Natural Gas Prices and Unnatural Propagation Effects: The Role of Inflation Expectations in the Euro Area*

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Abstract

This paper investigates the recent increases in natural gas prices and their propagation effects via inflation expectations. Using a structural vector autoregression, we identify a euro area natural gas price shock with a combination of sign and zero restrictions. We rely on market-based measures of inflation expectations and find that natural gas price shocks have strong effects on both inflation and inflation expectations. To understand the relative importance of the pass-through from inflation expectations to inflation after a natural gas price shock, we conduct a counterfactual analysis in which we turn off the expectation channel. Our findings indicate the presence of strong second-round effects via expectations. Our analysis provides guidance for policymakers to better understand the potential trade-offs of different policy responses to natural gas price shocks, especially with respect to discussions about inflation de-anchoring.

Keywords: Natural gas price shocks, Inflation expectations, Euro area, Counterfactual analysis.

JEL Codes: C32, E31, Q43.

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1. Introduction

European economies experienced dramatic energy price shocks due to jumps in natural gas prices after political tensions culminated in the Russian invasion of Ukraine in February 2022. These energy shocks led to the recollection of the sharp oil price increases in the 1970s and their detrimental effects on the macroeconomy. The natural gas market became structurally and economically more important in a short period of time and might behave differently compared to oil due to several market idiosyncrasies. This market is particularly interesting against the backdrop that the European Union (EU) has classified natural gas as one of the key elements for the green transition due to its special role as a *transition* energy (European Commission, 2021).[1] However, rather little is known about the macroeconomic consequences of distortions and shocks in this market. One of the most pressing consequences is depicted in Figure 1, in which short- and long-term market-based inflation expectations started to rise at the end of 2021 and gained utter momentum in 2022 along with natural gas prices. This leads to concerns about the "de-anchoring" of (long-run) inflation expectations among researchers and policymakers, which is particularly important for the successful conduct of monetary policy (Blanchard, 2022; Reis, 2022a; Steinsson, 2022).

The goal of this paper is thus to investigate the recent natural gas price surge and its implications for inflation expectations and its pass-through effects on prices. The literature focuses mostly on the effects of oil prices and their pass-through on inflation (expectations) (see, inter alia, Baumeister, Peersman and Van Robays, 2010; Clark and Terry, 2010; Wong, 2015; Aastveit, Bjørnland and Cross, 2023) and only attributes a limited role to oil price shocks in driving inflationary responses. Kilian and Zhou (2022b) investigate specifically the impact of rising oil prices on inflation in 2020-23 and find limited evidence on overall price developments. This paper, however, departs from these approaches and examines the *natural gas* price surge in Europe. Hence, we are interested in an array of questions: How do natural gas prices affect inflation and inflation expectations? What is the role of inflation expectations in propagating natural gas price shocks to inflation? What is the role of the inflation expectation horizon? And finally, do we find similar effects in the US?

We address these questions based on a structural vector autoregressive (SVAR) model of the relationship between real natural gas prices, industrial production, a short-term interest rate, inflation, and inflation

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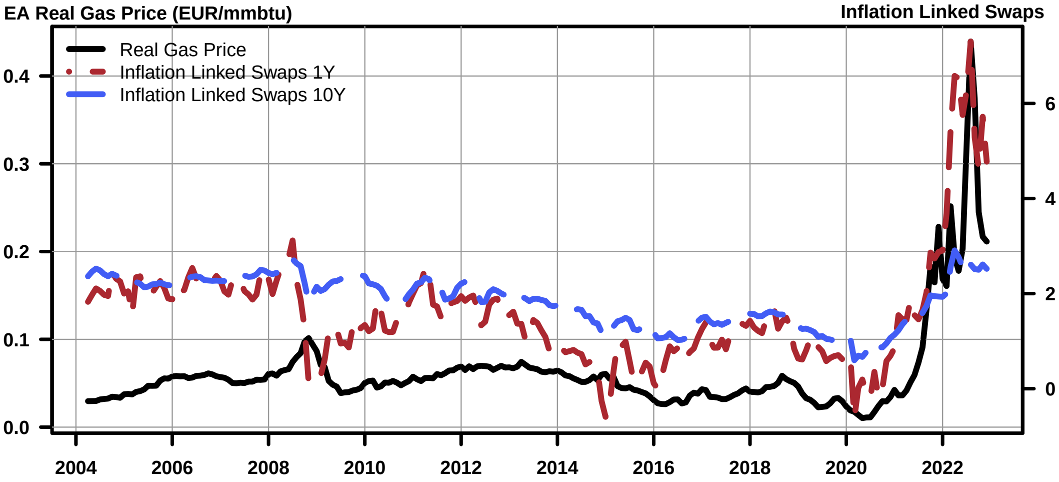
[1] The European Union (EU) is committed to its Green New Deal (European Commission, 2019) with the goal of zero net emissions of greenhouse gases by 2050. To achieve that, the EU financially supports investments in the expansion of using renewable energy sources. While using natural gas as an energy source also creates greenhouse gas emissions like other fossil fuels, it produces lower emissions and less air pollution compared to other hydrocarbons, like oil or coal.

Figure 1: Real Gas Prices and 1 and 10Y Ahead Inflation-Linked Swaps in the Euro Area (EA).



expectations. The time frame for the analysis covers January 2004 until the end of 2022. We abstract in the analysis from modeling exchange rate adjustments and transform the price of natural gas to Euro using the US dollar exchange rate. In terms of identification, we first identify the model via timing restrictions along the lines of Wong (2015). A possible drawback is that real natural gas prices are assumed to not react to demand shocks. As we argue in more detail below, natural gas markets are much more localized than other commodity markets (e.g., oil) as they are tied to local infrastructure. To alleviate these concerns, we also develop a sign restriction strategy that is based on but also extends the work by Kilian and Zhou (2022a). The sign restriction strategy allows us to also identify local demand-side shocks, which possibly affect natural gas prices contemporaneously. To this end, we identify euro area demand, supply, and monetary policy shocks. Additionally, we also identify an idiosyncratic inflation expectation shock along the lines of Kilian and Zhou (2022a). Second, in order to investigate the role of inflation expectations in propagating real gas price shocks, we conduct a structural scenario analysis (SSA) following the recent contribution of Antolin-Diaz, Petrella and Rubio-Ramirez (2021). The identification of an idiosyncratic inflation expectation shock allows us to use this particular shock to offset the transmission channel via expectations of a natural gas price shock.

The natural gas market comprises several features that make it an intriguing subject to study. First, natural gas is considered a crucial energy resource during the transitional period towards a green economy. It is supposed to replace oil and coal (see, e.g., the European Commission's green agenda) until the energy sector consists predominantly of green sources. Second, unlike oil, natural gas is traded much more locally due to necessary infrastructures, resulting in different price dynamics across the world. Third, the recent geopolitical events brought strong distortions in the natural gas market, revealing the vulnerability of Europe in particular to exogenous energy shocks. Understanding the impact and transmission of these shocks is of utmost importance for policymakers, as they might interfere with policy goals like stable growth and price stability.

Commodity prices in general, and natural gas in particular, can be the source of external shocks, which may feed into inflation. Conceptually, inflation arising from commodity price shocks can be separated into two components. The first is directly linked to the inputs of production, where higher energy costs increase overall costs. This cost channel can also be deemed as a *first-round effect*. On the contrary, *second-round effects* pertain to increases in inflation through the price setting or wage bargaining channel originating from higher inflation expectations. Werning (2022), for instance, shows for an array of pricing models that the pass-through from expectations is close to unity and decreases with increasing expectation horizon. We are particularly interested in the effects of the second channel because it opens an additional mandate for policy actions. Hence, for discussions about deanchoring dynamics, where inflation expectations unsustainably deviate from the policy target, this channel is of particular importance. To measure inflation expectations, we resort to inflation-linked swaps (ILS), which offer a market-based view of expectations.[2] Since ILS data is available on a high frequency (i.e., monthly in our case), this allows us to confidently estimate our SVAR on a rather short sample period. This comes with the cost that ILS also contain an inflation risk premium, which is part of our "expectational" component. Nevertheless, ILS provide better information than other market-based measures (e.g., inflation-indexed treasury yields) as shown by Haubrich, Pennacchi and Ritchken (2012). Market-based measures are similar to expectations of professional forecasters but less similar to household inflation expectations. The latter exhibit substantially higher expectations, as shown by D'Acunto, Malmendier and Weber (2023). Furthermore, Coibion and Gorodnichenko (2015a) document that there is also evidence of information rigidities in inflation expectations measured via ILS.

Moreover, inflation expectations and especially their anchoring to a target are important aspects for central banks in their conduct of stabilization policies (Clarida, Gali and Gertler, 2000). Elevated expectations may, directly and indirectly, affect the wage and price-setting behavior of an economy via the Phillips curve (Coibion, Gorodnichenko and Kamdar, 2018). Especially in the current situation, highly increased energy

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[2] In principle, these swaps are derivative products that are linked to some sort of price index. Per design, the swap is a forward contract between two parties, where the buyer party pays a (fixed) nominal rate and receives a real rate from the seller party. Hence, the swap's price depends on realized and expected inflation, such that they can be used for hedging inflation.

prices may pose a threat to inflation anchoring around the targeted level and therefore require appropriate actions by monetary policymakers (Reis, 2022b). Given the recent evidence of the flat Phillips curve (Del Negro et al., 2020; Hazell et al., 2022), the downward shift in long-run inflation expectations is a major explanation for the sharp drop in core inflation in the Volcker period. Hence, it is of utmost importance to understand the role of inflation expectations as a transmission channel of energy price shocks to realized inflation. Equipped with this information, central banks can tailor their measures adequately to combat inflation that is caused by rising energy prices and fulfill their stabilization goals.

Our results show that natural gas price shocks affect both inflation and inflation expectations. A one standard deviation shock (which is an about 5% price increase) to real gas prices moves inflation 0.2 percentage points up. By disentangling first- and second-round effects with our counterfactual exercise, the impulse response analysis points to a pronounced *expectation* channel and a rather muted *cost* channel. However, the pass-through of inflation expectations to realized inflation is clearly below unity. Furthermore, when examining the whole term structure of inflation expectations up to thirty years ahead, short-term inflation expectations show the strongest second-round effects. While long-run expectations are less affected, they still show a non-trivial increase. Hence, examining the full expectation horizon may point towards a de-anchoring potential, since we observe an upward shift along the term structure of inflation expectations. Our results are robust to using survey-based expectation indicators (based on the survey of professional forecasters). However, these effects are less precisely estimated, because this data is only available on a quarterly frequency. On the contrary, if we use the price of crude oil, the effects are far less pronounced. Interestingly, however, and in line with the literature, we do not find evidence for these effects in the US. The question regarding the differences can be answered on the one hand, with less strongly affected natural gas prices. On the other hand, short-run inflation expectations are not as firmly anchored in the euro area compared to the US. Nevertheless, other explanations arise, which we discuss further below.

The contribution of the paper is thus threefold. First, the paper provides an identification scheme for real natural gas price shocks by drawing on the literature on identifying oil price shocks. Second, we investigate the effects of commodity price shocks on inflation and inflation expectations in the euro area. Third, and most important, we specifically examine the pass-through of inflation expectations to inflation via a structural scenario analysis after commodity price shocks in the euro area. To the best of our knowledge, we are thus the first to highlight the potential euro area's inflationary risks stemming from second-round effects of commodity price shocks, particularly of natural gas price shocks.

The paper is organized as follows. Section 2 embeds the paper in the context of the relevant literature and Section 3 discusses the particularities of the natural gas market. Section 4 presents the econometric framework, the identification strategy, and how we construct the counterfactual experiment. Section 5 shows the baseline results and in Section 6 we offer some extensions. Finally, Section 7 concludes.

2. Related Literature

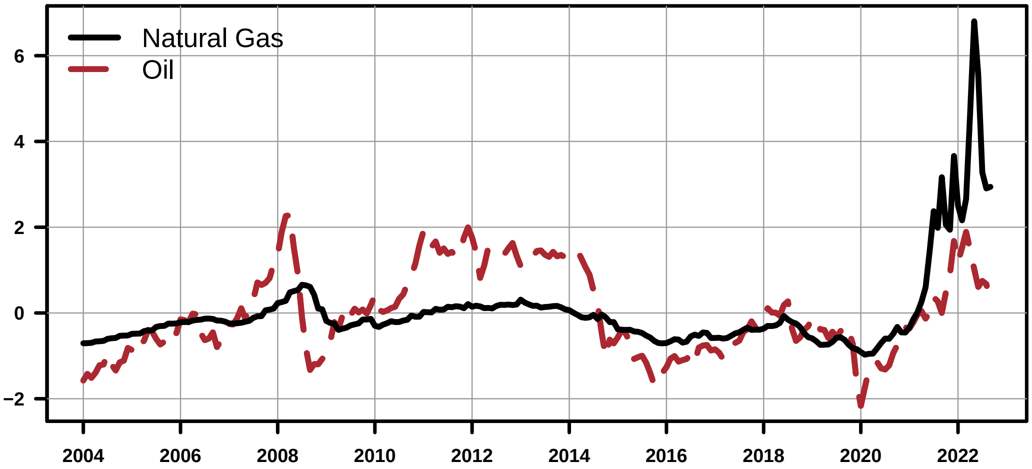
We connect to three strands of literature intersecting the field of the macroeconomic importance of commodity markets, the implications of inflation expectations for realized inflation, and, finally, to the literature about counterfactuals in time series models.

While there is abundant literature analyzing the impact of commodity prices on the macroeconomy, it focuses traditionally on crude oil and respective shocks in the 1970s (Barsky and Kilian, 2002; Hamilton, 2003; Kilian, 2008; Kilian, 2009; Bjørnland, Larsen and Maih, 2018). Studies explicitly tackling the role of natural gas in this setting are scarce. For instance, Nick and Thoenes (2014) find that a natural gas supply shortfall has significant effects for the German economy and should be tackled by both demand- and supply-side measures. More recently, contributions by Casoli, Manera and Valenti (2022) and Alessandri and Gazzani (2023) investigate the impact of natural gas price shocks, focusing particularly on their pass-through to the real economy in comparison to oil price shocks. Interestingly, Blanchard and Gali (2009) and Baumeister and Peersman (2013) show that the sensitivity of real variables to oil price fluctuations is attenuated over time. Together with overall increases in the efficiency of production processes, the usage of alternative energy resources in line with the goals of the green transition may serve as an explanation. This diminishing relevance over time can also be found for reactions of both expected and realized inflation after oil price shocks (Harris et al., 2009; Wong, 2015; Coibion and Gorodnichenko, 2015a; Conflitti and Luciani, 2019; Aastveit, Bjørnland and Cross, 2023). However, given the recent large economic distortions due to the Covid pandemic, both inflation expectations and the role of energy markets gained revived attention (Kilian and Zhou, 2022a; Kilian and Zhou, 2022b). Especially, (short-term) inflation expectations seem to play an important role for the impact and the transmission of energy price shocks. To this end, the present study focuses particularly on how inflation expectations are affected by natural gas price shocks and their role for realized inflation. As we show, another dimension concerns the management of inflation expectations to mitigate second-round effects on the real price of natural gas.

Secondly, we relate to the recent literature studying inflation anchoring and inflation surges. A recent contribution by Blanco, Ottonello and Ranosova (2022) studies inflation surges, how short- and long-run expectations react to that, and the respective optimal policy responses. Similarly, Reis (2021) inspects historical episodes in which inflation expectations became de-anchored. A couple of papers are looking more closely at the recent inflation surge, focusing on US data (Schmitt-Grohé and Uribe, 2022) or international evidence (di Giovanni et al., 2022). Gagliardone and Gertler (2023) investigate the recent inflation surge in the US and show that a combination of oil price shocks and loose monetary policy is responsible for the surge. Carvalho et al. (2023) show in a learning model that long-run inflation expectations are endogenous and driven by short-run inflation surprises. Episodes of de-anchored inflation expectations can thus arise due to large and persistent forecast errors, which lead firms to doubt a constant inflation target. Inflation expectations are also part of monetary policy, as frequently pointed out during policymakers' speeches (see, e.g., Mester, 2022; Lane, 2022). As highlighted by Ider et al. (2023), monetary policy can also affect energy price hikes through other channels as well. We contribute to this stream of literature by focusing on the recent natural gas price hikes and their effects on inflation expectations. Particularly, the model by Carvalho et al. (2023) suggests that a short price hike should not result in de-anchoring dynamics of long-run inflation expectations, which we empirically confirm.

Lastly, we also relate to the literature using counterfactuals in time series models. Counterfactual analysis is strongly tied to conditional forecasting, which goes back to Waggoner and Zha (1999). Baumeister and Kilian (2014) already provide the fundamentals for constructing forecast scenarios, applied to oil price dynamics. Building on these ideas, Antolin-Diaz, Petrella and Rubio-Ramirez (2021) provide a unified treatment of conditional forecasting and structural scenario analysis, relating them also to entropic tilting (Robertson, Tallman and Whiteman, 2005). Specifically, scholars have used counterfactuals to decompose *direct*, or first-round, effects and *indirect*, or second-round, effects. To study indirect effects, several contributions isolate the hypothetical impulse response of the variable under consideration to a particular shock by shutting down the indirect effects via counterfactuals. For instance, Bernanke et al. (1997) or Kilian and Lewis (2011) investigate the systematic component of monetary policy, while Breitenlechner, Georgiadis and Schumann (2022) focus on the spillback effects of monetary policy. Most closely related to our paper is Wong (2015), who studies how inflation expectations propagate the inflationary impact of real oil price shocks in the US. In contrast to this study, we examine more closely real natural gas prices and focus on the euro area. We discuss (and corroborate) these findings more closely when we re-do our analysis for the US.

Figure 2: Standardized Real Natural Gas Prices (Dutch TTF Benchmark) and Real Oil Prices (Brent).



3. The Natural Gas Market

Together with the increased demand after the Covid crisis, the recent geopolitical events brought mayhem to global energy markets, either due to sanctions or unilateral supply stops from Russia. While the price of almost all conventional energy sources surged during this period, three facts stand out. First, not all energy sources exhibit the same pace and magnitude in price increases. Second, the economic importance of the different energy sources changed over time. Both of these facts can be seen in the price developments of the three widely used energy commodities, depicted in Figure 2. Third and finally, there are marked differences in price increases of the same commodity across geographic locations, especially for natural gas.

Fossil fuels (still) provide the main resource for generating energy and, to a certain extent, for industrial processes. However, given the negative environmental effects of their usage, considerable efforts have been made to either make production processes more input-efficient or to find other, more environmentally friendly, sources of energy. This is reflected in the change in the composition of the final energy consumption for developed countries, like the US and the European Union (EU27). Tracing the final energy consumption over time reveals a transition from coal to crude oil and, finally, to natural gas. Most prominently, Europe put the stakes on natural gas as a transition energy source, which is less carbon-intensive compared to coal and oil, to facilitate the Green transformation. Eventually, this strategy is also reflected in the European Commission's recent reclassification of natural gas as a green energy source (European Commission, 2019).

Moreover, a significant share of natural gas across countries is not only used as a direct energy resource but also as an input for a broad range of production processes, with potentially very limited substitutability. According to the U.S. Energy Information Administration (2023), in 2021 both the electric power generation and the industrial sector accounted for over 70% of the natural gas demand in the US. In industrial processes, natural gas is consumed either as a source for heating or as a raw material for producing fertilizer or other chemical products. Considerably less demand stems from the residential and commercial sector, as well as from the transport sector. For the former two, natural gas serves as an input for space and water heating. The transportation sector (5% of total US demand) uses natural gas predominantly to operate the infrastructure and only a tiny share for fueling vehicles. In Europe, the residential sector accounts for the bulk of natural gas demand, followed by energy production and the industrial sector. Interestingly, European households predominantly use natural gas as their main source of energy. Between 2000 and 2020, consumption by the industrial sector, however, has declined by 20% with a shift to power generation by 15%. Over time, the EU27 demand profile changed considerably, again reflecting the switch from coal to natural gas and the measures intended by the Green transformation (European Union Agency for the Cooperation of Energy Regulators, 2023).

With less domestic production and higher demand, Europe and especially Germany secured its supply from Russia, which is not only rich in natural gas resources but also features the necessary infrastructure. Before the onset of the Russian invasion of Ukraine, this facilitated the flow of cheap energy reflected in very low volatility of the European natural gas price, as seen in Figure 2. After the implementation of sanctions and the Russian retaliation in terms of squeezing the energy supply towards Europe, the *locality* of the natural gas market became obvious. On the one hand, this is reflected in benchmark prices that differ markedly.[3] For instance, at the peak of the uncertainty right after the start of the war, the U.S. benchmark, the Henry Hub, quotes well below the European reference price, i.e., the Dutch TTF (Title Transfer Facility). The maximum price on the TTF spot market was slightly below 350 EUR/MWh on August 26, 2022, while on the same day, the Henry Hub benchmark quoted 32.35 USD/MWh. A first and rather straightforward explanation is given by the fact that the EU27 has cut its domestic production in the last ten years in half and has to import about 80% of its demand in 2021, from what about 41% is supplied by Russia (European Union Agency for the

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[3] Note, that there exists also a variety of crude oil types, but only three benchmarks, Brent, WTI, and Dubai Crude form the international reference price. While they differ in their refinery characteristics, they usually exhibit a very strong comovement. Only for the Russian sorts, we observe a pronounced spread since the implementation of the price cap of 60 USD as a sanction of the G7 against Russia applicable as of February 5, 2023.

Cooperation of Energy Regulators, 2023; Eurostat, 2023). The US, however, satisfies its own demand either through fracking or standard gas field exploitation and even became a net exporter of natural gas in recent years. Another factor, the locality of the market, concerns the rather static and thus less flexible infrastructure (e.g., pipelines) necessary for transport. This crucially impedes the finding of alternative suppliers, especially at short notice.[4] Moreover, while oil resources are still available and can be more or less flexibly adjusted, the situation for natural gas is more complex. On the one hand, gas extraction cannot easily be adjusted due to technological reasons, and, on the other hand, it operates with the existing gas fields at its capacity limit. Finally, gas is used not only as an energy resource but also as an input for a broad range of production processes, with very limited substitutability.

Together, these reasons give rise to the extraordinary increase in European natural gas prices, exacerbated by the member country's individual policy decisions to fill the storage before the heating season in 2022. As natural gas is either a direct component in the underlying price index (source of energy) or indirectly incorporated (as input for production processes), the surge episode resulted in increasing inflation. In addition, most of the global economies already arrived from the Covid crisis with strong inflationary pressures caused by pent-up demand, supply chain frictions, and expansive fiscal policy measures. Together with the prospect that natural gas will be an important factor during the green transition, understanding the propagation effects of shocks to it becomes paramount. Especially from a monetary policy perspective, the role of inflation expectations and potential drivers of de-anchoring need to be examined.

4. Empirical Methodology

To model the effects that gas price shocks exert on expected and actual inflation, we require a structural model to disentangle the sources of variation in the price of natural gas, inflation expectations, inflation, and demand-side fluctuations. Our focus primarily lies on the identification of real gas price shocks transformed into the domestic currency. We extend the proposed structural models of Wong (2015) and Kilian and Zhou (2022a) and add industrial production and the shadow rate (Wu and Xia, 2016) as a proxy of monetary policy to the model. In terms of identification, we first identify the model via timing restrictions. We assume that the real natural gas price is exogenous and none of the remaining variables react contemporaneously to real natural gas price innovations. However, the timing restrictions do not ensure that the identified shock is

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[4] The same holds true for the liquified version of natural gas, LNG. While being liquid and therefore simpler to transport by shipping, it again needs a special infrastructure for regasification. For the time being, LNG simply cannot fully satisfy Europe's gas demand.

free from aggregate demand aspects. To alleviate this concern, we also identify demand-side shocks in the structural model by using a combination of sign and zero restrictions for identification.

The econometric model is estimated on a monthly data frequency with a sample starting in January 2004 and ending in December 2022. The model features five variables $\boldsymbol{y}_t = [rgas_t, ip_t, sr_t, \pi_t^e, \pi_t]$, where $rgas_t$ denotes the log level of the real gas price (transformed into Euro from US dollar and deflated with the harmonized index of consumer prices, HICP), ip_t the log-level of euro area industrial production, sr_t shadow short-term interest rate of the euro area by Wu and Xia (2016), π_t consumer price headline inflation based on the HICP, and π_t^e inflation expectations measured through inflation swaps.[5] Since our sample period covers the Covid-19 pandemic, various strategies have been proposed to address the enormous outliers in this period. For a robustness check, we follow the strategy of Cascaldi-Garcia (2022) and introduce dummy observations for the months of March to May 2020. We will also provide robustness with respect to core inflation.[6] An overview of the exact variable definitions, transformations, and sources is available in Appendix A.

4.1 The Structural VAR Model

We proceed with our structural model where the reduced-form VAR model representation is

$$\boldsymbol{y}_t = \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \qquad \boldsymbol{u}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{4.1}$$

where $\boldsymbol{y}_t$ is an $n \times 1$ vector of macroeconomic variables, which are modeled as a function of its own past values, and an $n \times 1$ vector $\boldsymbol{u}_t$ of forecast errors with an $n \times n$ covariance matrix $\boldsymbol{\Sigma}$. For the sake of brevity, Equation 4.1 omits any possible deterministics such as the intercept and dummy variables (Cascaldi-Garcia, 2022). We allow up to $p = 12$ lags to enter the equation, accounting for the long and variable lags in the transmission of gas/oil price shocks (see Hamilton and Herrera, 2004). We pursue a Bayesian approach to estimation as done in Chan (2022) but with a variant of global-local shrinkage priors. Specifically, we use the Normal-Gamma prior outlined in Huber and Feldkircher (2019). A detailed discussion of the estimation routine and the prior specification is provided in Appendix B. We sample 35,000 draws from the posterior distribution, from which we discard the first 10,000 as burn-ins. Finally, we use a thinning factor of 2, meaning we keep every second posterior draw.

[5] As noted above, these derivatives also contain an inflation risk premium. Moreover, the liquidity of the ILS market might pose additional challenges, potentially giving rise to a liquidity premium. Reis (2021), for instance, argues that the inflation swap market was only reasonably liquid starting in 2009. However, the later presented results are robust if we start the analysis in 2010. This further alleviates possible concerns that the global financial crisis is driving the effects.

[6] Additional results are provided in the appendix, see Appendix D.

The reduced-form shocks are a linear combination of n orthogonal structural disturbances $\boldsymbol{\varepsilon}_t$, which we write as $\boldsymbol{u}_t = \boldsymbol{S}^{-1}\boldsymbol{\varepsilon}_t$. The structural VAR equation thus reads

$$\boldsymbol{S}\boldsymbol{y}_t = \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{B}_p\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}_n), \tag{4.2}$$

where $\boldsymbol{A}_j = \boldsymbol{S}^{-1}\boldsymbol{B}_j$ $(j = 1, \ldots, p)$ holds. By definition, structural shocks are mutually uncorrelated, i.e., $\text{Var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{I}_n$ being diagonal, and are thus identified up to a sign and scale convention. From the linear mapping of the shocks, $\boldsymbol{\Sigma} = (\boldsymbol{S}\boldsymbol{S}')^{-1}$ holds such that the identification amounts of finding a suitable matrix $\boldsymbol{S}^{-1}$.

We start to identify the effects of real gas price shocks by assuming that movements in the gas price are exogenous to inflation and inflation expectations. This yields a partially identified system achieved by ordering real gas prices first and has been commonly used in applied work (see, inter alia, Kilian and Vega, 2011; Wong, 2015; Kilian and Zhou, 2022b). We interpret the now identified structural shock as a real natural gas price shock: unpredictable surprises to the price of natural gas from the perspective of the European economy. As seen in Figure 1, the political turmoil ensuing from the Russian invasion of Ukraine in 2022 led to huge distortions in the natural gas market driving up its price tremendously.

Technically, the approach is simple to implement. We define the structural impact matrix $\boldsymbol{S}^{-1} = \boldsymbol{L}$, where $\boldsymbol{L}$ is the lower-triangular Cholesky factor of the variance-covariance matrix. A potential drawback of this identification procedure is that the natural gas market is a much more localized market than the global oil market. This means that shocks to the real natural gas price may also capture aggregate demand shocks. In the model with timing restrictions, we preclude by construction the possibility of any contemporaneous feedback effect from demand-side forces to the real price of natural gas. This can be seen from the assumption that the real natural gas price does not react to a demand shock. Hence, we move to our preferred identification scheme, which we implement via sign and zero restrictions. In this model, we identify both the real gas price shock as well as demand and supply shocks affecting the economy. The identification of this structural model exploits a combination of sign and zero restrictions on the structural impact matrix $\boldsymbol{S}$, as shown in Equation 4.3. We use the algorithm outlined in Arias, Rubio-Ramírez and Waggoner (2018). Specifically, we search for an orthonormal matrix $\boldsymbol{Q} = (\boldsymbol{q}_1, \ldots, \boldsymbol{q}_n)$, such that $\boldsymbol{Q}\boldsymbol{Q}' = \boldsymbol{I}$ holds. The algorithm searches for each column vector of the matrix $\boldsymbol{Q}$ recursively, conditional on the zero restrictions.[7] This yields the structural impact matrix $\boldsymbol{S}^{-1} = \boldsymbol{L}\boldsymbol{Q}$.

We proceed to outline our identification stance on a real natural gas price shock. We assume that an increase in the real price of natural gas leads on impact to a deterioration of industrial production as well as to a surge of inflation, driving a wedge between output and prices consistent with a cost-push shock.[8] Rising energy prices increase the costs of production, which firms pass through to final goods. The central bank is assumed to follow a Taylor rule and thus we have a positive response of the shadow rate on impact. The use of the shadow rate mitigates possible concerns related to the type of monetary policy because our sample period is characterized by both conventional and unconventional monetary policy actions. We also assume an increase in inflation expectations to a natural gas price shock given the evidence in Binder (2018). The identification of the demand, supply, and monetary policy shock is relatively standard. Generally, supply and demand shocks can be disentangled by putting different signs on the reaction of industrial production. A supply-side shock is thus assumed to raise inflation and inflation expectations and to lower industrial production on impact. In light of an aggregate supply shock, we do not restrict monetary policy to be active in the face of non-energy supply shocks. Otherwise, these restrictions coincide with the ones we assume for the natural gas price shock. In order to disentangle those two shocks, we assume on impact a negative reaction for real natural gas prices to a supply shock. Any other supply shock than an energy price shock (e.g., a markup shock or other production cost-related shocks) causes a reduction of production and less demand for energy. Also, a demand-side shock is assumed to raise real gas prices, inflation, inflation expectations but also industrial production. Compared to a supply shock, monetary policy becomes active and pursues a restrictive stance in light of a demand shock. For the monetary policy shock, we assume a central bank with Taylor-rule behavior: on impact, a monetary policy shock decreases the real gas price, industrial production, and inflation, consistent with targeting the demand side of the economy. In addition and consistent with recent developments to take expectations explicitly into account (e.g., mentioned in central banker's speeches, like Mester, 2022; Lane, 2022), inflation expectations are assumed to decrease after such a shock. Lastly, the model also features an idiosyncratic inflation expectations shock. The importance of

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[7] In more detail, we use the Algorithm 2 outlined in Arias, Rubio-Ramírez and Waggoner (2018) and not their proposed importance sampler in Algorithm 3, which extends Algorithm 2. We abstain from doing so because we depart from their normal-generalized-normal distribution. As they note, this is permissible with the drawback that the distribution is not invariant to a reordering of the shocks.

[8] In a recent paper, Alessandri and Gazzani (2023) show that the response of industrial production to natural gas price shocks is more delayed. In order to check whether this affects our results, we provide a robustness check. We implement the restriction on industrial production not on impact but only after six months and find that the specification is robust to this choice.

such a shock is highlighted in Madeira and Zafar (2015). It is assumed not to affect the real price of natural gas, industrial production, the shadow rate, and inflation on impact. Hence, all movements in expectations that impact actual consumer prices are then already captured by the remaining shocks.

These restrictions are consistent with sign restrictions approaches on other energy-related studies, like on gasoline prices as provided in Kilian and Zhou (2022a). We intend to purge real natural gas prices from any contemporaneous feedback effects from demand-side forces as induced by aggregate demand or monetary policy shocks. While a fully identified system is not necessary for our research purpose here, it can improve inference even if some shocks are not essential for the analysis (Canova and Paustian, 2011). Jointly, these restrictions imply

$$\begin{pmatrix} u_t^{rgas} \\ u_t^{ip} \\ u_t^{sr} \\ u_t^{\pi} \\ u_t^{\pi^{exp}} \end{pmatrix} = \begin{bmatrix} + & + & - & - & 0 \\ - & + & - & - & 0 \\ + & + & + & * & 0 \\ + & + & - & + & 0 \\ + & + & - & + & + \end{bmatrix} \begin{pmatrix} \varepsilon_t^{\text{real gas price shock}} \\ \varepsilon_t^{\text{demand-side shock}} \\ \varepsilon_t^{\text{monetary policy shock}} \\ \varepsilon_t^{\text{supply-side shock}} \\ \varepsilon_t^{\text{idiosyncratic inflation expectation shock}} \end{pmatrix}, \tag{4.3}$$

where a + denotes a positive and a − a negative reaction. A star $*$ indicates that we impose no sign restriction on impact.

4.2 Structural Scenario Analysis Counterfactuals

If a real gas price shock causes movements in inflation expectations that subsequently feed into inflation, we define this as a second-round effect. The first-round effect is the direct effect of real gas price shocks on inflation, while the second-round effect is any increase in inflation arising due to elevated inflation expectations. Ultimately, we are interested in measuring second-round effects. Note, that even if inflation expectations rise in response to a real gas price shock, this does not automatically imply that second-round effects are at work. Therefore, we resort to a counterfactual analysis by shutting down the effects originating from inflation expectations. Hence, we construct a counterfactual where inflation expectations are insensitive to real gas price shocks, thereby isolating first-round effects. Counterfactual analyses have a long tradition in macroeconomics and are also utilized in studying questions related to energy markets (see, among many others, Kilian and Lewis, 2011; Wong, 2015). Here, one creates a sequence of inflation expectations shocks, which mute out the inflation expectations response after a real gas price shock. A more recent contribution by

Antolin-Diaz, Petrella and Rubio-Ramirez (2021) builds on these ideas and introduces a *structural scenario analysis*, where structural shocks are allowed to deviate from their unconditional distribution. In what follows, we describe this approach for the case of impulse response analysis (similar to the approach in Breitenlechner, Georgiadis and Schumann, 2022).

The unconditional forecast of the observed variables in the VAR, denoted with the $nh \times 1$ vector $\boldsymbol{y}_{T+1,T+h} = (\boldsymbol{y}'_{T+1}, \boldsymbol{y}'_{T+2}, \ldots, \boldsymbol{y}'_{T+h})'$, can be written as

$$\boldsymbol{y}_{T+1,T+h} = \boldsymbol{b}_{T+1,T+h} + \boldsymbol{M}'\boldsymbol{\varepsilon}_{T+1,T+h}, \tag{4.4}$$

where the vector $\boldsymbol{b}_{T+1,T+h}$ is predetermined and depends on the full history of the observables and the reduced-form parameters. In the absence of any future shocks, $\boldsymbol{b}_{T+1,T+h}$ denotes the dynamic forecast of the system. The $nh \times 1$ vector $\boldsymbol{\varepsilon}_{T+1,T+h} = (\boldsymbol{\varepsilon}'_{T+1}, \boldsymbol{\varepsilon}'_{T+2}, \ldots, \boldsymbol{\varepsilon}'_{T+h})'$ thus denotes all future values of the structural shocks. Lastly, the $nh \times nh$ matrix $\boldsymbol{M}$ constitutes the dynamic propagation of future structural shocks and is a function of the structural VAR parameters. Note that if the VAR is stationary, in steady state at T, $\boldsymbol{b}_{T+1,T+h} = \boldsymbol{0}$, and if there is only a single future shock $\boldsymbol{\varepsilon}_{T+1,T+h} = (\boldsymbol{e}'_1, \boldsymbol{0}_{n(h-1)\times 1})$, then $\boldsymbol{M}$ reflects the usual impulse response functions to a unit shock. $\boldsymbol{e}_i$ denotes the unit vector with unity on the i-th position. For instance, for the impulse responses to a real gas price shock, we have $\varepsilon_{1,T+1} = 1$, $\varepsilon_{1,T+s} = 0$ for $s > 1$ and $\varepsilon_{j,T+s} = 0$ for $s > 0$ and $j \neq 1$. We denote this in the following as the *unconditional* impulse response function.[9]

In the framework of Antolin-Diaz, Petrella and Rubio-Ramirez (2021), the structural VAR parameters captured in $\boldsymbol{M}$ remain *unchanged* in the counterfactual. In principle, the analysis does not risk falling into the criticism put forward by Lucas (1976) as long as the structural shocks used to construct the counterfactuals are not *too unusual*. We use the modesty statistic proposed by Leeper and Zha (2003) and the q-divergence distribution proposed in Antolin-Diaz, Petrella and Rubio-Ramirez (2021) to safeguard us against these concerns. In Appendix C, we provide the details of how to implement these tests. In order to satisfy the imposed constraints on the impulse response $\tilde{\boldsymbol{y}}_{T+1,T+h}$, additional shocks are allowed in $\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h}$ to materialize over the impulse response horizon. We choose those values such that we offset the effects of inflation expectations to a real gas price shock.

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[9] Technically, the impulse response function is *conditional* on a shock in the first period. Nevertheless, we deem the term appropriate since both – the baseline impulse response and the counterfactual impulse response – are *conditional* on a shock in the first period. Hence, we distinguish between *conditional* counterfactual impulse responses and *unconditional* impulse responses to a shock in the first period.

We implement the constraints on the paths of one endogenous variable (i.e., inflation expectations) in $\tilde{\boldsymbol{y}}_{T+1,T+h}$ as follows

$$\overline{\boldsymbol{C}}\tilde{\boldsymbol{y}}_{T+1,T+h} = \overline{\boldsymbol{C}}\boldsymbol{M}'\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}\left(\overline{\boldsymbol{f}}_{T+1,T+h}, \overline{\boldsymbol{\Omega}}_f\right), \tag{4.5}$$

where $\overline{\boldsymbol{C}}$ is a $k_o \times nh$ selection matrix, $\overline{\boldsymbol{f}}_{T+1,T+h}$ is a $k_o \times 1$ vector, and $\overline{\boldsymbol{\Omega}}_f$ a $k_o \times k_o$ matrix. $\overline{\boldsymbol{f}}_{T+1,T+h}$ and $\overline{\boldsymbol{\Omega}}_f$ are the mean and covariance matrix restrictions. This formulation also accommodates the special case $\boldsymbol{\Omega}_f = \boldsymbol{0}$, which we will adopt. This resembles the classic "hard" conditional forecasting exercise as defined in Waggoner and Zha (1999). In the context of this study, we impose the restriction that the inflation expectations spillovers to real gas price shocks are zero. Furthermore, the constraints on the structural shocks are given by

$$\Xi\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}\left(\boldsymbol{g}_{T+1,T+h}, \boldsymbol{\Omega}_g\right), \tag{4.6}$$

where Ξ is a $k_s \times nh$ selection matrix. $\boldsymbol{g}_{T+1,T+h}$ is a $k_s \times 1$ vector and $\boldsymbol{\Omega}_g$ is a $k_s \times k_s$ matrix and denote the mean and covariance matrix restrictions. Again, we implement exact restrictions and fix $\boldsymbol{\Omega}_g = \boldsymbol{0}$. Here, we want the structural idiosyncratic inflation expectation shock to be the offsetting force such that the impulse response to inflation expectation to real gas price shocks is zero. Therefore, we impose that all structural shocks are zero over the whole impulse response horizon except the structural shock to natural gas prices in the first period and the structural shocks to inflation expectation along the impulse response horizon. Antolin-Diaz, Petrella and Rubio-Ramirez (2021) show how to obtain the solution in terms of $\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h}$, which satisfies the constraints in Equation (4.5) and Equation (4.6). The counterfactual impulse response is then given by $\tilde{\boldsymbol{y}}_{T+1,T+h} = \boldsymbol{M}'\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h}$. We refer to Appendix C for further technical details.

5. Results

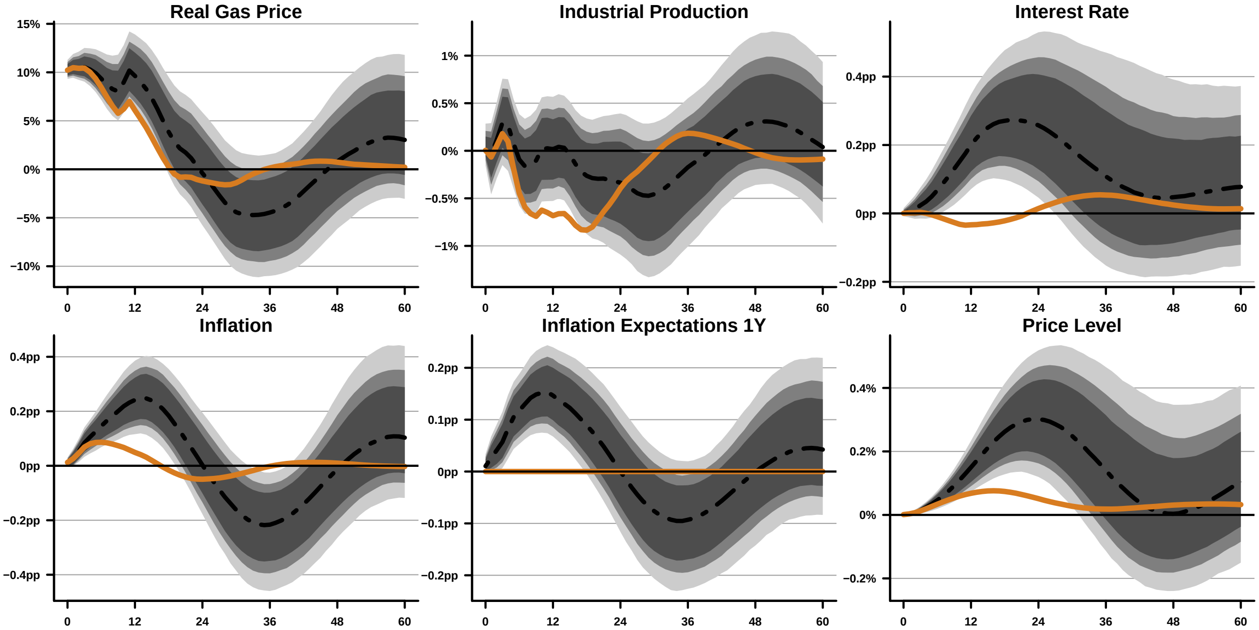
In this section, we report and discuss the results obtained with both of the above-elaborated identification strategies. In the next step, we investigate the second-round effects of inflation expectations and the role of their respective horizon. In all specifications, we use $p = 12$ lags in order to account for long and variable lags in the transmission of real gas price shocks. In terms of shock sizes, we standardize it to a one standard deviation increase in the real price of natural gas. From the impulse response of annualized inflation, we back out price level deviations by accumulating the effects. In all specifications, we report the median impulse response functions (IRFs) along with their 68/80/90 percent confidence bands. The black, dashed lines always denote the median IRF, while the orange, solid lines report the counterfactual, in which the the inflation expectation channel is shut off, discussed further in subsection 5.2.

5.1 The Effects of Natural Gas Price Shocks

We start by investigating the model identified with timing restrictions, where results are reported in Figure 3. We observe that a one standard deviation shock triggers about a 10% increase in real gas prices on impact. Both inflation and short-term inflation expectations start to increase and reach their maximum after about one year. While both reactions are very similar in terms of shape, inflation shows increases of two to three percentage points, which are of slightly stronger magnitude compared to its expectation. Moreover, both variables show an undershooting after about two years. Correspondingly, we observe an increase in the price level of about 0.3% at maximum. In the first year after the shock, industrial production remains rather stable with only minor declines after two years. However, monetary policy quickly turns restrictive and reaches its peak roughly after a bit more than a year. In comparison to the recent gas price surge in the summer of 2022, this shock can be considered an event of the magnitude of two to three standard deviations in real terms. This would amount to a total increase in the price level of about 0.6-0.9%. Hence, a rather strong increase in real gas prices leads to a comparably smaller effect on prices in the euro area economy. Also, for core inflation these effects appear to be rather stable as seen in Figure D1, however, less in magnitude.

However, this calls for further investigation as the employed identification scheme may not be suitable, because the real natural gas price shock possibly also captures aggregate demand shocks. Therefore, we move to our preferred identification scheme, where we implement sign and zero restrictions. Figure 4 presents the results. Overall, this identification scheme paints a qualitatively similar picture to the previous one, with one striking difference. Industrial production drops substantially by almost two percent, while a one standard deviation shock raises real gas prices by only about 5% on impact. Here, the imposed sign restriction to disentangle natural gas and demand shocks comes to work and points towards the fact that the timing restrictions are not capable of achieving that. Hence, a real natural gas price shock has strong adverse effects on industrial production. However, both inflation and its short-term expectations show similar reactions and again, we observe a strong mean-reverting behavior with undershooting after two years. However, the amplitudes are marginally smaller compared to the timing restrictions. Monetary policy turns slightly more restrictive, reaching the peak a few months later compared to the timing restrictions.

Figure 3: Impulse Response Functions to a Real Gas Price Shock (Timing Restrictions).



Notes: The model features five variables, where the shock is identified with timing restrictions and standardized to a one standard deviation increase in the real price of natural gas. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production and the price level are in percent, while the interest rate, inflation and inflation expectations are scaled to annualized percentage points.

The higher uncertainty and the smaller shock size of the real gas price shock in the first year may serve as an explanation for the slightly attenuated responses in this specification. However, the implied effects of the recent gas price surge (four to six standard deviations) are higher with this set of restrictions since the shock elicits an attenuated response of real gas prices. We observe a 0.2pp increase in inflation at a maximum of a 5% increase in the real gas price. Interestingly, this is quite consistent with evidence from microdata provided by Lafrogne Joussier, Martin and Mejean (2023), who examine the cost pass-through to inflation to energy price shocks in the French manufacturing sector. Again, these effects remain almost identical in shape and magnitude if we use core inflation as our target inflation measure as shown in Figure D2.[10]

Both identification schemes highlight that inflation expectations react positively to a natural gas price shock. This is consistent with the empirical evidence that inflation expectations are sensitive to commodity price (however, mostly oil price) shocks (Harris et al., 2009; Coibion and Gorodnichenko, 2015b; Aastveit, Bjørnland and Cross, 2023). In general, inflation expectations react less pronounced than the inflation

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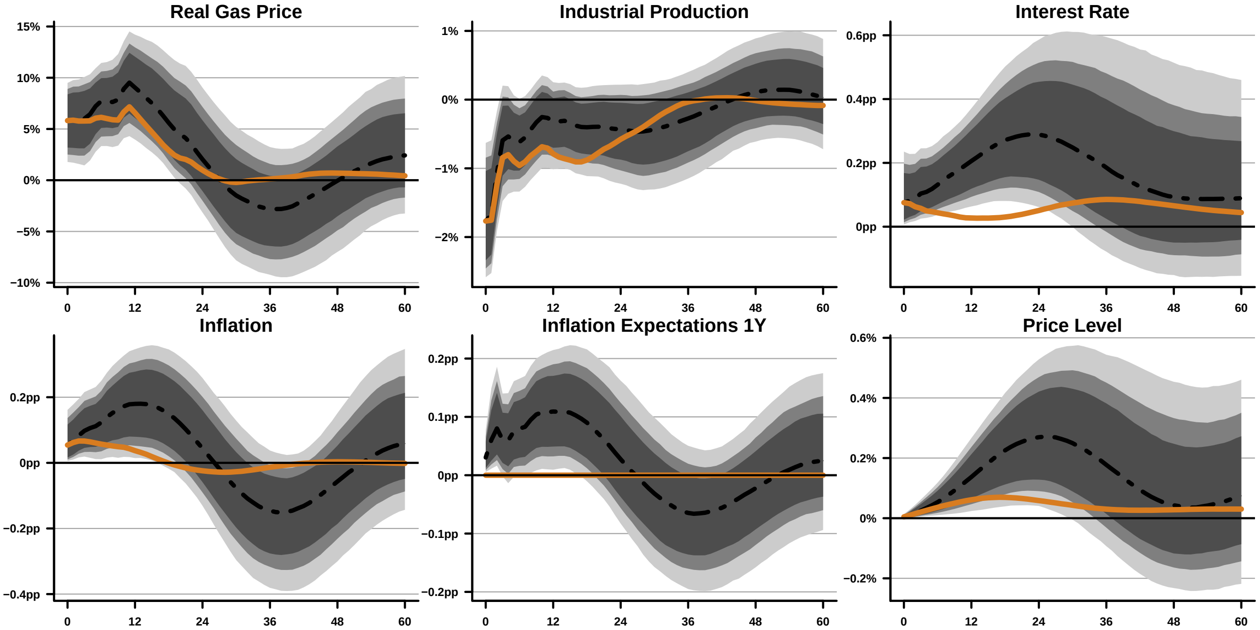
[10] Furthermore, the results are robust to a specification in which the sample starts after the Great Financial Crisis in January 2010. The outcomes remain basically unchanged. All results are available from the authors upon request.

Figure 4: Impulse Response Functions to a Real Gas Price Shock (Sign and Zero Restrictions).



Notes: The model features five variables, where the shock is identified with sign and zero restrictions and standardized to a one standard deviation increase in the real price of natural gas. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production and the price level are in percent, while the interest rate, inflation and inflation expectations are scaled to annualized percentage points.

series. This implies a persistent positive forecast error of inflation for about two years.[11] This is consistent with prior studies that document an underreaction of inflation expectations to economic shocks (Coibion and Gorodnichenko, 2012) and in general (Coibion and Gorodnichenko, 2015a). So far, we have not distinguished between first- and second-round effects. Hence, we cannot pin down the role of the inflation expectation channel in transmitting these kinds of shocks to other (real) variables, which we address in the next section through a counterfactual exercise.

5.2 Second-Round Effects of Inflation Expectations

In this section, we investigate whether movements in inflation expectations caused by natural gas price shocks have amplifying or propagating inflationary effects. We identify this second-round effect with the help of a structural scenario analysis counterfactual outlined above. By constructing a structural scenario analysis in which inflation expectations do not react to natural gas price shocks, we are able to examine the differential response to inflation. The intuition of this exercise is to isolate first-round effects. If the expectation channel

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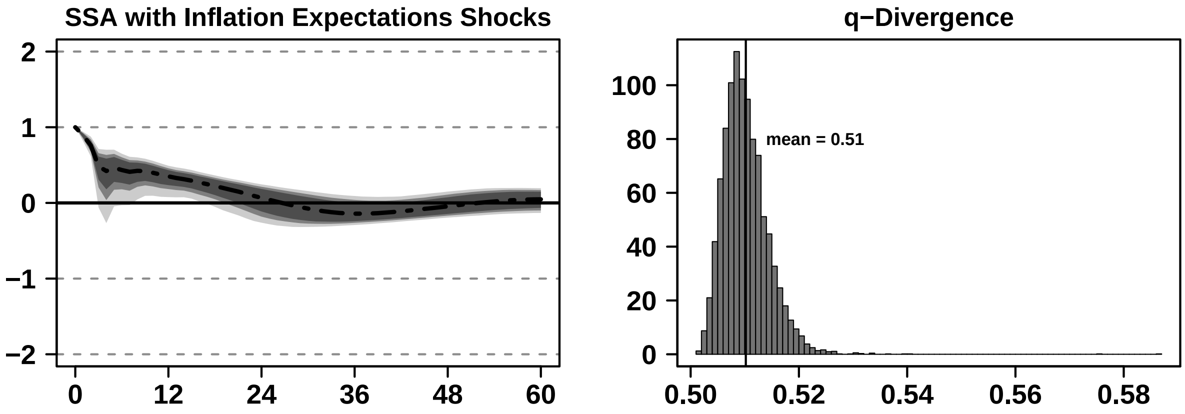
[11] We back out the implied forecast error impulse response function of inflation (constructed as the difference between realized inflation and the previous year's 1-year expected inflation) to validate this claim, as shown in Figure D3.

via inflation expectations is indeed an important propagation channel to inflation (the second-round effect), then the counterfactual impulse response of inflation will deviate substantially from the unconditional impulse response. This directly affects the implied Phillips curve relation as the natural gas price shock can be seen as a cost-push shock. Hence, the cost channel directly affects the price-setting behavior and has implications for marginal costs. To visualize the results of this exercise, the solid orange line in Figure 3 and Figure 4 depicts these counterfactual impulse responses. Furthermore, note that by construction only the structural shocks of inflation expectations are used to offset this effect. Put differently, only the idiosyncratic inflation expectation shock deviates from its unconditional impulse response, eventually changing the dynamics of the whole system while maintaining the estimated structural relationships.

We present the counterfactual responses as the orange, solid lines in the figures, where the IRF of inflation expectations is zero over the full impulse response horizon as assumed. We start discussing the model identified with timing restrictions in Figure 3. The counterfactual responses of the real gas price shock do not exhibit a strong deviation from its unconditional counterpart. The response of inflation and the corresponding price level reveal a substantial reduction in the inflation response. Inflation reacts only muted, even after one year, thus very different from the unconditional response. However, mean reversion is still visible, after reaching a very low maximum response after one year. The effect is also less pronounced for the corresponding price level. Industrial production, however, shows a stronger drop but an earlier mean reversion without second-round effects. Our model thus implies strong second-round effects via inflation expectations to a real gas price shock.

The overall conclusion stays qualitatively the same when using sign and zero restrictions, depicted in Figure 4. When shutting off the reaction of inflation expectations, both the real gas price and industrial production do not deviate strongly from their unconditional responses. On the contrary, interest rates show the same attenuated pattern as inflation. The counterfactual responses show more muted on-impact reactions, pointing to less nominal adjustments. Thus, the monetary authority reacts much more pronounced if the expectation channel is present. Taken at face value, this is a first suggestive evidence that the central bank is actively fighting any de-anchoring tendencies of inflation expectations. If anything, industrial production reacts a bit more pronounced and slightly longer without a response from inflation expectations. This corresponds to the mechanism of the Phillips curve, which offers a trade-off between economic slack and inflation. By shutting down adjustments via inflation expectations (resulting in lower inflation) to a cost-push shock, the economic slack partly captures the effect. Further, this finding is also in line with the

Figure 5: Plausibility Statistics of Counterfactuals.



Notes: The left figure shows the modesty statistic of Leeper and Zha (2003) and the right figure shows the distribution of the q-divergence proposed by Antolin-Diaz, Petrella and Rubio-Ramirez (2021). The modesty statistic reports the implied shocks that impose the counterfactual constraint for inflation expectations. The black dashed line denotes the posterior median responses while gray shaded areas depict the 68/80/90 percent confidence intervals.

theoretical predictions of Werning (2022), who investigates the pass-through of inflation expectations on current inflation with arbitrarily (non-rational) formed expectations. The pass-through is close to but clearly below unity. Finally, the maximum price level response is roughly only a quarter from the unconditional response, pointing again to a rather strong adjustment mechanism via the expectation channel.

The plausibility of the counterfactuals obtained by the structural scenario analysis depends on the offsetting structural shocks, i.e., the idiosyncratic inflation expectation shock. Specifically, we risk falling into the criticism by Lucas (1976) if the required shocks are unusually large or persistent. Under such a situation, agents may update their beliefs about the policy regime and the structure of the economy more substantially. Against this backdrop, we implement the modesty statistic of Leeper and Zha (2003) and the q-divergence proposed by Antolin-Diaz, Petrella and Rubio-Ramirez (2021), which are presented in Figure 5. The left figure shows the modesty statistic, which denotes the implied offsetting shocks that impose the counterfactual constraint for inflation expectations. The offsetting shocks are *modest* if the statistic is smaller than two in absolute values. This is confirmed and thus the materialization is unlikely to induce agents to adjust their expectation formation and beliefs about the structure of the economy leaving no room for the Lucas critique. In the right graph, the q-divergence indicates how strongly the distribution of offsetting shocks in the counterfactual deviates from their unconditional distribution translated into a comparison of the binomial distribution of a fair and a biased coin. Again, the test does not indicate that the distribution of offsetting shocks in the counterfactual is notably different from the unconditional distribution.

Overall, our results stand in stark contrast to the findings of the literature for other commodity price shocks. Wong (2015), for instance, uses a smaller model and conducts an analysis for the US and for oil price shocks. Nevertheless, he finds only limited evidence for second-round effects of inflation expectations and concludes that the US offers an environment where inflation expectations are well anchored. Further evidence for that is provided by Kilian and Zhou (2022b) who investigate the increase in oil and gasoline prices since mid-2020. They provide evidence that these kinds of shocks have not moved long-run household inflation expectations. We will return to these points when comparing the results to the US in several extensions below. Lastly, we assume that the inflation risk premium is not time-varying in this analysis and thus not a major driver of our findings. To alleviate possible concerns, we will return to this point later on when re-doing the analysis with inflation expectations originating from the survey of professional forecasters.

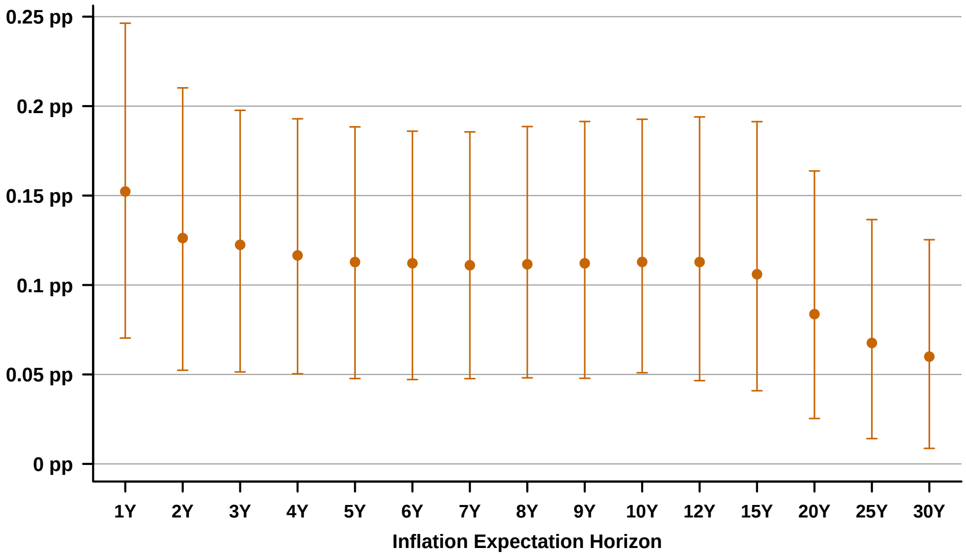
5.3 Does the Horizon of Inflation Expectations Matter?

In the next step of the analysis, we exploit one key advantage of using ILS inflation expectations, namely the availability of a variety of horizons up to thirty years. We re-estimate our model identified with sign restrictions with different horizons of our inflation expectation measure. Note that we exchange the measure of inflation expectations once at a time and do not pursue estimating a model including all the horizons.

We start with short-run expectations of one year ahead (see main results above) and move along until we reach long-run inflation expectations (30 years ahead). Then, for each estimated model we pick the maximum difference between the unconditional and the counterfactual impulse response of inflation. For example, we can directly compare the outcome of the maximum difference of 1Y inflation expectations to the difference in Figure 4. Here, the maximum difference between the impulse responses occurs shortly after 16 months with about 0.15 percentage points. Put differently, without second-round effects via the expectation channel, inflation is 0.15 (annualized) percentage points lower on average. Additionally, we also report confidence sets for the differences such that the whiskers in Figure 6 are the full 68 % confidence interval of the differences' posterior distribution.

Figure 6 reveals several interesting results. First, all maximum differences between the unconditional and counterfactual impulse responses are statistically and significantly different from zero. Second, the median difference response using short-term (i.e., one year) inflation expectations exhibits the highest difference. Although the effects gradually decrease from short- to long-term horizons, as expected, differences are not statistically significant. The differences in the medium-term expectations, from three to 15 years, remain

Figure 6: Effect Sizes for Inflation with Varying Horizon of Inflation Expectations.



Notes: Maximum difference between the unconditional and the counterfactual impulse response function of inflation in percentage points (pp) in the model identified with sign and zero restrictions. Dots refer to the median of the maximum response, while the whiskers denote the 68 percent confidence region.

rather constant, while the differences from 20 years onwards decrease significantly. The overall picture points to a downward shift of the complete term structure of inflation expectations once we purge for second-round effects. The effect of inflation expectations 10 years ahead lies still around 0.11 percentage points. Arriving at 30-year expectations a maximum difference of about 0.06 (annualized) percentage points can be seen. Furthermore, (not visible in the plot) the maximum responses are usually reached after about 16 to 22 months, typically quicker for shorter-term expectations. So overall, the picture shows that the channel via inflation expectations accounts for 0.1-0.15 percentage points of inflation. While our approach does not distinguish between movements of inflation risk premia in market-based inflation expectations, we nevertheless can conclude that the second-round effects of natural gas price shocks are non-negligible over the full term structure of expectations.

5.4 Discussion of the Results

Summing up the results so far, we show that real gas price shocks have inflationary tendencies both via first- and second-round effects. Specifically, the counterfactual analysis reveals strong second-round effects through the inflation expectations channel. However, the time frame of the sample is crucial for the results, which is already indicated by our motivational Figure 1. If we exclude the period of the recent natural gas price surge, we do not obtain these pronounced reactions.[12] Furthermore, our findings indicate that second-round effects are stronger for shorter-term inflation expectations than for longer-term expectations. This is consistent with evidence that short-term expectations are more important compared to longer ones in determining inflation (Fuhrer, 2011; Fuhrer, Olivei and Tootell, 2012). Nevertheless, a shift along the term structure is clearly visible.

Still, a few questions about the interpretation of the results remain. For instance, the results point to the fact that inflation expectations in the euro area are rather sensitive to natural gas price shocks or, at least, turned so in the last year. Why are these reactions comparatively strong and why do they actually drive inflation? Three possible – however, not mutually exclusive – interpretations offer an explanation. The first concerns issues around the anchoring of inflation expectations in the euro area. A second interpretation points towards the particularities of expectation formation processes. Finally, there could also be demand-side forces outside of our framework at work that affect inflation expectations.

With respect to the first question, we expect inflation expectations to not react strongly in an environment where they are well-anchored (Reis, 2021; Carvalho et al., 2023). Monetary policy authorities put an emphasis on managing inflation expectations to ultimately stabilize inflation through various factors. These include, inter alia, the choice of the policy regime, the precise actions taken, and their communication. For instance, if a central bank pursues an inflation-targeting regime committing to keep inflation at a specific rate or range over a specified period provides a clear and measurable target. With their strategy review finished in the summer of 2021, the ECB changed from an asymmetric ("below but close to") to a symmetric target of 2% annual inflation. This target features a clear signal to the public and helps to anchor inflation expectations as economic agents know that the central bank will react to deviations from this target. Furthermore, credible central banks use clear and effective communication of the economy's assessment and their decisions. For a further discussion on possible obstacles, see the discussion in Reis (2022b). As a result – and arguably in a perfect world – inflation should thus not respond beyond the cost channel, or, put differently, we should only observe first-round effects. Prima facie, our results allow the interpretation that expectations are susceptible to real natural gas price shocks. Moreover, we find substantial second-round effects (the pass-through to

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[12] For this exercise, we split the sample before the onset of the pandemic (end of December 2019) and before the recent gas price surge (end of June 2021). In both cases, natural gas price shocks do not reveal strong effects on inflation and inflation expectations. This holds specifically for natural gas prices and, to a lesser extent, for oil prices. Results are available from the authors upon request.

inflation), both for short- and long-run expectations. This opens a mandate for monetary policy to alleviate possible concerns of de-anchored inflation expectations and ultimately their pass-through to inflation.

Second, the expectation formation process of inflation expectations may be distorted in a way that it does not resemble rational expectation. A wide array of papers has shown that agents, may it be firms or households, are informationally constrained when forming inflation expectations, which holds true independently of how inflation expectations are measured (Coibion and Gorodnichenko, 2012; Coibion and Gorodnichenko, 2015a). We confirm this in our analysis with market-based expectations. Specifically, D'Acunto, Malmendier and Weber (2023) and Weber, Gorodnichenko and Coibion (2023) point out that information provided by policymakers is often ignored or wrongly interpreted by economic agents and that personal experience, human cognition or gender play a larger role for households in forming inflation expectations. In terms of monetary policy, the pervasiveness of information rigidities in the economy has led to the conclusion that an optimal policy should respond aggressively to fluctuations in inflation (Reis, 2009). All of the above-mentioned studies point to the fact that information frictions do not differ strongly between the US and the euro area. This empirical fact motivates our consecutive analysis, where we will re-do our analysis for the United States.

Third and lastly, inflation expectations may be affected by additional demand-side forces outside of our model. While natural gas prices have strongly gained momentum after the Russian invasion of Ukraine in February 2022, their elevation began already in mid-2021. In this time period, economies around the world were recovering economically from the Covid-19 pandemic. Part of this recovery process was generous fiscal transfers and support to households and firms, which we do not take explicitly into account with our model stance. Thus, these fiscally induced demand forces are not considered by our identification, unless they are captured by industrial production. According to Coibion, Gorodnichenko and Weber (2021) inflation expectations are sensitive to fiscal considerations, such as taxes and government spending. Specifically, news about future debt leads to anticipatory inflation expectation reactions, both in the short and long run. For example, using a new consumer survey in the euro area, Georgarakos and Kenny (2022) shows in a randomized control trial that a more positive assessment of fiscal interventions improves household expectations about income prospects or future access to credit and financial sentiment. Needless to say, this serves only as indirect evidence for an effect of inflation expectations. Still, we acknowledge that our approach can only partially filter out the effects of the various fiscal interventions during the Covid 19 pandemic, which we will thus leave for further research.

6. Extensions

We provide extensions along three lines. First, we re-do the analysis with the survey of professional forecasters (SPF) of the European Central Bank (ECB) on a quarterly frequency. Moreover, while the case of natural gas is particularly interesting due to its recent classification as a *transition* energy source and, more importantly, will thus still be a crucial input in the future, oil prices in general show a strong comovement (see the discussion in section 3). Hence, the second extension is based on the real price of oil instead of natural gas. The third extension tackles the aforementioned question if there is a different reaction to these shocks in the US. The main focus of the paper lies on the euro area, where natural gas plays an important role. Given the heterogeneous situation around structural and economic factors about natural gas in the euro area and the US, this is a particularly intriguing comparison. Moreover, it allows us to investigate whether the inflation expectation formation process plays a central role in driving the results.

6.1 Inflation Expectations based on the Survey of Professional Forecasters

We mainly re-do the analysis with the inflation expectations from the SPF of the ECB to provide robustness with a survey-based measure of inflation expectations, which compared to their marked-based counterpart does not feature liquidity risks or a latent risk premium component.[13] However, the SPF data is only available on a quarterly frequency, which leaves us with only 72 observations from 2004Q1 to 2022Q4. We use the 12-month ahead and longer-term forecast (5 years) of HICP for the analysis.

The results are presented in Figure 7. Overall, they confirm the picture presented so far. Real natural gas price shocks elicit a jump in the real gas price of about 10%. Industrial production drops while the monetary authority raises interest rates. Inflation and its expectations increase. Notably, longer-term expectations increase much less pronounced. The counterfactual exercise (solid orange lines) reveals that the second-round effects are quite sizable in the model with short-term expectations but basically vanish for longer-term expectations. The decrease in the pass-through is again corroborating the theoretical predictions of Werning (2022). The pass-through in short-term expectations is now only about 0.4-0.5, while long-term expectations do not alter the transmission channel visibly. Again, in both models (with 1- and 5-year expectations) expectations clearly underreact to new information. We corroborate our earlier findings that the duration

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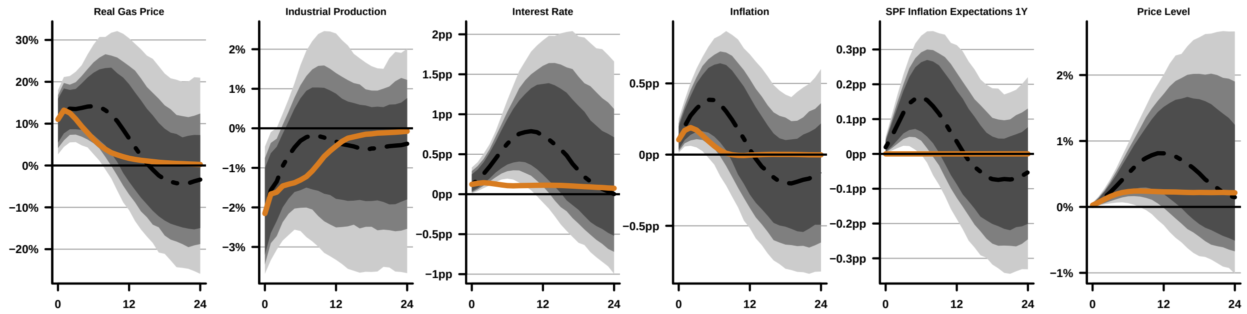
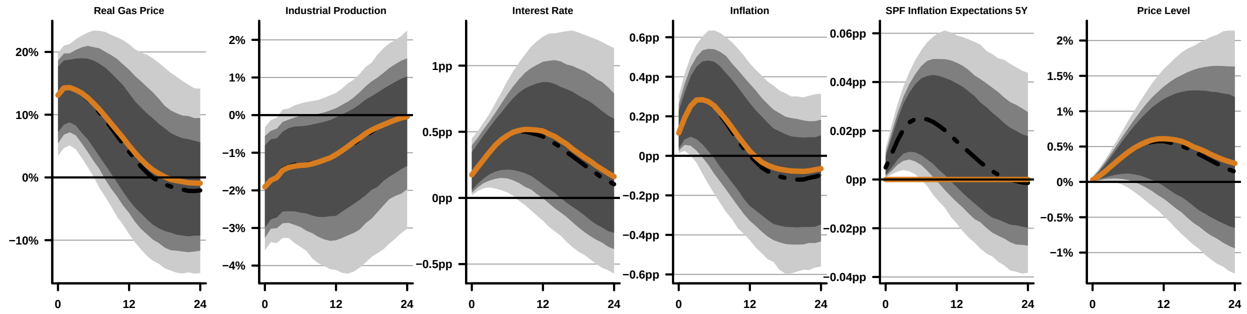
[13] The Federal Reserve of Cleveland provides an estimate of the inflation risk premium for the US. This series fluctuates mildly around a long-run mean and shows no obvious correlations to business cycle fluctuations and/or historical episodes (e.g., the high inflation period of the 1970s).

Figure 7: Impulse Response Functions to a Real Gas Price Shock (SPF).



(a) SPF: 1Y Ahead Inflation Expectations.



(b) SPF: 5Y Ahead Inflation Expectations.

Notes: The model features inflation expectations from the survey of professional forecasters (SPF) on quarterly frequency. The upper panel uses 1-year ahead and the lower panel 5-year ahead inflation expectations. The shock is identified with sign and zero restrictions and standardized to a one standard deviation increase in the real price of natural gas. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production, and the price level are in percent, while the interest rate, inflation, and inflation expectations are scaled to (annualized) percentage points.

of an underreaction to information is about two years (as seen in Figure D3) which is consistent with earlier findings (Coibion and Gorodnichenko, 2012; Coibion and Gorodnichenko, 2015a). Furthermore, the uncertainty bounds are generally more sizable, which is due to the limited time span of the sample.

The SPF data confirms our initial findings, although longer-term expectations react less pronounced. Interestingly, in the model with survey-based expectations, inflation shows more sensitivity towards natural gas price shocks, which yields also a stronger effect on the price level. Hence, the apparent smaller decrease in the model with 5Y expectations is still a sizable decrease of about 0.4 percentage points at the maximum in the price level. Therefore, these findings confirm that short-term inflation expectations matter most for the pass-through of commodity price shocks. They also show that longer-term expectations are more stable in the survey-based than in the market-based measure. We again conclude while inflation expectations did not show a de-anchoring dynamic, they still play an important role during energy price shocks.

6.2 Real Oil Prices as External Shocks

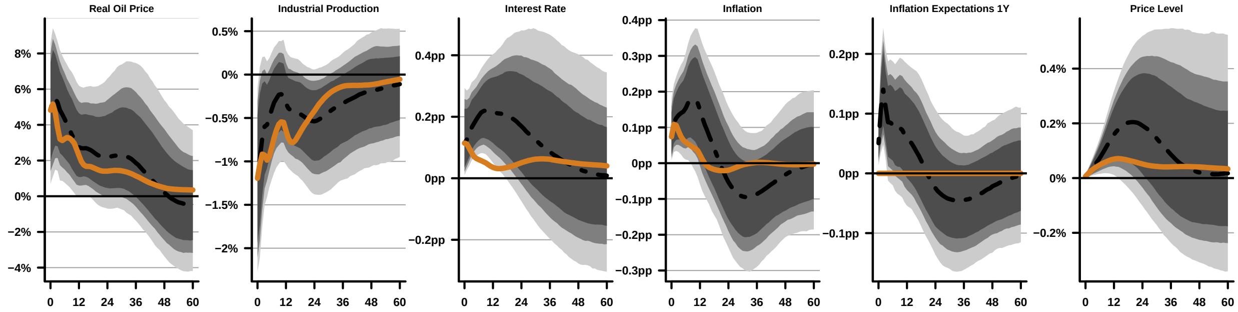
We look into an alternative fossil fuel used as production input (either as energy or as a direct input), thus also serving as external shocks to energy prices in the euro area: crude oil. Oil prices are historically an interesting case and still – while with a vanishing effect – important for economic activity. Crude oil exhibits a strong comovement, as can be seen in Figure 2, and natural gas and oil show a correlation coefficient of 0.45 in the total sample. Interestingly, the picture reverses if we end the sample before mid-2021, where the correlation coefficient increases to 0.76. This serves as preliminary evidence that natural gas and oil show a stronger comovement before the recent gas price surge with decoupling tendencies before.

The findings of this exercise are presented in Figure 8, where the real price of natural gas was substituted by the real price of oil (Brent). The identification strategy to isolate a real oil price shock resembles the same sign and zero restrictions as described in section 4. The oil price shock shows similar dynamics as in the model featuring the real gas price. Industrial production contracts on impact and inflation as well as inflation expectations increase. The increase in inflation expectations is much more short-lived than before. Short-term interest rates show a tightening monetary policy stance. The responses' magnitudes vary but are in the ballpark of the estimates before. Interestingly, the uncertainty around our responses is higher in the model with crude oil compared to the ones with natural gas. This can potentially be explained by the higher volatility of this commodity in our sample compared to natural gas.

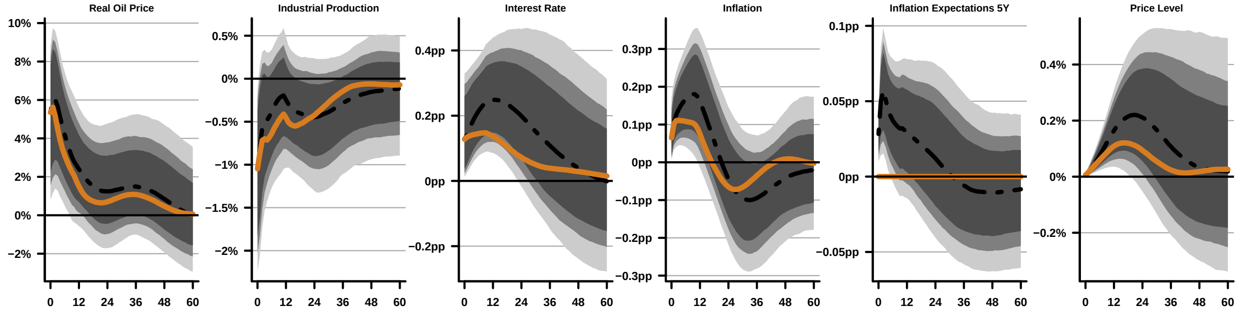
Turning to the counterfactual exercise, i.e., the orange lines in Figure 8, the outcomes are again qualitatively similar to the model with real gas price shocks. Similar to the decreased impact of inflation expectations on the real oil price shock, the counterfactual response of inflation is now more attenuated. Again, the impulse response of inflation expectations is nil to real oil price shocks by construction. Thus, the structural shocks of inflation expectations are responsible for creating the offsetting force. While the counterfactual impulse responses of the commodity prices and industrial production do not strongly deviate from their unconditional response, we see again an adjustment for interest rates and inflation. The implied price level is about 50-60% lower than in the unconditional response (moving from a 0.2% increase to less than a 0.1% increase). This is a somewhat smaller impact but still comparable to the decrease observed when analyzing a natural gas price shock.

We also re-estimated the model with the respective 5-year inflation expectations, where the results can be found in the lower panel of Figure 8. Both the impulse responses and the counterfactual responses are

Figure 8: Impulse Response Functions to the Real Price of Oil (Sign and Zero Restrictions).



(a) Alternative Commodity Price: Oil with 1Y Ahead Inflation Expectations.



(b) Alternative Commodity Price: Oil with 5Y Ahead Inflation Expectations.

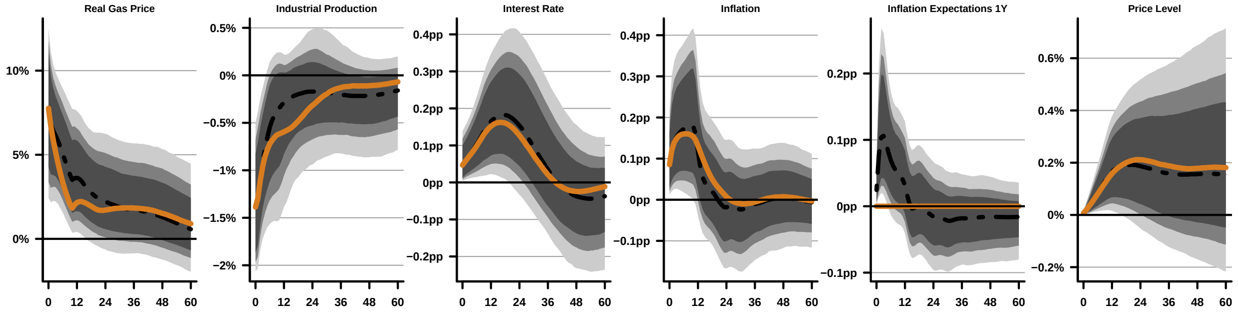
Notes: The model for the real price of Brent oil features five variables, where the shock is identified with sign and zero restrictions and standardized to a one standard deviation increase in the real price of crude oil. The upper panel uses 1-year ahead and the lower panel 5-year ahead inflation expectations (ILS). The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real oil price, industrial production, and the price level are in percent, while the interest rate, inflation, and inflation expectations are scaled to (annualized) percentage points.

similar to the exercise before. Inflation expectations with a medium-term horizon (such as five years) only react shortly and are less pronounced on impact. This is again in line with the evidence that longer-term inflation expectations are less important for determining inflation. Therefore, the counterfactuals point to a less strong deviation from the unconditional response.

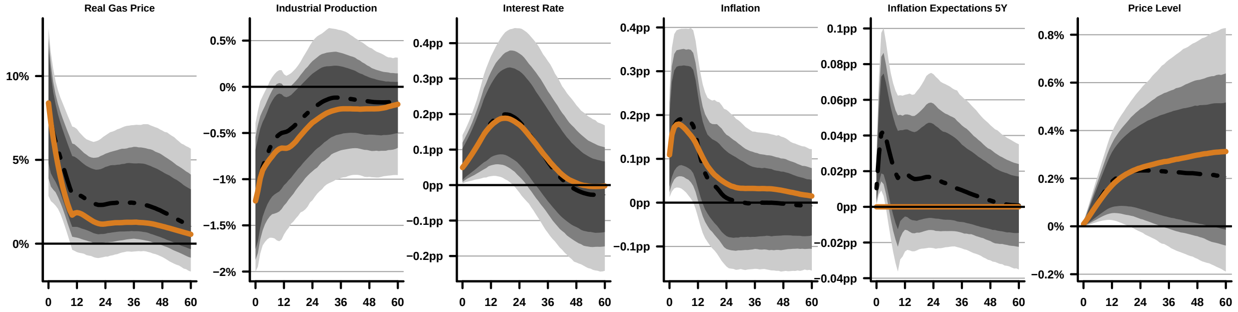
6.3 Real Gas Price Shocks in the US

Next, we examine whether we find similar effects in the US. To answer this question, we re-estimate the model identified with sign and zero restrictions again for the US. Hence, we use US variables and the US real gas price benchmark (Henry Hub). For the short-term interest rates, we use the US shadow rate (Wu and Xia, 2016), and inflation is characterized by the consumer price index. Inflation expectations are again

Figure 9: Impulse Response Functions to a Real Gas Price Shock for the US (Sign and Zero Restrictions).



(a) Real Gas Price Shock for the US with 1Y Ahead Inflation Expectations



(b) Real Gas Price Shock for the US with 5Y Ahead Inflation Expectations

Notes: The extended model for the US features five variables, where the shock is identified with sign and zero restrictions and standardized to a one standard deviation increase in the real price of natural gas. The upper panel (a) uses 1Y inflation expectations while the lower panel (b) 5Y expectations. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production, and the price level are in percent, while the interest rate, inflation, and inflation expectations are scaled to (annualized) percentage points.

inflation-linked swaps with the same characteristics and maturity structure as the euro area swaps. We refer to Appendix A for exact data details. Furthermore, we keep the sample starting in 2004M1 to 2022M11.

Results are presented in Figure 9. The real gas price increase loses power relatively quickly and industrial production drops only on impact before returning to zero after one year rather quickly. The interest rate reacts positively and mean reversion sets in after a year. Inflation is elevated for about one year, while inflation expectations shoot up only temporarily with a quick mean reversion. The counterfactual exercise, however, is remarkably different from the euro area results. Shutting down second-round effects via inflation expectations does not alter the unconditional responses substantially. This holds for short- and longer-run expectations, as seen in Figure 9a and Figure 9b, respectively. Most importantly, inflation does not show a strong difference from its unconditional response and thus we do not see a strong impact on the price level. Furthermore, these results are robust to using core inflation or using the real oil price instead of real gas prices (see Figure D5).

This corroborates the findings of Wong (2015), who investigates this in a simpler specification. Nevertheless, they also find only mild evidence (in a sample dating back to the early 80s) that inflation expectations feed into inflation reactions to a real oil price shock.

So, why do we see strong second-round effects in the euro area but not in the US? An intuitive explanation is again given by the anchoring of inflation expectations, by information rigidities in the formation of inflation expectations, and by demand-side forces due to the recovery from the Covid-19 pandemic. Coming back to our earlier discussion, Coibion and Gorodnichenko (2015a) show that information rigidities are relatively similar in a set of countries, including the US and the euro area. Hence, we discard the presence of information rigidities as a potential explanation for the differences between the US and the euro area. With regard to the remaining two explanations, our econometric model and identification distinguish between supply- and demand-side forces, but the Covid 19 pandemic and the respective fiscal responses hit both economies in a rather similar way. Hence, we are in line with Wong (2015) who points to expectation anchoring. He argues that inflation expectations in the US are tightly anchored, which immediately translates to less pronounced second-round effects.

7. Concluding Remarks

This paper investigates the recent natural gas price surge and its implications for inflation and inflation expectations in the euro area. In particular, we are interested in the second-round effects characterized as the pass-through of inflation expectations to inflation after a shock in natural gas prices. To investigate this issue, we develop a structural vector autoregressive model and use a combination of sign and zero restrictions to identify a natural gas price shock. Finally, we construct a counterfactual exercise in which the responses of inflation expectations to gas price shocks are nil. Furthermore, the paper is interested in the role of the horizon of inflation expectations. We also provide several extensions, in which we re-do the analysis with survey-based expectations, provide additional results with oil prices, and discuss the comparison of our findings to the case of the United States.

We find that both inflation and inflation expectations react positively to real natural gas price shocks. In a first step, we identify the effects with timing restrictions. To further purge real natural gas price shocks from demand-side fluctuations, we also utilize sign and zero restrictions. The counterfactual exercise reveals that inflation reacts much more muted when we zero out second-round effects via inflation expectations. This points to only a limited role of the cost channel and a more pronounced expectation channel. Furthermore, the expectation channel is stronger for short-term expectations compared to long-term expectations. This points towards a relatively stable inflation expectations anchor. These findings are robust to a number of design choices. We find the same outcomes if we use the survey of professional forecasters. Furthermore, we show in additional exercises that also crude oil shocks raise inflation and inflation expectations but the second-round effects are somewhat attenuated. The findings are sensitive to the inclusion of the period starting in mid-2021 and cannot be, in general, replicated for the US.

We discuss the potential drivers of these findings. A promising explanation points to the anchoring of inflation expectations. If the central bank does not stabilize inflation expectations at the onset of external commodity price shocks, this may trigger strong second-round effects. These effects describe inflationary pressures due to heightened inflation expectations. We also acknowledge that we cannot rule out entirely yet another explanation of de-anchored inflation expectations. In response to the Covid 19 pandemic, governments have provided generous stimulus packages which may also have affected inflation expectations. The proposed identification scheme is in principle designed to distinguish between demand- and supply-side forces but the pandemic has led to unprecedented policy responses, affecting both the supply and demand side. Nevertheless, the policy recommendations of the presented findings are straightforward because they hold even in the case of additional demand interventions. If there are signs that inflation expectations are starting to de-anchor, committed monetary policy reactions may tame heightened inflation expectations, especially in the presence of information rigidities (Reis, 2009). These findings are particularly important in the transition period to renewable energy sources. The EU has to import most of its natural gas demand, which it has recently classified as a source of *green energy*. Hence, the EU is also susceptible to supply-side disruptions in these markets, with additional threats to price stability particularly via the expectations channel. This logic broadly transfers to other supply-side disruptions as well. Therefore, a clear and credible policy of the central bank can manage the process and guide expectations.

Declaration of Interest

The authors declare to have no conflict of interest.

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A. Data Appendix

All series were gathered from the sources listed below, including the FRED database (McCracken and Ng, 2016), the World Bank Commodity Price Data (*Pink Sheet*) (The World Bank, 2023), the statistical data warehouse of the European Central Bank, or Macrobond. If necessary, series are seasonally adjusted with the X-13ARIMA-SEATS model. All series are approximately stationary.

Table A1: Variable Definitions.

Variable	Transformation	Details	Source
Euro area			
$\mathbf{rgas}_t$	$\ln\left(\frac{\mathtt{PGAS}_{it}}{\mathtt{E}_t^{US/EUR}\times\mathtt{HICP}_t}\right)$	real gas price	constructed
$\mathbf{roil}_t$	$\ln\left(\frac{\mathtt{POIL}_{it}}{\mathtt{E}_t^{US/EUR}\times\mathtt{HICP}_t}\right)$	real oil price	constructed
$\mathbf{ip}_t$	$100\times\ln\mathtt{IP}_t$	logarithm of industrial production	constructed
$\mathbf{sr}_t$	SR	Shadow rate for euro area by Wu and Xia (2016)	website of Jing Cynthia Wu
π_t	$100\times\ln\left(\frac{\mathtt{HICP}_t}{\mathtt{HICP}_{t-12}}\right)$	year-on-year growth rate of harmonized index of consumer prices	constructed
π_t^e	$\mathtt{ILS}^{xY}$	inflation-linked swaps with x year ahead	Macrobond
π_t^e	$\mathtt{SPF}^{xY}$	survey of professional forecasters with $x=\{1,5\}$ years ahead	SPF ECB
$\mathbf{PGAS}_t$	$\mathtt{PGAS}_t$	price of natural gas (TTF) in \$/mmBTU from Pink Sheet	World Bank
$\mathbf{POIL}_t$	$\mathtt{POIL}_t$	crude oil prices: Brent - Europe	FRED
$\mathbf{E}_t^{US/EUR}$	$\mathtt{E}_t^{US/EUR}$	US dollars to Euro spot exchange rate	FRED
$\mathbf{HICP}_t$	$\mathtt{HICP}_t$	harmonized index of consumer prices	FRED
$\mathbf{HICP}_t^{core}$	$\mathtt{HICP}_t^{core}$	harmonized index of consumer prices excluding food, energy, alcohol, and tobacco	FRED
$\mathbf{IP}_t$	$\mathtt{IP}_t$	industrial production index	SDW ECB
United States			
$\mathbf{rgas}_t$	$\ln\left(\frac{\mathtt{PGAS}_{it}}{\mathtt{CPI}_t}\right)$	real gas price	constructed
$\mathbf{roil}_t$	$\ln\left(\frac{\mathtt{POIL}_{it}}{\mathtt{CPI}_t}\right)$	real oil price	constructed
$\mathbf{ip}_t$	$100\times\ln\mathtt{IP}_t$	logarithm of industrial production	constructed
$\mathbf{sr}_t$	SR	Shadow rate for the US by Wu and Xia (2016)	website of Jing Cynthia Wu
π_t	$100\times\ln\left(\frac{\mathtt{CPI}_t}{\mathtt{CPI}_{t-12}}\right)$	year-on-year growth rate of harmonized index of consumer prices	constructed
π_t^e	$\mathtt{ILS}^{xY}$	inflation-linked swaps with x year ahead	Macrobond
$\mathbf{PGAS}_t$	$\mathtt{PGAS}_t$	price of natural gas (Henry Hub) in \$/mmBTU from Pink Sheet	World Bank
$\mathbf{POIL}_t$	$\mathtt{POIL}_t$	crude oil prices: West Texas Intermediate (WTI), US dollars per Barrel	FRED
$\mathbf{CPI}_t$	$\mathtt{CPI}_t$	consumer prices index for all urban consumers	FRED
$\mathbf{CPI}_t^{core}$	$\mathtt{CPI}_t^{core}$	consumer price index for all urban consumers excluding food and energy	FRED
$\mathbf{IP}_t$	$\mathtt{IP}_t$	industrial production index	FRED

B. Econometric Details

In this section, we briefly describe the estimation strategy of the macroeconomic model. The estimation of the VAR is based on a Bayesian framework with the Normal-Gamma shrinkage prior, a variant of a global-local shrinkage prior (Griffin, Brown et al., 2010; Huber and Feldkircher, 2019). Hence, following Equation (4.1), the reduced-form VAR(p) model for the time series process $\boldsymbol{y}_t$ reads

$$\boldsymbol{y}_t = \boldsymbol{c} + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{B}\boldsymbol{d}_t + \boldsymbol{u}_t, \quad \boldsymbol{u}_t \sim \mathcal{N}_n(\boldsymbol{0}, \boldsymbol{\Sigma}), \tag{B.1}$$

where p is the lag order, $\boldsymbol{c}$ is an $n \times 1$ vector of constants, $\boldsymbol{A}_1, \ldots, \boldsymbol{A}_p$ are $n \times n$ coefficient matrices, and $\boldsymbol{u}_t$ denotes an $n \times 1$ vector of reduced-form Gaussian distributed innovations with covariance matrix $\boldsymbol{\Sigma}$, factorized as follows $\boldsymbol{\Sigma} = \boldsymbol{H}^{-1}\boldsymbol{\Lambda}\boldsymbol{H}^{-1'}$. Additionally, the model may feature exogenous variables in the data matrix $\boldsymbol{d}_t$ of size $n_d \times 1$ and the corresponding coefficient matrix $\boldsymbol{B}$ of size $n \times n_d$. This allows us to introduce dummy variables for the pandemic months (Cascaldi-Garcia, 2022). We collect all VAR coefficients in $\boldsymbol{\alpha} = (\boldsymbol{c}', \boldsymbol{A}_1', \ldots, \boldsymbol{A}_p', \boldsymbol{B}')'$. $\boldsymbol{\Lambda}$ is a diagonal matrix with generic jth element λ_j. These coefficients are gathered in $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_n)'$. $\boldsymbol{H}^{-1}$ is a lower-triangular matrix with ones on its main diagonal.

Estimation. For the estimation, we pursue the approach by Chan and Eisenstat (2018) and Chan (2022). For that, we re-write the system in its triangularized form:

$$\boldsymbol{H}\boldsymbol{y}_t = \tilde{\boldsymbol{x}}_t\tilde{\boldsymbol{\alpha}} + \tilde{\boldsymbol{\varepsilon}}_t, \qquad \tilde{\boldsymbol{\varepsilon}}_t \sim \mathcal{N}\left(\boldsymbol{0}, \boldsymbol{\Lambda}\right), \tag{B.2}$$

where $\tilde{\boldsymbol{x}}_t = (1, \boldsymbol{y}_{t-1}', \ldots, \boldsymbol{y}_{t-p}', \boldsymbol{d}_t)$. We can easily recover the reduced-form parameters by $\boldsymbol{\alpha} = \boldsymbol{H}^{-1}\tilde{\boldsymbol{\alpha}}$, the reduced-form covariance matrix $\boldsymbol{\Sigma} = \boldsymbol{H}^{-1}\boldsymbol{\Lambda}\boldsymbol{H}^{-1'}$, and reduced-form shocks by $\boldsymbol{u}_t = \boldsymbol{H}^{-1}\tilde{\boldsymbol{\varepsilon}}_t$. Note that $\tilde{\boldsymbol{\varepsilon}}$ are not equal to the structural shocks $\boldsymbol{\varepsilon}$ of Equation 4.2. In the case of timing restrictions, the following holds $\tilde{\boldsymbol{\varepsilon}}_t = \boldsymbol{\Lambda}^{0.5}\boldsymbol{\varepsilon}_t$, which is rescaling the shocks with their respective standard deviation. In the case of sign-restrictions, the triangularized shocks $\tilde{\boldsymbol{\varepsilon}}_t$ do not coincide with the structural shocks $\boldsymbol{\varepsilon}_t$. Consequently, we re-write the ith equation of the system as

$$y_{i,t} = \tilde{\boldsymbol{w}}_{i,t}\boldsymbol{h}_i + \tilde{\boldsymbol{x}}_t\tilde{\boldsymbol{\alpha}}_i + \varepsilon_{i,t}, \qquad \tilde{\varepsilon}_{i,t} \sim \mathcal{N}(0, \lambda_i^2), \tag{B.3}$$

where $\tilde{\boldsymbol{w}}_{i,t} = (-y_{1,t}, \ldots, -y_{i-1,t})$ and $\boldsymbol{h}_i$ are the elements first $i - 1$ elements in the ith row of $\boldsymbol{H}$. Note that $y_{i,t}$ depends on the contemporaneous variables $y_{1,t}, \ldots, y_{i-1,t}$. We estimate the system in its triangular form and if we let $\boldsymbol{x}_{i,t} = (\tilde{\boldsymbol{w}}_{i,t}, \tilde{\boldsymbol{x}}_t)$, it simplifies to to

$$y_{i,t} = \boldsymbol{x}_{i,t}\boldsymbol{\theta}_i + \varepsilon_{i,t}, \qquad \tilde{\varepsilon}_{i,t} \sim \mathcal{N}(0, \lambda_i^2), \tag{B.4}$$

where $\boldsymbol{\theta}_i = (\boldsymbol{h}_i', \tilde{\boldsymbol{\alpha}}_i')$ is of dimension $k_i = np + i + n_d$. This allows us to estimate the VAR equation-by-equation, which allows us to impose asymmetries in the amount of shrinkage per variable and equation. Important to note here is that we specify priors directly on the *triangularized* coefficients and not the *reduced-form* coefficients. This variant of VAR estimation has no order invariance issues as in Carriero, Clark and Marcellino (2019) and Carriero et al. (2022). Now we can back out the reduced-form coefficients.

Prior Specification. We have to elicit a prior distribution on $(\boldsymbol{\theta}, \boldsymbol{\lambda})$. We assume that the parameters are a priori independent across equations, such that $p(\boldsymbol{\theta}, \boldsymbol{\lambda}) = \prod_{i=1}^{n} p((\boldsymbol{\theta}_i, \lambda_i)$.

Specifically, for $i = 1, \ldots, n$, we assume:

$$\boldsymbol{\theta}_i \sim \mathcal{N}(\boldsymbol{m}_i, \boldsymbol{V}_i). \tag{B.5}$$

Following Huber and Feldkircher (2019), we consider a Normal-Gamma (NG) shrinkage prior setup for the VAR coefficients, which is given by

$$V_{ij} \mid \kappa_i^2, \theta_{ij} \sim \mathcal{N}(\underline{V}_{ij}, 2\kappa_i^{-2}\theta_{ij}), \qquad \theta_{ij} \sim G(\tau_\theta, \tau_\theta), \quad \kappa_i^2 \sim \mathcal{G}(d_\kappa, e_\kappa), \tag{B.6}$$

where V_{ij} denotes the j-th diagonal element of the matrix $\boldsymbol{V}_i$. τ_{ij} denotes the *local* shrinkage parameter that is coefficient specific and λ_i is a *global* shrinkage term that pulls all elements in $\boldsymbol{V}_i$ towards zero. This can be viewed as a common equation-specific scaling factor with the θ_{ij} allowing for coefficient-specific deviations in light of a large value of κ_i^2. On both the global and local parameters, we impose Gamma distributed priors with hyperparameters τ_θ, d_κ, and e_κ. τ_θ controls the tail behavior of the prior with small values placing more prior mass on zero and leading to heavier tails. The remaining two hyperparameters d_κ and e_κ control the amount of global shrinkage with small values (i.e. of order 0.01) leading to heavy shrinkage towards the origin.

Finally, for the volatilities, we specify Inverse-Gamma prior distributions, which reads for $i = 1, \ldots, n$:

$$\lambda_i \sim IG(c_0, d_0), \tag{B.7}$$

where $c_0 = 3$ and $d_0 = 0.03$.

C. Details on Structural Scenario Analysis Counterfactuals

Building on the work of Waggoner and Zha (1999), the structural scenario analysis framework of Antolin-Diaz, Petrella and Rubio-Ramirez (2021) provides a general framework on how to impose specific paths on observed variables in a VAR model as conditional forecasts with and without constraints on the set of offsetting – or *driving* – shocks. Breitenlechner, Georgiadis and Schumann (2022) adapt this to the case of impulse response analysis with structural scenario analysis (SSA). Again, iterate the VAR model in Equation (4.1) forward and re-write it as

$$\boldsymbol{y}_{T+1,T+h} = \boldsymbol{b}_{T+1,T+h} + \boldsymbol{M}'\boldsymbol{\varepsilon}_{T+1,T+h}, \tag{C.1}$$

where the $nh \times 1$ vector $\boldsymbol{y}_{T+1,T+h} = (\boldsymbol{y}'_{T+1}, \boldsymbol{y}'_{T+2}, \ldots, \boldsymbol{y}'_{T+h})'$ denotes future values of the endogenous variables, $\boldsymbol{b}_{T+1,T+h}$ an autoregressive component that is due to initial conditions as of period T, and the $nh \times 1$ vector $\boldsymbol{\varepsilon}_{T+1,T+h} = (\boldsymbol{\varepsilon}'_{T+1}, \boldsymbol{\varepsilon}'_{T+2}, \ldots, \boldsymbol{\varepsilon}'_{T+h})'$ future values of the structural shocks. The $nh \times nh$ matrix $\boldsymbol{M}$ reflects the impulse responses and is a function of the structural VAR parameters. The definition of $\boldsymbol{M}$ is as follows

$$\boldsymbol{M} = \begin{bmatrix} \boldsymbol{M}_0 & \boldsymbol{M}_1 & \ldots & \boldsymbol{M}_{h-1} \\ \boldsymbol{0} & \boldsymbol{M}_0 & \ldots & \boldsymbol{M}_{h-2} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \boldsymbol{0} & \ldots & \boldsymbol{M}_0 \end{bmatrix}, \tag{C.2}$$

where $\boldsymbol{M}_0 = \boldsymbol{S}$ and $\boldsymbol{M}_i = \sum_{j=1}^{i} \boldsymbol{M}_{i-j}\boldsymbol{B}_j$ with $\boldsymbol{B}_j = \boldsymbol{0}$ if $j > p$. From this representation, it is clear that the matrix $\boldsymbol{M}$ only depends on the structural parameters. Furthermore, note that $\boldsymbol{M}'\boldsymbol{M}$ only depends on the reduced-form parameters. Thus, one only needs the history of observables and the reduced-form parameters to characterize the distribution of the unconditional forecast.

Then, the unconditional forecast is distributed

$$\boldsymbol{y}_{T+1,T+h} = \mathcal{N}\left(\boldsymbol{b}_{T+1,T+h}, \boldsymbol{M}'\boldsymbol{M}\right). \tag{C.3}$$

In the framework of Antolin-Diaz, Petrella and Rubio-Ramirez (2021), structural scenarios involve

i) *Conditional-on-observables* forecasting, i.e., specifying paths for a subset of observables in $\boldsymbol{y}_{T+1,T+h}$ that depart from their unconditional forecast, and/or

ii) *Conditional-on-shocks* forecasting, i.e., specifying the subset of structural shocks $\boldsymbol{\varepsilon}_{T+1,T+h}$ that are allowed to deviate from their unconditional distribution to produce the specified path of the observables in (i).

In the following, we will discuss how to implement both options. Therefore, one should note that

$$\tilde{\boldsymbol{y}}_{T+1,T+h} \sim \mathcal{N}\left(\boldsymbol{\mu}_y, \boldsymbol{\Sigma}_y\right), \tag{C.4}$$

denotes the distribution of the future values of the *constrained* observables. The goal is to determine $\boldsymbol{\mu}_y$ and $\boldsymbol{\Sigma}_y$ such that the constraints in (i) and (ii) are satisfied simultaneously.

Under (i), *conditional-on-observables* forecasting can be implemented as follows. Let $\overline{\boldsymbol{C}}$ be a $k_o \times nh$ selection matrix, with k_o denoting the number of restrictions. Then, *conditional-on-observables* restrictions can be written as

$$\overline{\boldsymbol{C}}\tilde{\boldsymbol{y}}_{T+1,T+h} \sim \mathcal{N}\left(\overline{\boldsymbol{f}}_{T+1,T+h}, \overline{\boldsymbol{\Omega}}_f\right), \tag{C.5}$$

where the $k_o \times 1$ vector $\overline{\boldsymbol{f}}_{T+1,T+h}$ is the mean of the distribution of the observables constrained under the conditional forecast, and the $k_o \times k_o$ matrix $\overline{\boldsymbol{\Omega}}_f$ is the associated variance-covariance matrix.

Under (ii), *conditional-on-shocks* forecasting can be implemented as follows. Let Ξ be a $k_s \times nh$ selection matrix, with k_s denoting the number of restrictions. Then, *conditional-on-shocks* restrictions can be written as

$$\Xi\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}\left(\boldsymbol{g}_{T+1,T+h}, \boldsymbol{\Omega}_g\right), \tag{C.6}$$

where the $k_s \times 1$ vector $\boldsymbol{g}_{T+1,T+h}$ is the mean of the distribution of the shocks constrained under the conditional forecast and the $k_s \times k_s$ matrix $\boldsymbol{\Omega}_g$ is the associated variance-covariance matrix. Under invertibility, the shocks can always be expressed as a function of observed variables and allow us to re-write the restrictions:

$$\begin{aligned} \Xi\boldsymbol{M}'^{-1}\tilde{\boldsymbol{y}}_{T+1,T+h} &= \Xi\boldsymbol{M}'^{-1}\boldsymbol{b}_{T+1,T+h} + \Xi\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \\ \underline{\boldsymbol{C}}\tilde{\boldsymbol{y}}_{T+1,T+h} &= \underline{\boldsymbol{C}}\boldsymbol{b}_{T+1,T+h} + \Xi\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h}, \end{aligned} \tag{C.7}$$

and thus

$$\underline{\boldsymbol{C}}\tilde{\boldsymbol{y}}_{T+1,T+h} = \underline{\boldsymbol{C}}\boldsymbol{b}_{T+1,T+h} + \Xi\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}\left(\underline{\boldsymbol{f}}_{T+1,T+h}, \underline{\boldsymbol{\Omega}}_f\right), \tag{C.8}$$

where $\underline{\boldsymbol{\Omega}}_f = \boldsymbol{\Omega}_g$.

Now we can combine the k_o restrictions on the observables under *conditional-on-observables* forecasting and the k_s restrictions on the structural shocks under *conditional-on-shocks* forecasting. This amounts to $k = k_o + k_s$ total restrictions. We define the $k \times nh$ matrices $\boldsymbol{C} = [\overline{\boldsymbol{C}}', \underline{\boldsymbol{C}}']'$ and $\boldsymbol{D} = [\boldsymbol{M}\overline{\boldsymbol{C}}', \boldsymbol{\Xi}']'$, which allows us to write

$$\boldsymbol{C}\tilde{\boldsymbol{y}}_{T+1,T+h} = \boldsymbol{C}\boldsymbol{b}_{T+1,T+h} + \boldsymbol{D}\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}\left(\boldsymbol{f}_{T+1,T+h}, \boldsymbol{\Omega}_f\right), \tag{C.9}$$

where the $k \times 1$ vector $\boldsymbol{f}_{T+1,T+h} = [\overline{\boldsymbol{f}}'_{T+1,T+h}, \underline{\boldsymbol{f}}'_{T+1,T+h}]'$ stacks the means of the distribution and the $k \times k$ matrix $\boldsymbol{\Omega}_f = \mathtt{diag}(\overline{\boldsymbol{\Omega}}_f, \underline{\boldsymbol{\Omega}}_f)$ denotes the associated variance-covariance matrix.

Following the framework in Antolin-Diaz, Petrella and Rubio-Ramirez (2021) and given the restrictions specified above, we can derive solutions for $\boldsymbol{\mu}_y$ and $\boldsymbol{\Sigma}_y$. Define the restricted future shocks

$$\tilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\boldsymbol{\mu}_{\varepsilon}, \boldsymbol{\Sigma}_{\varepsilon}), \tag{C.10}$$

where $\boldsymbol{\Sigma}_{\varepsilon} = \boldsymbol{I}_n h + \boldsymbol{\Psi}_{\varepsilon}$, such that $\boldsymbol{\mu}_{\varepsilon}$ and $\boldsymbol{\Psi}_{\varepsilon}$ denote the deviation of the mean and covariance matrix from their unconditional counterparts. Using Equation C.9, we match the first and second moments to get

$$\boldsymbol{f}_{T+1,T+h} = \boldsymbol{C}\boldsymbol{b}_{T+1,T+h} + \boldsymbol{D}\boldsymbol{\mu}_{\varepsilon}, \tag{C.11}$$

$$\boldsymbol{\Omega}_f = \boldsymbol{D}(\boldsymbol{I}_n h + \boldsymbol{\Psi}_{\varepsilon})\boldsymbol{D}'. \tag{C.12}$$

Depending on k, the number of restrictions, and nh, the length of $\tilde{\boldsymbol{y}}_{T+1,T+h}$, the systems of Equation C.11 and Equation C.12 may have multiple solutions ($k < nh$), one solution ($k = nh$), or no solution ($k > nh$). Since $k < nh$ is the most interesting case, the solution is given by

$$\boldsymbol{\mu}_{\varepsilon} = \boldsymbol{D}^{*}\left(\boldsymbol{f}_{T+1,T+h} - \boldsymbol{C}\boldsymbol{b}_{T+1,T+h}\right), \tag{C.13}$$

$$\boldsymbol{\Psi}_{\varepsilon} = \boldsymbol{D}^{*}\boldsymbol{\Omega}_f\boldsymbol{D}^{*'} - \boldsymbol{D}^{*}\boldsymbol{D}\boldsymbol{D}'\boldsymbol{D}^{*'}, \tag{C.14}$$

where $\boldsymbol{D}^{*}$ is the Moore-Penrose inverse of $\boldsymbol{D}$. Equation C.13 shows that the path of the implied structural shocks under the conditional forecast depends on its deviation from the unconditional forecast. Furthermore, Equation C.14 shows that the variance of the implied future structural shocks depends on the uncertainty the researcher attaches to the conditional forecast. If the uncertainty is zero ($\boldsymbol{\Omega}_f = \boldsymbol{0}$), then $\boldsymbol{\Sigma}_{\varepsilon} = \boldsymbol{0}$. This means that a unique path for $\boldsymbol{\mu}_{\varepsilon}$ can be found.

Combining Equation C.3, Equation C.13, and Equation C.14, we get

$$\boldsymbol{\mu}_y = \boldsymbol{b}_{T+1,T+h} + \boldsymbol{M}'\boldsymbol{D}^{*}\left(\boldsymbol{f}_{T+1,T+h} - \boldsymbol{C}\boldsymbol{b}_{T+1,T+h}\right), \tag{C.15}$$

$$\boldsymbol{\Sigma}_y = \boldsymbol{M}'\boldsymbol{M} - \boldsymbol{M}'\boldsymbol{D}^* \left(\boldsymbol{\Omega}_f - \boldsymbol{D}\boldsymbol{D}'\right) \boldsymbol{D}^{*'} \boldsymbol{M}. \tag{C.16}$$

As before, if $\boldsymbol{\Omega}_f = \boldsymbol{0}$, then $\boldsymbol{\Sigma}_y = \boldsymbol{0}$ and thus there is no uncertainty about the path of the observables under the imposed restrictions.

C1. Restrictions in the VAR

In our VAR, we have $\boldsymbol{y}_t = [rgas_t, ip_t, i_t, \pi_t, \pi_t^e]$ and want to constrain the effect of a real gas price shock on inflation expectations π_t^e to be zero. Denote with $\boldsymbol{e}_i$ an $n \times 1$ vector of zeros with unity at the i-th position.

Under (i), *conditional-on-observable* forecasting, we impose

$$\overline{\boldsymbol{C}} = \boldsymbol{I}_h \otimes \boldsymbol{e}_5', \tag{C.17}$$

$$\overline{\boldsymbol{f}}_{T+1,T+h} = \boldsymbol{0}_{h\times 1}, \tag{C.18}$$

$$\overline{\boldsymbol{\Omega}}_f = \boldsymbol{0}_{h\times h}. \tag{C.19}$$

These equations impose that the conditional forecast that underlies the impulse response of inflation expectations (which is ordered fifth in the VAR) is constrained to be zero over all horizons $T+1, \dots, T+h$. Furthermore, we do not allow for any uncertainty.

Under (ii), *conditional-on-shocks* forecasting, we impose

$$\boldsymbol{\Xi} = \begin{bmatrix} \boldsymbol{e}_1' & \boldsymbol{0}_{1\times n(h-1)} \\ (\boldsymbol{0}_{n-2\times 1}, \boldsymbol{I}_{n-2}) & \boldsymbol{0}_{n-2\times n(h-1)} \\ \boldsymbol{0}_{(h-1)(n-1)\times n} & \boldsymbol{I}_{h-1} \otimes (\boldsymbol{I}_{n-2}, \boldsymbol{0}_{n-2\times 1}) \end{bmatrix}_{h(n-1)\times nh} \tag{C.20}$$

$$\underline{\boldsymbol{f}}_{T+1,T+h} = \boldsymbol{g}_{T+1,T+h} = [1, \boldsymbol{0}_{1\times n-2}, \boldsymbol{0}_{1\times(n-1)(h-1)}]' \tag{C.21}$$

$$\underline{\boldsymbol{\Omega}}_f = \boldsymbol{\Omega}_g = \boldsymbol{0}_{h(n-1)\times h(n-1)} \tag{C.22}$$

The first row in Equation C.20 selects the real gas price shock ordered first in $\boldsymbol{\varepsilon}_t$ and the first row in Equation C.21 constrains it to be unity in the impact period $T+1$. In the second row in Equation C.20 we select the structural shock to industrial production, short-term interest rate, and inflation (ordered from the second to second-last position in the VAR) and the second entry of Equation C.21 constrains these structural shocks to be zero in period $T+1$. Hence, in $T+1$ the only structural shock which is allowed to vary is the one of inflation expectations. Similarly, the third row selects the first $n-1$ structural shocks over the remaining impulse response horizon $T+2, T+3, \dots, T+h$ and constrains them to zero in Equation C.21.

Hence, in $T+2, T+3, \ldots, T+h$ the only structural shock which is allowed to vary is again the one of inflation expectations. Lastly, Equation C.22 specifies that we allow for no uncertainty. It is also interesting to consider the stacked matrices $\boldsymbol{C}$ and $\boldsymbol{D}$ which look as follows

$$\boldsymbol{C} = \begin{pmatrix} \overline{\boldsymbol{C}}_{h\times nh} \\ \underline{\boldsymbol{C}}_{h(n-1)\times nh} \end{pmatrix}_{hn\times nh} , \qquad \boldsymbol{D} = \begin{pmatrix} \overline{\boldsymbol{C}}_{h\times nh}\boldsymbol{M}'_{nh\times nh} \\ \boldsymbol{\Xi}_{h(n-1)\times nh} \end{pmatrix}_{hn\times nh} , \tag{C.23}$$

where $\underline{\boldsymbol{C}} = \boldsymbol{\Xi}\boldsymbol{M}'^{-1}$.

C2. How plausible is the counterfactual?

Generally, structural scenario analysis counterfactuals based on SVARs are not prone to the Lucas critique (Lucas, 1976). However, if the implied shocks are so *unusual* the analysis might become subject to the Lucas critique anyway. Hence, measures of the plausibility of the created counterfactual scenario are a remedy. We use two measures: the q-divergence proposed in Antolin-Diaz, Petrella and Rubio-Ramirez (2021) and adapted to the case of impulse response functions by Breitenlechner, Georgiadis and Schumann (2022) and the modesty statistic proposed by Leeper and Zha (2003). These measures intend to measure how much the structural scenario deviates from its unconditional counterpart. When this deviation becomes too large, the scenario might be implausible.

Antolin-Diaz, Petrella and Rubio-Ramirez (2021) propose to use the Kullback-Leibler (KL) divergence as a measure of how plausible a scenario is. Denote with $\mathcal{D}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$ the KL divergence between the distributions of the structural scenario analysis $\mathcal{N}_{SS}$ and the unconditional distribution $\mathcal{N}_{UF}$. While it is straightforward to compute $\mathcal{D}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$, it is difficult to grasp whether any value for the KL divergence is large or small. In other words, the KL divergence can be easily used to rank scenarios, but it is hard to understand how far away they are from the unconditional forecast. Therefore, Antolin-Diaz, Petrella and Rubio-Ramirez (2021) propose to compare the KL divergence with the divergence between two binomial distributions, one with probability q and the other with probability $p = 0.5$. The idea is to compare the implied counterfactual distribution with their unconditional distribution, which translates into a comparison of the binomial distributions of a fair and a biased coin. If the probability q is near p, then this suggests that the distribution of the offsetting shocks is not at all far from the unconditional distribution. Antolin-Diaz, Petrella and Rubio-Ramirez (2021) suggest calibrating the KL divergence from $\mathcal{N}_{UF}$ to $\mathcal{N}_{SS}$ to a parameter q that would solve the following equation $\mathcal{D}\left(\mathcal{B}(nh, 0.5)||\mathcal{B}(nh, q)\right) = \mathcal{D}\left(\mathcal{N}_{SS}||\mathcal{N}_{UF}\right)$. The solution to the equation is

$$q = 0.5 * \left(1 + \sqrt{1 - \exp\left(-\frac{2z}{nh}\right)}\right) \quad \text{with} \quad z = \mathcal{D}\left(\mathcal{N}_{SS}||\mathcal{N}_{UF}\right). \tag{C.24}$$

As Breitenlechner, Georgiadis and Schumann (2022) point out, in the context of impulse responses the KL divergence has to be slightly adjusted because Antolin-Diaz, Petrella and Rubio-Ramirez (2021) propose their measure in the context of conditional forecasts relative to an unconditional forecast. As before, the unconditional scenario is the case with only a single shock of unity size, which occurs in $T+1$ with certainty. More formally, $\boldsymbol{\varepsilon}_{T+1,T+h} = (\boldsymbol{e}_1', \boldsymbol{0}_{n(h-1)\times 1})'$ denotes the *unconditional* impulse response of a natural gas price shock. $\boldsymbol{e}_i$ denotes the unit vector with unity on the i-th position. For the structural scenario analysis counterfactual, we impose the restrictions specified above (i.e., inflation expectations do not react to a natural gas price shock). Hence, we set

$$\texttt{UF:} \qquad \boldsymbol{\mu}_{UF} = \boldsymbol{M}'(\boldsymbol{e}_1', \boldsymbol{0}_{n(h-1)\times 1})' \tag{C.25}$$

$$\texttt{SS:} \qquad \boldsymbol{\mu}_{SS} = \boldsymbol{\mu}_y, \tag{C.26}$$

where $\boldsymbol{\mu}_y$ is given by Equation (C.15). Since we impose this with certainty, $\boldsymbol{\Psi} = \boldsymbol{0}$ such that the shocks have their unconditional variance. Hence, $\boldsymbol{\Sigma}_{UF} = \boldsymbol{\Sigma}_{SS} = \boldsymbol{\Sigma}_{\varepsilon} = \boldsymbol{I}$. The KL divergence between the distribution of the shocks under the unconditional and conditional scenario is then given by

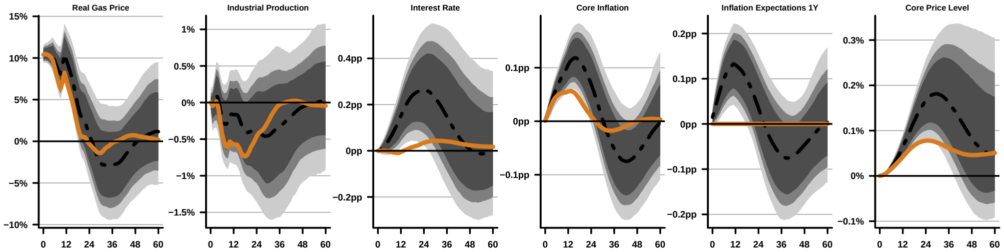
$$\mathcal{D}(\mathcal{N}_{SS}||\mathcal{N}_{UF}) = \frac{1}{2}\left(\operatorname{tr}\left(\boldsymbol{\Sigma}_{SS}^{-1}\boldsymbol{\Sigma}_{UF}\right) + (\boldsymbol{\mu}_{SS} - \boldsymbol{\mu}_{UF})'\boldsymbol{\Sigma}_{SS}^{-1}(\boldsymbol{\mu}_{SS} - \boldsymbol{\mu}_{UF}) - nh + \ln\left(\frac{\det \boldsymbol{\Sigma}_{SS}}{\det \boldsymbol{\Sigma}_{UF}}\right)\right), \tag{C.27}$$

where $\boldsymbol{\mu}_{\varepsilon}$ and $\boldsymbol{\Sigma}_{\varepsilon}$ are given by Equation (C.13) and Equation (C.14). Furthermore, we discard any SSA counterfactuals when the offsetting shocks are particularly unlikely. We set this to be above $q > 0.9$.

The second plausibility measure is the one of *modest intervention* or *modesty statistic* used in Leeper and Zha (2003). The measure reports how unusual the path for policy shocks is relative to the typical size of these shocks, which are needed to impose the counterfactual restriction. For instance, if the counterfactual implies a sequence of shocks close to their unconditional mean, the policy intervention is considered *modest*, in the sense that the shocks are unlikely to induce agents to revise their beliefs about policy rules and the structure of the economy. Instead, if the counterfactual involves an unlikely sequence of shocks, the analysis is likely to be prone to the critique by Lucas (1976). The offsetting shocks are considered to be modest if the statistic is smaller than two in absolute value.

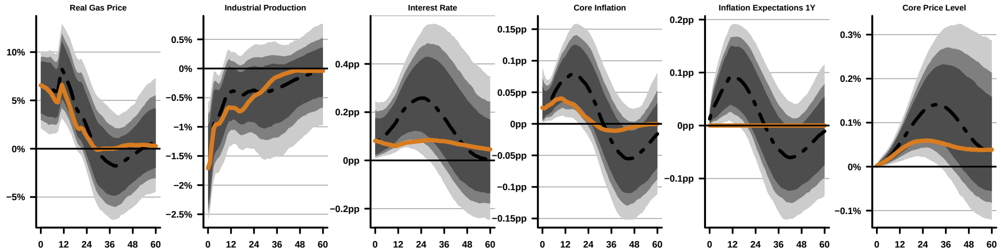
D. Additional Results

Figure D1: Impulse Response Functions to a Real Gas Price Shock (Timing Restrictions with Core Inflation).



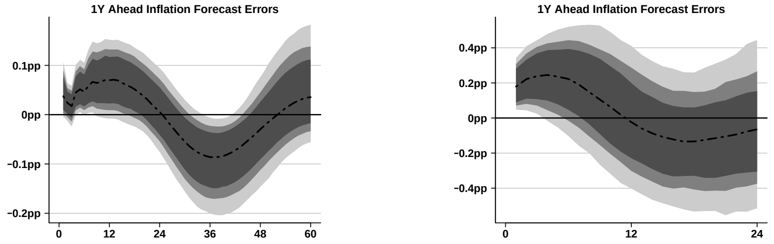
Notes: The model features five variables, where the shock is identified with timing restrictions and standardized to a one standard deviation increase in the real price of natural gas. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses, while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production and the price level are in percent, while the interest rate, core inflation and inflation expectations are scaled to annualized percentage points.

Figure D2: Impulse Response Functions to a Real Gas Price Shock (Sign and Zero Restrictions with Core Inflation).



Notes: The model features five variables, where the shock is identified with sign and zero restrictions and standardized to a one standard deviation increase in the real price of natural gas. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses, while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production and the price level are in percent, while the interest rate, core inflation and inflation expectations are scaled to annualized percentage points.

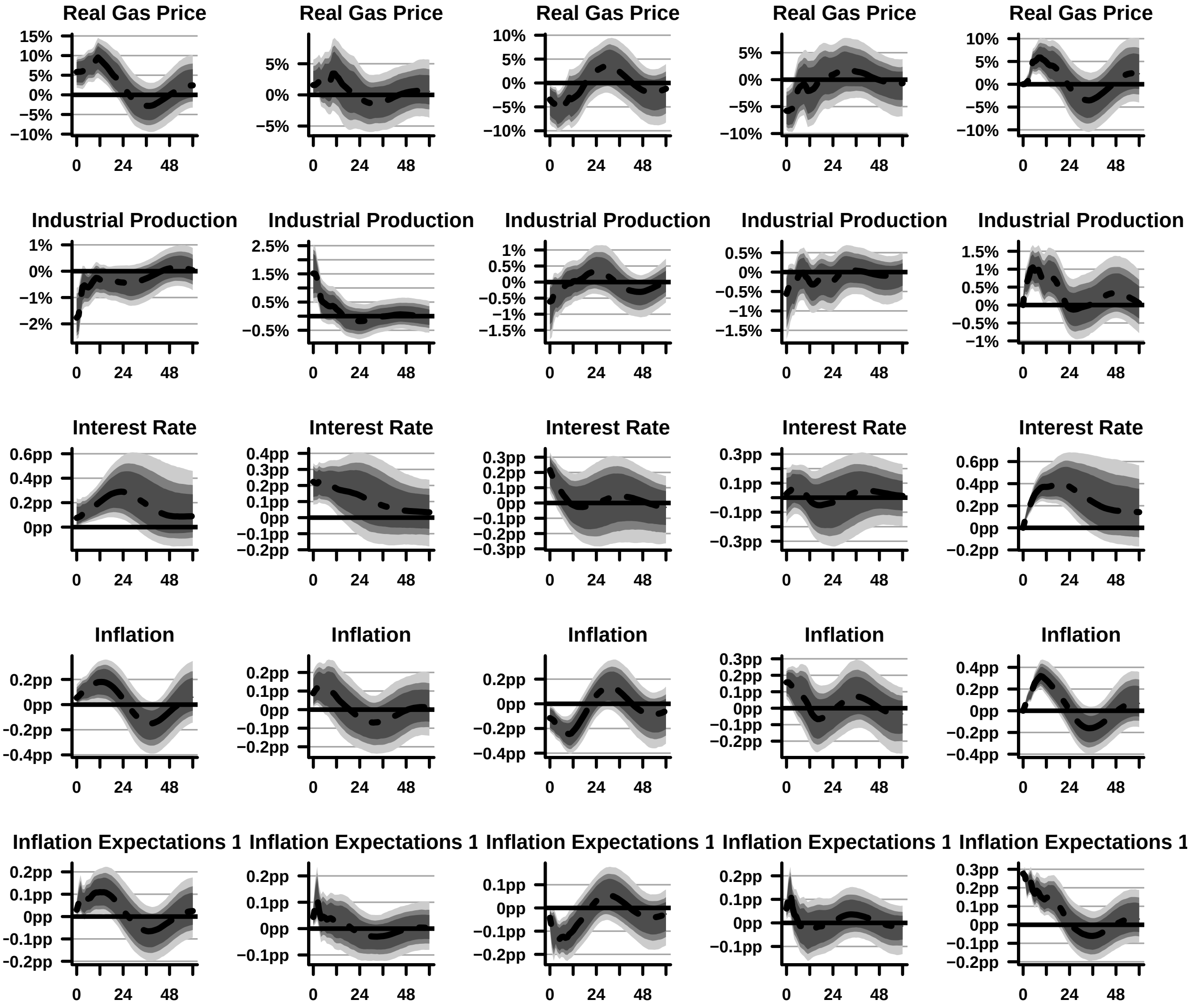
Figure D3: Implied Impulse Response Functions to a Real Gas Price Shock (Sign and Zero Restrictions).



(a) ILS: Implied Forecast Error. **(b)** SPF: Implied Forecast Error.

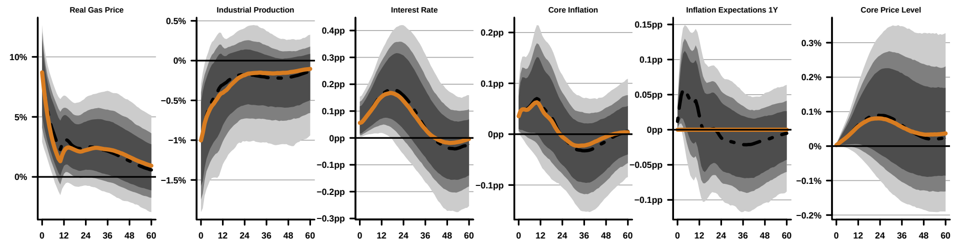
Notes: Implied impulse response function of forecast errors (constructed as the difference between realized inflation and the previous year's 1-year average expected inflation). The underlying model features five variables and is identified with sign and zero restrictions. Black dashed lines denote median responses, while gray shaded areas denote the 68/80/90 percent confidence intervals.

Figure D4: Full set of responses with 1Y ahead Inflation Expectations (Sign and zero Restrictions.

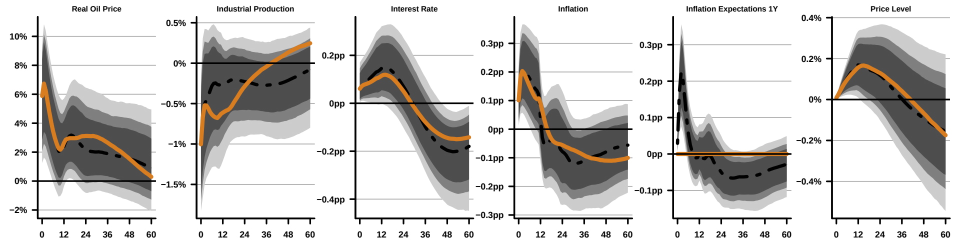


Notes: All impulse responses of the model identified with sign and zero restrictions. Black dashed lines denote median responses, while gray shaded areas denote the 68/80/90 percent confidence intervals. The responses of the real gas price and the price level are in percent, while inflation and inflation expectations are scaled in annualized percentage points.

Figure D5: Robustness: US Impulse Response Functions.



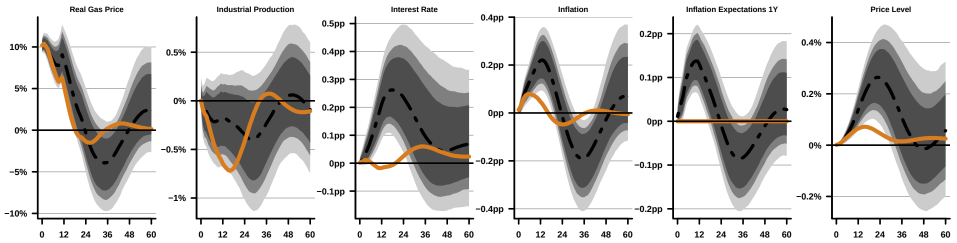
(a) US Real Gas Price Shock with Core Inflation.



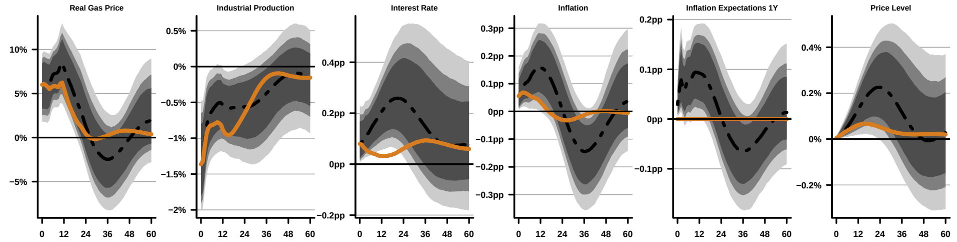
(b) US Real Oil Price Shock.

Notes: The US model features five variables and is identified with sign and zero restrictions. The price level is computed afterwards as cumulative sum of inflation response. Black dashed line denotes median response, while gray shaded areas denote the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise. The responses of the real gas price and the price level are in percent, while inflation and inflation expectations are scaled in annualized percentage points.

Figure D6: Robustness: Baseline with Pandemic Priors.



(a) Pandemic Prior: Timing Restriction



(b) Pandemic Prior: Sign and Zero Restrictions.

Notes: The model features five variables, where the shock is identified with timing restrictions (upper panel) and sign and zero restrictions (lower panel) and standardized to a one standard deviation increase in the real price of natural gas. Dummy variables are introduced for the months of March to May 2020 to control for Covid outliers. The price level is computed afterwards as cumulative sum of the inflation response. Black dashed lines denote the posterior median responses, while gray shaded areas depict the 68/80/90 percent confidence intervals. The orange solid line denotes the counterfactual exercise, where the expectation channel is shut off. The responses of the real gas price, industrial production and the price level are in percent, while the interest rate, core inflation and inflation expectations are scaled to annualized percentage points.