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ENERGY PRICE SHOCKS AND INFLATION IN THE EURO AREA

by Stefano Neri, Fabio Busetti, Cristina Conflitti, Francesco Corsello,
Davide Delle Monache and Alex Tagliabracci*

Abstract

This paper evaluates the role of supply shocks in driving inflation in the euro area since mid-2021, focusing in particular on shocks to energy prices. The analysis uses different empirical models (including Vector AutoRegressive models, time-varying Phillips curves and dynamic factor models) and shows that shocks to energy prices have had both direct and indirect effects on inflation. The contribution of these shocks to headline inflation is estimated to be around 60 per cent in the fourth quarter of 2022, while that to core inflation to range from 20 to 50 per cent, depending on the model. There is also evidence of an increase in the pass-through of energy prices to core inflation following the outbreak of the pandemic.

JEL Classification: C22, C32, C38, E31.
Keywords: inflation, energy prices, structural VAR, time-varying Phillips curve, Dynamic Factor model.
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Contents

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"[…] *The economy is experiencing large, negative supply shocks pushing output and inflation in opposite directions* […]. *the trade-offs facing monetary policy have become more complicated. In other words, monetary policy has become significantly more complex. In designing the appropriate monetary policy response, central banks need to make two key judgements: one on the origin of the shocks hitting the economy and another on their persistence*."

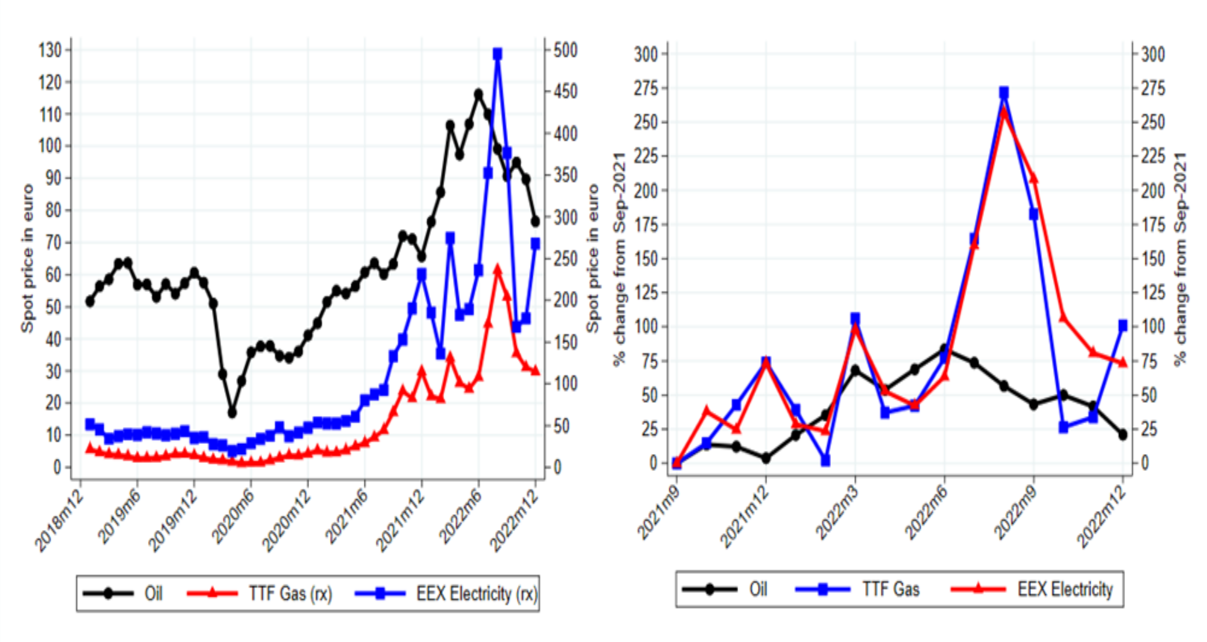
Fabio Panetta, "*The complexity of monetary policy*", speech at the European University Institute, Florence, 14 November 2022

1. Introduction[1]

Starting from mid-2021, energy prices have risen exponentially in global markets reaching historically high values. While the initial increase reflected a host of factors, including the rebound of real activity across the globe after the most acute phase of the Covid-19 pandemic and the below target production of oil by OPEC+, the economic consequences of the Russian invasion of Ukraine further fuelled the prices of energy commodities, especially gas, in Europe.

This upward trend characterized all energy components (Figure 1a), although to different extents: while the rise in oil prices was sizeable but not exceptional compared with past episodes, the magnitude of the increases in gas and electricity prices was unprecedented. As shown in Figure 1b, the spot price for these two commodities rose by almost 300 per cent in less than twelve months.

Figure 1. Developments in energy prices



Source: authors' calculations on Refinitiv data, monthly average. Last observation: December 2022. *Note*: Panel a) presents the prices of the three commodities while Panel b) considers their percentage variations with respect to their value in September 2021. For gas the TTF market price is used, which is the most relevant price in Europe.

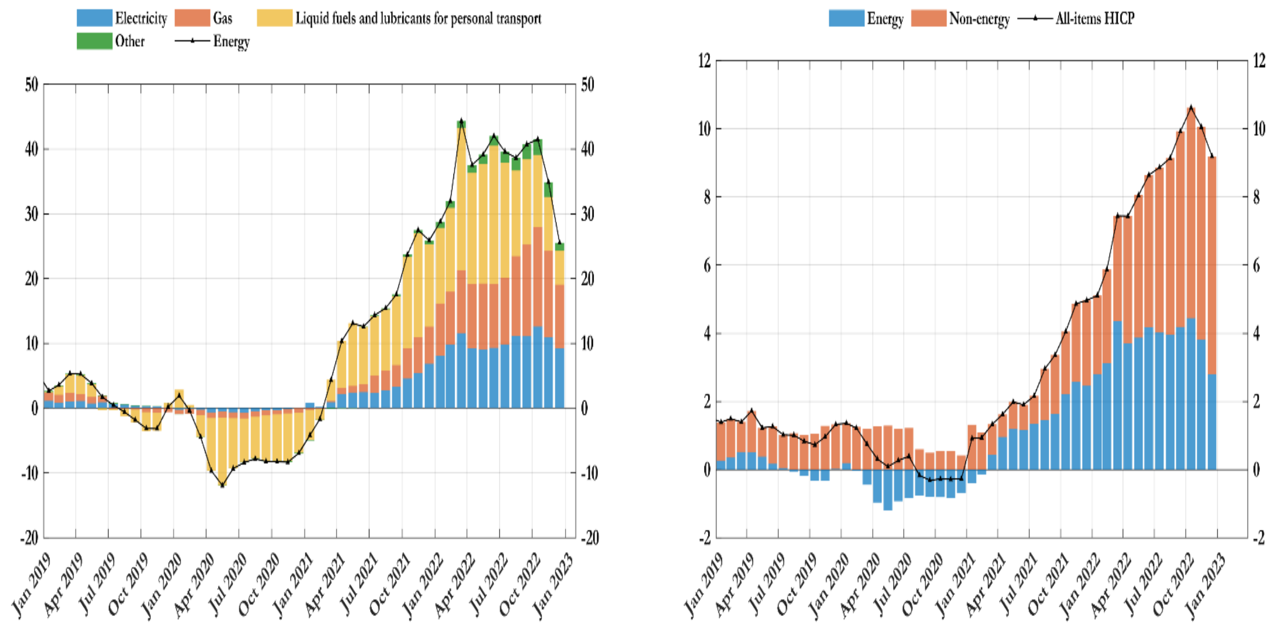
[1] *The views expressed in this article are those of the authors alone and do not necessarily represent the position of Banca d'Italia or the Eurosystem*. Without implications, we would like to thank Michele Caivano, Antonio Conti, Paolo Del Giovane, Matteo Luciani, Alessandro Notarpietro, Marianna Riggi, Tiziano Ropele, Alessandro Secchi, Giordano Zevi, Roberta Zizza and Francesco Zollino for useful suggestions and comments at different stages of this work. All errors are ours.

The global nature of the rise in energy prices led to a sequence of energy shocks, which hit consumer prices hard in the euro area.[2] Headline inflation reached double digits in October 2022 (to a historical record of 10.6 per cent), driven to a large extent by the dynamics of the energy component, which grew by more than 40 per cent year-on-year (Figure 2, panel a) and which directly contributes roughly 4 percentage points (p.p., henceforth) to the variation in the headline index (blue bars in Figure 2, panel b).[3] Euro-area core inflation reached unprecedented levels (over 5 per cent at the end of 2022), reflecting almost equally the contributions of non-energy industrial goods and services.

Figure 2. Energy inflation and its contribution to headline inflation in the euro area

(a) Decomposition of energy inflation (b) Contribution to headline inflation

(y-o-y variation; p.p. for the contributions) *(y-o-y variation; p.p. for the contributions)*



Source: authors' calculations on Eurostat data. Last observation: December 2022.

Assessing the relative importance of supply vs. demand shocks in driving inflation is key, first of all, to set the appropriate monetary policy stance. Contrary to the case of demand shocks, when the economy is hit by aggregate supply or energy price (cost-push) shocks, the central bank faces a trade-off, as countering the impact on inflation would amplify the negative effects on economic activity. In such cases, the central bank could in principle soften the trade-off by extending the horizon at which inflation is brought back to target. In doing so, however, other factors must be taken into consideration, in particular the risk of de-anchoring inflation expectations, igniting a wage-price

[2] With respect to the literature on the global nature of inflation, Ciccarelli and Mojon (2010) and Carriero et al. (2022) provide some empirical evidence for the commonality in the level and in the volatility of inflation rates, respectively.
[3] In October 2022, headline inflation reached historically high values in all the euro-area countries, although with some heterogeneity. This reflects to some extent the different contribution of the energy component, which was affected by several government interventions announced to attenuate the rise in the prices of energy.

spiral and negatively impacting financial stability. The more persistent is inflation, the greater these risks.[4]

This paper presents empirical evidence on the importance of energy shocks on inflation rates in the euro area since mid-2021. Since mid-2021, energy related shocks have played a prominent role in increasing euro-area inflation. The evidence is robust across empirical models (Vector Auto Regressive models, time-varying Phillips curves, dynamic factor models) and different identifications of the shocks. Shocks to energy prices have exerted both direct and indirect effects on inflation. The contribution of these shocks to headline inflation is estimated to have been around 60 per cent in the fourth quarter of 2022, while for core inflation it ranged between 20 and 50 per cent depending on the model (Table 1). There is also evidence of some increase in the pass-through from energy prices to core inflation since the outbreak of the pandemic.

Table 1. Percentage contribution of energy prices to euro area inflation in 2022

	Model	Core inflation	Headline inflation
A)	VAR (Cholesky)	20 (30)	60 (60)
B)	VAR (sign+zero restrictions)	21 (22)	57 (43)
C)	Phillips curve	29 (49)	N.A.
D)	Dynamic factor model	25 (27)	N.A.

Note: figures in brackets refer to the contribution in 2022:Q4. Row B): core inflation is measured with the headline HICP net of the energy component. The percentage contribution of energy and aggregate supply shocks to core inflation is 68 on average in 2022; the contribution of these shocks to headline inflation is 71, on average in 2022.

The remainder of the paper is organised as follows. Section 2 presents the results on the impact of energy shocks on headline and core inflation based on two VAR models. Section 3 presents the results based on a Phillips curve approach and Section 4 those based on a dynamic factor model. Section 5 offers some concluding remarks.

2. Vector Autoregressive models

Vector Autoregressive (VAR) models are well suited to assess the effects of identified shocks. An extensive literature, which started with Sims (1980), has developed VAR models to study the transmission of a variety of shocks, with a particular focus on monetary policy and oil price shocks.

[4] The medium-term orientation of the ECB's monetary policy provides the flexibility to look through temporary supply shocks and avoid unnecessary volatility in economic activity, if such flexibility does not lead to a de-anchoring of inflation expectations or to financial instability.

Recent advances in the literature have expanded the variety of approaches to the identification of the shocks (e.g. Rubio-Ramírez et al., 2010, and Antolín-Díaz and Rubio-Ramírez, 2018).

Section 2.1 presents the results of the estimation of a VAR that is used to quantify the impact of shocks to energy prices on inflation using a recursive identification scheme. Section 2.2 presents the results of the estimation of a VAR in which a set of shocks, including to energy prices and aggregate supply, are identified with a combination of sign and narrative restrictions. The two models differ with regards to: (*i*) the set of variables included; (*ii*) the frequency of observations; (*iii*) the mapping from the reduced-form residuals to the structural shocks.

2.1. Assessing the pass-through of energy prices to inflation

Following Corsello and Tagliabracci (2023), we use a standard VAR model with monthly data, which provides us with a flexible tool to deal with the inter-linkages between variables without imposing too much structure on the data. The model includes energy, food and core inflation and negotiated wage growth, all measured as year-o-year (y-on-y, henceforth) percentage changes, and the unemployment rate. The sample goes from 2002:M1 to 2022:M12. As a caveat, this specification, aimed at obtaining an empirical estimate of the pass-through, omits variables related to the monetary stance, such as policy rates and inflation expectations.

The model is estimated using Bayesian techniques with standard prior settings that are able to preserve efficiency in the presence of a large number of lags.[5] This specification allows us to study the impact of energy prices on core inflation controlling for labour market conditions (in the spirit of a Phillips curve specification) and wage dynamics.

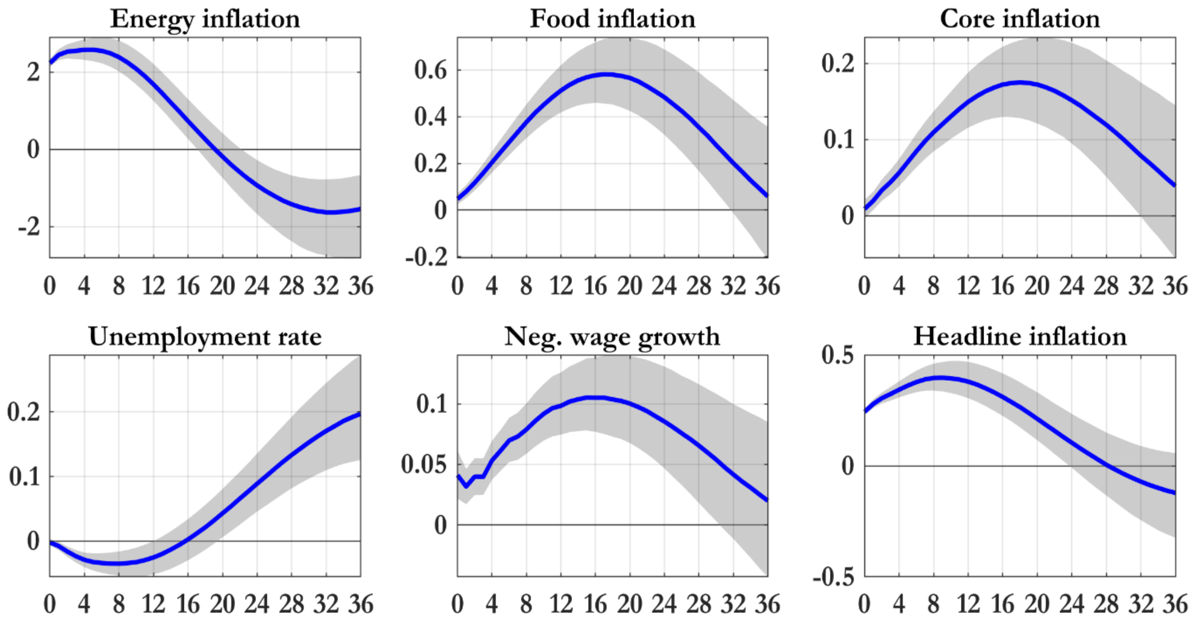
The identification of energy shocks is achieved by using a Cholesky decomposition of the variance-covariance matrix of the residuals. Following previous studies, in particular the seminal paper by Kilian (2008), energy price inflation is ordered first, such that structural innovations to energy prices in the VAR are exogenous with respect to all other current-period shocks. This amounts to assuming that energy prices can be simultaneously affected only by the structural shocks related to its own equation innovations. The ordering of variables and the Cholesky scheme imply that core inflation can react contemporaneously to both energy and food shocks.

We start our analysis by looking at the effects of a one standard deviation shock to energy prices, which corresponds to an impact increase of roughly 2 p.p. in terms of the y-on-y changes of the energy price index. Figure 3 shows the impulse responses. First, the effects on food and core inflation are statistically significant but overall contained, pointing to a largely incomplete pass-through. Second, the size of the impact on food inflation is roughly three times that on core inflation, signalling a higher sensitivity of food prices, in line with Baumeister and Kilian (2014). Third, the

[5] The model features time-invariant coefficients and hence it does not consider possible non-linearities that may have been at play in the last years of volatile macroeconomic data, due to the pandemic outbreak, the subsequent recovery and the surge in energy commodity prices. We have also considered a specification with time-varying coefficients and stochastic volatility but we found that the coefficients appear relatively stable over the sample period, suggesting that in our VAR a specification with time-invariant parameters is a reasonable choice. In Section 3 we further explore the possibility of time-variation in the transmission of an energy price shock with a Phillips curve model.

response of negotiated wages mimics in size and in shape the response of core inflation, suggesting that underlying inflation is closely related to nominal wage dynamics, hence being affected by energy prices only to a minor extent.[6] Looking at the response of unemployment, after a small decline in the first year, the energy shock causes a persistent rise in unemployment, which may reflect the persistent, although limited, increase in wage inflation and the likely contraction in economic activity.

Figure 3. Impulse responses to one standard deviation shock to energy inflation



Source: Authors' calculations on Eurostat data. *Note*: The blue line corresponds to the median response, while the grey areas represent 68 per cent posterior credible intervals.

The model allows us to quantify how the recent large energy shocks propagated to the other inflation components and to provide counterfactual estimates of the dynamics of core and food inflation absent the effects of such shocks (Fig. 4).[7] The negative energy shock at the beginning of the pandemic period exerted a downward pressure on core inflation, which lasted until the first half of 2021. Then, the contribution turned positive due to the positive energy price shocks that occurred in the second part of the year, which exerted a delayed upward pressure on core inflation. In the fourth quarter of 2022, the contribution of energy shocks account for about 1.5 p.p. of the 5.1 per cent value reached by core inflation; in the average of 2022, core inflation would have been 0.8 p.p. lower than the official figure (3.9 per cent) absent the energy shock.

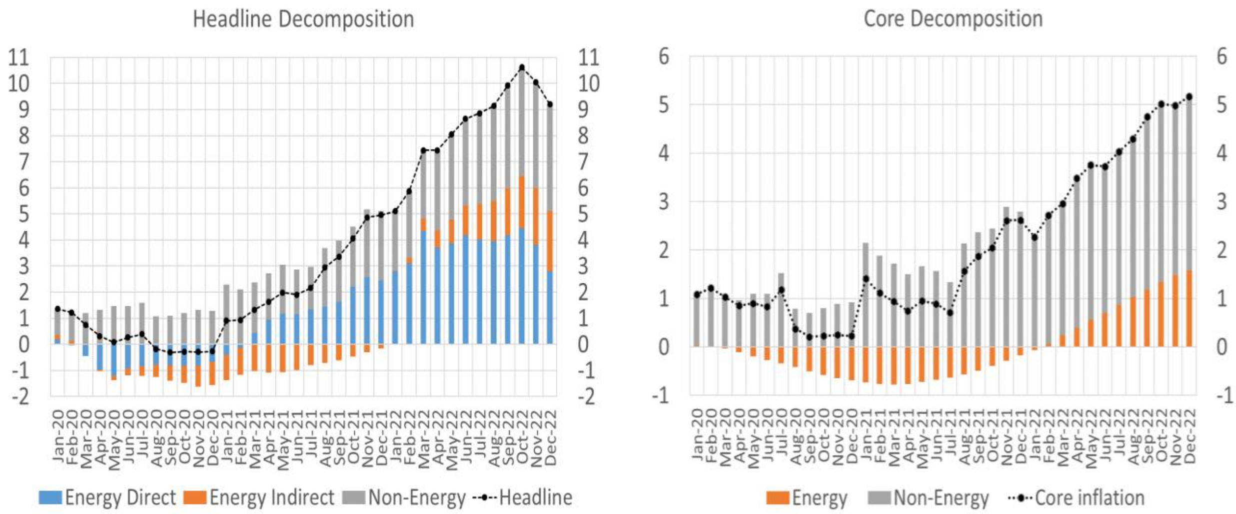
The results are qualitatively similar for food inflation, although with a different order of magnitude. Energy shocks had a large negative contribution to the dynamics of food inflation from mid-2020 until mid-2021. Since then, food prices have been pushed upward by energy shocks,

[6] Wage indexation regimes and more in general the institutions of wage bargaining can be different across euro area countries. The likelihood of wage-setting schemes triggering second-round effects based on inflation indexation is relatively limited, particularly when it comes to energy inflation. For instance, in Italy the reference for collective agreements is the HICP index net of imported energy. Koester and Grapow (2021) provide a comprehensive overview across euro area countries.
[7] For more details, see Section 3.2 in Corsello and Tagliabracci (2023).

explaining almost half of the increase in food prices. Net of these shocks, in the fourth quarter of 2022 food inflation would have been 5.5 p.p. lower than the official value (8.0 instead of 13.5 per cent). In the average of 2022, the contribution to the food component would have been quite sizeable, at 3.2 p.p. (out of 9.0 per cent).

In 2022:Q4, headline inflation was directly affected by the energy component by almost 4 p.p., while indirect effects contributed roughly 2 p.p. Energy inflation accounts for 60 per cent of headline inflation.

Figure 4. Contributions of energy components to headline and core inflation
(*per cent and p.p.*)



Source: Authors' calculations on Eurostat data. *Note*: The black solid line represents the series for headline inflation while the bars show the (direct and indirect) contributions of energy components.

2.2. Post-pandemic inflation in the euro area: the role of demand and supply shocks

This section provides an alternative VAR specification based on quarterly data and with a specific role for shocks to long-term inflation expectations, monetary policy, and aggregate supply.

2.2.1. Specification

The model includes five variables: the (mean point) SPF long-term inflation expectations, the (log of the) energy component of the euro-area consumer price index, the (log of the) headline consumer price index net of the energy component, (the log of) real GDP and the policy rate. These variables are chosen to identify a minimum set of shocks that typically drive inflation in the macroeconomic environment. The consumer prices and real GDP series are seasonally adjusted.

In order to take into account the effects of unconventional measures adopted by the ECB since the Global Financial Crisis, as a measure of the policy rate, we use the EONIA rate up to 2008:Q3 and the shadow short-term rate computed by Krippner (2013, 2020) afterwards.[8]

The estimation period goes from 2001:Q1 to 2022:Q4. The number of lags is set to four, the minimum number yielding serially uncorrelated residuals. We include a linear trend and a dummy variable taking value 1 in 2020:Q2 to account for the unprecedented collapse of output. We also estimate two alternative specifications of the VAR to assess the robustness of the findings to different ways of dealing with the elevated volatility of real GDP following the outbreak of the pandemic.[9] The results are very similar.

We use Bayesian methods for inference. As for the prior distribution, we assume a normal distribution for the coefficients with a Minnesota structure (Litterman, 1986 and Doan et al., 1983), with a mean prior equal to one for each variable's own first lag and zero elsewhere, and a diffuse prior for the covariance matrix of the error terms.[10] The posterior distribution of the reduced-form parameters and the covariance matrix is normal-inverse Wishart. We use the Gibbs sampling to conduct inference.

2.2.2. Identification

The identification of the structural shocks combines the sign restrictions proposed by Canova and De Nicolò (2002) and Uhlig (2005), and later refined by Rubio-Ramírez et al. (2010), and the narrative restrictions proposed by Antolín-Díaz and Rubio-Ramírez (2018). The restrictions are to a large extent based on Neri (forthcoming).

We focus on a parsimonious set of structural shocks that are relevant for studying inflation. To this end, we identify five shocks: aggregate demand and aggregate supply shocks, shocks to energy prices, monetary policy shocks and shocks to long-term inflation expectations. Table 2 shows the sign restrictions. A key assumption for implementing the restrictions is the number of periods over which they are imposed. Canova and Paustian (2011) show that the restrictions on the contemporaneous relationships among the variables are robust to misspecifications of the model used to derive the restrictions. For this reason, we impose them on impact.

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[8] Krippner (2020) estimates the shadow rate for the euro area by assuming a time-varying effective lower bound, which is set at the rate on the Eurosystem's deposit facility. The justification for using a shadow rate after autumn 2008 and before the adoption of asset purchases in late 2014 is that the ECB introduced the fixed rate full allotment procedure in all refinancing operations in October 2008, which allowed banks to obtain unlimited liquidity. The excess liquidity pushed the EONIA close to the deposit facility rate.

[9] The robustness of the results is tested along the following dimensions: the role of the Covid (2020:Q2) dummy, the specification of the VAR, with employment replacing real GDP, and the narrative restrictions. The first two exercises are meant to address the unprecedented magnitude of the fluctuations during the pandemic. Indeed, the decline in employment was smaller than that of real GDP (-3 per cent, compared with -11), as a result of the massive implementation of job retentions schemes. We also assess the robustness of the findings to removing the various narrative restrictions. Only when the NR7 restriction is removed, the contribution of energy and aggregate supply declines somewhat, to levels comparable to that of aggregate demand and monetary policy shocks.

[10] The overall tightness of the prior is set to 0.20, a standard value used in the literature. The tightness of the variance of the prior of each variable lags relative to the lags of the other variables is set to 0.5. The variance of the prior coefficients of the lags of each variable follows the harmonic decay $l^{-0.5}$. The priors for the constant and the coefficient on the linear trend are normal with a zero mean and standard deviation equal to 100.

A positive aggregate demand shock raises both net-energy consumer prices and economic activity, to which the ECB responds by raising the policy rate. A positive (adverse) aggregate supply shock leads to an increase in consumer prices and to a decline in economic activity. The sign of the response of long-term inflation expectations to aggregate demand and supply shocks is unrestricted. A negative shock to inflation expectations causes a decline in consumer prices and leads to a reduction in the policy rate. Energy prices do not respond to the shock to expectations. The response of output to a shock to inflation expectations is unrestricted. A positive shock to energy prices raises all consumer prices and lowers real GDP. Finally, a positive (contractionary) monetary policy shock raises the policy rate and causes a decline in (net-energy) consumer prices and output. The response of expectations to monetary policy shocks is unrestricted.

Table 2. Sign and zero restrictions

Variable / shock	Aggregate demand	Aggregate supply	Inflation expectations	Energy	Monetary policy
Inflation expectations			-		
Consumer prices net energy	+	+	-	+	-
Energy prices	+		0	+	
Policy rate	+		-		+
Real GDP	+	-		-	-

Note: a – means that the response is negative and a + means that it is positive; a blank space means that the response is unrestricted; a zero means the variable in the row does not respond to the shock in the column.

As for the narrative restrictions, we make the following assumptions, which are reported in Table 3. First, the shock to inflation expectations is positive in 2008:Q3 (NR1) and negative in 2019:Q2 (NR2). In these two periods, long-term inflation recorded historically large changes (Corsello, Neri and Tagliabracci, 2021). Second, we assume that the contribution of the shocks to the deviations of long-term inflation expectations from the baseline in 2019:Q2 is larger, in absolute value, than the sum of the contributions of the other shocks (NR3). Third, we assume that the monetary policy shock is positive in 2014:Q3 (NR4), when the ECB surprised markets and analysts and cut the rate on the deposit facility by 10 basis points, to -0.20 per cent. Indeed, only 7 per cent of the analysts interviewed by Reuters a few days before the meeting of the ECB's Governing Council were expecting a rate cut. Following Fink and Tillman (2023), we assume that the shocks to aggregate supply are positive in 2011:Q1 (Tōhoku earthquake in March 2011; NR5) and in 2021:Q1 (Suez Canal obstruction; NR6).[11] Finally, we assume that the contribution of shocks to energy prices to these prices is larger than the contribution of all other shocks in 2022:Q1, when Russia invaded Ukraine (NR7) and oil and gas prices, in particular, increased sharply amidst fears of massive supply disruptions.

[11] On March 11, 2011, the most powerful earthquake ever recorded in Japan shocked the Pacific Ocean off the coast of the Tōhoku region on the Japanese Island of Honshu. On March 23, 2021, Ever Given, one of the largest container ships blocked the Suez Canal. Both events caused major disruptions to global supply chains.

Table 3. Narrative restrictions

Narrative restriction 1 (NR1)	Shock to long-term expectations is positive in 2008:Q3
Narrative restriction 2 (NR2)	Shock to long-term expectations is negative in 2019:Q2
Narrative restriction 2 (NR3)	Absolute value of contribution of shock to long-term expectations in 2019:Q2 larger than the sum of the absolute values of the contributions of the other shocks
Narrative restriction 4 (NR4)	Shock to monetary policy is positive in 2014:Q3
Narrative restriction 5 (NR5)	Shock to aggregate supply is positive in 2011:Q1
Narrative restriction 6 (NR6)	Shock to aggregate supply is positive in 2021:Q1
Narrative restriction 7 (NR7)	Absolute value of contribution of shock to energy in 2022:Q1 larger than the sum of the absolute values of the contributions of the other shocks

2.2.3. Inference

Inference is based on 100,000 draws from the posterior distribution of the reduced form VAR parameters and 5,000 draws from the unitary sphere for each draw from the posterior. We discard around 65,000 draws from the posterior distribution of the VAR, as the maximum eigenvalue of the associated companion matrix implies explosive dynamics. Explosiveness of the OLS companion matrix of the VAR is detected when the estimation sample includes the observations for 2022:Q2 and 2022:Q3. About 4,600 draws are retained for inference. The low number of accepted draws is due to the many narrative restrictions imposed.

2.2.4. Historical decompositions

In this section, we discuss the results of the historical decomposition of (y-on-y) inflation ex-energy, energy inflation, real GDP (y-on-y) growth and the policy rate focusing on the 2021-2022 "high inflation" period. Figures 5 and 6 show the mean of the posterior distribution of the contributions of the various shocks in each quarter. The historical decomposition of inflation is computed, within the Gibbs sampling, as the weighted sum of the decompositions of consumer ex-energy and energy inflation. In order to highlight the role of demand and supply shocks, we group aggregate supply and energy shocks, isolate the aggregate demand shock and group together the monetary policy shocks with those to long-term inflation expectations. The latter choice reflects the interpretation of the shocks to inflation expectations in the second half of 2021 and in 2022 as the result of the review of the monetary policy strategy, which clarified the inflation target of the ECB and supported the re-anchoring of long-term inflation expectations.

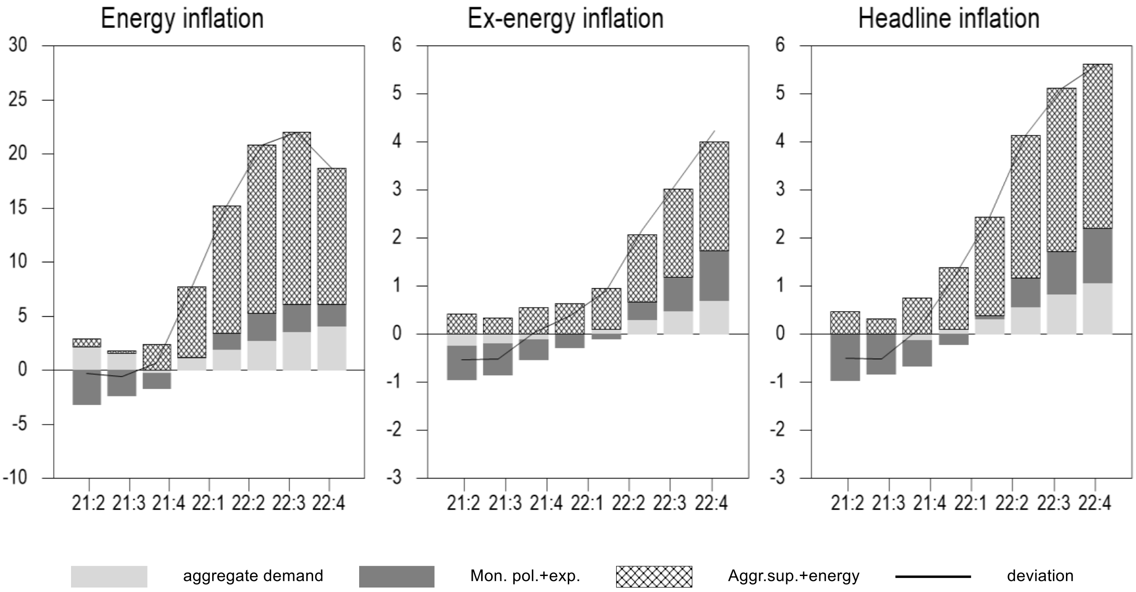
Since 2021:Q3, positive shocks to energy prices have pushed these prices to unprecedented levels. These shocks account for 13 p.p. of a total deviation from the baseline of 19 in 2022:Q4 (Figure 5, left panel), which is equivalent to 67 per cent of the deviation. This share is larger in 2021:Q4, amounting to almost the total deviation. In the case of ex-energy inflation, shocks to energy prices and to aggregate supply account for 2.3 p.p. out of a total deviation of 4.2 in 2022:Q4 (Figure 5, mid panel). Demand and monetary policy shocks account for 1.0 p.p. All shocks exert a growing contribution to ex-energy inflation in 2021 and 2022.

As for headline inflation, the contributions of energy shocks and shocks to aggregate supply also increase over time. The sum of their contributions reaches a maximum of 3.4 p.p., out of a total deviation of 5.6 in 2022:Q4 (63 per cent; Figure 5, right panel). This result shows that shocks to energy prices exert significant indirect effects on the prices of food, non-energy industrial goods and services. Shocks to aggregate demand account for 1.1 p.p. of the deviation of headline inflation in 2022:Q4.

Monetary policy shocks exert an upward pressure on all inflation rates, which is the result of the expansionary measures adopted since the outbreak of the pandemic, given the lags in the transmission of monetary policy. Monetary policy shocks and shocks to long-term inflation expectations, which capture their re-anchoring after the strategy review, account for 1.1 p.p. of the deviation from the baseline in 2022:Q4.

Figure 5. Historical decomposition: energy and ex-energy and headline inflation

(*p.p.; deviations from the baseline*)

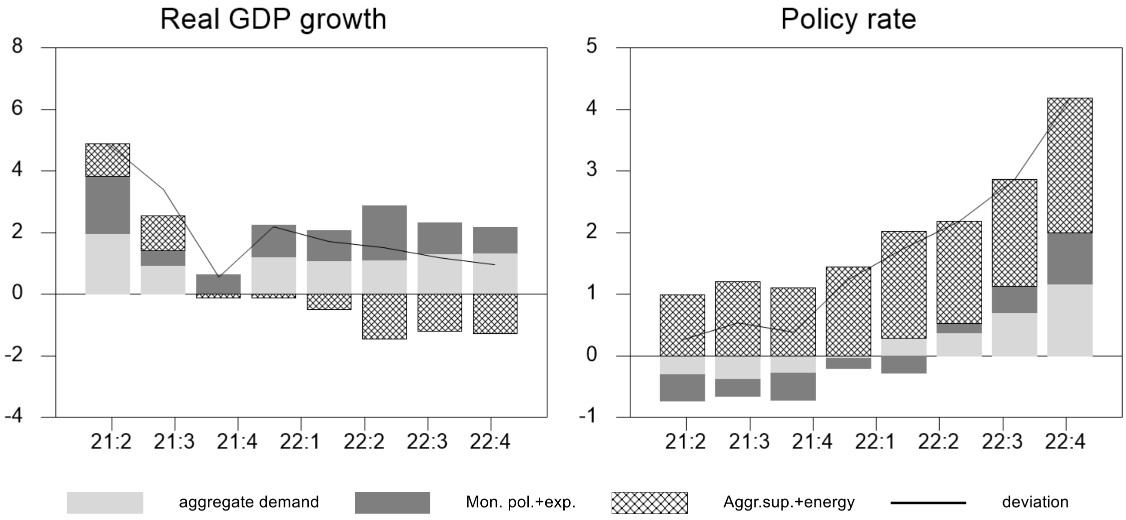


Note: mean of the posterior distribution of the contribution of the shocks to the deviation from the baseline in each quarter. The contributions to the various inflation rates are computed within the Gibbs sampling as the four-quarter difference of the contributions to the corresponding consumer prices.

Turning to real GDP growth, Figure 6 shows that the positive effects of the negative shocks to energy prices occurring in 2020 gradually faded away in the course of 2021 and started exerting a downward pressure on real GDP growth in early 2022. The impact of adverse shocks to energy and to supply reached a maximum of -1.4 p.p. in 2022:Q2. At the same time, positive aggregate demand shocks contributed to sustaining real GDP growth, by 1.2 p.p., on average, in 2022. Monetary policy shocks and shocks to long-term inflation expectations exerted a positive contribution to real GDP growth in all the quarters in 2021 and 2022, with the largest contribution in 2022:Q1 (1.9 p.p.).

Figure 6. Historical decomposition: real GDP growth and policy rate

(*p.p.; deviations from the baseline*)



Note: mean of the posterior distribution of the contribution the shocks to the deviation from the baseline in each quarter.

The deviations of the policy rate from the baseline are mainly due to energy and supply shocks and, to a lesser extent, contractionary monetary policy shocks and positive shocks to long-term inflation expectations. These results suggest that the ECB responded to the adverse shocks to energy prices and to aggregate supply by tightening monetary policy. The ECB also responded to positive shocks to aggregate demand in 2022.

All in all, adverse shocks to energy prices and to aggregate supply played an important role in shaping inflation and economic activity in 2021 and 2022, to which the ECB responded by reducing the degree of monetary accommodation and bringing the monetary policy stance in contractionary territory in the second half of 2022.

3. The impact of the energy shock on euro area core inflation: the role of nonlinearities

A key question is whether the exceptional nature of the energy shock may have triggered changes in economic behaviours and relationships. These potential changes may have modified the pass-through of energy commodity prices to consumer inflation.

This section provides an empirical investigation that allows for nonlinearities in the relationship between core inflation and its main drivers. The econometric specification is a Phillips curve model with time-varying parameters that is estimated using a range of alternative indicators for the energy price pressures and the economic slack.

3.1 OLS estimates

We start by estimating the linear Phillips curve type regression model

$$\pi_t = \alpha + \rho\pi_{t-1} + \delta' x_t + \varepsilon_t \tag{1}$$

with OLS, where π_t is euro area core inflation (measured as y-o-y percentage growth), x_t contains indicators of economic slack and energy prices, which are chosen among alternative options detailed below, and ε_t is an error term.[12]

Regarding energy price pressures, Figure 7 shows three alternative indicators (import deflator, industrial producer prices[13] and the energy component of the consumer price index) plotted with the series of core inflation (right-hand scale) over the period 1997:Q1-2022:Q4. These three indicators move relatively close to each other, although the fluctuations in the HICP energy are wider. It is also clear that energy prices affect core inflation with some delay. Goodness of fit considerations suggest that the import deflator and the HICP energy enter the regression model with a lag of four quarters, while industrial producer prices with a lag of three.

In principle, the import deflator should be the more appropriate indicator for modelling core inflation, in addition to a domestic demand covariate, since it includes all price pressures originated abroad and not only those related to energy commodities. The chart, however, shows that in the latest periods the spikes in producer and HICP energy prices were more pronounced than those of the import deflator and hence these two variables may be more suitable to capture the sharp rise of core inflation.

Regarding the economic slack, this variable is usually obtained by estimating an unobservable indicator, such as the output or unemployment gaps, by means of signal extraction methods. Recently, one additional difficulty in the measurement of economic slack is the treatment of the large outliers in economic activity that occurred during the COVID pandemic. Indeed, euro-area real GDP fell by over 3 and 11 per cent in the first and second quarters of 2020, to rebound by more than 12 per cent in the third quarter. Using standard models, these huge fluctuations would directly translate into a corresponding volatility of the output gap, even though they do not represent a lack of demand but mostly the result of the severe restraints in economic activity enacted to contain the pandemic. A proper statistical treatment would heavily discount those episodes in econometric modelling.[14] As a shortcut to more sophisticated approaches, we use the following strategy: (*i*) a standard time series model is fit to euro-area real GDP but assuming that the observations for 2020:Q1, 2020:Q2 and 2020:Q3 are unknown; (*ii*) these missing data are replaced by a model-based interpolation.[15] Figure 8 shows the three measures of economic slack: an unobserved component estimate of the cyclical component of GDP (denoted as UC output gap)[16], the percentage y-o-y change of GDP; and the unemployment rate.

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[12] The equation does not include a forward looking indicator of inflation expectations, such as a Consensus forecasts. However, as showed in Busetti, Caivano and Delle Monache (2021), the inclusion of an expectation term mainly affects the estimates of the intercept and, slightly, of the autoregressive parameter, leaving the other coefficients broadly unchanged. In a time-varying coefficients model (which in general calls for a parsimonious specification) changes in long-term inflation expectations are captured by the implicit long-term anchor of the model.

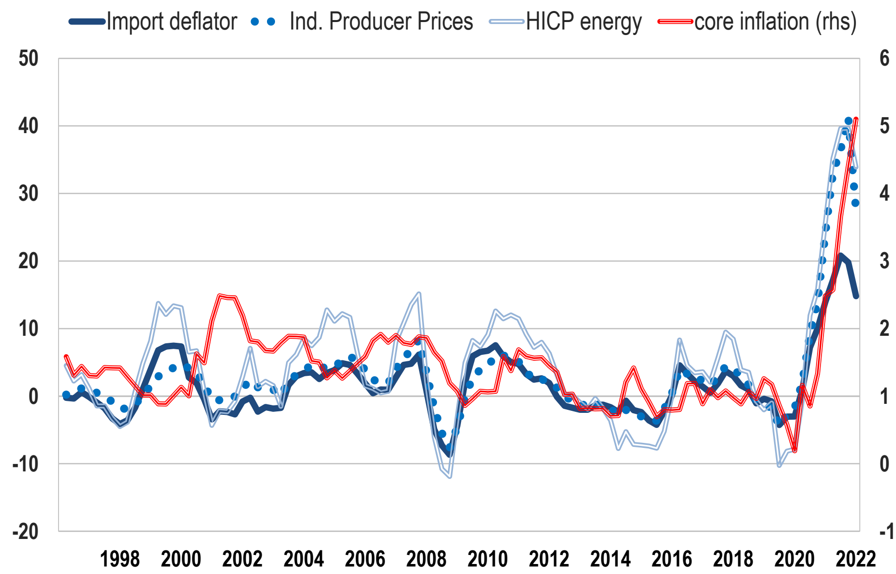
[13] The fluctuations of industrial producer prices are largely driven by the energy component. However, to a minor extent, they also include other sources of pressures at the origin, e.g. difficulties in supply chains.

[14] Allowing for outliers is particularly important for the case time-varying parameters models as the estimates of coefficients are obtained by ‘local’ correlations and hence they cannot be reliable in the presence of extreme values.

[15] The assumption of missing data in 2020:Q1-2020:Q3 can be regarded as a limiting case of discounting the contribution of those observations in the econometric estimates.

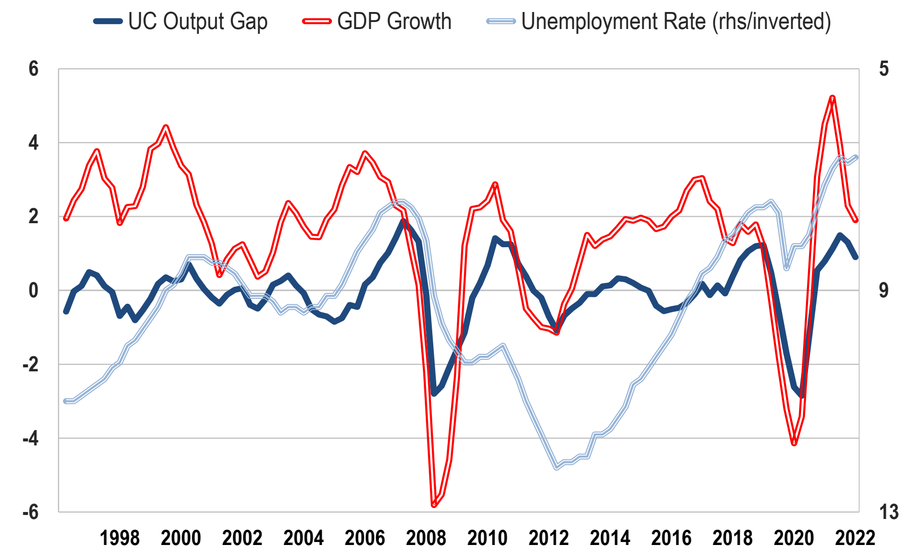
[16] This estimate of the output gap is obtained by an unobserved component (UC) model made of a smooth trend (integrated random walk) plus an AR(2) cycle.

Figure 7. Core inflation and alternative indicators of energy price pressures
(*y-on-y growth rates*)



The first two indicators are interpolated over the period 2020:Q1-2020:Q3 as described in the previous paragraph; for the unemployment rate the raw data are used, as the rise of unemployment during the peak of the pandemic was contained by the job retention schemes adopted in most countries. The two GDP-based indicators tell a similar story, but the fluctuations in actual real GDP growth are generally larger than those of the output gap.

Figure 8. Indicators of economic slack in the euro area



As a first step to investigate the stability of the Phillips curve type relationship, Table 4 provides OLS estimates over two different periods: the pre-pandemic subsample (1997-2019) and the sample extended to the most recent observations (1997-2022). The results of the estimation are reported for all combinations of energy price pressures and economic slack.

Table 4. OLS estimates for alternative indicators and over different samples
(*t-statistic in brackets*)

	MEASURE OF SLACK					
	(1) UC output gap		*(2) GDP growth (yoy)*		*(3) Unemployment rate*	
MEASURE OF ENERGY PRICES	2019	2022	2019	2022	2019	2022
(A) Import deflator						
Persistence	0.87 [18.8]	0.94 [16.6]	0.88 [19.2]	0.95 [17.1]	0.82 [16.7]	0.92 [15.9]
Slack	0.07 [2.82]	0.09 [2.92]	0.03 [3.21]	0.04 [3.12]	-0.04 [2.40]	-0.06 [2.80]
Energy*	0.13 [2.24]	0.14 [1.78]	0.15 [2.68]	0.16 [2.02]	0.11 [1.90]	0.13 [1.61]
Std. Err. Regression	0.18	0.27	0.18	0.27	0.18	0.27
(B) Producer prices						
Persistence	0.86 [17.7]	0.84 [13.2]	**0.87 [17.9]**	**0.85 [13.4]**	0.82 [16.1]	0.84 [12.9]
Slack	0.07 [2.74]	0.07 [2.46]	**0.03 [3.04]**	**0.03 [2.65]**	-0.04 [2.12]	-0.05 [2.20]
Energy*	0.14 [2.08]	0.28 [3.30]	**0.17 [2.43]**	**0.28 [3.42]**	0.11 [1.47]	0.27 [3.13]
Std. Err. Regression	0.18	0.26	**0.18**	**0.26**	0.19	0.26
(C) HICP energy						
Persistence	0.86 [18.5]	0.95 [16.5]	0.88 [18.9]	0.96 [17.1]	0.82 [16.4]	0.93 [15.7]
Slack	0.07 [3.01]	0.09 [3.02]	0.04 [3.36]	0.04 [3.12]	-0.04 [2.50]	-0.06 [2.96]
Energy*	0.08 [2.46]	0.05 [1.20]	0.09 [2.85]	0.06 [1.33]	0.06 [2.01]	0.05 [1.08]
Std. Err. Regression	0.18	0.27	0.18	0.27	0.18	0.27

* The regression coefficient for energy price pressures regressor is reported multiplied by 10

When the estimation sample includes only pre-pandemic data (columns labelled '2019') all 9 models provide similar results: the slack and the energy coefficients are in most cases statistically significant and the autoregressive parameter indicates substantial persistence, with values ranging from 0.82 to 0.88. The statistical fit of the models, measured by the standard error of the regression, is 0.18 in all cases but one.

The results change if the estimation sample is extended (columns labelled '2022'). When the import deflator or the HICP energy are used as regressors (panels (A) and (C) of Table 4), the estimates suggest an increase in the persistence (to values around 0.95) but not larger coefficients for energy prices which instead in some cases even lose their statistical significance. On the other hand, if industrial producer prices are used (panel B of Table 4) the persistence remains broadly unchanged compared to the pre-2019 figures, while there is a marked increase in the estimated impact of energy prices. The indicators of economic slack also retain their values and their statistical significance. In all cases, the statistical fit sharply deteriorates in the last part of the sample: the standard error of the regression increases by about 50 per cent when adding the observations that include the pandemic and the energy crisis.

Overall, the OLS results reported in Table 3 suggest that the most suitable model specification for both the pre-crisis and the extended sample is the one, highlighted in bold, in which industrial producer prices and GDP growth are used in the estimation.[17] Accounting for the most recent observations indicates that the pass-through of energy prices to core inflation has been stronger than in previous periods. This issue is investigated in the next section using an econometric model that allows for time variation in the coefficients.

[17] The results are very similar if the unobserved component estimate of the output gap is used in place of GDP growth. However, relying on GDP growth has the advantage that it is an observable series which is not subject to potentially large revision as new data becomes available. It is also likely that as more data become available the specifications in the panels (A) and (C) of the table would improve.

3.2 The impact of energy prices in a time varying coefficients model

Following Busetti, Caivano and Delle Monache (2021), the Phillips curve regression for core inflation is extended to the time varying parameter framework of Giraitis et al. (2014),

$$\pi_t = \beta_t' z_t + \varepsilon_t \tag{2}$$

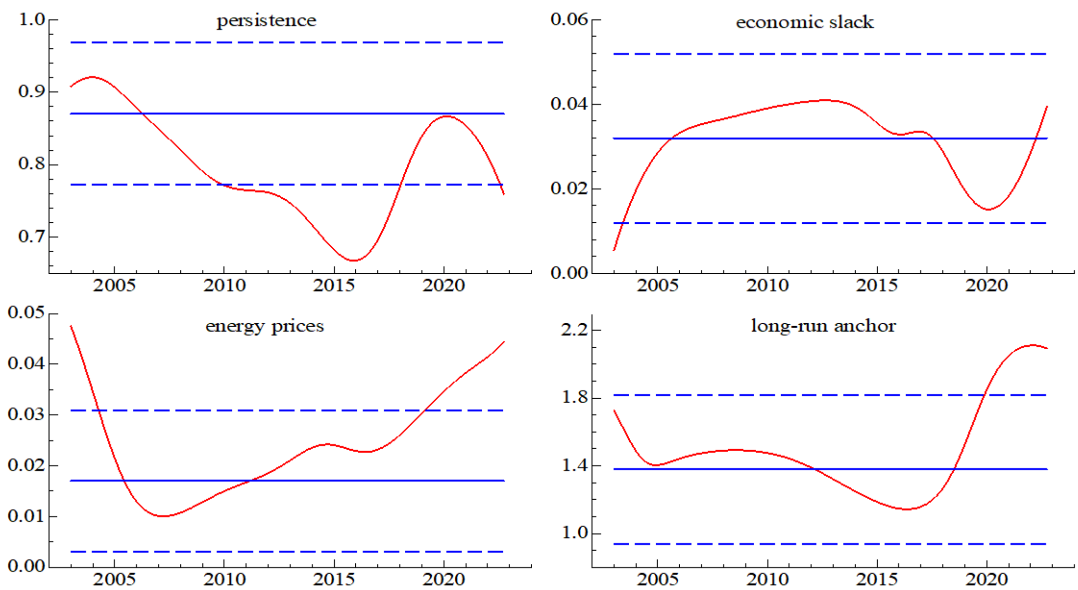
where the coefficients $\beta_t \equiv (\alpha_t, \rho_t, \delta_t{}')'$ are allowed to change over time, $z_t \equiv (1, \pi_{t-1}, x_t{}')'$, ε_t is the error term and $t = 1,2, \dots, n$. The estimator of β_t is kernel-based, given by:

$$\hat{\beta}_t = \left(\sum_{s=1}^{n} K\left(\frac{t-s}{H}\right) z_s z_s{}'\right)^{-1} \sum_{s=1}^{n} K\left(\frac{t-s}{H}\right) z_s \pi_s \, \varepsilon_t \tag{3}$$

where $K(x) \geq 0$ is a usual kernel function, e.g. $K(x) = \frac{3}{4}(1 - x^2)1(|x| \leq 1)$, and H is the bandwidth parameter that controls the degree of smoothing. Giraitis et al. (2014) derive the limiting properties of this estimator for a standard regression model with stochastic coefficients. As usual, H must increase at a slower rate than the sample size. Setting $H = n^{0.5}$ appears to work well in practice and this is the value selected in the analysis below.

Figure 9 shows the estimation results of the time-varying parameter model for the preferred specification (highlighted in bold in Table 4 of the previous section). The time varying coefficients are plotted with the fixed parameters, computed over the pre-pandemic sample 1997-2019, and their 95 per cent confidence intervals. The 'long-run anchor' is given by the ratio $\alpha_t/(1 - \rho_t)$. As the economic slack and energy price regressors have been previously demeaned, the anchor represents the underlying value of core inflation implied by the model and it can be interpreted as a measure of long-run inflation expectation.

Figure 9. Time varying and fixed coefficients for the core inflation regression model



Note: the blue lines correspond to the OLS coefficients. The 95 per cent confidence bands are computed over the pre-Covid sample.

While in the latest part of the sample the persistence parameter and the slope of the Phillips curve (i.e. the economic slack coefficient) have broadly remained within the confidence bands constructed using data up to 2019, the energy price coefficient and the long-run anchor have, instead, increased sharply, suggesting a break in their relationship with core inflation. According to these estimates, the impact of energy prices may have roughly doubled, compared to pre-pandemic values, while the underlying inflation anchor has reached values slightly above the ECB target of 2 per cent after 2020 (compared with an historical average of 1.4 per cent for core inflation) and it appears to have stabilized. The rise in the underlying anchor mirrors similar developments in long term inflation expectations based on experts' opinion, e.g. in the ECB Survey of Professional Forecasters.

The estimated Phillips curve relationship can be used to compute the contributions of the different drivers of core inflation. For the case of fixed coefficients, it is known that equation (1) can be re-written in terms of present and past values of the regressors and the error term,

$$\pi_t = \rho^t \pi_0 + \sum_{s=0}^{t-1} \rho^s (\alpha + \delta' x_{t-s} + \varepsilon_{t-s}) \tag{4}$$

where $\rho^t \pi_0$ is approximately zero for large t and the discounted sum of the terms in brackets provides the contributions of the intercept, the economic slack, the energy price pressures and the errors to the value of core inflation.

A similar decomposition can be obtained when the regression coefficients are time-varying,

$$\pi_t = \rho_1^t \pi_0 + \sum_{s=0}^{t-1} \rho_{t-s+1}^t (\alpha_{t-s} + \delta'_{t-s} x_{t-s} + \varepsilon_{t-s}), \tag{5}$$

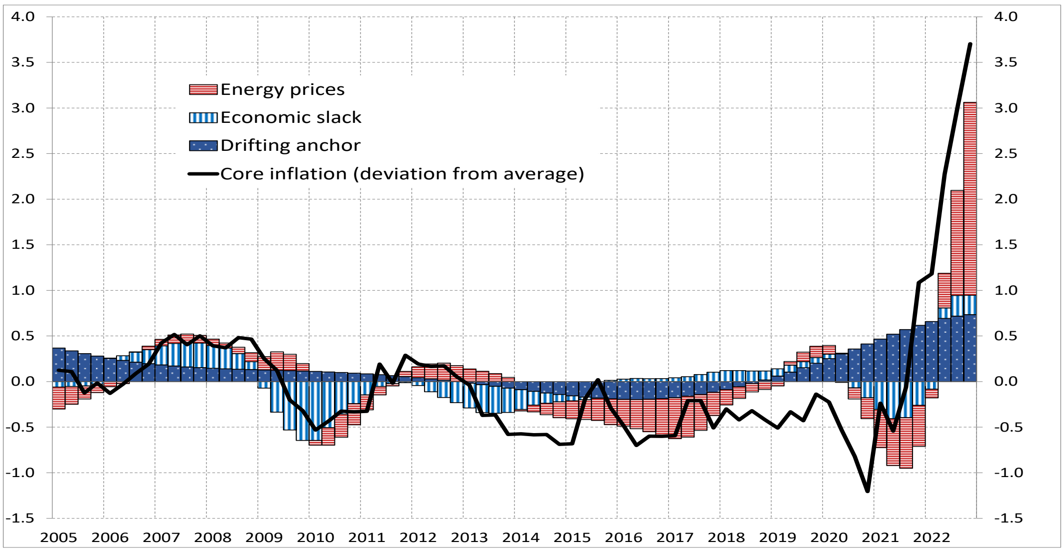
where $\rho_k^t = \prod_{i=k}^{t} \rho_i$ and ρ_{t+1}^t=1.

The results of the decomposition are showed in Figure 10. In the latest periods the rise of core inflation from its sample average is mostly driven by the energy price pressures (that account for 2.1 p.p. out of 3.7 in the fourth quarter of 2022) and, to a minor extent (0.7 p.p.), by the drifting anchor, which can be rationalized as an inflation expectation term.[18] The contribution of the economic slack has turned to positive although it remains modest. A non-negligible component remains unexplained due to the sequence of positive regression residuals in the latest periods (not reported) which may reflect factors not included in the model, such as, for example, the exchange rate.[19]

[18] The downwards contribution of the inflation expectation term during the period 2014-2019 is in line with the structural interpretation of Neri (2023).

[19] If the regressors are not demeaned, the contribution of energy prices increases to 2.5 p.p. and that of economic slack to 0.5 p.p. Hence, the energy price pressures would account for nearly 50 per cent of the level reached by core inflation in 2022:Q4 (2.5 pp out of 5.1), as reported in Table 1 in the introduction.

Figure 10. Contributions of different drivers to core inflation developments



Note: The figure shows the contribution of the different drivers of core inflation computed using equation (5). Both the data of core inflation and the contribution of the drifting anchor are represented in deviation from the sample average of 1.4.

If the decomposition is carried out for the fixed coefficient model (not shown) the contribution of energy prices becomes smaller (0.9 p.p. in 2022:Q4 if the regression is run on pre-Covid data and 1.7 p.p. if the whole sample is used) and, symmetrically, the unexplained part is bigger.

Finally, these nonlinearities also have implications for forecasting. All things being equal, a stronger pass-through of energy prices implies upside risks to inflation forecasts if these forecasts are produced by models that were estimated on pre-pandemic and energy crisis data. Conversely, a return of commodity prices towards the pre-energy crisis levels could translate into a larger than expected fall in inflation.

4 A disaggregated approach to measure the impact of commodity energy prices and consumer energy prices on core inflation

4.1 The empirical framework

In this section, we use a Dynamic Factor and a VAR model to disentangle the idiosyncratic (direct) effect of oil price changes on each sub-component of the HICP from the common/macroeconomic (indirect) effect that these changes have on all prices. We first estimate a dynamic factor model on a panel of consumer price indicators to separate common from idiosyncratic price changes, and then use the VAR to quantify the pass-through via the common and idiosyncratic components. The same procedure is then used to assess the role of gas prices.

Factor models are based on the idea that fluctuations in disaggregate prices are due to a few common (macroeconomic) shocks, which affect all prices, and to several idiosyncratic shocks that arise in specific sectors or are due to sampling errors. Accordingly, each price component can be decomposed into a common part χ_{it}, which is a linear combination of a small number r of common factors f_t driven by the common shocks, and an idiosyncratic part ξ_{it} that is driven by idiosyncratic shocks.

Let:

$$\pi_{it} = 1200\, log\left(\frac{P_{it}}{P_{it-1}}\right)$$

be the annualized month-on-month log-change in the i-th price at time t, where i=1,....,n and t = 1,....,T, we then have

$$\pi_{it} = \chi_{it} + \xi_{it} = \lambda_i' f_t + \xi_{it} \tag{6}$$

where λ_i is a 1 ×r vector containing the factor loadings of the i-th variable, and $\chi_{it} = \lambda_i' f_t$. Equation (6) represents the approximate dynamic factor model proposed by Stock and Watson (2002a, 2002b), which is a particular case of the generalized dynamic factor model studied by Forni et al. (2000) and Forni and Lippi (2001). Having estimated equation (6), a measure of core inflation is computed as follows:

$$\pi_{t,core} = \sum_{i\,\in\, core} w_{it}\chi_{it} + \sum_{i\,\in\, core} w_{it}\xi_{it}$$

where w_{it} is the HICP weight for item i provided by Eurostat. We then allow for the possibility that the common factors and the price of oil evolve according to a bivariate VAR. In Section 4.3, we substitute oil prices with gas prices. Since changes in energy prices contribute to macroeconomic fluctuations (Kilian, 2009, 2014, among others), they are likely to have a broad-based effect on all consumer prices. Let

$$y_t = \Delta \log\left(\frac{oil_t}{price_t}\right)$$

be the monthly oil price (or gas price) growth rate deflated with the core HICP index. We then have:

$$\boldsymbol{A}(L)\begin{pmatrix} y_t \\ \boldsymbol{f_t} \end{pmatrix} = \begin{pmatrix} v_t \\ \boldsymbol{u_t} \end{pmatrix} \tag{7}$$

where v_t is the energy price shock and $\boldsymbol{A}(L)$ is a polynomial matrix.

At the same time, given that firms employ energy in their production processes to various extents (i.e. energy costs represent a share of their total production costs, which is heterogeneous across sectors of activity and individual firms), changes in oil or gas prices may also have a direct effect on the prices in the HICP depending on the energy intensity of the sector producing these goods. Thus, a change in the price of oil could pass-through into core inflation also via the idiosyncratic components ξ_{it}. Therefore, we allow for the possibility that the energy price and each idiosyncratic component evolve over time according to a bivariate VAR. For the idiosyncratic components, the VARs are as follows:

$$\boldsymbol{B_i}(L)\begin{pmatrix} y_t \\ \xi_{it} \end{pmatrix} = \begin{pmatrix} v_t \\ e_{it} \end{pmatrix} \quad . \tag{8}$$

where $\boldsymbol{B_i}(L)$ is a polynomial matrix. Therefore, we end up with *n+1* VAR models: one for the common component and *n* for each idiosyncratic component. Once the energy price pass-through onto each disaggregate price is computed, we construct the pass-through into core price inflation by aggregating with the corresponding weights.[20]

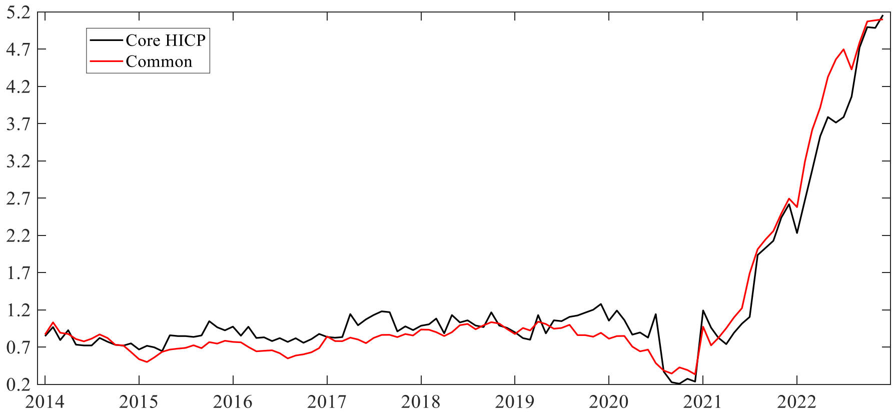
4.2 Oil price pass-through

The empirical analysis is carried out on a panel of euro area harmonized indices of consumer prices at a disaggregate level (93 series), available from January 1999 to December 2022.[21] Oil price is measured by the Brent spot crude oil price deflated with the core HICP index.

The results obtained by Conflitti and Luciani (2019) – based on data up to 2016 – are confirmed when we extend the sample to include the most recent data. The common component accounts for only 20 per cent of euro-area core inflation fluctuations.[22] Figure 11 shows how the common component for core inflation compares with the official estimate.

The common component is, as one would expect, smoother than the official index, especially between 2017 and 2020.[23] The benchmark specification is with one common factor (r = 1), six lags in the VAR models (6) and (7), and oil price shocks identified using a Choleski decomposition with the oil price ordered first, as in Conflitti and Luciani (2019).[24] The effect of an oil price shock on the real oil price is short-lived. After an unexpected 10 per cent increase, the real oil price increases further in the next month by approximately 2 per cent and then decreases between the second and fourth months.

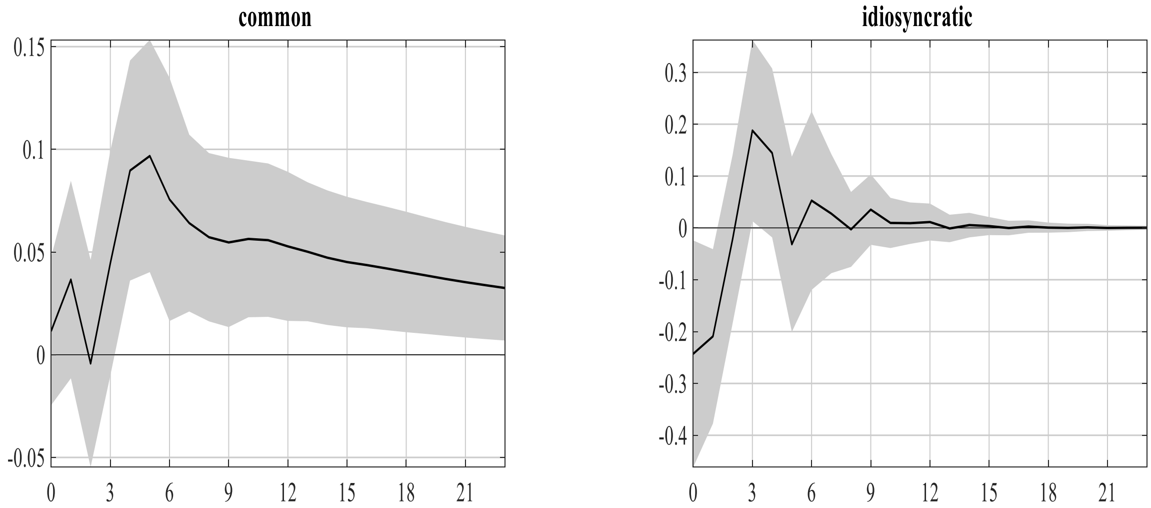
Figure 11. Core inflation and core common component



Note: The red line is the y-o-y common core inflation; the black line is the y-o-y official core inflation. Data up to December 2022.

[20] For more details, equation (4) in Conflitti and Luciani (2019).
[21] Given that Eurostat publishes seasonally adjusted series only for the aggregate indexes, we seasonally adjusted the disaggregated price series ourselves using X12 ARIMA.
[22] See also Conflitti (2020) and Luciani (2020).
[23] Since 2021, the common core is always higher than the official core.
[24] As for identification of the oil price shock, a Choleski decomposition with the oil price ordered first corresponds to the identifying assumption that energy prices are predetermined with respect to the U.S. economy at monthly frequency. In other words, in our framework an oil price shock is an unpredicted and unpredictable change in the oil price, and as such it has no "structural interpretation", that is we do not disentangle oil supply shocks from oil demand shocks.

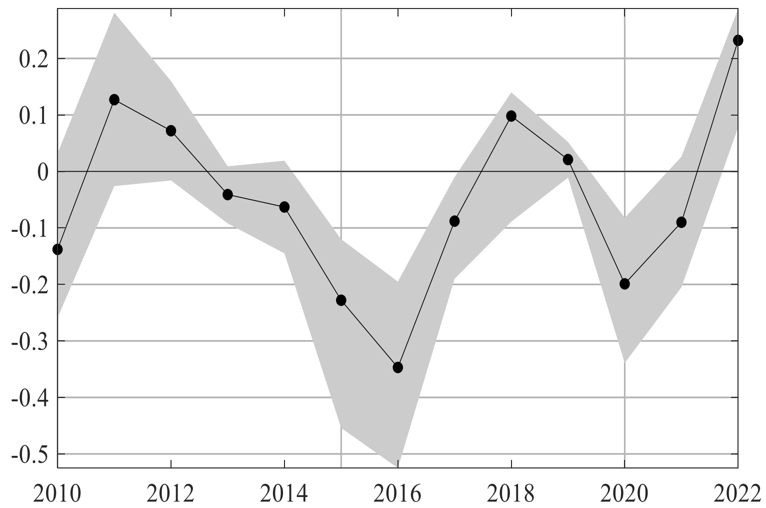
Figure 12. Impulse responses of core common and idiosyncratic components to oil price shocks



Note: The left plot shows the pass-through of an unexpected 10 per cent increase in the real oil price into the common component of core HICP prices, while the right plot shows the pass-through into the idiosyncratic component.

Figure 12 reports the estimated oil price impact on the common (left) and the idiosyncratic (right) components of core HICP prices, together with 90 per cent bootstrap confidence bands. The impact via the idiosyncratic component is statistically not significant, as in Conflitti and Luciani (2019), except for the first three months after the shock, while the impact through the common component is positive, small but persistent. Figure 13 shows the average contribution of changes in the oil price to common core inflation: the dynamic of oil prices in general provides a small (in absolute value) contribution to common core inflation, being equal to 0.23 p.p. in 2022.[25]

Figure 13. Contribution of oil price changes to core common inflation



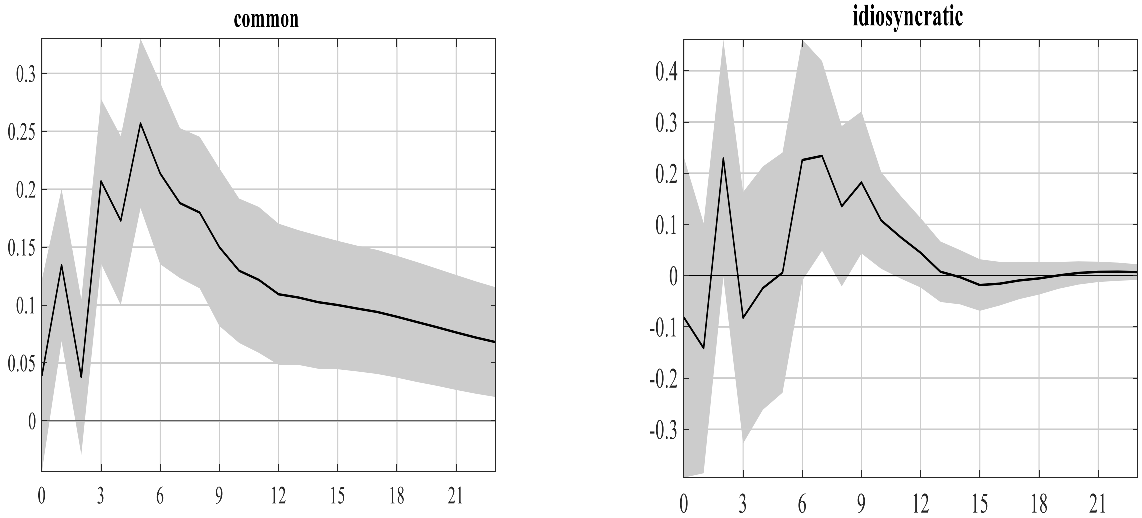
Note: This plot shows the average contribution per year of real oil price to common core HICP inflation measured in p.p. (y-axis). The shaded area is the 90 per cent confidence band.

[25] The historical decomposition is shown not for the annualized monthly percentage change, but as the average per each year. Given that we use log differences; this means that each dot in Figure 13 represents the part of the 12-month percentage change in December of year *j* that is accounted for by the oil price.

4.3 Gas price pass-through

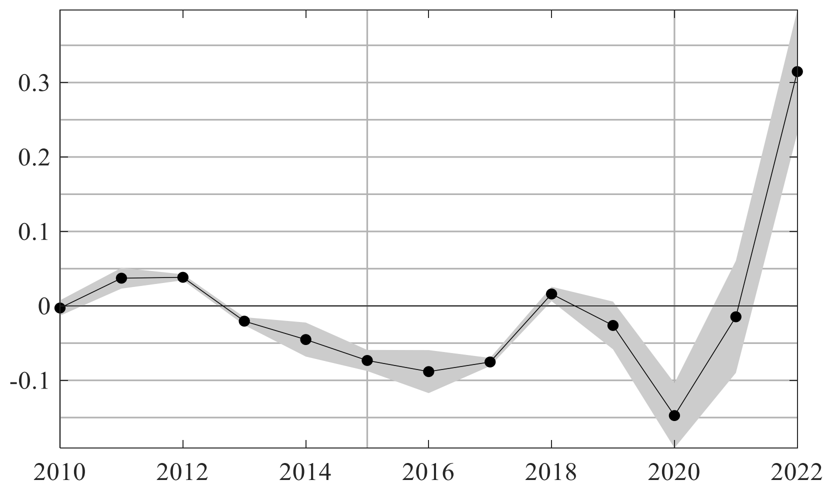
In this section, we replicate the exercise over the period 2000-2022 using the gas price series instead of the oil price series in equations (7) and (8). The gas series is mainly flat in history and presents a spike at the end of the sample. This could influence the estimates of the VAR. To take this into account, we also replicated the estimates by limiting the sample to the period up to June 2021 (when the gas price started skyrocketing). The results on the IRFs and the pass-through remain broadly valid, though the impact emerges as slightly smaller. The effect of a gas price shock on the real gas price is similar to the one for oil but slightly more persistent. Figure 14 reports the estimated gas price impact on the common (left) and the idiosyncratic (right) components of core inflation, together with 90 per cent bootstrap confidence bands.

Figure 14. Impulse responses of core common and idiosyncratic components to a shock to gas prices



Note: The left plot shows the pass-through of an unexpected 10 per cent increase in the real gas price into the common component of core HICP prices, while the right plot shows the pass-through into the idiosyncratic component.

Figure 15. Contribution of gas price changes to core common inflation



Note: This plot shows the average contribution per year of real gas price to common core HICP inflation measured in p.p. (y-axis). The shaded area is the 90 per cent confidence band.

As for the case of oil, the effect via the idiosyncratic component is very small and not statistically significant, while the effect via the common component increases over time and is statistically significant. Based on these estimates, we compute the contribution of changes in gas prices to the common core inflation. Figure 15 shows for each year the average contribution.[26] The contribution was nil up to 2020, became larger in 2021, and reached 0.30 p.p. in 2022.

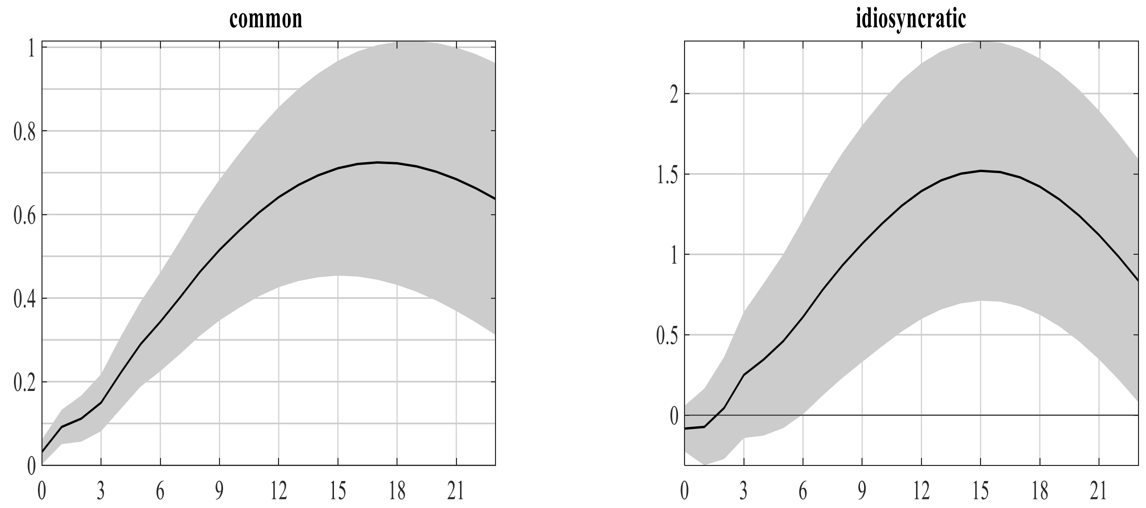
4.4 Total energy price pass-through

The pass-through coming from oil and gas prices taken separately is moderate. However, the energy component in the HICP is significantly larger than the sum of these two items. Indeed, the energy aggregate also includes fuel prices, which depend on crude oil prices but also on refining margins and excise duties, electricity, gas and other fuels (e.g. coal, solid fuels, butane and heating energy).

In this section, we therefore also consider an alternative approach to estimate the pass-through of changes in oil and gas prices onto core inflation, which takes into account the composition of the energy component of the HICP.

First of all, from the panel of consumer prices at a disaggregate level, we remove all the items related to energy (regulated electricity and gas, liquid and solid fuels, fuels and lubricants for personal transport equipment) and then we estimate the dynamic factor model to compute the common and idiosyncratic components. Then, we use the energy inflation HICP component in the VARs in (7) and (8). This approach allows us to encompass all the sources of the energy shocks that can be traced back to energy commodities and provides estimates that are comparable to those in Section 2

Figure 16 Impulse responses to core common and idiosyncratic components to shocks to energy prices



Note: The left plot shows the pass-through of an unexpected 10 per cent increase in the energy inflation into the common component of core HICP prices, while the right plot shows the pass-through into the idiosyncratic component.

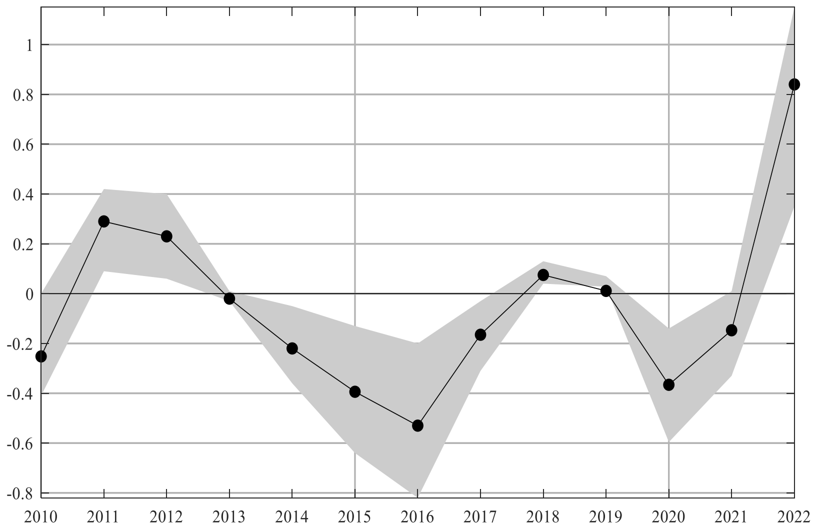
[26] See footnote 23.

Figure 16 shows the effects of a shock to energy prices on the common and idiosyncratic components. As in the case in which we consider oil and gas prices separately, the impact of a 10 per cent unexpected increase in energy inflation is statistically slightly significant for the idiosyncratic component. By contrast, the energy shock has an impact on common core inflation – as found in the previous two exercises – which increases gradually and reaches a peak of 0.7 per cent after one and a half years.

Figure 17 presents the average contribution in each year of energy prices to common core inflation: this contribution was negative in 2020 and 2021 and turned strongly positive in 2022, reaching 0.86 p.p. (in line with Corsello and Tagliabracci, 2023), which compares with an average common core inflation of 4.2 per cent in the period January-December 2022 (3.9, the official core inflation).

Figure 17. Contribution of energy changes to common core inflation

(*p.p.*)



Note: The chart shows the average contribution of energy price shocks to the common core inflation measured in p.p. The shaded area is the 90 per cent confidence band.

5 Concluding remarks

Assessing the relative importance of supply and demand shocks in driving inflation is of utmost importance to set the appropriate monetary policy stance. When the economy is hit by aggregate supply or energy price (cost-push) shocks, the central bank faces a trade-off, as countering the impact on inflation would amplify the negative effects on economic activity.

The econometric evidence suggests that since mid-2021, shocks to energy prices have played a prominent role in raising euro area inflation. This result is robust across models (Vector Auto Regressive models, time-varying Phillips curves, dynamic factor models) and identification of the shocks.

The unprecedented magnitude and persistence of the shocks to energy prices since mid-2021 call for close monitoring of the pass-through of these shocks to core and headline inflation in the euro area. Digging deeper to assess the dynamics of goods and services inflation in a more granular way would be a useful avenue for supporting monetary policy and understanding the persistence of the current inflationary pressures (Lane, 2023).

References

Antolín-Díaz, J. and J. F. Rubio-Ramírez (2018). "*Narrative sign restrictions for SVARs*", American Economic Review 108, 2802-2829.

Baumeister, C. and L. Kilian (2014). "*Do oil price increases cause higher food prices?*", Economic Policy 80, 691-747.

Busetti, F., Caivano, M. and D. Delle Monache (2021). "*Domestic and global determinants of inflation: evidence from expectile regression*", Oxford Bulletin of Economics and Statistics 83, 982-1001.

Canova, F. and G. De Nicolò (2002). "*Monetary disturbances matter for business fluctuations in the G-7*", Journal of Monetary Economics 49, 1131-1159.

Canova, F. and M. Paustian (2011). "*Business cycle measurement with some theory*", Journal of Monetary Economics 58, 345-361.

Carriero, A., F. Corsello and M. Marcellino (2022). "*The global component of inflation volatility*", Journal of Applied Econometrics 37, 700-721.

Ciccarelli, M. and B. Mojon, (2010). "*Global inflation*", The Review of Economics and Statistics 92, 524-535.

Conflitti, C. (2020) "*Alternative measures of underlying inflation in the euro area*", Bank of Italy Occasional Paper 593.

Conflitti, C. and M. Luciani (2019). "*Oil price pass-through into core Inflation*", The Energy Journal 40, 221-248.

Corsello, F., S. Neri and A. Tagliabracci (2021). "*Anchored or de-anchored? That is the question*", European Journal of Political Economy 69 102031.

Corsello, F. and A. Tagliabracci (2023). "*Assessing the pass-through of energy prices to inflation in the euro area*", Bank of Italy Occasional paper 745.

Doan, T., R. B. Litterman and C. A. Sims (1983). "*Forecasting and conditional projection using realistic prior distributions*", National Bureau of Economic Research Working paper 1202.

ECB (2018). Measures of underlying inflation for the euro area. Economic Bulletin June, European Central Bank.

Fink, D. and P. Tillman (2023). "*The macroeconomic effects of global supply chain disruptions*", IMFS Working Paper Series 178, Goethe University Frankfurt, Institute for Monetary and Financial Stability.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2000). "*The generalized dynamic factor model: Identification and estimation*", The Review of Economics and Statistics 82, 540-554.

Forni, M. and M. Lippi (2001). "*The Generalized Dynamic Factor Model: Representation Theory*", Econometric Theory 17, 1113-1141.

Giraitis, L., Kapetanios, G. and T. Yates (2014). "*Inference on stochastic time-varying coefficient models*", Journal of Econometrics 179, 46-65.

Kilian, L. (2008). "*The economic effects of energy price shocks*", Journal of Economic Literature 46, 871-909.

Kilian, L. (2009). "*Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market*", American Economic Review 99, 1053-1069.

Kilian, L. (2014). "*Oil price shocks: Causes and consequences*", Annual Review of Resource Economics 6, 133-154.

Koester, G. and H. Grapow (2021). "*The prevalence of private sector wage indexation in the euro area and its potential role for the impact of inflation on wages*", ECB Economic Bulletin 7/2021.

Krippner, L. (2013). "*Measuring the stance of monetary policy in zero lower bound environments*", Economics Letters 118, 135-38.

Krippner, L. (2020). "*Documentation for shadow short rate estimates*", available at https://www.ljkmfa.com/test-test/international-ssrs/ , data downloaded on 29 May 2021.

Lane, P. R. (2023). Interview with Philip R. Lane, Member of the Executive Board of the ECB, conducted on Friday, 24 February 2023 by Balázs Korányi and Frank Siebelt.

Litterman, R., B. (1986). "*Forecasting with Bayesian Vector Autoregressions - five years of experience*", Journal of Business and Economic Statistics 4, 25-38.

Luciani M. (2020). "*Common and idiosyncratic inflation*", Board of Governors of the Federal Reserve System Finance and Economics Discussion Series 2020-024.

Neri, S. (2023). "*Long-term inflation expectations and monetary policy in the euro area before the pandemic*", European Economic Review, forthcoming.

Panetta, F. (2022). "*The complexity of monetary policy*", speech at the European University Institute, Florence, 14 November 2022.

Rubio-Ramirez, J. F., D. Waggoner and T. Zha (2010). "*Structural Vector Autoregressions: Theory of identification and algorithms for inference*", Review of Economic Studies 77, 665-696.

Sims, C. A. (1980). "*Macroeconomics and reality*" Econometrica 48, 1-48.

Stock, J.H. and M.W. Watson (2002a). "*Forecasting using principal components from a large number of predictors*", Journal of the American Statistical Association 97, 1167-1179.

Stock, J.H. and M.W. Watson (2002b). "*Macroeconomic forecasting using diffusion indexes*", Journal of Business and Economic Statistics 20, 147-162.

Uhlig, H. (2005). "*What are the effects of monetary policy on output? Results from an agnostic identification procedure*", Journal of Monetary Economics 52, 381-419.