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Gas market shocks: tracing the effect on euro area inflation expectations

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Abstract

This paper examines the impact of natural gas market shocks on gas market dynamics, inflation expectations and realized inflation in the Euro Area using a BVAR model. Our contribution lies in a novel identification strategy that distinguishes between various types of shocks of unprecedented detail, leverages weekly rather than monthly data, and extends the analysis to both market-based headline and core inflation expectations. We find that, although conceptually distinct, pipeline and liquefied natural gas (LNG) supply shocks have comparable effects on realized variables such as gas prices and actual inflation. By contrast, LNG supply shocks play a more limited role in shaping inflation expectations. Precautionary demand and industrial demand shocks also emerge as important drivers of inflation dynamics. This reflects both the forward-looking nature of precautionary shocks, which capture changes in investor sentiment, and the broader macroeconomic relevance of industrial demand shocks, whose effects extend beyond the gas market.

Keywords: gas price, supply shocks, demand shocks, inflation-linked swaps, local projections

JEL Codes: C50, C54, E44, Q43

Non-technical summary

The sharp increase in European gas prices following Russia's invasion of Ukraine in 2022 pushed inflation to levels not seen in decades and exposed significant gaps in our understanding of how energy markets shape price dynamics. While the role of oil prices has been widely studied, natural gas received comparatively little attention prior to the recent crisis. As a result, understanding how developments in gas markets affect inflation has become a key priority for policymakers.

Against this background, this paper makes three main contributions to the emerging literature on the European gas market. First, it develops a new Bayesian vector autoregressive (BVAR) model that identifies, with unprecedented granularity, the different sources of fluctuations in this market. In particular, the model distinguishes between five types of shocks: disruptions to pipeline gas supply, changes in global liquefied natural gas (LNG) supply, variations in industrial demand, weather-related demand, and precautionary demand (reflecting concerns about future shortages). Second, the analysis relies on weekly data for Europe over the period 2018 to 2024, thus providing a higher-frequency perspective than the monthly data typically used in the literature and allowing for a more timely assessment of market developments. Third, the paper examines how these different shocks affect both headline and core inflation expectations.

The results are as follows. First, a detailed decomposition of gas market shocks helps explain the major movements in European gas prices during the 2022 energy crisis, with precautionary demand shocks playing a more prominent role than previously recognised. Second, we find that shocks to pipeline gas supply and LNG supply, although arising from different sources, have similar effects on gas prices and inventories. However, despite this similarity, LNG supply shocks exert a more limited influence on inflation expectations, possibly because they receive less attention from investors. Third, the findings indicate that, alongside pipeline supply shocks, precautionary demand shocks in the short term and industrial demand shocks in the medium term are key drivers of inflation expectations.

These findings have several implications for monetary policy. Developments in the European gas market need to be assessed within a global framework, as international LNG supply conditions play a crucial role. At the same time, precautionary demand can significantly influence inflation expectations even in the absence of actual supply shortfalls, underscoring the importance of closely monitoring market sentiment and expectations in real time. Moreover, distinguishing between different types of shocks is essential, as they imply different degrees of persistence in inflationary pressures. Overall, a granular, high-frequency analysis of gas market developments can enhance the assessment of inflation risks and support more informed policy decisions.

1 Introduction

The energy crisis triggered by the Russian invasion of Ukraine in 2022 renewed interest in the interplay between energy prices and inflation. While the economic effects of oil price shocks have been extensively studied (Baumeister and Hamilton, 2019; Caldara et al., 2019; Kilian, 2009; Kilian and Murphy, 2014; Peersman and Van Robays, 2009), far less attention has been devoted to understanding the role of natural gas prices, largely due to their relatively limited impact on inflation prior to 2022. In Europe, this was partly due to the indexation of natural gas prices to oil prices and the smaller weight of gas relative to oil in the consumer price index.[1]

This dynamic began to shift as natural gas prices started to rise in the fall of 2021, in the months leading up to Russia's invasion of Ukraine, culminating in an unprecedented surge in prices. The transition from oil price indexation to "gas-to-gas pricing" in 2015 (Adolfsen et al., 2022), increased the sensitivity of natural gas prices to supply and demand conditions. Combined with sharp reductions in gas inflows from the summer of 2021 onward, this led to an unprecedented surge in prices. The resulting inflationary pressures led central banks to confront inflation levels unseen since the oil crises of the 1970s and 1980s. It became clear that the existing knowledge about the economic role of oil prices was insufficient to guide the optimal policy response to the rapidly evolving dynamics of the natural gas market.

In this paper, we contribute to the emerging literature on the connection between natural gas prices and inflation in Europe, which gained traction during the recent energy crisis (Adolfsen et al., 2024; Alessandri and Gazzani, 2025; Bańbura et al., 2023; Buquet and Stalla-Bourdillon, 2024; Casoli et al., 2024; Güntner et al., 2024). Our contribution to this body of work is threefold.

First, we develop an empirical model with a granular identification of structural shocks in the natural gas market. Specifically, we propose a novel Bayesian Structural Vector Auto-regressive (BVAR) model for the European gas market that distinguishes between

[1] In 2025, HICP weights were 1.7% for natural gas and 4.4% for oil (liquid fuels and fuels, and lubricants for personal transport equipment).

five types of shocks: pipeline gas supply shocks, global LNG supply shocks, industrial demand shocks, weather-related demand shocks, and precautionary demand shocks.

This new identification strategy helps to better understand supply-side dynamics, as we distinguish between pipeline gas supply shocks and liquefied natural gas (LNG) supply shocks, a distinction that, to our knowledge, has not been made in the literature. Pipeline gas supply shocks mainly capture regional supply disturbances that affect gas delivered through Europe's fixed pipeline infrastructure, such as those caused by political conflicts or maintenance issues, making them localized in nature. By contrast, LNG supply shocks are more closely tied to global dynamics, as LNG is transported by ship and traded internationally, with Europe and Asia as the main destination markets. This distinction is particularly important given Europe's increasing reliance on LNG following the sharp decline in Russian pipeline gas imports, which has heightened the region's exposure to global economic and geopolitical developments.

On the demand side, our model extends beyond traditional classifications drawn from the oil market literature, which typically distinguish between demand driven by economic activity and precautionary inventory accumulation. In particular, we identify weather-related demand shocks, an often overlooked yet important driver of natural gas market dynamics. These shocks capture fluctuations in consumption arising from extreme weather conditions, such as cold winters that raise heating demand or droughts that constrain alternative energy sources, including hydropower and nuclear generation.[2] Importantly, weather-related demand shocks are largely orthogonal to the business cycle, which distinguishes them from industrial demand shocks that are closely linked to fluctuations in economic activity.

Second, we estimate our BVAR at a weekly frequency, unlike most existing studies that rely on monthly or even quarterly data. From a policy perspective, a higher observation frequency is particularly valuable during periods of heightened market volatility. In such environments, the ability to monitor developments and update assessments in near real time is essential for policymakers responding to rapidly evolving conditions. From

[2] Such events played a role in the European energy crisis, as highlighted by Emiliozzi et al. (2025).

a methodological perspective, weekly data are particularly useful for identifying shocks that may be obscured or averaged out in lower-frequency data, especially given the high responsiveness of financial variables to shocks. Working with weekly data also allows for a more targeted analysis of a sample period largely shaped by the 2022 energy crisis, without relying on observations from earlier periods characterized by fundamentally different conditions in the European gas market.

Third, we examine the pass-through of gas market structural shocks to market-based inflation expectations, thereby shedding new light on the transmission of energy price dynamics to inflation. Using a local projection framework following Jordà (2005) and building on the approach of Boeck and Zörner (2025), we extend the literature by jointly analyzing the effects of gas market shocks on both headline and core inflation expectations. To this end, we rely on market-based measures extracted from euro area inflation-linked swap (ILS) rates, including estimates for both headline and core inflation expectations from Grønlund et al. (2024). This setup allows us to capture potential second-round effects and provides a deeper understanding of how gas market shocks propagate beyond energy prices to influence underlying inflation expectations.

Our results yield several key findings. First, our BVAR model, as demonstrated by historical decomposition, effectively captures the major events that have shaped European gas prices. The granularity of our shock identification allows us to capture both localized dynamics, such as the impact of a cold spell in Asia on LNG supply in December 2020, and large-scale supply disruptions following the Russian invasion of Ukraine. Importantly, our richer specification reveals a more prominent role of precautionary demand as a driver of gas price increases during the 2021-23 energy crisis in Europe in comparison to existing literature. Second, the impulse response function (IRF) analysis reveals that while pipeline and LNG supply shocks originate from distinct sources, their effects on European gas prices and inventories are remarkably similar, highlighting the complementary role of these two energy sources. Third, along with pipeline supply shocks, our local projection analysis indicates that precautionary demand shocks in the short term and industrial demand shocks in the medium term are important drivers of inflation expectations. This reflects the forward-looking nature of precautionary shocks and the broader macroeconomic impact of industrial shocks, which are closely linked to business cycle fluctuations. This conclusion is supported by the local projection results for realized inflation, where the same two shocks also play a central role. In contrast, LNG shocks have a significant effect on realized inflation, but their influence is not fully captured in market-based measures of inflation expectations, pointing to a disconnect between observed dynamics and investor perceptions.

Our findings indicate that, because pipeline and LNG supply shocks have comparable effects (at least on realized price dynamics), the European gas market should not be examined in isolation from the broader global gas market. Furthermore, our results stress that precautionary shocks can affect ILS rates and core inflation expectations and lead to persistent increases in inflation, even without actual supply disruptions. The importance of precautionary demand shocks for inflation developments is a novel finding relative to existing literature and emphasizes that such shocks should not be overlooked by policymakers in their decision-making processes.

The remainder of the study is organized as follows: Section 2 reviews the relevant literature, Section 3 details the data and BVAR methodology, Section 4 presents our model results, Section 5 discusses the findings from local projections, Section 6 conducts robustness checks, and Section 7 concludes.

2 Literature Review

This paper contributes to two related aspects of the emerging literature on the European gas market. The first concerns the identification of gas market shocks, while the second, more specific, examines how gas price shocks originating from different sources are transmitted to inflation expectations.

Regarding the identification of structural shocks first, research on natural gas markets has initially drawn on the well-established oil market literature, notably the seminal contributions of Kilian and Murphy (2014) and Baumeister and Hamilton (2019). This body of work focuses on identifying and decomposing supply and demand shocks, with particular emphasis on economic activity, inventory dynamics, and geopolitical developments. These analytical frameworks have subsequently been extended to natural gas markets, albeit predominantly in the US context. For instance, Wiggins and Etienne (2017) apply sign restrictions following Kilian and Murphy (2014) to identify supply and demand shocks to natural gas prices, distinguishing between shocks related to economic activity and those driven by inventory adjustments. Similarly, Rubaszek et al. (2021) adopt an approach akin to Baumeister and Hamilton (2019) to disentangle comparable shocks in the US natural gas market.[3]

By contrast, the study of European natural gas markets has developed more recently, partly because European gas prices were historically indexed to oil prices. Within this newer strand of the literature, Adolfsen et al. (2024) use a monthly BVAR with sign and narrative restrictions to identify shocks in European gas prices and assess their inflationary effects. Güntner et al. (2024) follow a similar methodology with a focus on the German gas market. Alessandri and Gazzani (2025) propose an identification strategy based on daily news related to the European gas market to isolate supply shocks. Taking a broader perspective, Casoli et al. (2024) integrate both oil and gas markets within a large Bayesian SVAR framework to study the macroeconomic effects of energy price shocks. In comparison to these studies, our paper offers a richer and novel identification of structural shocks, notably LNG supply shocks and weather-related demand shocks. Whereas earlier research largely relied on frameworks developed for the oil market to analyze gas markets in a simplified manner, distinguishing these additional shocks has become increasingly important for understanding the specific dynamics of gas markets. This is due, first, to the heightened sensitivity of gas markets to weather conditions compared to oil markets and, second, to the dual reliance of the European gas market on both pipeline supply and LNG supply. Notably, the dynamics of the LNG market differ from those in the market for pipeline gas, with the latter having gained greater importance for Europe after Russia's invasion of Ukraine.

[3]Other studies on the US gas market include Arora and Lieskovsky (2014), Nick and Thoenes (2014), Jadidzadeh and Serletis (2017), and Hailemariam et al. (2019).

Additionally, within these frameworks, the use of higher-frequency data to analyze the real-time dynamics of gas markets remains relatively limited. Most existing studies rely on monthly or quarterly physical market data, with the notable exception of Alessandri and Gazzani (2025). Against this backdrop, our study stands out by proposing a new identification strategy for European gas markets that combines physical gas market data with financial market indicators at a weekly frequency, thereby enabling a more timely assessment of market dynamics. Alessandri and Gazzani (2025) focus on news about gas supply inspired by Känzig (2021)'s paper on oil markets. This implies that they capture both actual shocks to supply of pipeline and LNG gas as well as precautionary behavior driven by news about actual or potential supply shocks. As an example, they use the date of Russia's invasion of Ukraine to identify supply shocks, despite the fact that the immediate response of Russian gas flows to Europe remained very limited during the early phase of the war. Through our more granular shock decomposition, we show that the Russian invasion of Ukraine constituted a precautionary demand shock, where the ensuing inflation dynamics are distinct from those typically observed following a supply shock.

Second, the literature on the pass-through of natural gas price shocks to market-based inflation expectations, particularly in the euro area, remains sparse. Adolfsen et al. (2024) do analyze the effects of gas shocks on HICP inflation using local projections, but they focus solely on realized inflation and not inflation expectations. More recently, Boeck and Zörner (2025) study the impact of real natural gas price shocks on market-based inflation expectations, an objective closely related to ours. Their analysis, however, is conducted at a monthly frequency, which may not fully capture the high-frequency nature of market pricing. Moreover, their framework does not offer a detailed decomposition of gas price shocks originating within the gas market itself, thereby leaving the heterogeneous effects of distinct shock types unexplored. This omission contrasts with the insight from Kilian (2009) who demonstrates that the nature of energy shock is key for understanding the pass-through effects on the economy. Importantly, Boeck and Zörner (2025) examine pass-through to ILS rates without explicitly accounting for the inflation risk premium embedded in these instruments. Our paper addresses these gaps.

3 Gas Market BVAR

3.1 Data

The endogenous variables in our BVAR model include European gas prices (TTF), gas consumption, inventory levels, European pipeline imports, the spread between the Asian LNG prices (Japan Korea Marker or JKM) and the European TTF prices and a stock price index composed of companies that are particularly sensitive to gas market dynamics. All variables are expressed in log differences, except for the spread between Asian and European prices, which is taken in first differences given that it may take negative values. The model is estimated at a weekly frequency, with all variables aggregated as weekly averages to capture high-frequency dynamics while minimizing noise. Table 1 summarizes the sources and transformations for each series. The sample period spans from 1 January 2018 to 10 June 2024 and includes a total of 337 weekly observations.

Table 1: Data description

	Series and source	Transformation
TTF	TTF Dutch gas price via LSEG	Weekly average and first log differences
$CONS$	Gas consumption in NWE via LSEG	Moving average, seasonally adjusted and first log differences
INV	European inventory level via GIE	Seasonally adjusted, weekly average and first log differences
$PIPE$	EU pipeline imports via Bloomberg	Weekly average and first log differences
JKM	Spread between JKM LNG prices and TTF prices via LSEG	Weekly average and first differences
EQ	based on MSCI EMU sector indices (chemicals, paper, metals and minerals) via LSEG	Weekly average and first log differences

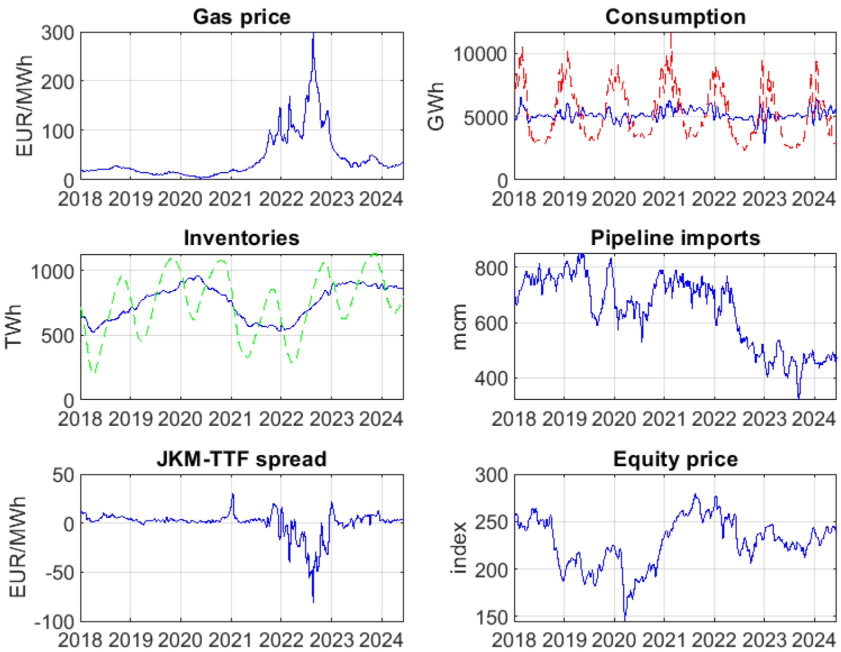
Notes: Seasonal adjustment and de-trending following Cleveland et al. (1990).

For European gas prices, we use the one-month futures contract of the Title Transfer Facility (TTF), the Dutch benchmark price, which is the most liquid and widely traded gas hub price (Heather, 2023). Gas consumption data are derived from daily consumption of local distribution zones (LDZ), representing household consumption, and non-local distribution zones (non-LDZ), which include large industrial users or other large consumers, for North-West Europe (NWE), comprising Germany, France, the Netherlands and Belgium. The use of NWE consumption is due to the lack of high-frequency data for other EU countries. Gas inventories are measured using the European Gas Storage index provided by Gas Infrastructure Europe (GIE), which reports end-of-day gas storage volume in TWh. Both gas consumption and inventories are seasonally adjusted following Cleveland et al. (1990).[4] EU pipeline imports are captured as the aggregate of daily net pipeline flows into the EU from Russia, Norway, Africa, Azerbaijan, and the UK, with data sourced from Bloomberg. In our robustness checks presented in Section 6, we also account for the recent downward trend in consumption stemming from structural changes in European energy usage driven by EU policy responses to the 2022 gas crisis. For Asian LNG prices, we use the JKM price index, which represents the Northeast Asian spot price for LNG delivered ex-ship to Japan and Korea, as assessed by S&P Global Platts. This index also accounts for cargo deliveries to Taiwan and China. The JKM-TTF price spread is a widely recognized metric to evaluate the relative tightness between the Asian market and the European market. For the equity price index, we use European MSCI indices of sectors with high gas intensity, as their stock prices are particularly sensitive to gas market fluctuations. This follows the idea of Gazzani et al. (2024) who also rely on stock prices as a high frequency measure of economic activity. Our focus on gas-sensitive sectors, such as chemicals, paper, metals, and minerals, enhances the precision of our identification strategy. Using sectoral equity prices rather than a broad market index helps ensure that the indicator captures economic developments that are directly linked to gas demand. Broad equity indices are frequently dominated by sectors whose performance is largely unrelated to energy markets (e.g. technology), and thus may fail to adequately capture effects of gas-intensive sectors.

All endogenous variables in our BVAR are presented in Figure 1.

[4] For gas consumption in particular, the absence of residual seasonality has been confirmed by examining the autocorrelation function of the seasonally adjusted series, which shows neither a negative correlation at six-month lags nor a positive correlation at twelve-month lags, as typically observed in non-adjusted gas market variables.

Figure 1: Data used in the endogenous variable vector of the BVAR



Note: The figures represent the different variables used in the endogenous vector of the BVAR, described in more detail in Table 1. TTF and JKM (i.e. the JKM-TTF spread) are in EUR/MWh, INV, CONS and PIPE in MWh and EQ represents an equity index in EUR. Blue solid lines indicate the series used in the BVAR, dashed lines refer to the corresponding series prior to seasonal adjustments (red for consumption, green for inventories).

3.2 Methodology: Structural Bayesian VAR

Our reduced-form VAR model can be represented as follows:

$$\mathbf{Y}_t = \mathbf{C} + \sum_{n=1}^{p} \mathbf{A}_n \mathbf{Y}_{t-n} + \mathbf{u}_t. \tag{3.1}$$

$\mathbf{Y}_t$ is a vector of endogenous variables and $\mathbf{u}_t$ represents the vector of residuals, assumed to follow an independent and identically distributed multivariate normal distribution: $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma})$. The lag order p is set to 13 based on standard information criteria. The model parameters are estimated using Bayesian methods, specifically by adopting the standard Minnesota priors with hyper-parameters selected as in Giannone et al. (2015) to optimize the posterior distribution. The variables included in $\mathbf{Y}_t$ are listed in Table 1.

To recover economically meaningful shocks, we employ a structural identification strategy, where the structural form of the model is given by:

$$\mathbf{B}_0\mathbf{Y}_t = \mathbf{B}_0\mathbf{C} + \mathbf{B}_0\sum_{n=1}^{p}\mathbf{A}_n\mathbf{Y}_{t-n} + \mathbf{B}_0\mathbf{u}_t, \tag{3.2}$$

or rewritten as

$$\mathbf{B}_0\mathbf{Y}_t = \mathbf{\Phi}_0 + \sum_{n=1}^{p}\mathbf{\Phi}_n\mathbf{Y}_{t-n} + \mathbf{e}_t \tag{3.3}$$

where $\mathbf{B}_0$ denotes the contemporaneous impact matrix and $\mathbf{e}_t$ the structural shocks with a diagonal variance-covariance matrix (normalized here to the identity matrix $\mathbf{I}$). It thus follows that $\mathbf{e}_t = \mathbf{B}_0\mathbf{u}_t$. The challenge in this framework is the identification of the contemporaneous impact matrix $\mathbf{B}_0$. The reduced-form residual covariance matrix $\mathbf{\Sigma}$ is linked to $\mathbf{B}_0$ through the relationship: $\mathbf{\Sigma} = \mathbf{B}_0^{-1}\mathbf{B}_0^{-1\prime}$. Without additional restrictions, $\mathbf{B}_0$ is not identified.

3.3 Shock Identification

Our objective is to identify economically meaningful structural shocks that characterize the dynamics of the European gas markets. We select a comprehensive set of shocks based on insights from the energy literature and the recent structural transformations of gas markets. To this end, we impose sign restrictions on the contemporaneous responses, as detailed in Table 2. In the table, a '+' (increase) or '-' (decrease) indicates the direction of the variable's response following a specific shock. Starting with the ***demand side***, we distinguish three specific shocks:

- The first shock is an ***industrial demand shock***, which captures increased gas consumption by energy-intensive European companies driven by an upswing in the European business cycle. A positive industrial demand shock is assumed to lead to an increase in TTF prices, higher gas consumption, and a decline in European gas storage levels. This shock is expected to trigger a positive supply response from pipeline flows, resulting in higher European pipeline imports. Since this shock signals favorable economic conditions, it also boosts the stock prices of gas-intensive companies. Additionally, as the shock reflects an improvement in the European business cycle specifically, it drives a proportionally larger rise in TTF prices compared to JKM prices, thereby affecting negatively the JKM-TTF spread.

- The second shock, building on the seminal identification of Kilian and Murphy (2014), is a ***precautionary demand shock*** linked to fears of future supply disruptions. This shock is characterized by an immediate increase in TTF prices and identified by a concurrent rise in European gas inventories, reflecting precautionary stockpiling by market participants. Since the disruption has not yet materialized, the stockpiling occurs via higher pipeline imports. The JKM-TTF spread is left unrestricted since a precautionary shock may arise from concerns about either pipeline flows or LNG market tightness. The consumption response to this shock is left unconstrained, though a decline is likely. On equity prices, we assume a negative impact as price increases will weigh on margins of energy-intensive sectors.

- The third shock is a ***weather-related shock***. Such shocks reflect unexpected weather events, such as colder-than-anticipated winters or heatwaves, which increase gas demand for heating or air conditioning beyond typical seasonal levels.[5] Weather conditions can affect electricity generation from non-gas power sources such as wind, solar, and hydropower. Even nuclear power plants can be impacted through river droughts affecting cooling systems.[6] Given the significant role these factors played in the European energy crisis, we argue that treating these phenomena as structural shocks is more appropriate than simply controlling for extreme temperatures, as done by Nick and Thoenes (2014).[7] Normalizing this shock by an increase in gas prices, we assume that it leads to higher gas consumption, lower gas inventories, increased pipeline flows, and a decline in gas-related equity prices following higher input prices of the sectors considered.[8] Since this shock is specific to the European

[5]As we seasonally adjust some of the variables in our BVAR, this shock will capture weather-related factors that represent strong deviations from seasonal patterns.

[6]We assume that episodes of unexpected declines in nuclear output, such as the one that affected the French fleet in 2022 due to stress corrosion, would be captured by this weather-related shock.

[7]Additionally, controlling for extreme temperatures does not account for periods of low wind farm output, among other factors.

[8]Note that equity prices in gas-sensitive sectors may vary both in response to changes in expected

market, it is expected to reduce the JKM-TTF spread.

On the ***supply side***, we identify two types of shocks in our BVAR model: one related to pipeline flows and the other to LNG flows. To our knowledge, this distinction has not been made before in the SVAR literature on gas markets.

- First, ***pipeline supply shocks*** capture unexpected declines in pipeline flows to Europe, such as the onset of the energy crisis in October 2021 when Russia unilaterally reduced its exports. Such shocks, characterized by a drop in pipeline flows, raise TTF prices, reduce European gas inventories, and lead to a drop in gas-related stock prices. Since localized pipeline shocks primarily affect Europe rather than Asia, the JKM-TTF spread is assumed to decrease.

- Second, ***LNG supply shocks*** capture global disruptions in LNG availability. These can arise from events such as strikes at export facilities or surges in Asian gas demand. Specifically, heightened Asian demand diverts LNG shipments away from Europe, reducing the availability of supply for European markets. From a European perspective, this reduction in LNG inflows is effectively experienced as a supply-side constraint. While the LNG supply shock shares similarities with the pipeline supply shock, it differs in two key respects: First, it induces an increase in pipeline flows to Europe as countries seek alternative sources of gas. Second, and most importantly, it leads to a widening of the JKM-TTF spread, reflecting that the shock affects more LNG Asian prices than European gas prices, as Asian markets tend to be more reliant on LNG and hence more sensitive to supply constraints.

Finally, one shock is left unrestricted to capture various factors influencing European gas market dynamics that are not explicitly accounted for by the five identified shocks. This residual shock may, for example, encompass disruptions in European domestic natural gas production. However, given that European production is on a long-term decline, covering only 16% of European consumption on average in our sample, see Figure A.1 in

cash flows and to variations in risk premia. However, this distinction is not critical in our setting, as both channels generate movements in equity prices that are sufficient to distinguish between "good" and "bad" news for the sector, and thus to differentiate industrial demand shocks from weather-related shocks.

Table 2: Sign restriction table

	EU ind. demand	EU prec. demand	EU weather-related demand	EU pipel. flow	Global LNG tightness	unre-stricted
TTF	+	+	+	+	+	
$CONS$	+		+			
INV	-	+	-	-	-	
$PIPE$	+	+	+	-	+	
JKM	-		-	-	+	
EQ	+	-	-	-	-	

Notes: TTF refers to the European TTF gas price, $CONS$ refers to gas consumption, INV refers to inventories, $PIPE$ refers to pipeline and JKM to the JKM-TTF spread. EQ refers to the average of gas intensive production industries' sectoral equity price indices.

the Appendix, it is reasonable not to focus extensively on this factor. This shock may also reflect additional forces at play during the 2022 energy crisis, such as non-linear dynamics arising in extreme market conditions that are difficult to capture within a linear framework, as well as speculative behaviour and portfolio adjustments by market participants during periods of heightened volatility (Brousse et al., 2023).

4 BVAR Empirical Results: Gas Prices Drivers

This section presents the results of our BVAR analysis, focusing on the drivers of European gas prices during the sample period.[9] The findings draw on insights from the historical decomposition and impulse response functions. Importantly, our results demonstrate that the model effectively identifies major events in the gas market and attributes them to the prevailing narratives, providing evidence of its ability to capture the underlying economic mechanisms.

4.1 Overall Evidence from the Historical Decomposition

The historical decompositions reveal that the European gas market is shaped by a complex interaction of supply and demand shocks. Figure 2 shows the decomposition of TTF prices, highlighting the relative contributions of the five identified shocks: pipeline supply shocks, LNG supply shocks, industrial demand shocks, precautionary demand shocks, and weather-related demand shocks. Initial conditions capture the contribution of pre-sample

[9] The estimation of our model is based on 1,000 accepted draws, corresponding to an acceptance rate of 0.0069%.

shocks that cannot be identified within the estimation window (Kilian and Lütkepohl, 2017).

Before the energy crisis, gas price dynamics were largely shaped by industrial demand, LNG supply and precautionary demand shocks. For instance, during the COVID-19 pandemic, the sharp decline in TTF prices was primarily due to negative industrial demand shocks, reflecting reduced energy consumption during the global economic downturn. LNG supply shocks also played a role, as lower demand for LNG globally increased supply availability and further suppressed prices.

The onset of the energy crisis in late 2021 marked a shift in the dynamics of the European gas market, with pipeline supply shocks and precautionary demand shocks identified by our model as dominant drivers of price increases. Notably, pipeline supply shocks kept pushing TTF prices higher from summer 2022 onward, reflecting the sustained decline in Russian pipeline deliveries, as discussed in more detail below. Similarly, precautionary demand shocks played a significant role during this period, as uncertainty surrounding the security of energy supplies led to stockpiling behavior and increased risk premiums.[10] Conversely, industrial demand shocks and LNG supply shocks helped moderate the price surge, particularly from the second half of 2022, as European governments implemented energy-saving measures and increased LNG imports. The latter was facilitated by the flexibility of US LNG exports amid extra capacity and a simultaneous slowdown in Chinese economic activity, which released additional LNG supply to the European market.

Weather-related demand shocks, while less prominent, also influenced TTF price dynamics during specific periods. For instance, in 2022, these shocks contributed to the price surge due to increased gas consumption resulting from reduced hydropower production in Spain and lower nuclear electricity generation in France (Emiliozzi et al., 2025).[11]

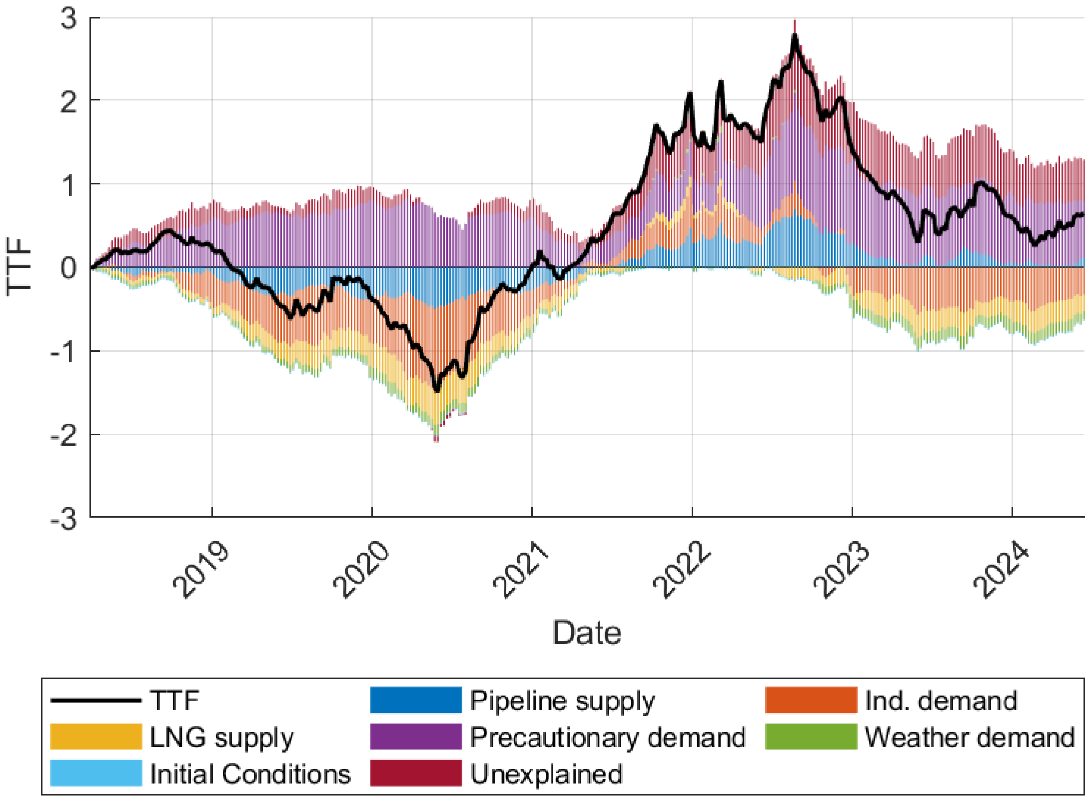
From 2023 onward, as these energy sources returned to normal production levels and

[10] Large precautionary demand shocks are particularly pronounced around the peak in gas prices in August 2022. Some analysts argue that these dynamics were partly driven by the 2022 policy requiring EU member states to meet mandatory gas storage targets. By encouraging market participants to secure storage ahead of others, this policy may have generated unintended coordination effects. Such behavior may have generated precautionary demand shocks and contributed to higher gas prices (see OIES, 2025).

[11] As the contribution of weather-related demand shocks turns from negative to slightly positive in 2022. Note that the unexpected declines in nuclear output in 2022, caused by stress corrosion affecting the French fleet, is categorized here as a weather-related shock.

Europe experienced relatively mild weather, these factors contributed to easing TTF prices, which our model captures as a negative driver in Figure 2. However, the most prominent driver of lower gas prices during this period was subdued industrial demand, likely driven by adverse impacts that high gas prices had on many European firms.

Figure 2: Historical decomposition of the cumulated changes in TTF prices



Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Our richer specification provides new insights into the drivers of gas prices during the 2021-23 energy crisis relative to Adolfsen et al. (2024), Güntner et al. (2024) and Alessandri and Gazzani (2025). First, we find a more prominent role of precautionary demand shocks, which contrast with the findings of existing studies that attribute the acceleration in gas prices mainly to supply shocks. Second, our analysis highlights the role of LNG markets in first amplifying gas shocks in early 2022 and subsequently contributing to their dampening, a channel that has remained largely unexplored in previous specifications. Third, we show that favorable weather conditions dampened gas prices, while existing studies conflate weather effects with industrial demand shocks (Adolfsen et al., 2024; Güntner et al., 2024). The distinctions have important policy implications, as the pass-through effects of these different types of shocks to inflation expectations and realized inflation differ substantially, as shown in Section 5.

Table B.1 in the Appendix further substantiates these results by reporting the contribution shares of each shock across different periods. Precautionary demand shocks emerge as the dominant driver throughout the historical decomposition, accounting for nearly 40 percent of changes in the TTF price. We also find that the contributions of pipeline and LNG supply shocks are similar in magnitude. By contrast, industrial demand shocks played a more prominent role prior to the crisis, reflecting the impact of the Covid pandemic on industrial gas demand.

Historical decompositions of variables beyond the TTF price also support our identification strategy. For example, Figure B.6 in the Appendix illustrates the decomposition of the JKM–TTF spread over time. One notable event captured by the model is the winter of 2021–2022, when a prolonged cold spell in Asia widened the spread of JKM-TTF and drove TTF prices higher, as JKM prices increased even more sharply.[12] The model attributes this development to an LNG supply shock driven by stronger Asian demand. Turning to 2022, the decomposition of the JKM–TTF spread provides additional insights into market dynamics. Comparing Figure 2 with Figure B.6, we observe that the JKM–TTF spread was pushed lower by a combination of pipeline supply shocks, precautionary demand shocks, and LNG supply shocks. However, the mechanisms underlying this decline differed across shocks. Pipeline supply and precautionary demand shocks reduced the spread by pushing up TTF prices, whereas positive LNG supply shocks, driven by the slowdown in the Chinese economy, narrowed the spread by dampening price increases in JKM more than in TTF. This illustrates how European gas prices were indirectly contained by developments in the global LNG market.

[12] See for example OIES (2021).

4.2 Zooming on Key Events during the European Energy Crisis

To further illustrate the dynamics captured by our model during the energy crisis, we focus on three key events that represented critical turning points in the European energy crisis. Figures B.3, B.4, and B.5 in the Appendix present historical decompositions of cumulative TTF price changes around these three events. These events represent a subset of those used in the external instrumental variable approach employed by Alessandri and Gazzani (2025) to identify gas supply shocks. While our results reaffirm the importance of supply shocks in driving gas price movements during these periods, they also reveal additional dynamics that contribute to price fluctuations.

- **October 2021: The Yamal Pipeline Reduction** The episodes mark the unofficial beginning of the European energy crisis in late September to early October 2021, when Russia abruptly halved gas exports via the Yamal pipeline. Initially perceived as a temporary measure, this reduction signaled the start of a gradual decline in European gas supplies. Analysts widely regarded this supply cut as unexpected, making it a textbook case of an immediate pipeline supply shock that significantly influenced price changes between September and October 2021. Our model identifies this episode as a significant pipeline supply shock, which contributed substantially to the sharp increase in TTF prices between September and October 2021.

- **February 2022: Russian Invasion of Ukraine** The second event is the Russian invasion of Ukraine on February 24, 2022. While this event did not immediately disrupt physical gas supplies, it generated significant uncertainty, leading to precautionary demand shocks. Our model rightfully attributes the corresponding price surge primarily to this shock, as European countries increased stockpiling amid fears of future supply interruptions.

- **June 2022: Reduction in Nord Stream 1 Flows** The third event occurred in early June 2022, when Gazprom announced reductions in gas supplies to the Netherlands, Denmark, and Germany. This decision followed heightened tensions between Russia and several European countries that rejected Moscow's demand to settle gas payments in rubles rather than euros, as stipulated in existing contracts. As a result, flows through Nord Stream 1 declined sharply. Our model correctly identifies this episode as mostly driven by pipeline supply shocks, although other shocks also contributed to the observed dynamics, notably precautionary demand shocks.

4.3 Insights from IRFs: Magnitude and Persistence of Shocks

The IRFs from our BVAR model, presented in Figure 3, provide additional insights into the magnitude and persistence of the identified shocks. Several key findings emerge.

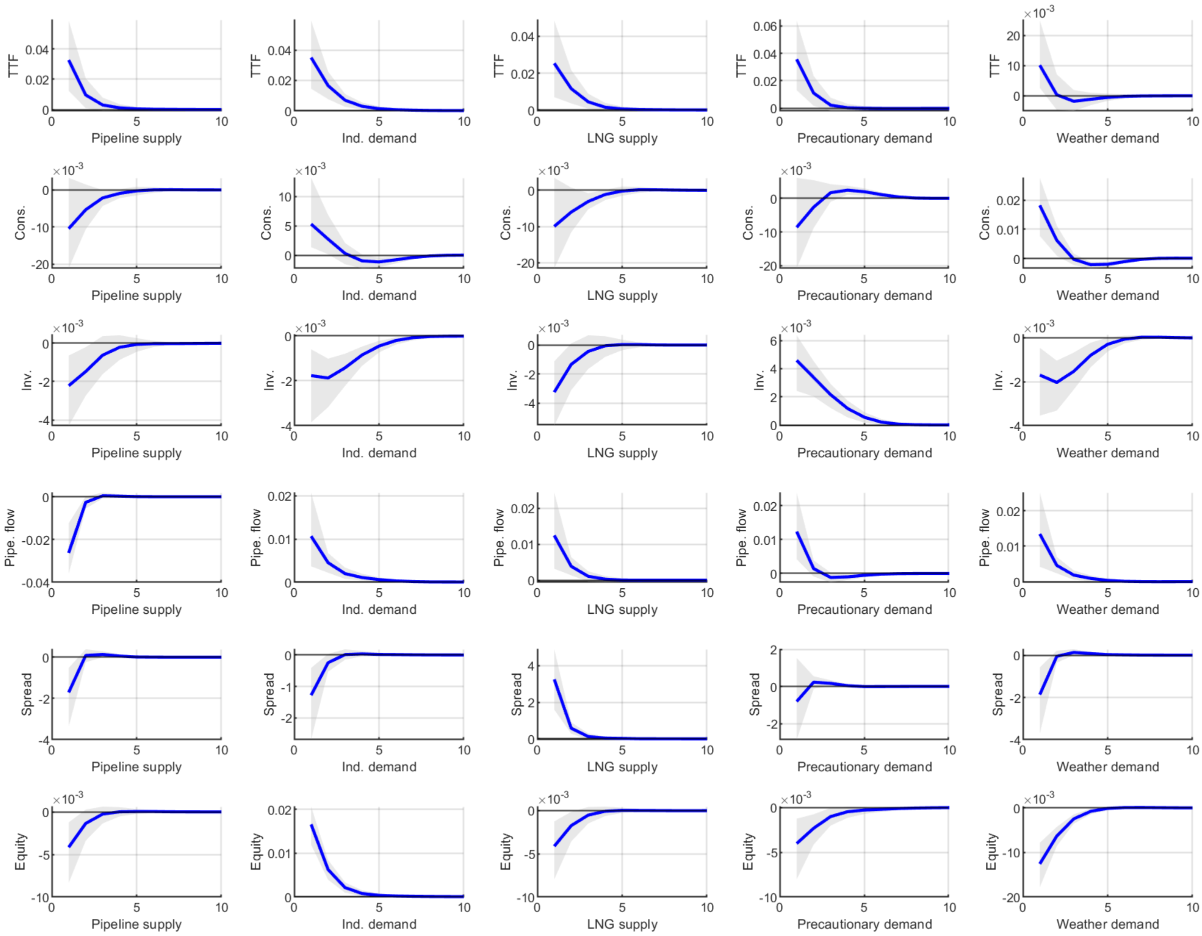
First, all five shocks exert a positive and significant effect on TTF prices, consistent with the imposed sign restrictions. However, the magnitude of the effects varies across shocks. Precautionary demand shocks generate the strongest response in gas prices, reflecting the immediate and pronounced impact of uncertainty and stockpiling behavior during periods of heightened geopolitical tension. Alongside the strong effects of industrial demand shocks, supply shocks, both pipeline and LNG, also have sizable impacts, as disruptions to gas flows translate directly into significantly higher prices. Weather-related demand shocks, while still significant, have the smallest impact on gas prices, as their effects are typically more localized and seasonal.

Second, although pipeline supply and LNG supply shocks are identified differently (see Table 2) and influence TTF price dynamics in distinct ways (see Figure 2), their effects on fundamental gas market variables are remarkably similar. A one standard deviation shock to pipeline supply and a comparable shock to LNG supply lead to similar impacts on TTF prices, gas consumption, and gas inventories. This similarity is sensible because, when normalizing by their effects on gas prices, and outside specific events like the congestion at LNG import terminals in the summer of 2022, a reduction in gaseous gas supplied by pipeline from Russia and a disruption in liquefied gas supplied to the European network should ultimately have analogous consequences.[13]

[13] During this period, as both LNG import capacity and pipeline capacity towards Northwestern Europe were saturated, any unexpected LNG inflows to Europe would have been unable to reduce TTF prices.

Third, industrial demand shocks exhibit the most persistent effects, particularly on gas inventories. This persistence reflects the broader economic implications of industrial demand shocks, which influence not only the gas market but also the overall European business cycle.

Figure 3: Impulse Response Functions from the BVAR



Note : The figure reports the IRFs from the baseline VAR (non-cumulated). The VAR is estimated under a Minnesota prior with 13 lags. The solid line represents the mean posterior IRF, whereas the bands report 68% credible set. All y-axes are measured in log changes (decimal units), except for the IRFs of the JKM-TTF spread, which are expressed in EUR/MWh.

5 Pass-through of Gas Price Shocks to Market-Based Measures of Inflation Expectations

Energy prices, particularly gas, have been widely discussed as key drivers of post-pandemic inflation (see ECB Strategy Review, 2025). However, far less is known about how financial markets have priced these shocks into inflation expectations.

To address this question, we rely on market-based measures of inflation compensation, namely ILS rates, which offer a distinct advantage for assessing the impact of gas price shocks on inflation dynamics. Unlike survey-based measures, ILS rates reflect real-time assessments by financial market participants and thus capture expectations about the persistence versus transitory nature of such shocks. Building on this insight, we employ a local projection (LP) framework in the spirit of Boeck and Zörner (2025) to analyze how natural gas shocks affect inflation dynamics. However, we apply different types of shocks to gas prices, while Boeck and Zörner (2025) use a single shock to gas prices that captures many different underlying dynamics. As an innovation, we evaluate the effects of structural shocks not only on market-based inflation compensation, but more importantly on inflation expectations purged of inflation risk premia, for both headline and core inflation, following the approach of Grønlund et al. (2024).

5.1 Data on Market-Based Measures of Inflation Expectations

Grønlund et al. (2024) aim to infer not only market-based headline inflation expectations but also core inflation expectations in the euro area, for which information is not directly observable in financial markets owing to the absence of financial instruments explicitly linked to core inflation. To overcome this, they estimate a model of traded headline ILS rates. This model is then used to price synthetic Euro Area core ILS contracts, hypothetical instruments tied to core inflation, and to infer underlying market-based core inflation expectations and inflation risk premia.

Their approach is based on several key assumptions. First, HICP inflation is assumed to be determined by a linear combination of a small set of pricing factors that follow a simple VAR process. Second, core inflation is also assumed to be a linear combination of the same pricing factors, a reasonable assumption given that HICP inflation is itself composed of core inflation and energy and food inflation. Third, the ILS market is assumed to be free of arbitrage opportunities, ensuring that headline and core ILS rates of any maturity are linear combinations of these pricing factors.

Using these assumptions, they estimate the model on a monthly dataset comprising ILS rates tied to HICP inflation, realized HICP and core inflation, as well as survey-based expectations of headline and core inflation from the ECB's Survey of Professional Forecasters (SPF). This allows them to generate plausible estimates of both synthetic core ILS rates and genuine market-based expectations for core and headline inflation. Both core and headline inflation expectations, i.e. ILS cleansed from premia, are incorporated into our analysis. In this exercise, we focus on genuine market-based expectations at the 1-year horizon. The corresponding time series are displayed in Figure A.2 in the Appendix.

5.2 Local Projection Methodology

We assess the spillover effects of gas market shocks on inflation expectations and realized inflation using local projections, following the methodology of Jordà (2005) and Cloyne et al. (2023). Specifically, we estimate the following equation recursively:

$$y_{t+h} = \alpha_j^h + \beta_j^h e_{jt} + \mathbf{X}_t'\mathbf{\Gamma_j} + w_{jt+h} \tag{5.1}$$

In the equation above, the term e_{jt} corresponds to one of the five structural shocks identified in our BVAR framework, while $\mathbf{X}_t$ denotes a set of control variables. y_{t+h} denotes either headline or core inflation expectations, averaged at a weekly frequency, or realized headline or core inflation, in which case the shocks e_{jt} are averaged at a monthly frequency.

Regarding the control variables, we adopt a parsimonious approach by including only Brent price returns as well as the lagged values of the dependent variable in $\mathbf{X}_t$. For the monthly local projections in Section 5.3.1, we additionally include the monthly growth rate of global industrial production to control for global economic conditions. Since our shocks are generated regressors, standard errors are inherently biased because they do not account for the uncertainty in Equation 3.2. In order to capture both uncertainty in the estimation and identification of the structural shocks in the BVAR, and the sampling uncertainty in the local projection coefficients conditional on those shocks, we construct confidence intervals using the bootstrap procedure described in Swanson (2021).[14]

Finally, for some of our local projection analyses, we also report the forecast error variance decompositions of the left-hand-side variables with respect to the different structural shocks. Following the methodology of Gorodnichenko and Lee (2020), we regress the forecast errors of Equation 5.1, $\hat{f}_{t+h}$, on the lead values of a given structural shock:

$$\hat{f}_{t+h} = a_{z,0} e_{jt+h} + ... + a_{z,h} e_{jt} + \tilde{v}_{t+h} \tag{5.2}$$

We then use the R^2 from Equation 5.2 as a measure of the contribution of shock e_{jt} to the forecast error variance decomposition of variable y_{t+h} in Equation 5.1.

5.3 Empirical results

Figures 4 and 5 present the results of our local projection analysis for market-based expectations of average headline and core inflation expectations over the next year, respectively, where shocks are rescaled so that they account for a 10% increase in gas prices on impact. Several key findings emerge.

First, **pipeline supply shocks** have a positive and statistically significant effect on headline inflation expectations. This effect, however, becomes statistically insignificant after a few weeks, indicating that the impact might only be transitory. By contrast, **LNG supply shocks** also induce a positive response, but the estimated effects remain statistically insignificant over the entire horizon. This divergence between the effects of pipeline and LNG supply shocks suggests that investors trading ILS linked to euro area inflation focus more on the former, which materialize directly within Europe, than on the latter, which originate in distant regions such as Qatar or the US. A comparison of Figures 4 and 5 shows that both shocks generate broadly similar responses in core inflation expectations, albeit with intuitively smaller magnitudes. The statistically significant positive response of core inflation expectations to pipeline supply shocks, even if

[14] We draw with replacement e_{jt} and w_{jt+h}, use these draws to generate pseudo-dependent variables y_{t+h}, estimate the coefficients β_j^h, and repeat this process 1,000 times to build the confidence intervals. However, note that confidence intervals based on standard errors computed with the Newey–West procedure yield broadly similar results.

more muted, indicates that market participants anticipate second-round effects, as higher energy costs gradually propagate through the broader production.

Second, **precautionary demand shocks** exert a particularly strong and statistically significant effect on both headline and core inflation expectations. Among gas-related structural shocks, thus excluding industrial demand shocks that may reflect broader macroeconomic conditions, they display the largest impact on inflation expectations after a few weeks.[15] This pronounced response is intuitive, as precautionary demand shocks themselves stem from shifts in expectations about future developments in gas markets. Following such a shock, both headline and core inflation expectations rise by around 0.2 percentage points after 4 weeks.

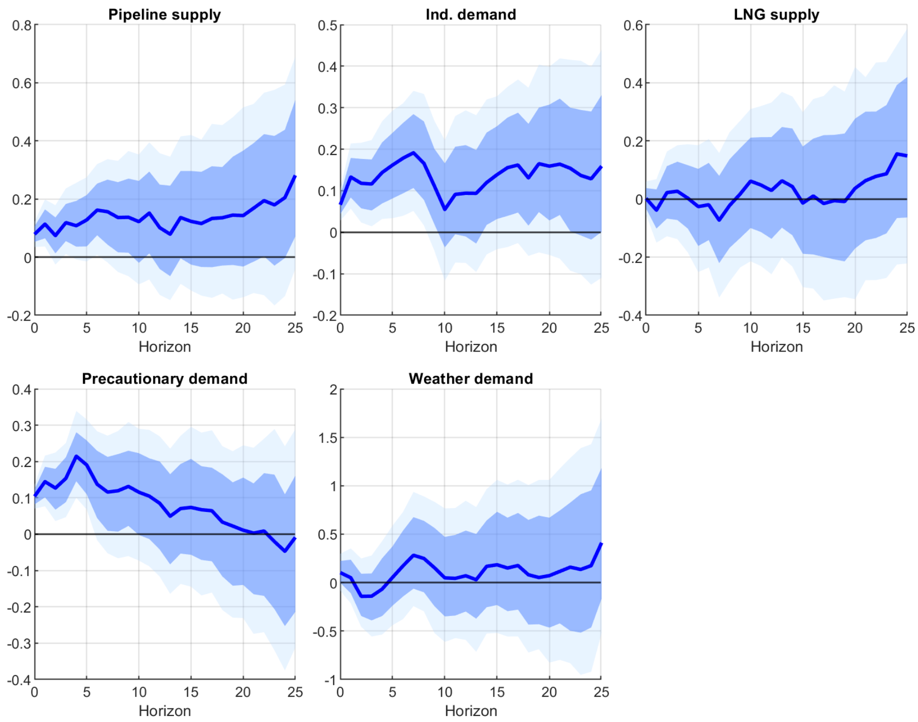
Third, **weather-related demand shocks** do not have a significant positive effect on either headline or core expectations on impact. This may be because, aside from prolonged events such as droughts or persistent cold spells, most weather-related disturbances are short-lived and not expected to exert lasting effects on consumer prices.

Finally, **industrial demand shocks** generate large and persistent effects on both headline and core inflation expectations. After a few weeks for example, headline inflation expectations increase by up to 0.2 percentage points. This comparatively strong response likely reflects the broad macroeconomic relevance of industrial demand shocks, which extend beyond the gas market to affect the European business cycle more widely.

The relative importance of the different shocks is further illustrated by the variance decomposition exercise described in Section 5.2. As shown in Figure C.7 in the Appendix, it appears that although the identified shocks explain only about 45 percents of the variance in inflation expectation proxies, the results confirm previous findings: pipeline supply shocks, precautionary demand shocks and industrial demand shocks emerge as the primary drivers of both headline and core expectations. By contrast, LNG supply

[15] Note that precautionary demand shocks may arise either from expectations of tighter future gas supply, as discussed in Section 3, or from changes in risk premia, for example when market participants perceive future supply as more volatile or when risk aversion increases. To assess the relevance of this latter channel, we examine, in unreported results, the effect of precautionary demand shocks on the slope of the gas futures curve, which is commonly interpreted as a proxy for investors' risk premia. We find that precautionary demand shocks leading to an increase in gas prices also significantly affect the slope, pushing the curve further into backwardation. This result indicates that precautionary demand shocks are not solely expectation-driven but also operate through a risk-premium channel.

Figure 4: Impulse Response Functions of headline inflation expectations to the gas BVAR structural shocks



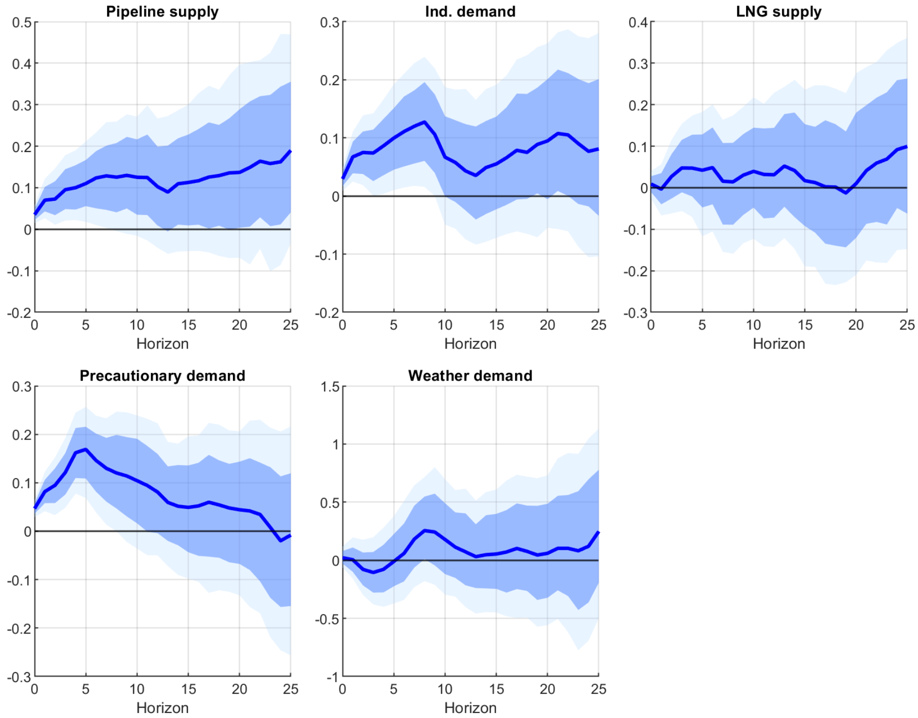
Note : The figure illustrates the response of market-based 1-year headline inflation expectations from Grønlund et al. (2024) to structural shocks in the gas BVAR model. The x-axis represents time in weeks, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

shocks and weather-related shocks account for only a marginal share of the variance in expectations. Thus, our results nuance the findings of Boeck and Zörner (2025), who document strong second-round inflationary effects from generic gas price shocks operating through inflation expectations. We show instead that the impact on expectations depends critically on the nature of the underlying shock, as effects from shocks to LNG supply and weather-related demand are limited, while the time profile of effects from the other types of shocks also differ. These differences highlight that policy responses to mitigate second-round effects from gas price shocks should differ across types of shocks.

5.3.1 Results for Realized Inflation

To complement the analysis, we also examine the impact of our shocks on realized inflation, rather than on inflation expectations, using the same methodology. Here, the left-hand-side variable y_{t+h} is the monthly series of HICP inflation for the Euro Area,

Figure 5: Impulse Response Functions of core inflation expectations to the gas BVAR structural shocks

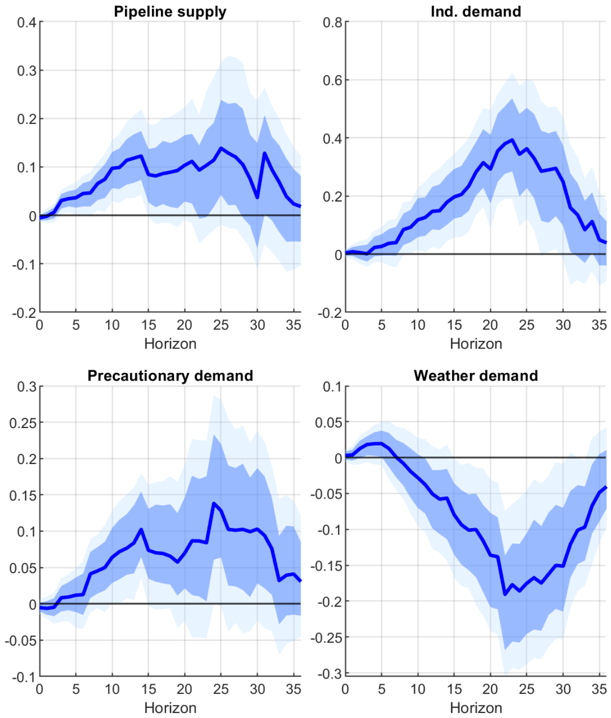


Note : The figure illustrates the response of market-based 1-year-ahead core inflation expectations from Grønlund et al. (2024) to structural shocks in the gas BVAR model. The x-axis represents time in weeks, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

either headline or core. To ensure consistency in frequency, the right-hand-side shocks e_{jt} are aggregated to monthly data using arithmetic averages. Figures 6 and 7 present the results for headline and core inflation, respectively. As before, the IRFs are rescaled so that the shocks correspond to a 10 percent increase in gas prices in the first month.

The findings broadly mirror those obtained for inflation expectations, reinforcing earlier conclusions. Strong influential inflationary effects again stem from **pipeline supply**, **precautionary demand**, and especially **industrial demand shocks**. The effects of precautionary demand shocks underscore the value of our more detailed shock decomposition relative to Adolfsen et al. (2024), who find only limited effects from inventory shocks. Their findings may partly reflect a less granular decomposition, in which inventory shocks capture offsetting dynamics in the gas market. Similar to inflation expectations, the overall magnitude of these effects, however, remains limited: for instance, a 10 percent gas price increase caused by an industrial demand shock raises inflation by only 0.4

Figure 6: Impulse Response Functions of realized headline inflation to the gas BVAR structural shocks



Note : The figure illustrates the response of realized Euro Area HICP inflation to structural shocks in the gas BVAR model. The x-axis represents time in months, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

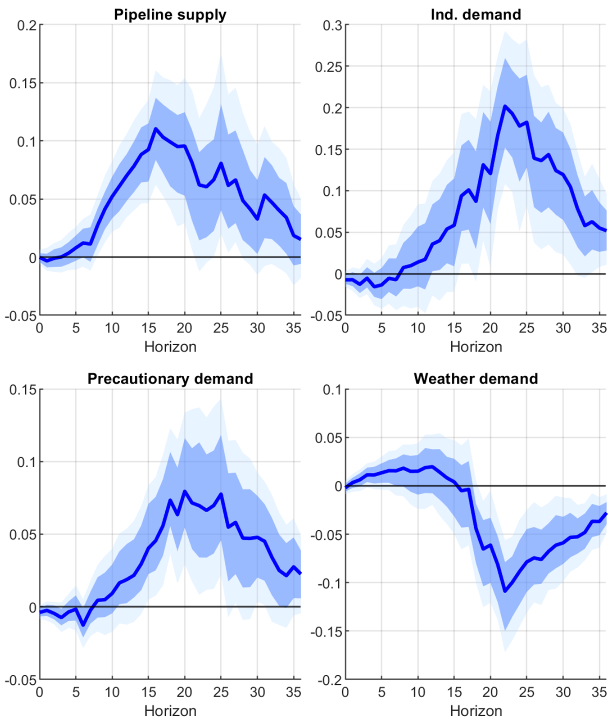
percentage point after two years.[16]

By contrast with inflation expectations, **LNG supply shocks** have a positive and statistically significant impact on both headline and core realized inflation, with magnitudes similar to those associated with pipeline supply shocks. This indicates that, for realized outcomes such as gas prices or actual inflation, LNG shocks are as influential as pipeline shocks, consistent with the evidence presented in Section 4.3. In other words, while LNG shocks materially influence observed outcomes, their role is less meaningful for market-based inflation expectations, indicating a disconnect between realized dynamics

[16]Despite the seemingly small estimated effects, a simple rule of thumb suggests that the magnitudes are broadly consistent with the price developments observed during the 2022 energy crisis. In our results, a 10% increase in gas prices driven by either a pipeline supply shock or a precautionary demand shock, the two main forces behind the crisis, leads to an increase in inflation of about 0.1% after roughly one year. Comparing the onset of the energy crisis with the peak of both variables, euro area inflation rose by 6.6 percentage points, from 4% in October 2021 to 10.6% in October 2022, while gas prices increased by about 550% from October 2021 to their peak. Within our framework, a 550% increase in gas prices would therefore imply a 5.5 percentage point rise in inflation, which is of the same order of magnitude as the observed increase (6.6).

and investor perceptions.[17]

Figure 7: Impulse Response Functions of realized core inflation to the gas BVAR structural shocks



Note : The figure illustrates the response of realized Euro Area core HICP inflation to structural shocks in the gas BVAR model. The x-axis represents time in months, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

Weather-related demand shocks display a pattern similar to that observed in the analysis of inflation expectations, with a negative contribution emerging after a few months, likely reflecting their dampening effect on demand. As this effect takes time to materialise in economic activity, it translates into a delayed impact on inflation. Finally, consistent with Section 5.3, all shocks exert a broadly less pronounced influence on core inflation than on headline inflation.

Overall, the richer shock specification in our paper provides important nuances to

[17]Note that, as our analysis is conducted at a weekly frequency for inflation expectations and at a monthly frequency for realized inflation, a direct assessment of investors' forecast errors is not straightforward. However, a natural comparison consists in relating the on-impact responses of one-year-ahead inflation expectations in Figures 4 and 5 to the responses at the 12-month horizon in Figures 6 and 7. In this respect, inflation expectations appear broadly consistent with subsequent developments in realized inflation. Two notable exceptions nevertheless emerge. First, pronounced forecast errors are associated with LNG supply shocks, for both headline and core inflation, as discussed. Second, investors seem to underestimate the medium-term deflationary effects of weather-related demand shocks, as also elaborated below.

Alessandri and Gazzani (2025) and Adolfsen et al. (2024) regarding the pass-through of gas price shocks to realized inflation. First, our results suggest that spikes in gas prices driven by precautionary demand may necessitate a stronger policy response than implied by the results in Adolfsen et al. (2024) to mitigate the risk of second-round effects materializing. Second, we find that pipeline supply shocks have a smaller impact on core inflation compared to the supply shocks effects reported by Alessandri and Gazzani (2025). This discrepancy likely stems from their identification strategy, which may conflate precautionary demand shocks in anticipation of supply disruptions and LNG shocks within their broader supply shock. Third, while Adolfsen et al. (2024) find significant and persistent effects on headline and core inflation from demand shocks that reduce gas inventories, our analysis shows these inflationary effects are not observed when the increase in gas demand is driven by weather factors.

6 Robustness Checks and Complementary Analyses

We assess the robustness of our results along eight dimensions. First, as discussed above, we maintain the same restrictions as in Table 2 but remove the downward trend in consumption observed in recent years. This decline reflects structural changes in European energy demand driven by EU policies implemented after the 2022 gas crisis. We test whether our results remain consistent once this adjustment is made.

Second, while keeping the same identification strategy, we relax the sign restrictions by dropping two constraints that are not strictly necessary for identifying orthogonal structural shocks. Specifically, we remove the assumption that pipeline supply and LNG supply shocks must exert a negative impact on gas-sensitive equity indices.

Third, we assess the robustness of our results to the exclusion of the weather-related demand shock. In other words, we examine whether the results hold when this shock is left unconstrained, resulting in two unrestricted shocks in this specification.

Fourth, we change the variable used to identify LNG supply shocks, replacing the JKM–TTF spread with actual LNG flows to Europe, available weekly from Bloomberg.

This modification creates greater symmetry in the identification of pipeline and LNG supply shocks, as in this case both shocks are identified by a drop in gas volumes. We then adjust the sign restrictions as detailed in Table 3. As shown in the table, this alternative identification strategy requires additional restrictions beyond those imposed in the baseline specification. Specifically, we assume that a negative EU pipeline flow shock reduces pipeline imports while inducing partial substitution through higher LNG imports, with the converse holding for LNG supply shocks. To rule out a one-to-one replacement between the two sources, we impose relative magnitude restrictions. In addition, for LNG supply shocks, we allow for delayed effects on LNG imports, pipeline imports, and inventories. While prices are expected to react immediately to disruptions in LNG shipments, the physical impact on imports occurs with a lag of one to three weeks, reflecting the time required for tankers to reach Europe depending on the shipping route.[18]

Fifth, given the relatively low persistence of the impulse response functions reported in Figure 3, we also re-estimate the BVAR using shorter lag lengths, namely 4 and 8 lags instead of 13.

Sixth, the baseline results in Section 5 are based on market-based headline and core inflation expectations estimated using the methodology of Grønlund et al. (2024). However, pure ILS rates, namely inflation compensations that include also inflation risk premia, are frequently used in policy discussions as a proxy for headline inflation expectations. We therefore also examine the effect of structural shocks on these alternative measures. In this case, headline inflation compensation reflects observable ILS rates, while core ILS rates are again model-based estimates from Grønlund et al. (2024).

Seventh, the structural parameters of the European gas market may have shifted with the energy crisis, reflecting changes such as the replacement of Russian pipeline flows by LNG supply. To test whether our findings are robust, we re-estimate the BVAR over a pre-crisis sample, from 1 January 2018 to 24 September 2021. As noted by Buquet and Stalla-Bourdillon (2024), this cutoff precedes the Ukraine invasion but coincides with the effective onset of the energy crisis, as GIE data show a complete halt to gas injections

[18] These estimates reflect the average shipping time to European ports, accounting for variation in routes, such as from the US or Qatar.

Table 3: Sign restriction table - Robustness check

	EU pipel. flow	Global LNG tightness	EU ind. demand	EU weather-related demand	EU prec. demand	unre-stricted
TTF	+	+	+	+	+	
$CONS$			+	+		
INV	-	-	-	-	+	
$PIPE$	-$*$	+$*$	+	+	+	
LNG	+$*$	-$*$	-	-	-	
EQ	-	-	+	-		

Notes: TTF refers to the gas price, $CONS$ refers to gas consumption, INV refers to inventories, while $PIPE$ and LNG refer to pipeline and LNG imports respectively. EQ refers to the average of gas intensive production industries' sectoral equity price indices. Restrictions denoted with $*$ are subject to further restrictions, namely relative magnitude and timing restrictions. EU pipeline flow shocks impact pipeline imports relatively more than LNG imports, while the opposite is true for global LNG tightness shocks. Sign restrictions are all imposed on impact, except for the global LNG tightness shock which is delayed to only impact LNG imports, pipeline imports and inventories after 1 to 3 weeks, with the impact on the gas price being set to 0 and 2 weeks.

into Poland on 28 September 2021, followed by numerous days of near-zero deliveries.

Eighth, we assess the robustness of our results on inflation expectations by replacing ILS-based measures with survey-based expectations from the ECB's Consumer Expectations Survey (CES), and evaluating the impact of the structural shocks accordingly.

Figures D.8, D.9, D.10, D.11, D.12 and D.13 in the Appendix show the historical decomposition of TTF prices based on the first four robustness checks. As these figures illustrate, the results remain broadly consistent regardless of changes in the treatment of endogenous variables, in the identification strategy or in the BVAR lag lengths. Figures D.14 and D.15 present the LP IRFs for inflation compensation. Switching from inflation expectations to inflation compensation has little effect on the results across the five structural shocks.

Figures D.16 and D.17 report the pre-crisis estimates. Pre-crisis estimates appear also broadly similar to previous results for both headline and core inflation. However, two differences stand out. First, LNG supply shocks appear, somewhat counterintuitively, to exert a stronger effect on inflation expectations in the pre-crisis sample than in the full-sample estimates. This pattern may reflect the prominent role of LNG supply shocks in driving the decline in gas prices in 2020, when the contraction in economic activity during the COVID crisis, especially in China, strongly affected gas prices relative to other shocks (see Figure 2). Second, precautionary demand shocks and pipeline supply shocks, which later became the main drivers of the energy crisis, have only very limited effects on inflation expectations on impact in the pre-crisis estimates. Although a detailed investigation lies beyond the scope of this study, this pattern likely reflects nonlinearities in the relationship between gas shocks and inflation expectations, whereas the framework outlined in Section 5 is linear. In other words, the full-sample estimates include substantially larger precautionary demand and pipeline supply shocks, which also interacted with elevated levels of uncertainty and may therefore have exerted disproportionately strong effects on inflation expectations, thereby generating the positive on-impact responses reported in Figures 4 and 5.

Finally, Figure D.18 in the Appendix presents the results for one-year-ahead CES inflation expectations (at monthly frequency). Several conclusions emerge. First, compared with ILS-based measures, survey-based expectations adjust more slowly to shocks. At the six-month horizon (corresponding to the end of the horizon in Figure 4), none of the shocks, except for pipeline supply and weather-related demand shocks, exert a statistically significant effect, and the overall magnitudes remain modest. Second, over the same horizon, CES-based inflation expectations appear more responsive to pipeline than to LNG supply shocks, in line with previous findings. Third, at longer horizons (around 15 to 20 months), inflation expectations increase in response to shocks, with a particularly pronounced effect for industrial demand shocks, consistent with the results for realised inflation. Overall, these results indicate that, intuitively, survey-based inflation expectations adjust more gradually than those derived from ILS rates.

7 Conclusion

This paper investigates the relationship between natural gas market shocks, market-based inflation expectations and realized inflation in the Euro Area, addressing a gap in the literature on energy price dynamics. Using a high-frequency (weekly) BVAR model, we distinguish between different types of gas market shocks to analyze how supply and demand disruptions influence broader price dynamics.

On the results side, based on these specifications, we first show that our BVAR effectively captures key events shaping European gas prices, as evidenced by their historical decomposition. Second, the impulse response function analysis further reveals that although pipeline and LNG supply shocks differ in nature, their effects on European gas prices and inventories are strikingly similar, underscoring the complementary role of these two energy sources. Third, our local projection analysis shows that inflation expectations are driven not only by pipeline supply shocks, but also by precautionary demand shocks in the short run and industrial demand shocks over the medium term. This pattern reflects the forward-looking nature of precautionary shocks and the broader macroeconomic relevance of industrial demand shocks, which are closely linked to business cycle fluctuations. These results are further corroborated by the local projection estimates for realized inflation, where the same three shocks again play a central role. Fourth, by contrast, LNG shocks significantly affect gas prices and realized inflation but are not strongly reflected in market-based inflation expectations, highlighting a disconnect between observed dynamics and investor perceptions.

The importance of precautionary demand shocks throughout the paper suggests that concerns about future gas availability, rather than actual supply disruptions, can play a much more crucial role in shaping gas market dynamics and market-based inflation expectations than suggested by existing literature. Moreover, our findings highlight the increasing integration of European and global gas markets, emphasizing the role of external factors in policymakers' assessments of inflation risks. Future research could explore the effects of policy interventions, such as strategic gas storage or price caps, on inflation expectations in energy markets.

References

Adolfsen, J. F., Kuik, F., Lis, E. M., Meyler, A., et al. (2022). Energy price developments in and out of the covid-19 pandemic–from commodity prices to consumer prices. *ECB Economic Bulletin*, 4.

Adolfsen, J. F., Minesso, M. F., Mork, J. E., and Van Robays, I. (2024). Gas price shocks and euro area inflation. *Journal of International Money and Finance*, 149:103183.

Alessandri, P. and Gazzani, A. (2025). Natural gas and the macroeconomy: not all energy shocks are alike. *Journal of Monetary Economics*, page 103749.

Arora, V. and Lieskovsky, J. (2014). Natural gas and us economic activity. *The Energy Journal*, 35(3):167–182.

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

Bańbura, M., Bobeica, E., and Hernández, C. M. (2023). What drives core inflation? The role of supply shocks. *ECB Working Paper Series*, (2875).

Boeck, M. and Zörner, T. O. (2025). Natural gas prices, inflation expectations, and the pass-through to euro area inflation. *Energy Economics*, 141:108061.

Brousse, C., Même, N., Saillard, M., and Stalla-Bourdillon, A. (2023). The impact of energy shocks on financial stability in the context of the 2022 episode [les conséquences des chocs énergétiques sur la stabilité financière à l'aune de l'épisode de 2022]. *Bulletin de la Banque de France*, (249).

Buquet, M.-A. and Stalla-Bourdillon, A. (2024). Identifying fundamental shocks on the European natural gas market. *Available at SSRN 4890626*.

Caldara, D., Cavallo, M., and Iacoviello, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics*, 103:1–20.

Casoli, C., Manera, M., and Valenti, D. (2024). Energy shocks in the Euro Area: disentangling the pass-through from oil and gas prices to inflation. *Journal of International Money and Finance*, page 103154.

Cleveland, R. B., Cleveland, W. S., McRae, J. E., Terpenning, I., et al. (1990). Stl: A seasonal-trend decomposition. *Journal of Official Statistics*, 6(1):3–73.

Cloyne, J., Jordà, Ò., and Taylor, A. M. (2023). State-dependent local projections: Understanding impulse response heterogeneity. *National Bureau of Economic Research Working Paper*, (30971).

Emiliozzi, S., Ferriani, F., and Gazzani, A. (2025). The European energy crisis and the consequences for the global natural gas market. *The Energy Journal*, 46(1):119–145.

Gazzani, A., Venditti, F., and Veronese, G. (2024). Oil price shocks in real time. *Journal of Monetary Economics*, 144:103547.

Giannone, D., Lenza, M., and Primiceri, G. E. (2015). Prior selection for vector autoregressions. *Review of Economics and Statistics*, 97(2):436–451.

Gorodnichenko, Y. and Lee, B. (2020). Forecast error variance decompositions with local projections. *Journal of Business & Economic Statistics*, 38(4):921–933.

Grønlund, A. M., Jørgensen, K., and Schupp, F. (2024). Measuring market-based core inflation expectations. *ECB Working Paper Series*, 2908.

Güntner, J., Reif, M., and Wolters, M. (2024). Sudden stop: Supply and demand shocks in the German natural gas market. *Journal of Applied Econometrics*, 39(7).

Hailemariam, A., Smyth, R., and Zhang, X. (2019). Oil prices and economic policy uncertainty: Evidence from a nonparametric panel data model. *Energy economics*, 83:40–51.

Heather, P. (2023). European traded gas hubs: Their continued relevance. OIES Paper: NG 183, The Oxford Institute for Energy Studies.

Jadidzadeh, A. and Serletis, A. (2017). How does the US natural gas market react to demand and supply shocks in the crude oil market? *Energy Economics*, 63:66–74.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

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

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

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

Kilian, L. and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3):454–478.

Nick, S. and Thoenes, S. (2014). What drives natural gas prices?—a structural var approach. *Energy Economics*, 45:517–527.

Peersman, G. and Van Robays, I. (2009). Oil and the euro area economy. *Economic Policy*, 24(60):603–651.

Rubaszek, M., Szafranek, K., and Uddin, G. S. (2021). The dynamics and elasticities on the US natural gas market. A Bayesian Structural VAR analysis. *Energy Economics*, 103.

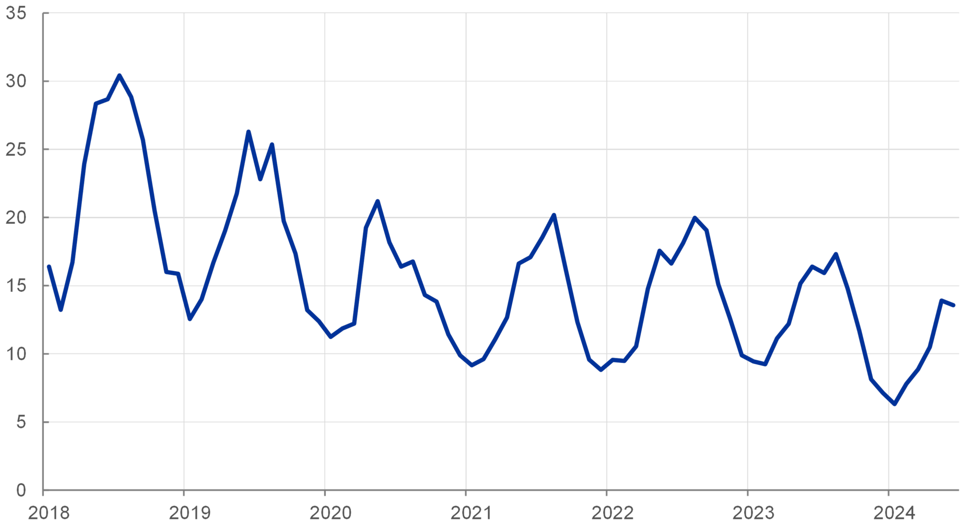
Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118:32–53.

Wiggins, S. and Etienne, X. L. (2017). Turbulent times: Uncovering the origins of us natural gas price fluctuations since deregulation. *Energy Economics*, 64:196–205.

Appendix

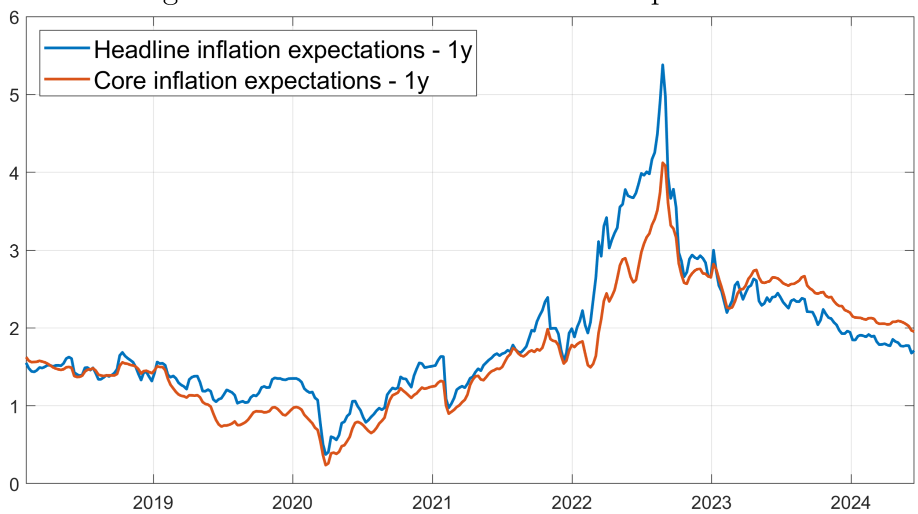
A Additional descriptive graphs

Figure A.1: European domestic natural gas production



Note: The figure represents the European domestic natural gas production (excluding Great Britain) divided by the corresponding natural gas consumption over time.

Figure A.2: Market-based inflation expectations



Note : The figure illustrates the market-based headline and core inflation expectations from Grønlund et al. (2024) (at a 1-year horizon). The x-axis represents time in weeks, while the y-axis denotes percentage changes.

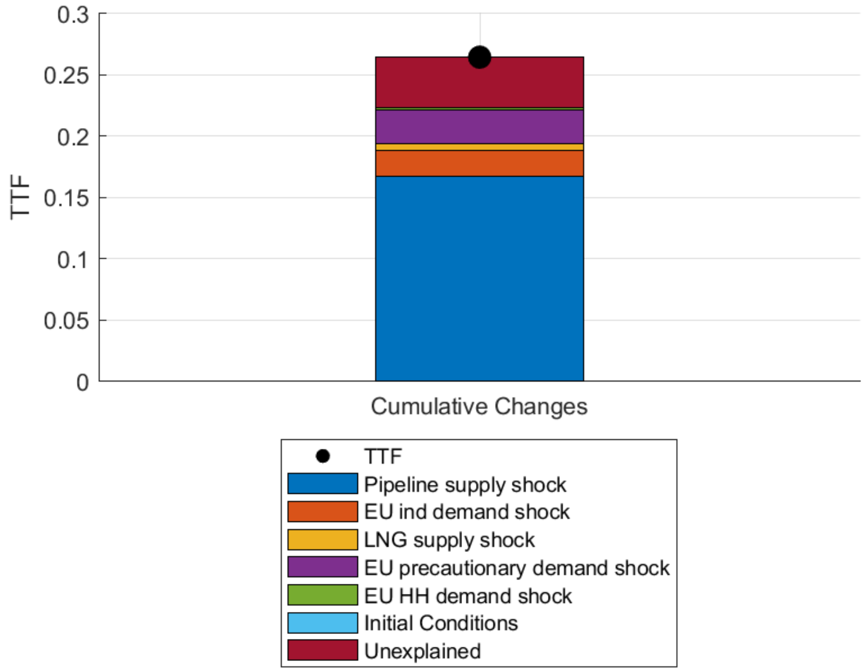
B TTF historical decomposition on specific events

Table B.1: Average shock contribution to TTF historical decomposition

	Ind. demand	Prec. demand	Weather demand	Pipel. supply	LNG tightness	unre-stricted	Init. cond.
Full sample	0.19	0.37	0.04	0.12	0.09	0.18	0.02
Pre-crisis	0.22	0.38	0.04	0.12	0.10	0.12	0.02
Crisis and post-crisis	0.15	0.36	0.04	0.12	0.07	0.25	0.01

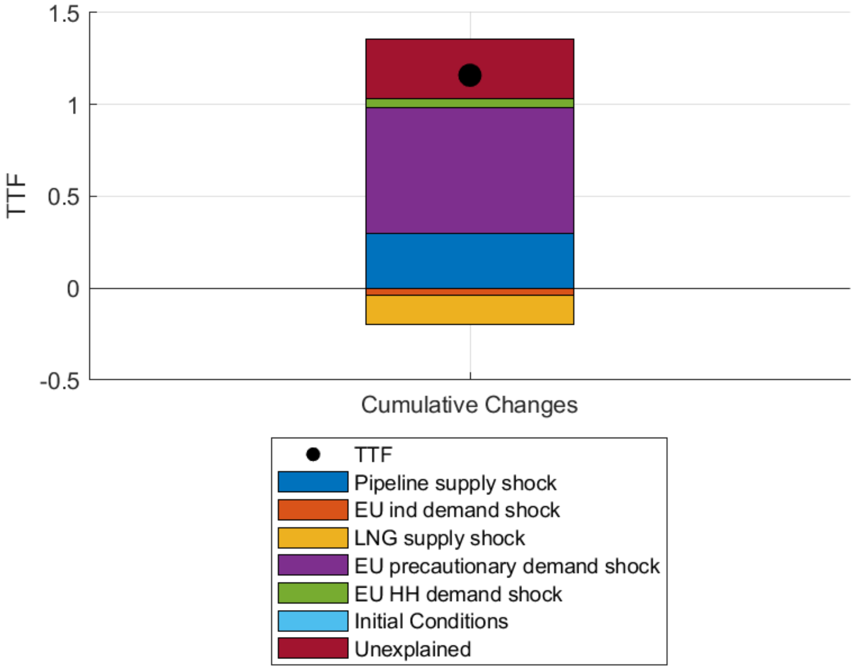
Note: Pre-crisis sample until 24 September 2021, Crisis and post-crisis sample starting from 25 September 2021. Details on the sample dates can be found in Section 6.

Figure B.3: Historical decomposition of the cumulated changes in TTF prices - Reduction in Russian flows, October 2021



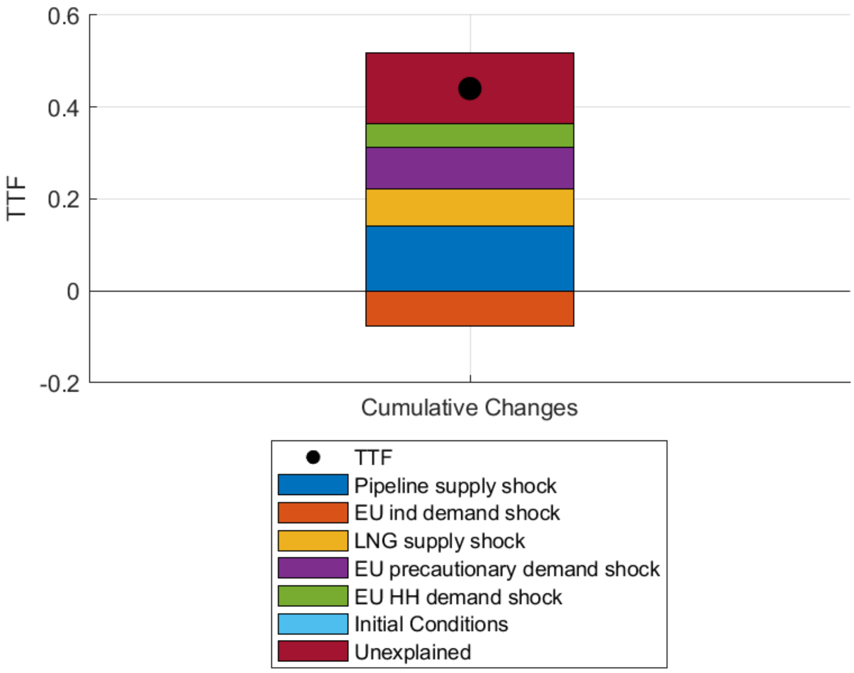
Note: The figure represents the historical decomposition, from 2021w40 to 2022w08, of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure B.4: Historical decomposition of the cumulated changes in TTF prices - Invasion of Ukraine, February 2022



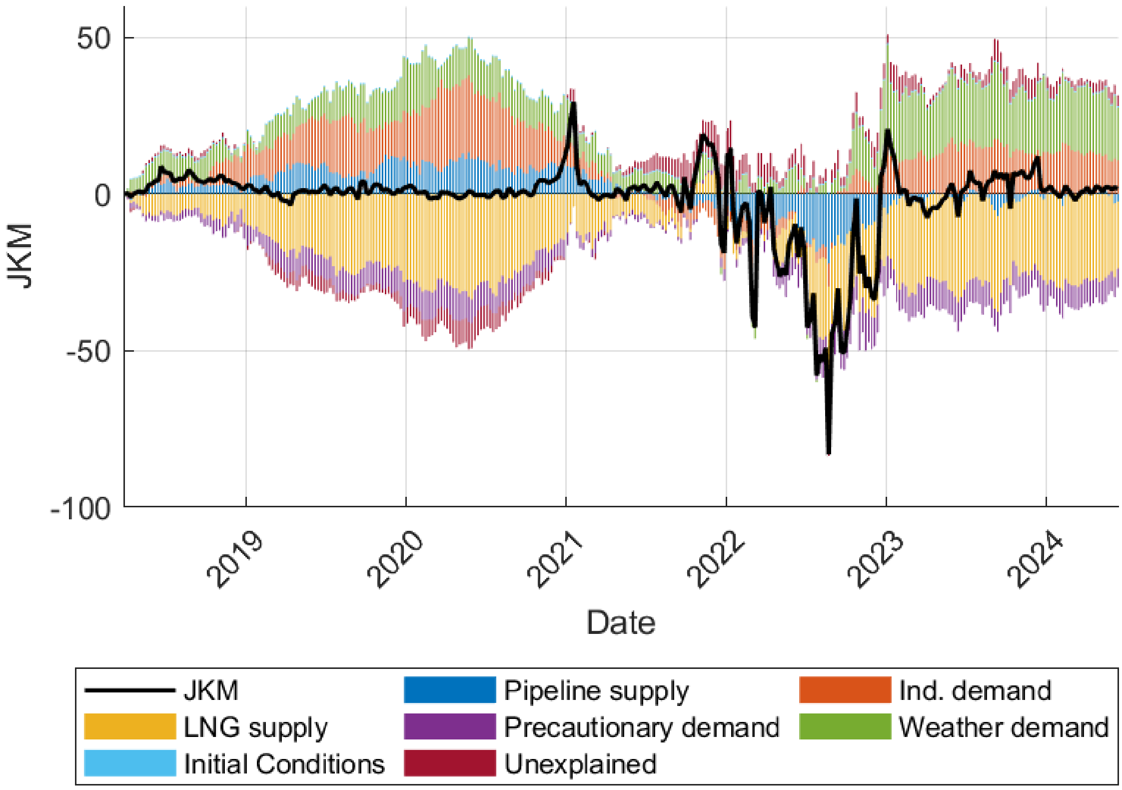
Note: The figure represents the historical decomposition, from 2022w09 to 2022w14, of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure B.5: Historical decomposition of the cumulated changes in TTF prices - Reduction in Russian flows, June 2022



Note: The figure represents the historical decomposition, from 2022w24 to 2022w25, of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

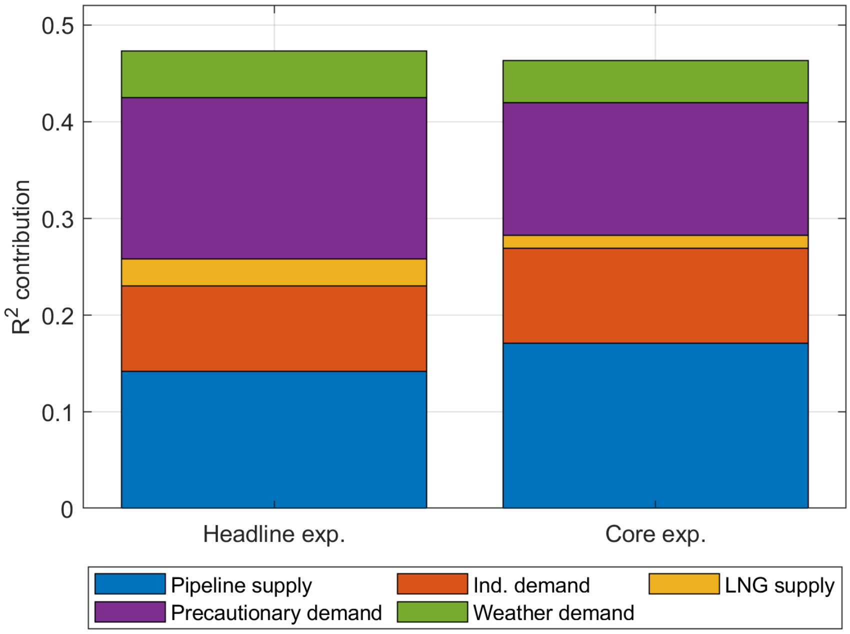
Figure B.6: Historical decomposition of the cumulated changes in the JKM-TTF spread



Note: The figure represents the historical decomposition of the cumulated changes in the JKM-TTF spread depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is EUR/MWh.

C Local projection analysis

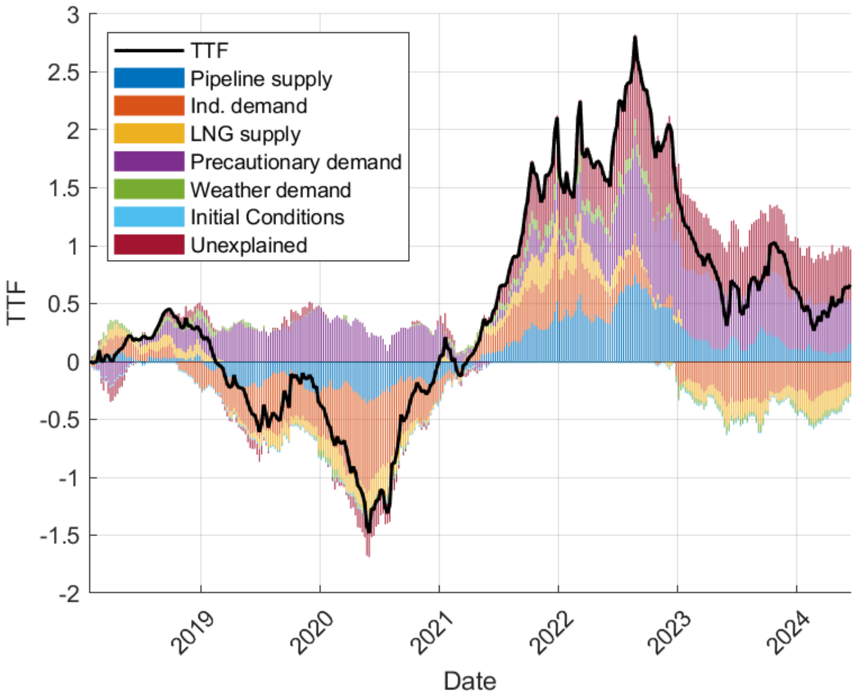
Figure C.7: Variance decomposition of headline and core inflation expectations



Note : The figure illustrates the variance decomposition of market-based headline and core inflation expectations from Grønlund et al. (2024) depending on structural shocks in the gas BVAR model. The variance decompositions have been estimated following the methodology of Gorodnichenko and Lee (2020).

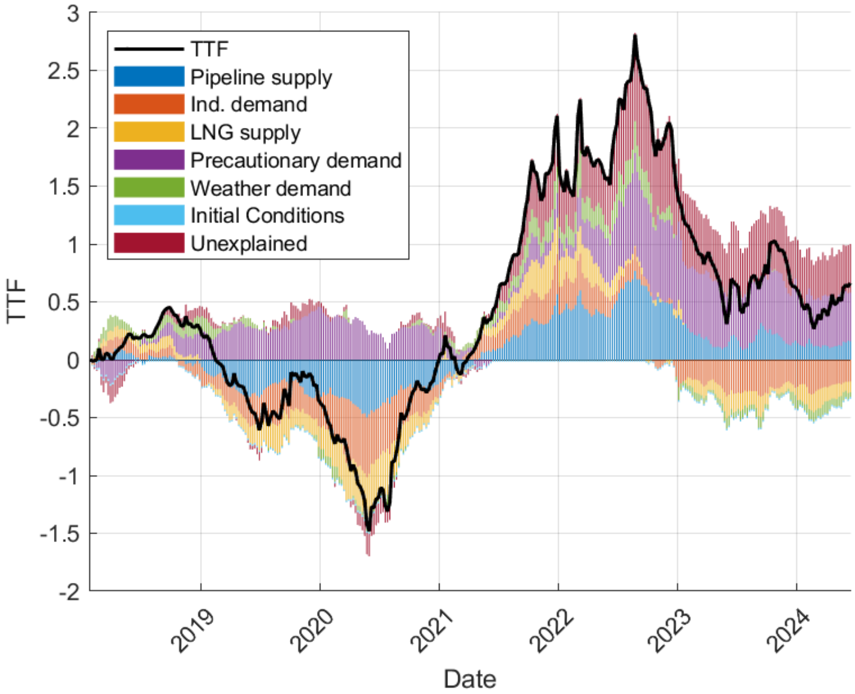
D Robustness checks

Figure D.8: Historical decomposition of the cumulated changes in TTF prices - Gas consumption detrended



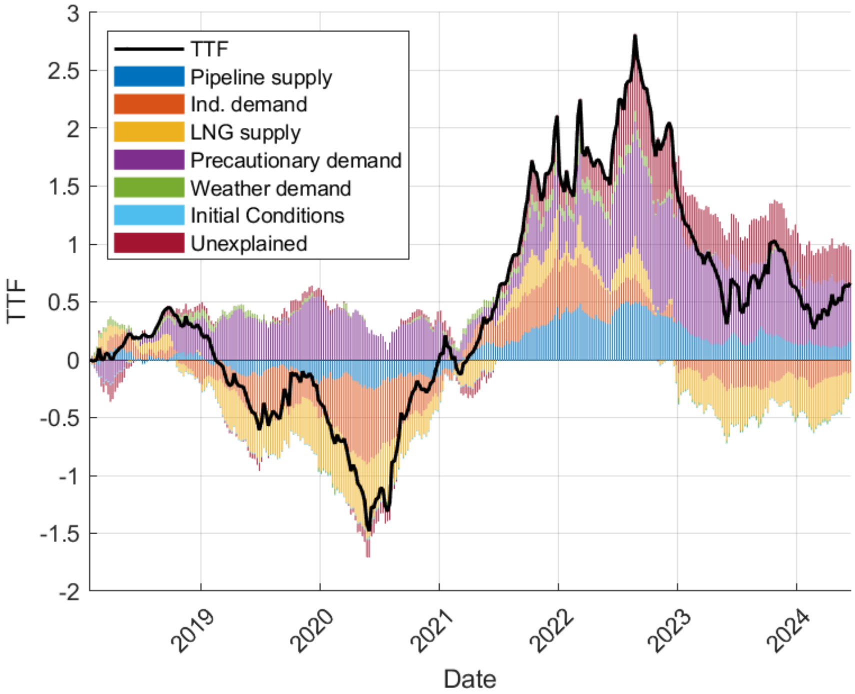
Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure D.9: Historical decomposition of the cumulated changes in TTF prices - Without restrictions on equity prices



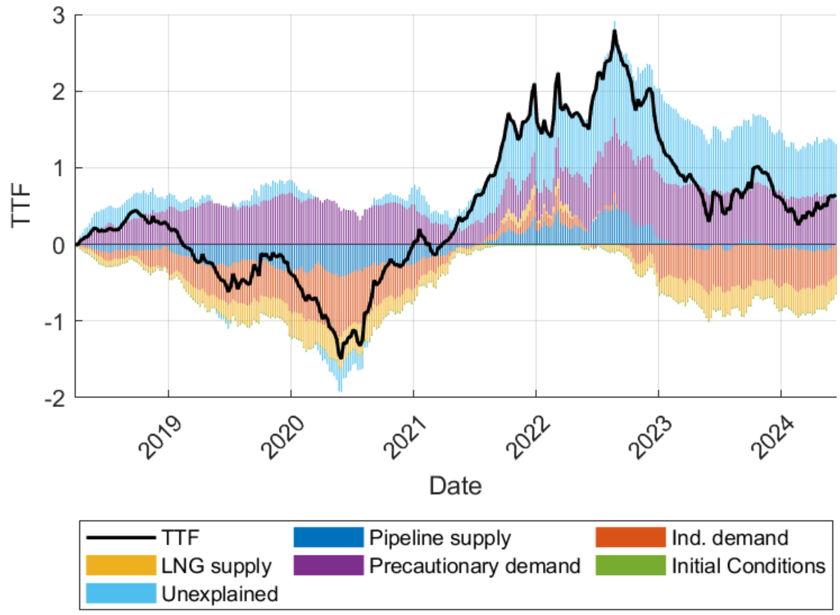
Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure D.10: Historical decomposition of the cumulated changes in TTF prices - Identification with LNG flows



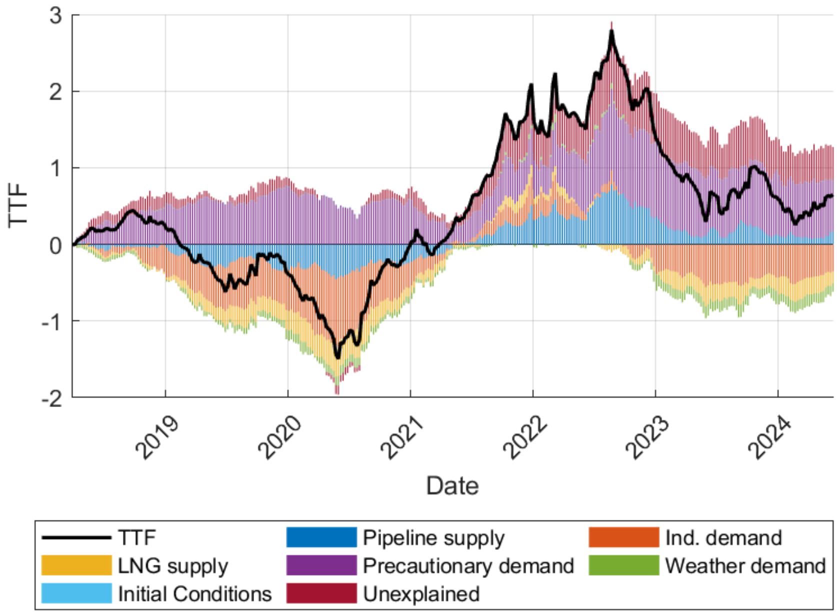
Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure D.11: Historical decomposition of the cumulated changes in TTF prices - Without weather-related demand shocks



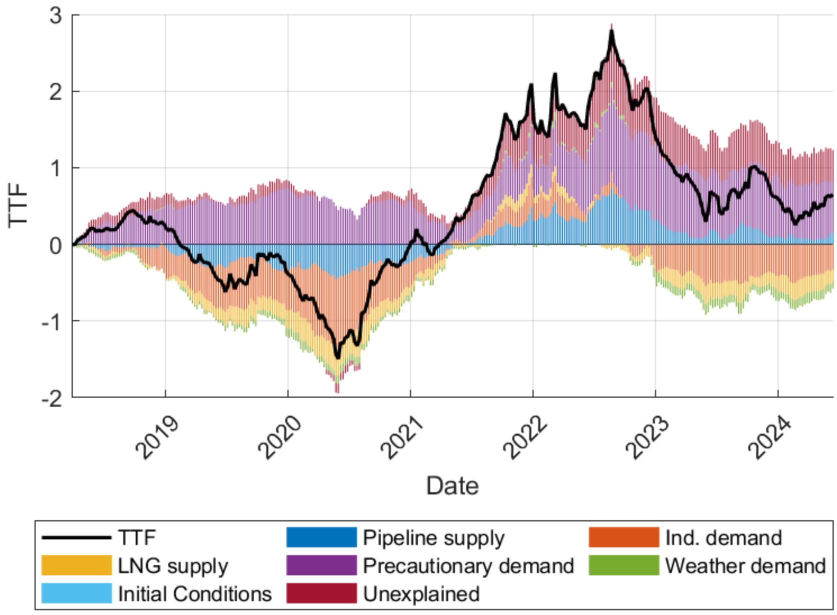
Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on four structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock and the precautionary demand shock. The y-axis is in cumulated log changes (decimal units).

Figure D.12: Historical decomposition of the cumulated changes in TTF prices - 8 lags



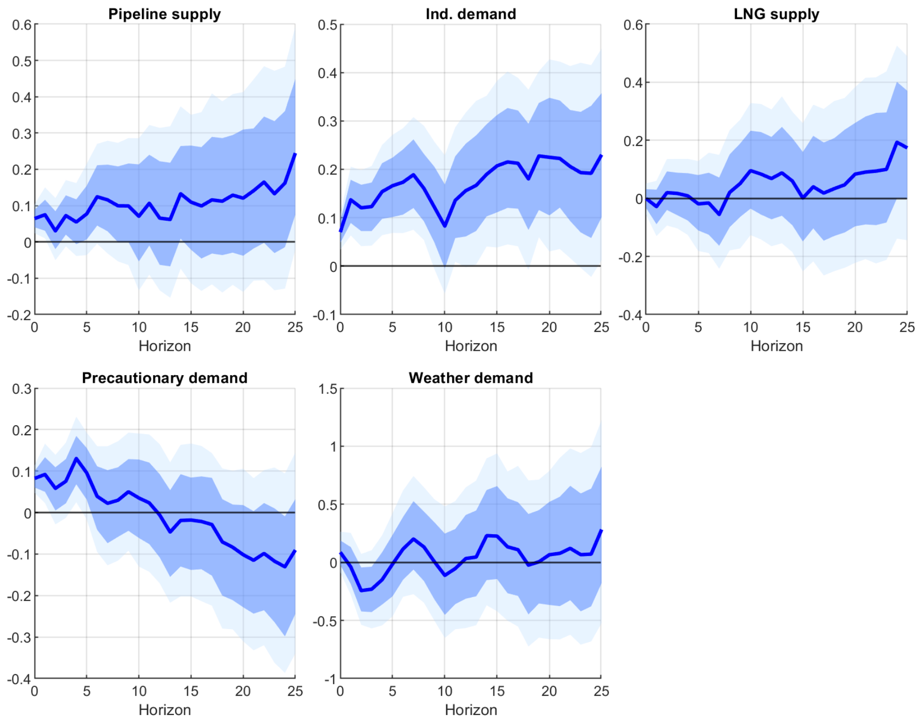
Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure D.13: Historical decomposition of the cumulated changes in TTF prices - 4 lags



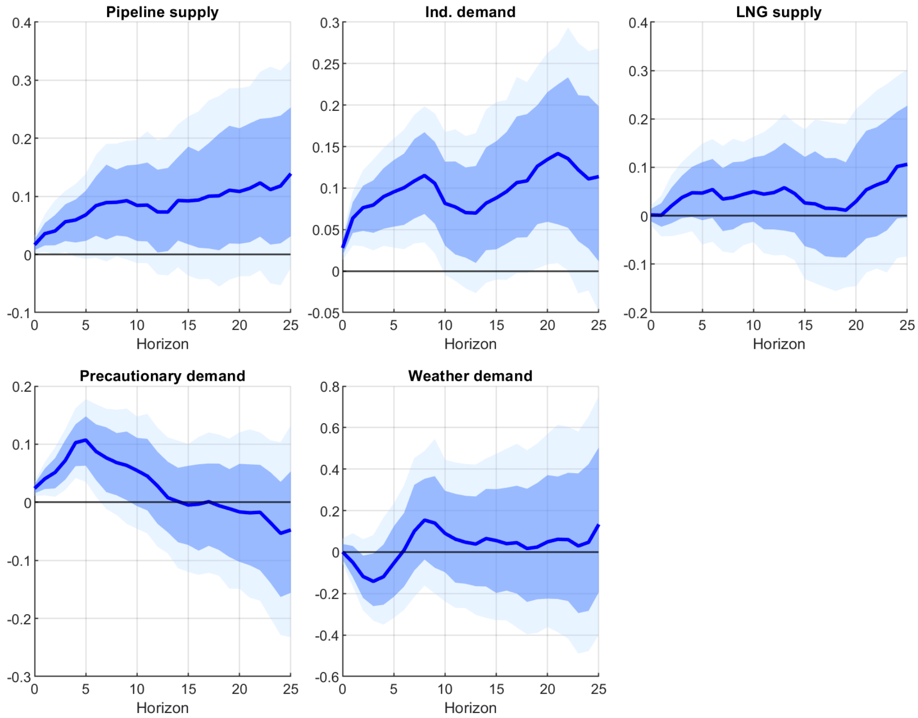
Note: The figure represents the historical decomposition of the cumulated changes in TTF prices depending on the five structural shocks outlined in Section 3: the pipeline supply shock, the LNG supply shock, the industrial demand shock, the precautionary demand shock and the weather-related demand shock. The y-axis is in cumulated log changes (decimal units).

Figure D.14: Impulse Response Functions of headline inflation compensations to the gas BVAR structural shocks



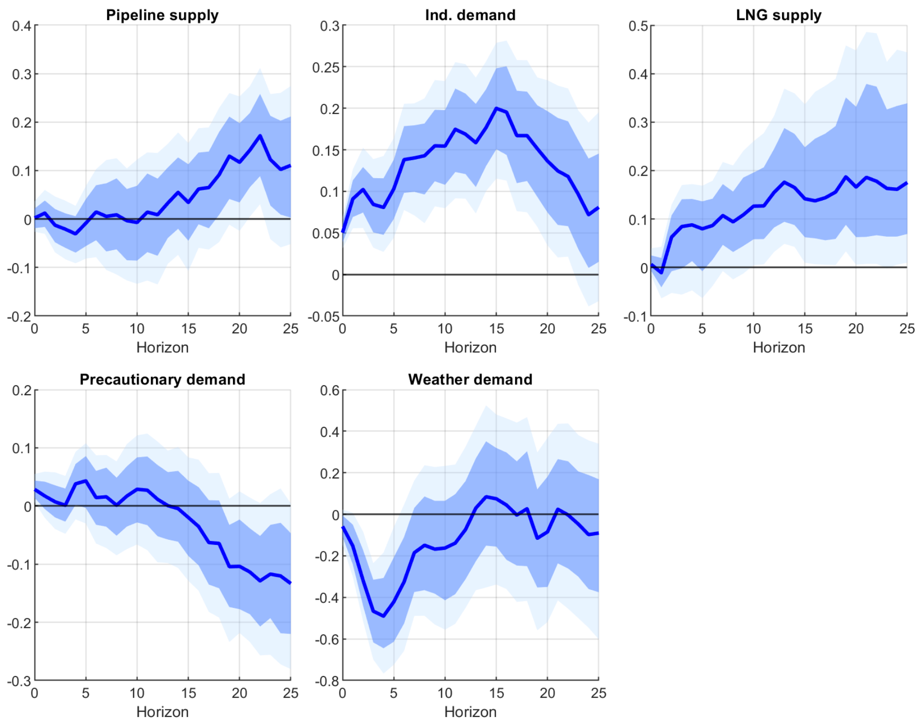
Note : The figure illustrates the response of market-based headline inflation compensations from Grønlund et al. (2024) to structural shocks in the gas BVAR model. The x-axis represents time in weeks, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

Figure D.15: Impulse Response Functions of core inflation compensations to the gas BVAR structural shocks



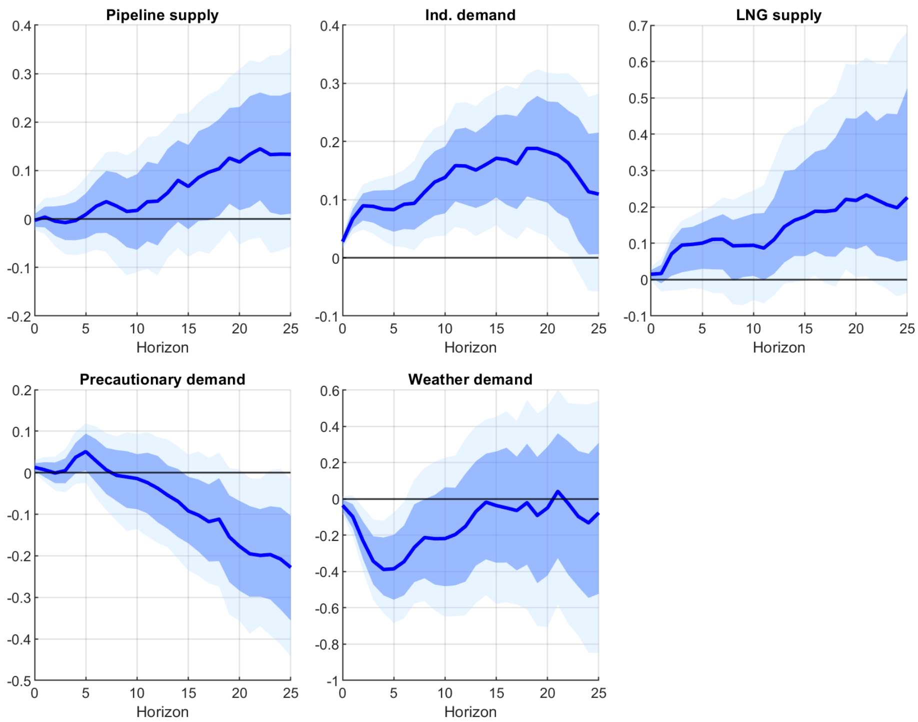
Note : The figure illustrates the response of market-based core inflation compensations from Grønlund et al. (2024) to structural shocks in the gas BVAR model. The x-axis represents time in weeks, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

Figure D.16: Impulse Response Functions of headline inflation expectations to the gas BVAR structural shocks - pre-crisis



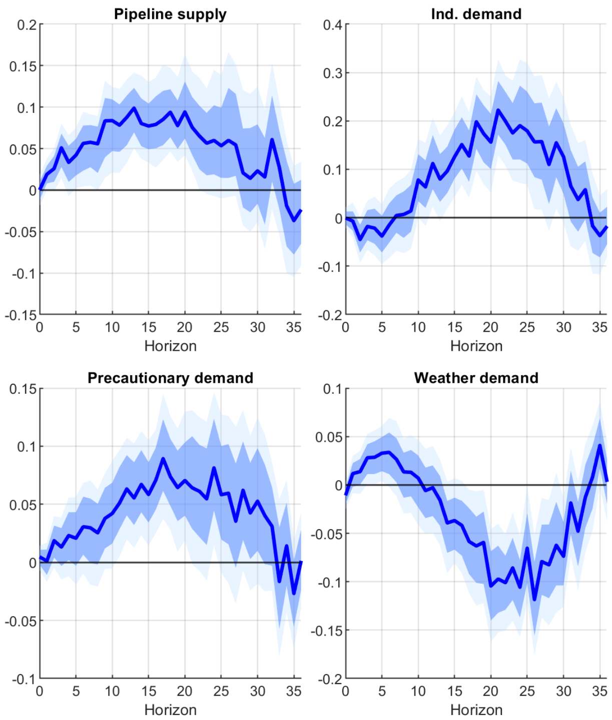
Note : The figure illustrates the response of market-based headline inflation expectations from Grønlund et al. (2024) to structural shocks in the gas BVAR model over the pre-crisis period. The pre-crisis period spans from 1 January 2018 to 24 September 2021, with the BVAR shocks estimated over the same interval. The x-axis represents time in weeks, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

Figure D.17: Impulse Response Functions of core inflation expectations to the gas BVAR structural shocks - pre-crisis



Note : The figure illustrates the response of market-based core inflation expectations from Grønlund et al. (2024) to structural shocks in the gas BVAR model over the pre-crisis period. The pre-crisis period spans from 1 January 2018 to 24 September 2021, with the BVAR shocks estimated over the same interval. The x-axis represents time in weeks, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

Figure D.18: Impulse Response Functions of headline inflation expectations (CES) to the gas BVAR structural shocks



Note : The figure illustrates the response of 1-year headline inflation expectations from ECB's CES to structural shocks in the gas BVAR model. The x-axis represents time in months, while the y-axis denotes percentage changes. Shocks are normalized so that they account for a 10% increase in gas prices on impact.

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