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What drives core inflation? The role of supply shocks

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This paper contains research conducted within the network "Challenges for Monetary Policy Transmission in a Changing World Network" (ChaMP). It consists of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB).

ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Melina Papoutsi and Gonzalo Paz-Pardo (both ECB), 7 central bank advisers and 8 academic consultants.

ChaMP seeks to revisit our knowledge of monetary transmission channels in the euro area in the context of unprecedented shocks, multiple ongoing structural changes and the extension of the monetary policy toolkit over the last decade and a half as well as the recent steep inflation wave and its reversal. More information is provided on its website.

Abstract

Considering key lessons from the post-pandemic high inflation episode, we propose a framework to understand euro area core inflation which: (i) accounts for a rich set of drivers and (ii) identifies "new" shocks, associated to gas prices and to global supply chain bottlenecks. We propose a structural BVAR with a factor structure in the reduced-form residual, an outlier correction, and treatment of ragged edges. We find that supply shocks explain most of the inflation surge, while monetary policy shocks played a limited role. An adjusted core inflation rate, abstracting from shocks linked to energy or supply chain bottlenecks, was more stable but still increased to record highs.

Keywords: Inflation, Bayesian VAR, Supply shocks, Gas prices, Supply chain bottlenecks
JEL codes: E31, C32, C38

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 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 an aggregate domestic and a foreign demand shock. On the supply side we identify shocks related to oil supply, oil-specific demand, gas prices, global supply bottlenecks, 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.

We find that core inflation has been largely driven by supply-side shocks in the post-pandemic recovery. Shocks related to supply-side bottlenecks, gas price, and the oil market have all pushed in the same direction supporting a "bad-luck" narrative to the high inflation episode. Monetary policy shocks played a limited role. We also find that considering a too restricted set of shocks and variables inadequately amplifies the importance of certain 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 energy and supply-side bottlenecks effects has been more stable after the pandemic.

1 Introduction

In this paper we propose a novel identification scheme to understand the drivers of core inflation in the euro area, defined as HICP inflation excluding energy and food, in order 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.

What drives inflation has always been a challenging question for both academics and policy makers, but the period following 2020 has been remarkable in several ways. In many countries, inflation rates reached levels that have not been seen for decades, with price pressures from many different sources hitting the economy at the same time. Given the well-known delays in the transmission monetary policy and the trade-offs central banks face in the presence of supply shocks, it has been key for policymakers to assess the relative importance of various supply and demand factors, as well as the persistence of their respective effects on headline and core inflation. We focus the analysis on *core* inflation, as it received special emphasis in central bankers communication recently, being considered a useful gauge of more domestic and more persistent inflation dynamics.

Until recently, structural inference for euro area inflation was often based on parsimonious vector autoregressive (VAR) models with a limited set of identified shocks (Conti et al., 2017; Bobeica and Jarocinski, 2019; Montes-Galdón and Ortega, 2022). However, while the post-pandemic inflation surge was partly driven by "traditional" culprits – food and oil prices – "new" inflationary drivers also emerged, most notably, global supply chain bottlenecks and, particularly in Europe, gas prices. The multitude of inflationary sources created the need to consider more types of shocks employing models incorporating a larger set of variables. This can alleviate informational deficiencies and substantially sharpen structural inference (Bernanke et al., 2005; Bańbura et al., 2010; Koop, 2013; Chan et al., 2022) as well as provide more complete narratives. It can also help to cross-check and reconcile results based on partial identification and/or small information sets.

The identification of new shocks comes 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. Our econometric framework builds on the Bayesian VAR with a factor structure in the residuals proposed by Korobilis (2022). In this model the factors are the structural shocks and identification is achieved via sign and zero restrictions on the factor loadings. Sign restrictions are implemented by drawing the loadings from truncated normal distributions. In comparison to the conventional accept-reject methods (e.g. Rubio-Ramirez et al., 2010; 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 does not occur.

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. 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.

In this framework we propose how to disentangle the multitude of inflationary sources by constructing a rich set of monthly variables relevant for inflation and putting forward the appropriate identifying (sign and zero) restrictions. Our baseline specification identifies 8 shocks in a 17-variable system. 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 bundles several aspects such as labour supply and wage bargaining. To our knowledge, we are the first ones to simultaneously disentangle supply-side shocks related to oil prices, gas prices, and global supply chains (and food prices in an augmented version) in a unified framework.

Increases in gas prices are sources of inflation that have been overlooked in the past. In particular, in Europe, wholesale gas prices used to be contractually indexed to oil prices, making them highly correlated with the latter and not considered as inflation drivers in their own right. However, starting around 2015, a gradual shift towards a deregulated gas market increased the likelihood of idiosyncratic gas price shocks. Since mid-2021, and especially following the Russian invasion of Ukraine in February 2022, European gas prices surged dramatically and significantly contributed to the increase in euro area energy inflation, given the high dependence of the European energy sector on natural gas (as recently documented by Alessandri and Gazzani, 2025; Adolfsen et al., 2024; Casoli et al., 2024; López et al., 2024). Looking ahead, natural gas is expected to play a larger role in the green transition, as it was classified as a sustainable energy source by the European Commission in 2022. For these reasons, the identification of gas price shocks, in addition to more traditional oil-related shocks, could be a crucial feature of inflation models going forward.

Our identification scheme accounts for the strong connection between oil and gas prices that existed in the past. This contrasts with several studies that either model gas prices separately from oil prices or combine the two as exogenous blocks (Casoli et al., 2024; Rubaszek et al., 2021; Adolfsen et al., 2024; Güntner et al., 2024). To allow for such a connection, we let gas prices contemporaneously react to oil price shocks. In order to differentiate the shocks in the oil market from those in the gas market, we rule out, by contrast, the contemporaneous reaction of oil prices to gas-specific shocks. This reflects the more global character of oil markets and aligns with empirical findings in the literature (see, e.g., Ramberg and Parsons, 2012; Szafranek and Rubaszek, 2024).

Global supply chain disruptions are another type of inflationary shock that was largely disregarded prior to the pandemic. However, the lockdowns and raw material shortages led to a significant slowdown or halt in production, causing an unprecedented disruption to these supply chains. Distinguishing global supply chain bottlenecks from more generic supply shocks might offer useful insights for understanding inflation developments, as their effects could be large and comparable to the effects from energy or food price shocks (see Benigno et al., 2022; Finck and Tillmann, 2022; Carrière-Swallow et al., 2023; Liu and Nguyen, 2023; Ascari et al., 2024; De Santis, 2024, among many others). Moreover, global supply chain disruptions are likely to reoccur, especially in an environment with high geopolitical tensions, trade disruptions and protectionist measures (Attinasi et al., 2024), which could have an important impact on future inflation dynamics.

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., 2024; Bai et al., 2024; De Santis, 2024; Kabaca and Tuzcuoglu, 2023, with the latter paper also adding restrictions on variance decomposition) and use shipping costs (e.g. Carrière-Swallow et al., 2023; Schuler et al., 2022) or composite indicators such as the Global Supply Chain Pressure Index (GSCPI) of Benigno et al. (2022). Our identification approach relies on sign and zero restrictions related to the GSCPI and the PMI supplier delivery times for the euro area. Compared to other studies we do not need to resort to narrative restrictions, we target the shocks that are more relevant for the euro area and we distinguish global supply chain shocks from many others in a single model.

In an extension to the baseline specification we also identify a monetary policy shock, following the internal instrument approach (Paul, 2020; Plagborg-Møller and Wolf, 2021; Noh, 2024) and using the monetary policy shock proxy of Jarociński and Karadi (2020). We assume that the proxy is driven only by the monetary policy shock and only contemporaneously. To implement this assumption we restrict to zero the VAR coefficients in the proxy's equation and set a small prior variance for the corresponding idiosyncratic component.

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. 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 relying on an overly limited set of shocks and variables might exaggerate the importance of certain selected drivers in the post-pandemic period, when many economic series featured simultaneous upward dynamics. We show this in particular for global supply chain shocks, pointing to risks of analysing their impact focusing on just this one or only a few shocks (as in e.g. Carrière-Swallow et al., 2023; Liu and Nguyen, 2023; De Santis, 2024). We also find a smaller impact of gas price shocks compared to e.g. Alessandri and Gazzani (2025). This suggests that one should include a wide range of shocks in a single model to better disentangle their individual contributions, especially as large contributions based on partial identification and/or small information sets are sometimes difficult to reconcile. Compared to studies who identify only generic supply and demand shocks, such as Giannone and Primiceri (2024) or Bergholt et al. (2024), we find a stronger role for supply in the high inflation period. Given sizable differences in the literature on the relative importance of both types of shocks, we argue it is important consider a wider range of inflation drivers.

Our results have implications for the way policy makers look at core inflation. As headline inflation is more strongly affected by external and/or supply shocks, which also tend to be more volatile, policy makers often turn to core inflation, which excludes food and energy items and is considered to be a useful gauge of more domestic and more persistent inflation dynamics. However, core inflation can be at times impacted by sizeable supply-side shocks and this is what happened after the pandemic (see also Lane, 2023). An important feature of the framework proposed in this paper is that one can estimate the developments in core inflation in the absence of certain shocks, which allows (policy makers) to see through them. An adjusted measure of core inflation that excludes the effects of energy shocks and global supply chain shocks has been more stable after the pandemic, although it too increased to record levels.

Finally, based on the specification augmented with monetary policy shocks we find that their size was rather limited in general and in the post-pandemic period in particular. This suggests that monetary policy has been affecting inflation mainly through its "systematic" component.

The rest of the paper is organised as follows. Section 2 describes the data set. Section 3 continues 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 and relates our approach to others in the literature. Section 5 presents inflation narrative based on the model. Section 6 reports counterfactual inflation estimates net of certain shocks and results based on the extension with monetary policy shocks. Section 7 discusses the role of model size. The last section concludes. Additional results are provided in the Appendix.

2 Data set

The econometric method comes with the challenge of finding an appropriate set of relevant variables so that the identified factors (shocks) explain a reasonable share of the dynamics of the variable(s) of interest.

We construct a medium-scale monthly data set covering different inflation measures and a broad array 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 of Benigno et al. (2022)[1] 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 December 2024. 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.

Figure A.1 in A plots the data used for the analysis. In particular, one can note some extreme volatility during the pandemic and the subsequent period as well as unprecedented rates of growth in HICP and several other indicators, including gas prices or measures of supply chain pressures.

[1]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). Benigno et al. (2022) 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.

Table 1: Data description

Variable	Description	Source	Trans.
HICP headline	Total HICP	Eurostat	log-diff
HICP core	HICP excluding energy and food	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	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 negotiated wages (the latter being available as year-on-year growth rates). Whenever no official seasonally adjusted data was available, we did the adjustment using X13. The oil price and border gas price are expressed in euro. EIA stand for Energy Information Administration. 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 backcasted 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, backcasted 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 backcasted using the same variable for the UK (historical correlation of 90%); PMI output starts in July 1998 and was backcasted using the economic sentiment index for total economy from the European Commission's survey (historical correlation of 85%).

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 problem, 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.[2] 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 (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, Λ, 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

[2] Chan et al. (2023) have recently proposed an approach to reduce the computational burden of such algorithms.

prior for the impulse responses (see the debate initiated by Baumeister and Hamilton, 2015).

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, $\xi_t = [\xi_{1,t}, \ldots, \xi_{N,t}]$, is given by:

$$\xi_{i,t} = \omega_i O_{i,t} e_{i,t}, \quad i = 1, \ldots, N, \tag{3}$$

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. (across time and cross-section) scaling factors that follow a mixture distribution, distinguishing between regular observations with $O_{i,t} = 1$ and outliers with $2 \leq O_{i,t} \leq 20$, thus down-weighting extreme observations (see Stock and Watson, 2016a, for details). By contrast, we do not scale down large factors/shocks, as these may be relevant for identification.[3]

We follow Korobilis (2022) and Stock and Watson (2016a) in setting the priors for the parameters. The priors for the coefficients, A_0, A_1, ..., A_p are conditionally normal, with prior variance imposing a local-global shrinkage of the "horseshoe" type of Carvalho et al. (2010). The priors for the factor loadings, Λ, are normal with relatively large variance (diffuse). In case there are identifying restriction related to an element Λ_{ij}, the prior for this element is truncated. The prior for the probability of an outlier ($2 \leq O_{i,t} \leq 20$) is Beta, set to imply a mean outlier frequency of once every 4 years. Draws from the posterior distribution are obtained via a Gibbs sampler. In particular, the restricted elements of the loading matrix are 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), Stock and Watson (2016a) and Carriero et al. (2022).

In addition, 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, conditional on a draw of model parameters, using a simulation smoother in a similar fashion as in Bańbura et al. (2015) but based on the algorithm of Carter and Kohn (1994). The obtained balanced data set can then be used in the subsequent step of the Gibbs sampler.[4]

[3] We also experimented with a specification augmented by stochastic volatility, as in Chan et al. (2022). However, this particular implementation of identification through heteroskedasticity resulted in rather counter-intuitive inflation narrative in the present case. This could be related to the issues discussed in Montiel Olea et al. (2022) and is an interesting avenue for future research. We thank Josh Chan for sharing his codes for the specification with stochastic volatility and for the implementation of outlier correction.

[4] Whereas not done here, this approach could be also used to account for missing observations at the

Finally, in the specification with monetary policy shocks we augment the model in order to identify monetary policy shocks via an internal instrument approach, following the ideas of Paul (2020), Plagborg-Møller and Wolf (2021) and Noh (2024). Let i denote the row of y_t corresponding to the internal instrument variable and j the position of the shock in F_t. We restrict the i^{th} row of the coefficient and loading matrices as follows:

$$A_{0,i\cdot} = A_{1,i\cdot}, \dots A_{p,i\cdot} = 0, \quad \Lambda_{i\cdot} = \Big[0, \dots, 0, \Lambda_{ij}, 0, \dots, 0\Big]. \tag{4}$$

In addition we impose a small prior variance for the corresponding idiosyncratic component, $\xi_{i,t}$. This allows for a measurement error in the proxy.

4 Identification of shocks

In the baseline version of the model, we identify 8 shocks, covering demand and supply drivers of inflation. On the supply side we consider shocks related to oil supply, oil-specific demand, gas prices, 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.[5]

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, relating them to the existing literature.

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

beginning of the sample.

[5] In order to identify the common component for r=8 shocks we need at least $2(r+1) = 17$ variables. In order to identify the loading matrix we further need at least $r(r-1)/2 = 28$ restrictions, see e.g., the discussion in Gorodnichenko (2005) and Korobilis (2022) and the references therein.

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.

line with the literature (see Peersman and Van Robays, 2009; Forni et al., 2015; Morana, 2017).

Oil-specific demand shocks capture fluctuations in the oil market due to uncertainty about future oil supply, changes in precautionary and speculative oil demand, and are *not* related to aggregate demand disturbances (see Kilian, 2009; Peersman and Van Robays, 2009; Caldara et al., 2019; Kumar and Mallick, 2024, among many others). A shock rising oil-specific demand results in an increase in oil prices 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 (see also Baumeister, 2023, for recent evidence for the euro area), as reflected in total and core HICP and total and energy-related producer prices, together with 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 (as modelled by Peersman and Van Robays, 2009).

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, wholesale gas prices in Europe were contractually indexed to oil prices. It was only starting around 2015 that a more visible movement towards gas being driven by gas market-specific forces and away from oil indexation occurred (for details see Box 1 in Adolfsen et al., 2022). Despite deregulation, gas and oil markets remain linked as they are shaped by common factors. As Szafranek and Rubaszek (2024) postulate, even with gas increasingly driven by its own market forces and moving away from oil indexation, a long-term link between the two markets still persists in Europe.

In our scheme, a positive gas price shock is identified via a contemporaneous increase in the euro area border gas prices (as also found or assumed in Alessandri and Gazzani, 2025; Adolfsen et al., 2024; Casoli et al., 2024; López et al., 2024), while crude oil prices are not influenced by this increase, based on results in the literature suggesting that oil prices tend not to be affected by shocks specific to natural gas markets (Ramberg and Parsons, 2012; Szafranek and Rubaszek, 2024). The rationale lies in the fact that the oil market has a larger global dimension compared to gas, which is typically traded regionally (see Alessandri and Gazzani, 2025, for details). Therefore, movements in gas prices most likely do not affect oil prices contemporaneously. 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.[6] On the other hand, there is no restriction on the contemporaneous reaction of gas prices to oil related shocks, given the links between the prices of those commodities described above.

Positive shocks related to gas prices 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 industrial production) is negatively affected. Headline inflation is also assumed to increase, while we are agnostic about core inflation.

The literature identifying the inflationary impacts of gas price shocks is still in its infancy, with a few papers approaching the topic in the post-pandemic recovery period. These studies typically focus on the implications of developments in gas markets, not identifying other types shocks, with the exception, in few cases, of oil price shocks. Focusing exclusively on the (European) gas market, Adolfsen et al. (2024) disentangle economic activity shocks from shocks in the natural gas market pertaining to supply and inventories through sign and narrative restrictions. Alessandri and Gazzani (2025) identify gas supply shocks via an external instrument based on gas market related news and high frequency changes in natural gas prices. Also not controlling for developments in oil markets, Güntner et al. (2024) study the impact of various shocks on the wholesale natural gas prices in Germany. Kilian and Zhou (2023) control for the link between oil and gas markets using a block-recursive, partially identified structural VAR to isolate shocks to

[6]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.

gasoline, diesel, jet fuel, natural gas, and electricity prices for the US. For the euro area, identification of gas price shocks in the context of other markets was firstly introduced by Casoli et al. (2024). They distinguish different types of gas price shocks in the euro area, modelling oil and gas markets as two independent energy blocks (following Rubaszek et al., 2021, for the US). Furthermore, López et al. (2024) distinguish gas supply shocks via narrative and sign restrictions, also controlling for oil price shocks (using the supply news shocks of Känzig, 2021).

These analyses find evidence of an inflationary impact of energy shocks in the euro area but there is sizable disagreement in terms of qualitative and quantitive estimates. While Casoli et al. (2024) and Alessandri and Gazzani (2025) document a similar effect of gas- and oil-related shocks on headline inflation, López et al. (2024) find a much small impact of the former. Regarding core inflation, Alessandri and Gazzani (2025) find that gas supply shocks have much larger impact compared to oil supply shocks and that they contributed around 50% to core inflation increase between 2021 and 2023.

It is important to clarify that, in contrast to the oil price case and some of the papers cited above, we do not disentangle various types of gas price shocks. We identify a generic supply-type gas price shock that creates inflationary pressures, while negatively affecting activity. It is distinct from an aggregate demand shock, which would push up domestic activity as well. Thus, the identified gas price shocks bundle gas supply shocks, as well as any remaining gas-specific demand shocks, or those linked to inventory build-up.[7]

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 chain disruptions 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 such shocks have been made (Benigno et al., 2022; Finck and Tillmann, 2022; Bai et al., 2024; Carrière-Swallow et al., 2023; Kabaca and Tuzcuoglu, 2023; Ascari et al., 2024; De Santis, 2024). These studies generally rely on a set of sign and narrative restrictions (Kabaca and Tuzcuoglu, 2023, also set restrictions on the variance decomposition) 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. By contrast, we identify global supply chain shocks within our encompassing approach.

We identify negative global supply chain shocks as those leading to shipment delays

[7]One challenge in distinguishing between various types of gas price shocks is that, as argued by e.g. Alessandri and Gazzani (2025), due to particular features of gas markets quantities might offer only a noisy signal on gas-specific demand.

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 in the product market and reflect increases in shipping costs other than those linked to energy prices.

Compared to other studies for the euro area (e.g. Ascari et al., 2024; De Santis, 2024) we do not need to resort to narrative restrictions and we target the identification of the shocks for the euro area by using the euro area PMI supplier delivery times. Importantly, we identify a larger number of shocks in a more encompassing information set and we clearly distinguish global supply chain bottleneck shocks from different types of energy shocks.

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. A labour market shock has a negative impact 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 aspects linked to labour supply, wage-bargaining, and matching efficiency (Peersman and Straub, 2009; Furlanetto and Groshenny, 2016; Foroni et al., 2018; Bobeica et al., 2019; Consolo et al., 2023). Output and wages negatively co-move and this restriction is key to distinguish shocks in the labour market from aggregate domestic supply (technology) shocks. The rationale behind 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 wages and output to labour market shocks can be explained by firms having trouble finding workers (due to an exogenous decrease in labour supply), 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 to 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 domestic supply shocks.

To distinguish the 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.[8]

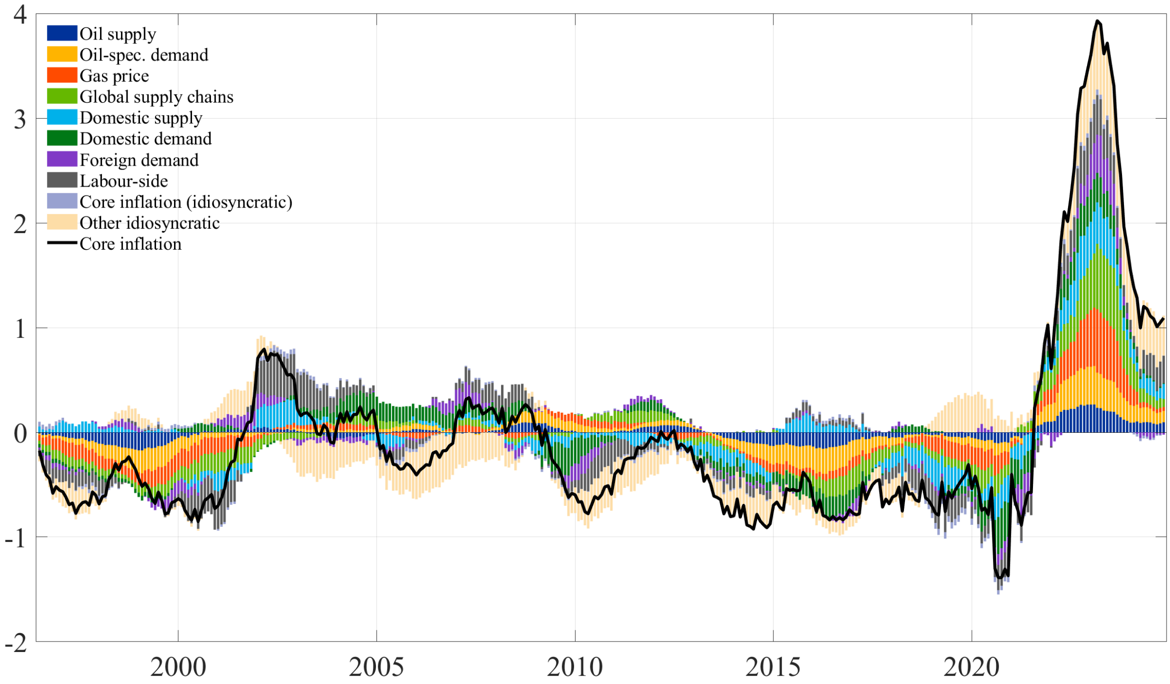
5 Drivers of core inflation

Figure 1 shows the contributions of the identified shocks to the fluctuations of year-on-year core inflation over time.[9] Overall, the post-pandemic 2021-2023 period was a perfect storm with large inflationary shocks occurring from different sources (Figure B.1 in B zooms on the most recent sample). Following the pandemic, much of the deviation of core inflation from its model-implied mean (of around 1.6%) comes from supply-side shocks, in particular those related to more global developments (energy and global supply chains).

[8]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 contemporaneously; (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.

[9]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. Whereas the model is estimated on month-on-month inflation rates, for clarity of exposition all historical decompositions are reported in year-on-year terms.

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).

Energy shocks explain about a third 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 the energy shocks share. While sizable, this estimate is much lower than the 50% of variation in core inflation explained by gas supply shocks reported in Alessandri and Gazzani (2025). Interestingly, the drivers behind the surge of oil and gas prices were somewhat different, see Figure B.2 in B.[10] A combination of demand and oil-related shocks were the main drivers of the rise in oil prices between 2021-2022, while the subsequently decline in oil prices was strongly driven by demand shocks. On the other hand, the contribution of gas price shocks to the fluctuations in oil prices was negligible, as also found by Rubaszek et al. (2021). In contrast, gas prices were strongly affected by gas-specific shocks. This is not surprising, given the less global character of natural gas markets and the ramifications of the Russian invasion of Ukraine for the supply of gas in Europe.[11]

Global supply chain shocks also had a sizeable impact in the post-pandemic inflation-

[10] Charts of the historical decompositions of other variables are available upon request.

[11] Adolfsen et al. (2022) also mention other drivers of European gas prices, for example, a colder than usual period at the end of 2020 and in the first half of 2021 as well as low winds during the summer, which led to the substitution from wind-generated to gas-generated energy. See also OIES (2022) and related reports.

ary episode, especially as of mid-2022 contributing with around 0.6 percentage points to the deviation of core inflation from its peak. Studies that identify a smaller number of shocks find a larger role for these bottlenecks (e.g. Ascari et al., 2024, find a contribution of around 2 percentage points to the deviation of total euro area inflation excluding energy at the peak). As can be seen in Figure C.1 in C gas price and global supply chain shocks have been particularly large since the start of the pandemic. This justifies the increased attention that these shocks have received in recent literature and policy circles.

Also in the case of headline inflation, our results indicate a larger contribution of the supply compared to the demand shocks, see Figure B.3 in B. This is in contrast to other studies, such as Giannone and Primiceri (2024) and Bergholt et al. (2024), who however only consider generic demand and supply shocks.

Focusing on periods outside the post-pandemic inflation surge, our model also sheds light on the drivers of previous important episodes for euro area inflation. 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. Energy shocks had a notable negative contribution during the period that followed the euro area sovereign debt crisis and the 2014-2015 oil price slump, when most shocks had a disinflationary impact.

Labour-market shocks were an important driver of low core inflation after the sovereign debt crisis and during the COVID-19 outbreak, reflecting the pass-through from low wage growth due to the implementation of reforms to labour market institutions and job retention schemes, respectively.

D shows the results of a specification augmented with food prices and food price shocks. The overall narrative for core inflation is very similar compared to the baseline specification,[12] with food price shocks having a rather limited impact (see Figure D.1). An interesting insight is that, according to the model, energy price shocks have been an important driver of consumer food prices after the pandemic (see Figure D.2).

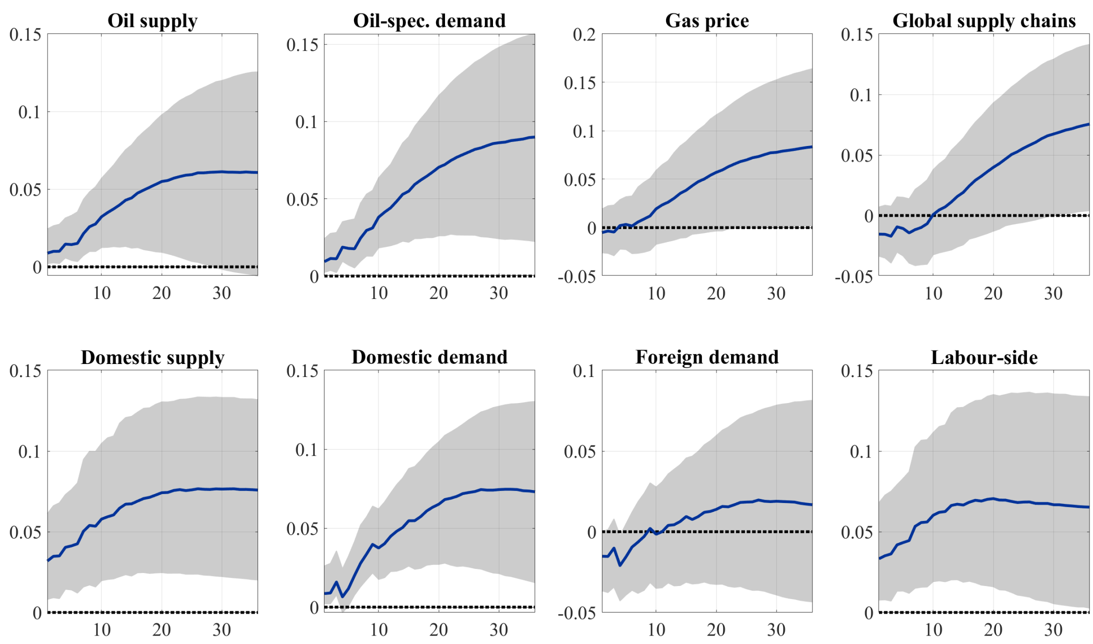
Even when considering numerous types of inflationary shocks, part of the post-pandemic increase in core inflation is unexplained. This shows up as a sizeable contribution of the idiosyncratic component of the reduced-form residuals (also stemming from other variables than core inflation). Beside the large contribution exhibited in the post-pandemic inflation surge, there is also a considerable share of idiosyncratic factors during great financial crisis and the low-inflation period between 2014-2019. This unexplained part is mainly associated to idiosyncratic factors not linked to core inflation, which are propagated through the dynamics of the model. Such idiosyncratic factors 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

[12] F shows that the results are also robust to different estimation samples.

using the chosen variables, 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; Bobeica et al., 2025). 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.

Figure 2 zooms into the cumulative responses of core HICP to the eight identified shocks up to three years ahead.[13] The impact of global supply chain shock appears to have very persistent effects, in line with previous findings (see Ascari et al., 2024). 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 contributing positively by the end of the sample (also shown in Figure B.1).

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).

[13]A full overview of the median contemporaneous impact of the shocks on the full data set is shown in Table C.1 in the Appendix.

The pass-through of energy shocks to consumer prices is lower than the pass-through to producer prices (see impulse responses in Figures C.2-C.7). 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 shocks to headline inflation is stronger than the pass-through to core inflation (Figures C.2-C.7). Conversely, certain shocks fade quicker from headline inflation, whereas the impact on core or services inflation is more persistent, reflecting the impact of second-round effects. For example, Figure B.3 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 (Figure B.4) it is still strong.

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.

6 Core inflation and monetary policy

6.1 Supply shocks and core inflation

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.[14]

Eliminating the influence of certain inflationary shocks in the aftermath of the COVID-

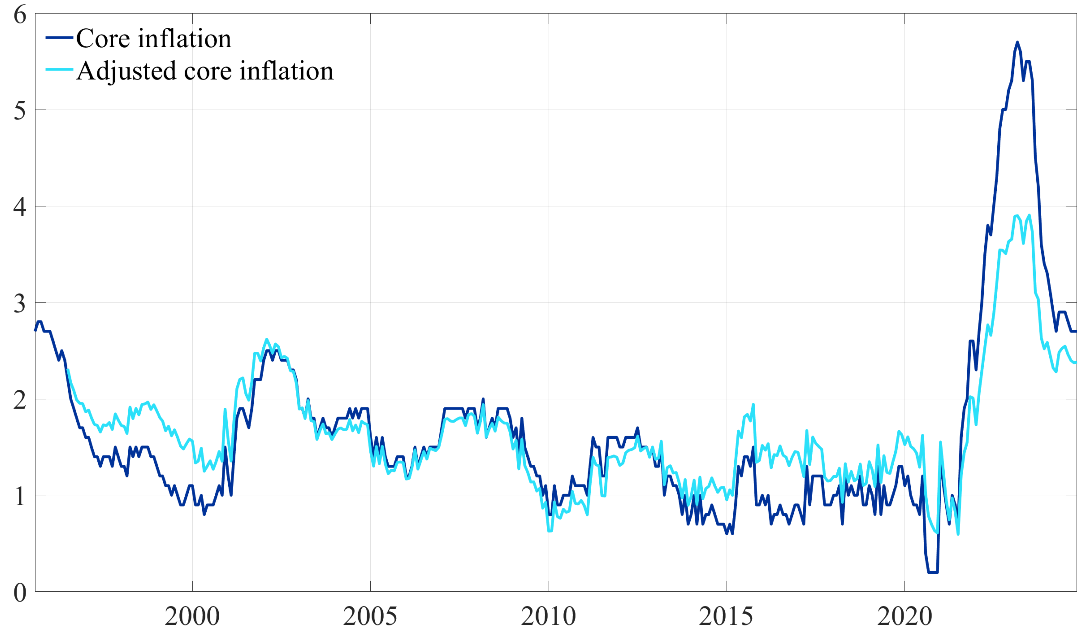
[14]Lane (2023) notes that in the post-pandemic period underlying inflation was significantly affected by a reverting component that was sufficiently long-lasting not to constitute pure noise but that can also be expected to fade out over the near term and hence policy makers should see through this.

19 pandemic is not straightforward and the result is surrounded by the inherent model and estimation uncertainty. Figure 3 compares core inflation with its adjusted 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, euro area core inflation adjusted for energy and global supply chain shocks was closer to 2% than the official statistic. Turning to the latest sample, adjusted core inflation is significantly lower but still exhibits a strong increase.[15] This suggests that there were indeed important shocks other than energy or global supply chain that played an important role during the surge and/or the transmission of these shocks was stronger. Such an exercise can be performed for any measure of underlying inflation, as shown in Figure E.2 in E. 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, covering exclusion- and model-based measures. When subtracting the contribution of shocks linked to energy and global supply chain bottlenecks the range of the considered underlying inflation measures would have been much narrower and lower during the post-pandemic inflation surge.

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 to 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 B.4 shows that also in the case of services supply-side shocks played a prominent role.

[15] Figure E.1 in E reports the uncertainty surrounding these contributions. In particular, one panel shows a significant contribution of the (sum of) energy and global supply chain shocks at the beginning of the sample and in the low and high inflation period (starting in 2015). The other panel shows a very narrow uncertainty surrounding the contribution of the deterministic component (see the discussion in Bergholt et al., 2024).

Figure 3: Core inflation and its adjusted measure free of energy and global supply chain shock effects



Note: The adjusted measure of core inflation assumes the absence of shocks linked to oil supply, oil-specific demand, gas price, and global supply chains.

6.2 Impact of monetary policy on core inflation

In this section we 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 variable in the VAR, following the internal instrument approach in the spirit of Paul (2020), Plagborg-Møller and Wolf (2021) or Noh (2024). Specifically, we restrict the coefficients and the loading matrix as explained in Equation (4). For normalisation, we set that the proxy 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).[16] Details of the identification scheme are provided in Table 3.

[16]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).

Table 3: 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									

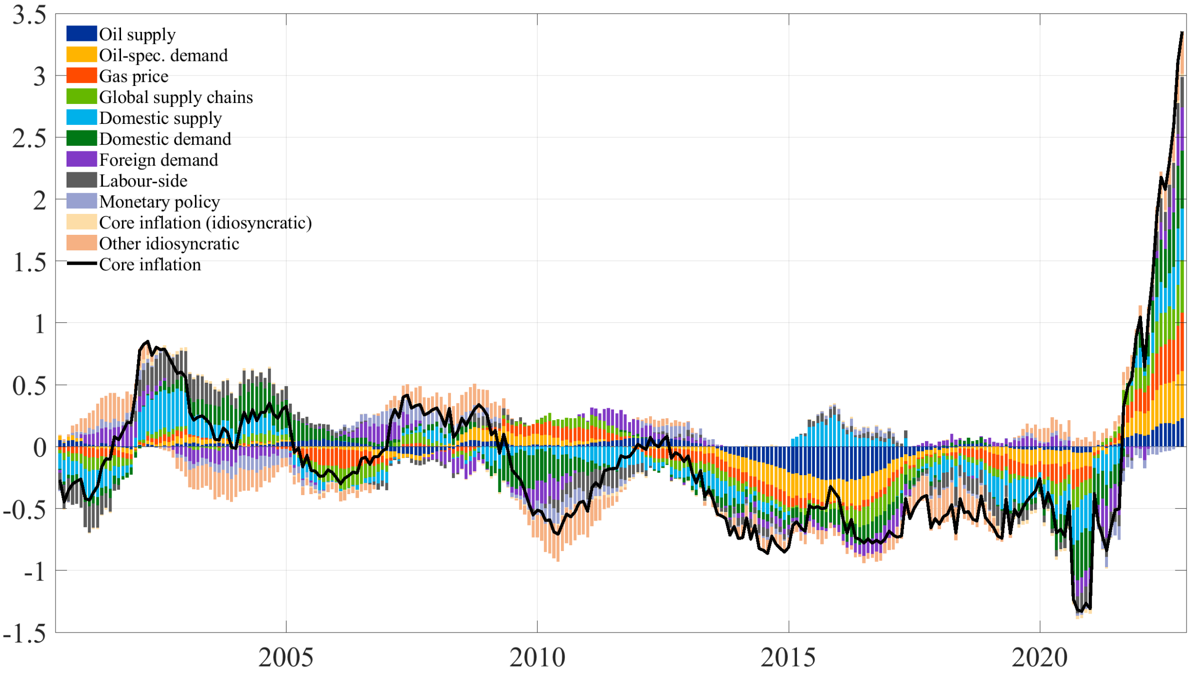
We present the results from this specification in Figure 4.[17] Our baseline results remain robust to the inclusion of the monetary policy shock. In particular, the correlations between the structural shocks estimated within the 8-shock baseline model and this augmented version are very high for all 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 ECB monetary tightening cycle to tackle the inflation surge.

It is important to note that the estimated contribution of the identified monetary policy shocks to core inflation has been overall small. A straightforward explanation is that monetary policy has been affecting core inflation mainly via its systematic component. Given the small impact of the shocks also in the recent period, it appears that there were no substantial differences in the systematic reaction compared to the past.

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

[17] The estimation is carried out with data spanning from January 1999 to October 2022, governed by the availability of the proxy. Alternatively, following Noh (2024) we could set the proxy to zero before 1999, without a change to the point estimates. In addition, we do not conduct the nowcasting step - as the proxy is only linked to a single shock, there is not enough information (from the timely variables) to get good predictions for it.

Figure 4: 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).

the idiosyncratic component compared to the baseline specification. This might indicate uncertainty related to the identification of monetary policy effects in particular, and more generally, highlight the fact that enlarging the model might on occasions introduce noise.

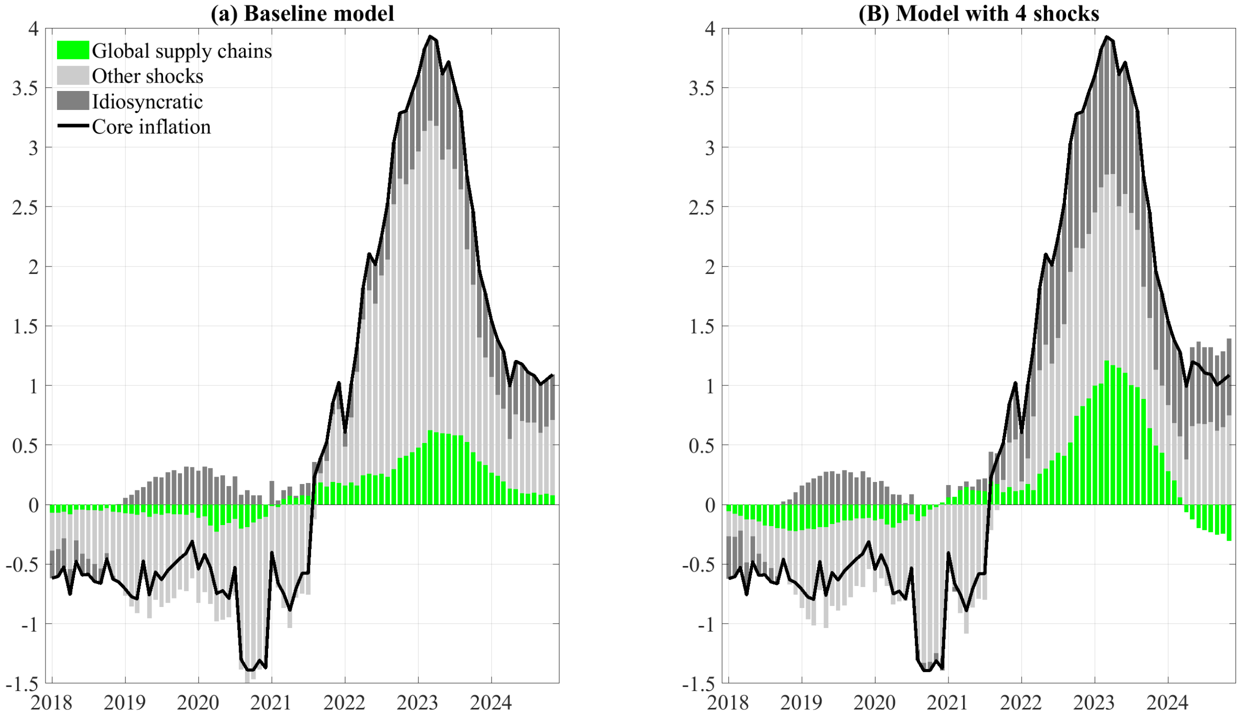
7 Size of the model and role of the global supply chain shocks

The post-pandemic inflation 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 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 4 for details). Figure 5 shows that in a smaller model the contribution of the global supply chain shock is exaggerated compared to our baseline model, especially over the high inflation period. Furthermore, the share of the idiosyncratic component is substantially larger for the smaller model during and after the post-pandemic inflation surge. 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.

Table 4: 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				

Figure 5: Global supply chain shocks – contributions to core inflation based on the baseline model and on a smaller model



Note: The chart shows the point-wise mean of the posterior distribution of the contributions to the historical decomposition of core inflation. The smaller model is based on the identification of four shocks using 13 variables, while our baseline model uses 17 variables and identifies eight shocks. The bars in green, light gray, and dark gray denote the contributions from global supply chains, the sum of other shocks identified in each model, and the sum of idiosyncratic components, respectively. The charts shows the annual % change of inflation, in deviations from the mean and from the contribution of initial conditions).

8 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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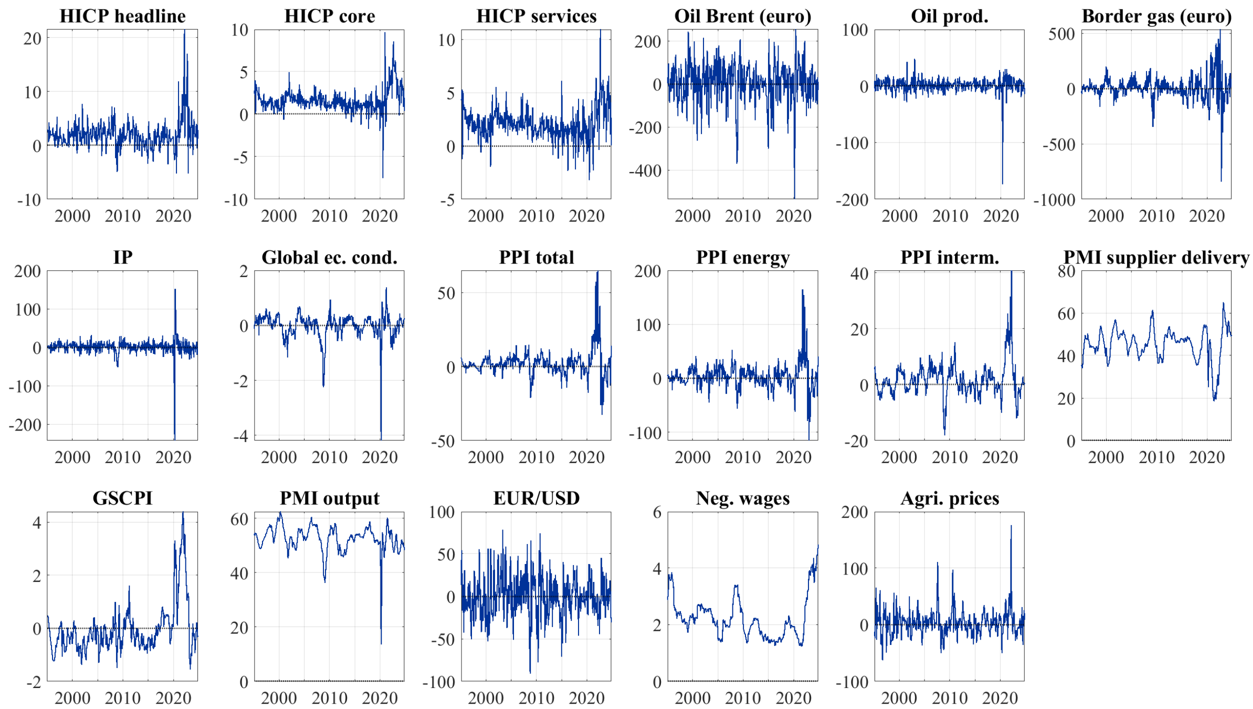
A Data

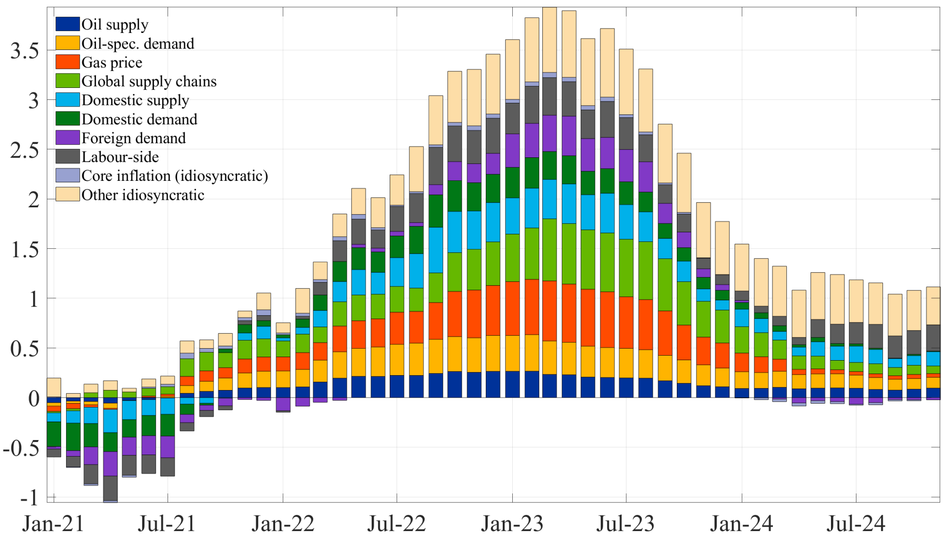
Figure A.1: Time series plots of the data



Note: Most series are portrayed in annualised month-on-month growth rates, except for the global economic conditions index of Baumeister et al. (2022), PMI supplier delivery times, PMI output, the GSCPI, and the indicator of negotiated wages.

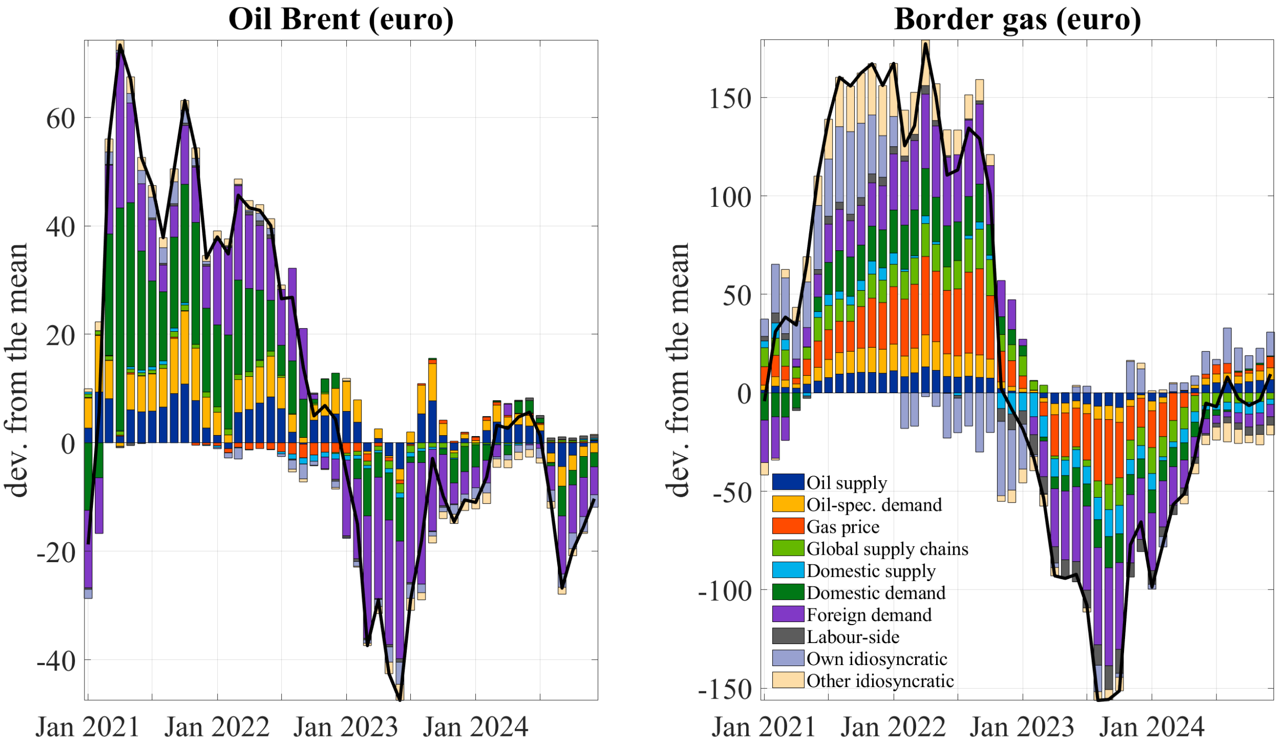
B Historical decomposition, additional results

Figure B.1: Drivers of core inflation as of January 2021



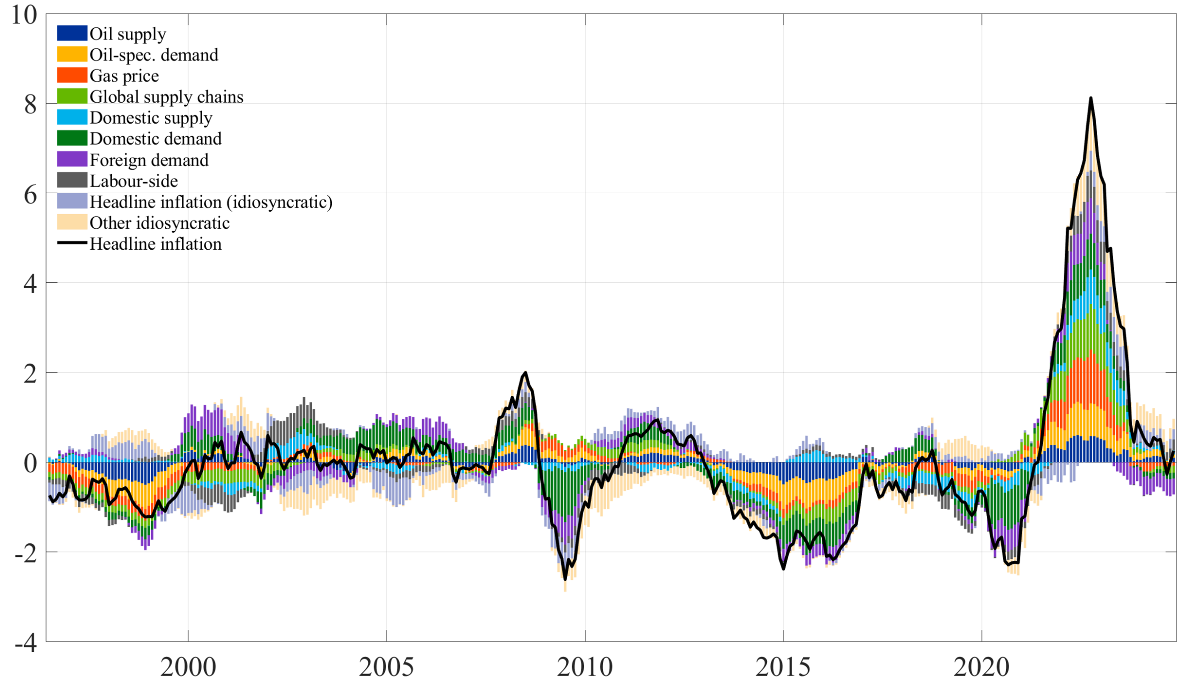
Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of core inflation (annual % change, in deviations from the mean and from the contribution of initial conditions).

Figure B.2: Historical decomposition of oil Brent prices (in euro) and border gas prices (in euro) after 2021



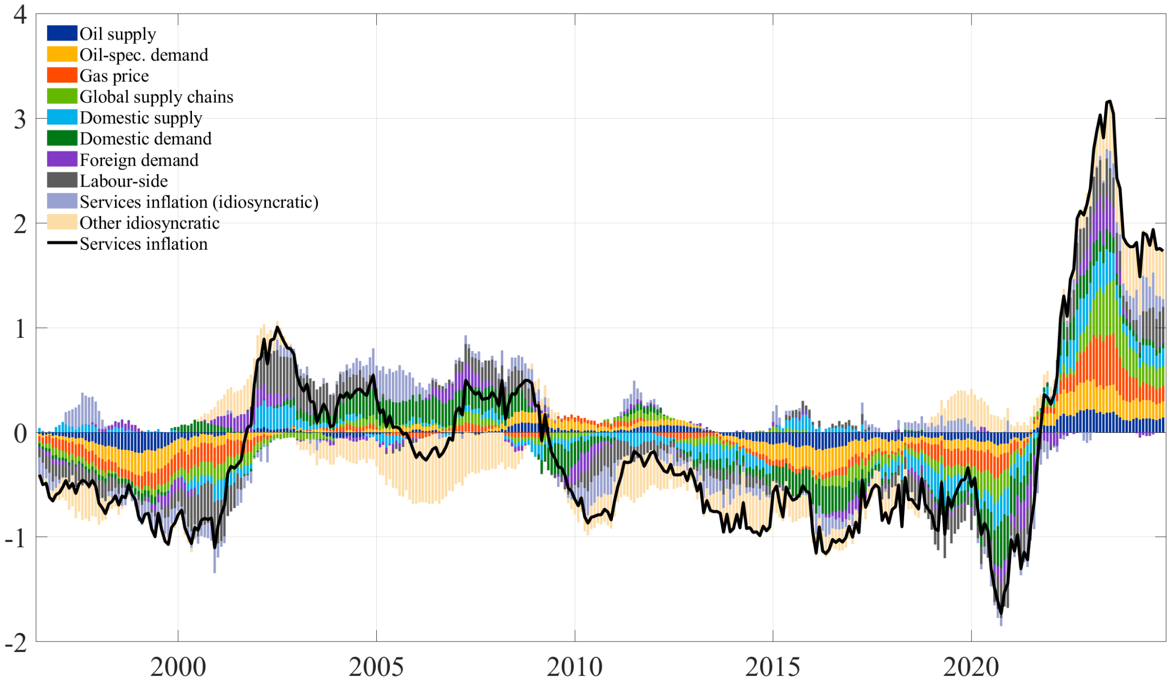
Note: The chart shows the point-wise mean of the posterior distribution of the historical decomposition of oil and gas prices after 2021 (annual % change, in deviations from the mean and from the contribution of initial conditions).

Figure B.3: 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).

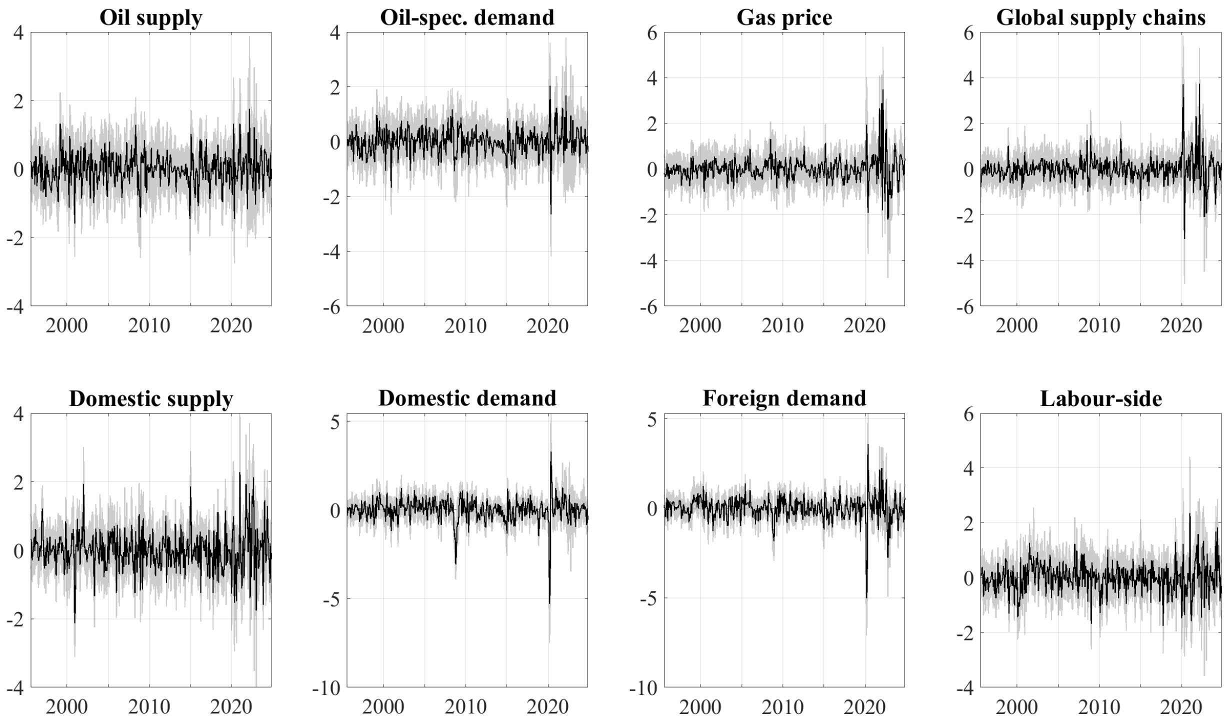
Figure B.4: Historical decomposition of services inflation



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).

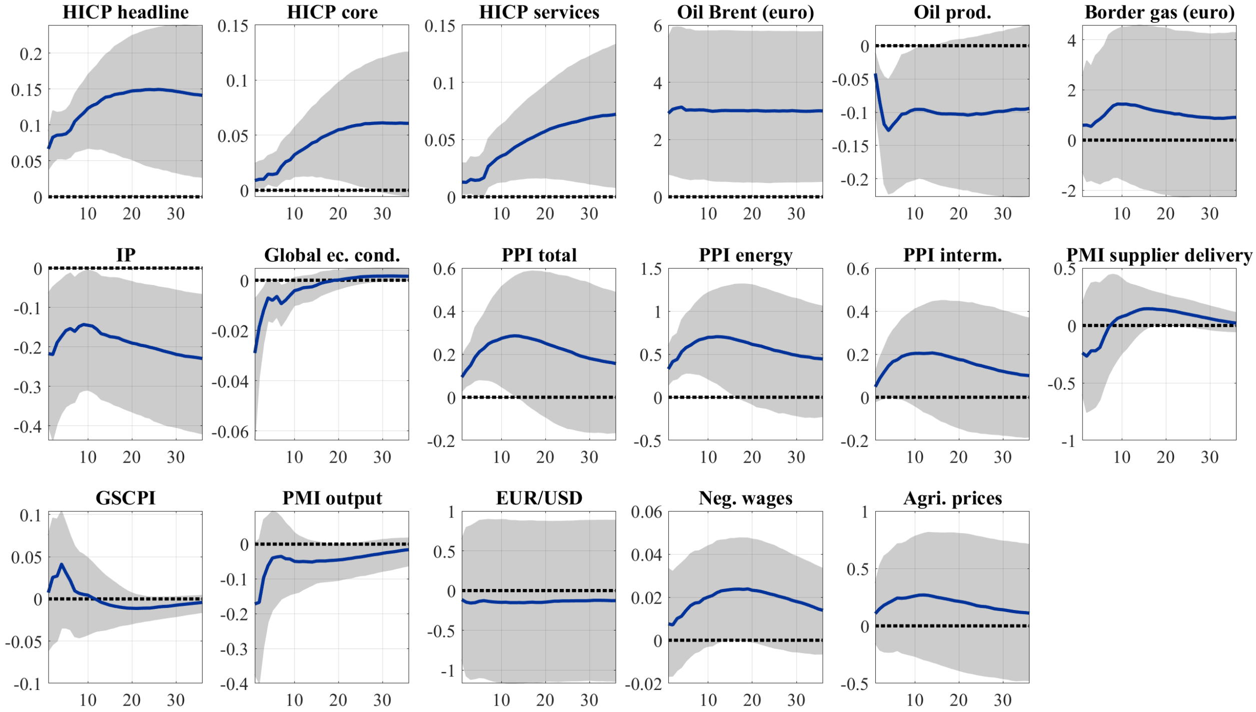
C Estimated shocks, impulse response functions and factor loadings (impact effects)

Figure C.1: Estimated factors (shocks)



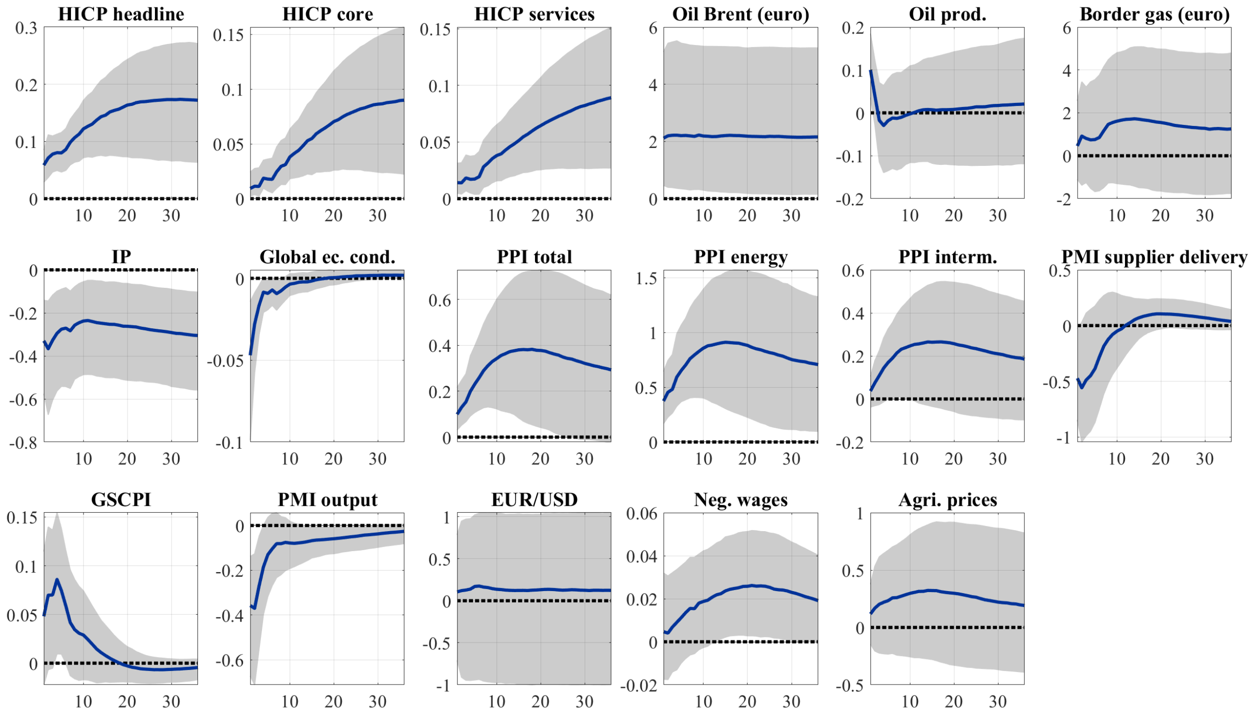
Note: The chart reports the median of the factors' posterior distribution (black line) and the 68% credibility bands (gray shaded areas).

Figure C.2: Impulse responses to oil supply shocks



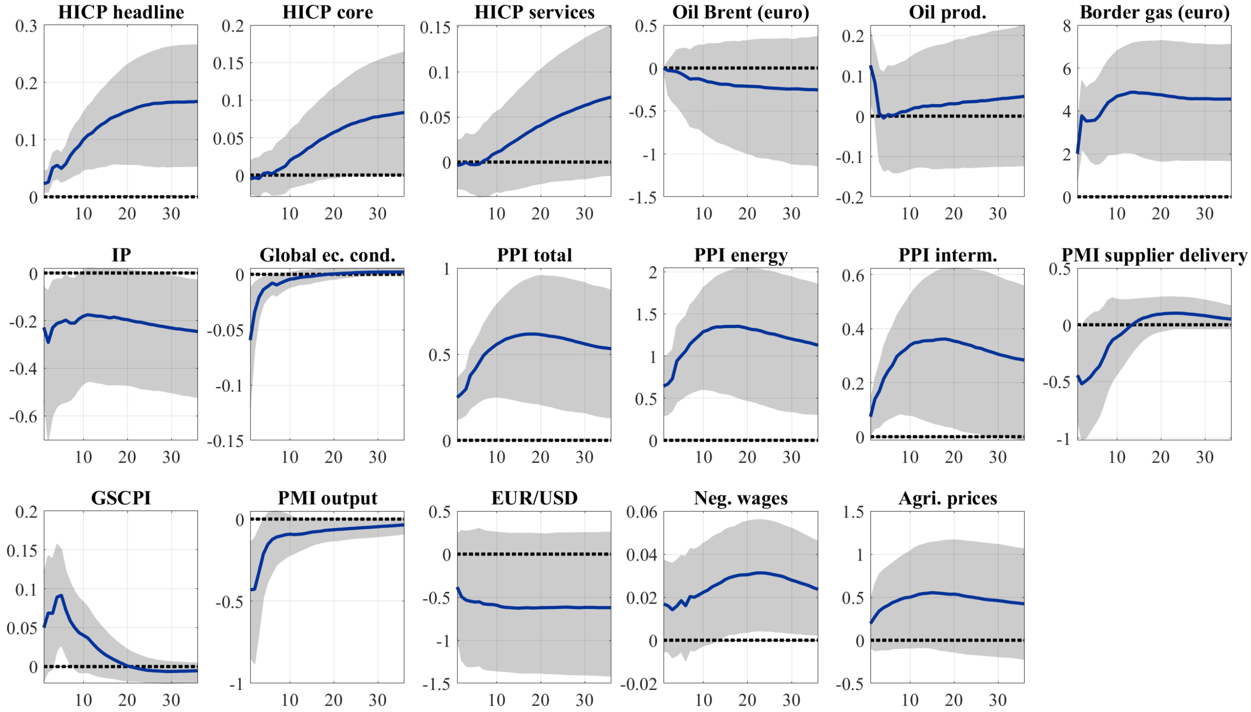
Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Figure C.3: Impulse responses to oil-specific demand shocks



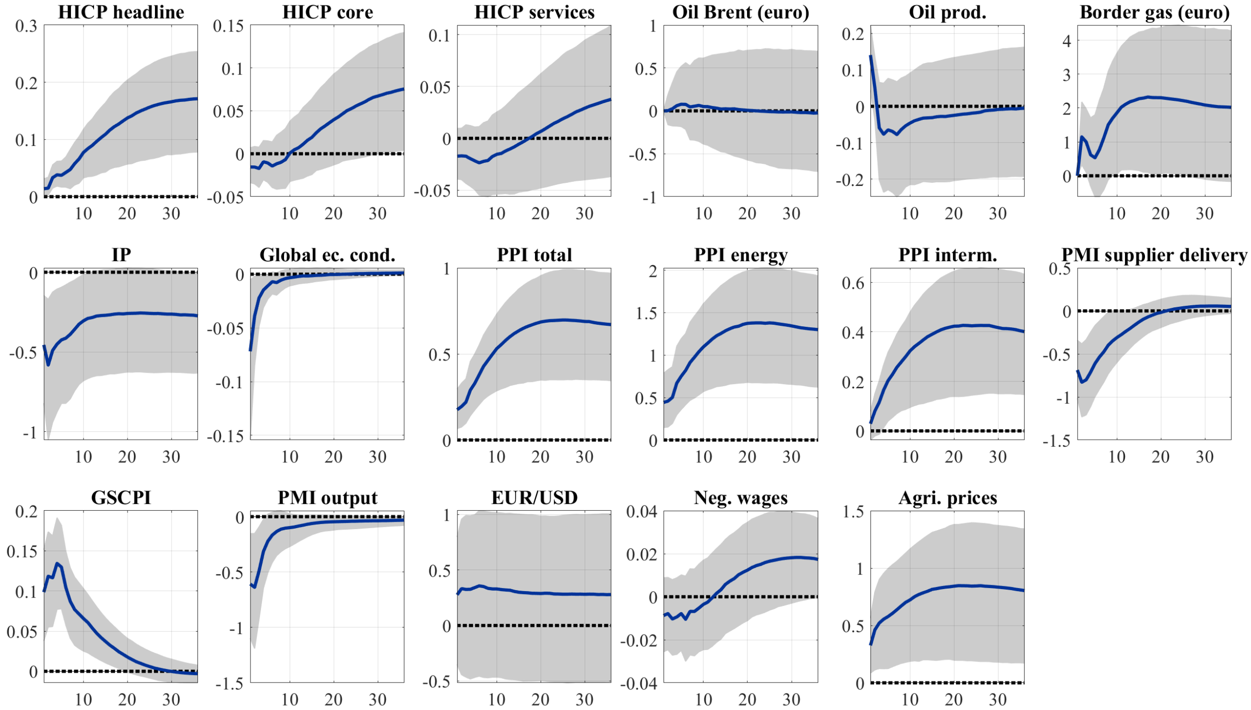
Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Figure C.4: Impulse responses to gas price shocks



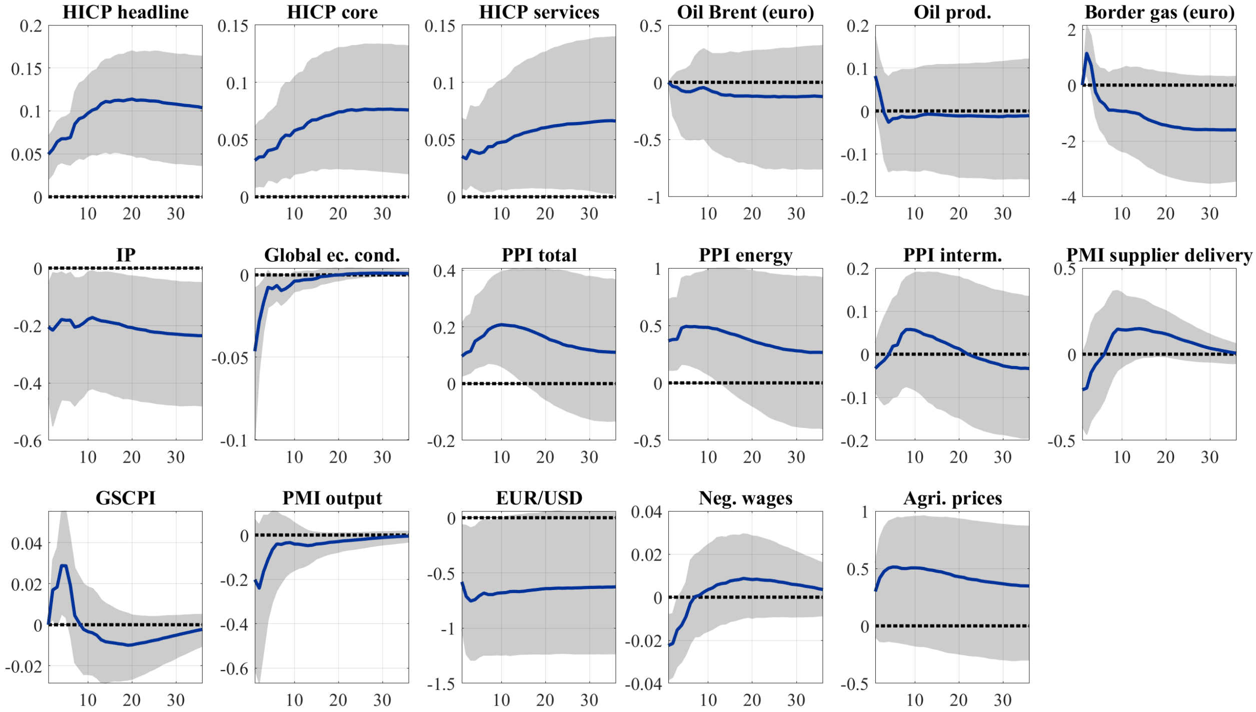
Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Figure C.5: Impulse responses to global supply chains shocks



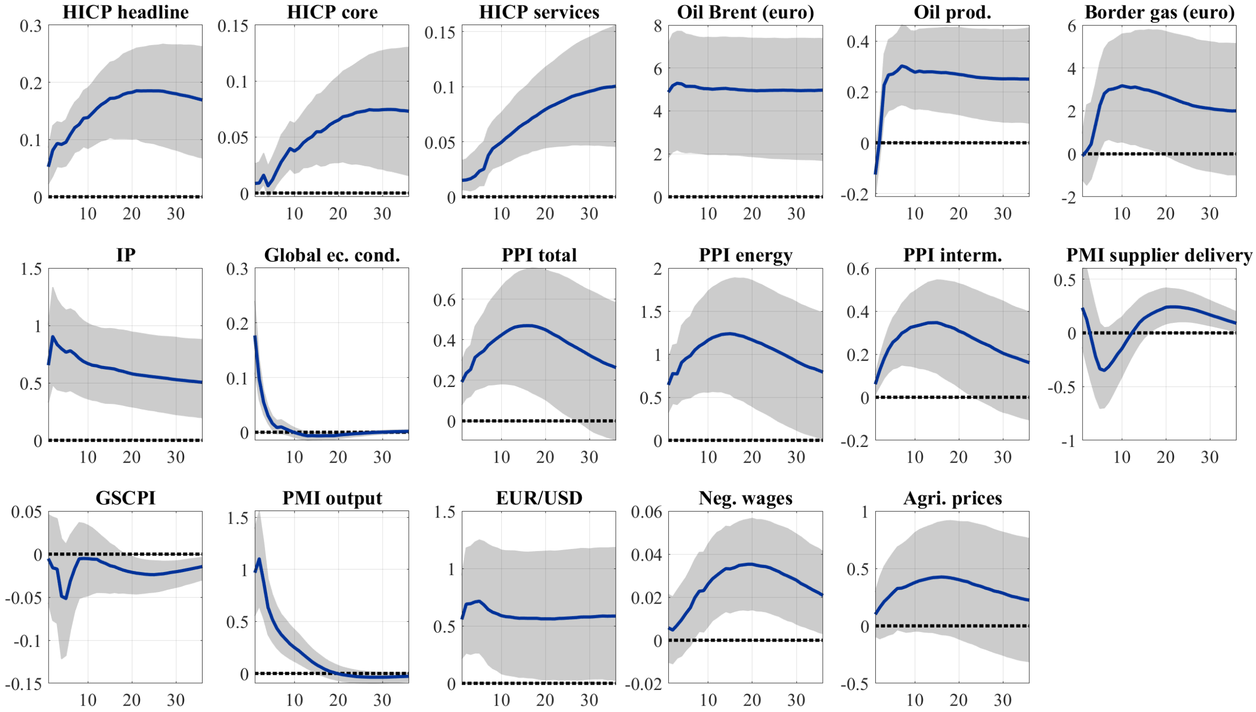
Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Figure C.6: Impulse responses to domestic supply shocks



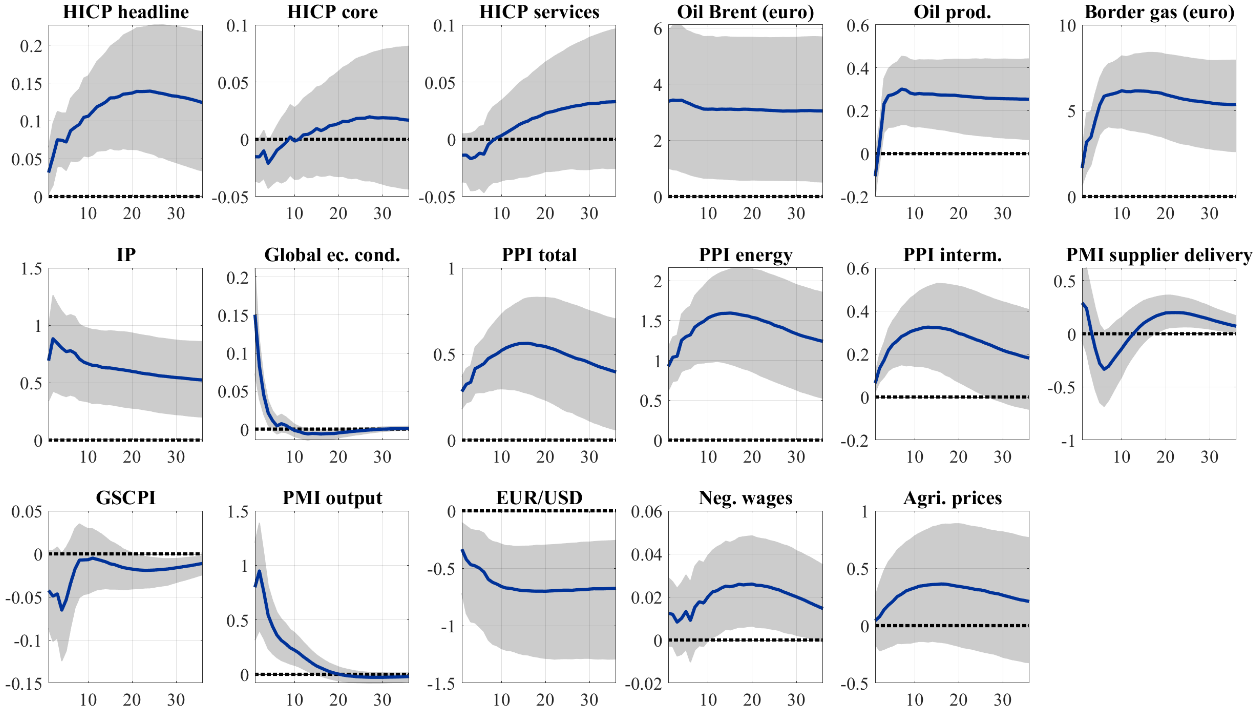
Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Figure C.7: Impulse responses to domestic demand shocks



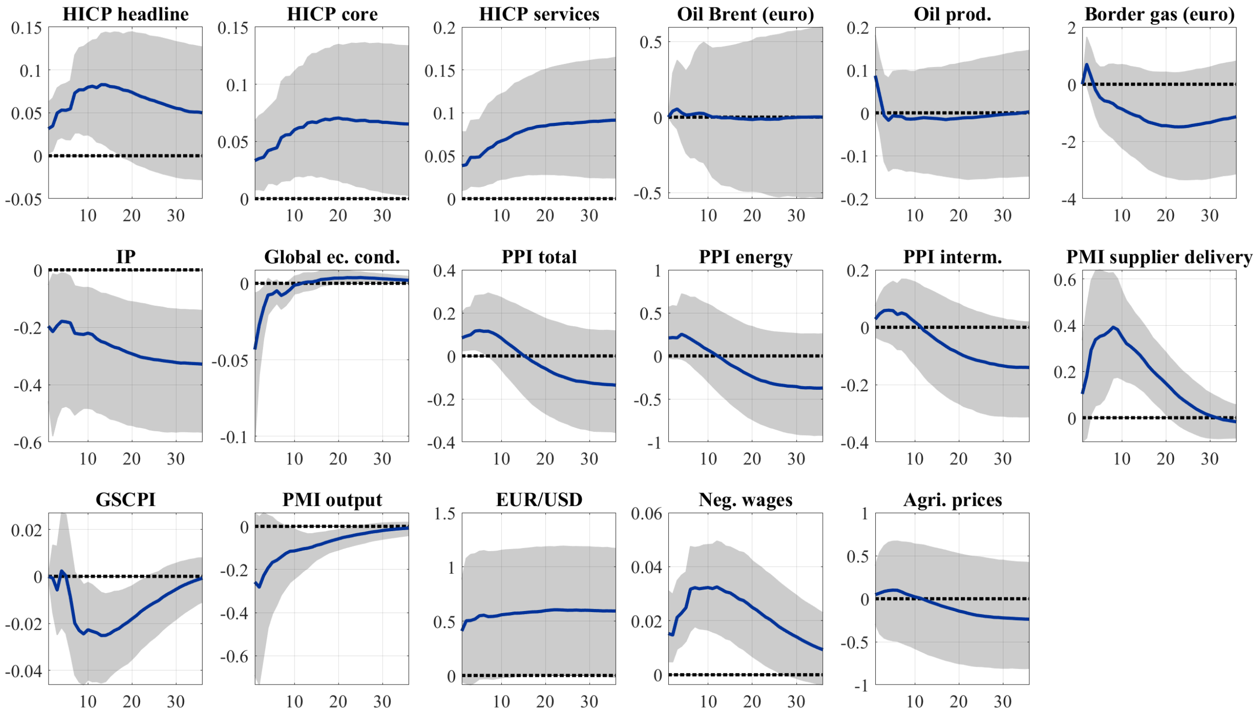
Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). We cumulate the IRFs for the variables transformed to growth rates.

Figure C.8: 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 C.9: 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 C.1: 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	0.28	0.25	0.11	0.08	0.21	0.14	0.24	0.15
HICP Core	0.11	0.11	-0.03	-0.10	0.28	0.30	0.11	-0.14
HICP Services	0.13	0.13	-0.02	-0.11	0.29	0.32	0.15	-0.12
Oil Brent (euro)	0.37	0.31	0.00	0.00	0.00	0.00	0.53	0.41
Oil prod.	-0.05	0.09	0.11	0.12	0.07	0.08	-0.10	-0.09
Border gas (euro)	0.06	0.07	0.21	0.00	0.00	0.00	-0.01	0.17
IP	-0.13	-0.19	-0.16	-0.26	-0.14	-0.13	0.36	0.36
Global ec. cond.	-0.07	-0.11	-0.13	-0.16	-0.11	-0.11	0.35	0.30
PPI total	0.14	0.15	0.31	0.23	0.15	0.14	0.25	0.35
PPI energy	0.17	0.19	0.31	0.22	0.19	0.12	0.31	0.43
PPI interm.	0.09	0.06	0.13	0.05	-0.06	0.04	0.11	0.13
PMI supplier delivery	-0.03	-0.06	-0.06	-0.09	-0.03	0.01	0.03	0.04
GSCPI	0.01	0.05	0.05	0.10	0.00	0.00	0.00	-0.04
PMI output	-0.04	-0.08	-0.10	-0.13	-0.05	-0.06	0.20	0.16
EUR/USD	-0.05	0.02	-0.17	0.11	-0.25	0.19	0.27	-0.19
Neg. wages	0.01	0.01	0.02	-0.01	-0.03	0.02	0.01	0.02
Agri. prices	0.06	0.06	0.10	0.16	0.13	0.03	0.05	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.

D 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.[18]

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 D.1. An increase in farm-gate price inflation[19] 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.

[18]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.

[19]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.

Table D.1: Augmented identification with food price shocks

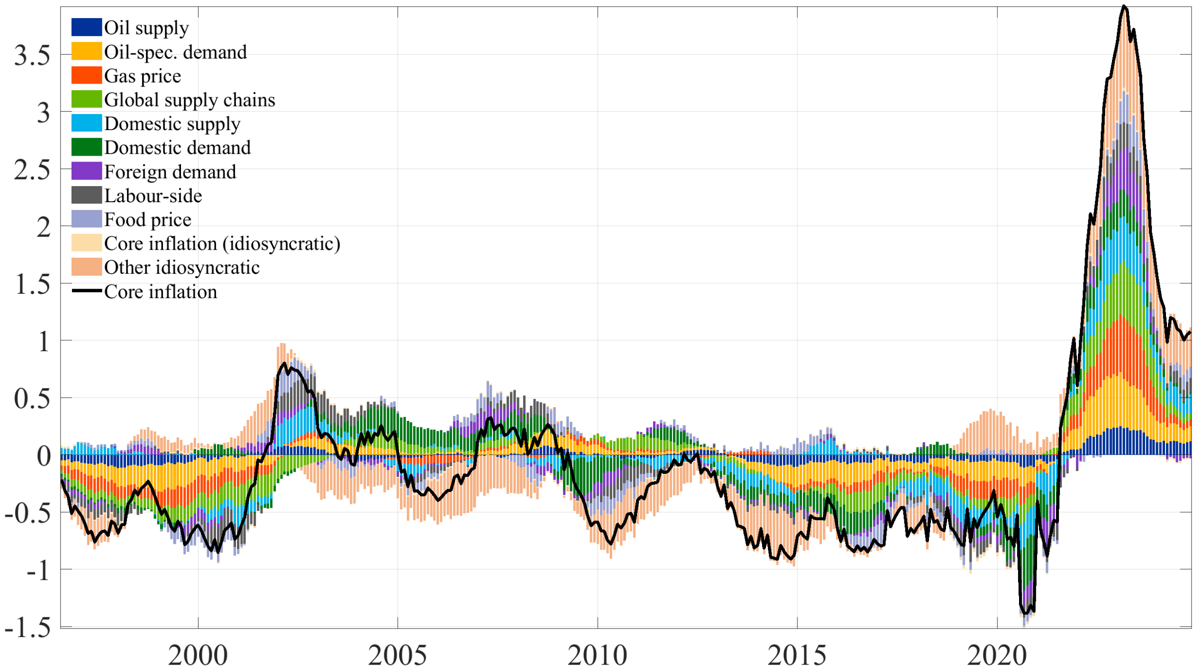
	Supply							Demand	
Variable	**Oil Supply**	**Oil-spec. Demand**	**Gas Price**	**Global Supply Chains**	**Supply**	**Labour-side**	**Food Price**	**Aggregate Demand**	**Foreign Demand**
HICP-Headline	+	+	+	+	+		+	+	
HICP-Food				0			+		
HICP-Core	+	+			+			+	
HICP-Services						+			
Oil Brent (euro)	+	+	0	0	0	0			+
Oil prod.	-	+					0		
Border gas (euro)			+	0	0	0	0		
IP	-	-	-	-	-	-		+	
IP food							-		
Global ec. cond.	-	-							+
PPI	+	+	+	+	+	+		+	+
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							+		

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 supply chain shocks (see Figure D.1).

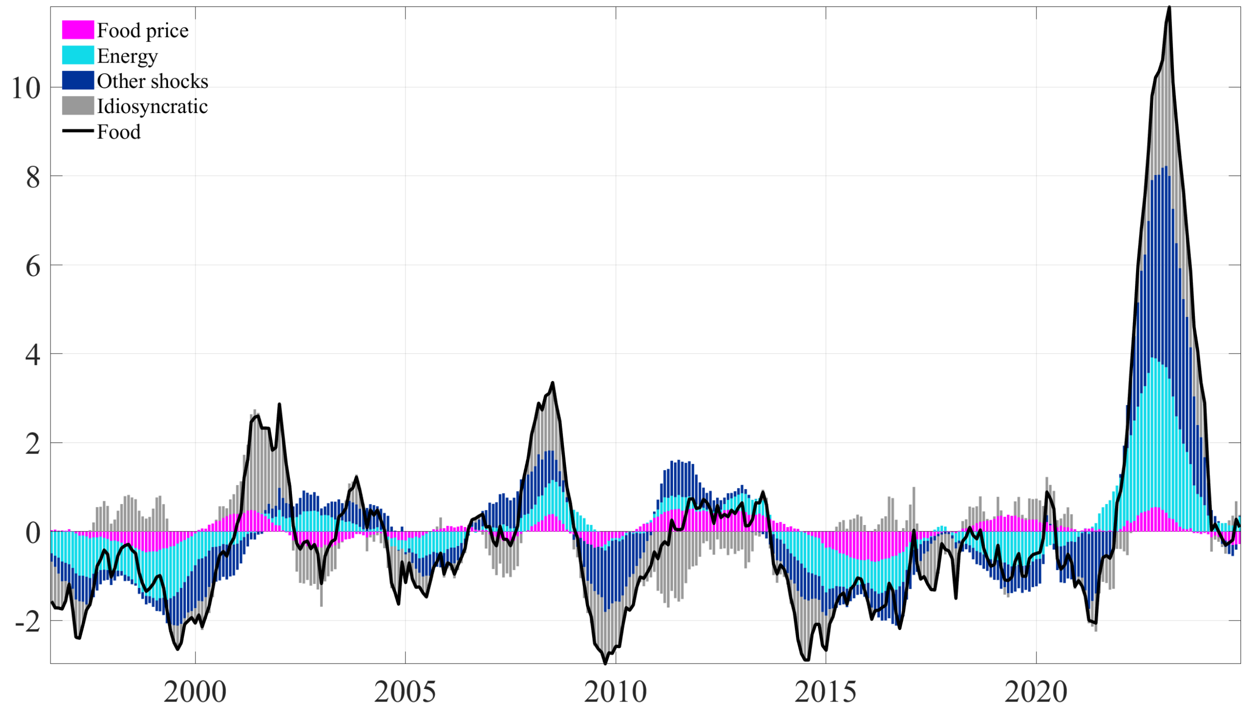
An interesting by-product of this specification is the historical decomposition of consumer food price inflation (see Figure D.2). The main drivers of consumer food prices turn out to be not that different compared to other consumer prices. Energy-related shocks exhibit a stronger contribution than those 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 D.2 is that energy costs play a sizeable role also for this component.

Figure D.1: 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).

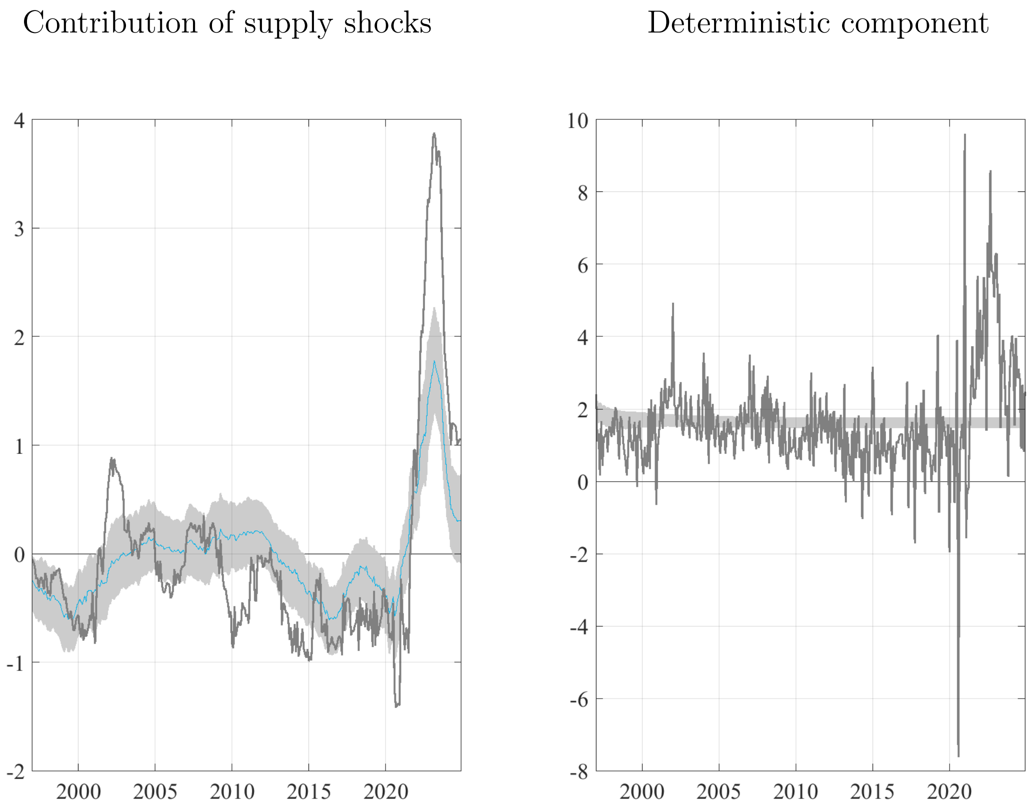
Figure D.2: Historical decomposition of food inflation



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).

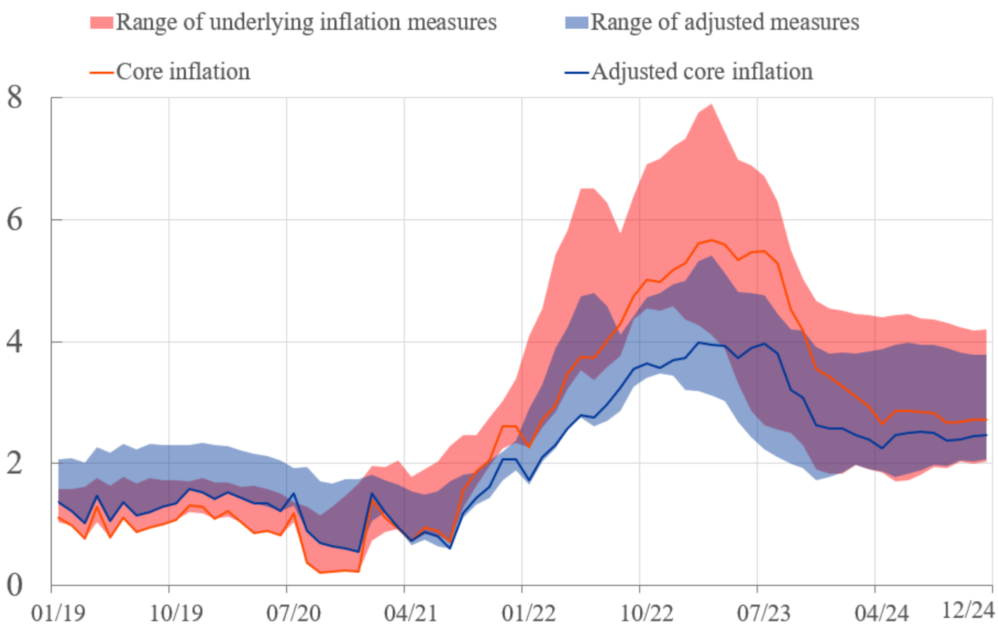
E Underlying inflation measures and their counterfactual estimates free of certain supply-side shocks

Figure E.1: Uncertainty around the historical decomposition of core inflation



Note: The chart reports the median of the posterior distribution (blue line) and the 68% credibility bands (gray shaded areas). Black lines show core inflation. Left hand panel: contribution of the sum of global supply chain and energy shocks to core inflation (in annual % change, in deviations from the mean and from the contribution of initial conditions). Right-hand panel: the estimates of the deterministic component (sum of the mean, the intercept and the initial conditions) for core inflation (in monthly % changes).

Figure E.2: 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.

F 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 - December 2024) 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 F.1. 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.

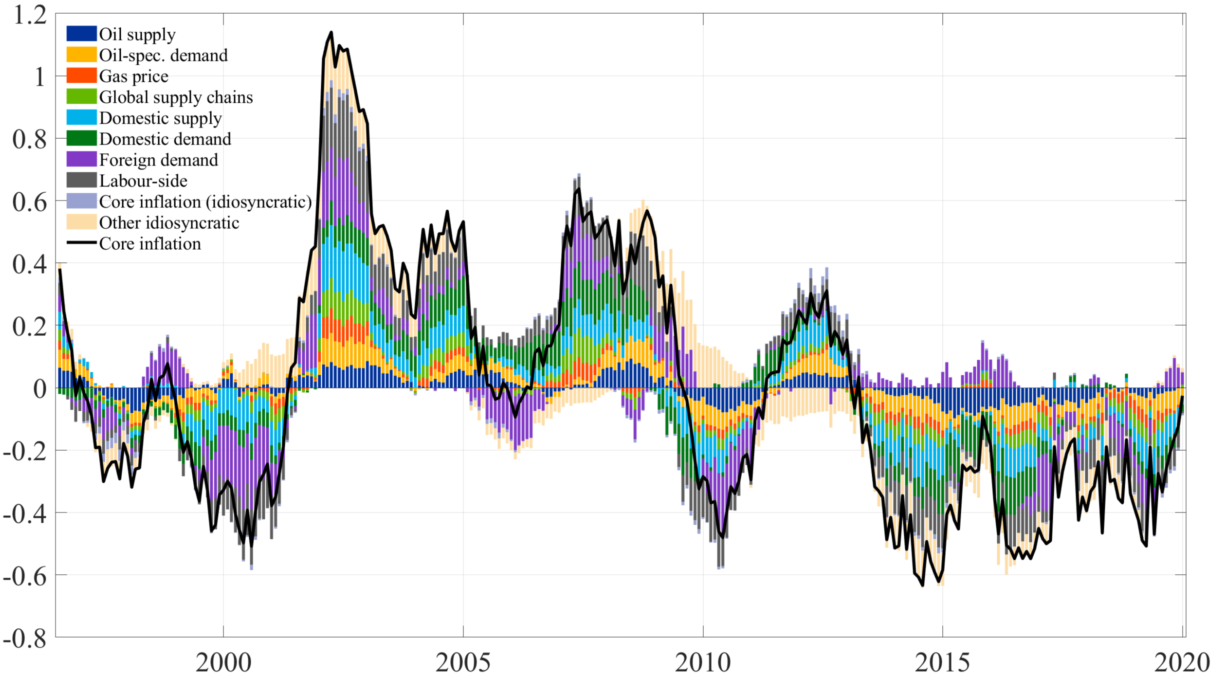
Table F.1: Correlation of shocks across samples

	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.

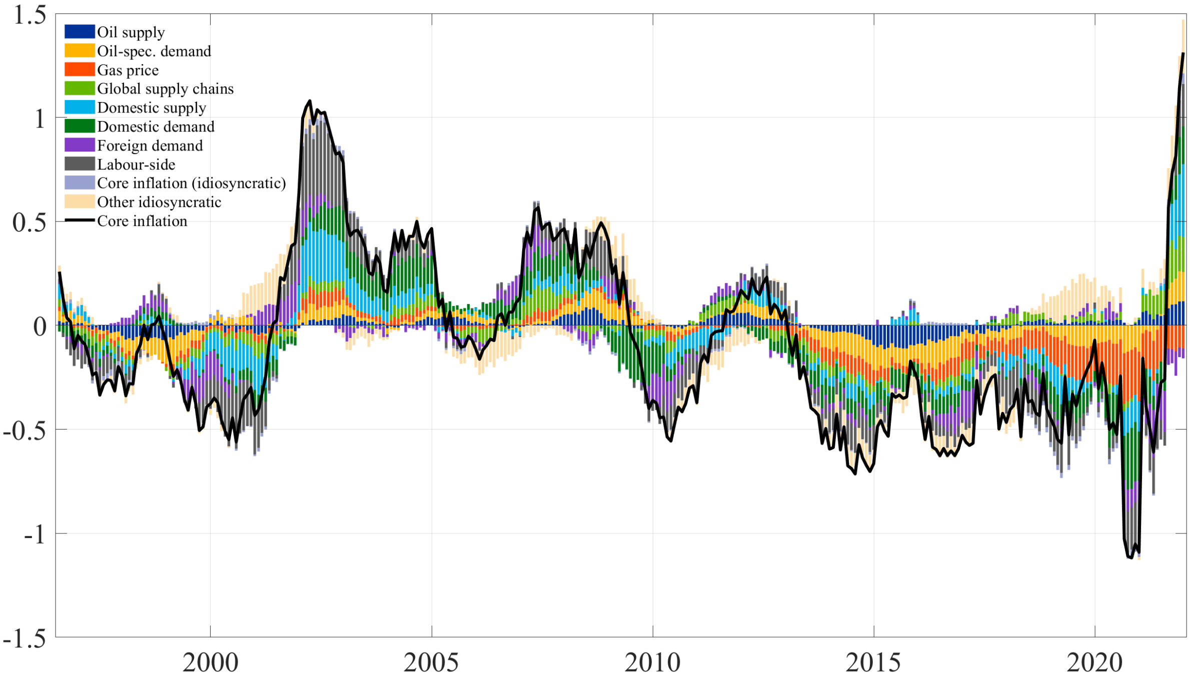
Historical decompositions remain robust to the exclusion of (post-)pandemic periods, see Figures F.1 and F.2. As shown in the charts, the contributions of the various drivers remain roughly similar across different estimation samples (for the overlapping periods), suggesting that the model is able to convey a robust narrative on what drove inflation in the euro area.

Figure F.1: 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 F.2: 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).

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