What drives core inflation? The role of supply shocks*

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February 27, 2024

Abstract

We propose a framework to identify a rich set of structural drivers of inflation in order to understand the role of the multiple and concomitant sources of the post-pandemic inflation surge. We specify a medium-sized structural Bayesian VAR on a comprehensive set of variables for the euro area economy. We analyse in particular various types of supply shocks, some of which were not considered relevant before the pandemic, notably global supply chain shocks and gas price shocks. The residuals of the VAR are assumed to admit a factor structure and the shocks are identified via zero and sign restrictions on factor loadings. The framework can deal with ragged-edge data and extreme observations. Shocks linked to global supply chains and to gas prices have exhibited a much larger influence than in the past. Overall, supply shocks can explain the bulk of the post-pandemic inflation surge, also for core inflation. Being able to gauge the impact of such shocks is useful for policy making. We show that a counterfactual core inflation measure net of energy and global supply chain shocks has been more stable after the pandemic.

Keywords: Inflation, Bayesian VAR, Supply shocks, Gas prices, Supply chain bottlenecks

JEL codes: E31, C32, C38

*We would like to thank Fabio Canova, Joshua Chan, Marek Jarociński, Massimiliano Marcellino, Carlos Montes-Galdón, Michele Lenza, Giorgio Primiceri and the members of the ESCB Working Group for Forecasting for useful discussions. The views expressed are those of the authors and do not necessarily reflect those of the ECB.

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Non-technical summary

We introduce a novel identification scheme to pin down inflationary forces in the euro area which is able to deal with the challenging period following the COVID-19 pandemic. We take an encompassing approach and identify a wide range of supply and demand shocks relying on a rich data set.

Understanding and identifying the drivers of inflation has always been a non-trivial task for both academics and policy makers. Yet, the post-pandemic recovery came with new challenges and triggered an unprecedented inflationary landscape, whereby a perfect storm of large shocks from different sources hit the economy at the same time. These were partly driven by the "traditional" culprits – food and oil prices – but "new" types of shocks also emerged, most notably, those related to gas prices and to global supply chain bottlenecks. In this challenging and dynamic environment and given the well known lags of monetary policy transmission, it has been key for central banks to be able to assess the relative importance of supply and demand factors as well as to understand the persistence of the respective effects on inflation.

We exploit the information contained in a rich monthly data set of euro area inflation drivers, including measures of global and domestic economic activity, indicators of supply chain bottlenecks as well as various commodity, producer and consumer price indices. Our baseline specification identifies 8 shocks in a 17-variable Bayesian Vector Autoregression (VAR). We are able to identify a larger number of shocks than traditionally done in the literature by adopting the approach of Korobilis (2022), in which the residuals of the VAR are assumed to admit a factor structure and the shocks are identified via zero and sign restrictions on factor loadings. To properly account for the unprecedented dynamics of most macroeconomic variables during the pandemic and the post-pandemic recovery, we adapt the original model to account for extreme observations. Furthermore, we adapt the estimation approach to deal with the different publication delays of the various considered economic indicators (i.e. with "ragged edges"). This step makes the results more timely and thus more useful for policy makers.

On the demand side we identify a domestic and a foreign demand shock. On the supply side we identify shocks related to oil supply, oil-specific demand, gas prices, global supply chains, domestic supply, and a shock bundling several aspects of the labour market. In extensions of our model we also identify monetary policy and food price shocks.

Our findings support the notion that core inflation has been largely driven by supply-side shocks in the post-pandemic recovery. Shocks related to global supply chains, gas price, and the oil market have all pushed in the same direction supporting a "bad-luck" narrative to the high inflation episode. We also find that considering a too restricted set of shocks and variables inadequately amplifies the importance of the selected driver(s) in the post-pandemic period, when many economic series featured simultaneous upward dynamics.

The results have implications for policy making. Central bankers look at core inflation trying to gauge the more persistent and/or domestic component of headline inflation. However, core inflation can be at times impacted by sizable supply-side shocks. We show that a counterfactual core inflation measure net of the effects of energy and global supply chain shocks has been more stable after the pandemic.

1 Introduction

'There is currently a substantial reverting component of inflation that is sufficiently long-lasting not to constitute pure noise but that can also be expected to fade out over the near term. Examples of the reverting component include: the passthrough of energy and food cost shocks to other sectors; the impact of bottlenecks; and pandemic re-opening effects ... this reverting component of inflation should be less important for monetary policy.' (P. Lane, 6 March 2023)

In this paper we propose a novel identification scheme in an attempt to overcome some of the challenges in explaining inflation dynamics since the COVID-19 pandemic. We explore a rich data set and identify a more encompassing range of shocks than traditionally accounted for, especially on the supply side. We apply this methodology to understand the drivers of core inflation in the euro area, defined as HICP inflation excluding energy and food.

What drives inflation has always been a challenging question for both academics and policy makers, but the period that came after 2020 has been remarkable in many ways. In many countries inflation rates reached levels that have not been seen for decades. These were partly driven by the "traditional" culprits – food and oil prices – but "new" types of shocks also emerged, most notably, those related to gas prices and to global supply chain bottlenecks. In this challenging and dynamic environment and given the well-known lags of monetary policy transmission, it has been key for central banks to be able to assess the relative importance of various supply and demand factors, as well as the persistence of the respective effects on inflation. Given the volatility of headline inflation rates, several central bankers placed special emphasis on *core* inflation in their communication, considered to be a useful gauge of more domestic and more persistent inflation dynamics. One of the questions of the paper is to which extent this has been the case, also in particular for the post-pandemic period.

Until recently, structural inference for inflation based on parsimonious vector autoregressive (VAR) models with a limited set of identified shocks has been found to deliver satisfactory answers (Conti et al. (2017), Bobeica and Jarocinski (2019), Montes-Galdón and Ortega (2022)). However, the multitude of inflationary sources in the post-pandemic period created the need to expand the relevant information set and consider more types of shocks identified based on a larger set of variables. This can alleviate the informational deficiency in smaller models and substantially sharpen the structural inference (Bernanke et al. (2005), Bańbura et al. (2010), Koop (2013), and Chan et al. (2022)). The identification of "new" shocks comes, however, with the challenge of how to best isolate them from other more standard demand and supply shocks and how to overcome computational difficulties related to many identifying restrictions.

In this paper we follow the approach of Korobilis (2022), with some modifications as detailed in the next paragraph. The model is a Bayesian VAR with a factor structure for the residuals. It is assumed that the factors are the structural shocks and identification is achieved via sign and zero restrictions on the factor loadings. In comparison to the conventional accept-reject methods (e.g. Rubio-Ramirez et al. (2010) and Arias et al. (2018)) the computational hurdles of imposing a large number of sign restrictions are alleviated as the problem of finding many non-admissible draws is not there anymore. The method comes, however, with the challenge of finding an appropriate set of relevant variables, so that the identified factors explain a reasonable share of the dynamics of the variable(s) of interest and the remaining idiosyncratic part is contained.

We modify the approach of Korobilis (2022) in a number of directions. First, we adapt the model to deal with extreme observations, an important feature since the COVID-19 pandemic. To that purpose we allow for "outliers" (in the spirit of Stock and Watson (2016a) and Carriero et al. (2022)) in the idiosyncratic errors. This extension is found to make the results more robust to the inclusion of the post-pandemic period, i.e., the estimates of the historical decomposition are not strongly affected by the observations after 2020. Second, we deal with the "ragged edge" of the data in the estimation step by nowcasting variables with missing observations due to publication delays. This makes the results more timely and thus useful for policy makers. Finally, in a set of extensions to the baseline specification we identify an additional structural shock, related to monetary policy, following the internal instrument approach (Ramey (2011) and Stock and Watson (2012)) and using the monetary policy shock proxy of Jarociński and Karadi (2020). Specifically, we restrict to zero the VAR coefficients in the proxy's equation and assume a small prior variance for the corresponding idiosyncratic component.

We exploit a rich set of monthly variables relevant for inflation in order to disentangle the multitude of inflationary sources, particularly focusing on the post-pandemic recovery. Our baseline specification identifies 8 shocks in a 17-variable system (the minimum amount given the number of shocks) and various extensions go beyond that. On the demand side we identify a domestic and a foreign demand shock. On the supply side we identify an oil supply shock, an oil-specific demand shock, one linked to the gas price, a global supply chain shock, as well as a domestic supply shock. Finally, we identify a shock linked to the labour market which can bundle several aspects such as labour supply and wage bargaining. To our knowledge, we are the first ones to disentangle shocks related to the price of oil and gas, to global supply chains (and food in an augmented version) in a unified framework. Existing studies tend to be partial analyses focusing on one or a few of such shocks (e.g. Carrière-Swallow et al. (2023)), which can amplify the contribution of a single shock.

Gas price developments is one of the inflationary sources that was previously less monitored and came to the fora following the Russian invasion of Ukraine. Papers studying external drivers of domestic inflation have traditionally not attempted to disentangle gas from oil price shocks, given the high correlation between prices of the two energy sources. This correlation is due to the wholesale gas price in Europe being contractually indexed to the oil price until about 2012. A similar contractual link between the two commodities existed in the US. Thereafter, a gradual shift towards a deregulated gas market increased the likelihood of idiosyncratic gas price shocks. Since the summer of 2021[1] and especially following the Russian invasion of Ukraine in February 2022, the increase in European gas prices had been particularly stark and played an important role in the increase in euro area energy inflation, given the high dependence of the European energy sector on natural gas. Looking forward, gas might be used more and more in the green transition process, having been labelled as a green energy source by the European Commission in 2022. For these reasons, the identification of shocks to gas prices on top of more traditional oil price related shocks could be a feature of inflation models going forward.

High correlation between the prices of oil and gas in the past makes it challenging to identify separate shocks in these markets. Casoli et al. (2022) compare reactions of inflation to both oil and gas price shocks, where the latter are identified within an exogenous block modelling natural gas fundamentals (following Rubaszek et al. (2021) for the case of the U.S.). Such identification does not account however for the strong connection that existed between oil and gas prices. Kilian and Zhou (2023) do control for this link and use a block recursive partially identified structural VAR to isolate shocks to gasoline, diesel, jet fuel, natural gas, and electricity prices. In this paper we make use of sign and zero restrictions and assume that positive shocks related to gas price developments increase a proxy for gas prices (the euro area border gas price), increase energy producer prices contemporaneously, and negatively affect activity. At the same time, crude oil prices are assumed not to react contemporaneously to gas price shocks, based on previous results in the literature finding that oil prices tend not to be affected by shocks specific to natural gas markets (Ramberg and Parsons (2012) and Rubaszek and Szafranek (2022)). This restriction ensures the differentiation of gas price shocks from oil-related shocks.

Another type of inflationary shock that was largely disregarded until the pandemic is that related to global supply chain bottlenecks (see the discussion in Carrière-Swallow et al. (2023) and the references therein). Historically, bottlenecks along supply chains have preceded upward pressures on import prices, producer prices and retail prices, especially for intermediate goods (Carrière-Swallow et al. (2023), Schuler et al. (2022)). After the COVID-19 pandemic struck, it became evident that such bottlenecks can have a major impact on inflation beyond the standard technology-related shocks associated with supply disturbances. Liu and Nguyen (2023) go so far as saying that supply chain pressures

[1]As explained in Adolfsen et al. (2022), demand for gas had been driven by the economic recovery following the pandemic, especially in China. Specific to Europe was a colder than usual period at the end of 2020 and in the first half of 2021. Furthermore, low winds during the summer led to the substitution from wind-generated to gas-generated energy.

accounted for about 60% of the U.S. post-pandemic inflation surge. Carrière-Swallow et al. (2023)) focus on dynamics in the Baltic Dry Index and argue that shocks to shipping costs have similar inflationary impacts to oil or food price shocks.

Identifying shocks linked to supply chain bottlenecks takes some effort into isolating them from other influences, particularly those related to developments in energy commodities, relevant for shipping costs. In VAR models, the post-pandemic studies tend to identify such shocks via a mix of sign and narrative restrictions (see Finck and Tillmann (2022), Ascari et al. (2023), Bai et al. (2023), De Santis (2023), Kabaca and Tuzcuoglu (2023)). The choice of narrative restrictions generally differs across papers and there is some subjective element in choosing them. The selected variables to identify such a shock also differ across studies. While some focus on shipping costs (e.g. Carrière-Swallow et al. (2023), Schuler et al. (2022)), others go for a more encompassing approach of looking at composite indicators such as the Global Supply Chain Pressure Index (GSCPI) of Benigno et al. (2022).[2] In this paper the identification approach relies on sign and zero restrictions related to the GSCPI and the PMI supplier delivery times for the euro area.

Our findings indicate that core inflation in the euro area has been largely driven by supply-side shocks in the post-pandemic recovery. We show that global supply chains, gas price and oil price shocks have all pushed in the same direction supporting a "bad-luck" narrative to the high inflation episode. In particular, the shocks linked to global supply chain pressures and to gas prices have exhibited a much larger influence than in the past. Energy related shocks have played a particularly prominent role and have contributed about a quarter to the surge in core inflation since the beginning of 2021 until its peak in early 2023 (gas price shocks accounted for about half of that contribution, even though typically in the past they had little effect on core inflation). Global supply chain shocks also had a large contribution, especially after the second half of 2022.

Another important finding is that considering a too restricted set of shocks and variables inadequately amplifies the importance of some selected driver(s) in the post-pandemic period, when many economic series featured simultaneous upward dynamics.

Our results have implications for the way policy makers look at core inflation. As headline inflation is strongly affected by external and/or transitory shocks, policy makers often turn to core inflation, which excludes food and energy items. However, core inflation can be at times impacted by sizable supply-side shocks and this is what happened after the pandemic (see also Lane (2023)). Focusing on services inflation does not offer a silver bullet, as it was also strongly affected by supply-side shocks in the post-pandemic period. An important feature of the framework proposed in this paper is that one can estimate

[2]The GSCPI summarises information from 27 monthly indicators of transportation costs (e.g. the Baltic Dry Index, the Harpex Index, and the Bureau of Labor Statistics airfreight cost indexes) and supply chain-related components from the Purchasing Managers' Index surveys for manufacturing firms in seven major economies (China, the euro area, Japan, South Korea, Taiwan, the United Kingdom, and the United States).

the developments in core inflation in the absence of certain shocks, which allows (policy makers) to see through them. A counterfactual core inflation measure net of the effects of energy and global supply chain shocks has been more stable after the pandemic, albeit also increasing to record levels.

The rest of the paper is organised as follows. The next section describes the data set, then we continue with the methodology behind identifying a large number of shocks in a VAR model. Section 4 explains the rationale behind the identification of each shock. Section 5 presents the results, then we continue with extensions and robustness checks in Section 6 and the last section concludes.

2 Data set

We construct a medium-scale monthly data set covering different inflation measures and a wide range of inflation drivers. In particular, we include consumer price inflation measures to which policy makers pay special attention and for which we try to pin down the structural drivers, namely headline, core, and services inflation.

Turning to the drivers and starting with external inflationary pressures, we include indicators related to energy (both oil and gas) and food commodities, as well as a proxy for global demand. We capture bottlenecks along the global supply chains via the composite GSCPI, as well as the euro area PMI indicator of supplier delivery times. Next, pipeline price pressures along the more domestic part of the supply chain are captured via producer prices for energy, intermediate goods and total economy. We also include hard indicators and surveys on domestic activity, the exchange rate of the euro against the US dollar, and negotiated wages accounting for domestic inflationary pressures coming from the labour market, see Table 1. The lower part of the table details the variables used in the extensions of the baseline specification, namely those used for pinning down additional shocks (monetary policy and food price shocks).

The data set is monthly, covering the period from January 1995 until September 2023. Most of the variables are seasonally adjusted and expressed in monthly growth rates. Some of the series required back-casting as described in Table 1.

Table 1: Data description

Variable	Description	Source	Trans.
HICP headline	Total HICP	Eurostat	log-diff
HICP core	HICP excluding food and energy	Eurostat	log-diff
HICP services	HICP services	Eurostat	log-diff
Oil Brent (euro)	Brent crude oil 1-month Forward (free on board) per barrel	DataStream	log-diff
Oil prod.	Global oil production (million barrels/day)	EIA/IEA	log-diff
Border gas (euro)	Gas price, average over European countries (Euros/MMBtu)	Haver	log-diff
IP	Industrial production, total excluding construction, euro area	Eurostat	log-diff
Global ec. cond.	Global Economic Conditions Index	Baumeister et al. (2022)	no trans.
GSCPI	Global Supply Chain Pressure Index	NY Fed	no trans.
PMI output	Purchasing Managers' Index, composite output	Markit	no trans.
PMI supplier delivery	Purchasing Managers' Index, manuf., supplier delivery times	Markit	no trans.
PPI total	Total Producer Price Index, domestic sales	Eurostat	log-diff
PPI interm.	Producer Price Index, domestic sales, MIG intermediate goods industry – NACE Rev2	Eurostat	log-diff
PPI energy	Producer Price Index, domestic sales, MIG energy NACE Rev2	Eurostat	log-diff
EUR/USD	Exchange rate EUR/US dollar	ECB	log-diff
Neg. wages	Negotiated wages excluding one-off payments (year-on-year)	ECB	no trans.
Agri. prices	Farm-gate and wholesale market agricultural prices in euro, total, experimental aggregate	ECB	log-diff
Shadow rate	Estimated shadow rate	Krippner (2013)	de-trended
MP proxy	Monetary policy shock proxy	Jarociński and Karadi (2020)	no trans.
HICP food	HICP food	Eurostat	log-diff
PPI food	Producer Price Index, domestic sales, food	Eurostat	log-diff
World food price index	Monthly index based on world prices of cereals, oils and meals and other food	World Bank	log-diff
IP food	Industrial production, manufacture of food products	Eurostat	log-diff

Note: Most variables are seasonally adjusted except for oil prices, oil production, border gas prices, the GSCPI, EUR/USD and negotiates wages (the latter being available as year-on-year growth rates). Whenever no official seasonally adjusted data was available, we transform the variables using X13. The oil price and border gas price are expressed in euro. EIA/IEA stand for Energy Information Administration / International Energy Agency. The euro area border gas price is an average of prices in hubs in Belgium, France, Germany, Italy, The Netherlands, and Spain. GSCPI is available since September 1997, we have back-casted it to January 1995 using the Baltic Dry index, world PMI supplier delivery times, as well as the UK PMI stocks of finished products. Negotiated wages exclude one-off payments, which can strongly affect their developments at times and are mainly due to payments in Germany. The agricultural price series is an aggregate series of farm-gate and wholesale market prices in the euro area collected and transmitted by national Ministries of Agriculture of the various member states and made publicly available by the Directorate-General for Agriculture and Rural Development (DG AGRI) of the European Commission; the series is available starting in December 1996, back-casted using an index of global food commodity prices from World Bank's pink sheet; the global food commodity index is expressed in USD. Euro area PMI supplier delivery times starts in June 1997 and it was back-casted using the same variable for the UK (historical correlation of 90 per cent); PMI output starts in July 1998 and was back-casted using the economic sentiment index for total economy from the European Commission's survey (historical correlation of 85 per cent).

3 Methodology

We make use of the algorithm proposed by Korobilis (2022) and adapt it to account for extreme observations (outliers). This is an important feature for samples including COVID-19 observations and subsequent large inflationary shocks. Moreover, we implement a nowcasting step for certain variables in the system, which are subject to longer publication delays. As our variable of interest is inflation, for which a flash estimate is available as early as at the end of each month (as opposed to other economic indicators) this additional step makes our results more timely and thus useful for policy makers, who are particularly interested in the latest developments.

Let y_t denote the $N \times 1$ vector of HICP inflation rates and additional variables as expounded in the previous section. y_t is assumed to follow a standard Vector Autoregressive (VAR) process:

$$y_t = A_0 + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{1}$$

where the matrices A_ℓ, $\ell = 1, \cdots, p$, contain the VAR coefficients, A_0 is a vector of intercepts, and $u_t \sim \mathcal{N}(0, \Sigma)$ is a vector of reduced-form errors.

A standard practice in the structural VAR (SVAR) literature is to assume that the reduced form residuals are linked to the structural shocks via a matrix of impact effects: $u_t = B\varepsilon_t$. The identification of the structural shocks, ε_t, proceeds then often via sign and zero (and potentially also magnitude) restrictions on B (Uhlig (2005), Rubio-Ramirez et al. (2010), Arias et al. (2018)). Further, it is often assumed that the dimension of the reduced-form errors matches the number of structural shocks, which typically limits the model to a relatively small number of variables and shocks. However, a model with a small information span could induce an omitted variable bias which has implications for parameter estimation and structural identification. The preference for smaller models in SVARs identified with sign and zero restrictions stems from the computational burden of standard accept-reject algorithms (Rubio-Ramirez et al. (2010), Arias et al. (2018)), which are only feasible when estimated using a small number of variables. Hence, many analyses zoom in on the effect of a specific shock on the economy, but this could exaggerate the contribution of that specific shock (or of limited set of identified shocks).

In order to circumvent these problems the approach of Korobilis (2022) relies on the assumption that a large data set is driven by a number of structural factors (shocks) that is strictly smaller than the number of included variables and hence reduced-form errors. In contrast to structural factor models (Forni et al. (2009)) or factor-augmented VARs (Bernanke et al. (2005)), Korobilis (2022) draws on the reduced-rank identification idea of Gorodnichenko (2005) and assumes that the reduced-form errors admit a static factor model:

$$u_t = \Lambda F_t + \xi_t. \tag{2}$$

The vector $F_t \sim \mathcal{N}(0, I_r)$ contains r primitive factors that approximate the true structural shocks, Λ is an $N \times r$ matrix of factor loadings and $\xi_t \sim \mathcal{N}(0, \Omega)$ is a vector of idiosyncratic components with a diagonal covariance matrix Ω.

The identification of the shocks boils down to restricting the elements of the matrix of factor loadings through sign and zero restrictions. The factor model is static, which implies that the restrictions are contemporaneous. An important feature of the algorithm is that it does not rely on draws of rotation matrices which can induce an informative prior for the impulse responses (see debate initiated by Baumeister and Hamilton (2015)).

Instead, sign restrictions are imposed through elements of the loading matrix being directly sampled from truncated normal distributions, following the derivations of Botev (2017). For further information on the priors and the estimation we refer the Reader to Korobilis (2022).

In order to make the estimates more robust to some extreme (and idiosyncratic) observations, particularly pertinent to the (post-)pandemic era, following the ideas of Stock and Watson (2016a) and Carriero et al. (2022), we introduce outlier correction by assuming that the idiosyncratic component is given by:

$$\xi_{i,t} = \omega_i O_{i,t} e_{i,t}, \tag{3}$$

where $e_{i,t} \sim \mathcal{N}(0,1)$ and ω_i is the standard deviation that is constant over time. $O_{i,t}$ are i.i.d. scaling factors that follow a mixture distribution, distinguishing between regular observations with $O_{i,t} = 1$ and outliers with $O_{i,t} \geq 2$, thus downweighting extreme observations (see Stock and Watson (2016a) for details). By contrast, we do not scale down the impact of large factors/shocks, as these may be relevant for identification.[3]

Finally, we adapt the estimation procedure to deal with ragged edges, i.e., missing values at the end of the sample due to distinct publication delays. To this end, we introduce an additional step in the Gibbs sampler in which the model is cast in a state space representation and the missing observations are drawn using a simulation smoother (see e.g. Bańbura et al. (2015)). The obtained balanced data set can then be used in the subsequent steps of the Gibbs sampler.

4 Identification of shocks

In the baseline version of the model, we identify eight shocks, covering demand and supply drivers of inflation. On the supply side we consider shocks related to oil supply, oil-specific demand, gas commodity price, global supply chain bottlenecks, domestic supply, as well as shocks pertaining to the labour market. On the demand side we consider a domestic demand and a foreign demand shock.

Table 2 shows the sign and zero identification restrictions that we assume on the contemporaneous impact of the shocks. The following subsections provide the rationale behind our identification approach for each structural shock in more detail.

[3]As robustness check, we experimented with models augmented by stochastic volatility (as in Chan et al. (2022)). However, this particular identification through heteroskedasticity does not seem to work in the present case. This could be related to the issues discussed in Montiel Olea et al. (2022). We thank Josh Chan for sharing his codes for the specification with stochastic volatility and for the implementation of outlier correction.

Table 2: Identification of structural shocks

	Supply						Demand	
Variable/Shock	**Oil supply**	**Oil-spec. demand**	**Gas price**	**Global supply chains**	**Domestic supply**	**Labour-side**	**Domestic demand**	**Foreign demand**
HICP headline	+	+	+	+	+		+	
HICP core	+	+			+		+	
HICP services						+		
Oil Brent (euro)	+	+	0	0	0	0		+
Oil prod.	-	+						
Border gas (euro)			+	0	0	0		
IP	-	-	-	-	-	-	+	
Global ec. cond.	-	-						+
PPI total	+	+	+	+	+	+	+	+
PPI energy	+	+	+					+
PPI interm.								+
PMI supplier delivery				-				
GSCPI				+	0	0		
PMI output								
EUR/USD							+	-
Neg. wages					-	+		
Agri. prices								

Note: An entry with +/- denotes a positive/negative contemporaneous response of the variable to the specific shock. A 0 indicates no contemporaneous response and an empty cell denotes an unrestricted response.

4.1 Oil-related shocks

Extensive literature shows that oil market fluctuations have different macroeconomic implications depending on the nature of the shocks, with the demand versus supply distinction making a difference (see Kilian (2008, 2009), Kilian and Murphy (2014), Baumeister and Hamilton (2019)). To properly capture such differentiated effects, we follow the literature and identify an oil supply shock and an oil-specific demand shock, in addition to foreign demand shocks described later on. A negative oil supply shock is identified via a contemporaneous decline in international oil production (e.g. linked to disruptions related to geopolitical conflicts or cuts in production quotas set by the Organization of the Petroleum Exporting Countries (OPEC)) and an increase in the price of oil. Such a shock has negative real activity effects for both the global economy and the euro area, in line with the literature (see Peersman and Van Robays (2009)).

Oil-specific demand shocks capture fluctuations in the oil market due to uncertainty about future oil supply and are *not* related to aggregate demand disturbances (Kilian (2009), Peersman and Van Robays (2009)). An unfavourable oil-specific demand shock results in an increase in the oil price and has a negative impact on both global and domestic activity.

The rise in oil prices (stemming from both an oil supply shock and an oil-specific demand shock) generates upward inflationary pressures, as reflected in total and core HICP and total and energy-related producer prices, together with some negative domestic economic effects as captured by the impact on industrial production. What differentiates between the two shocks is the reaction of oil production: it falls in case of an inflationary oil supply shock and it increases in case of an inflationary oil-specific demand shock.

All other variables are left unrestricted, as oil shocks might have complex effects with uncertain lags.

4.2 Gas price shocks

A challenge in identifying gas price shocks is to disentangle them from fluctuations in the oil market. For much of the covered sample, the wholesale gas price was contractually indexed to the oil price. It was only starting around 2012 that a more visible movement towards gas being driven by gas market-specific forces and away from oil indexation occurred. Yet, despite this deregulation process, a link between gas and oil still exists as energy commodities tend to be shaped by common factors.

The literature on identifying the inflationary impacts of gas price shocks is still at its infancy, with a few papers approaching the topic in the post-pandemic recovery period. Casoli et al. (2022) are the first ones to distinguish different types of gas price shocks in the euro area and assess their impact on inflation, but they model oil and gas markets as two independent energy blocks. Such identification does not account, however, for the strong historical connection that existed between oil and gas prices. As shown by Rubaszek and Szafranek (2022), despite a gradual movement towards gas being driven by its market-specific forces and away from oil indexation, the long-run link between oil and gas is still present in Europe. Kilian and Zhou (2023) do control for this link in their study of US inflation and use a block recursive partially identified structural VAR to isolate shocks to gasoline, diesel, jet fuel, natural gas, and electricity prices.

In our scheme, a positive gas supply shock is identified via a contemporaneous increase in the euro area border gas prices, while crude oil prices are not influenced by this increase, based on previous results in the literature saying that oil prices tend not to be affected by shocks specific to natural gas markets (Ramberg and Parsons (2012), Rubaszek and Szafranek (2022)). This zero restriction on the oil price ensures that what we capture is inherent to gas price movements and distinct from impacts coming from oil.[4]

Positive shocks related to the gas commodity price generate contemporaneous inflationary impacts for total and energy producer prices and, as is the case with all commodity price supply shocks, economic activity in the euro area (as proxied by the industrial production) is negatively affected. Headline inflation is also assumed to increase, while we are agnostic about core inflation.

It is important to clarify that we do not aim to disentangle various types of gas

[4]Deviations between oil and gas price movements can be triggered by various factors, such as weather, storage, supply-side disruptions etc. Also, unlike oil, gas is traded on local markets, which can be strongly affected by regional developments. For example, the US gas reference price (i.e., Henry Hub sort) remained rather stable in the recent years, while European border gas prices skyrocketed following the Russian invasion of Ukraine.

price shocks. The generic type identified here is one that creates inflationary pressures, while negatively affecting activity. It is distinct from shocks related to global economic activity, which would push up domestic activity as well. Thus, the identified gas price-related shocks bundle gas supply shocks, as well as any remaining gas-specific demand shocks, or those linked to inventory build-up.[5]

4.3 Global supply chain shocks

Apart from going more granular on the energy front, another contribution of the paper is identifying the inflationary impact of supply-side shocks capturing various factors such as global shipping capacity being constrained by logistical hurdles and bottlenecks or shortages in shipping equipment.

Following the COVID-19 pandemic, several attempts to identify these shocks have been made (Benigno et al. (2022),[6] Finck and Tillmann (2022), Ascari et al. (2023), Bai et al. (2023), Carrière-Swallow et al. (2023), De Santis (2023), Kabaca and Tuzcuoglu (2023)). These studies generally rely on a set of sign and magnitude restrictions and identify inflationary effects via local projections or directly within a VAR. A common feature of the mentioned papers is that they study this shock in isolation or within a small set of shocks, which could potentially amplify its contribution. Here, we identify global supply chain shocks within our encompassing approach.

We identify negative global supply chain shocks as those leading to shipment delays and increases in global supply chain pressures as measured by the GSCPI index. Since our paper is focused on the euro area economy, we further assume that the euro area supplier delivery times increase (which is synonymous to a decrease in the related PMI indicator). As these shocks are purely supply-driven, they decrease industrial production while increasing total producer prices and headline HICP.

To distinguish these shocks from energy-related supply ones, we assume that a global supply chain shock has no contemporaneous impact on oil and gas prices; such bottlenecks originate more on the product market and reflect increases in shipping costs other than those linked to energy.

4.4 Labour-side shocks

We identify a generic labour market shock linked to an increase in negotiated wages that has macroeconomic effects akin to a supply-side shock. It has a negative impact

[5] The most noteworthy hurdle in further differentiating across gas price shock types is the lack of a readily available time series of natural gas production at a monthly frequency.

[6] The authors construct the GSCPI isolating the supply component in all the indicators that enter the composite index. More specifically, the indicators are regressed against the 'New Orders' PMI sub-component, as a proxy of demand, and then only the residuals from these regressions are used as inputs in constructing the GSCPI.

on industrial production while contemporaneously rising HICP services, given that it is a more labour-intensive sector. Moreover, we also assume that total PPI increases, as wages are an important cost factor. This generic labour market shock can bundle several ones such as those linked to labour supply, wage-bargaining, and mismatch shocks (Foroni et al. (2018), Bobeica et al. (2019), Consolo et al. (2023)). Output and wages react in a different way and this restriction is key to distinguish shocks in the labour market from aggregate domestic supply (technology) shocks. The rationale behind it is that the co-movement in output and wages in case of classical technology shocks is driven by an exogenous increase in productivity. By contrast, the opposite reaction of these two variables to labour market shocks can be explained by firms having trouble finding workers (due to an exogenous decrease in labour supply), or by higher costs of hiring workers (due to a decrease in matching efficiency), or by a rise in the bargaining power of workers to demand higher wages.

Finally, domestic shocks linked to the labour market are assumed not to impact energy commodity prices and have no effect on the GSCPI. The latter restriction allows us to disentangle the labour-side shock from the global supply chain shock.

4.5 Domestic demand and domestic supply shocks

Aggregate domestic demand and supply shocks are identified with standard restrictions whereby activity and prices (total and core consumer prices, as well as producer prices) react in the same direction following demand shocks, and in opposite directions following supply shocks.

To distinguish the aggregate domestic supply (technology) shock from the energy-related shocks, we rely on zero restrictions on oil and gas prices. These restrictions reflect the fact that the euro area is a net importer of energy and domestic supply does not influence the international prices of oil or gas on impact. Moreover, we disentangle the domestic supply shock from the global supply chain shock by assuming that the former has no contemporaneous impact on the GSCPI.

4.6 Foreign demand shocks

In order to identify shocks related to foreign demand we make use of the global economic conditions indicator of Baumeister et al. (2022). We disentangle between foreign and domestic demand following Conti et al. (2017), who assume that a positive foreign demand shock depreciates the exchange rate of the euro vis-a-vis the dollar, based on the rationale of home bias in open economy models. In addition, we further assume that a foreign demand shock leads to a rise in oil prices, total producer prices, as well as its energy and intermediate goods component.[7]

5 Results

Figure 1 shows the contributions of the identified shocks to core inflation over time.[8] Following the pandemic, much of the deviation of core inflation from its model-implied mean (of around 1.7%) comes from supply-side shocks, in particular those related to more global developments. Specifically, energy-related shocks have played a prominent role in the increase in core inflation during this time, explaining about a quarter of the surge in core inflation between the beginning of 2021 and it's post-pandemic peak in March 2023, with gas price shocks contributing to around half of that. Global supply chain shocks also had a sizeable impact in this inflationary episode, especially as of mid-2022. This justifies the increased attention that these shocks have received in recent literature and policy circles.

Overall, the post-pandemic recovery was a perfect storm with large inflationary shocks occurring from different sources. Shocks that mattered little in the past had a major contribution after the pandemic. For instance, the ones linked to the gas market played a negligible role until the post-pandemic surge in core inflation and a larger-than-usual role can also be attributed to shocks linked to global supply chain bottlenecks. Energy related shocks had a notable contribution also during the low inflation period that followed the euro area debt sovereign crisis, when most shocks had a disinflationary impact. Demand shocks stemming from both domestic and global markets played a dominant role in the core inflation downturn following the Great Financial Crisis. Their negative contribution was sizeable also when the pandemic hit, but then domestic supply shocks were equally important as the domestic demand ones.

[7] We conducted a series of robustness checks related to the identification of these shocks. For instance, (i) we assumed a magnitude restriction whereby a foreign demand shock has a larger effect on global economic conditions than on euro area industrial production. (ii) we assumed that wages do not react to a foreign demand shock at the contemporaneous horizon; (iii) we considered oil prices in real terms; (iv) we relaxed the positive reaction of oil prices to a foreign demand shock. Results from these exercises remain very close to those from our baseline model.

[8] We estimate the model introduced in Section 3 with six lags and 400000 draws, discarding the first 10% as burn-in and keeping every 200th draw for inference.

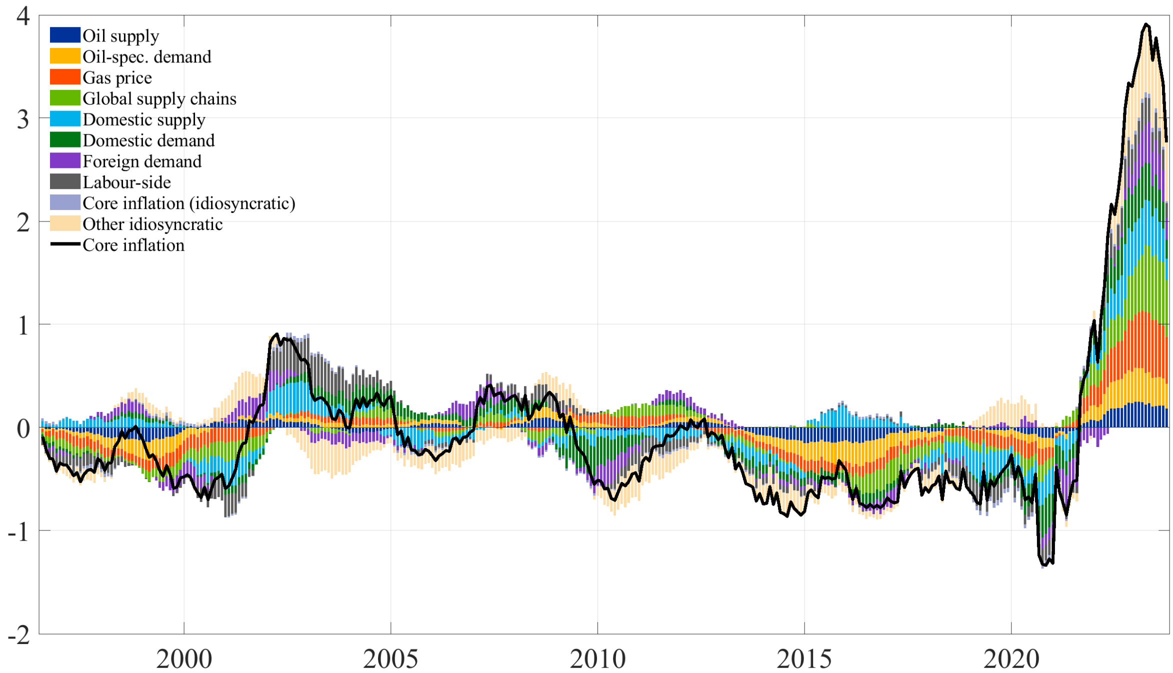

Figure 1: Historical decomposition of core inflation

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

Even when considering numerous types of inflationary shocks, part of the post-pandemic increase in core inflation is unexplained. This shows up as a sizable contribution of the idiosyncratic component of the reduced-form residuals (also stemming from other variables than core inflation). This unexplained part can reflect different elements, like measurement errors or changes in collection methodology in the case of prices and other statistics, imprecision in grasping the structural shocks using the chosen variables,[9] or the possibility that some relevant shocks are not identified. It could be also related to the fact that in abnormal times the transmission of the various shocks might be different than usual, for instance some non-linearities can be at play whereby larger shocks are transmitted more strongly and/or more quickly (Cavallo et al. (2023)). As such factors are almost impossible to be fully dealt with, the existence of a residual is a desirable feature of the employed approach; it also gives an indication on when it is harder and when it is easier to explain the target variable or on the direction it is pushed to by the unexplained drivers. Figure 1 shows that after the pandemic, inflation increased by more than can be explained by the identified shocks and confirms the abnormal nature of this episode.

[9]The median estimated factors (shocks) of our model are depicted in Figure 19 in Appendix B, together with the 68% credibility bands capturing uncertainty of estimation and identification.

Figure 2 zooms into the responses of core inflation to the 8 identified shocks up to three years ahead.[10] Despite an initial non-significant negative effect, the impact of global supply chain shock turns positive and it appears to have very persistent effects, in line with previous findings (see Ascari et al. (2023)). This persistent effect is also reflected in the historical decomposition, since the contribution of a global supply chain shock had its peak in March 2023 despite prior easing in the related indicators and it remains the shock with the largest contribution by the end of the sample (also shown in Figure 3).

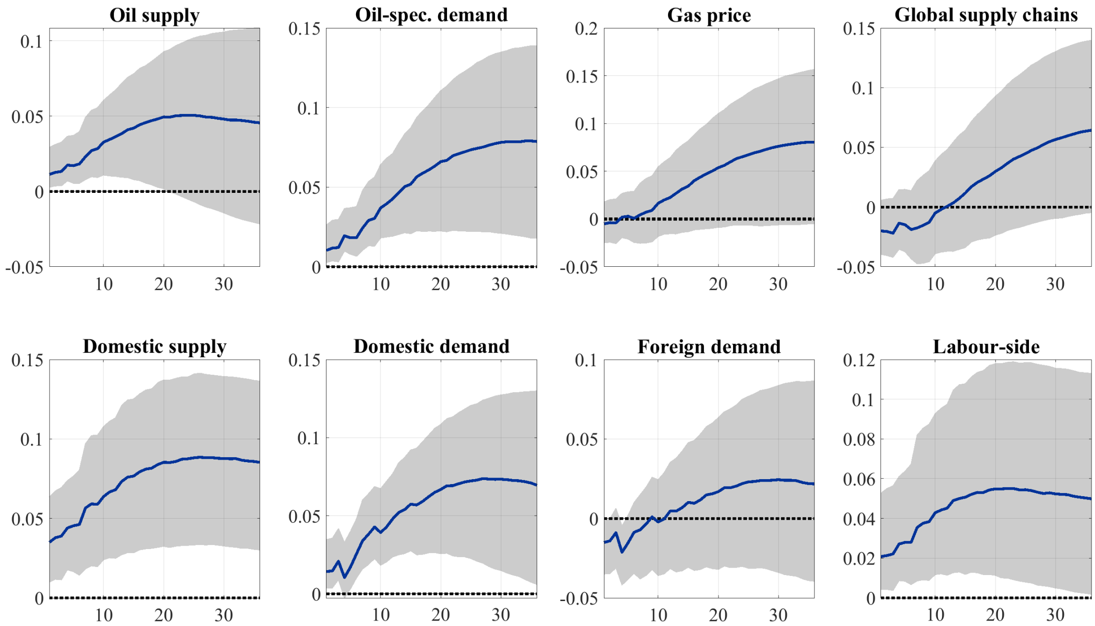

Figure 2: Cumulated responses of core HICP to the identified shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas).

[10] A full overview of the median contemporaneous impact of the shocks on the full data set is shown in Table 4 in the Appendix.

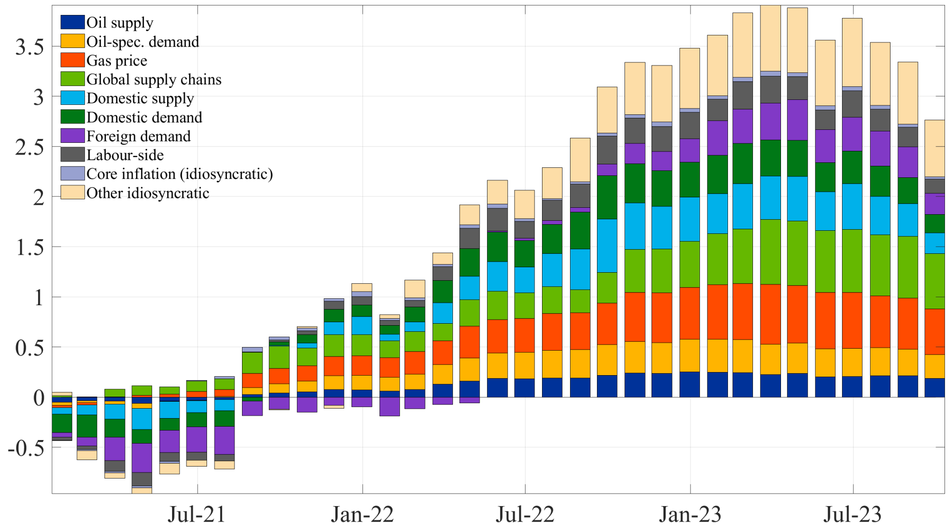

Figure 3: Drivers of core inflation as of January 2021

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

The pass-through of energy commodity price shocks to producer prices is higher than the pass-through to consumer prices (see impulse responses in Figures 11-16). The intuition is rather straightforward: the strength of pass-through is directly linked to the relative size of commodity inputs. As the share of non-commodity inputs to production – such as wages, rents, and packaging – increases when one moves from intermediate to final stages of production, the size of the pass-through becomes smaller.

Also, as expected, the pass-through of energy commodity price shocks to headline inflation is stronger than the pass-through to core inflation (Figures 11-16). While energy shocks affect headline inflation in a direct way via consumer energy prices, the impacts on core inflation are transmitted indirectly via the production chain or potential reactions of wages, profits and inflation expectations. Grasping the magnitude and the nature of such indirect and second-round effects is key to understanding how they will unwind and weigh on core inflation looking forward.

As headline inflation can be volatile, policy makers trying to see through such volatility look at various measures of underlying inflation in order to distil the signal on the medium-term inflationary pressures relevant for monetary policy. Among such measures, core inflation (usually defined as total inflation excluding energy and food components) plays a central role as it is easy to communicate to the public. Yet, underlying inflation more generally and core inflation more specifically are not a perfect panacea, they can be affected by large, but transitory shocks that policy makers should see through. Lane (2023) argues that this was particularly the case during the post-pandemic inflationary episode, when major economic dislocations like economic reopening following the pandemic or disruptions to supply chains caused by the war affected core prices in significant manner and as a consequence an additional layer of 'filtering' is needed to understand the medium-term signal embedded in core inflation.[11]

Eliminating the influence of certain inflationary shocks in the aftermath of the COVID-19 pandemic is not straightforward and the result is surrounded by the inherent model and estimation uncertainty. Figure 4 compares core inflation with its counterfactual version when energy shocks (oil supply, oil-specific demand, gas price shocks) and those linked to global supply chains are filtered out. Such shocks might occasionally play a large role but are also expected to fade out. What is interesting is that for large part of the sample core inflation was very close to its adjusted counterpart. During the low inflation period that followed the sovereign debt crisis in the euro area the counterfactual core inflation was closer to 2% than the official statistic. Turning to the latest sample, adjusted core inflation is sizably lower but exhibits also a strong increase. This suggests that there were indeed important shocks other than energy or supply chain related that played a role and/or the transmission of shocks was stronger. Such an exercise can be performed for any measure of underlying inflation, as shown in Figure 20 in Appendix C. There we illustrate the results where instead of core inflation we include in the model various measures of underlying inflation that are regularly monitored by the European Central Bank, be it exclusion- or model-based. When subtracting the contribution of shocks linked to energy and global supply chain bottlenecks the range of considered underlying inflation measures would have been much narrower and lower during the post-pandemic inflation surge.

[11]Lane (2023) notes that in the post-pandemic period underlying inflation was significantly affected by a reverting component that was sufficiently long-lasting not to constitute pure noise but that can also be expected to fade out over the near term and hence policy makers should see through this.

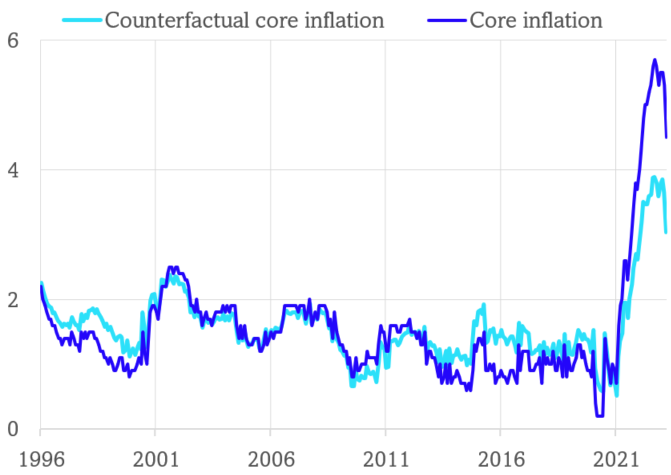

Figure 4: Core inflation and its counterfactual measure free of energy and global supply chain shock effects

Note: The counterfactual core inflation assumes the absence of shocks linked to oil supply, oil-specific demand, gas price, and global supply chains. Last observation: September 2023.

The extent to which core inflation was affected by large, but transitory shocks made policy makers turn their eyes to services prices, even more than before. For instance, Powell (2022) referred to the price dynamics of services excluding housing in the US to explain why the FOMC expected that the federal funds rate would have to remain high for a longer time. Among core components, services prices receive special attention as they tend to be more persistent compared goods prices, which typically react more to transitory supply-side shocks. The distinction between the two is especially relevant during and after the pandemic when the ensuing shocks affected services and goods inflation very differently (see e.g. Lane (2022)). Demand shifted in the first stage from services to goods, which, combined with supply bottlenecks, pushed up goods inflation. Subsequently, it came down strongly, when the environment re-normalised. Services inflation has been less volatile, but looking at this particular component is not the silver bullet either when trying to gauge the more persistent component of inflation. Figure 5 shows that also in the case of services supply-side shocks played a prominent role.

Certain shocks fade quicker from headline inflation, whereas the impact on core or services inflation is more persistent. For example, Figure 6 shows that the impact of gas price and global supply chain shocks on headline inflation largely faded out towards the end of the analysed sample, whereas on core or services prices it is still strong.

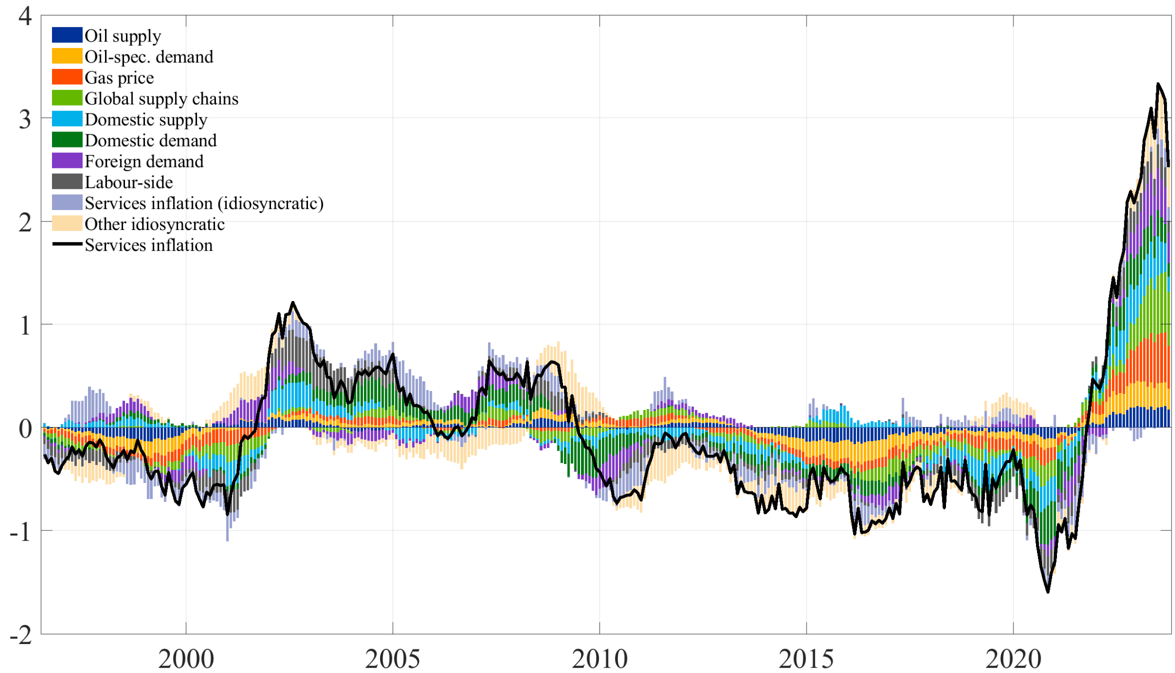

Figure 5: Historical decomposition of services inflation

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of services inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

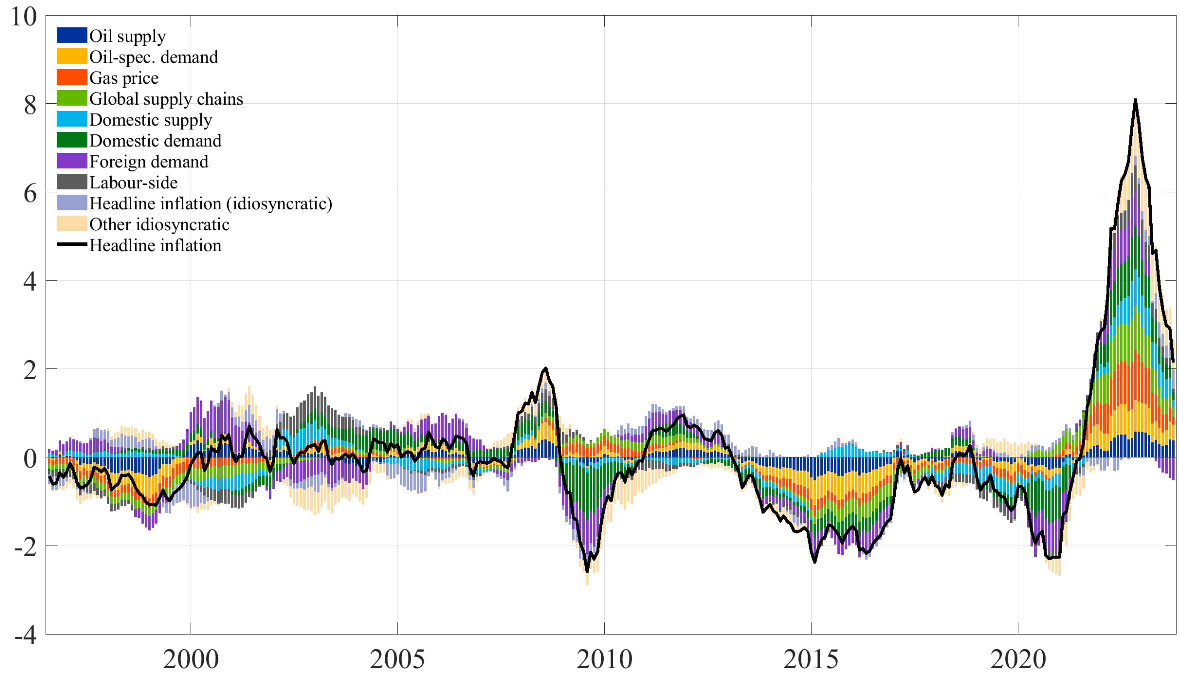

Figure 6: Historical decomposition of headline inflation

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of headline inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

6 Extensions and robustness checks

6.1 Comparison across different estimation samples

We assess the robustness of the results to the exclusion of the COVID-19 and the subsequent high inflation period. To that end we compare shocks and historical decompositions obtained on the full sample (January 1995 - September 2023) to the corresponding results based on two sub-samples: "Pre-war" (January 1995 - December 2021) and "Pre-COVID" (January 1995 - December 2019).

The correlations of the shocks estimated over the different samples are in general high, see Table 3. The exceptions are the energy-related and the global supply chain shocks, especially when comparing the full sample with the pre-COVID period. We consider this result to be an interesting insight, possibly pointing to the fact that recent dynamics are helpful for identification of certain shocks.

Table 3: Correlation of shocks across samples

	Oil supply			**Domestic supply**		
	Pre-COVID	Pre-war	Full-sample	Pre-COVID	Pre-war	Full-sample
Pre-COVID	1	0.91	0.85	1	0.88	0.69
Pre-war		1	0.78		1	0.86
Full-sample			1			1
	Oil-spec. demand			**Domestic demand**		
	Pre-COVID	Pre-war	Full-sample	Pre-COVID	Pre-war	Full-sample
Pre-COVID	1	0.76	0.63	1	0.85	0.87
Pre-war		1	0.84		1	0.94
Full-sample			1			1
	Gas price			**Foreign demand**		
	Pre-COVID	Pre-war	Full-sample	Pre-COVID	Pre-war	Full-sample
Pre-COVID	1	0.71	0.55	1	0.93	0.94
Pre-war		1	0.89		1	0.97
Full-sample			1			1
	Global supply chains			**Labour-side**		
	Pre-COVID	Pre-war	Full-sample	Pre-COVID	Pre-war	Full-sample
Pre-COVID	1	0.77	0.76	1	0.91	0.72
Pre-war		1	0.88		1	0.86
Full-sample			1			1

Note: The correlations are based on the median of the shock's posterior distribution.

Historical decompositions remain robust to the exclusion of (post-)pandemic period, see Figures 21 and 22 in Appendix D.1. As shown in the charts, the contributions of the various drivers remain roughly similar across different estimation samples (for the overlapping periods), suggesting that the model is able to convey a robust narrative on what drove inflation in the euro area.

6.2 Inclusion of monetary policy shocks

We further augment our identification scheme to account for the effects of monetary policy. To do so we include the monetary policy shock proxy by Jarociński and Karadi (2020) as an endogenous variable in the VAR and follow the internal instrument approach (Ramey (2011) and Stock and Watson (2012)). Specifically, we follow the "observed shock" approach, whereby we restrict to zero the VAR coefficients in the proxy's equation and assume a small prior variance for the corresponding idiosyncratic component. We assume that the proxy is exogenous to all other shocks and reacts negatively to the monetary policy shock (i.e. we normalise the latter as an expansionary shock). To further sharpen the identification, we assume that an expansionary monetary policy shock decreases the interest rate measured by the shadow rate of Krippner (2013).[12] The details of the identification scheme are provided in Table 5 in Appendix D.

We present the results from this specification in Figure 7.[13] The results point to positive demand effects, causing industrial production and prices to increase.[14] Our baseline results remain robust to the inclusion of the monetary policy shock. In particular, the correlations between the structural shocks estimated within the 8-shock baseline model and this augmented version are very high for all shocks (close to 1). Nevertheless, we gain additional insights into the drivers of core inflation. For instance, this model further breaks down the demand-type contributions to core inflation and suggests that monetary policy was a driver during the Great Financial Crisis. Furthermore, monetary policy also contributed to push core inflation upwards between 2015 and 2019, a period characterised by stubbornly low inflation and the deployment of different non-standard monetary policy measures by the ECB. For the post-pandemic period, the model estimates a negative contribution of monetary policy, reflecting the series of policy rate rises.

It is important to note that the estimated contribution of the identified monetary policy shocks to core inflation has been overall small. A potential explanation is that monetary policy has been affecting core inflation mainly via its systematic component. Moreover, a large part of the sample covers the period of unconventional monetary policy and to capture the specific effects of tools related to quantitative easing and forward guidance, a more comprehensive model might be needed. This is however beyond the scope of this paper.

[12] In order to account for the trending behaviour of the interest rate, we de-trended the shadow rate with the bi-weight filter as in Stock and Watson (2012, 2016b).

[13] The estimation is carried out with data spanning from January 1999 to October 2022, governed by the availability of the proxy. In addition, we do not conduct the nowcasting step, since the proxy is considered as an observed shock and therefore it is not predictable.

[14] Charts of the impulse responses are available upon request.

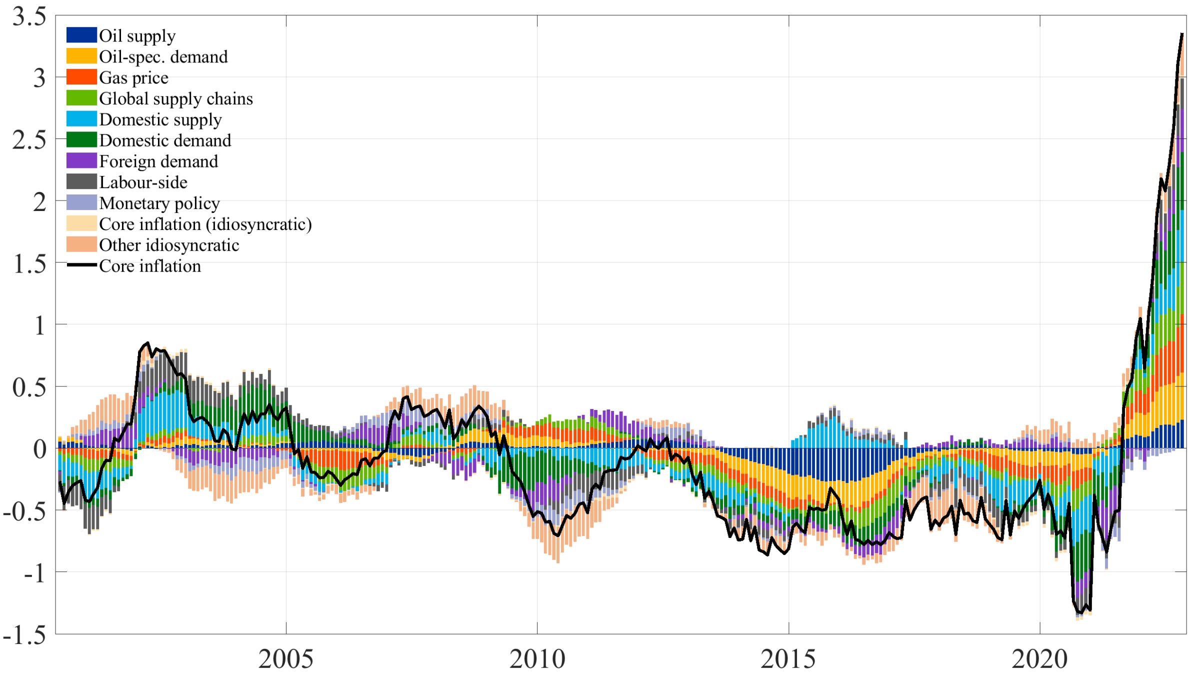

Figure 7: Historical decomposition of core inflation with monetary policy shocks

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

Despite the fact that it is less comprehensive, we favour the 8-shock model as our baseline specification as it can produce more timely results, which is key in policy environment. Whereas the insights from the augmented model are not materially different, its timeliness is constrained by the availability of the proxy, which comes with a considerable delay. Another point is that the augmented model features a larger contribution of the idiosyncratic component compared to the baseline specification. This might be an indication of the uncertainties related to the identification of monetary policy effects in particular and more generally point at the fact that enlarging the model might on occasions introduce noise.

6.3 Inclusion of food price shocks

As an additional extension, we augment our baseline specification and introduce a supply shock linked to developments in euro area food prices and production. As pointed out by Peersman (2022), shocks linked to food commodity prices should be studied as an independent driver of inflation, differentiated in particular from the energy commodities, since they are affected by specific supply disruptions and can have sizeable impacts (see also De Winne and Peersman (2021)).

One challenge in identifying food related shocks is that pinning down their nature or source is not straightforward. They can be global or pertaining to regional developments, they can be weather-related, driven by geopolitical events like wars, or by pests or viruses affecting specific crops or livestock. Instead of looking into the origin of the various types of food price shocks, we label a generic *food price shock*, which has supply type effects on the euro area food sector.[15]

To achieve the identification of the shock, we augment our data set by consumer price inflation, producer price inflation and industrial production, all related to the food sector in the euro area. We also include the food commodity price index from the World Bank. We detail the identification scheme in Table 6 in Appendix D. An increase in farm-gate price inflation[16] is accompanied by an increase in producer price inflation for the food sector, increases in consumer food and total prices, as well as a reduction in the euro area industrial production for food. Given the limited importance of this particular sector in the euro area, we do not impose contemporaneous restrictions on variables measuring total economic activity. We also leave the contemporaneous reaction of services inflation unrestricted, despite HICP services including items such as dining in restaurants or canteens. This is in line with the finding of Peersman (2022), who shows that the pass-through of food commodity price shocks to prices that consumers have to pay in restaurants or for catering is modest and in line with the very small share of food commodities to produce these services.

We distinguish the food price shock from the energy-related ones by assuming that it does not have a contemporaneous effect on oil production or gas prices. Furthermore, it has no contemporaneous impact on negotiated wages or on the exchange rate. We also assume that a global supply chain shock does not have an impact on food consumer prices, as, given the composition of the GSCPI series, the global supply chain shock that we are targeting is mainly linked to manufacturing.

The inflation narrative that comes out of our baseline specification is robust to the inclusion of the food price shock - the correlation between the corresponding shocks remains high, at around 0.9 overall. Similar to other supply-side shocks, food price shocks also contributed positively to the surge in core inflation in the post-pandemic period. However, their contribution is smaller in comparison to energy-related and global

[15]Here the focus is not on disentangling between foreign and domestic food-related supply shocks. Identifying solely external shocks would require not only information on food commodity prices but also international food production as in Peersman (2022). Latter data is not available at monthly frequency.

[16]The restriction is imposed on the euro area farm-gate prices and not on international food commodity prices. Ferrucci et al. (2012) discuss the differences between the two and argue that to a large extent, it can be attributed to the presence of a system of agricultural subsidies and programs implemented in the EU by the European Commission, which cushions the transmission of global shocks to EU internal prices. This makes the Agri. prices series less volatile than counterparts on international markets. Plus, several crops are produced in Europe and HICP food prices show higher correlation with EU internal market prices than with international prices, suggesting that the former may be a better gauge of commodity input cost pressures faced by producers and retailers in the euro area.

supply chain shocks (see Figure 8).

An interesting by-product of this specification is the historical decomposition of consumer food price inflation (see Figure 23 in Appendix D.3). The main drivers of consumer food prices turn out to be not that different compared to other consumer prices. Energy-related shocks exhibit a stronger contribution than those related to developments specific to the food sector. Domestic demand and supply conditions also play a role as reflected in the sizeable contribution of *other shocks*. Part of food inflation developments is unexplained by this model, which can be traced back to the multifaceted nature of the shocks that can affect the various food components, beyond what can be captured by the series for the total food sector. While going more granular on possible drivers of food prices is beyond the scope of this paper, what comes out clearly from Figure 23 is that energy costs play a sizeable role also for this component.

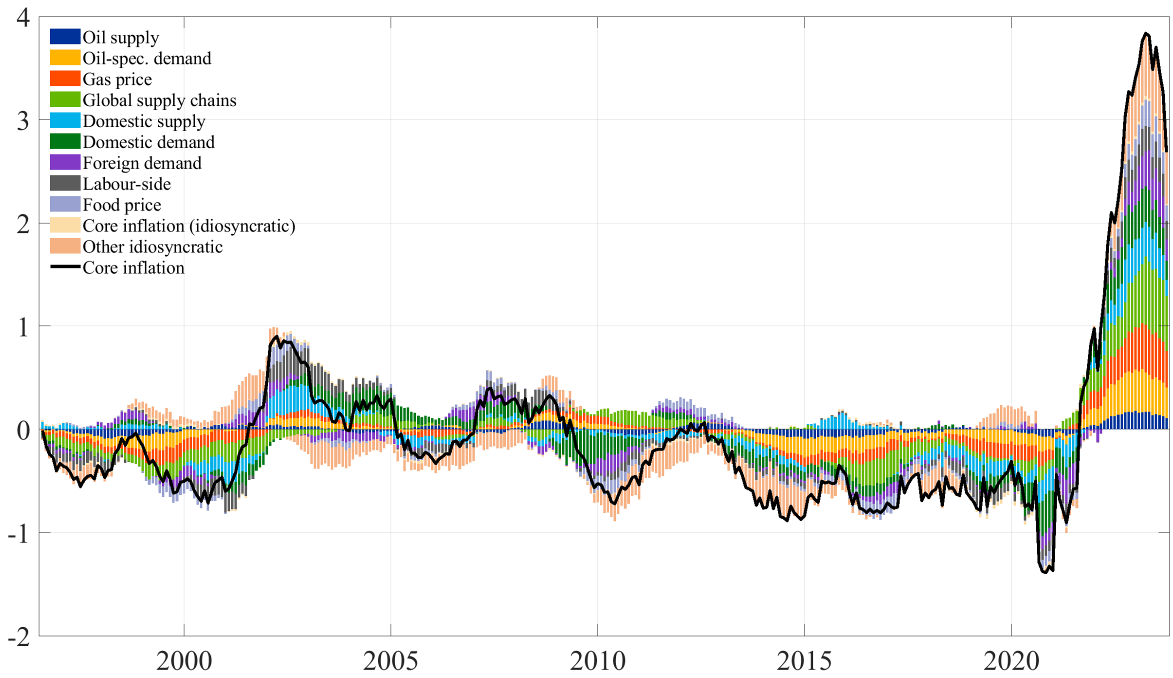

Figure 8: Historical decomposition of core inflation with food price shocks

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

6.4 Inclusion of monetary policy and food price shocks

As the final extension, we consider a larger model incorporating both additional shocks just discussed, i.e., the baseline specification augmented with monetary policy and food price shocks. The resulting identification scheme with 10 structural shocks is presented in Table 7 in Appendix D. The broad messages of what drives core inflation derived from the baseline specification remain, which suggests limited gains in going beyond a certain number of identified shocks. In fact, there seems to be some trade-off between the amount of signal and noise that additional variables bring.[17] Similarly as for the specification discussed in Section 6.2, the version with 10 shocks also results in larger contributions of idiosyncratic components (of other variables than core inflation, see Figure 9). Given the observations in this and previous sections, we keep the 8-shock model as the preferred specification to draw a robust picture of the drivers of core inflation.

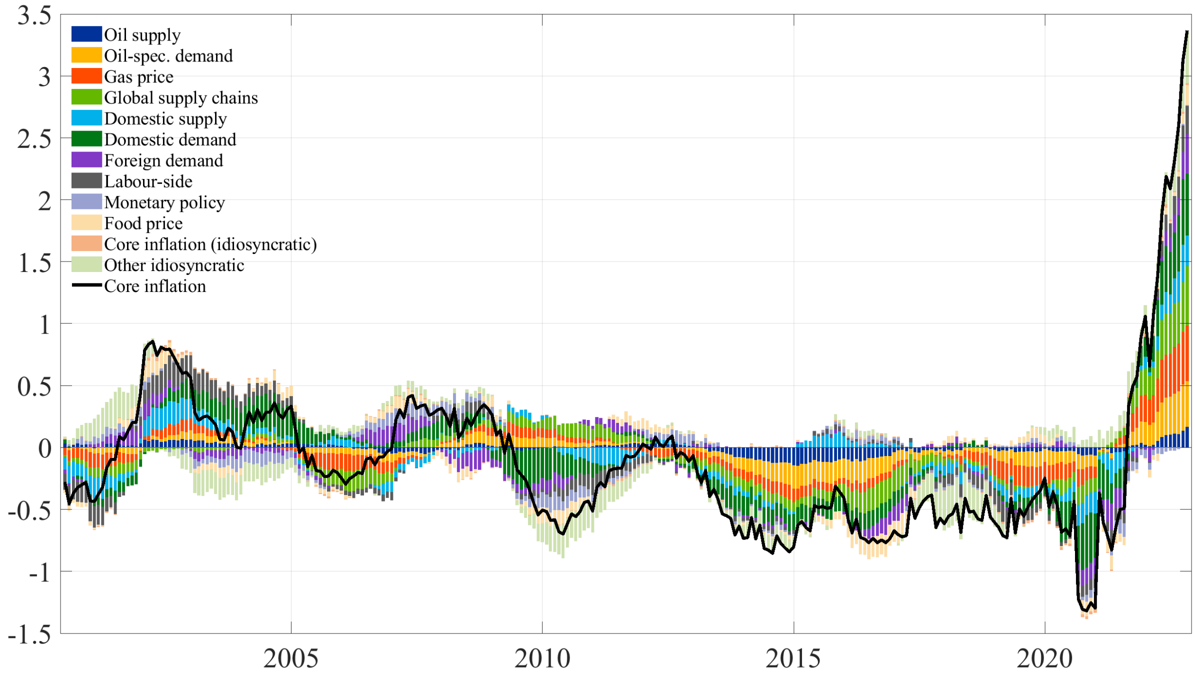

Figure 9: Historical decomposition of core inflation with monetary policy and food price shocks

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

6.5 Small model with 4 shocks

The recent episode appears to feature a perfect storm of various shocks hitting inflation in the same direction. This raises a question whether the strong upward dynamics visible in many variables might induce spurious correlations and one has to control for a sufficient number of shocks not to attribute to one specific shock more importance than one should. We investigate this question focusing on the global supply chain shocks, which have been in the spotlight in the post-pandemic period. We compare the size of

[17] Similar issues have been observed in the context of forecasting with factor models, see Bai and Ng (2008).

the contributions of this shock in our baseline specification to that in a smaller model, identifying a generic demand, supply, energy and global supply chain shock (see Table 8 in Appendix D.5 for details). Figure 10 shows that in a smaller model the contribution is exaggerated compared to our baseline model. Consequently, when modelling inflation after the pandemic, it is important to account for a sufficiently large number of shocks since focusing on one specific inflationary driver or a too restricted set of shocks might inadequately amplify their importance.

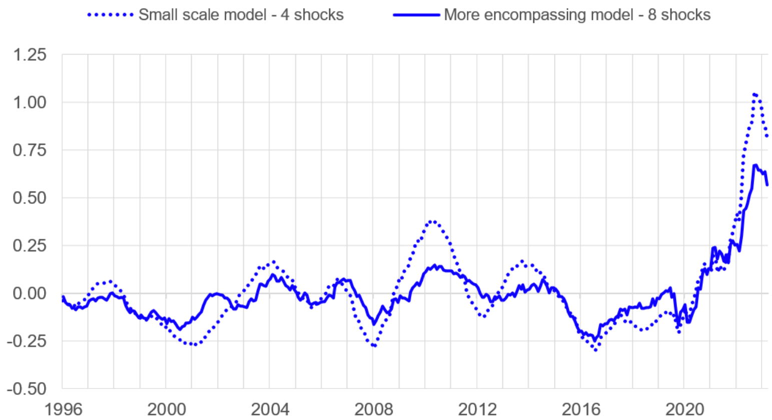

Figure 10: Contribution to core inflation of shocks linked to global supply chains

Note: The chart shows the point-wise mean of the posterior distribution of the contributions to the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

7 Conclusions

We introduce a novel identification scheme to disentangle inflationary forces in the euro area, especially during the challenging period following the COVID-19 pandemic. We take an encompassing approach and identify a wide range of supply and demand shocks relying on a rich data set. In particular, we identify "new" types of shocks that have become prominent in the post-pandemic recovery, most notably, those related to gas prices and to global supply chain bottlenecks.

Our findings indicate that core inflation in the euro area has been largely driven by supply-side shocks in the post-pandemic recovery. In particular, we show that supply-side bottlenecks, gas and oil price shocks have all pushed in the same direction supporting a bad luck narrative to the high inflation episode. Those linked to global supply chain pressures and to gas prices have exhibited a much larger influence than in the past. Importantly, we also find that one needs a more encompassing model in terms of shocks and variables to hedge against the risk of overestimating the contribution of one specific shock.

Our results have implications for the way policy makers look at core inflation. We show that core inflation can be at times impacted by large (temporary) supply-side shocks and this was the case after the pandemic. The same holds also for services price inflation. Being able to gauge the impact of such shocks is useful for policy making. A counterfactual core inflation measure net of energy and global supply chain bottleneck effects has been more stable after the pandemic, albeit increasing to record levels.

Looking forward, as the model proposed in this paper is quite flexible, it could be adapted to incorporate other shocks that might become relevant for inflation developments in the future. New shocks could for example relate to developments specific to electricity prices or more generally to the ongoing transition towards green energies. Further extensions might account for possible non-linearities or time-variation in the pass-through, which might be empirically relevant in certain episodes.

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A Impulse responses and factor loadings (impact effects)

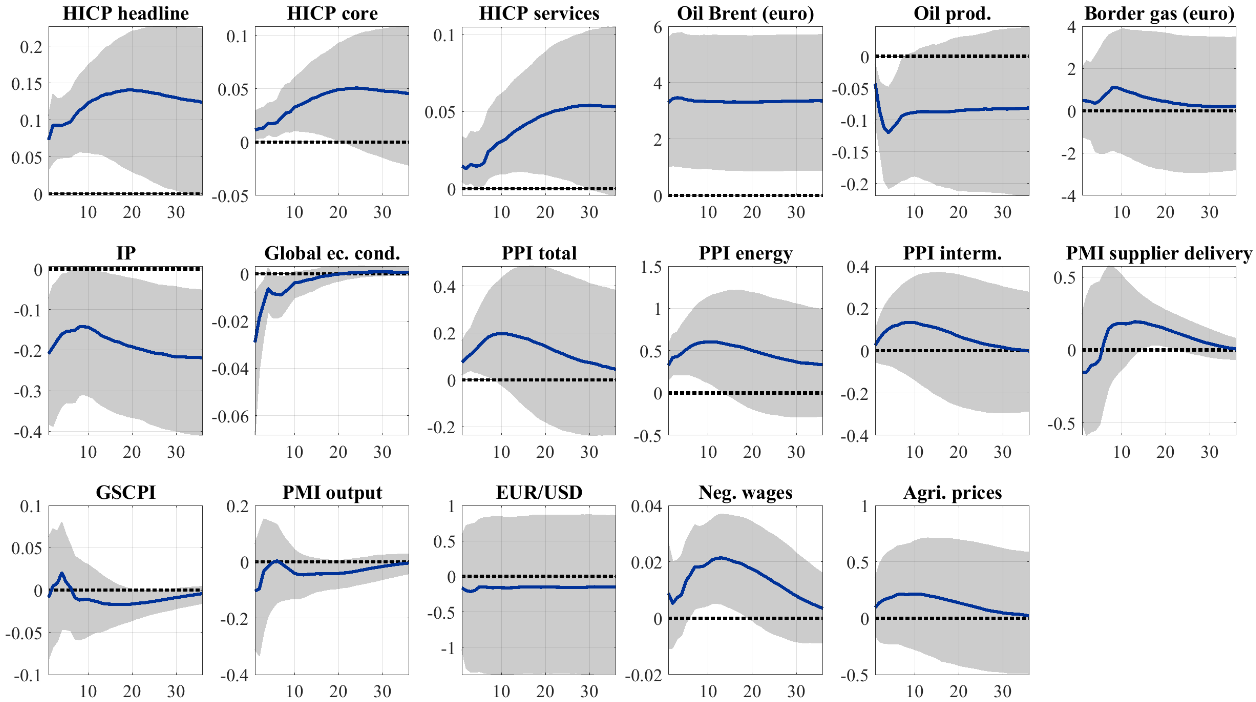

Figure 11: Impulse responses to oil supply shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

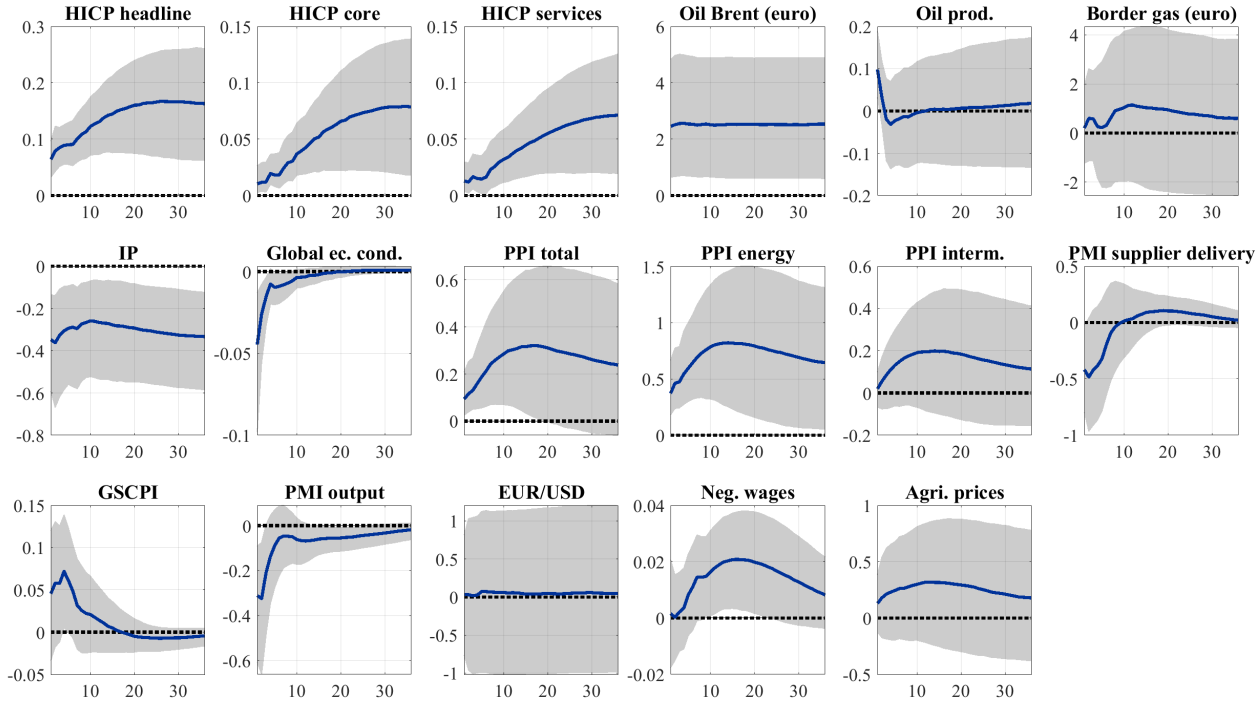

Figure 12: Impulse responses to oil-specific demand shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

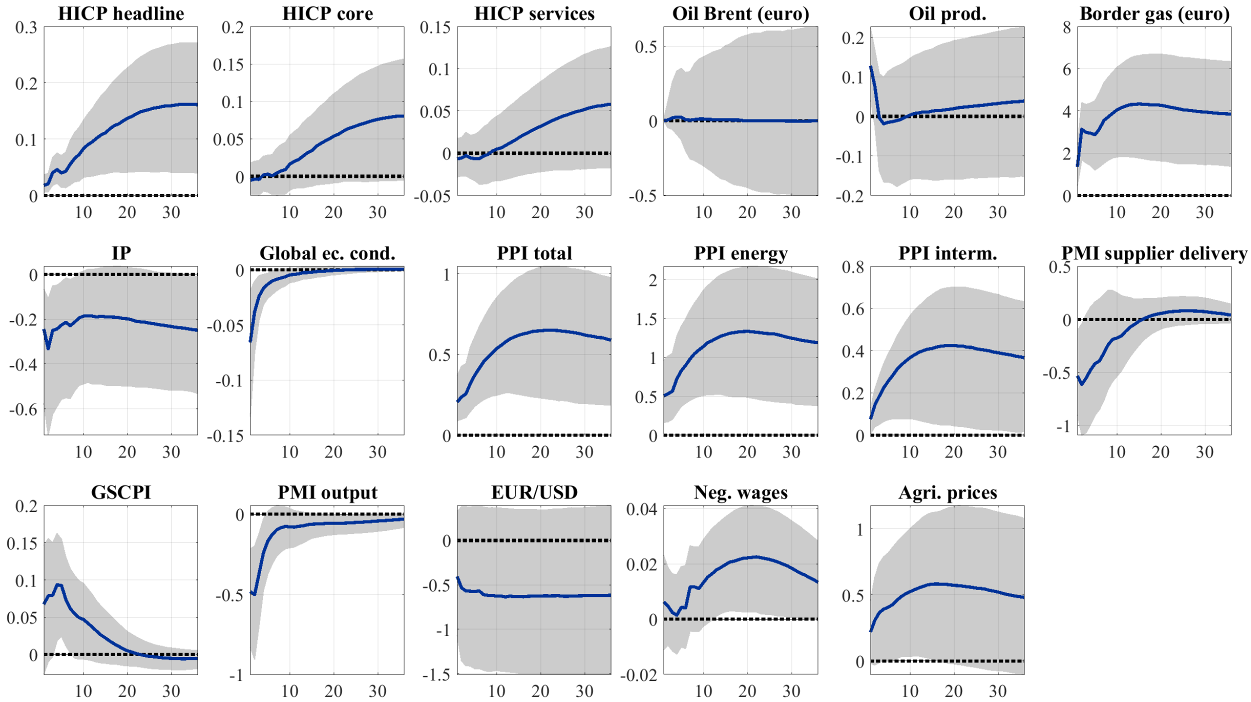

Figure 13: Impulse responses to gas price shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

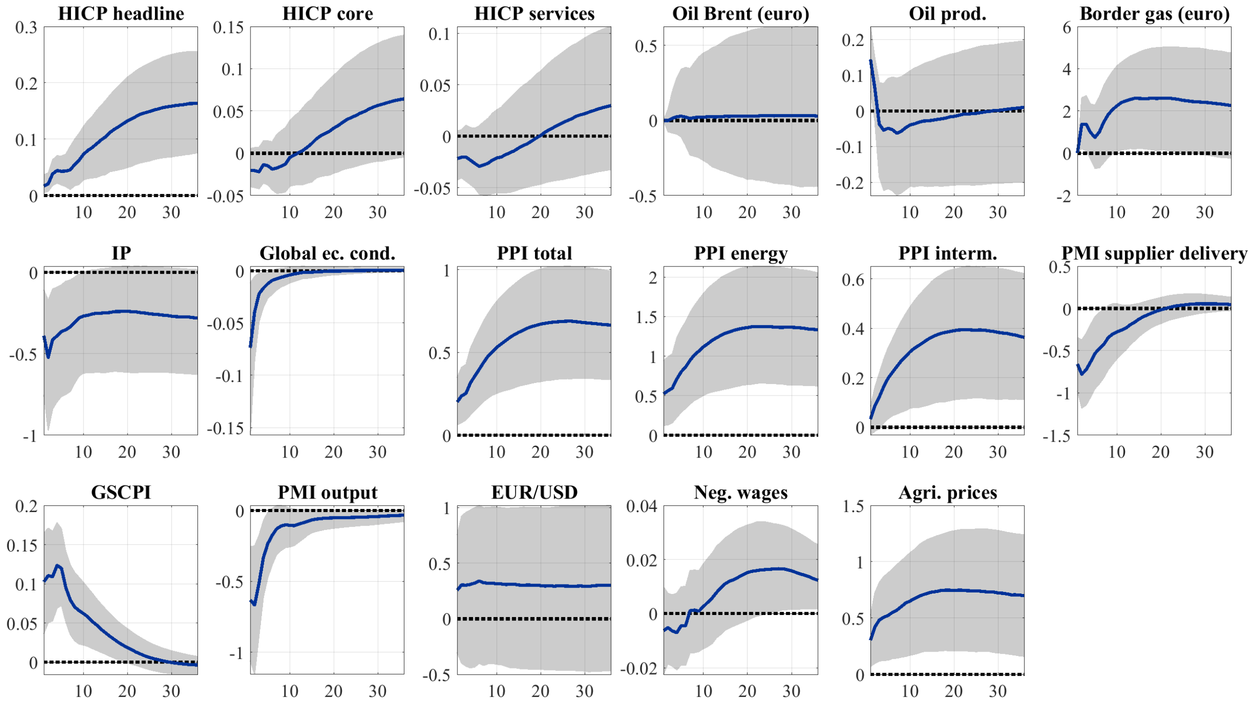

Figure 14: Impulse responses to global supply chains shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

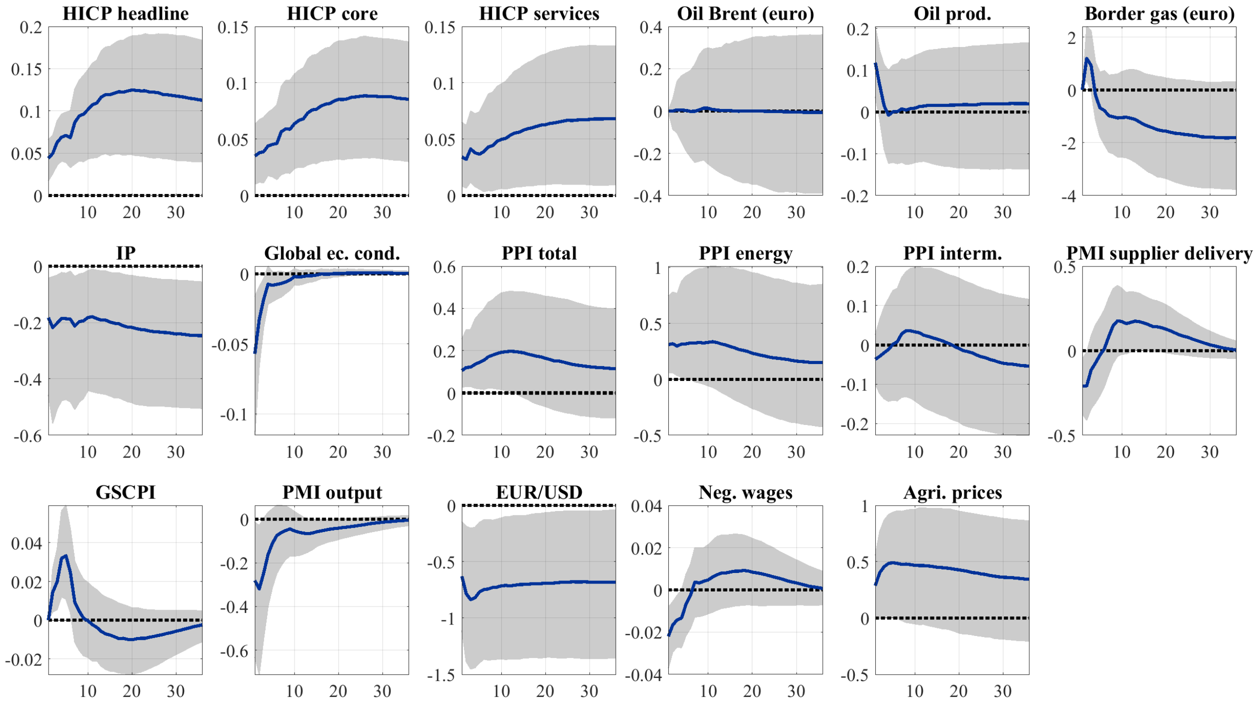

Figure 15: Impulse responses to domestic supply shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

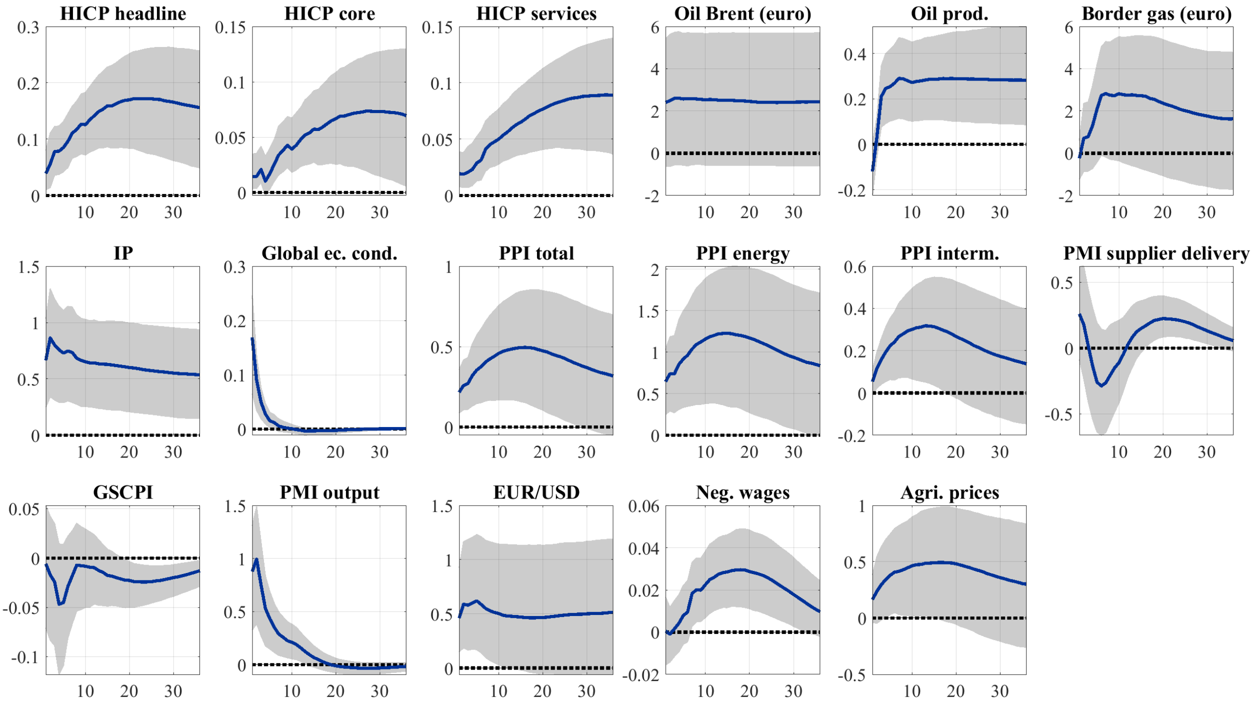

Figure 16: Impulse responses to domestic demand shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

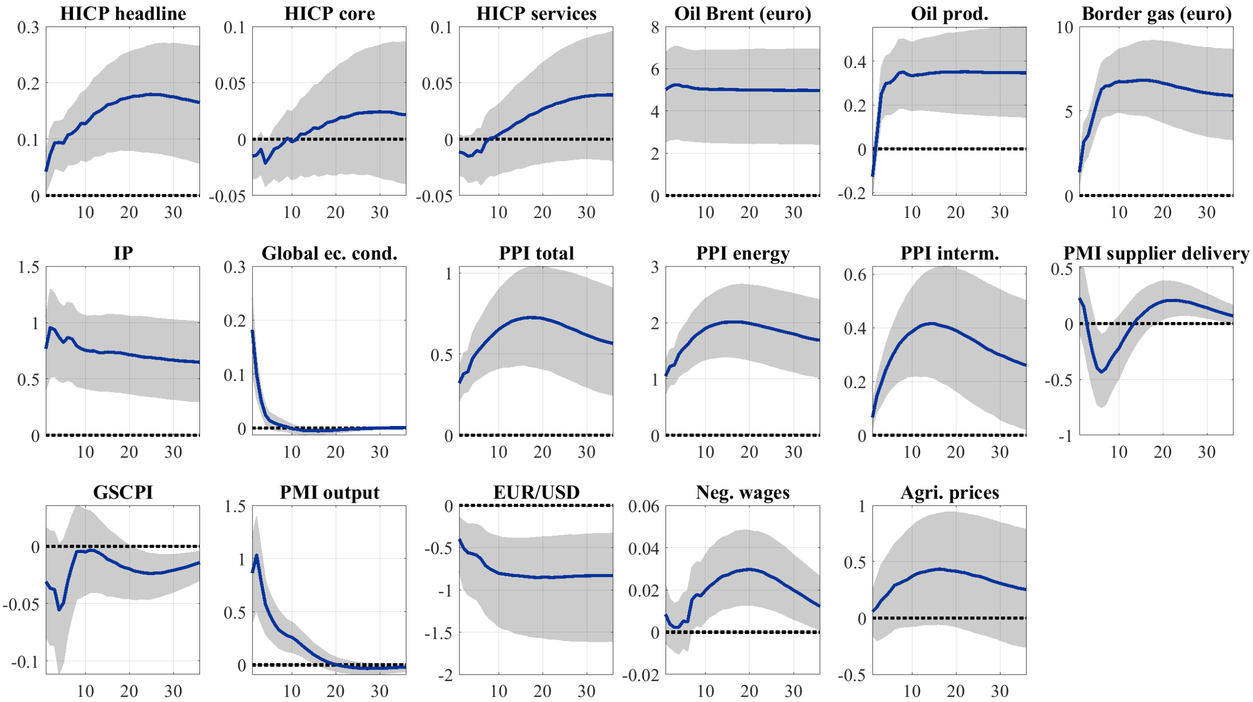

Figure 17: Impulse responses to foreign demand shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

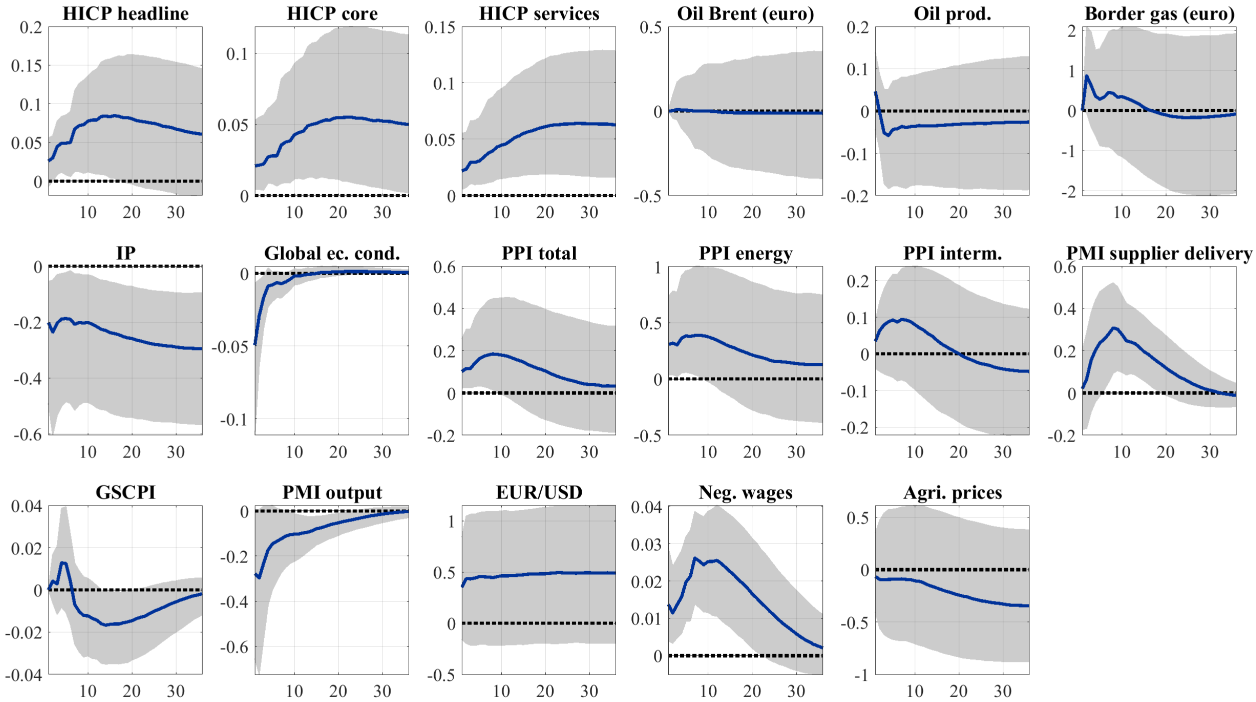

Figure 18: Impulse responses to labour-side shocks

Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Table 4: Estimated factor loadings

	Supply						Demand	
Variable/Shocks	**Oil supply**	**Oil-spec. demand**	**Gas price**	**Global supply chains**	**Domestic supply**	**Labour-side**	**Domestic demand**	**Foreign demand**
HICP Headline	0.31	0.28	0.09	0.09	0.19	0.10	0.19	0.18
HICP Core	0.13	0.12	-0.03	-0.14	0.30	0.22	0.15	-0.15
HICP Services	0.15	0.13	-0.04	-0.14	0.29	0.23	0.18	-0.11
Oil Brent (euro)	0.39	0.32	0.00	0.00	0.00	0.00	0.28	0.56
Oil prod.	-0.05	0.09	0.11	0.12	0.10	0.04	-0.10	-0.10
Border gas (euro)	0.04	0.03	0.15	0.00	0.00	0.00	-0.03	0.14
IP	-0.12	-0.19	-0.16	-0.23	-0.13	-0.14	0.34	0.38
Global ec. cond.	-0.08	-0.11	-0.15	-0.16	-0.13	-0.12	0.32	0.35
PPI total	0.11	0.14	0.26	0.24	0.16	0.16	0.26	0.37
PPI energy	0.16	0.19	0.25	0.24	0.17	0.16	0.29	0.46
PPI interm.	0.04	0.03	0.13	0.05	-0.07	0.05	0.10	0.13
PMI supplier delivery	-0.02	-0.05	-0.07	-0.09	-0.03	0.00	0.03	0.03
GSCPI	-0.01	0.04	0.06	0.11	0.00	0.00	-0.01	-0.03
PMI output	-0.03	-0.07	-0.11	-0.13	-0.07	-0.07	0.17	0.17
EUR/USD	-0.09	0.02	-0.17	0.11	-0.28	0.16	0.24	-0.21
Neg. wages	0.01	0.00	0.01	-0.01	-0.04	0.03	0.00	0.01
Agri. prices	0.05	0.07	0.11	0.15	0.14	-0.02	0.08	0.02

Note: The numbers represent the median of the factor loadings posterior distribution, which capture the contemporaneous effect of the shocks on each of the variables.

B Estimated shocks

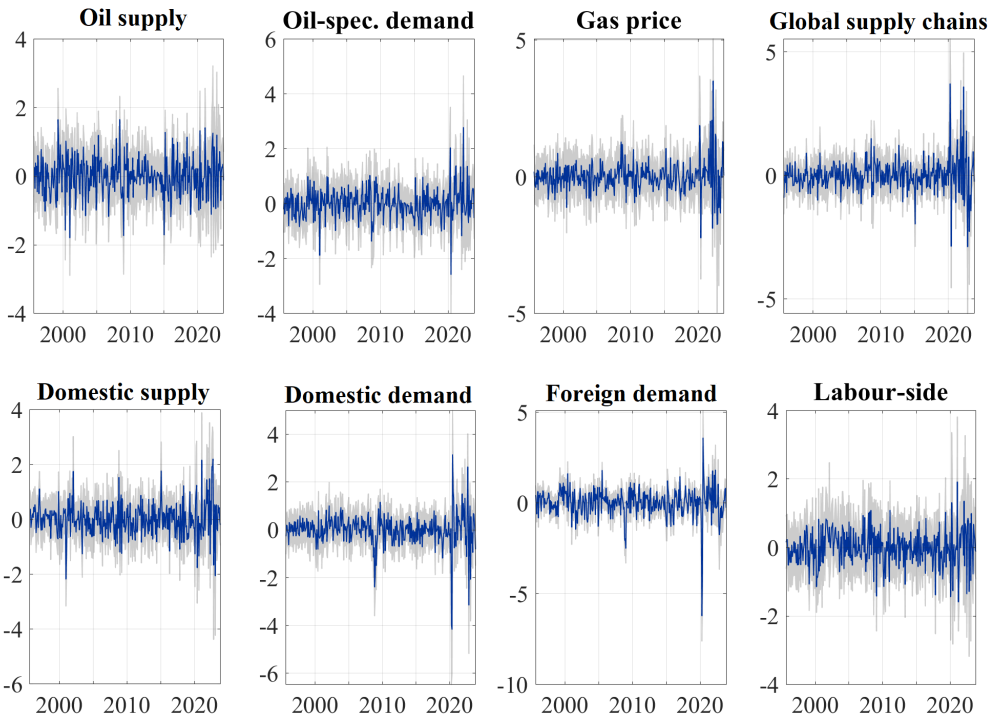

Figure 19: Estimated factors (shocks)

Note: The chart reports the median of the factors' posterior distribution (blue line) and the 68% credibility bands (gray shaded areas).

C Underlying inflation measures and their counterfactual estimates free of certain supply-side shocks

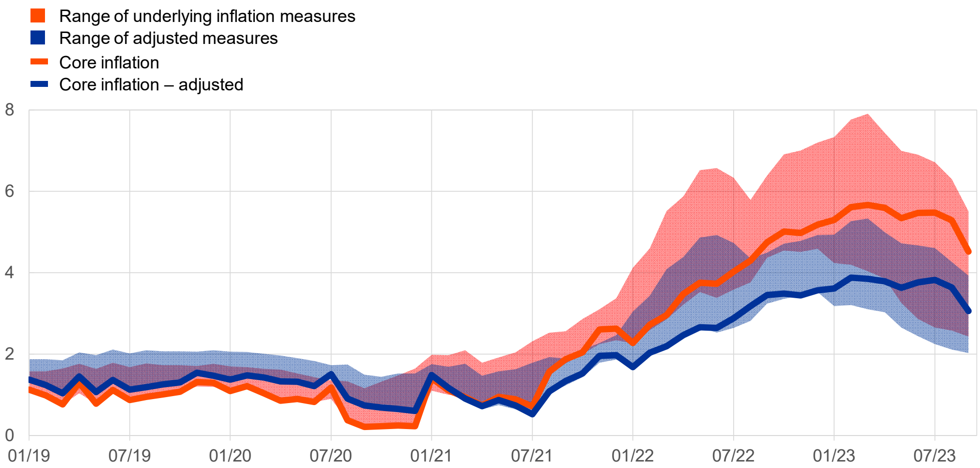

Figure 20: Range of underlying inflation measures and measures adjusted for impact of global supply chain and energy shocks

Note: The range covers the underlying inflation measures for the euro area regularly monitored by the European Central Bank. More precisely the measures included are: (1) core inflation, namely HICP excluding energy and food (HICPX); (2) HICPXX - HICP excluding energy, food, air travel-related items, clothing and footwear; (3) HICP inflation excluding energy; (4) HICP inflation excluding unprocessed food and energy; (5) Domestic inflation - aggregate of HICPX items for which the import intensity does not exceed 18 per cent; (6) Supercore - aggregate of HICPX items sensitive to slack, as measured by their forecast performance in a reduced-form Phillips curve using the output gap; (7) PCCI - the Persistent and Common Component of Inflation, see Bańbura and Bobeica (2020) and (8) PCCI excluding energy. The adjusted range includes these measures free of energy and global supply chain shocks impacts. The estimation is performed using the seasonally adjusted index in month-on-month terms for each measure, apart from the PCCIs, which are included at face value.

D Extensions and robustness checks

D.1 Comparison across different estimation samples

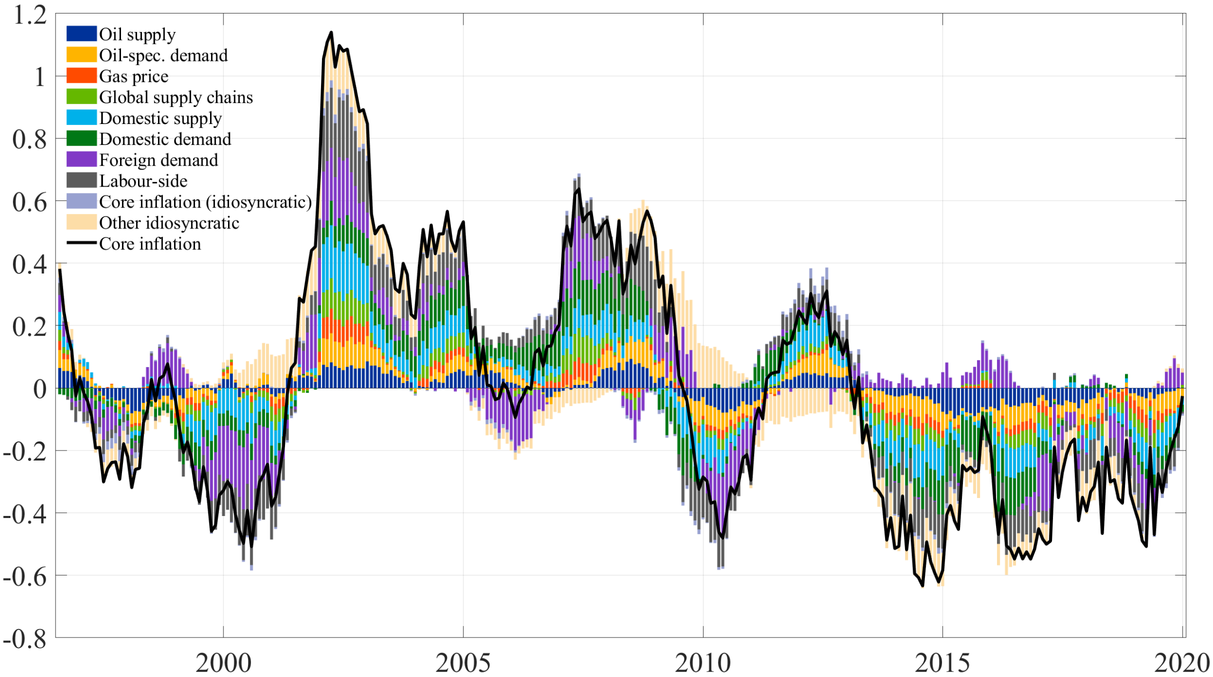

Figure 21: Historical decomposition of core inflation (Pre-COVID, until December 2019)

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

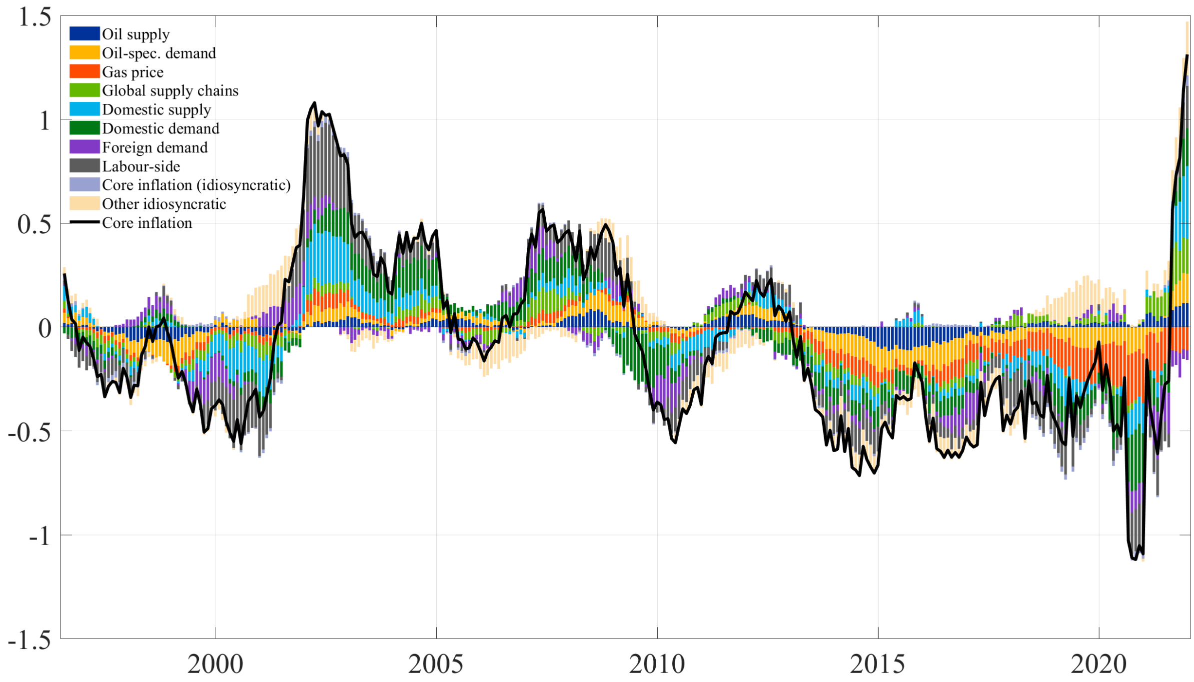

Figure 22: Historical decomposition of core inflation (Pre-war, until December 2021)

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

D.2 Augmented identification 1: including monetary policy shocks

Table 5: Augmented identification with monetary policy shocks/proxy

	Supply						Demand		
Variable/Shocks	**Oil supply**	**Oil-spec. demand**	**Gas price**	**Global supply chains**	**Domestic supply**	**Labour-side**	**Domestic demand**	**Foreign demand**	**Monetary policy**
HICP headline	+	+	+	+	+		+		
HICP core	+	+			+		+		
HICP services						+			
Oil Brent (euro)	+	+	0	0	0	0		+	
Oil prod.	-	+							
Border gas (euro)			+	0	0	0			
IP	-	-	-	-	-	-	+		
Global ec. cond.	-	-						+	
PPI total	+	+	+	+	+	+	+	+	
PPI energy	+	+	+					+	
PPI interm.								+	
MP proxy	0	0	0	0	0	0	0	0	-
Shadow rate									-
PMI supplier delivery				-					
GSCPI				+	0	0			
PMI output									
EUR/USD							+	-	
Neg. wages					-	+			
Agri. prices									

D.3 Augmented identification 2: including food price shocks

Table 6: Augmented identification with food price shocks

	Supply							Demand	
Variable	**Oil supply**	**Oil-spec. demand**	**Gas price**	**Global supply chains**	**Domestic supply**	**Labour-side**	**Food price**	**Domestic demand**	**Foreign demand**
HICP headline	+	+	+	+	+		+	+	
HICP food				0			+		
HICP core	+	+			+			+	
HICP services						+			
Oil Brent (euro)	+	+	0	0	0	0			+
Oil prod.	-	+					0		
Border gas (euro)			+	0	0	0	0		
IP	-	-	-	-	-	-		+	
IP food							-		
Global ec. cond.	-	-							+
PPI total	+	+	+	+	+	+		+	+
PPI energy	+	+	+						+
PPI interm.									+
PMI supplier delivery				-					
GSCPI				+	0	0			
PMI output									
EUR/USD							0	+	-
Neg. wages					-	+	0		
PPI food							+		
World food price index									
Agri. prices							+		

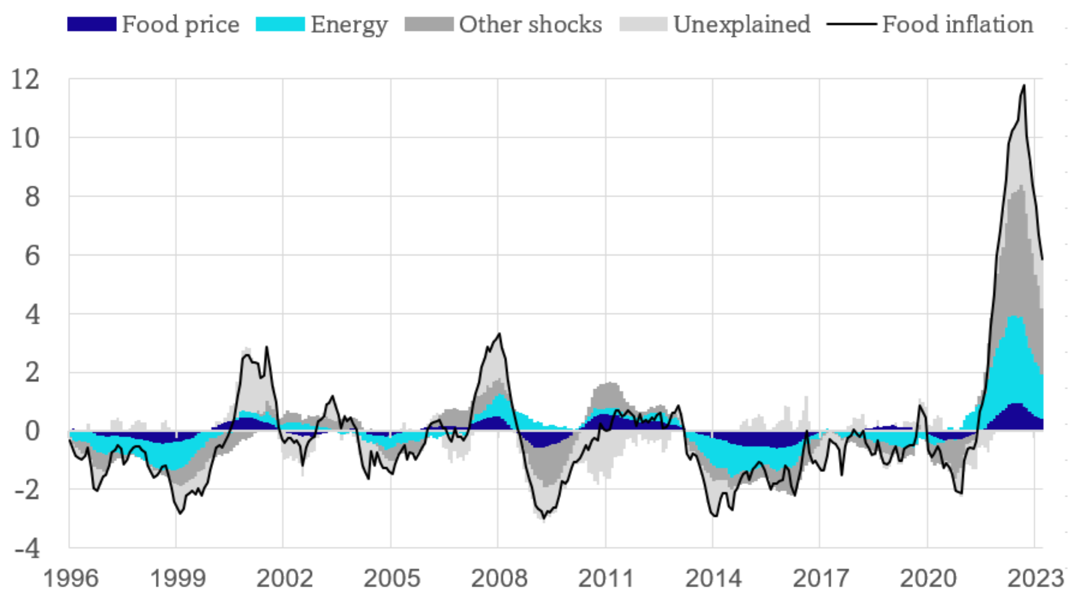

Figure 23: Historical decomposition of food inflation

Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of food inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

D.4 Augmented identification 3: including monetary policy and food price shocks

Table 7: Augmented identification by monetary policy (proxy) and food price shocks

	Supply							Demand		
Variable/Shocks	Oil supply	Oil-spec. demand	Gas price	Global supply chains	Domestic supply	Labour-side	Food price	Domestic demand	Foreign demand	Monetary policy
HICP headline	+	+	+	+	+		+	+		
HICP food				0			+			
HICP core	+	+			+			+		
HICP services						+				
Oil Brent (euro)	+	+	0	0	0	0			+	
Oil prod.	-	+					0			
Border gas (euro)			+	0	0	0	0			
IP	-	-	-	-	-	-		+		
IP food							-			
Global ec. cond.	-	-							+	
PPI total	+	+	+	+	+	+		+	+	
PPI energy	+	+	+						+	
PPI interm.									+	
MP proxy	0	0	0	0	0	0	0	0	0	-
Shadow rate										-
PMI supplier delivery				-						
GSCPI				+	0	0				
PMI output										
EUR/USD							0	+	-	
Neg. wages					-	+	0			
PPI food							+			
World food price index										
Agri. prices							+			

D.5 Augmented identification 4: small model with 4 shocks

Table 8: Small model based on four shocks

	Supply			Demand
Variable/Shocks	Oil supply	Global supply chains	Domestic supply	Domestic demand
HICP headline	+	+	+	+
HICP core	+		+	+
HICP services				
Oil Brent (euro)	+	0	0	
Oil prod.	-			
IP	-	-	-	+
PPI total	+	+	+	+
PPI energy	+			
PPI interm.				
PMI supplier delivery		-		
GSCPI		+	0	
PMI output				
Neg. wages				