs, varying significantly in terms of liquidity and gas infrastructure, as reported by the Oxford Institute for Energy Studies (Heather, 2021).[6] Despite the 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) 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. Figures C17 and C19 and Table C5 show that the dynamics of the different hub prices are greatly correlated. Indeed, most studies that study 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).

However, these papers do not consider the increasing role of LNG in the European market. We here provide evidence that, whilst the dynamics of LNG price historically has not followed closely that of the TTF price, as the importance of LNG has increased over time, the two have become closed and more correlated. This is shown in Figure C18 and motivates the use of the TTF price as a single reference price for the whole European market.

In contrast, in the United States, most natural gas transactions involve pricing mechanisms linked to the price of gas quoted at the Henry Hub (HH) (CME Group, 2023). 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.

[5]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.

[6]While there are approximately 30 gas trading hubs in Europe, it's important to note that not all of them are actively operational.

2.1.2 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 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 calculations based on the TTF spot price). Indeed, on the same day, European Union leaders urged the Commission to propose contingency measures aimed at ad-

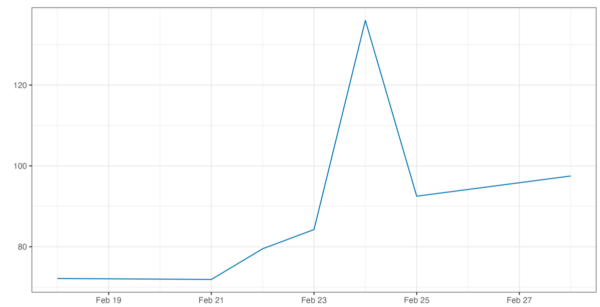


Figure 2: *Putin announces Ukraine invasion*

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

dressing 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 reference 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. Following Känzig (2021a), 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 3 shows the resulting monthly surprises series.

To evaluate the adequacy of the gas surprise series, we perform a comprehensive series of checks. One major concern regarding the high-frequency approach is that non-gas-related news might affect the gas price during the event window. This issue is potentially relevant for our study for two main reasons. First, we use a one-day event window as opposed to narrower intra-day windows. Secondly, as discussed in Section 2.1.1, the recent disruptions of the gas market have heightened the sensitivity of gas prices to a diverse array of news. This includes institutional news, such as the energy measures implemented by the European Council, and geopolitical events, notably those associated with the conflict in Ukraine. These factors can impact gas prices through various mechanisms, not limited to supply disruptions.

In assessing the extent of background noise within the surprise series, we compare the daily changes in gas future prices on gas-related news to the price changes on a sample of control days. These control days are chosen at random and do not contain gas supply news.

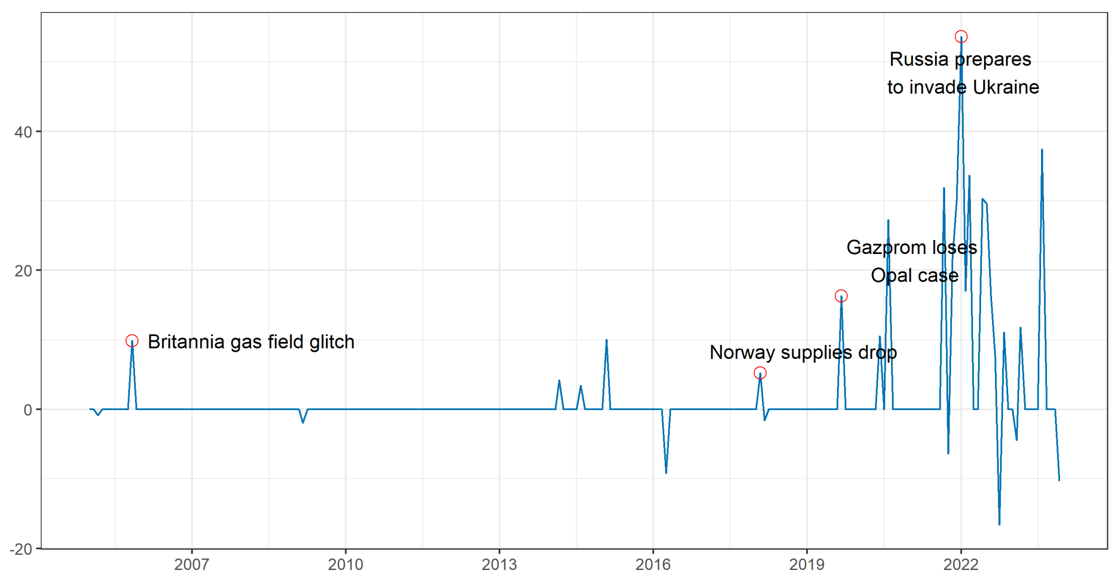
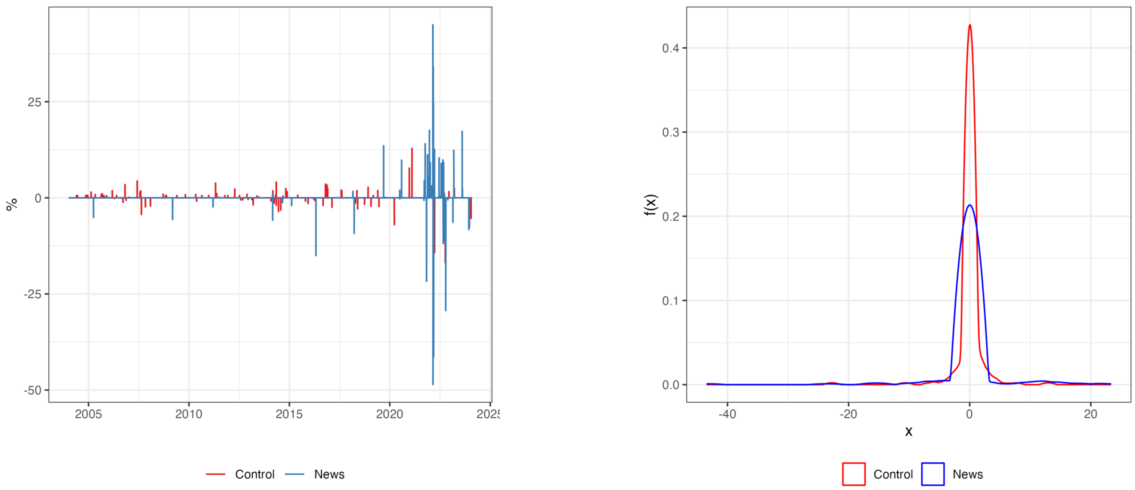


Figure 3: *The gas supply surprises series*

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 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 capped Gazprom's dominance in the gas market, and in 2022M2 the invasion of Ukraine started.



(a) Daily surprises

(b) PDF

Figure 4: *Gas news 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, features not 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).

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

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,[7] 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 **??** 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.[8] Figure 5 shows the resulting ETI for the considered sample of countries.

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

[7]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).

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

[9]These correlations and F-statistics refer to the smaller VAR specification (see section 3) but are robust to different specifications.

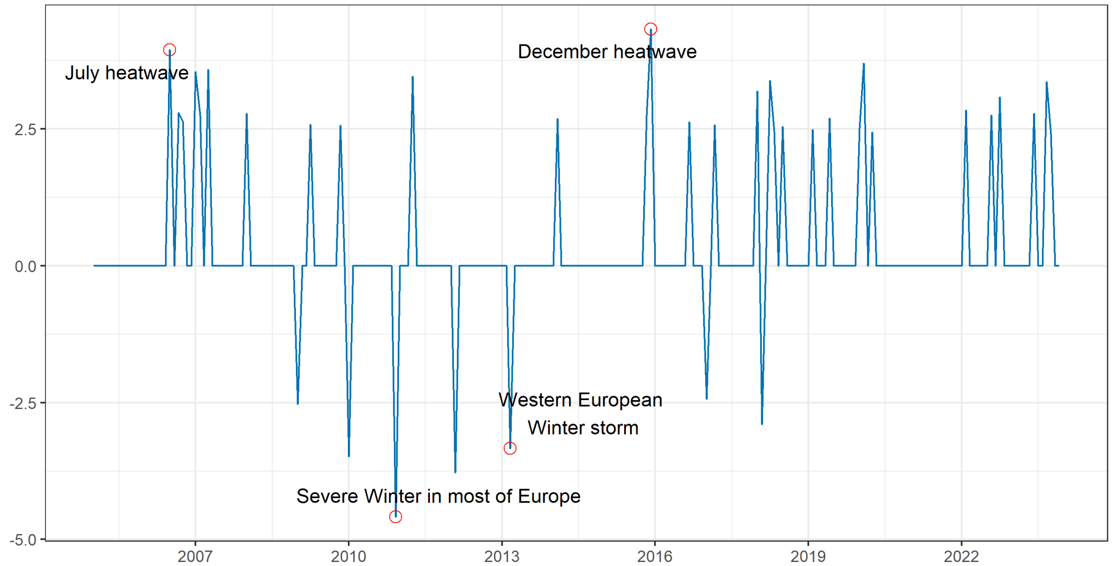


Figure 5: *Extreme temperatures index (ETI) for Europe.*

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).[10] Figure E22 shows the averaged CCD and HHD for the same sample of countries that we use to construct the ETI.[11]

When we restrict the sample to months when the HDD is low,[12] 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

[10]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.

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

[12]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,[13] 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.[14] Conveniently, we have that most of the spikes in the ETI (both positive or negative), as shown in Figure 5, 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 E23 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.

2.2 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.[15] We argue that this variable is unlikely affected by the other shocks of the

[13]We choose 5 as a threshold.

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

[15]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 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 E26 shows the oil supply surprise series, and the corresponding WTI oil surprise series can be found in Appendix Figure E27.

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.[16]

3 Results

We first focus on the Euro Area and show that gas price shocks have important macroeconomic effects and that there are few 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 pronounced compared to those in the Euro Area.

For all specifications our estimation sample is 2004M1-2023M12 and we include 12 lags, so that the effective estimation sample is 2005M1-2023M12.[17]

[16] 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.

[17] We start from January 2004 as that's the earliest for which TTF natural gas futures are avaiable.

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 6 shows the impulse responses to the identified gas demand and gas supply news shocks, normalized to increase the real gas price by 1 standard deviation.[18] 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.[19]

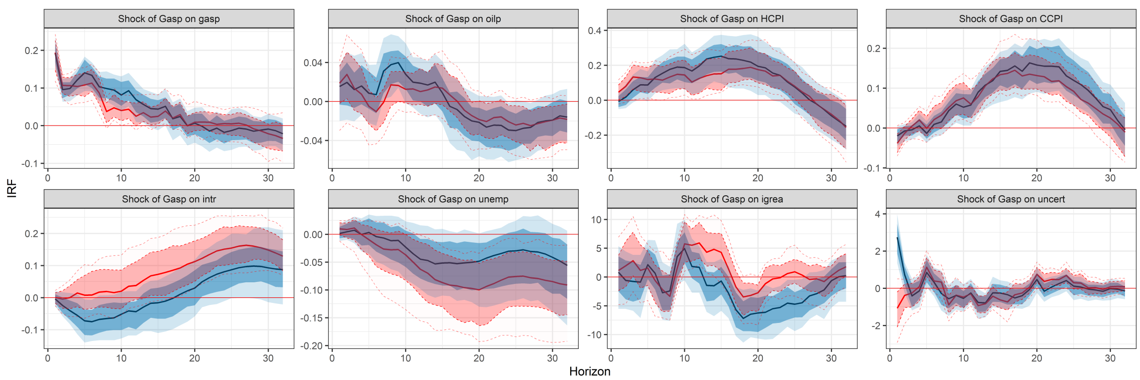


Figure 6: *Macroeconomic Effects of Gas Price shocks in the Euro Area*

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 YoY 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 effect on prices manifests more swiftly in response to supply shocks compared to demand shocks. The energy and food components of inflation naturally respond earlier to

[18]Only 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.

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

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 demand and supply shocks on interest rates differ considerably. While supply shocks increase interest rates throughout the response, demand shocks lead to a negative effect on interest rates initially, which then turns positive after 15 months. These findings suggest that the ECB exhibits varied responses to different types of energy shocks, with a tendency to underreact to gas demand shocks, despite their greater inflationary impact compared to gas supply shocks. This result could possibly be attributable to the ECB's closer monitoring of supply-related news, which may result in more immediate policy adjustments in response to supply shocks. 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 7, which shows the responses to a supply news shock in the real price of oil, identified as in Känzig (2021a).

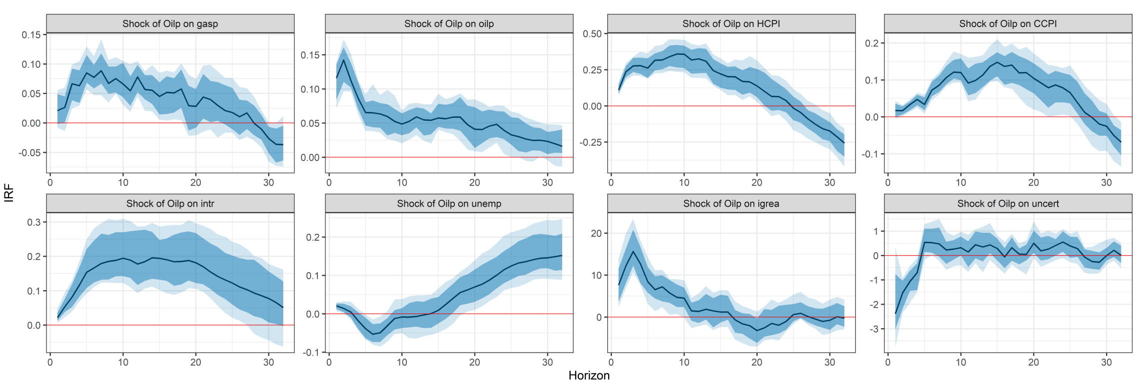


Figure 7: *Macroeconomic Effects of Oil Price shocks in the Euro Area*

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. This contrast is particularly evident in the response of interest rates: ECB promptly reacts to inflationary oil price shocks, while its response to gas price shocks is less pronounced and delayed, as previously noted.

Regarding the relationship between the oil market and the gas market, we have that the gas price responds significantly with a 7% increase after a 10% increase in the oil price. This is shown in greater detail in Figure E28, 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 demand 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.[20] 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.

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.

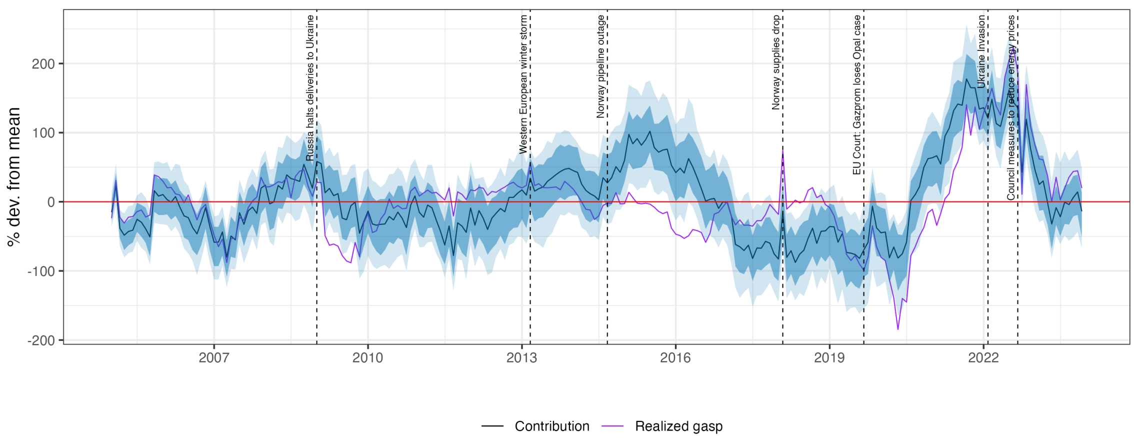


Figure 8: *EA: Historical decomposition of the real price of gas*

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 8 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

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

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 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.

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. 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 2.2, 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 9.

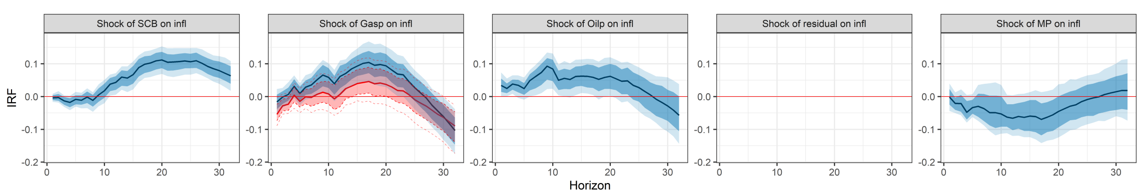


Figure 9: *Responses of YoY inflation to macroeconomic shocks*

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 9 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 10 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.

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 10, 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).[21]

[21] See the ECB blog at this link.

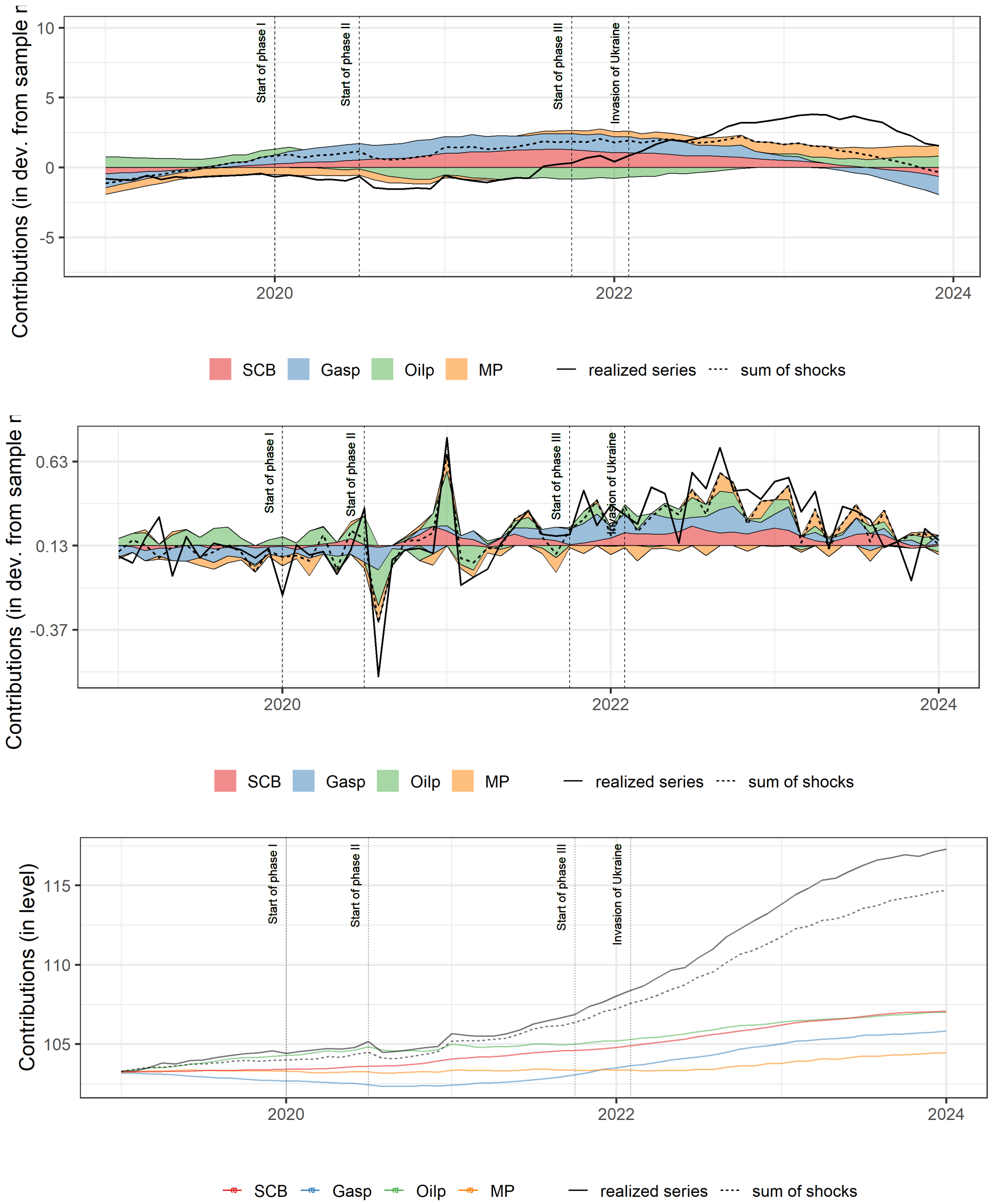


Figure 10: *Historical decompositions of YoY, MoM inflation and price level, selected sample.*

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).

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

$$\hat{y}_{kt}^{(j)} = \sum_{s=0}^{t-1} \theta_{kj,s} w_{t-s} \tag{3.2.1}$$

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

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

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

$$\frac{\sum_{t=q}^{r} |\hat{y}_{kt}^{(j)}|}{\sum_{k=1}^{K} \sum_{t=q}^{r} |\hat{y}_{kt}^{(j)}|} \tag{3.2.2}$$

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)[22] 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 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.3.2.2, 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:

$$\hat{y}^{(j)}_{kr} - \hat{y}^{(j)}_{kq} \tag{3.2.3}$$

where $\hat{y}^{(j)}_{kt}$ denote the cumulative contribution of shock j to variable y_{kt} at time t, in line with Eq.3.2.1. 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 10, 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

[22] 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.

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 10), 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.*

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 the instruments are adapted using US temperatures (see Appendix D.1) for the gas demand instrument, the Henry Hub futures for the gas supply instrument, and the WTI futures for the oil supply news shocks.

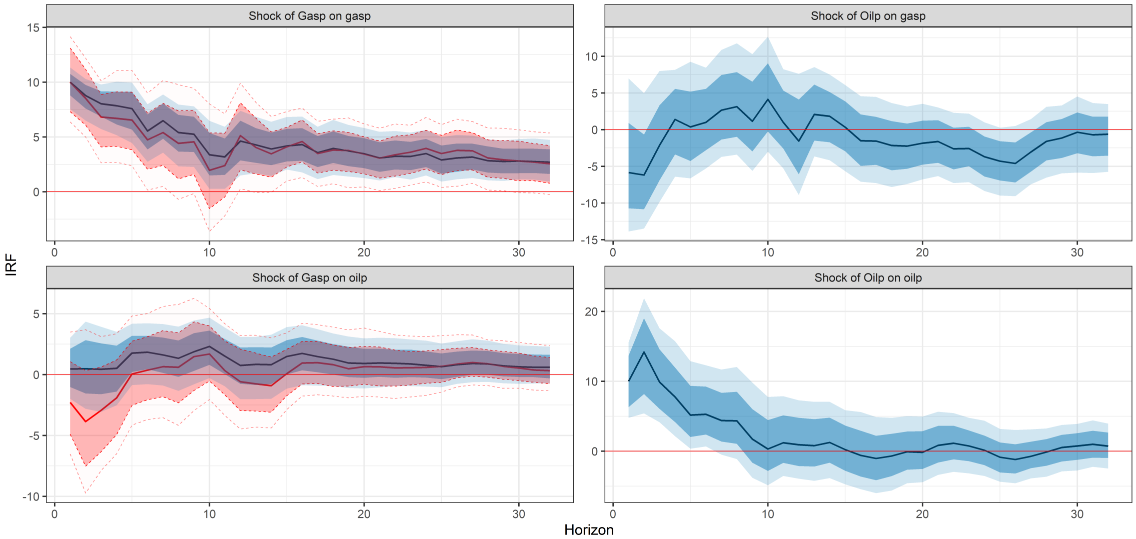


Figure 11: *Interrelation of Gas and Oil markets in the US*

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

Figure 11 is the analogous for the US of Figure E28 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 12 shows that headline and core inflation are less impacted by gas price shocks in the US than in the EA (compare with Figures 6 and 7). In contrast, oil price shocks bear a similar impact on both EA and US inflation, although the responses in the EA are more persistent (up to 20 months in the EA and up to 12 months in the US).

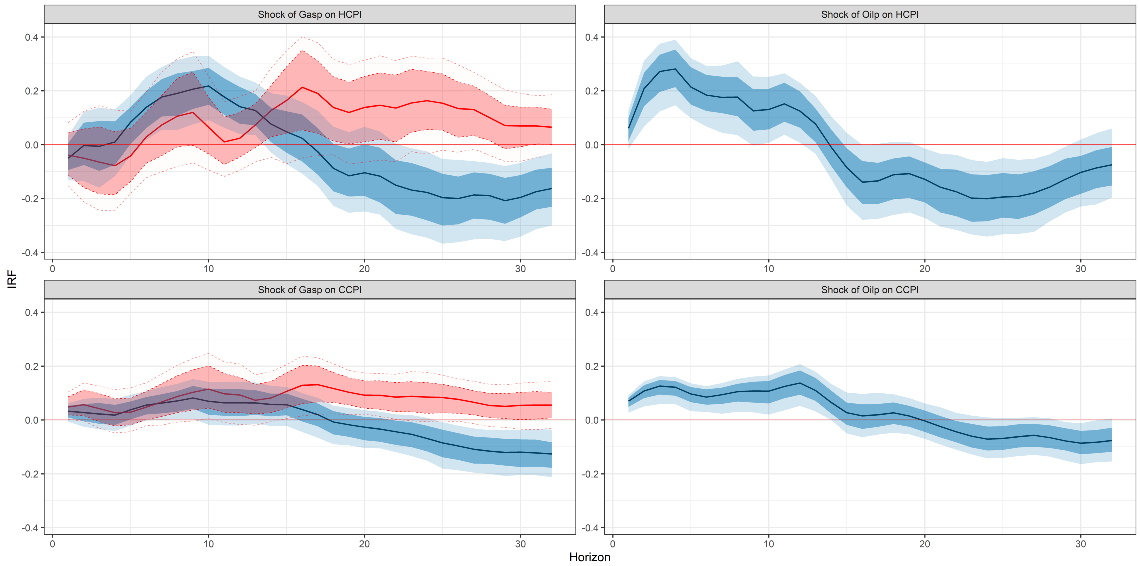


Figure 12: *Inflation IRFs in the US*

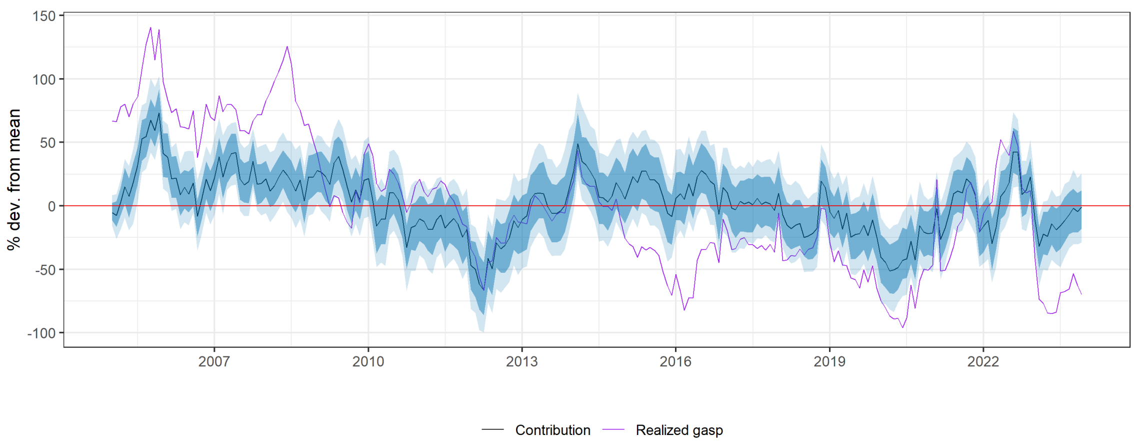


Figure 13: *US: Historical decomposition of the real price of gas*

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).

Finally, Figure 13 shows the equivalent historical decomposition of Figure 8 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.

Energy pass-through to inflation. Historically, the literature has focused mostly on estimating the pass-through of oil price shocks on inflation. 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 US 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 US 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) study the role of inflation expectations by using sign and zero restrictions to identify a gas price shock in a VAR. They find a low pass-through of 2-3% to headline and 1.1% to core inflation. Moreover, in a recent working paper, Adolfsen et al. (2024) decompose price variations into supply, demand (economic activity) and gas inventories shocks, via a VAR also identified by sign restrictions. They 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 offering a fresh approach to identify gas price shocks using external instruments (Lunsford, 2015; Stock & Watson, 2018) We further separately identify demand and supply gas price shocks. Moreover, we present, to the best of our knowledge, a first comprehensive comparison of the impacts of both oil and gas shocks in both the US and the EA.

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, particularly in the Euro Area compared to the United States. Specifically, in the Euro Area, the gas and oil markets appear significantly interdependent, and core inflation is more persistently impacted by gas shocks. Our separate identification strategy allows to distinguish between the effects of demand and supply disruptions in the gas market, 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, despite these bearing a stronger effect on inflation. 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. Furthermore, we find that the latter shock 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,[23] 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:

$$\hat{\beta}_1 = \left(\frac{1}{T}\sum_{t=1}^{T} z_t z_t'\right)^{-1}\left(\frac{1}{T}\sum_{t=1}^{T} z_t u_{1,t}\right)^{24}$$

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

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:

$$\mathbf{s}_1'\mathbf{\Sigma}^{-1}\mathbf{u}_t = \mathbf{s}_1'(B_0^{-1}B_0^{-1\prime})^{-1}u_t = \mathbf{s}_1'B_0'B_0B_0^{-1}\mathbf{w}_t = \mathbf{e}_1'\mathbf{w}_t = w_{1,t},^{25}$$

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[26] (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

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

Appendix B 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 B3, 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 B4). Notably, we find that the series is not significantly correlated with oil-specific, uncertainty, and global demand shocks.

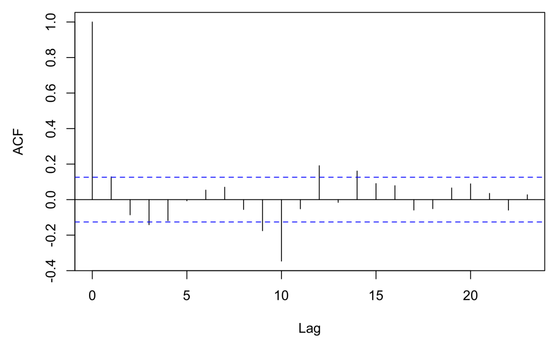


Figure B14: *Sample Autocorrelation Function of the gas surprise series.*

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 B3: *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.

Shock	ρ	p-value	n
proxies_PC_oil	-0.13	0.04	242
Target	0.03	0.63	234
MP_pm_mpd	0.03	0.65	234
TARGETEA_MP	-0.03	0.68	207
CCI	0.11	0.17	144
GEPU_current	0.07	0.30	240
Hamilton	0.02	0.79	168
BHsupply	0.10	0.21	168
KilianAERSupply	-0.21	0.16	48
KilianAERdemand	0.02	0.88	48
KilianAERspecific	-0.16	0.29	48
GertlerKaradiFF4	-0.00	0.96	156
Bloom	0.03	0.71	168
BakerBloomDavis	0.10	0.19	168
Gilchrist	0.02	0.82	144

Table B4: *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.

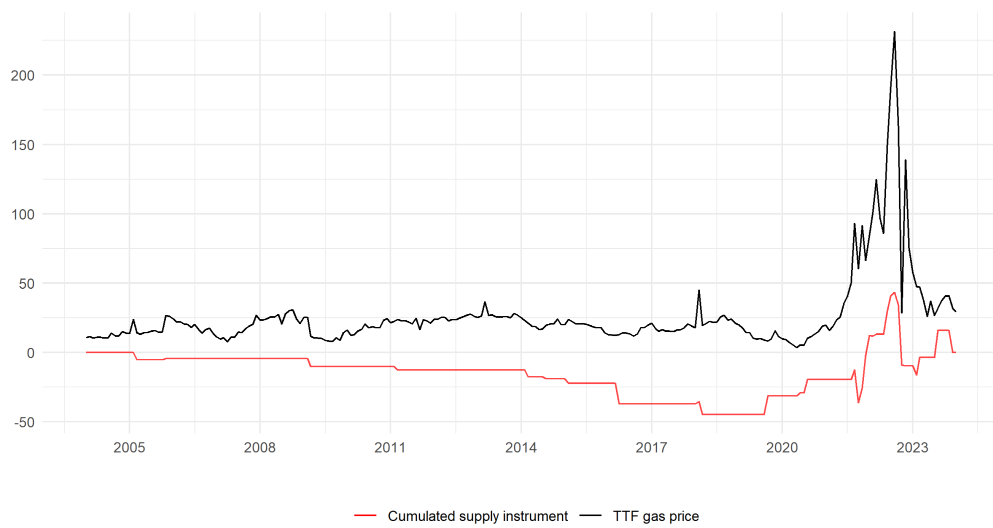


Figure B15: *TTF price and cumulated gas surprises.*

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

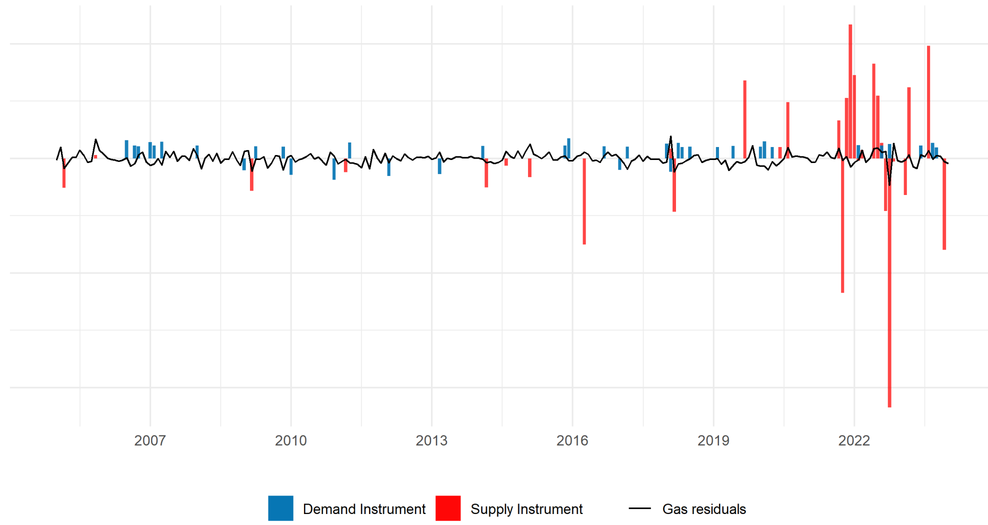


Figure B16: *Supply and demand instruments strength.*

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 C 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 C17 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 C5 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.

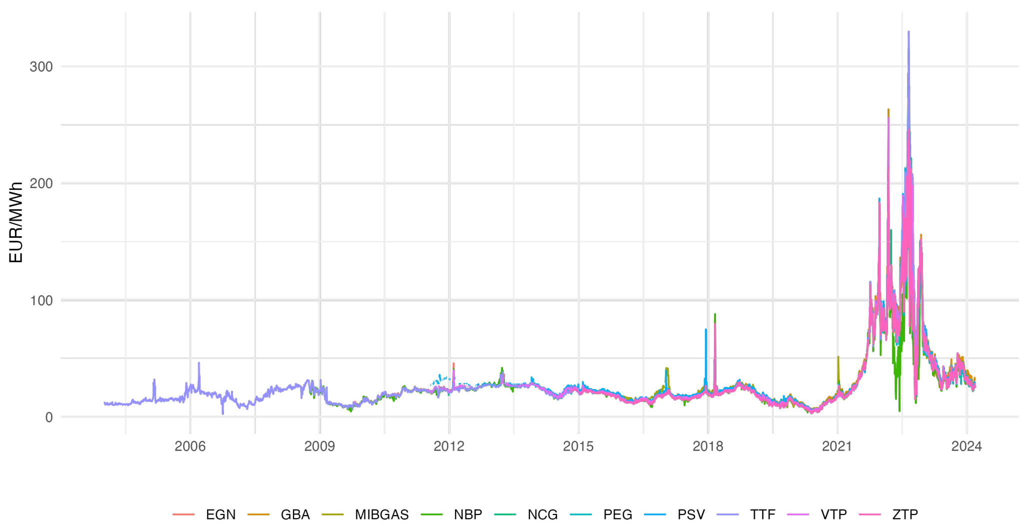


Figure C17: *TTF and other European gas prices.*

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 C18 , while Figure C19 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 C5: *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.

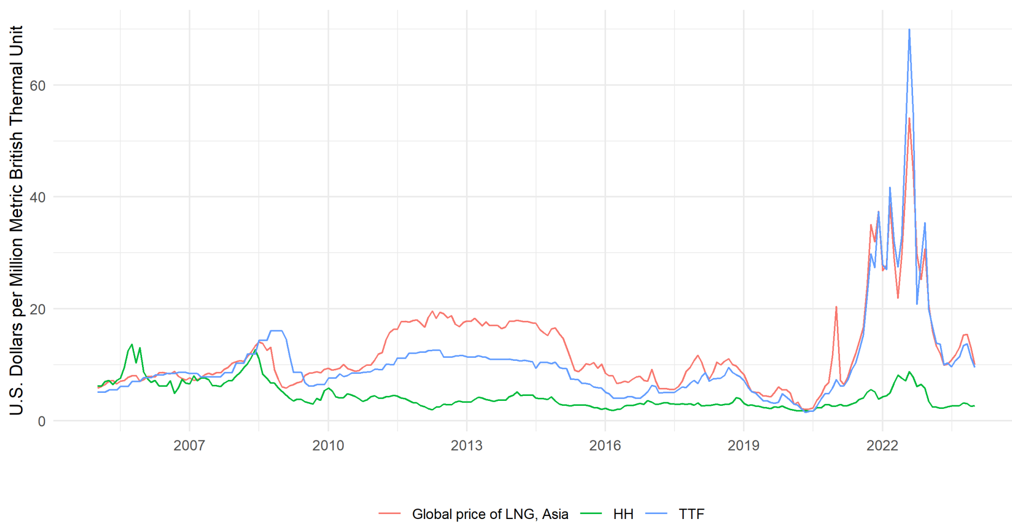


Figure C18: *TTF, HH and Global LNG prices.*

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

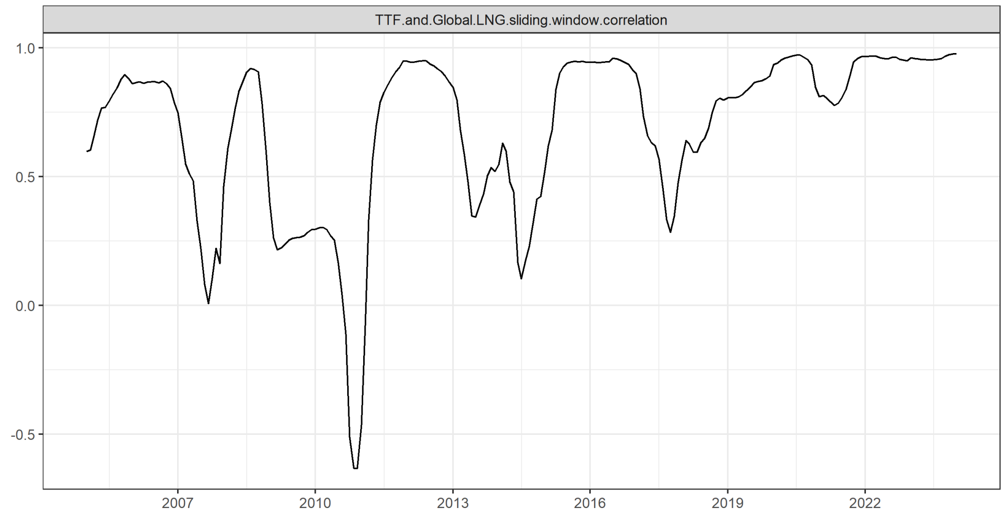


Figure C19: *TTF and Global LNG gas prices correlation.*

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

Appendix D Data sources

Table D6 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				
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)				
SCB	GSCPI index of supply chain pressures (constructed as a latent factor)	FED	1997M1-2024M1	$100 * \log$
gasp	Dutch TTF spot natural gas price (TRNLTTD1) in Euro per MWh and deflated by EA HICP all-items index	Datastream	2004M1-2024M1	$100 * \log$
oilp	Brent spot crude oil price (DCOILBRENTEU) in Euro per barrel and deflated by EA HICP all-items index	FRED	1987M3-2024M1	$100 * \log$
coreinflation	HICP index excluding energy and food seasonally adjusted (ICP.M.U2.Y.XEF000.3.INX)	EUROSTAT	2001M1-2024M1	100Δ log YoY
intrate	Money market EURIBOR rate, 3-month rate (IRT_ST_M)	EUROSTAT	1994M1-2024M1	None
US Variables				
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
gasp_nymex	NYMEX Henry Hub spot natural gas price (MHHNGSP) in Dollar per Million BTU and deflated by CPI all-items index	FRED	1997M1-2024M1	$100 * \log$
oilp_wti	WTI spot crude oil price (WTISLC) in Dollar per barrel and deflated by EA HICP all-items index	FRED	1974M1-2024M1	$100 * \log$
core_cpi	Core CPI (USACPGRLE01IXOBSAM) index	FRED	1960M1-2024M1	100Δ log YoY
fedfund	Effective federal funds rate	FRED	1974M1-2024M1	None
Additional Variables				
indprod	industrial production (STS_INPR_M)	EUROSTAT	1991M1-2024M1	100Δ log YoY
unemployment	unemployment rate, seasonally adjusted (LFSI.M.I8.S.UNEHRT.TOTAL0.15_74.T)	EUROSTAT	1998M4-2023-M1	None
igrea	Kilian's (2009) index of real economic activity	Kilian's webpage	1974M1-2024M1	None
EM_volatility	Baker *et al.* (2019) Equity Market volatility tracker (EMVOVERALLEMV)	FRED	1985M1-2024M1	None

Table D6: *Data description and sources*

D.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.[27][28]

Extreme temperatures index. The monthly ETI is computed as described in Equation D.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 D20 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.

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

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;

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

[28] When using US temperature data we average across all US 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.

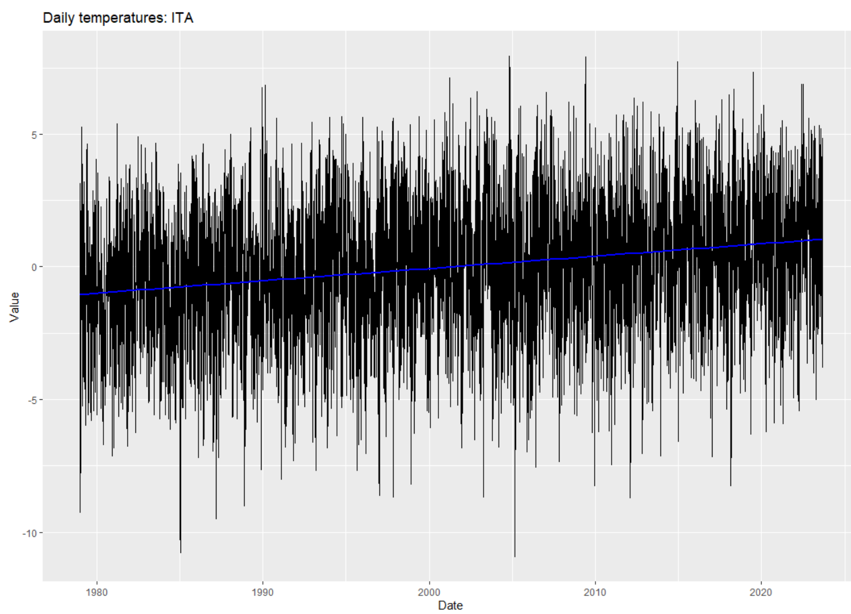


Figure D20: *Daily seasonally adjusted temperatures for Italy, not detrended.*

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;

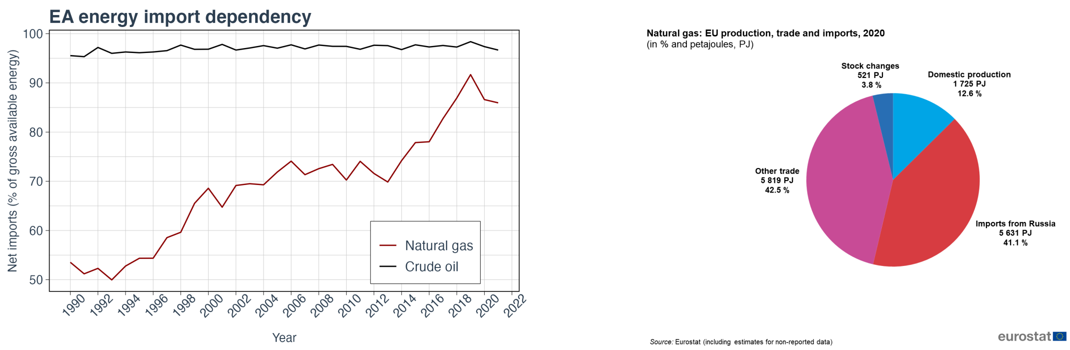
- weighting the daily temperature series using (2015) population or (2015) night lights;

- 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 E Additional figures

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

E.1 Descriptive Statistics



(a) Natural Gas import dependency

(b) Import from Russia

Figure E21: *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.

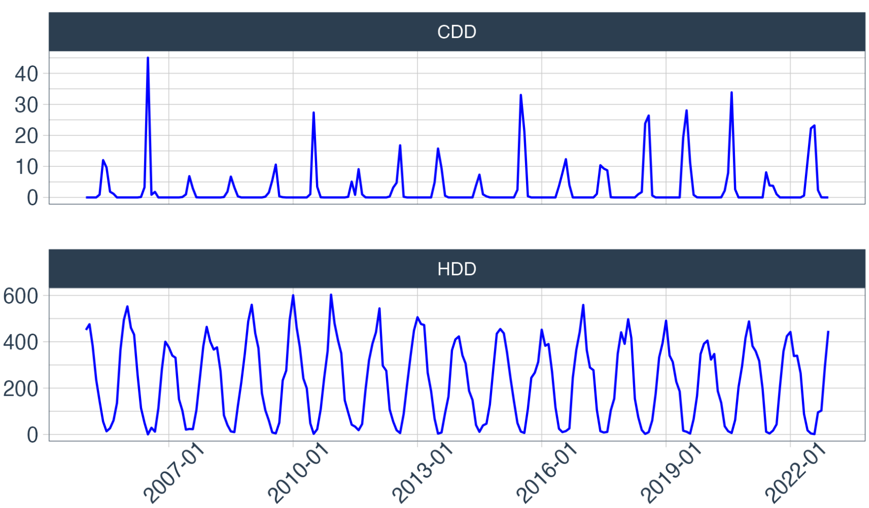


Figure E22: *Cooling degree days and heating degree days, average across selected European countries.*

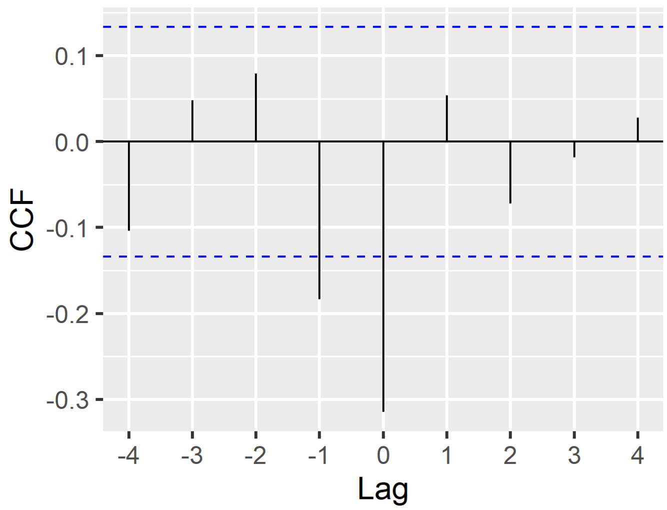


Figure E23: *Cross-correlation function of the reduced-form residuals of the price of gas (at time t) and the extreme temperatures index (at time $t + Lag$).*

E.2 Data used in the VAR models

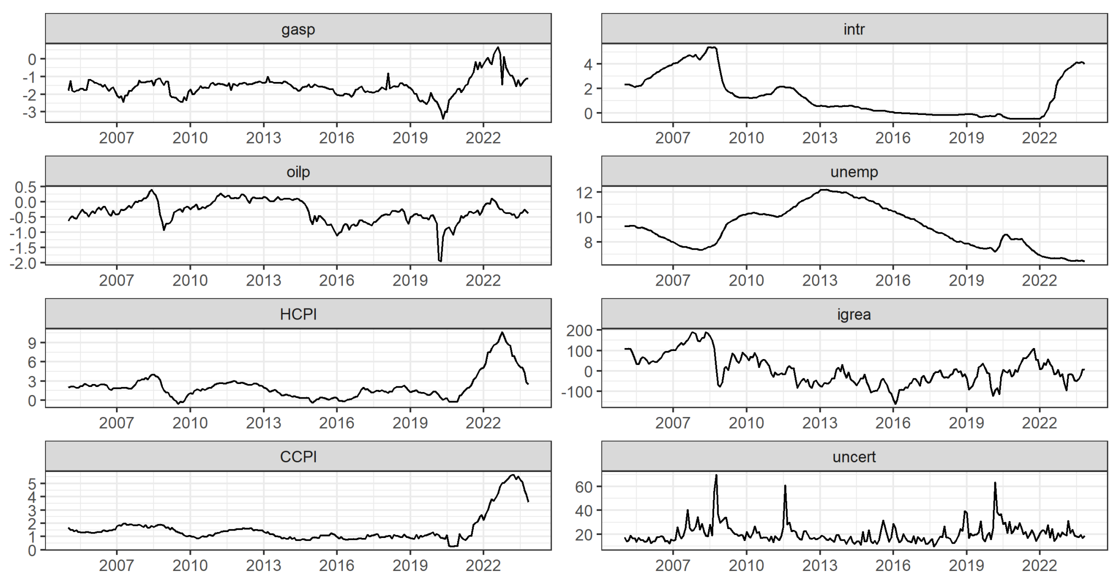


Figure E24: *Data used in the main specification.*

Notes: Gasp and oil prices are deflated using the headline price level, headline and core inflation are YoY 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.

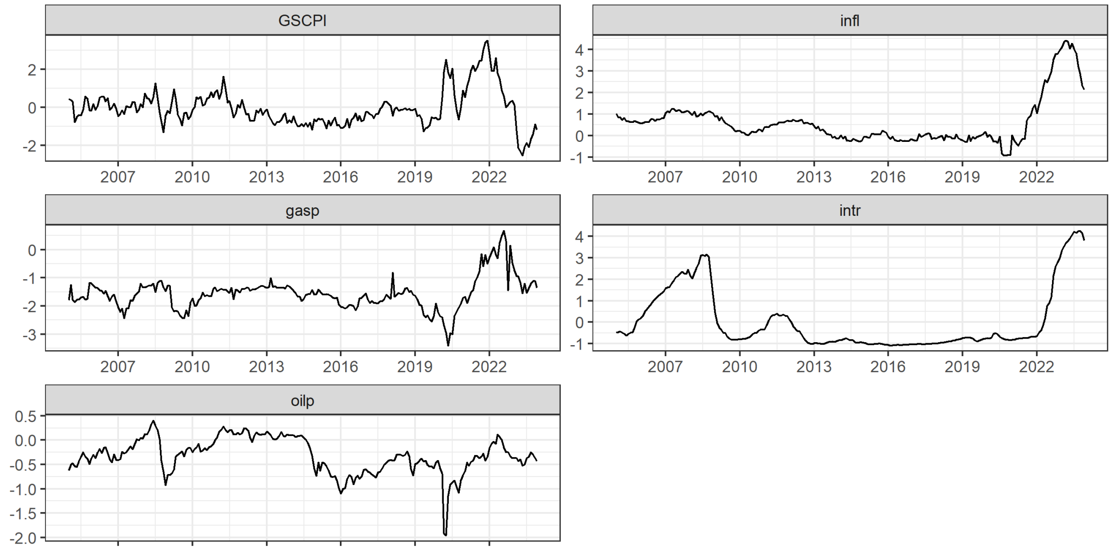


Figure E25: *Data used in the smaller specification*

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 YoY core inflation seasonally adjusted, and the interest rate is the 1Y ECB rate.

E.3 Brent and WTI oil surprises

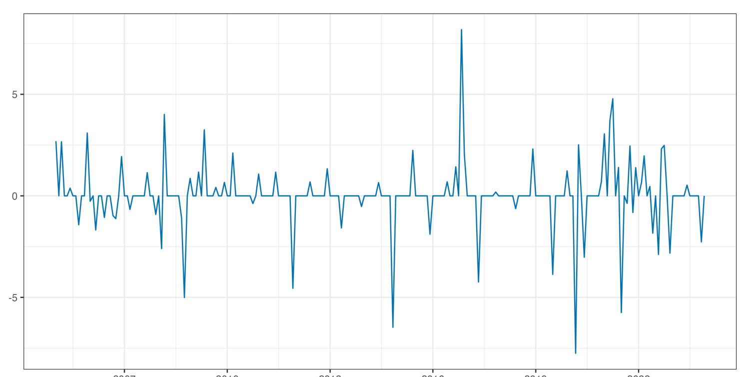


Figure E26: *The Brent oil supply surprises series*

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.

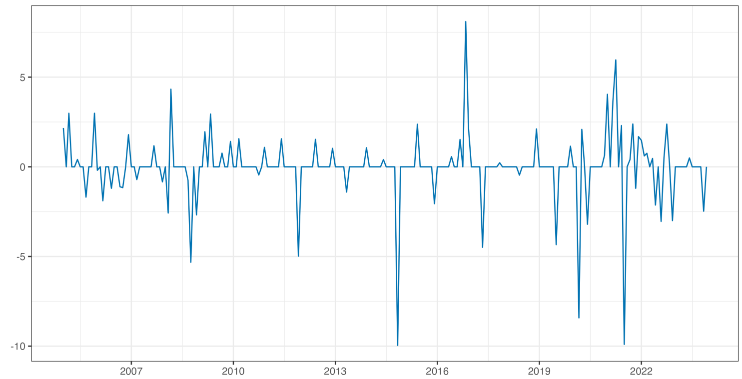


Figure E27: *The WTI oil supply surprises series*

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

E.4 EA: Gas and oil markets interrelation

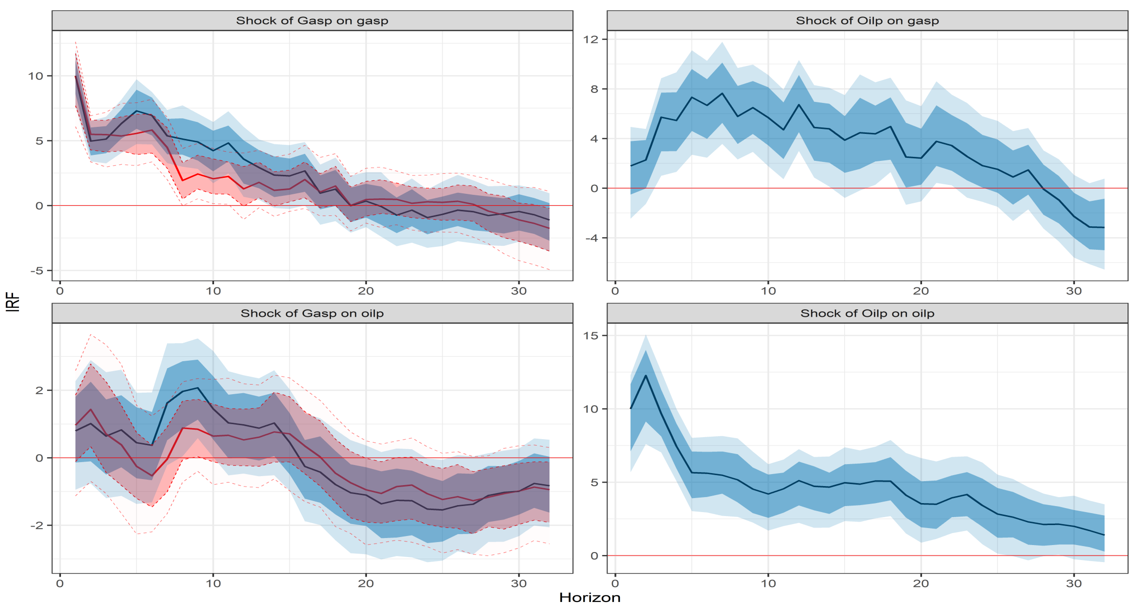


Figure E28: *Interrelation of Gas and Oil markets in the Euro Area*

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.