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Supply chain disruption and energy supply shocks: impact on euro area output and prices

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Abstract

We identify jointly supply chain disruptions shocks and energy supply shocks together with demand shocks using a structural BVAR with narrative restrictions. The impact of adverse supply chain disruption shocks on inflation expectations and core HICP is strong and rather persistent, while the impact is small and transitory after energy supply shocks. Supply chain disruption shocks and favourable demand shocks explain the large fraction of output fluctuations in the 2020-2022 period. The dynamics of core prices and inflation expectations are instead mostly explained by supply chain disruption shocks and to a lesser extent by adverse energy supply shocks.

Keywords: Supply chain disruption shocks, energy supply shocks, inflation expectations, SVAR, narrative identification

JEL Classification: C32, E32

Non-technical summary

After a prolonged period of low inflation rates, since the beginning of 2021, the euro area recorded extraordinary large increases in expected inflation in the medium term, headline and core consumer prices, as measured by the Harmonized Index of Consumer Prices (HICP). Two supply forces associated to global supply-chains and energy played a key role in the dynamics of output and prices during the 2020-2022 period. With the reopening of the economic after the restrictions due to the pandemic, also demand forces contributed to the dynamics of the business cycle.

We identify jointly both supply shocks together with demand shocks using a Bayesian Structural VAR with narrative restrictions. To identify the supply-chains disruption shocks, we use the automotive suppliers' delivery times, which captures the extent of supply chain delays in the vehicle sector, together with vehicle production and prices, and the extreme volatility recorded in the suppliers' delivery times when the pandemic hit. As for the identification of the energy supply shocks, we employ retail energy prices together with the output of the energy-intensive sector and the extreme volatility in retail energy prices recorded with the gas shortages in the Autumn 2021 and the begin of the war in Ukraine.

Both adverse supply-chain disruption shocks and retail energy supply shocks can explain a large fraction of output and price fluctuations in the 2020-2022 period. Between January 2020 and September 2022, the supply shocks account for two thirds of the 8% increase (excl. trend) in HICP, about 55% of the 2.7% increase in core HICP and about 60% of the 0.6 percentage point increase (excl. trend) in 2-year ahead inflation expectations. Since the partial reopening of the economy in the summer of 2021, 10% of the 3.4% increase in core HICP and 20% of the 0.6% increase in 2-year ahead inflation expectations are attributed to demand shocks.

As for the real side, supply-chain disruption shocks played a key role when the pandemic hit, explaining about 35% of the drop in GDP in March-April 2020. The re-organization of the supply chains was rather fast in the summer 2020, but such shocks hit activity again in the autumn 2020. With the collapse of world trade in April 2020, cargo ships were not able to run at full capacity and many containers were left to pile up in western countries' ports due to the lockdowns. After the summer of 2020, once global demand had picked up

again, the lack of containers to transport these goods from Asia to the United States and Europe, as well as numerous vessels arriving at their destinations well outside of schedule (exacerbated by the massive container ship that blocked the Suez Canal), led to considerable supply bottlenecks. Since the beginning of 2020 and by September 2022, real GDP would have been 1.9% higher in absence of supply chain disruption shocks. The contribution of demand forces was particularly strong after the first round of vaccination from Covid in the spring 2021.

The situation has been volatile since October 2021 because adverse energy supply shocks started to cause a reduction in output, as the energy crunch intensified in the euro area culminating in the war of Russia against Ukraine. However, energy supply shocks have only marginally affected real GDP also because fiscal policy were employed to limit the rise in energy prices.

Also demand shocks contributed to the dynamics of real GDP. They explain about 25% of the drop in GDP in March-April 2020. The demand recovery was fast and steady. The contribution of demand forces were particularly strong after the first round of vaccination from Covid in the spring 2021. Since the beginning of 2020 and by September 2022, real GDP would have been 2.4% lower in absence of the favourable demand shocks.

Similarly, manufacturing production of motor vehicle and energy-intensive sectors were strongly affected by supply-chain disruption shocks and adverse retail energy supply shocks.

On the one hand, supply-chain disruption shocks are very persistent; on the other hand, the small and transitory effect of the retail energy supply shocks on core HICP and expected inflation was accompanied by a number of consecutive large adverse energy supply shocks. This implied an important contribution of both supply shocks to the business cycle, including its effects on expected inflation in the medium term. Persistent and strong supply forces and favourable demand shocks required the tightening of the monetary policy stance in 2021 and 2022.

I Introduction

After a prolonged period of low inflation rates, core Harmonised Index of Consumer Prices (HICP) and the 2-year ahead inflation expectations of the Survey of Professional Forecasters (SPF) rose sharply from the beginning of 2021. This prompted the ECB to tighten its policy stance by lifting sharply the interest rates and discontinuing their asset purchases in 2022.

Supply shocks to supply chains and energy markets might have adversely impacted economic activity and caused elevated inflation in the euro area. Are real GDP, core prices and medium-term expected inflation persistently affected by such supply shocks? To answer this question, we identify jointly supply chain disruption shocks and retail energy supply shocks together with demand shocks using a Bayesian structural vector autoregression (SVAR) model with sign and narrative restrictions.

We show that the impact of adverse supply chain disruption shocks on inflation expectations and core HICP is strong and rather persistent, while the impact of energy supply shocks is small and transitory. GDP instead drops immediately after a supply chain disruption shock and in the medium term after a retail energy supply shock.

Motor vehicle output in the euro area was strongly affected by disruptions in global supply chains. It is a critical sector and, across sectors, it is characterized by the longest supply chain (Boranova et al., 2022). Therefore, to identify supply chain disruption shocks, we use the suppliers' delivery times in the motor vehicle sector, which captures the extent of supply chain delays in such sector.

Typically, the 2020 period is shut down in empirical models through dummies (Finck and Tillmann, 2022) or handled through methods addressing heteroskedasticity (Lenza and Primiceri, 2022). In this study instead, after having shown that the stochastic trends remain stable over the entire 1999-2022 sample period, the extreme volatility characterizing March-May 2020, with automotive production essentially halting in April, is used to identify the supply chain disruption shocks. Macroeconomic shocks are better identified when they are relatively large (Rigobon, 2003). Specifically, we assume that the forecast errors of the suppliers' delivery times in March-April (May) 2020 are primarily driven by positive (negative) supply chain disruption shocks. This assumption is corroborated by microeconomic evidence: by using difference-in-difference approach, Lebastard et al. (2023) found that the

performance of French firms more exposed to global supply chains was much worse than simple exporters in March-April 2020, while the opposite was true with the recovery in May 2020.

Gas supplies from Russia to the European Union (EU) were cut significantly at the beginning of the autumn 2021, contributing to the slow replenishment of gas inventories in Europe ahead of the winter season, and at the end of February 2022 Russia invaded Ukraine. Both historical episodes caused a sudden surge in energy prices. To disentangle demand from supply shocks, we assume that the forecast errors of energy prices in October-November 2021 and March 2022 are driven primarily by energy supply shocks.

These set of narrative restrictions are sufficient to identify the specific supply shocks. In the baseline model, sign restrictions are added only to sharpen the identification. The response of the other three main variables of the structural model, medium-term expected inflation, HICP excl. food and energy (core HICP) and real GDP, is always left unrestricted also on impact. This allows us to be completely agnostic about the impact of the two supply-shocks on the key variables of the business cycle.

We show that both supply chain disruptions shocks and energy supply shocks were key drivers over this period, but the former played the larger role. Cumulatively, between January 2020 and September 2022, they explain about 60% of the increase in inflation expectations and core HICP. Conversely, demand shocks played a smaller role.

Supply chain disruption shocks played a key role when the pandemic hit, explaining about 35% of the drop in GDP in March-April 2020. The re-organization of the supply chains was rather fast in the summer 2020, but such shocks hit activity again in the autumn 2020. With the collapse of world trade in April 2020, cargo ships were not able to run at full capacity and many containers were left to pile up in western countries' ports due to the lockdowns. After the summer of 2020, once global demand had picked up again, the lack of containers to transport these goods from Asia to the United States and Europe, as well as numerous vessels arriving at their destinations well outside of schedule (exacerbated by the massive container ship that blocked the Suez Canal), led to considerable supply bottlenecks, affecting primarily the manufacturing sector. Energy supply shocks also caused a marginal decline in real GDP since October 2021, affecting however primarily the manufacturing

sector. The energy crunch played a far limited role because 70%-80% of euro area value added is produced by the less energy-intensive service sector. Also demand shocks contributed to the dynamics of real GDP. They explain about 25% of the drop in GDP in March-April 2020. The demand recovery was fast and steady. The contribution of demand forces was particularly strong after the first round of vaccination from Covid in the spring 2021.

The literature on global value chains is large (see for a review Antras and Chor, 2022), studying the optimal allocation of ownership rights along the value chain (Antras and Chor, 2013) and investigating the effects of demand (Alfaro et al., 2019), interest rate (Antràs, 2023), financing conditions (Kim and Shin, 2023) and risk (Ersahin et al., 2023). However, the identification of supply chain disruptions shocks and retail energy supply shocks is at its infancy and, to the best of our knowledge, nobody has studied the impact of these shocks on expected inflation, core prices and real GDP and nobody has identified these two supply shocks jointly. Supply chain disruption shocks have been identified using sign and narrative restrictions (De Santis, 2021; Finck and Tillmann, 2022; Celasun et al., 2022; Kemp et al., 2023; Kabaca and Tuzcuoglu, 2023). di Giovanni et al. (2022) instead study the propagation of shocks through interconnected sectors defining the supply chain disruptions as labour shortages. Other studies analyse the impact of rising shipping costs on inflation finding a positive statistical significant effect (Herriford et al., 2016; Carrière-Swallow et al., 2023). As for the retail energy supply shocks, De Santis et al. (2022) and De Santis and Tornese (2023) use sign and narrative restrictions on retail energy prices and the energy-intensive sector. Another strand of the literature for the United States looks at gasoline prices (Edelstein and Kilian, 2009; Kilian and Zhou, 2022a).¹

From a methodological point of view, we use the techniques devised by Antolín-Díaz and Rubio-Ramírez (2018), but we deviate from it along three dimensions: 1) Antolín-Díaz and Rubio-Ramírez (2018) impose narrative restrictions on top of an already fully self-identified system, in order to sharpen the identification of some specific shocks. In our setting, the narrative restrictions are the identifying assumptions and sign restrictions are intended to sharpen the identification. 2) We refrain from applying the importance resampling scheme

¹Knotek and Zaman (2021) assess the asymmetric responses of consumer spending to energy prices, but ordering energy inflation first in the Cholesky factorization followed by core inflation and real consumption growth and therefore using the reduced form residuals for the analysis.

as suggested by Giacomini et al. (2020). 3) We remove the restriction on the relative sizes of the various shocks on the dates in which we impose narrative shock restrictions, as suggested by De Santis and Van der Weken (2022).²

The paper is structured as follows. Section II describes the shock identification strategy and the dataset. Section III presents the key results. Section IV studies the impact on headline HICP. Section V compares our shocks with those estimated in the literature. Section VI provides some robustness checks. Section VII concludes.

II Framework and Identification

II.A Supply chains and energy prices

We provide in this section information on the variables used to identify the supply shocks. Panel A of Figure 1 shows the variables used to identify the supply chain disruption shocks, Panel B shows the variables used to identify the energy supply shocks.

The motor vehicle industry is present in several euro area countries covering 93.6% of euro area GDP in 2021 and, therefore, making the sector a good proxy for the analysis.³ The lengthening of the motor vehicle suppliers' delivery times in March and April 2020, its shortening in May 2020 and its lengthening again since the autumn 2020 is noticeable. Vehicle production moved in tandem with the suppliers' delivery times dropping after the pandemic restrictions, recovering immediately, but then dropping again in the autumn 2020. Vehicle prices started to rise sharply since the end of 2020. This suggests that supply chain disruption shocks played a key role in this period.

The remarkable drop in energy-intensive output together with the surge in energy prices

²Baumeister and Hamilton (2015) raised some concern about the undesired effect of uniformly distributed (Haar) priors for generation the rotation matrix. In this context, Baumeister and Hamilton (2015) warn that the uniform prior specified for the rotation matrix can translate into unintentionally informative conditional priors for objects of interests, such as impulse responses, that will drive the results even asymptotically. The key point is that posterior inference could be governed by the prior over the set of orthogonal matrices, which is assumed to be uniform. Arias et al. (2022) show that the posterior medians and probability intervals tend to be quite different from the corresponding statistics based on the prior (see also Inoue and Kilian, 2022). In addition, using the multiple-prior Bayesian approach described in Giacomini and Kitagawa (2021), Arias et al. (2022) confirm that posterior inference about the mean of the impulse responses is robust to the uniform prior over the set of orthogonal matrices embedded in the conventional method.

³According to the European Automobile Manufacturers' Association, or ACEA, motor vehicles were produced in the following 12 euro area countries: Austria, Belgium, Finland, France, Germany, Italy, Lithuania, the Netherlands, Portugal, Slovakia, Slovenia and Spain.

since the autumn 2021 suggest that energy supply shocks might have played a key role in the dynamics of the business cycle since then. The energy-intensive sector is defined by aggregating the production of chemicals, chemical products and basic metals, as they are by far the largest-scale users of energy (e.g. EIA, 2021; Gunnella et al., 2022). We use time-varying weights provided by Eurostat to construct the index. These sub-sectors account on average for about 10% of euro area industrial production.

Two key variables used to identify the supply shocks, the euro area motor vehicle suppliers' delivery times and the euro area retail energy prices, are less known and detailed information is provided next.

II.A.1 Suppliers' delivery times in the vehicle sector

The suppliers' delivery times index from Standard and Poor's (S&P) global (previously IHS Markit's) Purchase Manager Index (PMI) business surveys captures the extent of supply chain delays in an economy, which in turn acts as a useful barometer of capacity constraints.⁴

Purchasing managers of the vehicle sector participating in business surveys are asked if it is taking their suppliers more or less time to provide inputs to their factories on average. The precise question wording is: "Are your suppliers' delivery times slower, faster or unchanged on average than one month ago?" The percentage of companies reporting an improvement, deterioration or no change in delivery times are weighted to derive a 'diffusion index' as follows: $\alpha + \beta/2$, where α and β are the percentages of survey panel responding 'Faster' and 'Same', respectively. Hence readings of 50 indicate no change in delivery times on the prior month, readings above 50 indicate that delivery times have improved (become shorter, or faster) and readings below 50 indicate that delivery times have deteriorated (become longer, or slower).⁵

In each euro area country, the panel of companies is carefully selected to accurately represent the true structure of the chosen sector of the economy as determined by official

⁴The aggregate manufacturing suppliers' delivery times index became widely watched in the 1990s by high-profile users such as US Fed Chair Alan Greenspan, who cited the index (produced at the time by the NAPM - now known as the ISM) as his preferred leading indicator of inflation. According to the Wall Street Journal of 6 April 1996, "Mr Greenspan, speaking in congressional testimony, said that suppliers' deliveries are "far more relevant than the Fed's own capacity utilization figures at gauging price pressures in the economy".

⁵The index is seasonally adjusted to strip out normal variations in delivery performance for the time of year.

data. A weighting system is also incorporated into the survey database that weights each response according to the workforce size.

Because of their just-in-time strategy, highly personalized car configurations and stringent safety demands requiring specific chips, the shortage has made delivery planning harder for car makers. A shortage of chips and other components needed to assemble new motor vehicles implied an unprecedented reduction in supply in the 2020-2022 period.

On the supply side, container vessel activity sustained a major shock because of the pandemic. The global misallocation of containers as a result of the collapse of world trade in March and April 2020 and the rescheduling of numerous cargo vessels arriving late at their destinations led to considerable supply bottlenecks.⁶ The disruptions in the cargo activity affected all manufacturing sectors and particularly those characterised by the longest-supply chains, such as automotive. Another issue that exacerbated these supply bottlenecks was the renewed lockdown measures resulting from the spread of the Delta variant in some countries of the Asia-Pacific region (e.g. Malaysia, Singapore, Thailand and Vietnam), which are key to the semiconductor chip production generating a crisis in the supply of semiconductors.

Therefore, the use of suppliers' delivery times of the vehicle sector shown in Figure 1 is a suitable candidate to identify disruption in supply chains. Notice that the index rose during the global financial crisis in 2008-2009 and the sovereign debt crisis in 2010-2011 because they were driven by negative demand shocks, which tend to shorten the suppliers' delivery times, given that more resources are available to satisfy diminished demand. Instead, the index dropped in March and April 2020, it jumped back in May 2020 and it recovered in the summer 2020 to drop again in the autumn 2020. The sharp lengthening recorded after the pandemic hit in March 2020 can be exploited, because it was driven by supply considerations, as we can exclude the hypothesis that demand rose sharply in that period. Instead, the lengthening recorded in the autumn 2020 can be either driven by the sharp recovery in demand (for work-related electronic equipment) or by adverse supply shocks to the supply chain. We exploit the extreme volatility during the spring 2020 to identify the

⁶ According to UNCTAD, the average time spent by container vessels in ports in the first half of 2021 was 11% higher compared with the pre-pandemic average in 2018-19. In Europe, due to congestion, scheduling delays and infrastructure constraints, German and French ports saw a very large increase in average port stays (e.g. 42% and 25% higher than their average in 2018 and 2019), thus standing even higher than those seen in the United States.

supply chain disruption shocks.

To demonstrate the additional sensitivity of the automotive industry to global supply chains, we show in Figure 2 the suppliers' delivery times in several sectors. Motor vehicle is part of the consumer goods and it features the largest drop in suppliers' delivery times until February 2021. Machinery and equipment remained flat for another nine months, while computers and electronics started to lift in the summer 2021. It is well known that also these two sub-sectors suffered strongly from supply bottlenecks. However, the advantage of using the automotive industry for the identification of supply chain disruption shocks is that this sector is more homogeneous than machinery and equipment and computers and electronics. Therefore, the dynamics of the three variables used to identify the supply chain disruption shocks - suppliers' delivery times, vehicle output and vehicle prices – are in principle more strongly related.

II.A.2 Energy prices

Energy supply shocks are typically studied through the global crude oil market⁷ However, the prices of other sources of energy, are only weakly correlated with oil prices. According to monthly data provided by the U.S. Energy Information Administration (EIA), available for a long period between January 1997 and December 2019, the correlation between the Henry Hub natural gas spot price and the West Texas Intermediate (WTI) spot price is 20%. Gas and renewable sources like wind, solar, geothermal and hydropower have become important alternative sources in the last two decades for energy supplies' security motives and for environmental issues. Therefore, we employ the HICP category "Energy (ENRGY)" for goods and services, rather than oil prices to identify energy shocks. The retail energy price includes electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment.

Energy price developments are shown in Figure 1. Unprecedentedly, energy prices rose by 62% cumulatively from the beginning of 2021 until September 2022. In order to identify the retail energy supply shocks, we exploit the extreme volatility in October and November

⁷Among others, see Kilian (2009); Baumeister and Peersman (2013); Kilian and Murphy (2014); Aastveit et al. (2015); Baumeister and Kilian (2016); Baumeister and Hamilton (2019); Caldara et al. (2019); Känzig (2021); Aastveit et al. (2023); Kilian and Zhou (2022b).

2021, when HICP energy rose by 8.7% due to the initial gas supply cuts from Russia, and in March 2022, when energy prices surge by 12.2% due to the Russian invasion of Ukraine.

II.B Model specification

The reduced-form VAR is given by

$$x_t = a_0 + \sum_{k=1}^K A_k x_{t-k} + u_t, \quad (1)$$

$$\mathbf{u}_t = B\varepsilon_t \sim N(0, \Omega), \quad (2)$$

where x_t denotes the vector of endogenous variables, a_0 is a vector of constants, A_k captures the dynamic relations (lag order $K = 6$), u_t the reduced form errors, ε_t are uncorrelated structural shocks and the impact matrix B comprises the contemporaneous responses of the variables to all shocks. The model is estimated with Bayesian techniques. We assume natural conjugate Normal-Inverse-Wishart (N-IW) priors. The IW priors for Ω have $n + 2$ degrees of freedom and diagonal scale matrix with the i -th diagonal elements equal to the mean squared error from estimating an AR(1) for the i -th variable. Conditional on Ω , the priors for A_k are Normal with Minnesota-type mean and variance (Doan et al., 1984), and complemented with a dummy-initial observation prior (Sims, 1993) that is consistent with the assumption of cointegration.⁸ The sample spans over the monthly period January 1999 to September 2022. The interpolation of GDP to a monthly frequency is carried out using the Chow and Lin (1971)'s method employing industrial production excl. construction, construction production and service production. Therefore, it is a coincident indicator of economic activity. Narrative identification is more accurate at higher frequency.

The vector $\mathbf{x}_t = [\pi_t^e, p_t, p_t^v, p_t^e, y_t, y_t^v, y_t^e, s_t^v]'$ defines the eight variables of the SVAR, where π_t^e denotes the SPF 2-year inflation expectations,⁹ p_t core HICP, p_t^v the vehicle producer

⁸The hyperparameters take standard values from the literature. The hyperparameter, which determines the tightness of the Minnesota prior, is set equal to 0.2. The parameter, which governs the variance decay with increasing lag order, is set equal to 2. The hyperparameter, which determines the tightness of the "dummy-initial-observation" prior is set equal to 1, a value recommended by Sims and Zha (1998).

⁹The European Central Bank's SPF collects information on the expected rates of inflation in the euro area at several horizons, ranging from the current year to the longer term. The SPF began in 1999. The aggregate results and microdata are published four times a year. The quarterly observations are linearly interpolated to obtain the monthly frequency.

price, p_t^e the energy price, y_t real GDP, y_t^v the vehicle output, y_t^e the output of the energy-intensive sector and s_t^v the suppliers' delivery times of the vehicle sector. All variables, except s_t^v and π_t^e , are defined in logs.

The impulse response functions (IRFs) that trace out the dynamic effects of the structural shocks ε_t can be obtained by inverting the VAR in equation (1) into a moving average process $x_t = \phi_0 + \sum_{k=1}^{\infty} \Phi_k B \varepsilon_{t-k}$. They are, however, not uniquely identified as any orthogonal rotation of B delivers a different MA-process that is equally consistent with the data. In the following sections, we describe how this problem is solved by combining restrictions on B with narrative information in the likelihood function.

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

II.C Narrative sign restrictions

Antolín-Díaz and Rubio-Ramírez (2018) impose narrative restrictions on top of an already fully self-identified system, in order to sharpen the identification of some specific shocks. We instead rely on two kinds of narrative restrictions, the “narrative sign restrictions” and the “signed contribution restrictions”, to obtain orthogonal shocks. Sign restrictions are used only to sharpen identification. The baseline model contains sign and narrative restrictions. A comparison with a model using only narrative restrictions is also provided.

Narrative sign restrictions. As in Antolín-Díaz and Rubio-Ramírez (2018), a narrative sign restriction on a structural shock imposes that the value of the identified structural shock i on a specific date t is either positive or negative:

$$\varepsilon_{i,t} > 0 \text{ or } \varepsilon_{i,t} < 0 \text{ at a given } t. \quad (3)$$

The signs in Panel A of Table 1 indicate whether the shock is positive or negative in the correspondent dates.

In March and April 2020, the economy froze due to the restrictions introduced by the governments to contain the pandemic. Intermediate goods could not be supplied timely and the demand of goods and services dropped because people were forced to stay at home. Therefore, we assume that both the supply chain disruption shocks were positive and demand shocks were negative in March and April 2020. The sharp fall in economic activity was followed by a dramatic rise in May 2020. In order to characterize the V-shape recovery, we assume that in May 2020 supply chain disruption shocks were negative and demand shocks were positive.

In autumn 2021 and again in March 2022, euro area energy prices rose sharply, as a result of the cut in Russian gas supplies to Europe via the Yamal-Europe pipeline and in the aftermath of the Russian invasion of Ukraine. Almost 30% of the EU crude oil imports, 40% of the EU natural gas imports and 50% of EU solid fossil fuel (mostly coal) imports originated from Russia. By keeping deliveries to Europe deliberately tight, Russia engineered an energy crunch and the ballooning of gas prices. Over the same period, the production of the energy intensive sector (chemicals and basic metals) dropped. We assume that energy supply shocks are positive in these three months.

The aggregate demand shocks should be fully captured by the sign restrictions, including the discretionary reaction of fiscal policy, which has been rather significant over the period 2020-22. However, there are some effects of reopening that can be captured only through narrative restrictions. We assume that all demand shocks were negative in March and April 2020, as households were constrained to consume being forced to stay at home. At the same time, we assume that all demand shocks were positive in May 2020 with the partial reopening of the activities. The success of the vaccination programme against Covid-19 allowed governments to lift the restrictions from March 2021. In Germany, for example, hairdressers were allowed to reopen from March 1, 2021. Subsequently, Germany announced the reopening to tourists on June 15th. In March and June 2021, euro area monthly real GDP growth rose by 2.5% and 2.1% month-on-month, respectively.¹⁰ Finally, we assume that the demand shocks were positive in May 2022, as output rose strongly in that month, despite the

¹⁰In March and June 2021, retail sales rose by 3.9% and 2.5% month-on-month, and service production rose by 3.5% and 3.7% respectively, mainly due to higher demand for high contact-intensive services, such as hotels, restaurant, arts, entertainment and transport.

war in Ukraine. Most of the unexpectedly robust growth was due to strong activity in the services sector following the lifting of most pandemic-related restrictions (see ECB, 2022). We assuming that all demand shocks in these three months are positive. Nevertheless, we will show that the results are robust to such assumptions.

Signed contribution restrictions. We also impose, on key restricted dates, that the supply-disruption shocks and the energy supply shocks are the most important contributor to the one-step ahead forecast error of the vehicle suppliers' delivery times and energy prices, respectively. This assumption is made in March-May 2020 for the vehicle output suppliers' delivery times and in October 2021, November 2021 and March 2022 for energy prices (see Panel A of Table 1). The sharp drop of the vehicle suppliers' delivery times recorded after the pandemic hit in March 2020 can be exploited to identify the supply chain disruption shocks, because we can exclude the hypothesis that demand rose sharply in that period. Following De Santis and Van der Weken (2022), the identification is less restrictive than Antolín-Díaz and Rubio-Ramírez (2018), as we allow the unrestricted shocks to have an even larger contribution to the one-step ahead forecast error of the vehicle output suppliers' delivery times and energy prices, if the contribution of that unrestricted shock moves such forecast errors in the opposite direction.

Table 1: Sign and narrative restrictions

	Supply chain disruption	Energy supply	Demand
Dates	Panel A: <i>Narrative sign and signed contribution restrictions</i>		
03/20-04/20	+, delivery times ↓		-
05/20	-, delivery times ↑		+
10/21-11/21		+, Energy prices ↑	
03/22		+, Energy prices ↑	
03/21			+
06/21			+
05/22			+
Variables	Panel B: <i>Sign restrictions on the impact matrix A_0^{-1}</i>		
Expected inflation 2-year ahead			
Core HICP			+
Real GDP			+
Vehicle prices	+		
Vehicle output	-		
Vehicle suppliers' delivery times	-		-
Energy prices		+	+
Energy-intensive industrial production		-	

Note: The sign restriction on vehicle output and energy-intensive output after supply chain disruption shocks and energy supply shocks holds for three consecutive periods.

Sign restrictions. To refine the identification of the supply chain disruption shocks, we assume that they reduce vehicle output for three months consecutively, decrease the

suppliers' delivery times instantaneously and increase motor vehicle prices at impact. By imposing sign restrictions on the vehicle output on impact and for the following two periods, we reduce the probability of confounding supply chain disruption shocks with the frequent and temporary output adjustments that characterize this sector.

To refine the identification of the retail energy price shocks, we assume that they rise retail energy prices at impact and reduce the output of the energy-intensive sector, also in this case for three months to reduce the probability of confounding energy supply shocks with the frequent and temporary output adjustments that characterize this sector.

For demand shocks, we assume that at impact the one-step ahead forecast errors of HICP, HICP energy and GDP move in the same direction, while that of the suppliers' delivery times moves in the opposite direction as capacity constraints can limit the production expansion required to satisfy the increased demand. These restrictions are listed in Panel B of Table 1.

III Business Cycle Response to Economic Shocks

III.A Stochastic trends

Given that the identification makes use of the extraordinary volatility during the Covid-19 period, we need to ensure that there are no relevant structural breaks in 2020. A visual inspection of the stochastic trend of all variables, estimated simulating the BVAR forward in absence of shocks, indicate without any doubt that the extreme variation of some variables did not distort the trend relations characterizing the Bayesian VAR (see Figure 3).

Formally, we test a potential structural break using the Chow forecast test before and after March 2020. We compute both the F-statistics, which compares the residual sum of squares of the restricted and unrestricted models, and the log-likelihood ratio statistics, which is based on the comparison of the restricted and unrestricted maximum of the Gaussian log likelihood function. Neither of the forecast test statistics reject the null hypothesis of no structural change in any of the variables before and after March 2020 (see Table 2).

The difference between the observed values and their stochastic trend can be explained by macroeconomic shocks, which we need to identify.

Table 2: Stability of the stochastic trends before and after March 2020

	F-Statistics	Likelihood ratio
Expected inflation 2-year ahead	1.000	1.000
Core HICP	1.000	1.000
Real GDP	0.092	0.051
Vehicle prices	1.000	1.000
Vehicle output	1.000	1.000
Vehicle suppliers' delivery times	1.000	1.000
Energy prices	0.997	0.994
Energy-intensive industrial production	1.000	1.000

Notes: This table shows the P-value of the F-statistics and the log-likelihood ratio statistics of the Chow forecast test before and after March 2020, under the H_0 of no structural change. The equation takes the following specification $\Delta x_t = \alpha + \beta x_{t-1} + \gamma_1 D + \gamma_2 D x_{t-1} + u_t$, where x_t denotes the stochastic trend of each of the variable of the VAR, D a dummy variable, which takes the value of one after March 2020 otherwise zero, and u_t the OLS residuals. Under the assumption of no structural change, $H_0 : \gamma_1 = 0, \gamma_2 = 0$.

III.B Response functions, shocks and contributions

We identify the shocks as described in Table 1, using narrative and signed contribution restriction. The IRFs are displayed in Figure 4. Each panel shows the median IRFs (solid black line) and the corresponding posterior 68% pointwise credible sets (dashed lines). The yellow line is the median of the model with only narrative restrictions to identify the supply chain disruption shocks and energy supply shocks.¹¹

The results suggest that both supply chain disruption shocks and retail energy supply shocks behave like cost-push shocks; but their transmission is very different. The professional forecasters' 2-year inflation expectations and core HICP rise in response to positive demand shocks and to adverse supply chain disruption shocks, while the impact is small and transitory after energy supply shocks. The impact of supply chain disruption shocks is very persistent. Particularly, the impact on the SPF's 2-year inflation expectations and core prices of supply chain disruption shocks becomes economically relevant after about 10 months and it gets stronger over time reaching the peak after 24 and 36 months, respectively. Correspondingly, GDP drops after the adverse supply shocks and rise after the favourable demand shocks. Particularly the impact on GDP is on average much stronger in the short-term after a supply

¹¹The acceptance rate in the share of rotations that satisfy the restrictions imposed amounts to 0.163% in the benchmark model and to 0.484% in the model with only narrative restrictions, three times as larger.

chain disruption shock and in the medium term after a retail energy supply shock. Given that these three variables are left unrestricted, the identified IRFs are very informative.

As for the other variables, vehicle and energy prices tend to increase after both adverse supply shocks. While a supply chain disruption shock causes a drop in vehicle output and energy-intensive sector output, an energy supply shocks causes a drop in the energy intensive sector and on average it reduces vehicle output, but the credible set includes zero. Therefore, the impact of energy shocks on vehicle output is more uncertain.

It is worth emphasising that the suppliers' delivery times are driven by both demand and supply forces. First, demand shocks have a strong negative impact on the vehicle output suppliers' delivery times and the lengthening of the supply chain lasts about 9 months. Then, the dynamics mean-reverts fully with a shortening of the delivery times reaching the peak after 20 months. The vehicle output suppliers' delivery times returns to its equilibrium prior to the demand shock after 2 years and half. Second, supply chain disruption shocks also lengthen the delivery time of material and equipment and the delay of the supply chain lasts about 15 months. Then, the dynamics mean-reverts with a shortening of the delivery times reaching the peak after 30 months. The vehicle output suppliers' delivery times returns to its equilibrium prior to the supply shock after 4 years. Interestingly, energy supply shocks are accompanied by a shortening of the supply chain. Possibly, firms tend to gain production efficiency in order to offset the rise in firms' energy costs.

Demand shocks tend also to increase the production of vehicles and energy-intensive sectors, as well as vehicle prices, which are left unrestricted also at impact.

We have been arguing that sign restrictions used to identify the supply shocks are redundant and that only narrative restrictions are fundamental to orthogonalise the macroeconomic system. The macroeconomic responses of the model where the two supply shocks are identified only using narrative restrictions have similar median responses across all variables (see orange line in Figure 4). The sign restrictions tend to narrow the credible set on some variables subjects to such restrictions, such as vehicle prices after a supply chain disruption shock and energy-intensive output after an energy supply shock; but they have also an implication on the response of GDP and automotive production after an energy supply shock (see Figure 5).

Finally, Figure 6 shows the 90% pointwise credible sets of the baseline model and the conclusions, which can be drawn, are the same.

The three identified shocks are shown in Figure 7. Demand shocks were strongly negative (4 standard deviations) when the Covid-19 pandemic hit in March 2020 for two consecutive months. Similarly, supply chain disruption shocks were strongly adverse in these two months (4-6 standard deviations). Instead, in line with the existing narrative, energy supply shocks did not play any role in that period. In the course of 2021 and 2022, a number of adverse supply chain disruption shocks continue to hit the economy. Energy supply shocks began to be an important driver of the macroeconomy after the summer 2021 with the gas rationing from Russia and then after the invasion of Ukraine in February 2022.

III.C The drivers in 2020-2022 period

The historical decomposition of the shocks allows to quantify the role of each driver on each macroeconomic variable. Through the lenses of our model, we can look at the economic forces at play during the 2020-2022 period (see Figure 8).

Looking first at the nominal side, aggregate core consumer prices and 2-year inflation expectations were marginally affected in the initial phases of the pandemic in line with the hump shaped IRFs and the limited response at impact. The role of adverse demand shocks started to become relevant in the second half of 2020, causing a 0.1-0.2 percentage point decline in expected inflation. The situation reverted dramatically since the beginning of 2021, when initially large adverse supply chain disruption shocks and, since summer 2021, large adverse energy supply shocks caused a surge in core HICP and expected inflation. Since January 2021 and by the end of the sample period in September 2022, supply chain disruption shocks contributed to about 35% of the increase in both core HICP and expected inflation, respectively; while retail energy supply shocks contributed to 12% and 9% respectively. In aggregate, the great supply shocks since the beginning of 2020 account for about 55% of the 2.7% increase in core HICP and about 60% of the 0.6 percentage point increase in 2-year inflation expectations. These findings are not very dissimilar from the results of di Giovanni et al. (2022), who found that sectoral labor shortages, their proxy of supply chain “bottlenecks”, explain around half of the observed inflation in the euro area. Since the

partial reopening of the economy in the summer of 2021, only about 10% of the 3.4% increase in core HICP and about 20% of the 0.6% increase in 2-year ahead inflation expectations are attributed to demand shocks.¹²

Similar relative dynamics are recorded in vehicle and energy prices, despite the former is used to identify supply-chain disruption shocks and the latter is employed to identify energy supply shocks.

Looking at the real GDP, the results suggest that supply chain disruption shocks played a key role in the output dynamics recorded in March and April 2020, explaining 35% of the 19% drop in April 2020 since the beginning of the year. Similar results are found also for the two manufacturing sectors. Also demand forces played a negative role in March and April 2020 with a 25% contribution. Given that we do not impose any supply chain disruption restrictions on GDP, this result corroborates the role of supply chain disruption shocks as a key driver of the business cycle, when the Covid-19 pandemic shocked the global economy.

Between May 2020 and September 2020, positive supply chain disruption shocks and demand shocks helped the output recovery, again the supply shocks playing a key role. The situation changed substantially since the Autumn 2020, as demand forces continued to remain favourable, while supply chain disruption shocks pull down GDP. The lack of semiconductors and memory chips, plus the mis-allocation of containers globally and the stop at the ports of cargo-ships due to Covid-19 restriction policies in key Asian countries lengthened the delivery times of key intermediate inputs stopping part of the production in the euro area. Between January 2020 and September 2022, we estimate that real GDP would have been 1.9% higher in absence of supply chain disruption shocks. The contribution of demand forces was particularly strong after the first round of vaccination from Covid in

¹²Gonçalves and Koester (2022) adopt a disaggregated approach to analysing the role of supply and demand factors in each core HICP component, exploiting the fact that a supply shock affects activity and inflation in opposite directions while a demand shock affects them in the same direction. Based on this approach suggested by Shapiro (2022), for each month each core price category can then be labelled as predominantly demand-driven, as predominantly supply-driven or as ambiguous. Their decomposition suggests that supply and demand factors have played broadly similar roles in core inflation. We instead find that demand shocks have played a smaller role in the dynamic of core prices. These differences can be explained by three main reasons. First, the Shapiro's approach assumes that the decomposition is static, as shocks affect core HICP only at impact. Second, the immediate response of core HICP (e.g. the impact matrix implicitly) is not estimated, but it is equal to the weight of each sector in the core HICP basket. Third, our approach leaves unidentified the sectoral shocks associated to the automotive production and energy-intensive sector, which instead Gonçalves and Koester (2022) would attribute either to supply or to demand shocks. Therefore, the full comparison across the two methods is not possible.

the spring 2021. Since the beginning of 2020, our model suggests that the real GDP would have been 2.4% lower in absence of demand shocks. Expansionary fiscal policies, directed in particular to protect employment through job retention schemes, but also to fund increased health spending, plus the use of households' accumulated savings fully counteracted the negative effects from the adverse supply shocks.

The situation has been volatile since October 2021 because adverse energy supply shocks started to cause a reduction in output, as the energy crunch intensified in the euro area culminating in the war of Russia against Ukraine. However, energy supply shocks have only marginally affected real GDP also because fiscal policy were employed to limit the rise in energy prices. In contrast, the output of the energy-intensive sector has been mostly adversely affected.

Manufacturing production of motor vehicle and energy-intensive sectors were strongly affected by supply chain disruption shocks. The dynamics of sectoral industrial production suggests that their output was heavily affected by supply chain disruption shocks in the course of the entire 2020-2022 period. Relative to the beginning of 2020, by September 2022, in absence of supply chain disruption shocks, vehicle output and the production of the energy-intensive sector would have been 27.4% and 2.8% higher, respectively. Therefore, the impact on automotive has been heavily disruptive.

The energy-intensive sector has been heavily affected by the energy supply disruptions. It lost 2.8% of production since September 2021 amid the gas shortages.

Finally, the decomposition of the suppliers' delivery times is informative because it disentangles the supply chain disruption shocks from the demand forces. When the pandemic hit, the adverse demand shocks shortened the delivery of intermediate inputs, while the supply chain disruption shocks lengthened such delivery causing important supply constraints. The shift to remote working during the pandemic increased the demand for electronic equipment (work-related as well as for home appliances), further pushing up the demand for semiconductors. This phenomenon become relevant in the fall 2020, when favourable demand forces contributed to the lengthening of the suppliers' delivery times. However, the major contributor remained the adverse supply forces, associated to the global pandemic restrictions and the disruption in global logistic. They are identified as the main drivers of the lengthening

of the suppliers' delivery times since the fall 2020.

IV Using Headline HICP

How would the shocks be modified if using headline HICP instead of core HICP? What is the impact of demand and supply shocks on headline HICP? We substitute core HICP with headline HICP in the BVAR and run in this section the same empirical exercises carried out earlier. A summary of key findings is shown in Figure 9.

First, the results confirm that the extreme variation of macroeconomic variables recorded in 2020 did not create a worrying break in the stochastic trend of headline HICP (see Panel A), a conclusion corroborated by the Chow forecast test before and after March 2020.

Second, the three identified shocks using the two versions of the BVAR, one with core HICP and one with headline HICP, are well aligned on the 45-degree line (see Panel B). This suggests that similar shocks are identified using headline HICP and the IRFs and the historical decomposition across common variables are very similar.¹³

Third, supply shocks do affect headline HICP (see Panel C). Headline HICP rise in the first two year and half and then gradually declines after a supply chain disruption shock. The impact of a retail energy supply shock on headline HICP is much stronger at impact in line with the 10% weight of HICP energy in the HICP basket, but it is transitory, as the impact remains stable for about a year and then declines.

Finally, looking at the historical decomposition of the shocks in the 2020-2022 period (see Panel D), negative demand shocks reduced headline HICP in the initial phases of the pandemic. From the beginning of 2021, the rise in HICP was driven by supply chain disruption shocks and by the autumn of 2021 the surge in goods prices was also caused by the energy supply shocks. Cumulatively, between January 2020 and September 2022, supply chain disruption shocks and retail energy supply shocks contributed to 41% and 26% of the increase in headline HICP, respectively.

¹³All comparisons are available upon request.

V Cross-Checking with other Measures

How does the euro area vehicle supply chain versus global supply chain pressure index vary? Similarly, are the identified euro area retail energy supply shocks correlated with oil market developments? Despite the regional dimension of our identified shocks, one could still expect a positive correlation with the global gauges.

V.A Euro area versus global supply chain pressure index

Although the supply chains disruption shocks are estimated using euro area vehicle data, the global competition and the length of the supply chain characterising the automotive sector allow to compare the identified regional shock with the Global Supply Chain Pressure Index (GSCPI) proposed by Benigno et al. (2022). It is a parsimonious global measure designed to capture supply chain disruptions using a range of indicators. They use measures of transportation costs, associated to shipping and airfreight costs, and sub-components of country-level manufacturing data from the PMI surveys, covering the euro area, China, Japan, South Korea, Taiwan, the U.K., and the U.S., such as the suppliers' delivery times, "backlogs", which quantifies the volume of orders that firms have received but have yet to either start working on or complete, and "purchased stocks," which measures the extent of inventory accumulation by firms in the economy.

To isolate the supply-side drivers of each data series, they regress delivery time, backlogs, and purchased stocks against the "new orders" PMI subcomponent, which captures the extent of customer demand for firms' products; and they regress the global transport cost measures against a GDP-weighted average of the aforementioned "new orders" PMI subcomponents as well as a similarly weighted average of the "quantities purchased" PMI subcomponents for their seven economies. The residuals from these regressions for each country are used as inputs in constructing the global supply chain pressure index through a principal component analysis.

Our definition of euro area supply chain pressure index is the historical contribution of supply chain disruption shocks on the euro area vehicle output suppliers' delivery times. Despite the two approaches are very different, the correlation reported in Panel A of Figure

10 is positive (e.g. the blue dots refer to the period between July 1990 and December 2019. The red dots refer to the period between January 2020 and September 2022.).¹⁴ The statistical significant of these relations are shown in Table 3. The contemporaneous relation between the NYFED global supply chain pressure index and the euro area motor vehicle supply chain pressure index is tight and depends on the 2020-2022 period, given that the coefficient on the GSCPI is halved when an interacted dummy, which is equal to one after January 2020, is included in the regression.

V.B Retail energy versus crude oil supply shocks

The Eurostat' HICP price index of energy goods includes various components, such as electricity, gas, liquid fuels, solid fuels, heat energy, and fuels and lubricants for personal transport equipment. Therefore, the underlying retail energy supply shocks are in principle able to capture broader developments in the energy markets. We check this by comparing the median of our identified retail energy supply shocks with the median of the crude oil supply shocks estimated in Känzig (2021). Panel B of Figure 10 displays the cross-plot of the two shocks over the sample period. The contemporaneous relation between the oil supply shocks and the euro area retail energy supply shocks is positive and does not depend on the 2020-2022 period (see Table 3).

Table 3: Correlation between euro area and global supply chain and energy measures

	Euro area supply chain pressure index	Euro area supply chain pressure index	Euro area retail energy shocks	Euro area retail energy shocks
Global supply chain index	0.657*** (0.044)	0.322*** (0.093)		
Global supply chain index*Dummy		0.088 (0.145)		
Dummy		1.054*** (0.299)		
Oil supply shocks			0.590*** (0.070)	0.626*** (0.077)
Oil supply shocks*Dummy				-0.200 (0.181)
Dummy				0.076 (0.134)
Adj. R-squared	0.447	0.492	0.203	0.202

Notes: This table shows the OLS regression coefficients and in brackets the standard errors. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. "Dummy" is a dummy variable which takes the value of 1 from January 2020. The coefficients on the intercept are not shown. Sample period: July 1999 - September 2022.

¹⁴Given that the GSCPI is measured in standard deviation, we standardise the historical contributions.

VI Model validation

VI.A The drivers during the Global Financial Crisis

It could be argued that the model might fit well the identified supply shocks' narrative during the pandemic period, while failing in other key periods. For example, we should expect that demand shocks should be rather prominent during global financial crisis. The historical decomposition of shocks in 2008-2010 period suggests that this is the case (see Figure 11). Half of the drop in GDP is attributed to adverse demand shocks and the other half is attributed to other types of unidentified shocks. The same conclusions can be drawn looking at the decline in expected inflation after the collapse of Lehman Brothers in September 2008.

VI.B Robustness checks

The narrative restrictions on the demand shocks shown in Table 1 could be redundant, as the sign restrictions, together with the narrative restrictions for the other two supply shocks, are sufficient to select the IRFs characterising the demand forces underlying the business cycle. The robustness check of the results consists of excluding all narrative restrictions underlying the demand shocks in the baseline. The new IRFs with the credible sets are shown in Figure 12 together with the median estimate of the baseline. The results are similar. The median estimates of the responses of GDP, vehicle output and energy-intensive output are slightly smaller at impact after a demand shock. However, the credible sets of the two manufacturing sectors' responses include zero after the demand shocks. The results are invariant on all prices and on expected inflation. Therefore, the narrative restrictions to identify the demand shocks are useful for manufacturing.

In March 2021, the Suez Canal was totally blocked for six days by a 400 metre-long container ship. The obstruction created a massive traffic jam in the vital passage, straining supply chains already burdened by the coronavirus pandemic. Therefore, we assume that the supply chain disruption shocks were positive in that month providing the largest contribution to the one-step ahead forecast error of the suppliers' delivery times. A similar assumption is made by De Santis (2021), De Santis et al. (2022) and Finck and Tillmann (2022), while Furceri et al. (2022) use the Suez Canal obstruction in March 2021 as an exogenous instru-

ment for the identification of shipping shocks. The results displayed in Figure 13 are very similar to the baseline model, but the numbers of accepted draws declines somewhat.

It could be argued that energy demand shocks could also lead to a decline in production in the energy-intensive sector (due to the higher cost of energy inputs). To consider this possibility, we assume that after a demand shock the energy-intensive sector declines at impact and for the subsequent two months. The results are provided in Figure 14. The responses of all variables to the supply chain disruption shocks and energy supply shocks remain invariant. The variables' responses to demand shocks are different in sign only for the energy-intensive output which declines due to the underlying hypothesis.

VII Conclusions

We investigate the transmission mechanism of supply-chain disruption shocks and energy supply shocks on output and prices using a Bayesian SVAR with narrative restrictions, leaving unrestricted the impact on GDP, core prices and expected inflation.

We show that the impact of adverse supply chain disruption shocks on inflation expectations and core HICP is strong and rather persistent, while the impact is small and transitory after energy supply shocks. GDP instead drops immediately after a supply chain disruption shock and in the medium term after a retail energy supply shock.

We find that supply chain disruption shocks and energy shocks played a key role in shaping core prices and expected inflation in 2020-2022 period, but the former contributed most, also because they are rather persistent. Conversely, the favourable demand shocks played a more negligible role. Real GDP was also negatively affected by supply chain disruption shocks and only marginally by the adverse retail energy supply shocks; instead GDP was strongly affected by demand shocks also in the post pandemic recovery.

The lockdown was an extremely large and complex event and the war in Ukraine (and the preceding events) did not only trigger energy price shocks, but also a general increase in uncertainty. Since, from a set identification principle, distortions from other shocks are properly accounted for from wider credible sets, it can be argued that supply chain disruption shocks have implications on output and can be entrenched in core HICP and expected inflation for

a prolonged period of time and this would require more attention by policymakers.

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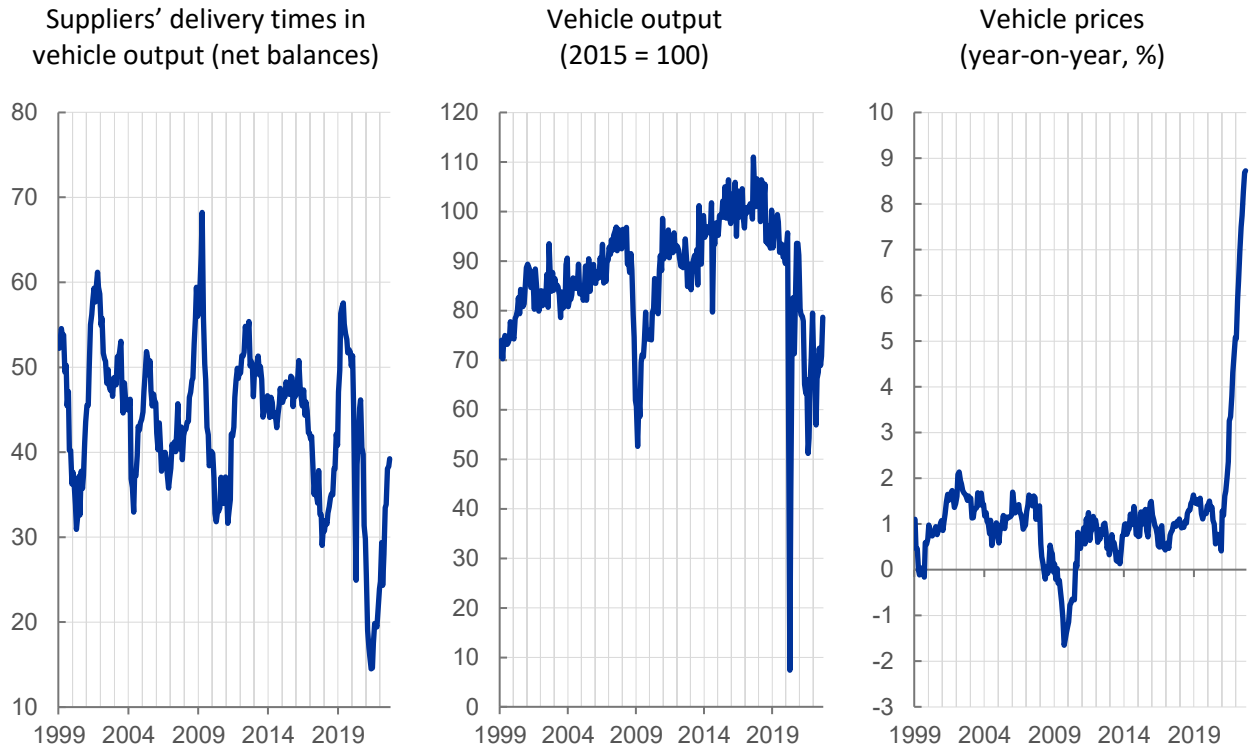
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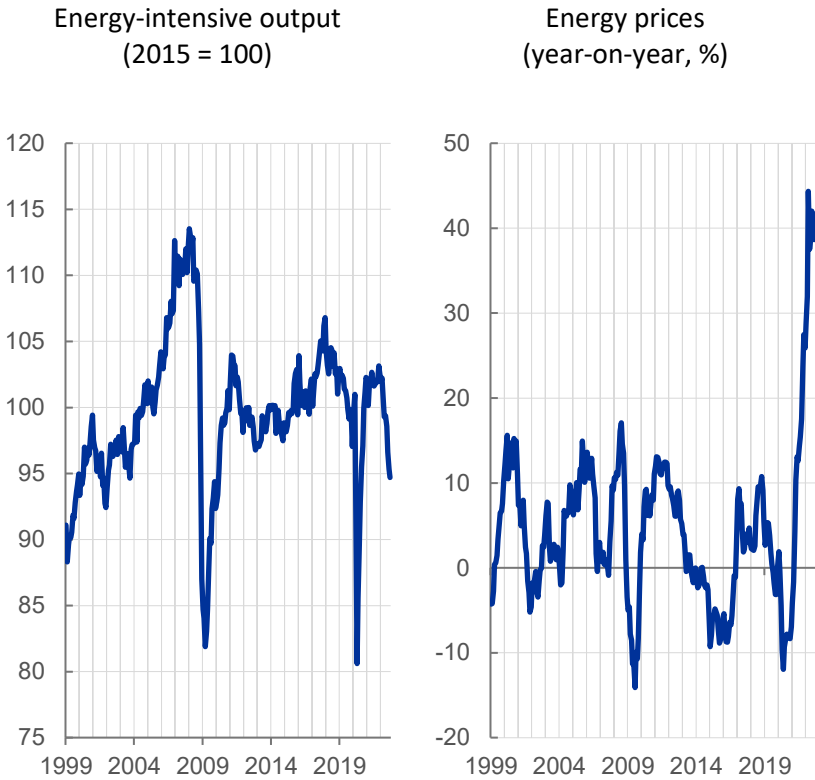
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Figure 1: Variables Used to Identify the Great Supply Shocks

Panel A: Variables used to identify the supply-chain disruption shocks



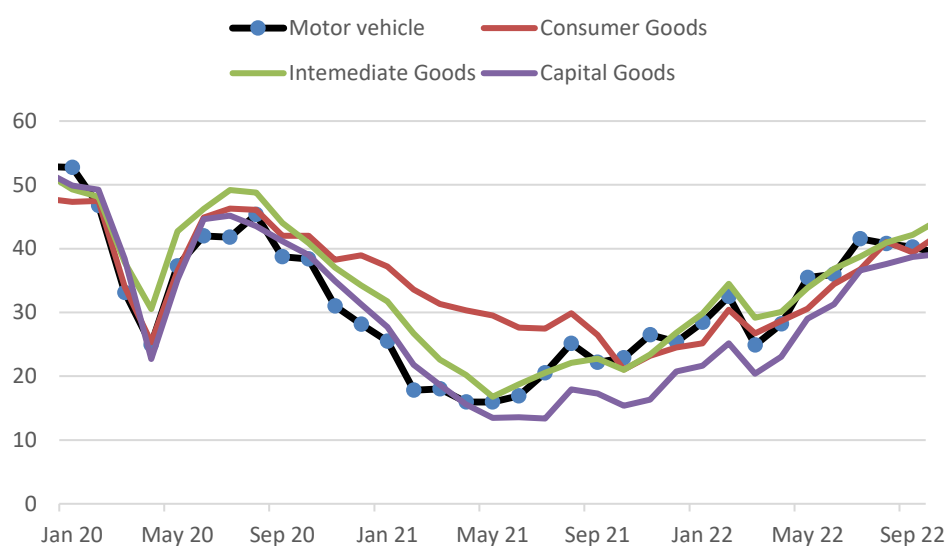
Panel B: Variables used to identify the retail energy supply shocks



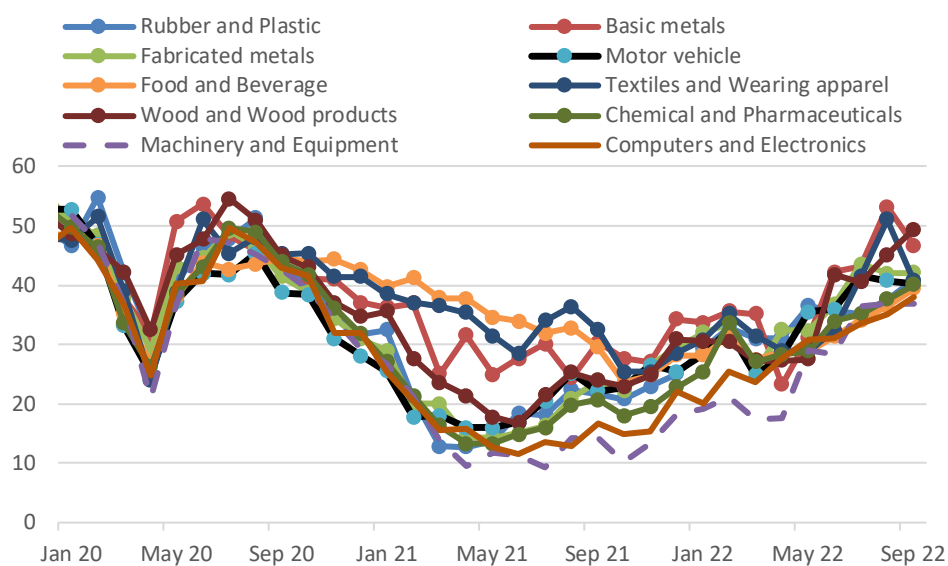
Sources: Eurostat and S&P Global.

Figure 2: Suppliers' delivery times in vehicle output and other Sectors (net balances)

Panel A: Aggregate Sectors

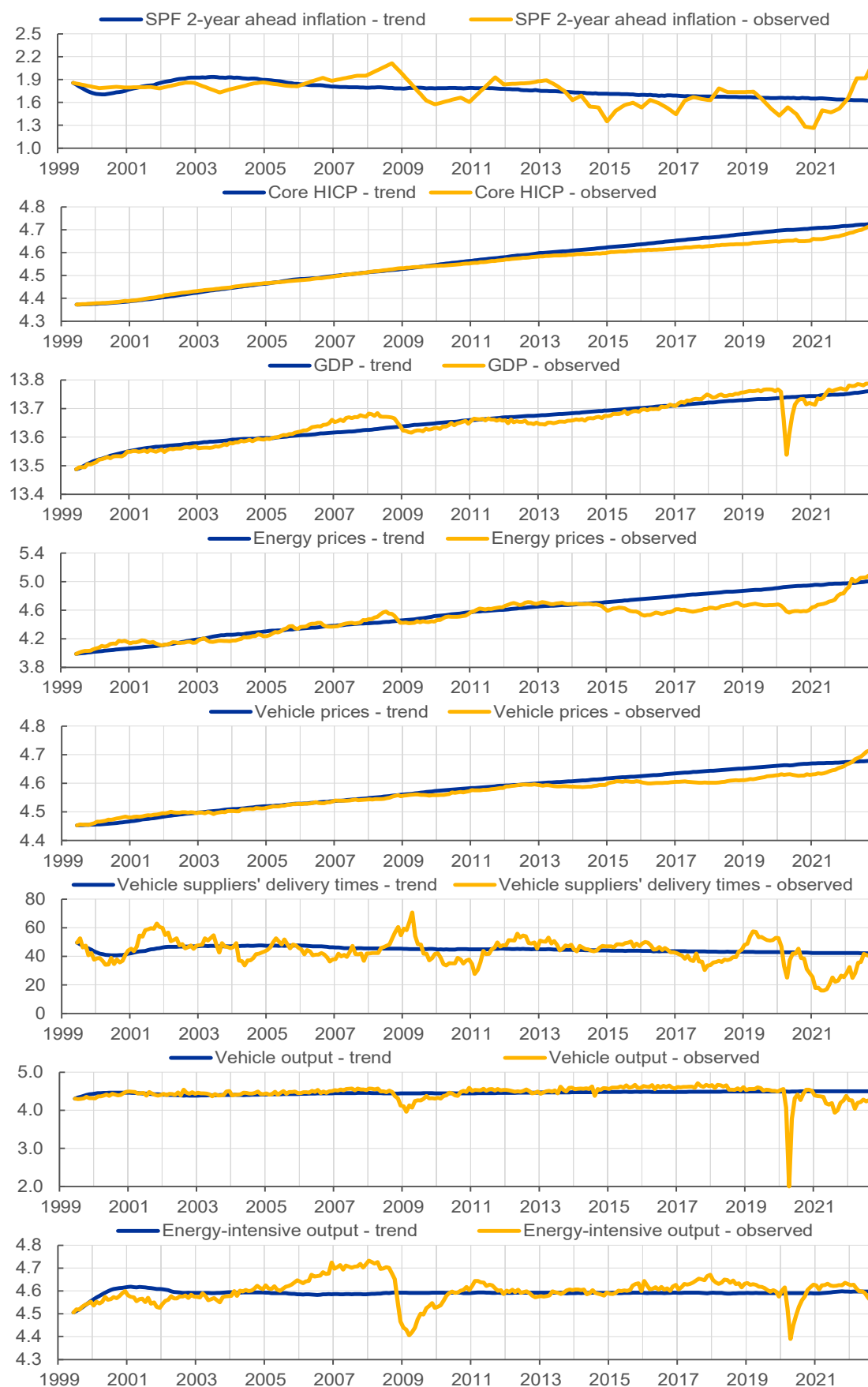


Panel B: Sub-Sectors



Sources: Eurostat and S&P Global.

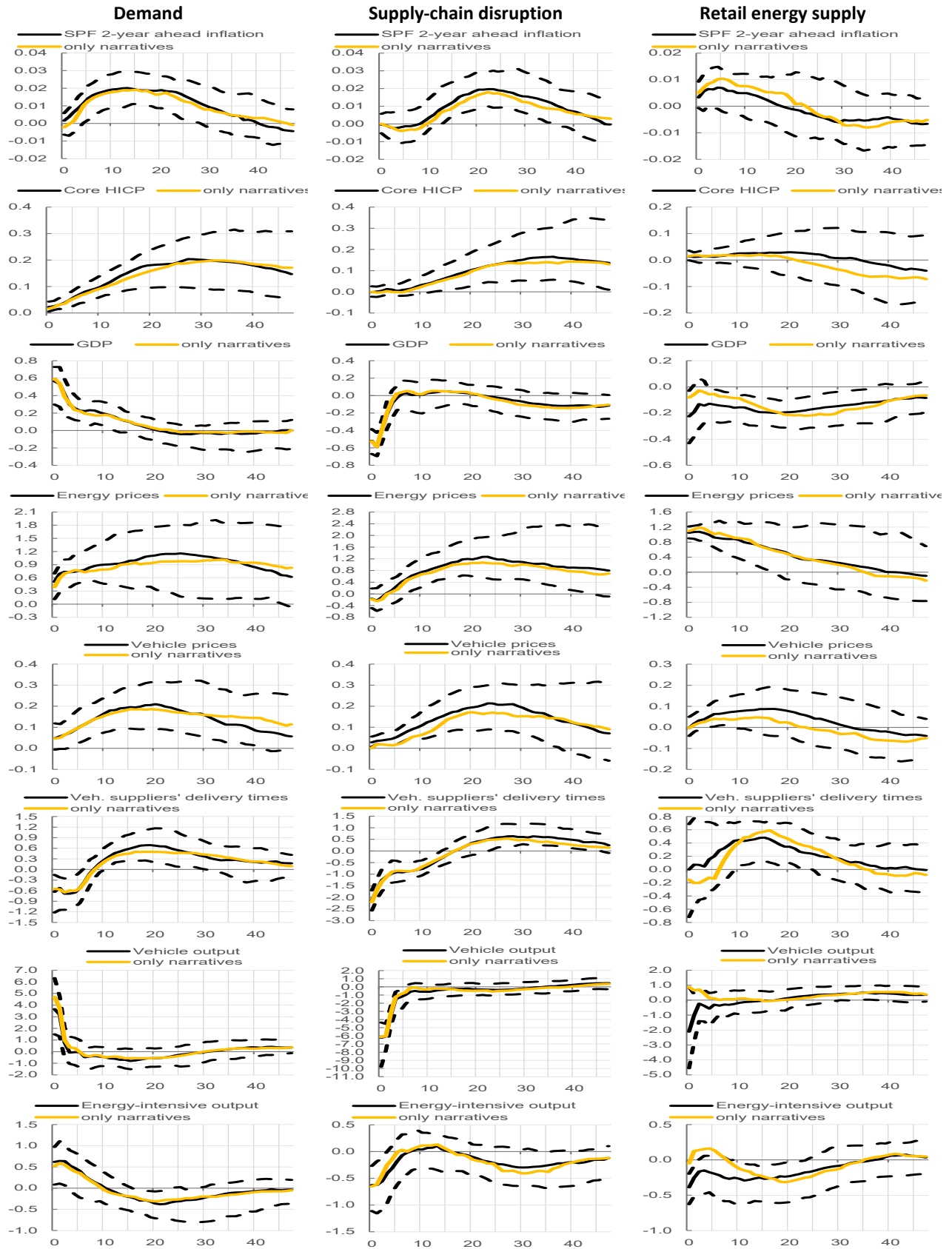
Figure 3: Observed Variables and Stochastic Trends (indices, net balance and %)



Notes: The stochastic trends provide the model simulation of each variable in absence of shocks. All variables except SPF inflation 2-year ahead and motor vehicle suppliers' delivery times are in natural logarithm. SPF inflation 2-year ahead is in percent and year-on-year growth rate. Motor vehicle suppliers' delivery times is in net balances.

Figure 4: Impulse Response Functions (IRFs)

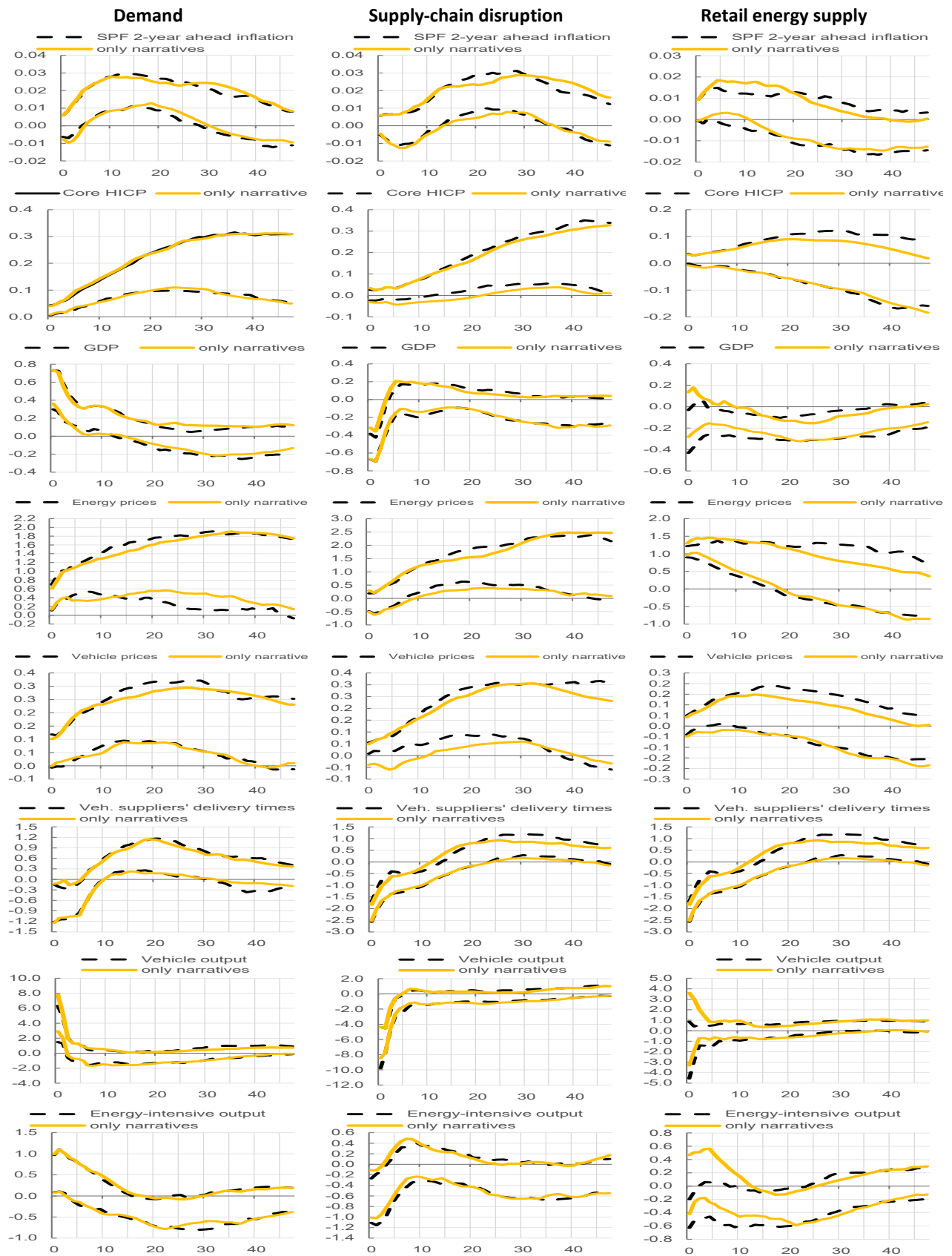
(impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)



Notes: The identifying assumptions are collected in Table 1. Each panel shows the median IRFs and the corresponding posterior 68% pointwise credible sets (dashed lines). The orange line is the median of the model with only narrative restrictions to identify the supply chain disruption shocks and energy supply shocks.

Figure 5: IRFs' Credible Sets: Baseline versus only Narrative Restrictions

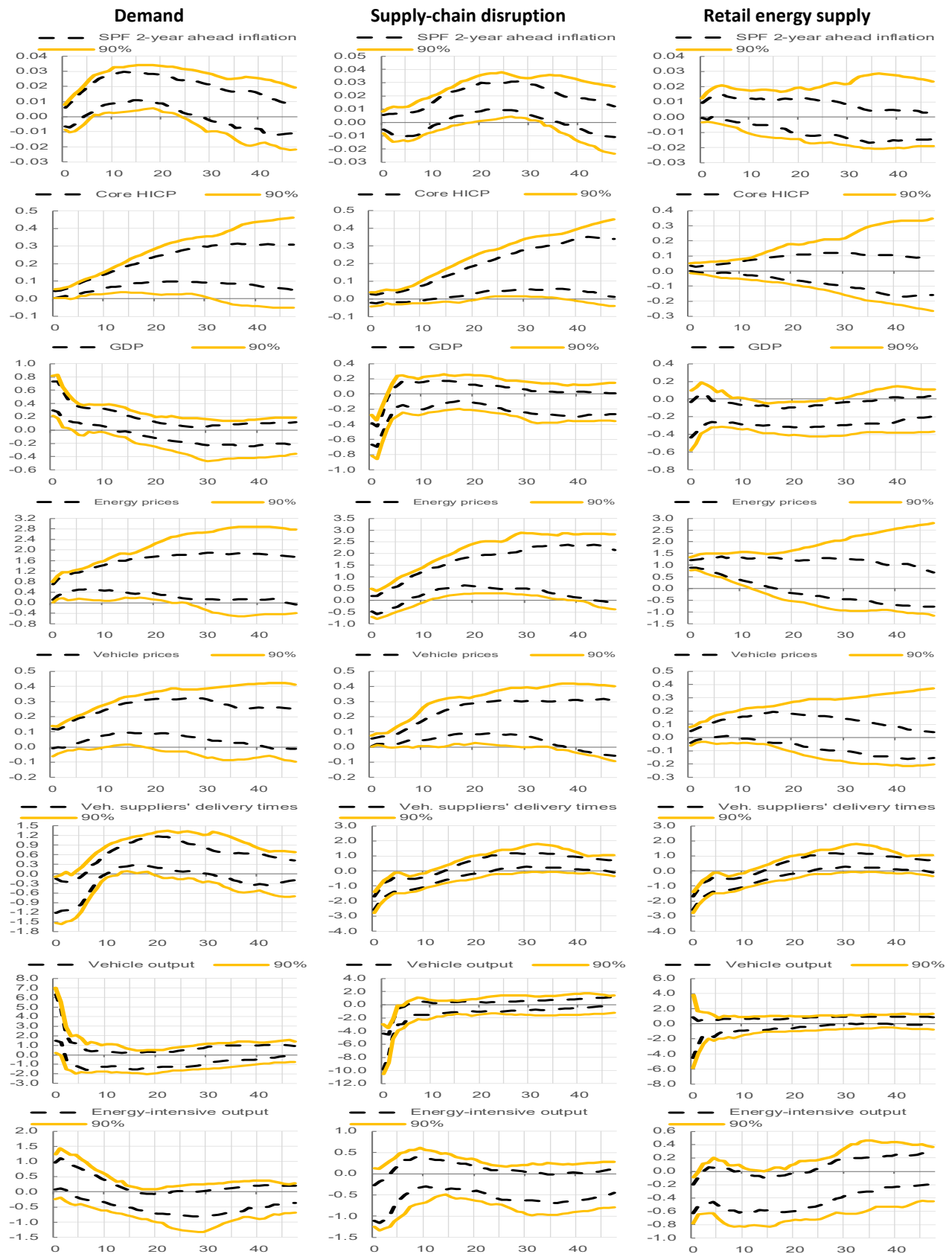
(impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)



Notes: The identifying assumptions are collected in Table 1. Each panel shows the IRFs' posterior 68% pointwise credible sets. The black dashed lines are the 16% and 84% posteriors of the baseline model. The orange lines are the 16% and 84% posteriors of the model with only narrative restrictions to identify the supply chain disruption shocks and energy supply shocks.

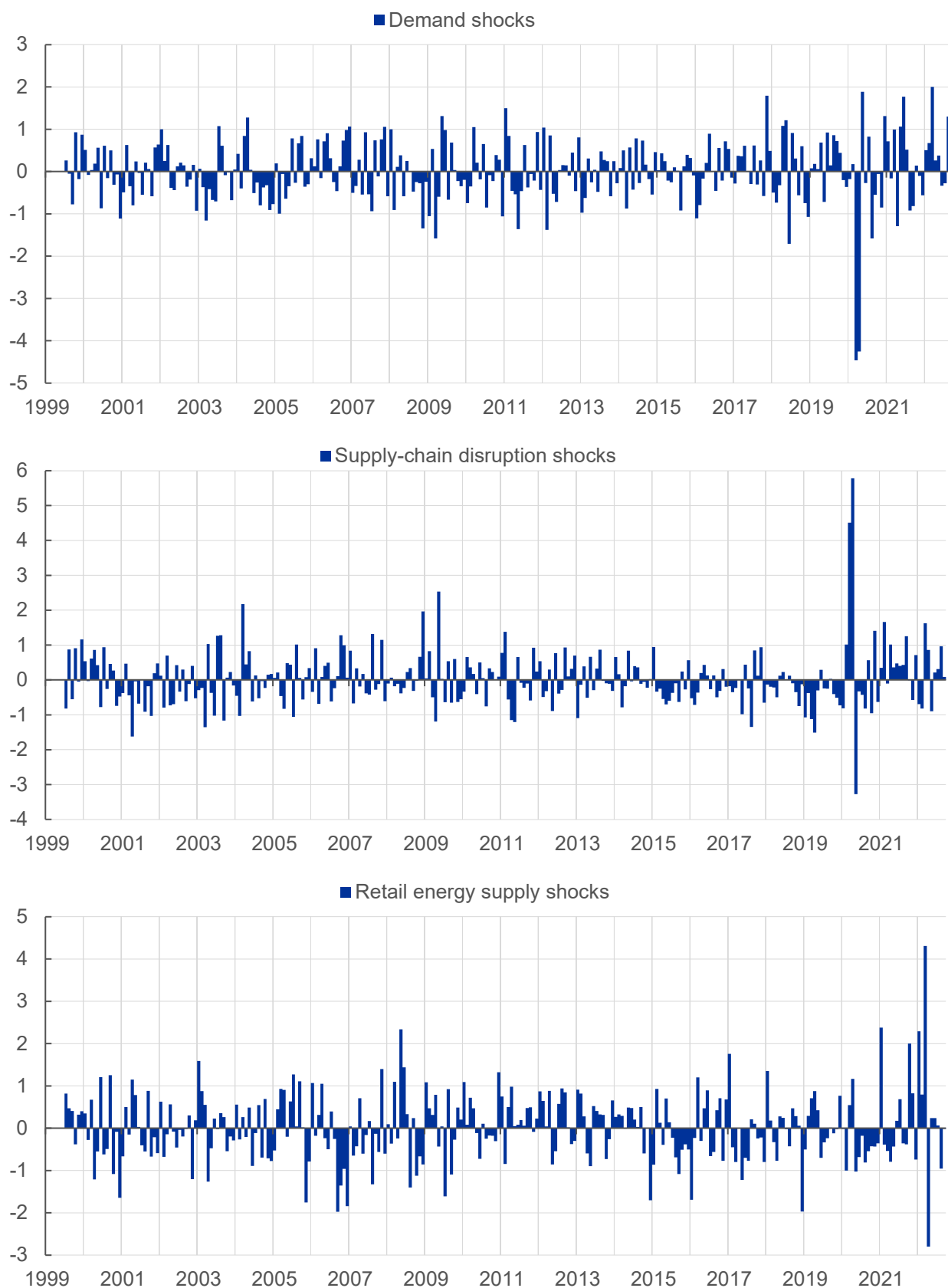
Figure 6: IRFs' Credible Sets: Baseline with 68% versus 90% pointwise credible sets

(impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)



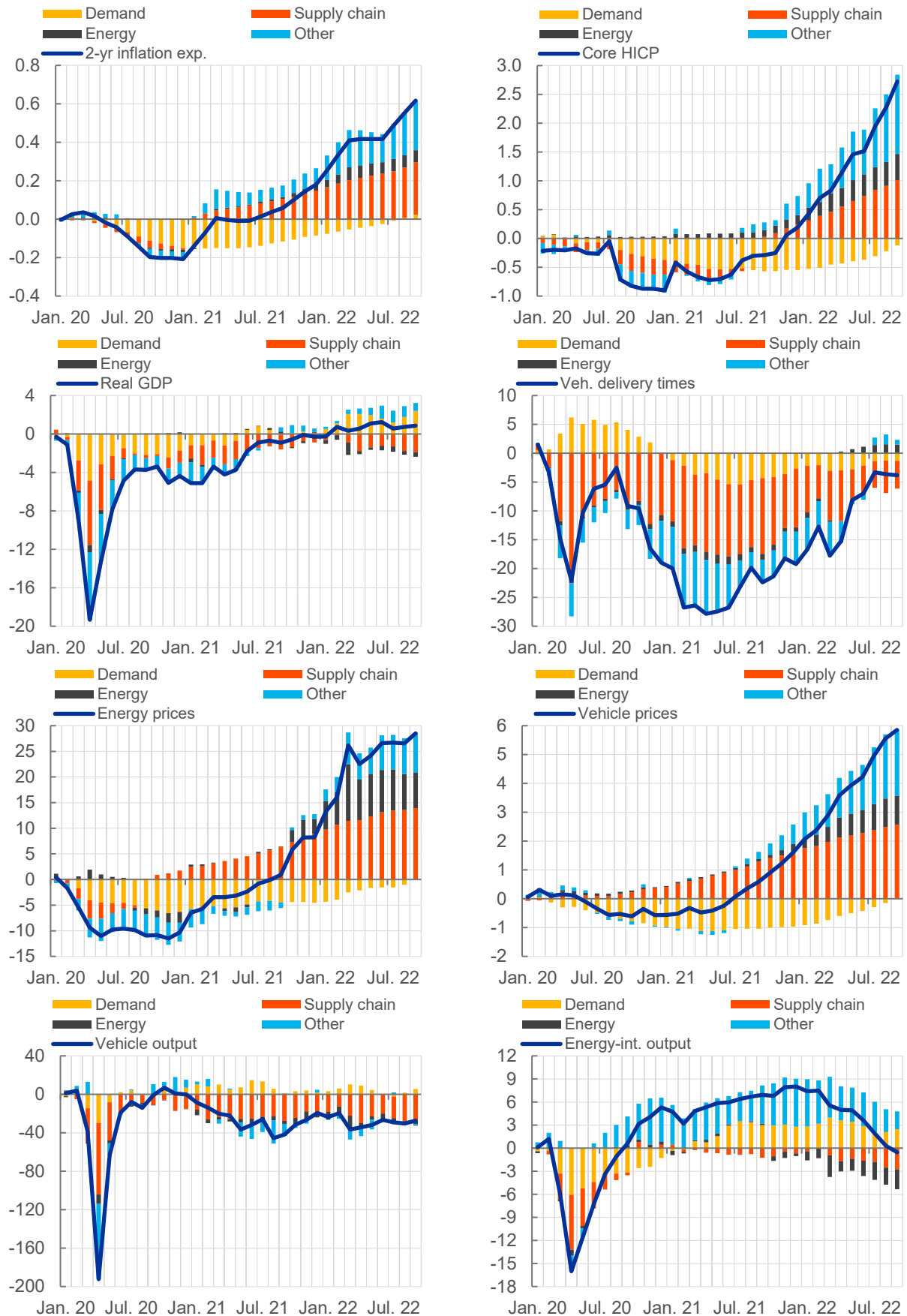
Notes: The identifying assumptions are collected in Table 1. Each panel shows the IRFs' posterior 68% and 90% pointwise credible sets. The black dashed lines are the 16% and 84% posteriors of the baseline model. The orange lines are the 5% and 95% posteriors of the baseline model.

Figure 7: Demand and Supply Structural Shocks (standard deviations)



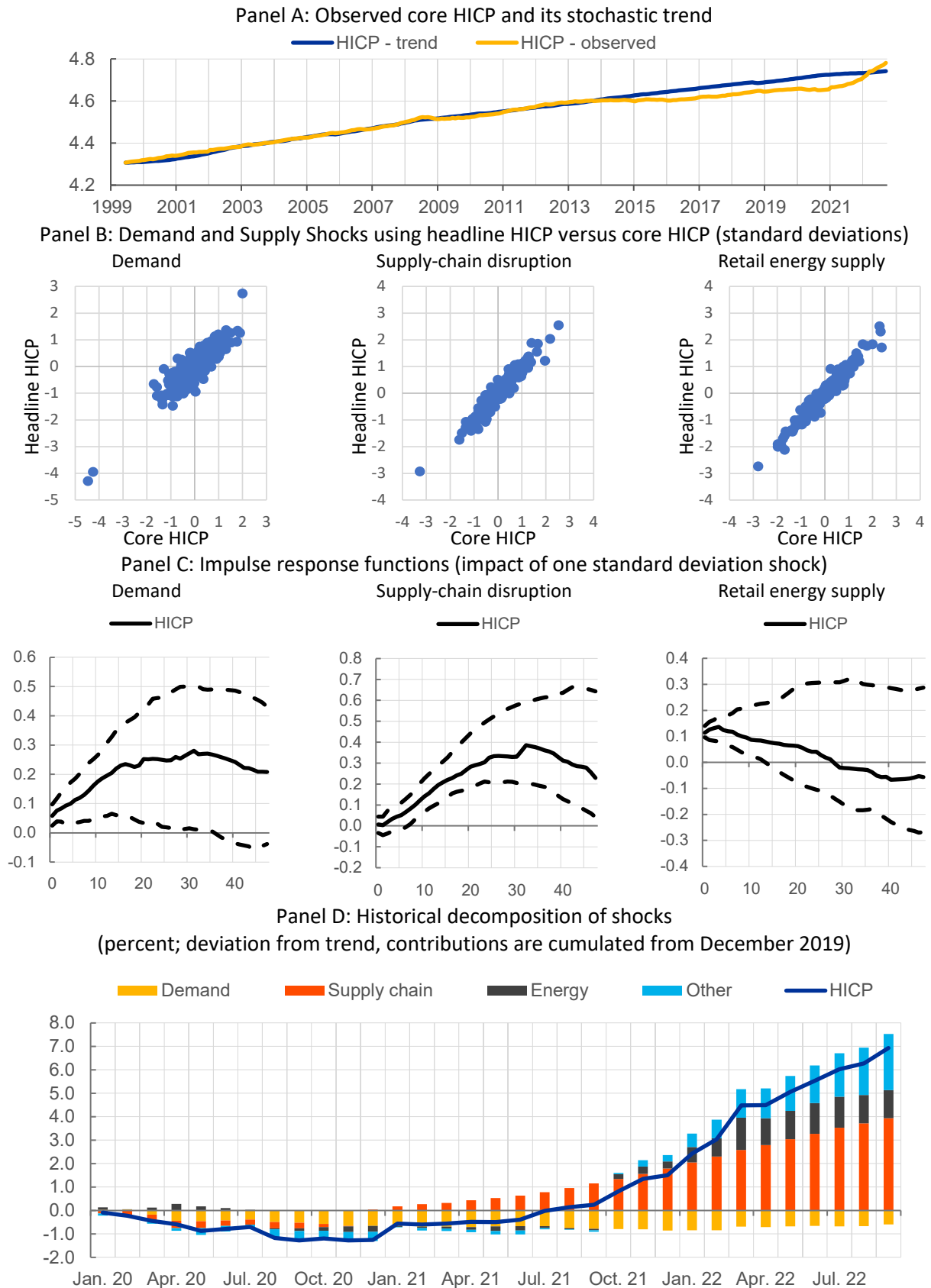
Notes: The identifying assumptions are collected in Table 1. Each panel shows the median structural shocks.

Figure 8: Historical Decomposition of Shocks during the Pandemic Period
(percent, percentage points, deviation from stochastic trend)



Notes: All contributions are cumulated from December 2019.

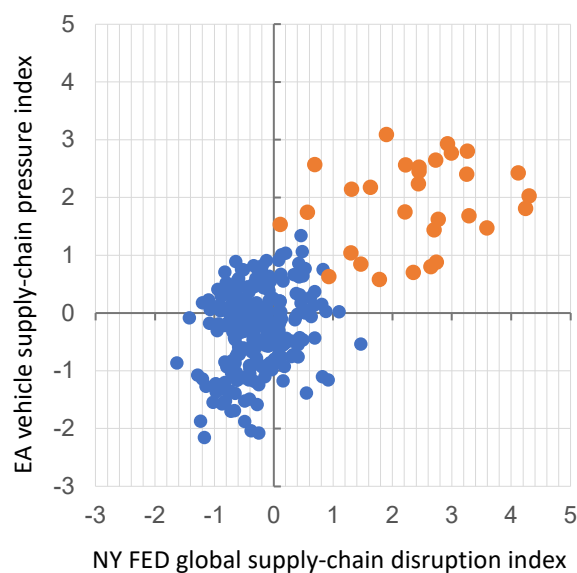
Figure 9: Impact of Demand and Supply Shocks on headline HICP (percent)



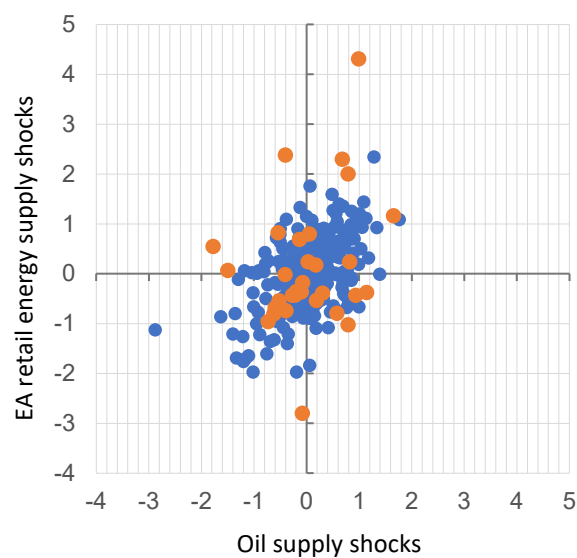
Notes: The represented SVAR contains 8 variables: the 2-year inflation expectations, headline HICP, the vehicle output price, the energy price, real GDP, the vehicle output, the output of the energy-intensive sector and the suppliers' delivery times of the vehicle sector. The identifying assumptions are collected in Table 1.

Figure 10: Supply-Chain Pressure Indices and Energy Shocks

Panel A: Supply-chain pressure indices (standard deviations)

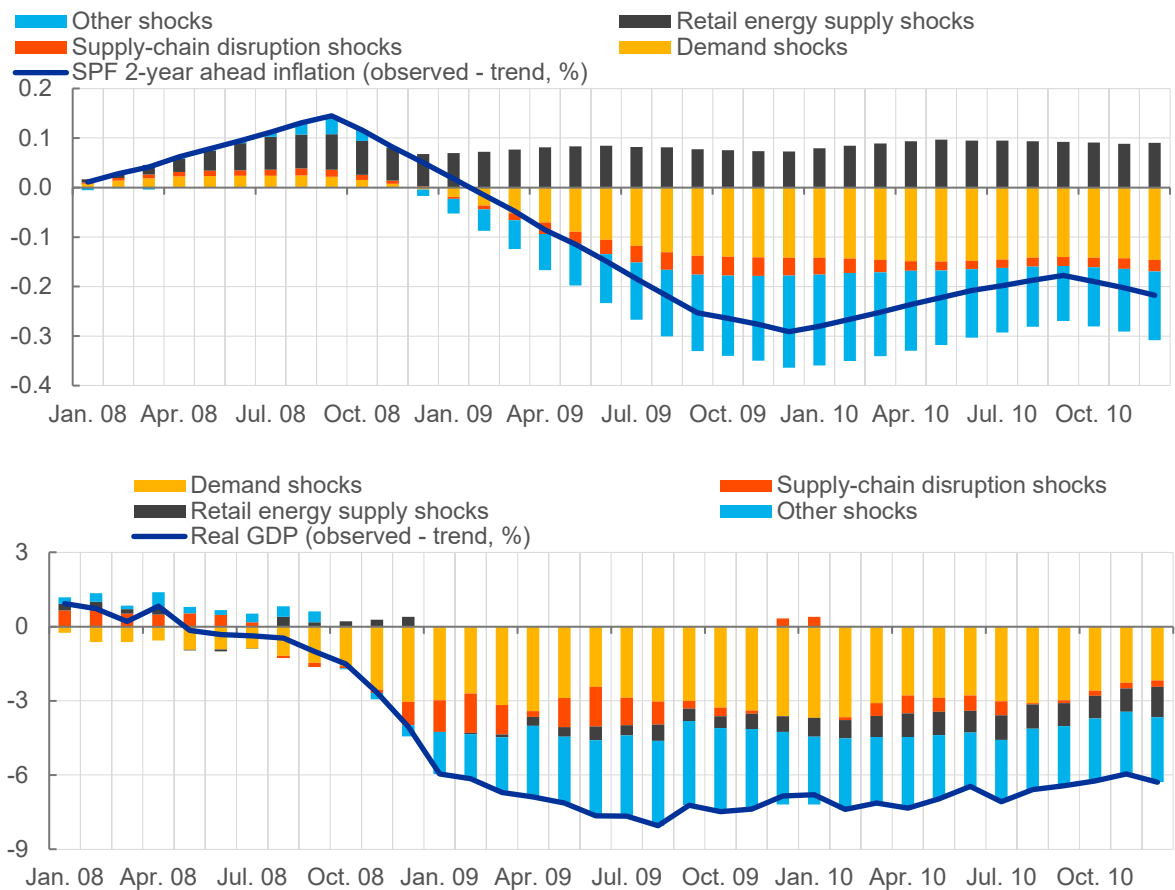


Panel B: Energy shocks (standard deviations)



Sources: Benigno et al. (2022), Känzig (2021) and own calculations. The blue dots refer to the period between July 1990 and December 2019. The red dots refer to the period between January 2020 and September 2022. The identifying assumptions are collected in Table 1.

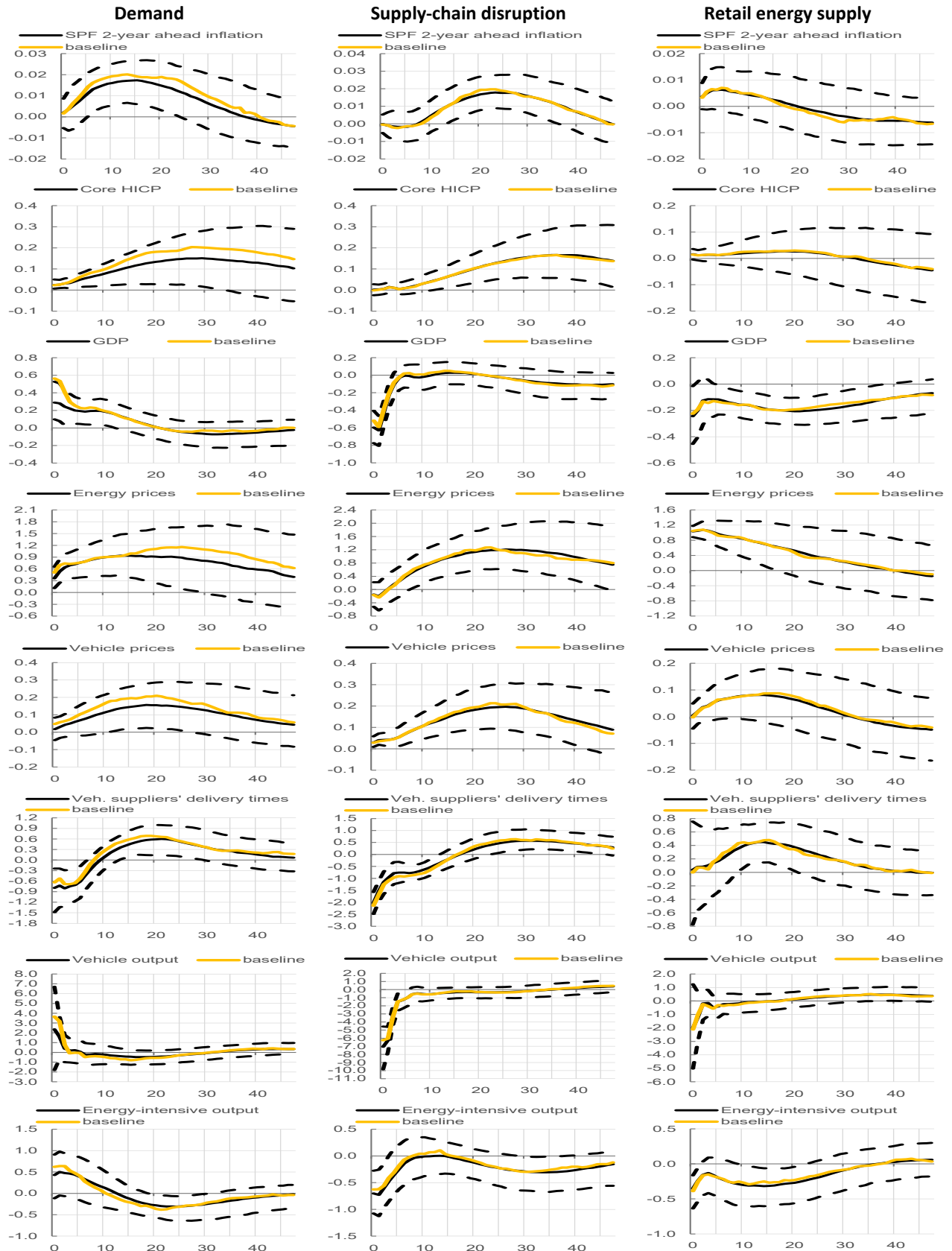
Figure 11: Historical Decomposition of Shocks during the Global Financial Crisis
 (percent, percentage points and net balances; deviation from trend)



Notes: The identifying assumptions are collected in Table 1. All contributions are cumulated from December 2007.

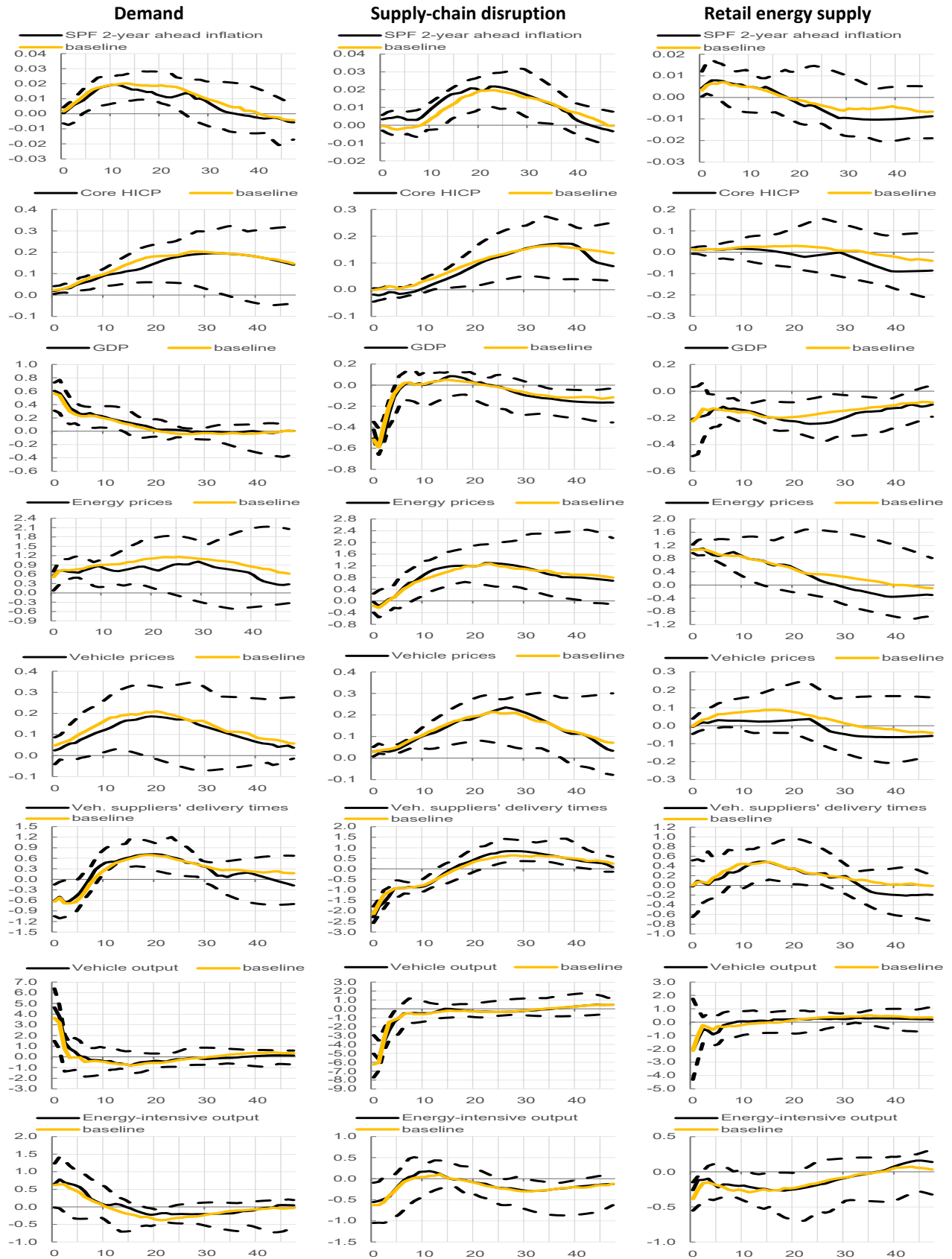
Figure 12: IRFs – excl. the Narratives on the Demand Shocks

(impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)



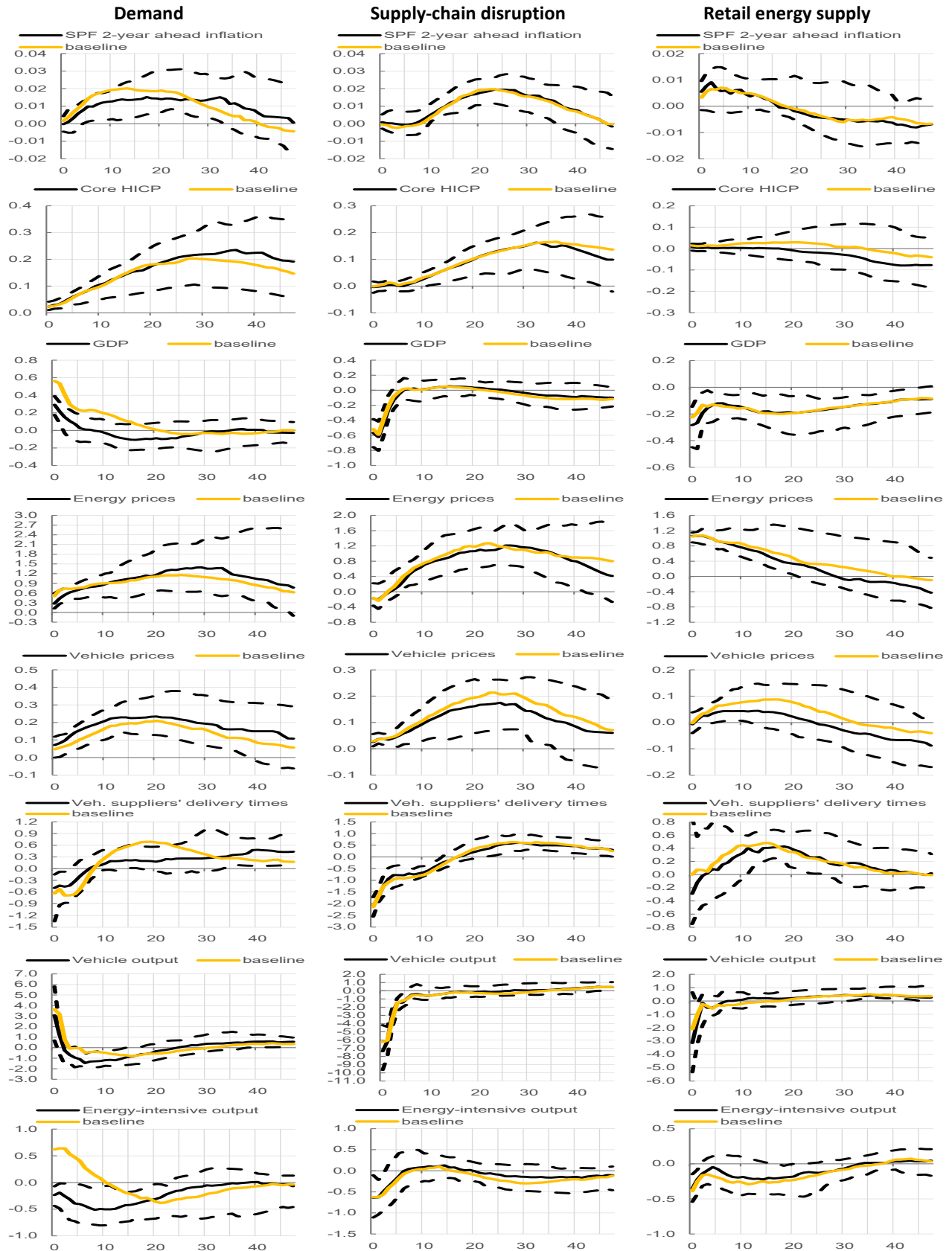
Notes: The identifying assumptions for the baseline are collected in Table 1. The identifying assumptions for the alternative model are those of Table 1, excluding the narrative restrictions on the demand shocks. Each panel shows the median IRFs of the baseline model (orange), the median IRFs of the alternative model (black) and the corresponding posterior 68% pointwise credible sets (dashed lines).

Figure 13: IRFs – incl. March 2021 on the Supply-Chain Disruption Shocks
(impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)



Notes: The identifying assumptions for the baseline are collected in Table 1. The identifying assumptions for the alternative model are those of Table 1, including the March 2021 narrative restrictions on the supply chain disruption shocks. Each panel shows the median IRFs of the baseline model (yellow), the median IRFs of the alternative model (black) and the corresponding posterior 68% pointwise credible sets (dashed lines).

Figure 14: IRFs – incl. a Negative Response of the Energy Intensive Sector Output after Demand Shocks (impact of one standard deviation shock; y-axis: percent or net balance; x-axis: months)



Notes: The identifying assumptions for the baseline are collected in Table 1. The identifying assumptions for the alternative model includes the negative response of the energy-intensive output for three consecutive months after demand shocks. Each panel shows the median IRFs of the baseline model (orange), the median IRFs of the alternative model (black) and the corresponding posterior 68% pointwise credible sets (dashed lines).

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