Working Paper Series

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Energy supply shocks' nonlinearities on output and prices

No 2834

Abstract

We use a Bayesian Threshold Vector Autoregression model identified through sign and narrative restrictions to uncover non-linearities in the propagation of energy supply shocks. We find that the transmission of energy supply shocks on consumer prices is stronger in high-inflation regimes, supporting nonlinear models. The faster pass-thorough of energy supply shocks to consumer prices (excl. energy) cushions the drop in output in the short term. Energy supply shocks have a stronger impact on output in the medium-term with manufacturing being more adversely affected than GDP. Large energy supply shocks shift the economy to another state but after two and half years the mean-reversion to lower inflation implies a more moderate transmission mechanism, highlighting the importance of state-dependent impulse responses. The energy supply shocks between July 2021 and June 2022 are massive amounting to 3.9 standard deviations on average each month.

Keywords: Business cycles, energy shocks, non-linearities, TVAR, narrative identification

JEL Classification: C32, E32

Non-technical summary

We use a Bayesian Threshold Vector Autoregression model identified through sign and narrative restrictions to uncover non-linearities in the propagation of energy supply shocks. We show that the transmission of retail energy supply shocks on output and prices is state dependent, while responses within the same regime are broadly symmetric across different sizes and signs of shocks.

We find that the transmission of energy supply shocks on consumer prices is stronger in high-inflation regimes, supporting state-dependent models. The faster pass-thorough of energy supply shocks to consumer prices (excl. energy) cushions the drop in output in the short term. Energy supply shocks have a stronger impact on output in the medium-term with manufacturing being more adversely affected than GDP, given the lion share of less-energy intensive services in the value added of the euro area economy. Large energy supply shocks shift the economy to another state but after two and half years the mean-reversion to lower inflation implies a more moderate transmission mechanism, highlighting the importance of state-dependent impulse responses.

The results of the model are important also for policymakers, as we have estimated the median energy supply shocks between July 2021 and June 2022 to be massive, amounting to 3.9 standard deviations on average each month, with important negative repercussion for industrial production, as the multipliers are more than twice as large relative to GDP in the high-inflation regime. There is a high risk of permanent drop in the production of the European energy-intensive sectors, such as chemicals and basic metals, if the energy crisis is not resolved.

Moreover, we estimate that in absence of energy supply shocks year-on-year HICP inflation would have amounted to 2.3%, rather than the observed 8.3% in June 2022. Instead, the counterfactual obtained from the linear model suggests a much higher inflation rate equal to 5.3%. This is explained by the fact that the pass-through of energy supply shocks on consumer prices is larger in the high-inflation regime and the euro area economy shifted to the high-inflation regime in August 2021. Therefore, energy supply shocks contributed more extensively relative to the suggestions from linear models in explaining the unprecedented rise in consumer prices since autumn 2021.

Finally, the results are useful for the existing literature on Dynamic Stochastic General Equilibrium (DSGE) models. Workhorse macroeconomic models used in many central banks and other policy institutions typically capture the price adjustment mechanism via the "Calvo" approach whereby the repricing rate, which represents the degree of price flexibility in the economy, is constant and the response is linear. The Calvo approach could be a good approximation only when inflation is low and shocks are small. Our results suggest that these models should allow for a nonlinear or state-dependent Phillips curve.

I   Introduction

Is there a differential effect of the transmission of retail energy price shocks on output and prices, when an economy is in a low- or a high-inflation regime? Does the transmission depend upon the size and the sign of the shocks? The nonlinear pass-through of energy supply shocks on aggregate consumer prices, depending upon the level of underlying inflation, and their output implications are important questions, which have not received much academic attention, despite the investigation could shed some light on whether aggregate prices behave as state-dependent models suggest.

Empirical analysis based on individual goods prices indicates that prices change infrequently (e.g. Bils and Klenow, 2004; Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2010; Nakamura and Zerom, 2010; Eichenbaum et al., 2011; Gautier et al., 2022), are more flexible in response to large shocks (e.g. Dias et al., 2007; Fougère et al., 2007; Gautier and Saout, 2015; Alvarez et al., 2017; Karadi and Reiff, 2019; Gautier et al., 2022) and change more frequently when inflation is high (Nakamura et al., 2018; Alvarez et al., 2019).

These are features of micro-founded state-dependent models of nominal rigidities Alvarez et al. (2011, 2021), which unlike time-dependent pricing models (Rotemberg, 1982; Calvo, 1983), assume that the individual firm can change its price, subject to an adjustment cost. Price changes are firms' endogenous decisions. Yet, there is little evidence verifying whether aggregate prices behave as predicted by state-dependent models. Ascari and Haber (2022) investigate the price-state dependent transmission of monetary policy shocks on aggregate prices using local projections. However, Goncalves et al. (2022) show that, when the state of the economy is endogenous, the local projections' estimator of the response function tends to be asymptotically biased except for the impact response. Harding et al. (2023) assume the same price stickiness à la Calvo, but propose a nonlinear Philips curve, where the response of inflation to cost-push shocks depends on the initial inflation rate.

Energy supply shocks are suitable candidates to address whether aggregate prices are state-dependent, because micro evidence suggests they increase the frequency of price adjustments (Cornille and Dossche, 2008; Gautier et al., 2022). Nonlinear models of price adjustment are built on the notion that price changes depend on the level of inflation, the size and the direction of shocks to nominal costs. We address the nonlinear effects of retail

energy price shocks on the euro area economy identified - for the first time to the best of our knowledge - with narrative restrictions (Antolín-Díaz and Rubio-Ramírez, 2018; Ludvigson et al., 2021) within a threshold vector autoregression (TVAR). We construct the nonlinear structural impulse response functions (IRFs) following the conditional expectation approach as in Koop et al. (1996). In a nonlinear model, the IRFs can depend differentially on the magnitude and sign of the shock, as well as on the history of previous shocks. We compute the nonlinear responses by iterating on the estimated parameters of the nonlinear model and by taking into account the possibility that shocks can affect the state.

We show that the transmission of retail energy supply shocks on output and prices is state dependent, while responses within the same regime are broadly symmetric across different sizes and signs of shocks. Retail energy supply shocks have an immediate and mean-reverting impact on consumer prices. The effects are larger in the high-inflation regime and highlight that prices are sticky only in the low-inflation regime. The price impact is in line with the findings obtained from individual goods prices, which suggest that price changes occur more frequently when inflation is high. The faster pass-thorough of energy supply shocks to consumer prices (also excl. the energy component) favours firms, which tend not to drop output in the short term, but to reduce it in the medium-term with manufacturing being more adversely affected than GDP, given the lion share of less-energy intensive services in the value added of the euro area economy. Conversely, an adverse energy supply shock hitting in the low-inflation regime forces firms to reduce output immediately, because prices are sticky.

The results also suggest that the monetary policy rate tends to decline after an adverse retail energy supply shock in the low-inflation regime. Conversely, it increases immediately in the high-inflation regime, but to drop after about half year. The persistence of higher headline and core consumer prices in the high-inflation regime might be related to the drop in the policy rate.

Energy supply shocks are typically studied through the global crude oil market and using linear frameworks.[1] Oil prices have also been used in non-linear models. Holm-Hadulla and Hubrich (2017) use a Markov Switching vector autoregression without distinguishing the

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[1]Among others, see Kilian (2009b); Kilian and Murphy (2014); Aastveit et al. (2015); Baumeister and Kilian (2016); Baumeister and Hamilton (2019); Caldara et al. (2019); Känzig (2021); Aastveit et al. (2021); Kilian and Zhou (2022b). Another strand of the literature has looked at gasoline prices (Kilian and Zhou, 2022a).

source of oil price shocks, while (Mumtaz et al., 2018) identify demand and supply oil price shocks using a TVAR with sign restrictions and find nonlinear patterns in the response of output and prices. Baumeister and Peersman (2013) investigate the time-varying effects of oil supply shocks on the US economy, but the method is agnostic about the reason why the effects of the shocks may have changed over time. Herrera et al. (2011) find a strong nonlinear response of U.S. energy-intensive production to oil prices, highlighting the importance of carrying out sectoral analysis to assess the transmission of oil price shocks.[2] This evidence suggests to include the output of the energy-intensive sector to improve the identification. Knotek and Zaman (2021) assess the asymmetric responses of consumer spending to energy prices, but ordering energy inflation first in the Cholesky factorization followed by core inflation and real consumption growth and therefore using the reduced form residuals for the analysis.

The focus of this paper is the transmission of retail energy supply shocks on euro area consumer prices and output conditioned on being in a low- or high-inflation regime. Gas and renewable sources like wind, solar, geothermal and hydropower have become important alternative sources in the last two decades for energy supplies' security motives and for environmental issues.[3] The 2022 Russian invasion of Ukraine and the dispute with Europe clearly indicate the important role of gas and the difficulty in reducing reliance on Russian energy in the short term: while oil can be easily transported globally, gas typically flows through pipelines. For these reasons, we cannot use oil prices; instead, we focus on the energy component of the Harmonized Index of Consumer Prices (HICP), which is an aggregate retail price index available from January 1990 that includes electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment.

The identification is achieved constraining the behaviour of structural shocks around key historical events. Specifically, we impose restrictions on the structural shocks associated with the significant cut of gas supply from Russia to the European Union (EU) in autumn

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[2]Kilian and Vigfusson (2011) find little evidence of nonlinearity in the relation between oil prices and U.S. GDP growth, but they address the question using linear methods. One key criticism made by Hamilton (2011) to Kilian and Vigfusson (2011)'s approach is that one cannot rely on linear models to address nonlinearities. He also showed that nonlinearities are the consequence of large movements in oil prices.

[3]The prices of other sources of energy, however, are only weakly correlated with oil prices. According to monthly data provided by the U.S. Energy Information Administration (EIA), available for a long period between January 1997 and December 2019, the correlation between the Henry Hub natural gas spot price and the West Texas Intermediate (WTI) spot price is 20%.

2021 for geopolitical reasons, which contributed to the slow replenishment of gas inventories in Europe ahead of the winter season, and in the spring 2022 after the Russian invasion of Ukraine, which caused an unprecedent increase in energy prices. Moreover, we consider periods when large drops in oil production occurred caused by a oil supply shock, as indicated by Caldara et al. (2019) and Känzig (2021): the Iraq's invasion of Kuwait in 1990 and the strikes in Venezuela in 2002. We assume that the rise in retail energy prices that took place in August-September 1990, December 2002-January 2003, October-November 2021 and March-April 2022 was caused by adverse energy supply shocks that dominated the contribution of other shocks to the unforecastable increase of retail energy prices. We show that the extraordinary large energy supply shocks estimated since July 2021 do not depend upon the narrative restrictions imposed over this period. The results are robust to a number of robustness checks including when controlling for energy-specific demand shocks.

To sharpen the identification, we assume that retail energy supply shocks rise at impact retail energy prices and reduce the output of the energy-intensive sector (i.e. chemicals and basic metals). The response of the other three main variables of the structural TVAR model, GDP, industrial production and HICP, are left unrestricted also on impact.[4]

We follow the methodology proposed by Antolín-Díaz and Rubio-Ramírez (2018) to produce Bayesian inference about structural vector autoregressions (SVARs) identified through narrative and sign restrictions, but we refrain from applying the importance resampling step of the algorithm, as suggested by Giacomini et al. (2020), and we remove the restriction on the relative sizes of the various shocks on the dates in which we impose narrative shock restrictions, as suggested by De Santis and Van der Weken (2022). Our narrative restrictions are sign-dependent: we impose that the restricted shock, among the shocks that move the selected variable's forecast error in the same direction, is the most important contributor to this forecast error. Thereby, we allow the unrestricted shocks to exert an even stronger effect on the selected forecast error, as long as the contribution of those shocks has the opposite sign of the contribution of the restricted shock.

We also differ from Ludvigson et al. (2021), because their "event constraint" requires

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[4]Edelstein and Kilian (2009) study the impact of US retail energy price shocks on US consumer expenditure using a linear bivariate VAR identified through timing restrictions. Sign restrictions have been proposed as a better alternative approach to identify energy supply shocks (Kilian and Murphy, 2012, 2014).

that the identified shocks must be large in specific periods (e.g. k standard deviations above the mean). In our framework, the shock of interest is the most important among those moving the selected variable's forecast error in the same direction and in the same period, but it does not require necessarily to be large compared with those of the same type, which happened in other periods.

The paper is structured as follows. Section II presents the model. Section III describes the shocks' identification strategy. Section IV discusses the key results. Section V provides robustness checks. Section VI concludes.

II   Framework

We employ a Bayesian TVAR, where transitions across states (i.e., low- and high-inflation regimes) are defined by an endogenously determined underlying inflation, and shocks are identified using sign and narrative restrictions.

II.A   Model specification

In the spirit of Balke (2000), the reduced-form TVAR takes the following form

$$
\begin{aligned}
\mathbf{X}_t = (\mathbf{c}_{Low} + \mathbf{\Pi}_{Low}(\mathbf{L})\mathbf{X}_{t-1})I\{z_{t-1} < z^*\}+ \\
(\mathbf{c}_{High} + \mathbf{\Pi}_{High}(\mathbf{L})\mathbf{X}_{t-1})I\{z_{t-1} \geq z^*\} + \mathbf{u}_t,
\end{aligned}
\tag{1}
$$

$$
\mathbf{u}_t \sim N(0, \mathbf{\Omega}_t),
\tag{2}
$$

$$
\mathbf{\Omega}_t = \mathbf{\Omega}_{Low}I\{z_{t-1} < z^*\} + \mathbf{\Omega}_{High}I\{z_{t-1} \geq z^*\},
\tag{3}
$$

where $\mathbf{u}_t$ denotes the $n \times 1$ vector of reduced form residuals, $\mathbf{\Omega}_t$ the state-contingent covariance matrix of the residuals, z_t the state variable, z^* a threshold of z_t, $\mathbf{c}_{Low}$ and $\mathbf{c}_{High}$ the vector of intercepts in the two regimes and $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$ the lag polynomials. The regime switches are governed by the indicator function I and are indexed by $t-1$ to avoid endogeneity problems.

The vector $\mathbf{X}_t = [p_t, p_t^e, y_t, y_t^{ip}, y_t^e]'$ defines the endogenous variables, where p_t is the harmonised index of consumer prices (HICP), p_t^e stands for the energy component of HICP,

y_t denotes real GDP, y_t^{ip} denotes industrial production and y_t^e is the output of the energy-intensive sector.[5] All variables are defined in logs. We set the lag order p to 6 in order to use the narrative identification in August 1990. The use of six lags in a monthly VAR is not unusual (e.g., for example, Ludvigson et al., 2021; Caggiano et al., 2021; Cascaldi-Garcia and Galvao, 2021) As for linear VARs, the stability condition of a TVAR requires that all the roots, r, of $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$

$$|\mathbf{\Pi}_R(r)| = |\mathbf{I_n} - \mathbf{\Pi}_{R,1}r - \mathbf{\Pi}_{R,2}r^2 - .... - \mathbf{\Pi}_{R,p}r^p| = 0, \quad R \in (Low, High),$$

lie outside the unit circle, $|r > 0|$. This guarantees that the system of equations is stationary.

The state variable, z_t, is assumed to depend on current and past month-on-month consumer price inflation rates using an exponentially weighted moving average (EWMA), which gives larger weights, α, to the most recent observations and geometrically declining weights to past inflation rates, $z_t = \sum_{i=0}^{\infty} \alpha(1-\alpha)^i(p_{t-i} - p_{t-1-i})$. Hence, z_t is a function of the entire history of p_t and can be written as:

$$z_t = \alpha(p_t - p_{t-1}) + (1-\alpha)z_{t-1}, \quad \alpha \in (0,1). \tag{4}$$

The reduced form TVAR is estimated in a Bayesian framework using a multivariate version of the sampler developed in Chen and Lee (1995), which allows to draw from the posterior of the model parameters. For the parameters of both regimes, we assume natural conjugate Normal-Inverse-Wishart (N-IW) priors. The IW priors for Ω_{low} and Ω_{high} have $n+2$ degrees of freedom and diagonal scale matrix with the i-th diagonal elements equal to the mean squared error from estimating an AR(1) for the i-th variable. Conditional on Ω_{low} and Ω_{high}, the priors for Π_{low} and Π_{high} are Normal with Minnesota-type mean and variance (Doan et al., 1984), and complemented with a dummy-initial observation prior (Sims, 1993) that is consistent with the assumption of cointegration. The sample spans over the monthly period January 1990 to December 2019. The estimation sample excludes the Covid-19 crisis

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[5]The energy intensive sector is defined by aggregating the production of chemicals, chemical products and basic metals using time-varying weights provided by Eurostat. The energy-intensive sector accounts on average for about 10% of euro area industrial production.

that may cause parameter instability.[6]

We show the results of the model excluding all together the period after December 2019. However, the baseline analysis is performed up to June 2022, as we use the sudden change in energy prices resulting from the geopolitical risk in the autumn of 2021 and the war in Ukraine in the spring 2022, as an out-of-sample narrative to identify the retail energy price shocks. Specifically, after having estimated $\mathbf{c}_{Low}$, $\mathbf{c}_{High}$, $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$ in sample, $\mathbf{u}_t$ is constructed out-of-sample by inverting Equation 1 and exploiting the full available sample. The complete time series of $\mathbf{u}_t$ and z_{t-1} over the entire sample period are then used to estimate $\mathbf{\Omega}_{Low}$ and $\mathbf{\Omega}_{High}$, which are required to identify the structural shocks. The underlying assumption is that the parameters governing the transmission of the shocks ($\mathbf{c}_{Low}$, $\mathbf{c}_{High}$, $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$) are constant within each regime before and after the pandemic period, which is a plausible assumption, given the rebound of the euro area economy since May 2020.

II.B   The state variable

In several studies, the state variable is computed using a moving average of the last months of the variable of interest (e.g. Tenreyro and Thwaites, 2016; Ramey and Zubairy, 2018; Knotek and Zaman, 2021). This approach tends by construction to postpone the potential change in regime, if the shock is not relatively large. The solution proposed by others is to take a centered moving average, between $t - h$ and $t + h$ (e.g. Auerbach and Gorodnichenko, 2012; Ascari and Haber, 2022). However, this provides inconsistent estimates, because the state variable ought to be predetermined, so that it is uncorrelated with the shock happening at time t or in future periods.

Therefore, we construct the state variable, z_t, using equation 4. A relatively larger weight to the most recent observations allows to better capture the timing of the regime change. Specifically, z_t is calculated using month-on-month HICP inflation starting from February 1970, as a number of observations are required to estimate the underlying inflation, and setting $\alpha = 0.125$. It is worth to point out that underlying inflation and year-on-year HICP inflation move in tandem. Over the sample period January 1990 - December 2019 or up

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[6]The interpolation of GDP to a monthly frequency using the Chow and Lin (1971)'s method employs industrial production and real retail sales; thereby, including supply and demand considerations. The data source for all variables is Eurostat and ECB. The database is available from January 1990 due to the availability of the retail energy prices.

to June 2022, the correlation between the two series is irrespectively 97% (see Figure 1). The median of our annualised monthly state variable and of the annual headline HICP inflation rate is 1.99% and 2.03%, respectively, in line with the inflation objective of the ECB. Therefore, knowing the transmission mechanism of an energy supply shocks above the 2% threshold is meaningful from a policy perspective.

As an alternative benchmark, the threshold is estimated through a grid search over possible values of the observations' percentiles. The marginal likelihood is maximised at percentile 0.59, which suggest setting the threshold for underlying inflation at 2.2% annualised. We will show that the results are the same using either of the two thresholds.

Figure 1 shows that underlying inflation above the 1.99% threshold was relatively high in four different periods: (i) in the first half of the 1990s, (ii) from autumn 2007 to the summer 2008 before the bankruptcy of Lehman Brothers, inducing the European Central Bank (ECB) to tighten its monetary policy stance in July 2008, (iii) during the hikes of the euro area sovereign debt crisis in 2011, inducing the ECB to tighten in July 2011, (iv) since the summer 2021 due to the mounting geopolitical risks associated to the gas shortages from Russia, again inducing the ECB to start tighten in December 2021 by first reducing the net asset purchases, then in March 2022 by ending of net purchases under the pandemic emergency purchase programme and then in July 2022 by shifting the deposit facility rate from -0.50% to 0%.

Underlying inflation was also relatively low in four different periods: (i) between the spring 1997 and the summer of 2000 around the finalisation of the economic and monetary union (EMU) of the European Union, inducing the ECB to start reducing the policy rates in April 1999; (ii) between the winter 2008 and the winter 2010 as a consequence of the global financial crisis, inducing the ECB to start reducing the policy rates in November 2008; (iii) between the spring 2013 and the summer 2018, which induced the ECB to further loose its monetary policy stance and adopt unconventional methods such the introduction of negative policy rates and the announcement of the first Targeted Long-Term Refinancing Operations (TLTROs) in June 2014, the purchase of government bonds announced in January 2015 and of corporate bonds announced in March 2016; (iv) between the end of 2018 and the beginning of 2021, which led the ECB to further cut the deposit facility to its lowest level in

September 2019 (-0.50%) and, in response to the pandemic, to launch a new asset purchase programme – the pandemic emergency purchase programme (PEPP) – and a new series of TLTROs.

In a nutshell, the state variable is capturing well underlying inflation in the euro area, which is behind the key changes in ECB monetary policy's decisions.

III Shocks' Identification

The reduced form residuals over the entire sample period can be written as

$$\mathbf{u}_t = (\mathbf{B}_{0,Low}^{-1} I\{z_{t-1} < z^*\} + \mathbf{B}_{0,High}^{-1} I\{z_{t-1} \geq z^*\})\epsilon_t, \tag{5}$$

where $\mathbf{B}_{0,Low}^{-1}$ and $\mathbf{B}_{0,High}^{-1}$ are the structural impact multiplier matrices in the low- and high-inflation regimes, and ϵ_t is the vector of standard Normal structural shocks. The differences in the propagation of shocks across regimes is then due to differences in the impact matrices $\mathbf{B}_{0,Low}^{-1}$ and $\mathbf{B}_{0,High}^{-1}$ and differences in lag polynomial $\mathbf{\Pi}_{Low}$ and $\mathbf{\Pi}_{High}$.

The set of permissible impact matrices is infinite and the impact matrices cannot be identified uniquely from the data. Shocks are identified adapting the narrative identification method of Antolín-Díaz and Rubio-Ramírez (2018) to the non-linear setting, refraining from applying the importance weighting step as suggested by Giacomini et al. (2020) and using the less restrictive signed contribution restrictions suggested by De Santis and Van der Weken (2022).

III.A Narrative Sign Restrictions

To avoid the necessity to form *a priori* a thorough judgment regarding the sign and the timing of the propagation of the shock, for energy supply shocks we only assume that the one-step ahead forecast errors of energy prices at impact and of production of the energy intensive sector over one quarter move in opposite directions. By imposing sign restrictions on the production of the energy-intensive sector on impact and for the following two periods, we reduce the probability of confounding energy supply shocks with the frequent and temporary

output adjustments that characterise this sector. The responses on the other three variables - HICP, GDP and industrial production - is endogenously determined also at impact.

As suggested by Canova and Paustian (2011), inference related to the shocks of interest may be improved by identifying additional macroeconomic shocks, even though they are not of primary interest for the analysis. Therefore, in addition, we also identify traditional demand and supply shocks. Two shocks are left unlabelled. The restrictions are listed in Table 1. For demand shocks, we assume that at impact the one-step ahead forecast errors of HICP, HICP energy, GDP and industrial production move in the same direction. We keep the response of the energy-intensive output unsigned, because if energy prices rise substantially after a favourable demand shock the specific sector could potentially suffer from it. For supply shocks other than energy, we assume that at impact the one-step ahead forecast error of HICP and the one-step ahead forecast errors of both GDP and industrial production move in opposite direction.

Table 1: Sign and Narrative Restrictions

Variables	Energy Supply	Other Supply	Demand
	Sign restrictions on the impact matrix A_0^{-1}		
Energy HICP	+		+
Headline HICP		+	+
Real GDP		-	+
Industrial production		-	+
Energy-intensive industrial production	-		
	Narrative sign and signed contribution restrictions		
08/90-09/90	$\uparrow u_t^{p_t^e}$		
12/02-01/03	$\uparrow u_t^{p_t^e}$		
10/21-11/21	$\uparrow u_t^{p_t^e}$		
03/22-04/22	$\uparrow u_t^{p_t^e}$		

The sign restrictions are not sufficient to identify shocks, as demand and other supply shocks would be perfectly compatible with the energy supply shocks. We rely on narrative restrictions to obtain shocks that we can label energy supply shocks and we will show that the sign restrictions are added mainly to sharpen the identification.

Narrative sign restrictions. We assume that the energy supply shocks $\varepsilon_{i,t}$ are positive on a specific date t:

$$\varepsilon_{i,t} > 0 \ at \ a \ given \ t. \tag{6}$$

The dates are selected relying on the "narrow criterion" adopted by Caldara et al. (2019),

that is if the domestic oil production in month t drops by more than 2% of global oil production, in combination with positive oil supply shocks identified by Känzig (2021). This is the case with the Iraq's invasion of Kuwait in August 1990 and the political unrest in Venezuela in December 2002. Moreover, we propose two additional episodes associated to the cut in energy supplies by Russia in Autumn 2021, when Russian gas supplies via the Yamal-Europe pipeline fell dramatically, and in the aftermath of the Russian war against Ukraine in March 2022. It is important to emphasise that almost 30% of the EU crude oil imports, 40% of the EU natural gas imports and 50% of EU solid fossil fuel (mostly coal) imports originated from Russia. By keeping deliveries to Europe deliberately tight, Russia engineered the energy crisis.

Cumulated over the subsequent two months, HICP energy prices rose by 8.7% in August-September 1990, 3.4% in December 2002 and January 2003, 8.7% in October-November 2021, and 7.7% in March-April 2022, respectively; while the production of the energy intensive sector (chemicals and basic metals) declined by 0.1%, 0.5%, 1.0% and 1.3%, respectively.[7]

Signed contribution restrictions. Following Antolín-Díaz and Rubio-Ramírez (2018), we also impose, on the restricted dates, that the energy supply shock is the most important contributor to the one-step ahead forecast error of energy prices. However, following De Santis and Van der Weken (2022), the identification is less restrictive, as we allow the unrestricted shocks to have an even larger contribution to the one-step ahead forecast error of energy prices, if the contribution of that unrestricted shock moves the forecast error in the opposite direction of the energy supply shock.

Our narrative restrictions are sign-dependent. More precisely, let $h_{i,t}$ denote the contribution of the shock of interest to the one-step ahead forecast error of the variable of interest i at time t and $H_{i,t}$ the $(n-1) \times 1$ vector that collects the contributions of the other shocks in the VAR to the same forecast error on the same date. We can then compute the vector-valued indicator function $B_{i,t} = \mathbb{1}((H_{i,t} \cdot sign(h_{i,t})) > 0)$ and the the vector-valued function $\mathbb{S}(H_{i,t}, B_{i,t})$ that selects the elements from $H_{i,t}$ for which the corresponding element in the

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[7]Producers of chemicals and basic metals are by far the largest-scale users of energy (e.g. EIA, 2021; Gunnella et al., 2022).

same-sized vector $B_{i,t}$ equals one. A draw is selected if the following condition is fulfilled

$$|h_{i,t}| > max\left(\$(|H_{i,t}|, B_{it})\right),\qquad(7)$$

while the traditional approach by Antolín-Díaz and Rubio-Ramírez (2018) imposes that $|h_{i,t}| > max(|H_{i,t}|)$.

The arrows (i.e. ↑) in Table 1 indicate that the identified energy supply shocks are positive in that specific months. Most importantly, we assume that the energy supply shocks are relatively large such that, among all the other shocks contributing to a rise in energy prices in these months, they explain the largest fraction of the HICP Energy's one-step ahead forecast errors, $u_t^{pe_t}$. These set of narrative restrictions are sufficient to identify the energy supply shocks. Three of these events occurred in the regime with a high-inflation regime (August-September 1990, October-November 2021 and March-April 2022) and one event occurred in the region with a low-inflation regime (December 2002 and January 2003). Investigating the impact on output is particularly interesting, because aggregate manufacturing production and GDP rose after the three events selected to identify shocks in the high-inflation regime.

III.B   Nonlinear Structural Impulse Responses

Structural shocks, ϵ_t, may have nonlinear effects on $\mathbf{X}_t$. They depend on the history of the data and on the sign and magnitude of the structural shocks with effects from t to $t+k$. z_{t-1} is a function of p_{t-1} and, therefore, z_t, z_{t+1},...., z_{t+k-1} are endogenously determined in the TVAR. To construct the structural response functions, the feedback from future changes in z_{t-1} into the dynamics of macroeconomic system ougth to be taken into account.

Following Balke (2000) in a TVAR setting and Koop et al. (1996),[8] who proposed the construction of the response functions using the conditional expectations, we compute the nonlinear structural IRFs as the difference between the expectations of the realizations $\mathbf{X}_{t+k}$ at horizon k, conditional on ϵ_t and the information set at time $t-1$, Γ_{t-1}, and the expectations

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[8]Koop et al. (1996) were not concerned about structural identification, they used the reduced form residuals. Given that we focus on structural identification, the algorithm differs from Koop et al.'s approach. See also Kilian and Lütkepohl (2017, Chapter 18) for a discussion of state dependent IRFs.

of the realizations $\mathbf{X}_{t+k}$ conditioned only on Γ_{t-1}:

$$IRF_{\mathbf{X}}^{S}(\epsilon_t, \Gamma_{t-1}) \equiv \mathbb{E}(\mathbf{X}_{t+k} | \Gamma_{t-1}, \epsilon_t) - \mathbb{E}(\mathbf{X}_{t+k} | \Gamma_{t-1}), \tag{8}$$

where $S \in \{0, 1\}$ indicates whether the economy is in the low- or high-inflation regime at time $t + k$. The conditional expectations are calculated by simulating forward the model.

It is worth emphasizing that the switch among regimes is treated as endogenous, as the economy can shift from low to high inflation regimes or *viceversa* over the simulation horizon, depending on the sign, the size of the shock, the estimated parameters and the specific history of the system prior to the shock. The starting points are assumed to be the median of all the in-sample observations in each regime, in order to obtain the most representative picture of the dynamics associated to each regime.

IV   The macroeconomic impact of energy supply shocks

IV.A   Retail Energy Supply Shocks

The estimated energy supply shocks are displayed in Figure 2. The upper panel provides the shocks estimated in-sample and the bottom panel provides the shocks out-of-sample. We exclude the year 2020 due to the uninformative sharp dynamics of the variables that characterized the Covid-19 period. Between May 1999 and April 2008, all energy supply shocks were below 2 standard deviations and 88% of them were below 1 standard deviation. These results are in line with Hamilton (2009), Kilian (2009a), Baumeister and Peersman (2013) and Kilian and Murphy (2014), who argue that most of the surge in the real price of oil between 2003 and mid 2008 were mostly driven by the strong global demand, particularly from emerging markets; a view recently corroborated by Aastveit et al. (2021). A large (median) energy supply shock (2.9 standard deviations) is estimated in May 2008. In that month, energy prices soared against the background of declining production in a number of non-OPEC nations, including Mexico, United Kingdom and Norway. According to the Energy Information Administration, slow growth in non-OPEC oil supply coincided with

disruption in supplies from some OPEC countries, such as Nigeria.[9] Moreover, Norway, the world's fifth-biggest oil exporter and Western Europe's biggest gas exporter, cut in May 2008 its projection for 2008 gas sales to 100 from 108 billion cubic meters. Coupled with strong demand growth, the WTI crude oil prices and the Henry Hub natural gas spot price rose on average by about 11% in May 2008.

Conversely, energy supply shocks from July 2021 onward were very large and unprecedented relative to the period under investigation. The energy supply shocks between July 2021 and June 2022 are massive amounting to 3.9 standard deviations on average each month. Only in March 2022 soon after the Russian invasion of Ukraine began, the energy supply shock amounted to about 10 standard deviations. The out-of-sample estimates are in line with the overwhelming shared view that the energy supply shocks are behind the dynamics of energy prices since the summer 2021 when Russian gas supplies fell.

IV.B   Impulse Response Functions

We start our analysis on the transmission mechanism by considering the effects of the energy supply shocks in the linear model. The resulting IRFs are displayed in Figure 3. In this and all subsequent figures, the dashed red lines and shaded bands around the median IRFs provide the corresponding posterior 68% credible sets. One standard deviation energy supply shock implies an immediate increase by about 1.1% in energy prices and by about 0.1% in HICP, and an immediate drop by 0.3% in the production of energy-intensive sectors and industrial production and by 0.1% in real GDP. The response of future energy prices peaks after a short delay, indicating that the typical energy supply shock during the sample period is of relatively short duration. Yet, the decay of the energy price's response is only gradual. The impact on HICP is also temporary, but more persistent and long lasting. The negative impact on output instead is very long lasting. At through, after about two years and on average, the production of the energy-intensive sector drops by 0.5%, industrial production by 0.4% and real GDP by 0.2%.

The last four rows of Figure 3 plots the corresponding nonlinear IRFs with associated credible sets in the low- and high-inflation regimes, taking into account the size and the

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[9]Energy Information Administration, "Short-term Energy outlook", June 10, 2008, Press Release.

direction of the shocks and any feedback from the dynamic system. We allow for the possibility that a shock shifts the economy to another state and the mean-reverting properties of the dynamics system could in principle after a number of months bring the state back to its equilibrium. The responses in the two regimes are quite different.

Panels B and C display the impact of structural shocks, which increase energy prices on impact by 10% and 40% to resemble developments since July 2021. An energy supply shock has an impact on HICP, which is higher and much more persistent, in the high-inflation regime. One could expect that a higher price adjustment is accompanied by a less persistent pass-through of shocks into prices, because more firms change their prices immediately after the shock. Instead, the results suggest that the effects on consumer prices not only are larger, but are also more persistent in the high-inflation regime, because the transitory impact on energy prices dissipates fully after about 5 years, twice the time needed to reverse in the low-inflation regime. An adverse energy supply shock causing a 10% rise in energy prices initiated in the low-inflation regime shifts the economy in the high-inflation regime only for about half year, then the dynamics of the system brings the economy back to the initial state. Conversely, the same shock initiated in the high-inflation regime and the dynamics of the model keep the economy in the same state for about two and half years; thereafter the economy moves to the low-inflation regime. A very high energy supply shock causing a 40% rise in energy prices initiated in the low-inflation regime shifts the economy to the high-inflation regime for about one and half year. While the same shock initiated in the high-inflation regime shifts the economy to a low-inflation regime again after about two and half years, owing to the transitory nature of the shocks.

Instead, the impact response of GDP and aggregate industrial production is immediate, strong and negative in the low-inflation regime, while their response is negative in the high-inflation regime only after about two years. The negative output response is much more muted in the short term in the high-inflation regime, because firms can pass-through the rise in energy prices to consumers to a larger and more persistent extent. The IRFs converge in the two regimes after about four years in the case of GDP and after about two years in the case of industrial production. The median impact response of the production of the energy-intensive sector is negative and somewhat similar across regimes with the effects being more

negative in the first year in the case of the low-inflation regime.

Panels D and E display the nonlinear IRFs arising from favourable energy supply shocks, which decrease energy prices on impact by 10% and 40%, respectively, so that we can assess the role of the sign relative to the size of the shocks. Such shocks initiated in the low-inflation regime keeps the economy in the same state. A 10% shock initiated in the high-inflation regime keeps the economy in the same state for about two and half years and only afterwards it moves to the low-inflation regime, in a symmetric fashion as in the case of a 10% adverse shock. Instead, a 40% favourable shock moves the economy to the low-inflation regime immediately.

A summary of the multipliers, which provide the largest impact (in absolute value) on the considered variables after a normalised 10% increase or decrease in energy prices (due to different energy supply shock in sign and size), is displayed in Table 2. All estimates, including the 16%-84% credible set range, are normalised for comparability such that they represent the change in the variables for each 10% increase of energy prices.

The multiplier in low- and high-inflation environments has a differential effect on consumer prices, real GDP and manufacturing production, while it is more homogeneous in the energy-intensive sector. The multipliers are larger than those of the linear model in the case of inflation, if the initial state is the high-inflation regime, and in the case of GDP and industrial production, if the initial state is the low-inflation regime. A 10% increase in energy prices due to energy supply shocks implies (i) an increase in HICP by about 1% in the low-inflation regime (a complete pass-through given the 10% weight of energy goods in the household consumption basket) but by 1.6% in the high-inflation regime; (ii) a drop in real GDP by about 3.1% in the low-inflation regime and 1.5% in the high-inflation regime; (iii) a drop in industrial production by about 4.7% in the low-inflation regime and 3.7% in the high-inflation regime; (iv) a drop in the production of the energy-intensive sector by about 4.4% in the low-inflation regime and 4.6% in the high-inflation regime. In the high-inflation relative to the low-inflation regime, the multiplier on HICP is 60% larger and the drop in GDP is about half. This corroborates the suggestion that price flexibility cushions from the output drop.

The multipliers instead are somewhat similar when looking at the sign and the size of

the shocks within regimes, particularly if we consider the full range of the credible sets. Overall, looking at the bands characterising the credible sets, the transmission mechanism differ substantially across regimes, while the size and the sign of the shocks within the same regime seem to provide more symmetric developments.

Table 2: Multipliers for 10% Increase or Decrease in Energy Prices across Regimes

	HICP			GDP			Ind. production			Energy-intensive prod.		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
Increase in energy prices												
Linear 10% rise	1.0	1.2	1.4	-3.4	-2.3	-1.5	-5.8	-4.3	-3.0	-7.0	-4.9	-3.1
Nonlinear 10% rise: Low	0.7	1.0	1.4	-4.3	-3.1	-2.0	-7.4	-4.7	-2.7	-7.8	-4.4	-1.6
Nonlinear 10% rise: High	1.3	1.6	1.8	-2.6	-1.5	-0.5	-5.6	-3.7	-1.8	-7.0	-4.6	-2.3
Nonlinear 40% rise: Low	0.7	1.0	1.3	-4.2	-3.0	-2.0	-7.4	-4.9	-2.9	-8.9	-5.3	-2.5
Nonlinear 40% rise: High	1.3	1.6	1.8	-2.4	-1.3	-0.3	-5.1	-3.3	-1.3	-6.6	-4.0	-1.6
Decrease in energy prices												
Nonlinear 10% drop: Low	-1.2	-1.0	-0.7	1.5	2.8	4.5	1.0	3.0	5.7	1.2	3.5	7.2
Nonlinear 10% drop: High	-3.0	-2.3	-1.6	0.9	2.1	3.8	2.7	4.7	7.2	2.8	5.4	8.3
Nonlinear 40% drop: Low	-1.3	-1.0	-0.7	1.4	2.8	4.5	1.2	3.1	5.3	1.1	3.5	7.2
Nonlinear 40% drop: High	-1.9	-1.6	-1.3	0.0	1.1	2.5	0.8	2.5	4.4	1.4	3.0	5.1

Notes: This table shows the largest impact (in absolute value) of a normalised 10% increase or decrease in energy prices due to energy shocks on HICP, GDP, the industrial production and the production of the energy-intensive sector in low- and high-inflation regimes as well as in the linear setting. Four different energy supply shocks are considered, which increase or decrease energy prices by 10% and 40%. The table provides the median (50%) response and the 16%-84% credible set range.

To show that the crucial elements to identify energy supply shocks are the narrative restrictions, Figure 4 compares the nonlinear IRFs of the baseline model (blue), identified through both narrative and sign restrictions, with the nonlinear IRFs obtained assuming that the shock is identified uniquely with narrative restrictions (red). The results on prices are almost equivalent, while the results on output are qualitatively similar. The negative impact on output is slightly smaller in the model with narrative restrictions only, because at impact the energy-intensive sector does not decline. It is worth emphasising that the model with sign and narrative restrictions is characterised by a narrower posterior 68% credible sets, pointing to clearer results. The comparison with a model characterised by fully set-identified sign restrictions is shown in the robustness section.

We selected for the baseline model a threshold amounting to 1.99% of the annualised underlying inflation rate, as the transmission mechanisms of the energy supply shocks across the two regimes is of interest for the ECB given its inflation objective. An alternative estimate can be provided through a grid search method. The grid search is carried out over possible values of the observations' percentiles ranging between 0.25 and 0.75 such that we have enough data points to estimate the model. The marginal likelihood is maximised at percentile 0.59 of the sample, which suggest setting the threshold for annualised underlying

inflation at 2.2%. The results with the new threshold remain invariant (see Figure 5).

IV.C   On the Role of the Out-of-Sample Narratives in 2021/2022

The aforementioned results are obtained assuming that the one-month ahead forecast errors in the energy prices in October and November 2021 and in March and April 2022 arise primarily from energy supply shocks. Given that the median estimate of the energy supply shock in March 2022 is 9.5 standard deviations, it could be argued that this extraordinary large size is uniquely assumption-driven.

One could also argue that there is an inconsistency, because we exclude part of the sample for the estimation to avoid distortions from the special period since 2020, but then we use the out-of-sample narratives, as if the data generating process had not changed relative to the estimation period. The assumption on which the exercise is based is that the "Covid structural break" affects the data generating process only for a limited number of months in 2020. We believe that, after those months, and during the months associated with our narrative restrictions, the economic dynamics is the same as the one that generated the data we use for estimation.

Therefore, we assess how much our main results rely on these assumptions by excluding from the set of restrictions the narrative episodes of March and April 2022, associated to the developments in energy prices at the onset of the Russia's war in Ukraine. The results are displayed in Figure 6. The size of the median shock in March 2022 is only 1 standard deviation lower than the median shock estimated including among the assumptions the narratives on the Ukraine' war. The sum of the shocks at their median between July 2021 and June 2022 amount to 36 standard deviations, 11 standard deviations lower than suggested by the more restrictive model, but still unprecedentedly and extraordinarily large. All in all, the energy supply shocks estimated with the two set of narrative restrictions are very similar, as they are aligned on the 45 degree line. Consequently, the nonlinear IRFs shown in Figure 7 are equivalent to the baseline model discussed in Section IV.B.

All results are corroborated if also the other out-of-sample narrative restrictions in October and November 2021, associated to the gas cut from Russia, are relaxed. The remaining narratives in August and September 1990 used for the high-inflation regime and in December

2002 and January 2003 employed for the low-inflation regime, together with the sign restrictions on retail energy prices and the production in the energy-intensive sector, generate macroeconomic responses similar to those so far discussed (see Panel B of Figures 7).

All in all, the 2021 and 2022 narrative restrictions are not necessary to draw the suggested conclusions. The main evidence remains unchanged when the 2021 and 2022 narrative restrictions are ignored.

IV.D   On the Pass-Through to Prices and Wages

The pass-through of energy supply shocks is complete in the low-inflation regime, regardless of the direction of the shocks. Instead, there is evidence of over-proportional pass-through in the high-inflation regime. This implies that consumer prices excluding energy should not respond to such shocks in the low-inflation regime, while they should be positively (negatively) affected in the high-inflation regime, if the shock is adverse (favourable). The non-linear IRFs reported in Figure 8 (left panel) make the point. The responses are constructed as $\sum_{k=0}^{K} \mathbb{E}(\Delta p_{t+k} - 0.1\Delta p_{t+k}^e | \epsilon_t, \Gamma_{t-1})$, where Δ is the first difference operator and 0.1 is the weight of energy in the consumer basket. In response to energy shocks increasing energy prices by 10%, consumer prices excluding energy are unaffected in the low-inflation regime, while they increase immediately by 0.5% in the high-inflation regime with a 1% peak after about two years.

These results imply that core prices, that is HICP excluding food and energy, should only marginally respond to energy shocks in the low-inflation regime, while they should rise (decline) more in the high-inflation regime in response to a positive (negative) energy supply shock, although food prices could explain the dynamics in HICP in the high-inflation regime. We corroborate this intuition by including core prices in the TVAR. The six variable TVAR is estimated using the assumption displayed in Table 1. The results provided in the second panel of Figure 8 are fully consistent with the response of HICP excluding energy. Energy supply shocks do not pass-through to core prices in the low-inflation regime, while their pass-through in the high-inflation regime (8-10% depending upon the direction of the shock) is about half the pass-through on headline prices, reaching the peak after about two and half years with the shock dissipating after about five years. The median pass-through is stronger

when shocks are favourable in line with the findings for headline prices. All in all, the more core prices rise, the more headline prices increase.

The difference of the response between HICP excluding energy and core HICP in the short term suggest that food prices react much faster than core prices, as corroborated by the TVAR model that includes food prices (see third panel of 8). The response of food prices is rather strong. A 10% increase in energy prices due to an energy supply shock causes a 2% rise in food prices after about a year.

With headline prices rising, workers could seek higher wages to compensate for a loss in their purchasing power, which would imply further price increases. This so-called second-round effects could also be an additional channel behind the rise in prices after an energy shock. We have shown that energy supply shocks have a transitory impact on headline prices, fully dissipating after about 2-3 years in the low-inflation regime, but after 5 years in the high-inflation regime, while core prices respond in an economically significant manner only in the high-inflation regime with the energy shocks also dissipating after about 5 years. For that reason, an energy shock could have an impact on nominal wages particularly in the high-inflation regime. We investigate this hypothesis by adding year-on-year wage growth at monthly frequency in the TVAR, as compensation of employee is only available on a quarterly basis.[10] The results, which are displayed in Figure 8, suggest some effects on wage growth in both the low- and high-inflation regimes, pointing out that second-round effects exist, but remain limited particularly when shocks are adverse.

IV.E   On the Response of Monetary Policy Rates

The main result of the paper is that the transmission of energy supply shocks is stronger on prices in the high-inflation regime and more adverse on output in the low inflation regime and this can be explained if the supply curve is steeper in the high-inflation regime. A natural question is whether the monetary policy response could also explain some of these differences. In the last panel of Figure 8, we show the nonlinear response to energy supply shocks of the shadow short rate. The time series is provided for the euro area by Halberstadt

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[10]The monthly indicator of negotiated wage rates is provided by the European Central Bank from January 1991 onward. The 1990 year has been estimated using data for Italy, France and Belgium.

and Krippner (2021), through the method developed by Krippner (2013, 2020).[11] The results suggest that the shadow rate tends to decline after an adverse retail energy supply shock in the low-inflation regime. Conversely, the shadow short rate increases immediately in the high-inflation regime, but drops after about half year. The persistence of higher headline and core consumer prices in the high-inflation regime might be related to the drop in the policy rate.

IV.F   On the Relative Importance of Energy Supply Shocks

The historical decomposition of shocks allows to investigate the relative importance of a shock in each period. To study the importance of energy shocks in specific periods, we consider a counterfactual in which energy shocks are set to zero. This exercise is carried out for both the linear and the nonlinear models in order to appreciate the differences. The counterfactual from the linear and the TVAR models are displayed in Figure 9.

The first key result is that in absence of energy supply shocks yearly HICP inflation would have amounted to 2.3%, rather than the observed 8.3% in June 2022. Instead, the counterfactual obtained from the linear model suggests a much higher inflation rate equal to 5.3%. This is explained by the fact that the pass-through of energy supply shocks on consumer prices is larger in the high-inflation regime and the euro area economy shifted to the high inflation regime in June 2021, when annualised underlying inflation reached 2%. Therefore, energy supply shocks contributed more extensively relative to the suggestions from linear models in explaining the unprecedented rise in consumer prices since autumn 2021.

The second key result is that our model corroborates the argument by Hamilton (2009); Kilian (2009a); Baumeister and Peersman (2013); Kilian and Murphy (2014), recently confirmed by Aastveit et al. (2021), that energy supply shocks played a marginal role during the sharp rise in oil prices between September 2003 and April 2008: during this period, the WTI tripled and HICP energy prices rose by 40%. The counterfactual from the TVAR is

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[11]The shadow short rate is available from 1995 on https://www.ljkmfa.com/. We chain the first five years of the sample through the 2-year government bond yield for the euro area compiled by the ECB, given the high correlation between the two series over the common sample before the lower bound period. The results are qualitatively similar if using the time series provided by Wu and Xia (2016), available only from 2004, which we chained backward using the Krippner's time series.

even closer to the observed value than the counterfactual from the linear model, suggesting smaller energy supply shocks implied by the nonlinear specification.

The third key result is that linear and nonlinear models provide differential results also in a state with low inflation. In 2015 and 2016, when underlying inflation and yearly HICP inflation fluctuated around zero, the counterfactual from the TVAR relative to the linear model suggests a 0.6-1.0 percentage point lower yearly HICP inflation rate. This is due to smaller energy supply shocks implied by the nonlinear specification and to a lower pass-through to consumer prices in the low-inflation regime.

IV.G Retail Energy versus Crude Oil Supply Shocks

An interesting question is whether the identified retail energy supply shocks are dominated by oil market developments, for which extensive empirical evidence is already available, or if they represent a broader driving force reflecting a more general definition of energy supply innovations, which can prove essential as the reliance of the economy on oil decreases.

The Eurostat HICP price index of energy goods includes various components, such as electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment. Therefore, the underlying retail energy supply shocks are in principle able to capture broader developments in the energy markets. We check this by comparing the median of our identified retail energy supply shocks with the median of the crude oil supply shocks estimated in Känzig (2021). Figure 10 displays the cross-plot of the two shocks from July 1990 to June 2022, excluding the Covid-19 period. As expected, the relationship is positive, but rather feeble, and particularly weak in the course of 2021 and 2022 (see red dots), when energy gas skyrocketed. Between July 2021 and June 2022, the cumulative crude oil price shocks amounted to a mere 1.5 standard deviation, insufficient to explain the dynamics in retail energy prices in the euro area, which increased by 42% over the same period. Overall, our model allows for a more comprehensive analysis of the energy supply shocks in the retail market. We believe that the broader definition of our shock is especially useful when analyzing current economic events and that it is bound to become crucial as fossil fuels are replaced by alternative sources.

IV.H   On the Response of Wholesale Energy Prices

Rising oil and gas prices in the global markets allows euro area energy companies to sell their energy products at higher wholesale prices. The difference between wholesale and retail energy prices depends on variable and fixed transport costs within the euro area, as well as on taxes, regulations and contracting practices. Therefore, the pass-through of energy supply shocks to wholesale energy prices could differ from that to retail prices. We assess this pass-through by including in the TVAR the domestic producer prices of electricity, gas, steam and air conditioning supply, a time series constructed by Eurostat from 1981.

The results, which are shown in the first three panels of Figure 11 and are based on the restrictions summarised in Table 1, corroborate that wholesale energy prices (last column) respond immediately to energy supply shocks, but with an increase amounting to about half the increase in retail energy prices. However, the nonlinear IRFs present a hump-shaped trajectory with an adverse shock remaining above the instantaneous reaction for about two years in the low-inflation regime and for about one year in the high-inflation regime, while the retail energy prices tend to decline immediately. Subsequently, the shock gradually fades away in the low-inflation regime, while the effect tends to be more long lasting in the high-inflation regime. The differential impact across regimes is even more evident if the energy supply shock is favourable. In this case, the decline in wholesale energy prices is much larger in the high-inflation state, reaching the through after about one year and remaining below the instantaneous impact for about five years. The drop in wholesale energy prices, initially half the drop in the retail market, resembles the drop in retail energy prices after about one year. The results of the other five variables are broadly invariant relative to developments described in Figure 3.

Given that both energy wholesale and retail prices rise after an energy supply shock, which is also confirmed by the anecdotal evidence during the events selected to identify the energy supply shocks,[12] we run the following robustness check. We impose the same sign restrictions, narrative sign restrictions and signed contribution restrictions on both retail and wholesale prices to identify the energy supply shocks. The other shocks are left invariant.

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[12]Cumulated over the subsequent two months, the wholesale energy prices rose by 0.4% in August-September 1990, 2.2% in December 2002 and January 2003, 20.7% in October-November 2021, and 11.3% in March-April 2022, respectively.

The results displayed in the last three panels of Figure 11 resemble those of the first three panels, suggesting that the results are robust.

V Robustness Checks

V.A Controlling for Energy-Specific Demand Shocks

One could argue that the energy supply shocks could be confounded with energy-specific demand shocks. For example, a dramatic change in temperature could vary the demand for energy, affecting energy prices and with the opposite sign the production in the energy-intensive sector. This can be tested in our framework using our narrative approach as described in Table 3. The energy supply and demand shocks have the same sign restrictions, but they can be disentangled through the narrative restrictions.

Table 3: Sign and Narrative Restrictions with Energy-Specific Demand Shocks

	Energy Supply	Other Supply	Other Demand	Energy-Specific Demand
Variables	*Sign restrictions on the impact matrix A_0^{-1}*			
Energy HICP	+		+	+
Headline HICP		+	+	
Real GDP		-	+	
Industrial production		-	+	
Energy-intensive industrial production	-			-
	Narrative sign and signed contribution restrictions			
08/90-09/90	$\uparrow u_t^{p_t^e}$			
12/02-01/03	$\uparrow u_t^{p_t^e}$			
10/21-11/21	$\uparrow u_t^{p_t^e}$			
03/22-04/22	$\uparrow u_t^{p_t^e}$			
02/12-02/12				$\uparrow u_t^{p_t^e}$
11/14-11/14				$\downarrow u_t^{p_t^e}$

A deadly cold wave started in Europe on January 27, 2012, and brought snow and freezing temperatures to much of the continent in February. On February 29, it was reported that there was snowfall in Nicosia (Cyprus). There were more than 820 reported deaths in both Europe and North Africa. According to the average temperature statistics of the Climate Change Knowledge Portal provided by the World Bank, the median temperature in Europe in February 2012 was -4 degrees Celsius below the average of all February months computed since 1990.

Another useful statistic is the degree days, which measures how cold or warm a location

is. A degree day compares the mean (the average of the high and low) outdoor temperatures recorded for a location to a standard temperature. The more extreme the outside temperature, the higher the number of degree days. A high number of degree days generally results in higher levels of energy use for space heating or cooling. According to Eurostat the heating and cooling degree days amounted to 573 in February 2012 as a median across European countries, which is 31% higher than the same statistics estimated on average over all February months since 1990. Therefore, we use this narrative to identify the energy-specific demand shocks in the high-inflation regime.

November 2014 tied as one of the warmest November in north Europe. Austria and Switzerland had their warmest November since national records began in 1767 and 1864, respectively. With national records dating back to 1900, France and Germany had their second warmest fall. The median temperature in Europe across countries in November 2014 was 1.7 degrees Celsius above the average of all November months since 1990. Similarly, the heating and cooling degree days amounted to 309 as a median across European countries, which is 12% lower than the same statistics estimated on average over all November months since 1990. Therefore, we use this narrative to identify the energy-specific demand shocks in the low-inflation regime.

Figure 12 compares the nonlinear responses to an energy supply shock from the baseline model (blue) with the nonlinear IRFs of the same shock from an alternative model, which conditions also on identified and orthogonal energy-specific demand shocks. The results are equivalent.

V.B   Fully set-identified TVAR

To show that our results are valid also in the context of a fully set-identified model with sign restrictions, that is a model with enough sign restriction to disentangle all the driving shocks, we impose additional structure to our SVAR assuming that: 1) after a favourable demand shock, the output of the energy-intensive sector rises; 2) after an adverse supply shock, which is not an energy supply shock, both the output of the energy-intensive sector and the retail energy price decline (see Table 4.

A comparison between our baseline model and a fully set-unidentified TVAR shows that

Table 4: Sign and Narrative Restrictions in a fully Set-Identified TVAR

	Energy Supply	Other Supply	Demand
Variables	*Sign restrictions on the impact matrix A_0^{-1}*		
Energy HICP	+	-	+
Headline HICP		+	+
Real GDP		-	+
Industrial production		-	+
Energy-intensive industrial production	-	-	+
	Narrative sign and signed contribution restrictions		
08/90-09/90	$\uparrow u_t^{p_t^e}$		
12/02-01/03	$\uparrow u_t^{p_t^e}$		
10/21-11/21	$\uparrow u_t^{p_t^e}$		
03/22-04/22	$\uparrow u_t^{p_t^e}$		

the results are equivalent, with the advantage that the former are obtained imposing fewer restrictions (see Figure 13).

V.C The role of the prior

The Bayesian methodology proposed by Antolín-Díaz and Rubio-Ramírez (2018) to conduct inference about the parameters of a SVAR model identified through sign and narrative restrictions specifies a uniform prior over the family of orthonormal matrices, Q, that are used to transform the reduced form parameterization into the structural parameterization. As the data are known to be only informative about the reduced form parameters in a Gaussian setting, the likelihood is necessarily flat over the set of rotation matrices, Q, that are compatible with the identifying restrictions. This, in turn, implies that, in some regions of the parameter space, the prior is never updated by the information brought in by the data in the formation of the posterior distribution. In this context, Baumeister and Hamilton (2015) warn that the uniform prior specified for the rotation matrix can translate into unintentionally informative conditional priors for objects of interests, such as IRFs, that will drive the results even asymptotically.

Arias et al. (2022) alleviate the concern about this problem showing that a uniform prior for Q is not only sufficient, but also necessary, if one wants to specify a uniform joint unconditional prior for the vector of IRFs. Even though the theoretical result provided by Arias et al. (2022) reassures about the fairness of the results obtained using the Antolín-Díaz and Rubio-Ramírez (2018) method, we follow the suggestion of Inoue and Kilian (2023) and

show in Figure 14 that the prior distribution we have assumed throughout the paper does not imply unintentionally informative unconditional priors about individual IRFs either. Figure 14 indeed shows that the credible sets derived from the sole prior information for the non-linear IRFs in our baseline model are centred at zero for the unsigned variables, and the range is very wide and increasing over the horizon for all variables in both the low- and high-inflation regimes.

VI   Conclusions

The pass-through of retail energy price shocks on consumer prices and their output implications depending upon the state of the economy have not received much academic attention. We close this knowledge gap by addressing the issue with a nonlinear VAR (e.g. TVAR), which identifies the shocks using narrative restrictions and constructs state-dependent impulse responses.

The results suggest that the transmission of energy supply shocks is stronger on prices in high-inflation regimes and on output in the low-inflation regime. The price impact is in line with the findings obtained from individual goods prices, which suggest that price changes occur more frequently when inflation is high, while they are sticky in the low-inflation regime. The fast pass-through of energy shocks on consumer prices (excluding energy) explains why the negative impact on output is far smaller in the high-inflation regime. Moreover, we find that energy supply shocks have a mean-reverting impact on consumer prices. Therefore, starting from the low-inflation regime and following large energy supply shocks, the transmission mechanism is that associated to the high-inflation regime; but, as the economy smoothly returns to a state with lower inflation after about two and half years, the transmission mechanism is that associated to the low-inflation regime.

The results of the model are important also for policymakers, as we have estimated massive energy supply shocks between July 2021 and June 2022 with important negative repercussion for industrial production, as the multipliers are more than twice as larger relative to GDP in the high-inflation regime. There is a high risk of a permanent drop in the output of the European energy-intensive sectors, such as chemicals and basic metals, if the energy

crisis is not resolved.

Finally, the results are useful for the existing literature on Dynamic Stochastic General Equilibrium (DSGE) models. Workhorse macroeconomic models used in many central banks and other policy institutions typically capture the price adjustment mechanism via the "Calvo" approach whereby the repricing rate, which represents the degree of price flexibility in the economy, is constant. The Calvo approach could be a good approximation only when inflation is low and shocks are small. Our results suggest that these models should allow for a nonlinear or state-dependent Phillips curve.

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Tables and Figures

Figure 1: Exponential Weighted Moving Average Annual Inflation Rate (%)
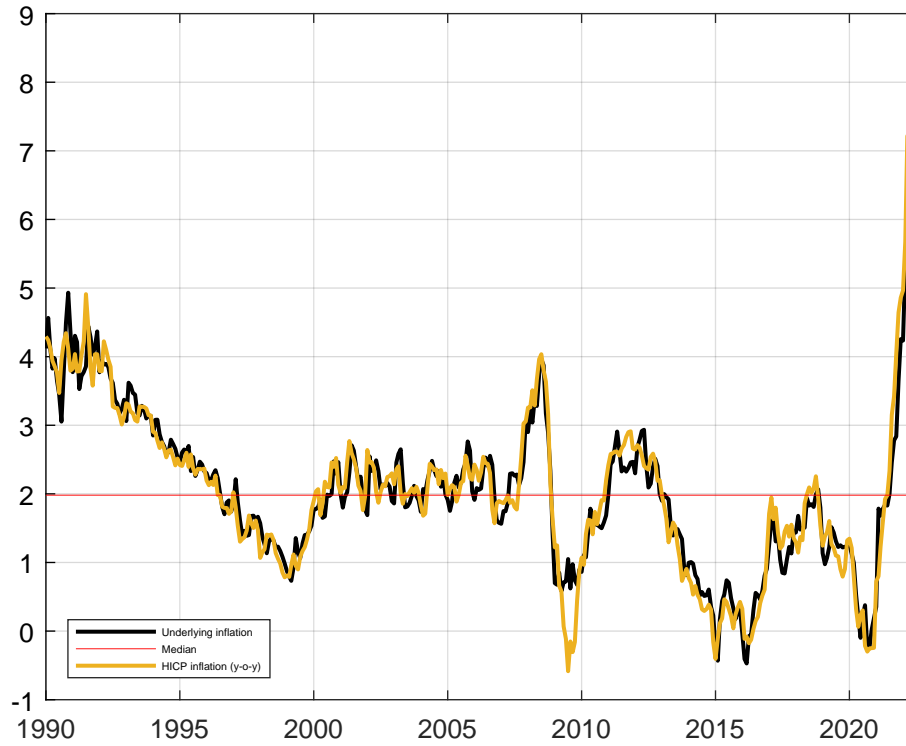
Notes: The state variable is calculated as $z_t = \alpha(p_t - p_{t-1}) + (1 - \alpha)z_{t-1}$, where p_t is the log of headline HICP. Underlying inflation is shown annualised and in percent. HICP inflation is computed a $100 * (p_t - p_{t-12})$.

In-sample: July 1990 - December 2019
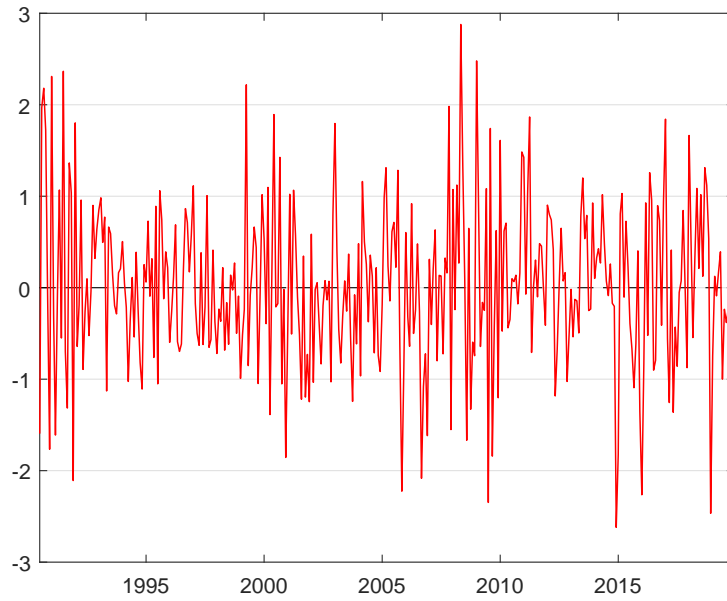
Out-of-sample: January 2021 - June 2022
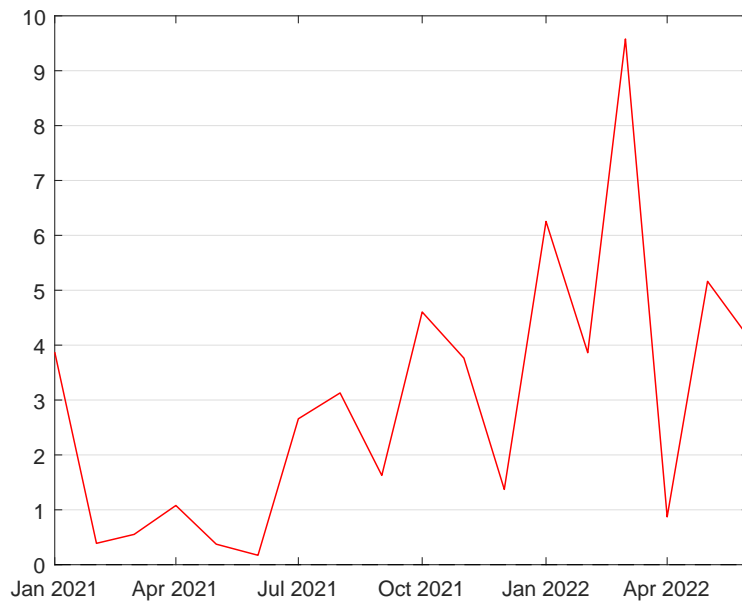
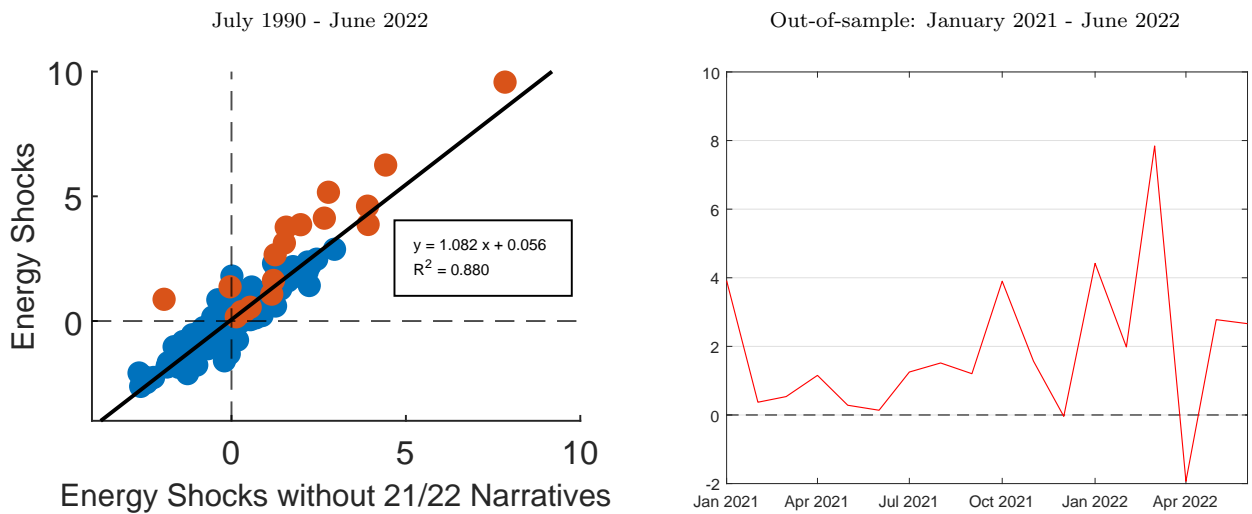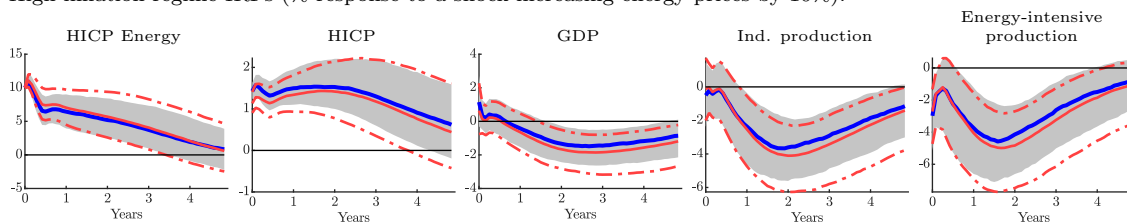*Notes:* The structural shocks are estimated using a TVAR with five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The identifying assumptions are collected in Table 1. The upper panel shows the energy supply shocks estimated in-sample. The bottom panel shows the energy supply shocks estimated out-of-sample

Figure 3: Responses to Energy Supply Shocks
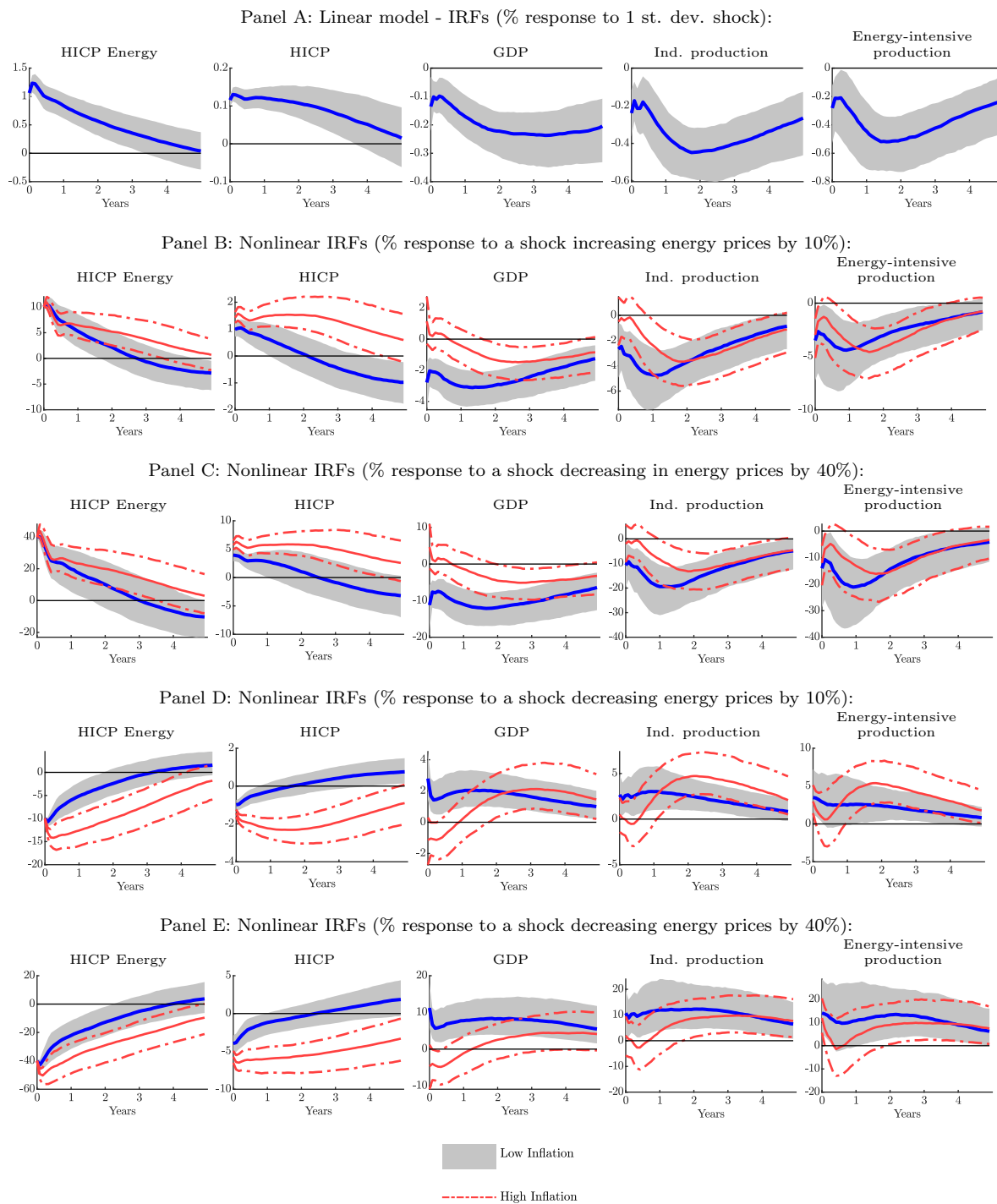
Panel A: Linear model - IRFs (% response to 1 st. dev. shock):

Panel B: Nonlinear IRFs (% response to a shock increasing energy prices by 10%):

Panel C: Nonlinear IRFs (% response to a shock decreasing in energy prices by 40%):

Panel D: Nonlinear IRFs (% response to a shock decreasing energy prices by 10%):

Panel E: Nonlinear IRFs (% response to a shock decreasing energy prices by 40%):

Low Inflation

High Inflation

Notes: The represented linear VAR and TVAR contains five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The red (blue) lines of the TVAR model are associated to the high (low) inflation regime.

Figure 4: Responses to Energy Supply Shocks: Sign/Narrative versus only Narrative Restrictions
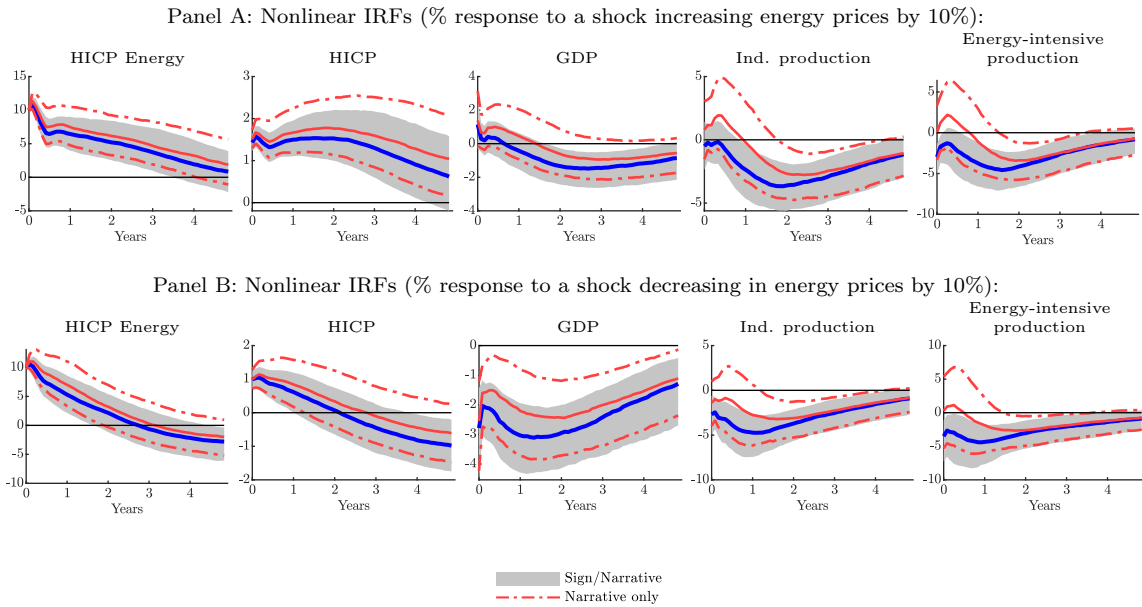
Panel A: Nonlinear IRFs (% response to a shock increasing energy prices by 10%):

Panel B: Nonlinear IRFs (% response to a shock decreasing in energy prices by 10%):

Notes: The represented TVAR contains five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The IRFs of the baseline model with sign and narrative restrictions as in Table 1 are in blue. The IRFs of the alternative model where the energy supply shocks are only identified with narrative restrictions as in Table 1 are in red.

Figure 5: Responses to Energy Supply Shocks: Threshold at 2% versus 2.2% grid search estimate
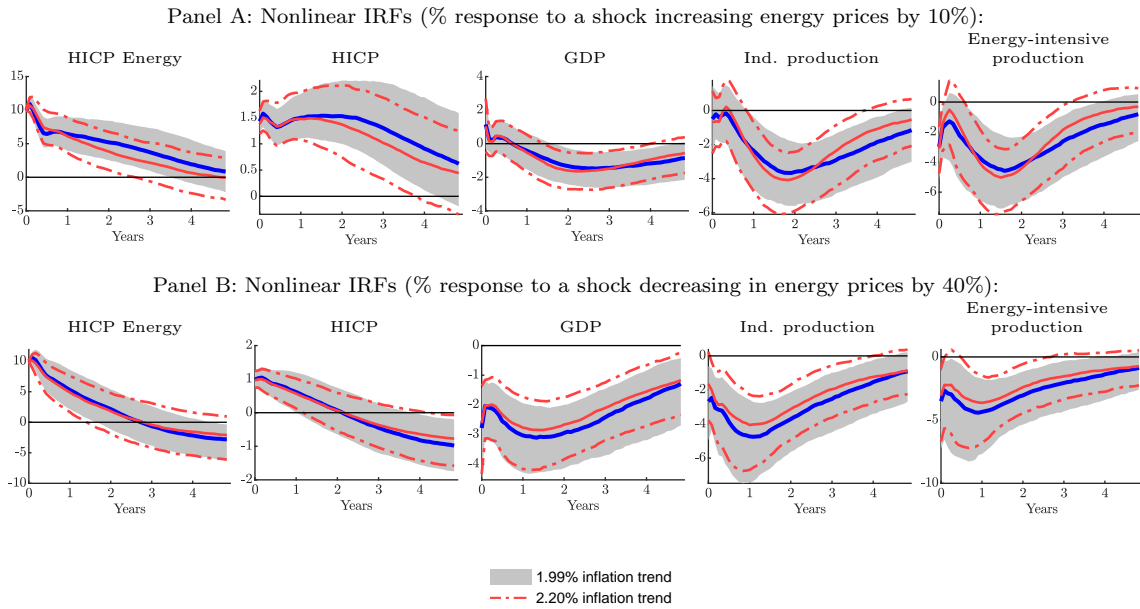
Panel A: Nonlinear IRFs (% response to a shock increasing energy prices by 10%):

Panel B: Nonlinear IRFs (% response to a shock decreasing in energy prices by 40%):

Notes: The represented TVAR contains five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The IRFs of the baseline model with the threshold at at 2% are in blue. The IRFs of the alternative model where the 2.2% threshold is estimated using a grid search are in red. The threshold is estimated through a grid search optimization over possible values of the observations' percentiles ranging between 0.25 and 0.75 such that we have enough data information to estimate the model. The marginal likelihood is maximised at percentile 0.59, which suggest setting the threshold for annualised trend inflation at 2.2%.

Figure 6: Estimated Energy Supply Shocks excluding the Narratives on the Ukraine's War

Panel A: TVAR without narrative restrictions in March-April 2022
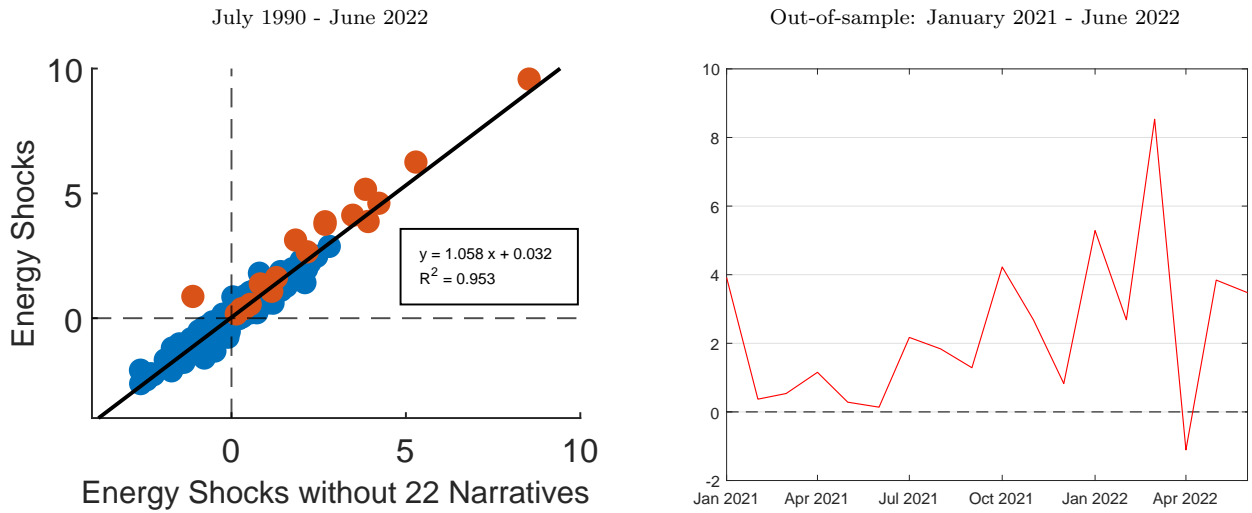
Panel B: TVAR without narrative restrictions in October-November 2021 and in March-April 2022
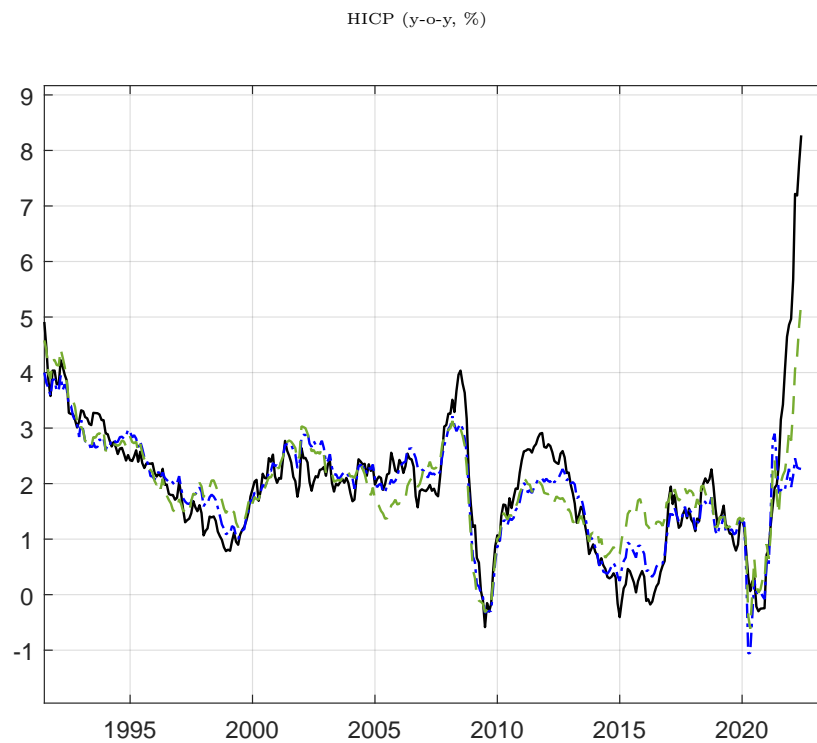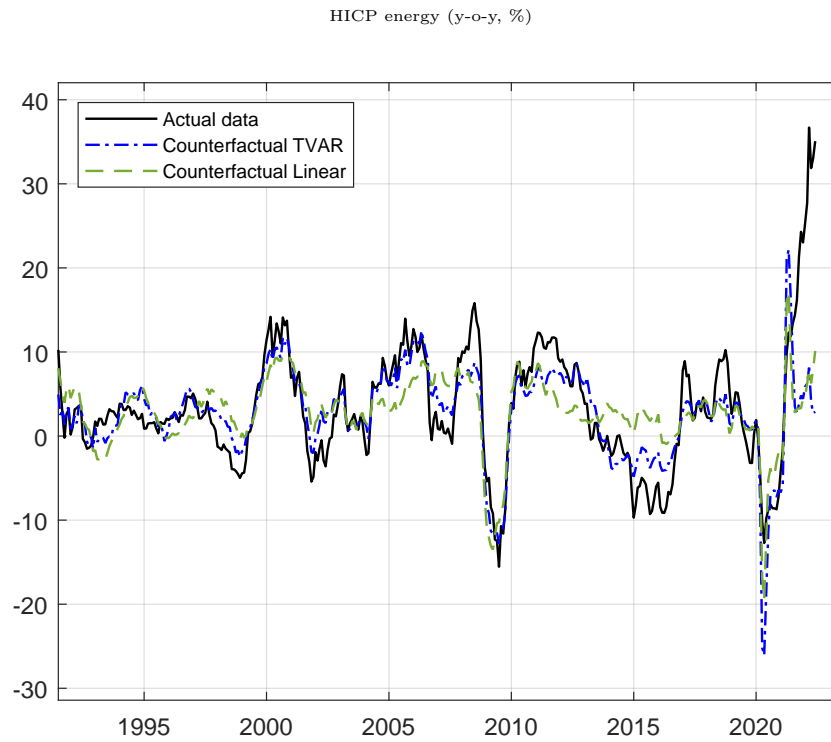

Notes: The structural shocks are estimated using a TVAR with five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The identifying assumptions are collected in Table 1 excluding the narrative restrictions on the Ukraine's war in March and April 2022 in Panel A and the narrative restrictions on the gas cut from Russia in October and November 2022 in Panel B. The left panel shows the energy supply shocks estimated in-sample. The right panel shows the energy supply shocks estimated out-of-sample

Figure 7: Responses to Energy Supply Shocks with and without Out-of-Sample Narratives

Panel A: TVAR without narrative restrictions in March-April 2022

High-inflation regime IRFs (% response to a shock increasing energy prices by 10%):

Low-inflation regime IRFs (% response to a shock decreasing in energy prices by 10%):
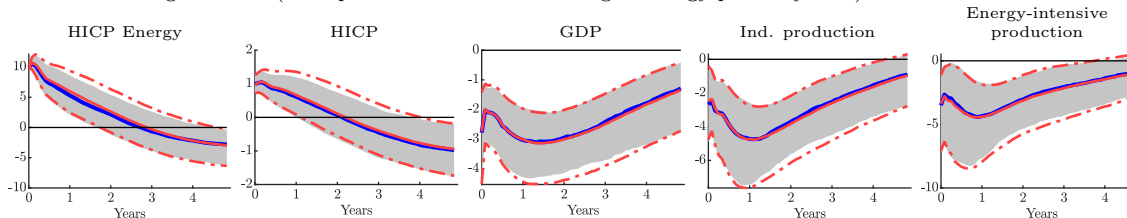
Baseline
without 2022 narratives

Panel B: TVAR without narrative restrictions in October-November 2021 and in March-April 2022

High-inflation regime IRFs (% response to a shock increasing energy prices by 10%):
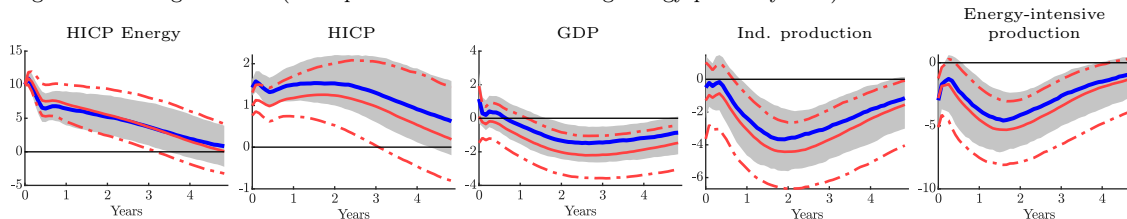
Low-inflation regime IRFs (% response to a shock decreasing in energy prices by 10%):
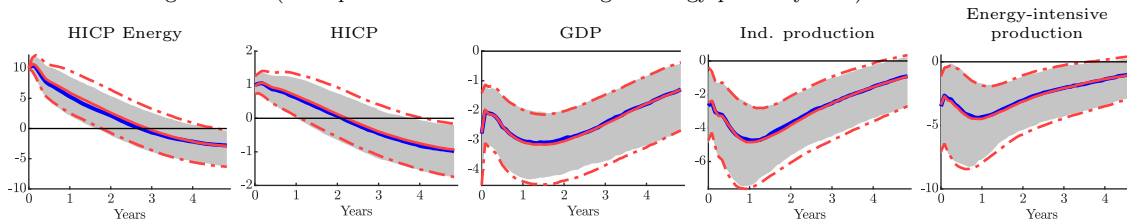
Baseline
without 2021/2022 narratives

Notes: The structural shocks are estimated using a TVAR with five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets. The blue lines are associated to the baseline model. The red lines are associated to the same model excluding the narrative restrictions on the Ukraine's war in March and April 2022 in Panel A as well as the narrative restrictions on the gas cut from Russia in October and November 2022 in Panel B.

Figure 8: Responses of Prices, Wages and Shadow Short Rate to Energy Supply Shocks

Panel A: Nonlinear IRFs (% response to a shock increasing energy prices by 10%):

Panel B: Nonlinear IRFs (% response to a shock decreasing in energy prices by 10%):

Low Inflation

High Inflation
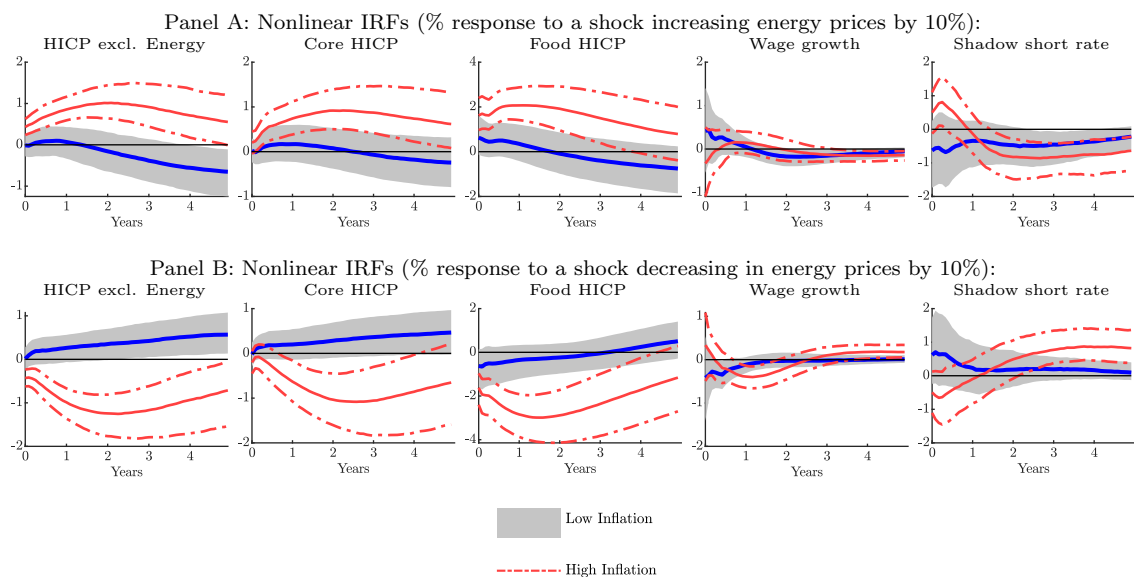
Notes: The five-variable TVAR used to estimate the response of HICP excl. Energy contains HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The responses of HICP excl. Energy are constructed as $GIRF_{pxe_{t+g}}(g, \epsilon_t, \Gamma_{t-1}) \equiv \sum_{h=0}^{g} \mathbb{E}(\Delta p_{t+h} - 0.1\Delta pe_{t+h} | \epsilon_t, \Gamma_{t-1})$, where Δ is the first difference operator and 0.1 is the weight of energy in the consumer basket. The 6-variable TVARs used to estimate the response of core prices, food prices, wage growth and shadow short rate contains additionally core HICP, food HICP, year-on-year wage growth and shadow short rate. The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The red (blue) lines are associated to the high (low) inflation regime.

Figure 9: Counterfactual without the Estimated Energy Supply Shocks

HICP energy (y-o-y, %)

HICP (y-o-y, %)

Notes: The counterfactual is obtained by setting the energy supply shocks at zero. The structural shocks are estimated using a TVAR with five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The identifying assumptions are collected in Table 1.

Figure 10: Retail Energy versus Crude Oil Supply Shocks
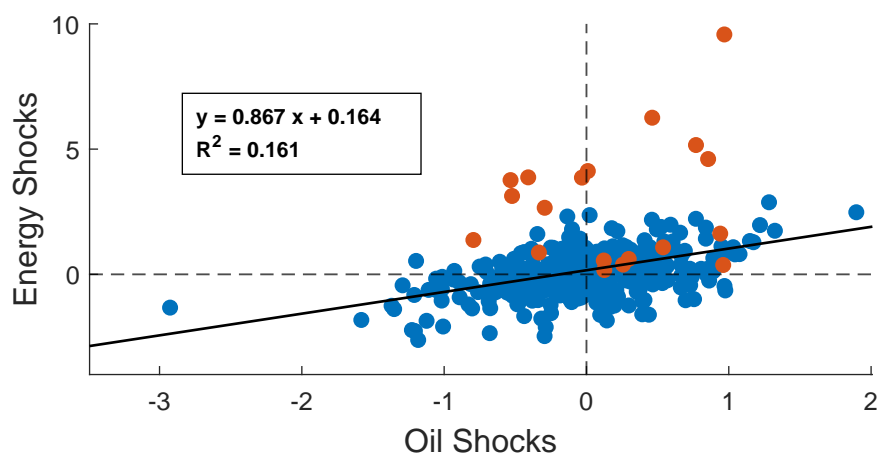
Notes: This figure shows the scatter plot between the retail energy supply shocks identified with the TVAR and the crude oil supply shocks identified by Känzig (2021) over the period July 1990 and June 2022 excluding the Covid-19 period. The red dots refer to the sub-period January 2021-June 2022.

Figure 11: Wholesale Energy Price's Response to Energy Supply Shocks

A: TVAR without restrictions on wholesale energy prices

Panel A: TVAR GIRFs (% response to a shock increasing energy prices by 10%):
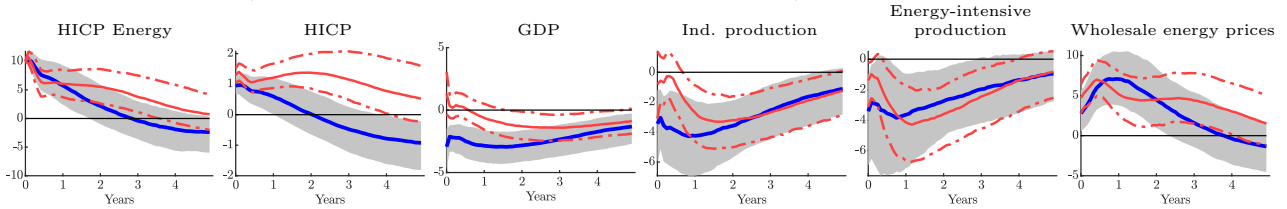
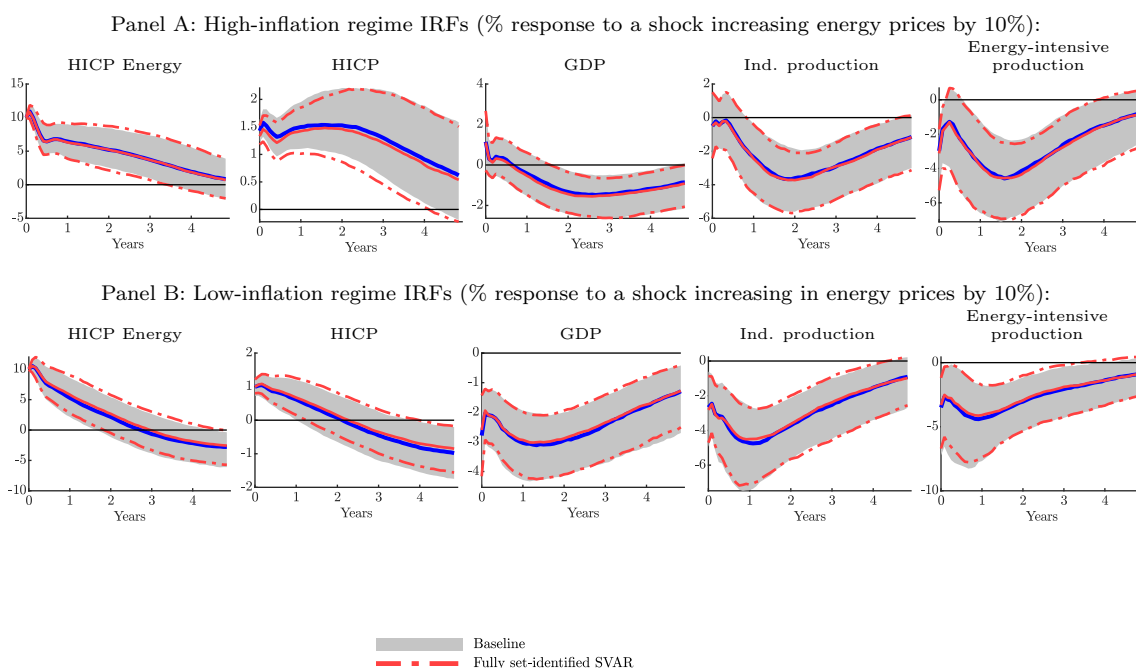Panel B: TVAR GIRFs (% response to a shock decreasing energy prices by 10%):
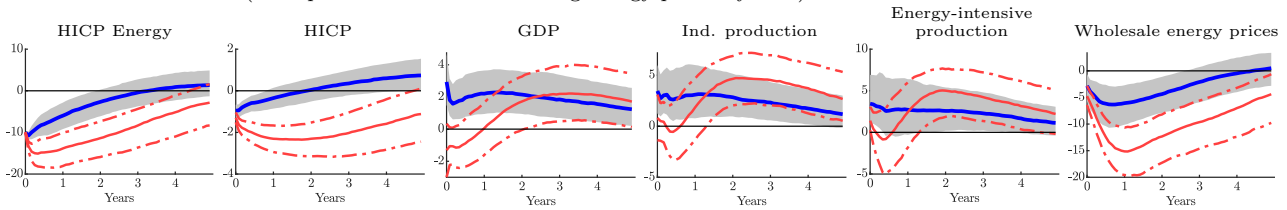
B: TVAR with restrictions on wholesale energy prices

Panel C: TVAR GIRFs (% response to a shock increasing energy prices by 10%):
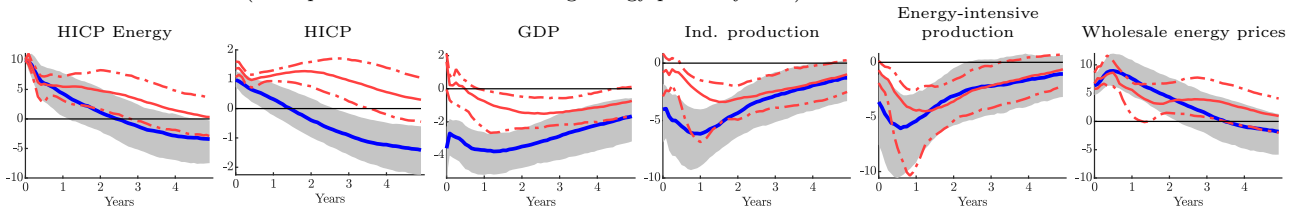
Panel D: TVAR GIRFs (% response to a shock decreasing energy prices by 10%):
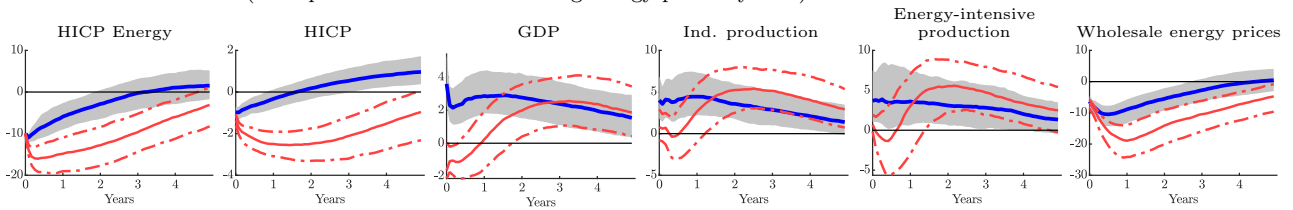
Low Inflation

High Inflation

Notes: The TVAR contains six variables: HICP energy, HICP, GDP, industrial production, industrial production of the energy-intensive sector and wholesale energy prices. The identifying assumptions underlying Panels A-B are collected in Table 1. Panels C-D are obtained assuming in addition that sign restrictions, narrative sign restriction and signed contribution restrictions to identify the energy supply shocks apply also to wholesale energy prices. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The red (blue) lines are associated to the high- (low-) inflation regime.

Figure 12: Robustness: Baseline versus a Model including Energy-Specific Demand Shocks
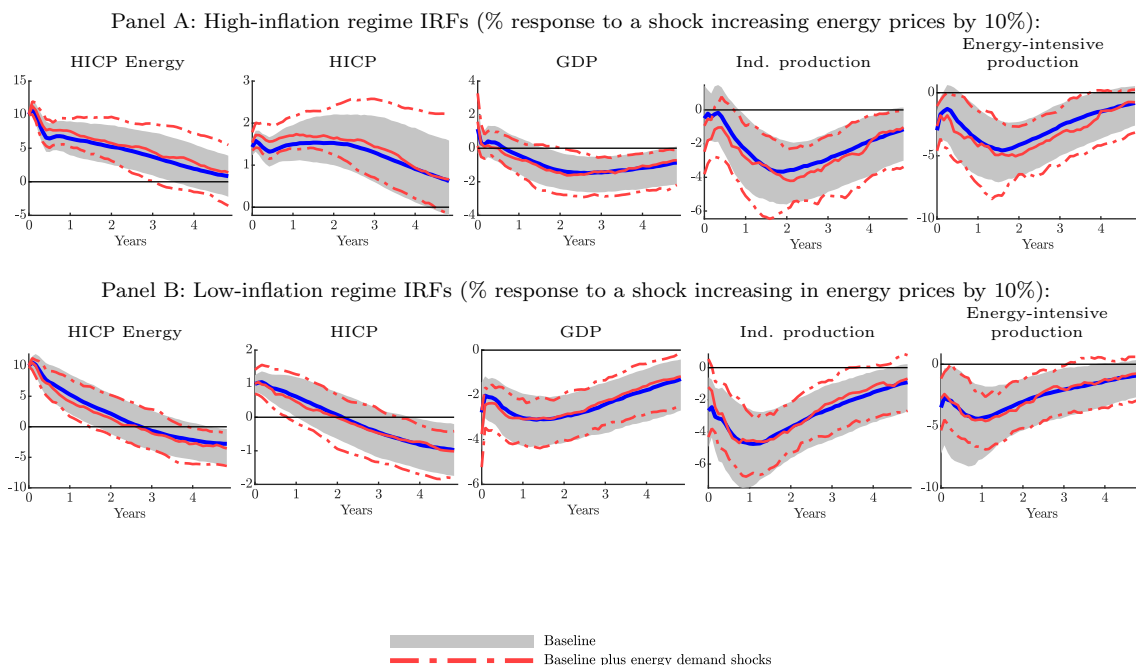
Panel A: High-inflation regime IRFs (% response to a shock increasing energy prices by 10%):

Panel B: Low-inflation regime IRFs (% response to a shock increasing in energy prices by 10%):
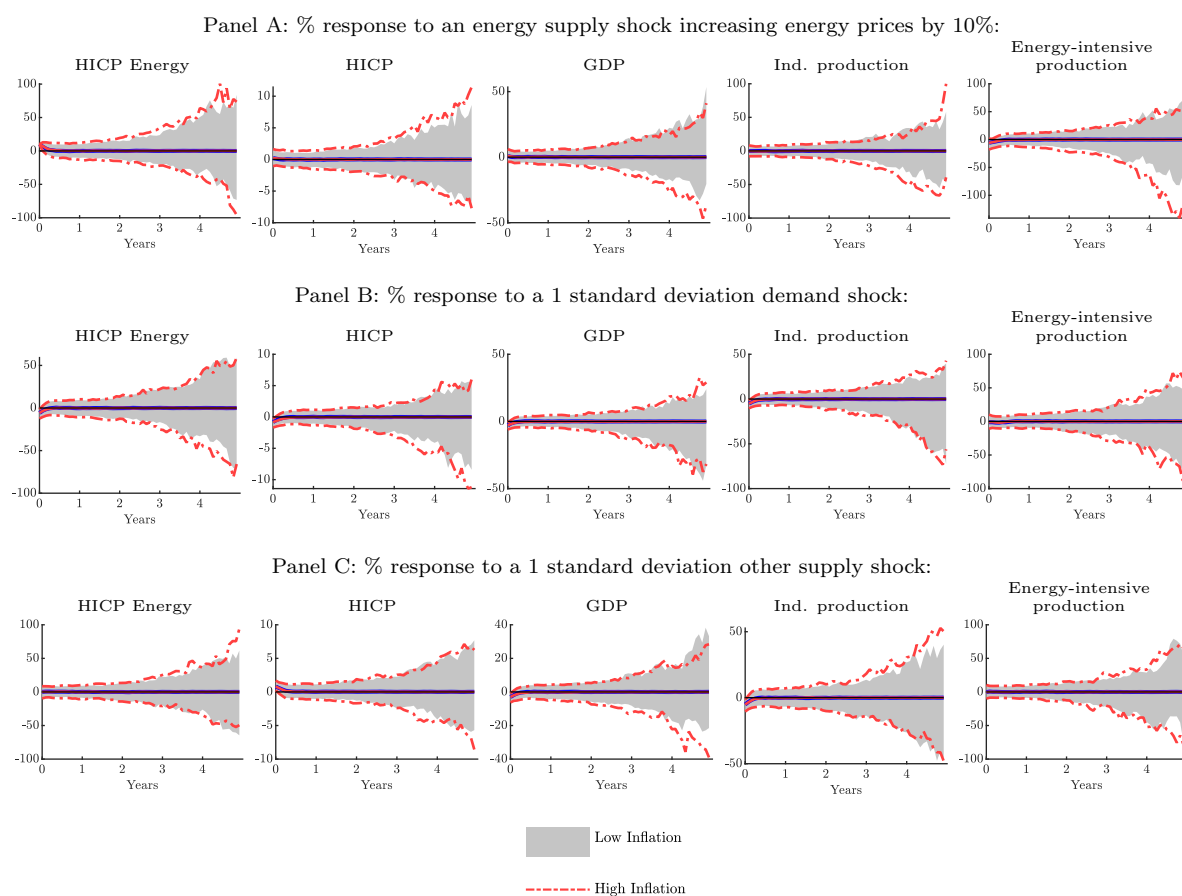

Baseline
Baseline plus energy demand shocks

Notes: This figure shows the responses to an energy supply shock. The represented TVARs contain five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The IRFs of the baseline model with three shocks are in blue. The IRFs of the alternative model, where an additional energy-specific demand shock is identified, are in red.

Figure 13: Robustenss: Baseline versus a fully Set-Identified Model

Panel A: High-inflation regime IRFs (% response to a shock increasing energy prices by 10%):

Panel B: Low-inflation regime IRFs (% response to a shock increasing in energy prices by 10%):

Baseline
Fully set-identified SVAR

Notes: This figure shows the responses to an energy supply shock. The represented TVARs contain five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. Each panel shows the median IRFs and the corresponding posterior 68% credible sets (dashed red lines and shaded bands). The IRFs of the baseline model with three shocks are in blue. The IRFs of the alternative model with a fully set-identified structure are in red.

Figure 14: Nonlinear Impulse Response Priors

Panel A: % response to an energy supply shock increasing energy prices by 10%:

Panel B: % response to a 1 standard deviation demand shock:

Panel C: % response to a 1 standard deviation other supply shock:

Low Inflation

High Inflation

Notes: The represented linear VAR and TVAR contains five variables: HICP energy, HICP, GDP, industrial production and industrial production of the energy-intensive sector. The identifying assumptions are collected in Table 1. Each panel shows the median impulse response priors and the corresponding posterior 68% credible sets (dashed red lines and shaded bands) using the approach suggested by Inoue and Kilian (2023). The red (blue) lines of the TVAR model are associated to the high (low) inflation regime.

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