EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

Anastasia Allayioti, Lucyna Górnicka,
Sarah Holton, Catalina Martínez Hernández

Monetary policy pass-through to consumer prices: evidence from granular price data

ChaMP

No 3003

Challenges for Monetary Policy Transmission in a Changing World Network (ChaMP)

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

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

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

Abstract

We document that about 33% of the core inflation basket in the euro area is sensitive to monetary policy shocks. We assess potential theoretical mechanisms driving the sensitivity. Our results suggest that items of a discretionary nature, as reflected in a higher share in the consumption baskets of richer households, and those with larger role of credit in financing their purchase, tend to be more sensitive. Non-sensitive items are more frequently subject to administered prices and include non-discretionary items such as rents and medical services. Energy intensity does not seem to drive our results and the sensitive items are not dominated by durable goods, but are relatively evenly split between goods and services. Estimations over different samples show that the impact of monetary policy shocks on sensitive core inflation has become larger recently.

JEL Classification: E30, E50, C32

Keywords: Monetary policy, inflation, euro area, BVAR

Non-technical summary

Monetary policy affects consumption and consumer prices through various channels, meaning that its impact – both in terms of speed and the peak – can vary across consumption items. As a result, the full effect of policy changes on aggregate inflation can potentially materialize only with long lags. This paper serves as a complement to the analysis of aggregate inflation by providing a granular assessment of the impact of monetary policy on prices.

The paper makes three main contributions. First, using data on 72 consumer prices that are a part of the Harmonised Index of Consumer Prices excluding food and energy items (HICPX) in the euro area, we categorise items according to their price reaction to monetary policy shocks. Second, we analyse the characteristics of the most sensitive items and explore the theories and mechanisms driving the sensitivity to monetary policy shocks. Third, we use the granular categorisation of items according to their price sensitivity to document the speed and extent of the pass-through of monetary policy shocks to inflation in the euro area and assess whether transmission has changed in the recent, most pronounced period of monetary tightening.

We derive a number of important findings. First, we find that items classified as sensitive account for around 33% of the HICPX basket. In line with theoretical predictions, discretionary items and items with a more prominent role of credit in financing their purchase are more sensitive to monetary policy shocks, while items that typically have administered prices are not sensitive. Although the frequency of price adjustments is a relevant channel for explaining differences in the relative responsiveness of different consumer prices to monetary policy, it is not a significant channel for explaining the relative responsiveness across core inflation items (i.e. excluding food and energy items), where rather the absolute size of price changes matters. Third, we find that the impact of monetary policy shocks is more than two times larger on the prices of highly sensitive items than on the prices of moderately sensitive items and that the pass-through of monetary policy to these HICPX items has also become faster and stronger in the most recent tightening cycle compared to the past.

By identifying the items most sensitive to monetary policy and by establishing the relevance of the different transmission channels, we enhance the understanding of the monetary transmission mechanism, which is a prerequisite for the successful conduct of monetary policy. As aggregate developments can obscure the dynamics in individual items where the effects of these channels are more apparent, a granular approach also allows for a more accurate and timely assessment of the impact of monetary policy on inflation.

1 Introduction

Monetary policy affects the economy through direct and indirect channels - known as the monetary transmission mechanism - and the full effects on aggregate inflation can come with long and variable lags. Consumption and consumer prices are affected directly by interest rate changes that alter households' propensity to save and spend, via the intertemporal substitution of consumption channel. More indirect channels, via the impact on growth and employment, can then feed through to household incomes and have an additional impact on consumption and prices. The lagged overall response of aggregate inflation to monetary policy obscures the effects of the multifaceted transmission channels, which can vary across consumption items. For instance, consumption items with high intertemporal elasticities of substitution, like costlier discretionary or durable goods, may respond to shocks more quickly, while items with administered prices may respond more slowly. Therefore, understanding the heterogeneous pass-through of monetary policy to granular prices provides key insights on monetary policy transmission and serves as a crucial complement to aggregate analysis to more accurately evaluate the effects of monetary policy on inflation in real time. Despite the recognition that transmission channels lead to disparate pass-through of monetary policy shocks to prices, there is currently little empirical evidence on the topic, especially in the euro area.

This paper provides a granular assessment of the impact of monetary policy on disaggregated prices in the euro area. We make several contributions. First, we identify the consumption items with the strongest price responses to monetary policy. Second, we explore the consistency of our findings with theoretical predictions regarding the impact of monetary policy on prices and assess which channels are most relevant. Third, we document the speed and extent of the monetary policy pass-through to inflation and assess whether transmission has changed during the most recent monetary tightening episode. Our empirical analysis focuses on core inflation, which captures medium-term inflationary pressures. We estimate item-specific Bayesian Vector Autoregressions (BVARs) for each of the 72 consumer prices comprising the Harmonised Index of Consumer Prices excluding food and energy (HICPX). To identify the effects of monetary policy we use the shock series of Jarociński and Karadi (2020) which enters the BVARs as an internal instrument (Ramey (2011), Paul (2020), Plagborg-Møller and Wolf (2021), Noh (2024)). We then classify items according to the magnitude and significance of their impulse responses into two categories: monetary policy sensitive and non-sensitive (including non-significant and positive responses). In a second step, we explore if characteristics of sensitive items are consistent with various theories of monetary policy pass-through. Finally, we investigate the speed and extent of monetary policy transmission within sensitive categories and investigate whether the pass-through has changed over time.

Our findings suggest that sensitive items are evenly split between goods and services, but a higher share of items within goods is classified as highly sensitive to monetary policy, than within services. We document that our categorisation of core inflation items based on monetary policy sensitivity aligns well with theories linked to discretionary spending and the credit channel. Sensitive core inflation items tend to be more prevalent in consumption baskets of wealthier households (such as jewelry and recreation-related items like package holidays) and rely more on credit (such as cars). Items with administered prices are generally non-sensitive. The frequency of price adjustment does not impact the relative responsiveness of core inflation items to monetary policy (while it is relevant when considering a broader range of consumption items, including energy and food). Instead, tentative evidence points to a higher relevance of the size of price changes relative to the frequency of price changes. We additionally find that the pass-through of monetary policy is heterogeneous also within the sensitive category, as the impact of monetary policy shocks is 2.5 times larger on highly sensitive prices compared to moderately sensitive ones. We also find that the pass-through of monetary policy to sensitive items has become faster and stronger in the most recent tightening cycle compared to the past.

We build on a vast literature studying monetary policy transmission through the lens of relative prices (Balke and Wynne (2007), Boivin et al. (2009), Baumeister et al. (2013)). Studies have shown that monetary policy impacts consumption and prices heterogeneously and can affect discretionary items first, owing to inter-temporal substitution and utility loss from delayed consumption (Mankiw (1985), Parker (1999), Chernis and Luu (2018)). For instance, consumption of luxury and small durable goods is easier to postpone, considering the state of the good's durability, but also consumers' wealth and short-term economic conditions (Browning and Crossley (2000)) and past literature has also classified consumer spending into essentials and non-essentials based on their income elasticity (Aguiar and Bils (2015)). Further evidence suggests that a monetary tightening reduces spending on discretionary goods but increases spending on consumer staples, likely due to substitution effects (Grigoli and Sandri (2023)). Overall, our evidence on the heterogeneous effects of monetary policy across consumption items aligns with the findings of Aruoba and Drechsel (2024) showing that there are considerable differences in the timing and size of the responses of disaggregated consumer prices to monetary policy shocks in the US. They find that some prices even increase following a monetary tightening, which they posit could come from a cost channel of higher interest rates.

In addition, we explore other transmission channels that can prompt a heterogeneous pass-through of monetary policy to prices. For instance, we find evidence in support of the credit channel, following the literature that suggests that costlier items or items linked to housing investment, that require credit to finance their purchases are typically affected more quickly as borrowing costs rise (Bernanke and Gertler (1995)). We also show there are differences in transmission for prices that tend to be administered, rather than market determined (Tobin (1983) and Ehrmann et al. (2006)). Furthermore, following the literature suggesting that prices of items with a higher frequency of price adjustment may be more responsive to monetary policy (Hong et al. (2023), Alvarez et al. (2024), and Gautier et al. (2024)), we examine the relevance of price flexibility for transmission. While we find evidence of this channel when considering all consumption items, we do not find that the frequency of price adjustments is related to the sensitivity of core inflation items. These findings reflect that food and energy prices are more flexible than goods and services prices, as shown in Gautier et al. (2024) and Dedola et al. (2024).

Our work relates to the literature on the distributional effects of monetary policy. Evidence using the full consumption basket finds the prices of high-income households' baskets to be less responsive to monetary policy than those of middle-income households (Cravino et al. (2020)). Orchard (2022) finds that prices of necessities, primarily purchased by low-income households, rise more during recessions, making their spending share countercyclical and finds that contractionary monetary policy shocks increase both the relative price and share of necessities compared to other items. Ampudia et al. (2023) show that monetary policy affects inflation diversely across the income distribution, though the overall effect is ambiguous owing to two opposing channels related to i) differences in the structure of consumption baskets across income levels, and ii) differences in the scope for adjusting shopping behaviour depending on income (substitution effect). Focusing on the core inflation basket, which excludes necessities like food and energy (that constitute a higher share of the consumption basket of lower income households), we find that high-income households' baskets are more tilted towards sensitive items than those of low-income households, which is in line with a substitution effect at play and fits the hypothesis that demand will shift away from luxuries in response to a contractionary shock (Orchard (2022)).

We further contribute to the literature on the pass-through of monetary policy to prices in the euro area. Oftentimes this literature finds a relatively modest or no impact of monetary policy on aggregate inflation (Jarociński and Karadi (2020), Slacalek et al. (2020), Corsetti et al. (2021)). In line with these studies, we find that a monetary policy shock reduces core inflation overall, though the effect is not significant. However, digging into our granular results, we find that about a third of the core basket is significantly sensitive to monetary policy changes. From a time-varying perspective, Ciccarelli et al. (2014) show that inflation responds stronger to monetary policy during times of financial distress, affected by the financial fragility of sovereign, banking and non-financial borrower sectors. Adding to this evidence, we find that the pass-through of monetary policy to sensitive prices in the core inflation basket has become stronger since the tightening cycle in response to the post-pandemic inflation surge. Variation in central banks commitment to disinflation has been identified as a critical source of the variation in the success of disinflationary attempts.[1] Therefore, the recent hiking cycle, which was the steepest in ECB history, may have contributed to the strength of transmission. Moreover, the internationally aligned central bank response to the global surge in inflation may have amplified the impact of monetary policy on inflation in the most recent episode (Auclert et al. (2023)).

The rest of this paper is organised as follows. Section 2 describes the economic context and the data used in our analysis. Section 3 identifies the consumption items with prices more sensitive to monetary policy and explores theoretical mechanisms driving the sensitivity. Section 4 discusses what the granular results imply for the pass-through of monetary policy to core inflation in the euro area. Section 5 summarises a series of robustness checks. We conclude in section 6.

2 Economic context and data description

2.1 Economic context

The period covered in our analysis, starting at the beginning of Economic and Monetary Union (EMU) in 1999 until late 2023, comprises a number of distinct regimes. During approximately the first decade of EMU, the euro area economy experienced average annual growth of about 2% and predominantly upside risks to inflation. However, following the start of the euro area sovereign debt crisis in 2009-2010, the euro area faced a period dominated by weaker growth and largely disinflationary shocks, which required an active and accommodative monetary policy to ward off risks of deflation and to try to bring inflation up towards the medium-term target (Rostagno et al. (2019)).

The most recent period has been one of major dislocations - including the pandemic, geopolitical conflicts, and energy shocks. The COVID-19 pandemic prompted severe health, economic, and financial implications and governments and central banks responded

[1] See Romer C.D. (2024), “Lessons from history for successful disinflation”, speech at the Federal Reserve Bank of Cleveland, 24 October.

with a decisive policy package aimed at supporting the economy during the shut-down. This response ensured a sufficiently accommodative policy stance, provided liquidity to the banking system, and stabilised financial markets. As the economy reopened, the staggered recovery in the supply capacity combined with the strong and swift recovery in demand - facilitated by accumulated savings - pushed prices higher. Concerns that inflation might be on the rise emerged in 2021 and the energy shock stemming from Russia's invasion of Ukraine in February 2022 further prolonged and aggravated an exceptional sequence of inflationary shocks, with headline and core inflation peaking in the euro area at 10.6% in October 2022 and at 5.7% in March 2023, respectively. In response, the ECB forcefully unwound its accommodative monetary policy stance in several phases, resulting in a tightening impulse that stands out in the history of the monetary union. Between July 2022 and September 2023, the ECB increased key interest rates by 450 basis points. Headline inflation fell swiftly, while core inflation and services inflation exhibited higher persistence.

Given the unprecedented series of shocks to inflation, the scale and speed of the latest tightening episode and bearing in mind that the full effect of monetary policy transmits to the real economy and aggregate variables with a considerable lag, our analysis provides a timely examination of the impact of monetary policy on prices at a granular level, explores the mechanisms underlying the effects and assesses whether the response of prices to monetary policy shocks has changed over time.

2.2 Dataset

We use monthly data on consumer prices included in the euro area HICPX (core) basket (i.e. HICP basket excluding food and energy) that are available from Eurostat under the COICOP product classification.[2] The most disaggregated COICOP-5 level contains 286 product categories, but the time series are relatively short, going back to 2016 only. Thus, we use the COICOP-4 level data on 72 product categories that enter the HICPX basket, which start in 1999 for most of the items.[3] A full overview of the COICOP-4 classification is presented in Table 7 in Appendix A. The product category with the shortest time series goes back to December 2000. We seasonally-adjust each of the COICOP-4 series.[4]

[2]The Classification of Individual Consumption by Purpose (COICOP) classifies the items in the consumption basket in a largely standardised way across countries. The four-digit classification in the euro area includes a total of 93 categories of prices. For further detail see the Eurostat website.

[3]Overall, there are 93 COICOP-4 items but we exclude energy and food items.

[4]The data is seasonally adjusted based on TramoSeats specifications using the software Demetra. Furthermore, the item "Combined passenger transport" was adjusted for the effects of the introduction of subsidised public transportation tickets in Germany, i.e., the 9-Euro ticket and the Deutschland ticket.

To identify the effect of monetary policy on price indices, we use monetary policy shocks from Jarociński and Karadi (2020). They study surprises in market interest rates and stock prices during short windows around the ECB policy decision announcements and distinguish between pure monetary policy shocks and central bank information shocks. The latter capture new information about the economic outlook and conditions that the central bank reveals via its monetary policy decision and the former the surprise purely related to the announced change in the policy rate. A positive monetary policy shock raises market interest rates and reduces stock prices, while a positive central bank information shock raises both. The data starts in January 1999 and we extend the original Jarociński and Karadi (2020) shocks until September 2023 using the euro area monetary policy event-study database of Altavilla et al. (2019).

Beyond granular consumer prices our data set comprises a wide range of variables that help us assess relevant aspects in the transmission of monetary policy. First, we include the headline and core HICP aggregates in order to properly capture inflation entering central bank's policy function. Beyond consumer prices, our data base also includes total producer prices and oil prices. As measures of economic activity we consider total industrial production (IP) excluding construction and the unemployment rate. As key indicator of the policy rate we take the yield on the one-year German Bund, to better account for the period of unconventional monetary policy, and we complement it with the short-term rate measured by the Euribor at three months maturity. We additionally include the corporate BBB bond spread as a measure of financial conditions. To account for the effect of global supply chains, our data base integrates the PMI supplier delivery times survey and the Global Supply Chain Pressures Indicator (GSCPI) of Benigno et al. (2022). Furthermore, we include annual grow in negotiated wages, the EuroSTOXX 50 index, and the nominal effective exchange rate. More details as well as information on sources and transformations are included in Table 6 in Appendix A.

3 Price sensitivity to monetary policy

3.1 Identifying consumption items sensitive to monetary policy

First we consider a general model to estimate the effects of monetary policy on headline and core HICP based on the following Bayesian Vector Autoregression (BVAR) model:

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

where Y_t is an $N \times 1$ vector of data. A_0 is a vector of intercepts, and A_ℓ are the matrices governing the dynamics of the data for $\ell = 1, \cdots, p$ lags, u_t is a vector of reduced-form errors.

We closely follow Chan (2020) and assume that the reduced-form errors are distributed as $u_t \sim \mathcal{N}(0, (\Sigma \otimes \Omega))$, such that the total covariance is split into the $N \times N$ matrix Σ and the $T \times T$ matrix Ω, which capture cross-sectional and serial correlations, respectively. Furthermore, we assume that matrix $\Omega = \text{diag}(\lambda_1, \cdots, \lambda_T)$, with the generic λ_t following the prior $\lambda_t|\nu \sim IG\left(\frac{\nu}{2}, \frac{\nu}{2}\right)$, which characterises the marginal distribution of the reduced-form errors as a multivariate t distribution with ν degrees of freedom, zero mean and scale matrix Σ.[5] For the matrices of lagged effects, $A = [A_1, \cdots, A_p]$, we consider standard normal-inverse-Wishart priors (as in Kadiyala and Karlsson (1997)) such that:

$$\text{vec}(A)|\Sigma \sim \mathcal{N}\left(\text{vec}(\bar{A}), (\Sigma \otimes V_A)\right) \tag{2}$$

$$\Sigma \sim \text{IW}\left(S_0, \alpha\right). \tag{3}$$

The prior matrix $\bar{A}$ follows a Minnesota prior structure such that the elements of the covariance matrix associated to the first lag is diagonal with entry i equals to 1 if variable i follows a random walk and 0 otherwise, for $i = 1, \cdots, N$. The prior covariance matrix V_A is assumed to be diagonal with its elements defined as $v_{A,jj} = \frac{c_2}{c_3 \ell \hat{\sigma}_i^2}$, for $j = 1, \cdots, N \times p + 1$, ℓ refers to the lag, the hyperparameter c_2 rules the degree of shrinkage while c_3 imposes a larger shrinkage to more distant lags. The prior covariance matrix $\hat{\sigma}_i^2$ is estimated based on univariate autoregressive models with p lags. The first element in $v_{A,11} = c_1$ is associated to the intercept term and the hyperparameter c_1 is normally set to a large number such that the prior is diffuse.[6] For the priors associated to the covariance matrix, Σ, we set the prior scale matrix S_0 to an identity matrix and the shape parameter α to $N + 2$ as in Kadiyala and Karlsson (1997).

As noticed by Bobeica and Hartwig (2023), the fat-tailed distribution of the reduced-from errors help addressing the unprecedented dynamics of data during the COVID-19 outbreak. We further take an additional assumption regarding the reduced-form errors. Specifically, we correct potential outliers in the reduced-form errors such that their effect is weighted down in the estimation of the covariance matrix. We follow Stock and Watson (2016) and Carriero et al. (2022) to construct a $T \times N$ matrix of i.i.d. scaling factors O, such that element $o_{i,t} = 1$ whenever an observation is regular and $o_{i,t} \geq 2$ when

[5] See Appendix in Chan (2020) for technical details.

[6] In this exercise we set the hyperparameters to $c_1 = 100$, $c_2 = 0.2^2$ and $c_3 = 2$, standard numbers selected in the literature.

an observation is identified as an outlier. The outliers are drawn based on a mixture distribution, such that $o_{i,t} = 1$ with probability $(1-\rho)$ and $o_{i,t} = U[2, 10]$ with probability ρ. The prior for the probabilities follow a beta distribution as in Stock and Watson (2016).

The estimation of the model carried out is based on a Gibbs sampler, drawing each block of parameters based on their conditional posterior distributions. For the simulation of the parameter associated to the degrees of freedom in the (marginal) multivariate t distribution, ν, we follow Chan (2020) and consider an independence-chain Metropolis-Hastings step.[7]

So far the model in equation (1) is set in a reduced-form but it can be bridged to a structural model as follows:

$$u_t = B\varepsilon_t. \tag{4}$$

where B is a matrix of impact effects and ε_t denotes the structural shocks which can be identified by imposing restrictions on the elements of B. In this paper we are exclusively interested in the identification of monetary policy shocks, which without loss of generality we will assume are placed in the first column of B. By doing so, we follow closely the literature related to the *internal instrument approach* which relies on an instrument or proxy for a structural shock and includes it in the model as an additional endogenous variable (see Ramey (2011), Paul (2020), Plagborg-Møller and Wolf (2022), Noh (2024)). The shock is thus identified via a recursive approach, positioning the internal instrument in the first position of vector Y_t. As a proxy measure of monetary policy shocks we consider the estimates of Jarociński and Karadi (2020) related to the pure policy shocks.

The set of endogenous variables comprises the variables in Table 6 in the Appendix and introduced in Section 2.

Figure 8 in the Appendix shows impulse responses from the baseline BVAR for the full set of variables. A contractionary monetary policy shock normalised such that increases of 25 basis points in the German Bund at the 1 year maturity decreases both consumer (headline HICP) and producer prices, as well as industrial production.

As we are interested in the monetary policy effect from a granular perspective, we estimate 72 models along the lines of equation (1), one for each HICP core item, such that a generic BVAR for item $j \in \{1, \cdots, 72\}$ has the following form:

$$Y_{t,j} = A_{0,j} + A_{1,j}Y_{t-1,j} + \cdots + A_{p,j}Y_{t-p,j} + u_{t,j}. \tag{5}$$

[7]See Appendix in Chan (2020) for details on the proposal distribution and the implementation.

For each model j, we use the same endogenous variables as in model (1) but augment it by the $j-$th HICP item. Similar to the general model, we position the monetary policy proxy in the first position of the matrix of data Y_j and proceed with a recursive identification focusing only on the monetary policy shock.

All models are estimated using 6 lags and are based on 20000 draws, discarding the first 50% as a burn-in sample, keeping every 10th draw for inference in order to avoid serially-correlated Markov Chains.

To assess the sensitivity of individual COICOP-4 items to monetary policy shocks, we first normalise the impulse responses such that they represent an increase of 25 basis points in the German Bund at 1 year maturity. Then, for each item, we identify periods (within 36-months after the shock) with at least three consecutive months of a negative and statistically significant response to a tightening shock. Items for which at least one such period exists are categorised as sensitive, and all remaining items–as non-sensitive.

An overview of all consumption items classified according to monetary policy sensitivity is included in Table 8 in Appendix B and the results are summarised in Table 1 and Figure 1. Sensitive items account for around 33% of the HICPX basket, and are evenly split between goods and services (goods account for 50.1% and services for 49.9% of sensitive items). The items classified as sensitive are concentrated in durable goods, services and goods related to maintenance and repair of dwellings, and transport and recreation services (accommodation, food).[8] Overall, sensitive items account for 43.9% of the goods category in the HICPX basket, and for 26.4% of the services category. As we will document in subsequent sections, higher monetary policy sensitivity is broadly consistent with a discretionary character of many of the items and the important role of credit in financing their consumption. Notable non-sensitive items include non-discretionary categories (that also tend to be tightly regulated in many countries) such as rents and medical services.

[8] "Durability" of production outputs has been previously studied in the context of distributional effects of monetary policy changes in euro area member countries. For example, studies by Dedola and Lippi (2005) and Peersman and Smets (2005) link the considerable cross-sectional heterogeneity in the policy effects on output to, among others, the durability of the goods produced in each sector.

Table 1: Share of monetary policy sensitive items in the HICPX basket

	HICPX	Sensitive	Non-sensitive
Number of items	72	33	39
Weight in HICP (HICP=1000)	697.4	230.2	467.2

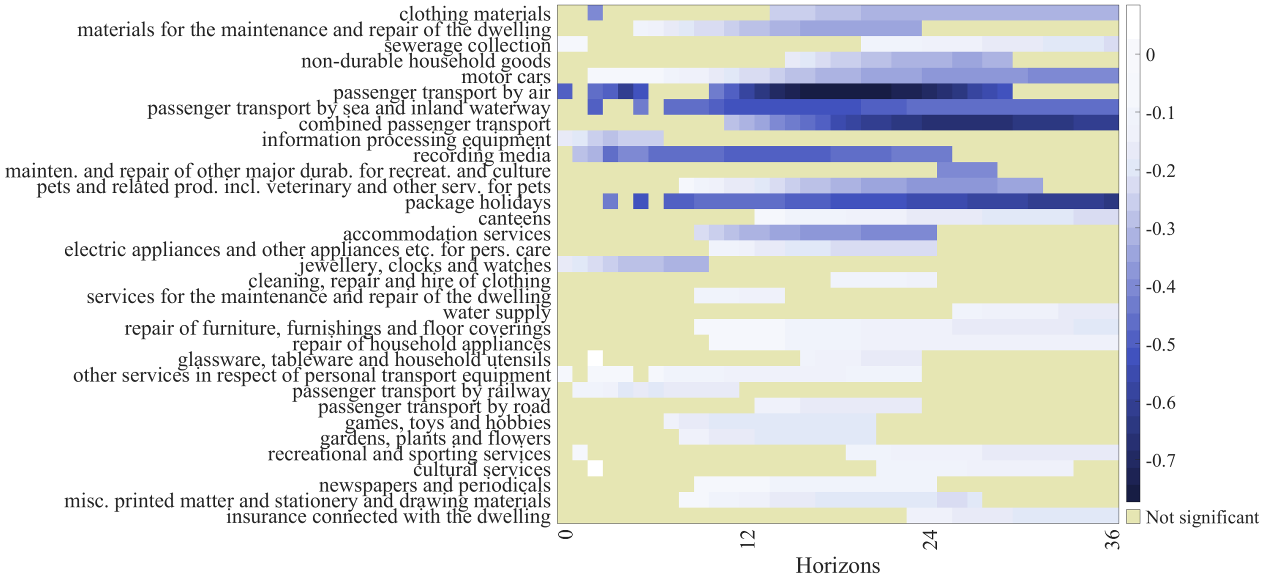
Notes: The table shows the number and share in the HICP basket of items identified as sensitive and non-sensitive to monetary policy shocks. To compute HICP shares, end-2023 weights from Eurostat are used.

In such a disaggregated analysis, there is a risk of mis-classifying items as being monetary policy sensitive when they are not (type II error), or indeed vice versa (type I error). For instance, water supply and sewerage collection services–two items with heavily regulated prices–are picked by the model as sensitive.[9] Second, not only does the speed and extent of the responsiveness of prices to monetary policy vary across items (as illustrated in Figure 1), but also the responsiveness of an individual item can vary across time. Figure 7 in Appendix B shows the results of a recursive estimation to identify sensitive items and illustrates that, while the categorisation for some items is stable over time, for others it can vary significantly. Certain items are always classified as sensitive to monetary policy - for instance, durable goods like cars or services linked to recreation and culture - and others are never identified as sensitive - for instance, essential items like pharmaceutical goods, medical services, rents and education. However, in light of the inherent uncertainty, we use an alternative approach to classify items and present evidence using a Smooth Local Projection (SLP) following Barnichon and Brownlees (2019), which delivers qualitatively similar results, as shown in Appendix D.[10]

[9]Sewerage collection is picked as sensitive in one and water supply in none of the three alternative model specifications presented in Appendix. All the results in the paper are robust to excluding those two items from the sensitive items. We investigate the role of administered prices in our results in Section 3.2.4.

[10]Local projections and vector autoregressions can be estimated with either frequentist and Bayesian methods. Various studies discuss each method's strengths and weaknesses, and document, at times, significantly varying findings depending on the variable under investigation and on the horizon of interest, i.e., Ramey (2016), Plagborg-Møller and Wolf (2021) and Ho et al. (2024).

Figure 1: Monetary policy pass-through across sensitive components



Notes: The heatmap shows impulse responses of the HICPX items sensitive to monetary policy based on the point estimate from the BVAR. The darker (lighter) the color, the stronger (weaker) response of the item to a monetary policy shock leading to a 25 basis points increase in the policy rate (proxied by the 1-year German Bund yield). Yellow segments indicate non-significant responses. The x-axis corresponds to the monthly horizons after the shock.

3.2 Mechanisms of price sensitivity to monetary policy

This section explores whether the characteristics of monetary policy sensitive items are consistent with theories of monetary policy pass-through to prices. Specifically, we explore whether there is evidence relating to the relevance of discretionary spending, the credit channel, the frequency of price changes and administered prices.

3.2.1 Monetary policy sensitivity and discretionary spending

According to theory, discretionary spending should be more sensitive to monetary policy shocks (Mankiw (1985)). Empirically, Aguiar and Bils (2015) classify consumption items into necessities and discretionary – or luxury – items and show that the latter are more frequently purchased by higher income households. To investigate this hypothesis, we use data from the Household Budget Survey (HBS) on the shares of COICOP-3 items in consumption baskets by households' income quintile. The HBS is conducted every five years by Eurostat, but the euro area aggregates are available only until 2010. Thus, we report the consumption shares also for five out of six largest euro area economies for the

2010, 2015 and 2020 waves.[11]

After aggregating our COICOP-4 results on monetary policy sensitivity to COICOP-3 level aggregates,[12] we see that the sensitive items are more frequently purchased by high-income households relative to low-income households (Table 2). For example, in 2010 the sensitive HICPX items had a 52.8% higher share in the consumption basket of high-income households compared to the low-income households in the euro area, while non-sensitive items had a a 14% lower share (Table 2, first row). The results hold also when comparing consumption baskets of high- vs low-skilled workers and of low-skilled workers vs unemployed (see Tables 9 and 10 in Appendix C). They are also robust to comparing *average* consumption shares of individual COICOP-3 items (instead of their combined shares) classified as sensitive or non-sensitive (Tables 11-13 in Appendix C).

Table 2: Difference in the share of consumption baskets spent on core inflation items by their monetary policy sensitivity: High-income versus low-income households (%).

	2010		2015		2020	
	Non-sens.	Sensitive	Non-sens.	Sensitive	Non-sens.	Sensitive
EA	-14.0	52.8				
BE	-10.3	52.2	-21.0	74.4	-31.1	53.2
DE	-19.2	55.6	-26.1	57.3	-24.0	52.0
ES	0.7	61.3	2.4	63.6	-7.4	57.4
FR	-26.2	43.5	-27.5	49.4	-27.5	49.4
NL	-14.1	35.8	-27.0	62.8	-24.0	56.0
No. items	21	13	21	13	21	13

Notes: The Table shows percentage differences in the share of consumption baskets spent on items sensitive- and non-sensitive to monetary policy shocks by households in the 5th quintile of income distribution compared to households in the 1st income quintile. The shares of (selected) COICOP-3 items in consumption baskets come from the 2010, 2015 and 2020 waves of the HBS.

Table 2 shows that high-income households have consumption baskets more tilted towards items sensitive to monetary policy shocks than low-income households. However, two recent papers find that inflation experienced by lower- and middle-income households is more responsive to monetary policy shocks: Cravino et al. (2020) for the US and

[11] Data for Italy is only available for comparison of consumption baskets of manual workers, non-manual workers and unemployed. See Appendix C.

[12] We classify a COICOP-3 consumption category as monetary policy sensitive if the total weight of COICOP-4 items classified as sensitive to monetary policy shocks in Section 3.1 is at least 33% of that COICOP-3 category (using item HICP shares as weights).

Ampudia et al. (2023) for euro area. An important difference between our analysis and theirs is that while we focus on goods and services only, the two papers consider entire consumption baskets, i.e., including food, beverages and energy. In fact, Ampudia et al. (2023) find largest differences in consumption shares among high-income and low-income households for food, beverages, electricity, gas and other fuels categories (with low-income households having higher consumption shares for all those items).[13] At the same time, our findings speak in favour of a strong *substitution* channel, also documented in Ampudia et al. (2023), whereby high-income households have more room to change their shopping patterns and switch away from more expensive items, as compared to low-income households following an adverse income shock. Our results would imply this channel to be stronger for core HICP items compared to food and energy items (i.e. *necessities*).

3.2.2 Monetary policy sensitivity and the credit channel

Another channel through which monetary policy can have a heterogeneous impact on the prices of different consumption items is via the credit channel.[14] More specifically, we expect that flows of consumer loans will have a larger impact on prices of those HICPX items, for which households rely relatively more on credit for financing their purchases. To investigate this hypothesis, we consider a *panel* local projection regression of the 72 core inflation items on changes in monthly consumer loan flows:[15]

$$y_{i,t+h} - y_{i,t} = \alpha_i^{(h)} + \beta_1^{(h)} \Delta CCredit_t + \beta_2^{(h)} \Delta CCredit_t \times \mathbf{I}_i + \sum_{j=1}^{M} \gamma_j^{(h)} X_{i,t-j} + u_{i,t+h}. \quad (6)$$

$\mathbf{I}_i$ is a dummy variable equal to one if the i-th core inflation item is (highly) sensitive to monetary policy changes and where $\Delta CCredit_t$ stands for the month-on-month change in new consumer loan volume (excluding revolving loans and overdrafts, convenience and

[13] Comparing top-1% income households with the middle of income distribution, Cravino et al. (2020) find that middle-income households exhibit highest expenditure shares relative to the top 1% in goods such as gasoline, electricity, and used cars.

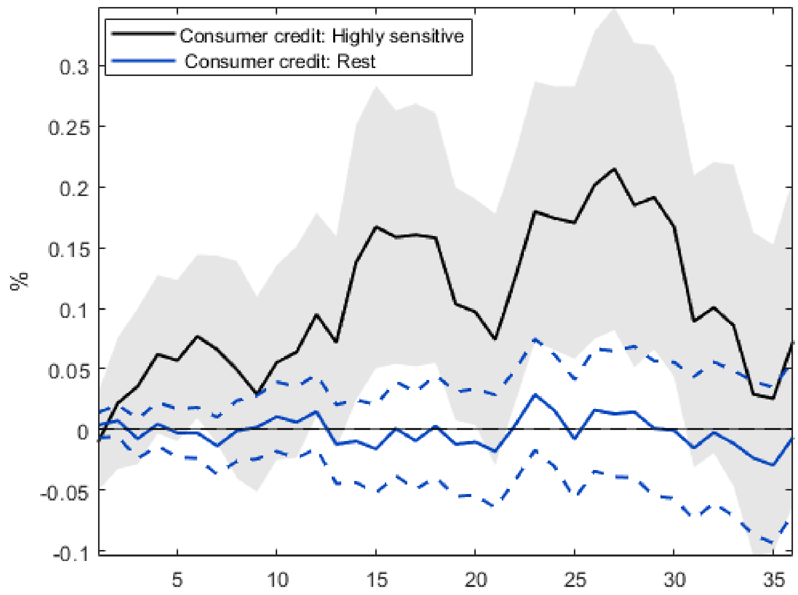
[14] Past literature indicates a non-negligible quantitative role of credit frictions in the transmission of monetary policy, in line with the predictions obtained from quantitative general equilibrium models, e.g. Bernanke (1999). For example, Dedola and Lippi (2005) show that the impact of monetary policy is stronger in industries that have greater financing requirements and a smaller borrowing capacity (i.e., smaller firm size and higher leverage ratio). More recently, studies that have provided evidence in support of different branches of the credit channel include, among others, Ciccarelli et al. (2015).

[15] We do not consider mortgage loans as the link between consumer credit and consumption items is the most direct one. In principle, higher mortgage loan flows could affect spending on some consumption items (e.g., related to dwelling maintenance and furnishing) as new home owners renovate their houses and purchase furniture, but the consumption link is less direct and may occur with some lags.

extended credit card debt). We instrument $\Delta CCredit_t$ with twelve lags of the monetary policy shocks from Jarociński and Karadi (2020). The set of controls, $X_{i,t-j}$ follows specification (1), but includes also a dummy for the COVID-19 years (2020-2021). A positive $\beta_2^{(h)}$ in (6) means that an increase in the consumer credit flow is associated with a larger increase in the prices of monetary policy sensitive items between t and $t+h$ compared to the non-sensitive ones.

In line with our priors, we find that the inflation of highly sensitive items rises more strongly after a positive change in the monthly consumer credit flows compared to moderately and non-sensitive items (Figure 2), although the results are much weaker when considering the full set of monetary policy sensitive items, i.e., items highly and moderately sensitive in Table 8. A one standard deviation increase in the growth rate of new consumer loans is associated with an increase in the price of an average highly-sensitive item by 0.22% at about 27 months, but no statistically significant rise in the prices of all remaining items.

Figure 2: Responses of prices of core consumption items to changes in consumer credit flows



Notes: The figure shows the average cumulative price changes across COICOP-4 items characterised as highly monetary policy-sensitive (black line) and as moderately and not sensitive (blue line) over 36 months after a one percentage point increase in the monthly flows of new consumer loans in the euro area. The grey areas and dashed blue lines correspond to 90% confidence bands.

3.2.3 Monetary policy sensitivity and the frequency of price changes

Next, we look at the frequency of price changes. Recent literature has demonstrated that items with more frequent price changes also show higher relative responsiveness to monetary policy: Hong et al. (2023) for producer prices in the US, and Alvarez et al. (2024) for producer and consumer prices in France. We follow their approach and investigate whether cumulative price responses to the monetary policy shocks among core inflation items are positively associated with their average frequency of price changes. Compared to these two papers, however, our focus is on prices of goods and services only.

We use data from Gautier et al. (2024), who calculate the average frequency of price changes between 2011-2019 for a subset of COICOP-5 HICP items in the euro area. We aggregate their estimates at the COICOP-4 level and compute the average frequency of price changes for monetary policy sensitive and non-sensitive items. Table 3 shows the results when using frequency of price changes excluding sales. While this is our preferred measure, the results do not change when considering frequency of price changes including sales. Among the 51 HICPX COICOP-4 items for which we can compute the frequency of price changes, 23 are sensitive to monetary policy and 28 are not. Sensitive items have an average frequency of price changes of 6.9%, which is slightly below the average for non-sensitive items of 7.2%.

Table 3: Frequency of price changes and monetary policy sensitivity of core inflation items (excl. sales)

	HICPX	Sensitive	Non-sensitive
Number of items	51	23	28
Weight in HICP (HICP=1000)	499.2	160.2	339.0
Average across items	7.0%	6.9%	7.2%
Weighted average	6.4%	8.0%	5.7%

Notes: The number of items reported in the Table refers to the COICOP-4 items for which Gautier et al. (2024) provide an estimate of the average frequency of price change. Weighted average frequencies of price change are computed using average weights of COICOP-4 items between 2016-2019 in the HICP basket. The dfference in average frequencies between sensitive and non-sensitive categories that are reported in the Table is not statistically significant.

Next, we test the link between the average frequency of price changes and sensitivity to monetary policy across HICPX items by considering two *panel* local projection regressions:

$$y_{i,t+h} - y_{i,t} = \alpha_i^{s,(h)} + \beta_1^{s,(h)} MP_t + \beta_2^{s,(h)} MP_t \times \mathbf{I}_i + \sum_{j=1}^{M} \gamma_j^{s,(h)} X_{i,t-j} + u_{i,t+h}^{s}, \tag{7}$$

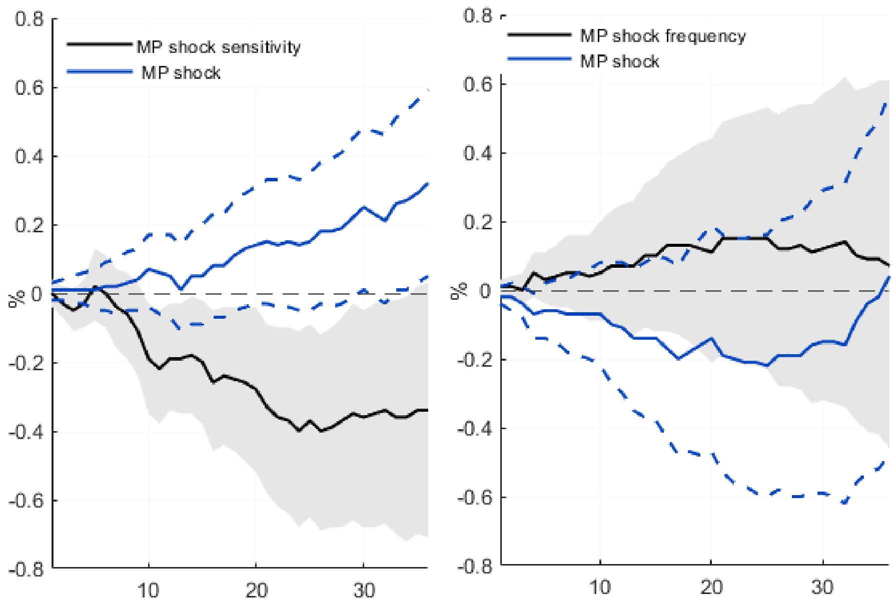
$$y_{i,t+h} - y_{i,t} = \alpha_i^{f,(h)} + \beta_1^{f,(h)} MP_t + \beta_2^{f,(h)} MP_t \times Freq_i + \sum_{j=1}^{M} \gamma_j^{(h)} X_{i,t-j} + u_{i,t+h}^{f}, \tag{8}$$

where $\mathbf{I}_i$ in equation (7) is a dummy variable equal to one if the i-th core inflation item is sensitive. Instead, $Freq_i$ in equation (8) is the estimate of average price change frequency (between 2010-2019) for item i from Gautier et al. (2024). A negative $\beta_2^{s,(h)}$ in equation (7) means that a contractionary monetary policy shock has a more negative impact on the prices of monetary policy sensitive items between t and $t+h$ compared to the non-sensitive ones. A negative $\beta_2^{f,(h)}$ in equation (8) means that a higher average frequency of price changes is associated with a larger negative impact of a positive monetary policy shock on prices. The set of controls, $X_{i,t-j}$, in both regressions follows specification (1) but includes also a dummy for the COVID-19 years. To ensure consistency with the sample for which we have the average frequencies of price changes, we estimate both equations using data until end-2019.

Figure 3 shows the estimates of coefficients $\beta_1^{k,(h)}$ and $\beta_2^{k,(h)}$ for $h = 1, 2, ..., 30$ and $k \in \{s, f\}$. The coefficient on the dummy for sensitive items is negative and statistically significant, while the standalone monetary policy shock – reflecting the impact on non-sensitive HICPX items – is insignificant. Such results therefore corroborate our evidence from the BVARs through the lens of panel local projections. In comparison, the interaction term of the monetary policy shock with the frequency of price changes is consistently insignificant over the 36-months horizon. This holds also when, instead of the average frequency of price change, we interact the monetary policy shock with a dummy equal one for items with a frequency of price changes above the sample median.

These results suggest that frequency of price changes does not explain the relative sensitivity of core items to monetary policy shocks. This may reflect that the frequency of price changes is generally lower for goods and services, compared to food and energy, as documented by Gautier et al. (2024) and Dedola et al. (2024). One additional element that might help us to justify the documented result speaks to the fact that the period for which the frequency estimates are available was a time of low inflation and a relatively low frequency of price changes across all goods and services, making identification more difficult. At the same time, when we regress price changes on the average absolute size of price adjustments instead of frequency, we find that a larger size of price changes is associated with higher responsiveness to monetary policy (Figure 9, Appendix C).

Figure 3: Impulse responses of the prices of core inflation items to a monetary policy shock



Notes: The figure shows impulse responses to a monetary policy shock (blue lines) and coefficients on the interaction term of monetary policy shock with a dummy equal one for monetary policy-sensitive items (left panel) and with the frequency of price changes (right panel) from equations (7) and (8) (black lines), estimated on a sample ending in December 2019. Grey areas and dashed blue lines correspond to 90% confidence bands.

When considering an extended sample of all HICP items (i.e., including food and energy items) and re-estimating equation (8), the findings are similar to Hong et al. (2023) and Alvarez et al. (2024). Figure 10 in the Appendix shows that after including the additional HICP categories, a higher frequency of price changes implies a larger and a statistically significant price effect from monetary policy shocks. These differential results for HICP and core inflation baskets point to diverse price setting mechanisms for different items and, therefore, to the different channels of monetary policy pass-through at play. For example, the fact that food and energy have a higher average frequency at which they are purchased and consumed, together with their higher responsiveness to global commodity prices, could make the frequency of price adjustments particularly relevant for those categories.

3.2.4 Monetary policy sensitivity and administered prices

Finally, we assess the role of administered prices among sensitive and non-sensitive items. We use the definition of administered prices from Eurostat. As a rule, Eurostat classifies a consumption item as administered when items with regulated prices account for more than 50% of households' expenditure on items in that category. The assignment of the administered price status is done at the country level. For our purposes, we use the 2021 Eurostat classification to exclude the impact of price regulations introduced in some euro area countries in response to the 2022 energy price surge. We mark a consumption item as administered if it had a regulated status in countries accounting for at least 50% of the euro area HICP basket. Using this definition, we identify 13 COICOP-4 items as comprising a considerable share of products with administered prices (Table 4). These include water supply, refuse and sewerage collection, goods and services related to health (pharmaceutical products plus hospital, dental, and medical services), postal services, education, social protection, as well as combined passenger transport and passenger transport by road.

Table 4: Administered prices and monetary policy sensitivity of COICOP-4 HICPX items

	HICPX	Sensitive	Non-sensitive
number of items	72	33	39
weight in HICP	697.4	230.2	467.2
number of items with admin. prices	13	4	9
weight in HICP (HICP=1000)	103.8	18.1	85.7

Notes: The Table shows the number of items with administered prices among the 72 COICOP-4 HICPX items in the euro area. An item is classified as administered if it was classified as such by Eurostat in 2021 in countries accounting for at least 50% of the euro area HICP basket.

The majority of the items with administered prices in the HICPX basket are also non-sensitive to monetary policy shocks. In total, 9 out of 39 core inflation items classified as non-sensitive to monetary policy are administered. In comparison, only 4 out of 33 sensitive items are identified as administered (water supply, sewerage collection, combined passenger transport and passenger transport by road). Overall, the share of regulated prices in the euro area HICP is relatively high at 10.7%. It increases to 15.7% for the core inflation basket.[16]

[16]The results hold also when identifying a COICOP-4 item as having administered prices if it is

4 Monetary policy and core inflation in the euro area

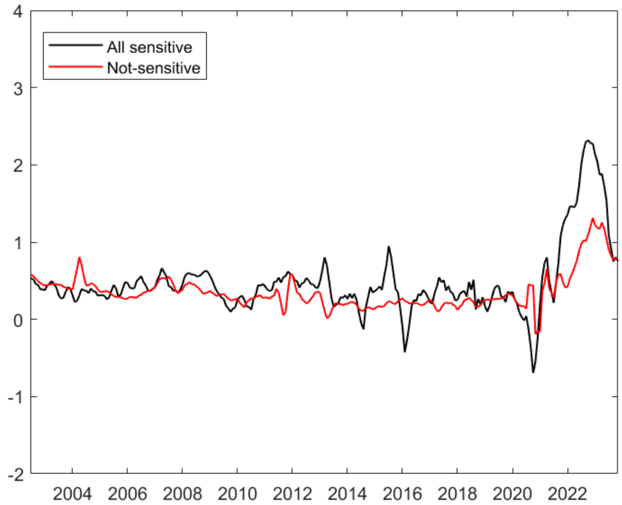
In this section we illustrate how the results from the granular analysis based on the item-specific BVARs can be used to assess the pass-through of monetary policy to core inflation in the euro area, particularly since the 2022-2023 tightening.

4.1 Monetary policy sensitivity and core inflation dynamics over time

We begin the discussion by focusing on the time series evolution of sensitive and non-sensitive aggregates over time. Based on the item categorisation described in Section 3.1, we construct two aggregate price indicators: one for sensitive and one for non-sensitive items. Figure 4 shows the evolution of the inflation momentum (3 month-on-3 month growth rate) of the two price indices over time. Price changes of core sensitive items have experienced larger volatility over the past 20 years compared to those from non-sensitive items. Zooming into the post-COVID inflation surge, the inflation rate of the sensitive category started rising earlier on, albeit with some fluctuations, and more abruptly than the inflation rate of non-sensitive HICPX. Once the peak was attained around autumn 2022, the inflation of the sensitive category started declining more forcefully and has recently fluctuated around levels similar to those observed for the the non-sensitive index.

classified as such by Eurostat in at least one of six euro area economies with the largest contributions to the euro area core inflation price index (Germany, France, Italy, Spain, the Netherlands and Belgium). In this case, the number of administered and interest-sensitive items increases to 8, while the number of administered and non-sensitive items increases to 13.

Figure 4: Inflation momentum of sensitive and non-sensitive core inflation over time (3m-on-3m percentage changes)



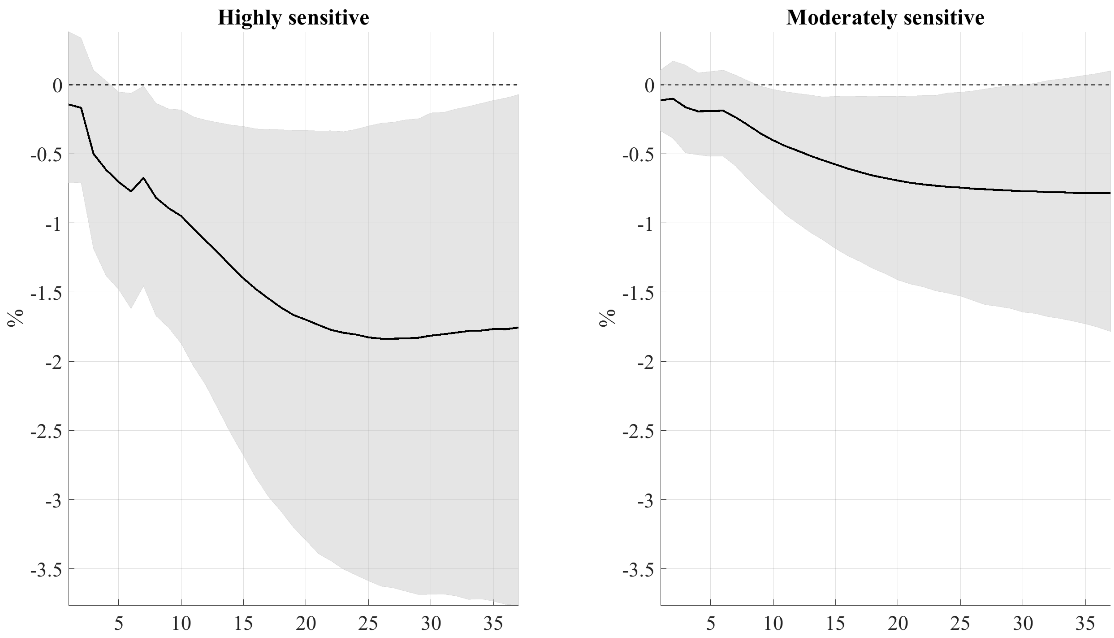
Notes: The figure shows the momentum of inflation in monetary policy sensitive items ,non- sensitive items. The two sub-indices are constructed by aggregating individual HICPX COICOP-4 items using the 2023 HICP basket weights from Eurostat.

4.2 Pass-through of monetary policy to prices

The previous subsection illustrated that the time series evolution of sensitive and non-sensitive categories of items exhibits important differences. In this subsection, we look at the responses of the monetary policy sensitive core inflation aggregate. Recognising that the degree of sensitivity to monetary policy shocks varies substantially also within the category of sensitive items, we further decompose it into two sub-groups: i) highly-sensitive items, i.e., those for which the peak impulse response is larger in absolute terms than the median peak response among all sensitive items, and ii) moderately-sensitive items, i.e., items with absolute peak response smaller than the median absolute peak among all sensitive items.

Subsequently, we construct aggregate impulse responses for both sensitive categories using 2023 HICP basket weights. The aggregate impulse responses and the corresponding uncertainty bands originating from the posterior distribution are presented in Figure 5. The effect of monetary policy shocks is approximately 2.5 times larger on highly-sensitive items than on the moderately sensitive items. After around 25 months, a 25 basis points tightening shock lowers the cumulative price change by around 1.8 percentage points for the highly-sensitive aggregate and by around 0.7 percentage points for the moderately-sensitive one. Overall, when we aggregate the impulse responses for all items (i.e. taking into account also core inflation items we classify as non-sensitive), our results imply that a 25 basis points monetary tightening shock decreases HICPX by around 0.7% over 36 months.

Figure 5: Monetary policy pass-through to highly vs moderately sensitive HICPX items



Notes: The figure shows the responses of HICPX sub-indices classified as highly (left panel) and moderately (right panel) sensitive to monetary policy shocks, based on estimation of equation (5). Black lines represent the median of the distribution of weighted average responses based on the items' weights in the HICPX basket. Shaded areas represent the 68% credibility bands of the IRFs. The IRFs are normalised to a positive monetary policy shock that increases the 1Y German Bund by 25 basis points.

4.3 Changes in monetary policy pass-through over time

Finally, we investigate whether the pass-through of monetary policy shocks to HICPX items has changed over time. This question is particularly relevant in the context of the most recent policy rate hiking cycle initiated by the ECB in July 2022, which has been the fastest and strongest - in terms of the total change in the policy rates - since the start of the monetary union. For this purpose, we estimate equation (5) over different samples, aiming to provide insights on the potentially shifting dynamics over time. Our first sample covers the period from 1999/early 2000 (depending on when the COICOP-4 item price series start) until end of 2019 to capture pre-COVID dynamics. We further consider the estimation of the model ending in 2021 and June 2022, to cover pre-tightening periods that were governed by the COVID-19 pandemic, the reopening of the economy and the Russian invasion of Ukraine. The last estimation corresponds to the full sample stopping in September 2023 which includes the historical tightening.

Figure 6 shows the impulse responses for the highly- and moderately-sensitive core inflation aggregates based on selected samples. The impact of monetary policy shocks appears to be stronger over the full period that includes the most recent tightening in response to the post pandemic inflation surge (red impulse responses). Specifically, focusing on the highly-sensitive core inflation aggregate, within 25 months a 25 basis points tightening shock lowers the cumulative price change by around 1.8 percentage points. In contrast, the cumulative response of the earlier samples over the same horizon is less than 1.4 percentage points.[17] Recent work by Zlobins (2024) also finds that the transmission of policy to inflation has been stronger following the historically exceptional tightening in the euro area.

What explains the stronger response of consumer prices to monetary policy in the most recent tightening cycle that we document? The steep and decisive shift in policy stance in response to the surge in inflation has most likely been an important contributing factor, with potential non-linear effects linked to it.[18] For example, the recent surge in inflation was a global phenomenon and the monetary policy response was concerted across international central banks, thus, this globally aligned policy response may have amplified the impact of monetary policy on inflation (Auclert et al. (2023)). Alternative hypotheses link the amplified tightening impulse responses with channels operating through bank and firm balance sheets.[19] Moreover, the large shocks in 2022 triggered an increase in the frequency of price adjustments (Dedola et al. (2024)). In our cross-sectional analysis, documented in Sub-section 3.2.3, we do not find evidence of this channel, potentially due to the fact that we focus on a period ending in 2019 due to data availability. However, a change in the frequency of price adjustment could have been another factor influencing the speed at which changes in the monetary stance have been transmitting to consumer

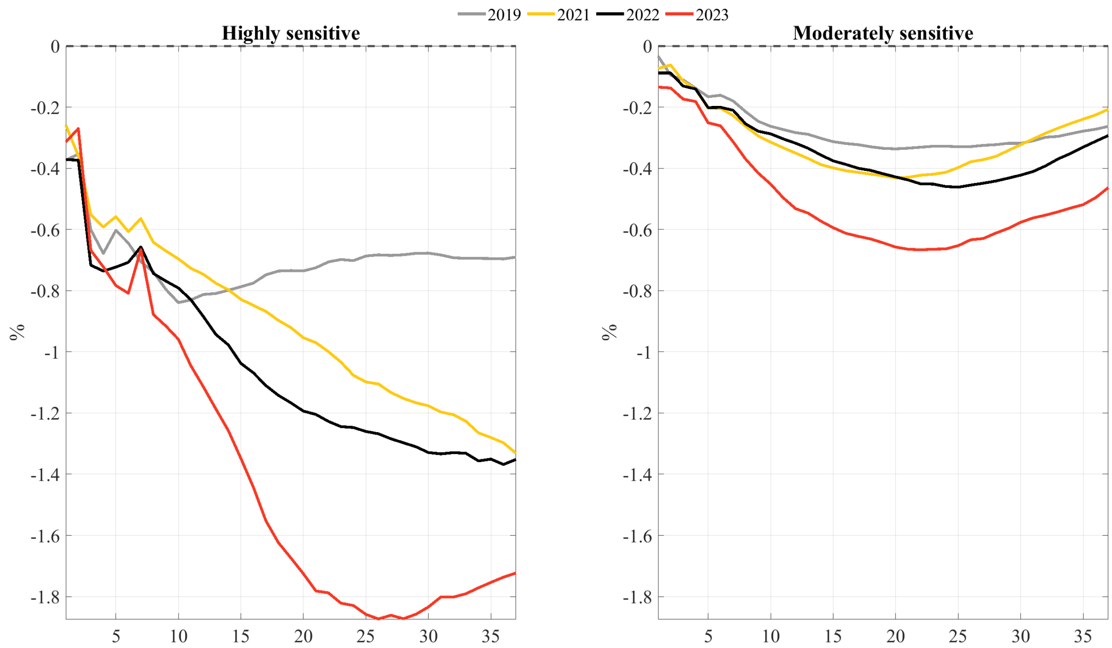
[17] Zooming in at expanding window BVARs covering last two-three years, two clusters of impulse responses to a monetary policy shock are noticeable: i) IRFs based on models estimated including observations at most until summer 2022, which are closely aligned to the IRFs based on the pre-COVID sample, ii) IRFs based on models that go beyond summer 2022, which show much more pronounced responses of disaggregated prices to the monetary policy shock.

[18] Models central to monetary theory postulate that extreme values of inflation (too high or too low) cause distortions to relative prices. While our current work does not seek to address questions of such concern, changes in consumption behaviour arising from shifts to relative prices might present as a relevant mechanism driving the documented time-varying dynamics.

[19] See, e.g., Lane, Philip, 2024, "The analytics of the monetary policy tightening cycle", 2nd May 2024, guest lecture at Stanford Graduate School of Business.

prices, and future work should further investigate this relationship.

Figure 6: Monetary policy pass-through to core inflation over time



Note: The figure shows the responses of COICOP-4 HICPX items to a tightening monetary policy shock normalised to a 25 basis points increase in the 1Y German Bund, across selected samples. The highly (moderately) sensitive panel corresponds to the aggregation of more (less) sensitive items based on their weights in the core HICP basket. The grey, yellow and black lines correspond to the pre-COVID, COVID, and post-COVID period, respectively, while the red line highlights the IRF including the last period in the sample.

4.4 Energy prices and the role of energy costs

Energy costs account for a smaller share of input costs of core goods and services (compared to food for example), but large movements in energy prices can also have a very substantial impact on core inflation - via both direct and indirect effects. In all models, we control for oil prices, but to ensure that our results are not being driven by the volatile moves in energy markets, we provide evidence on the energy-intensity of our selection of sensitive items compared to non-sensitive items.

Overall, the share of total energy inputs (both direct and indirect, i.e., via the use of intermediate inputs from other industries) in the production of HICPX COICOP-4 items is relatively small, but it is larger for monetary policy sensitive items. Table 5 shows that total energy costs account for a weighted average of around 7.5% of the total output costs for monetary policy sensitive items versus 3.7% of non-sensitive items. At the same time, however, the difference seems to be largely driven by a few highly sensitive items, including passenger transport by air (energy share of 26.2%) and electric appliances for personal care (energy share of 14.9%). The median energy shares across monetary policy sensitive items (5.1%) is much closer to the median among non-sensitive (3.6%) items too, suggesting the volatile moves in energy over this period are not likely to be driving our results.[20] Nevertheless, to ensure our results are not driven by energy intensity during the last energy price spike, we re-classify the items and re-estimate regression (7) excluding five monetary policy sensitive items with highest energy shares from the sample. The results shown in Figure 3 and Figure 5 remain unchanged: monetary policy shocks lead to larger price responses of items identified as (more) monetary policy sensitive.

Table 5: Implied energy shares in euro area HICPX items (%).

	HICPX	Sensitive	Non-sensitive
median	4.8%	5.1%	3.6%
average	5.3%	7.2%***	3.7%
weighted average	5.0%	7.7%	3.8%
No. items	72	32	39

Notes: Implied energy shares are calculated relative to total output at NACE-2 sectoral level using the Eurostat symmetric input-output table for 2019 and consist of direct (share of energy used for production) and indirect (via the use of intermediate inputs from all other sectors of the economy) energy costs. Energy shares in the production of COICOP-4 items in the HICPX are computed after mapping of NACE-2 sectors into COICOP-4 categories. Weighted average share uses weights of individual COICOP-4 categories in the HICP basket. See Fagandini et al. (2024) for details. For the non-weighted average reported in the sensitive category, the Table also reports significance level for the t-test for equality of means (H0: sample means are equal) compared to the non-sensitive category ($^{***} - p < 0.01$, $^{**} - p < 0.05$ and $^{*} - p < 0.1$).

5 Robustness

The Appendix includes additional exercises to test the robustness of the results. For instance, to estimate impulse responses, we alternatively use smooth local projections (SLP), a univariate framework that alleviates inference and jagged responses in standard local projections (see Barnichon and Brownlees (2019) for details). We confirm the existence of substantial heterogeneity in the transmission mechanism of monetary policy to

[20] It should be noted that indicators computed using input-output tables and reported in Table 5 do not capture second-round effects on consumer prices via subsequent possible adjustments in prices and wages.

the euro area core inflation consumption basket. These findings are based on an SLP with identical lags and controls as the baseline multivariate specification, we document these results in Appendix D. Furthermore, we find a considerable overlap of the selected items sensitive to monetary policy in comparison to our baseline approach.

We further show that qualitative results hold when we introduce more lags to the granular BVAR system (p=12) and when we control for a slightly different information set (Appendix E).

6 Conclusions

This paper sheds light on monetary policy transmission to euro-area consumer granular prices and assesses the impact of the large monetary policy response on prices following the post-pandemic surge in inflation. The granular approach provides an anatomy of a tightening cycle and allows for a timely and detailed understanding of the associated disinflation process. Given the different propagation channels in the monetary transmission mechanism, sub-components of the inflation basket respond differently to monetary policy shocks, both in terms of the size and the speed. This paper identifies which items of the inflation basket tend to be most sensitive to changes in monetary policy, and the mechanisms driving the relative sensitivity of different items.

We estimate an empirical Bayesian multivariate model to measure the effects of monetary policy shocks on the prices of individual consumption items in the euro area core inflation basket. Having pinned-down the individual responsiveness of items to monetary policy, we aggregate categories according to their sensitivity. We find that our classifications are consistent with economic theories suggesting that prices of discretionary and credit-intensive items respond quicker to changes in monetary policy, while administered prices respond less. Our empirical analysis also illustrates that there is considerable heterogeneity in responsiveness to monetary policy shocks also within the sensitive items category. For example, the impact of monetary policy shocks on prices within the highly sensitive category is around 2.5 times larger than the impact on prices of moderately sensitive items, with the documented pass-through appearing to be also faster. We additionally offer tentative evidence on the presence of time-varying dynamics, documenting that the 2022-2023 tightening cycle of monetary policy in the euro area has been overall stronger compared to previous episodes.

Overall, the analysis highlights the merits of examining the inflation process at a granular level. This can serve as a complement to the study of aggregate responses to monetary policy, since monetary policy changes take time to fully materialise on aggregate inflation, with some channels usually blurred in the aggregate response. Understanding the evolution of granular price data is key in assessing the transmission of monetary policy in real time, particularly in an environment characterised by numerous policy-relevant drivers and shifting dynamics.

References

Aguiar, M. and Bils, M. (2015). Has Consumption Inequality Mirrored Income Inequality? *American Economic Review*, 105(9):2725–2756.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179.

Alvarez, F., Ferrara, A., Gautier, E., Le Bihan, H., and Lippi, F. (2024). Empirical Investigation of a Sufficient Statistic for Monetary Shocks. *The Review of Economic Studies*, page rdae082.

Ampudia, M., Ehrmann, M., and Strasser, G. (2023). The effect of monetary policy on inflation heterogeneity along the income distribution. *BIS Working Paper No 1124*.

Aruoba, S. B. and Drechsel, T. (2024). The long and variable lags of monetary policy: Evidence from disaggregated price indices. *Journal of Monetary Economics*, page 103635.

Auclert, A., Monnery, H., Rognlie, M., and Straub, L. (2023). Managing an Energy Shock: Fiscal and Monetary Policy. NBER Working Papers 31543, National Bureau of Economic Research, Inc.

Balke, N. S. and Wynne, M. A. (2007). The relative price effects of monetary shocks. *Journal of Macroeconomics*, 29(1):19–36.

Barnichon, R. and Brownlees, C. (2019). Impulse response estimation by smooth local projections. *Review of Economics and Statistics*, 101(3):522–530.

Baumeister, C., Liu, P., and Mumtaz, H. (2013). Changes in the effects of monetary policy on disaggregate price dynamics. *Journal of Economic Dynamics and Control*, 37(3):543–560.

Benigno, G., Di Giovanni, J., Groen, J. J., and Noble, A. I. (2022). The gscpi: A new barometer of global supply chain pressures. *FRB of New York Staff Report*, (1017).

Bernanke, B. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, 1.

Bernanke, B. S. and Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Bobeica, E. and Hartwig, B. (2023). The covid-19 shock and challenges for inflation modelling. *International journal of forecasting*, 39(1):519–539.

Boivin, J., Giannoni, M. P., and Mihov, I. (2009). Sticky prices and monetary policy: Evidence from disaggregated us data. *American Economic Review*, 99(1):350–84.

Browning, M. and Crossley, T. F. (2000). Luxuries Are Easier to Postpone: A Proof. *Journal of Political Economy*, 108(5):1022–1026.

Carriero, A., Clark, T. E., Marcellino, M., and Mertens, E. (2022). Addressing COVID-19 Outliers in BVARs with Stochastic Volatility. *The Review of Economics and Statistics*, pages 1–38.

Chan, J. C. (2020). Large bayesian vars: A flexible kronecker error covariance structure. *Journal of Business & Economic Statistics*, 38(1):68–79.

Chernis, T. and Luu, C. (2018). Disaggregating household sensitivity to monetary policy by expenditure category. Technical report, Bank of Canada.

Ciccarelli, M., Maddaloni, A., and Peydró, J.-L. (2015). Trusting the bankers: A new look at the credit channel of monetary policy. *Review of Economic Dynamics*, 18(4):979–1002.

Ciccarelli, M., Maddaloni, A., and Peydró, J.-L. (2014). Heterogeneous transmission mechanism: monetary policy and financial fragility in the eurozone. *Economic Policy*, 28(75):459–512.

Corsetti, G., Duarte, J. B., and Mann, S. (2021). One Money, Many Markets. *Journal of the European Economic Association*, 20(1):513–548.

Cravino, J., Lan, T., and Levchenko, A. A. (2020). Price stickiness along the income distribution and the effects of monetary policy. *Journal of Monetary Economics*, 110:19–32.

Dedola, L., Henkel, L., Höynck, C., Osbat, C., and Santoro, S. (2024). What does new micro price evidence tell us about inflation dynamics and monetary policy transmission? *Economic Bulletin Articles*, 3.

Dedola, L. and Lippi, F. (2005). The monetary transmission mechanism: evidence from the industries of five oecd countries. *European Economic Review*, 49(6):1543–1569.

Ehrmann, M., Smets, F., and Altissimo, F. (2006). Inflation persistence and price-setting behaviour in the euro area: a summary of the IPN evidence. Occasional Paper Series 46, European Central Bank.

Fagandini, B., Goncalves, E., Rubene, I., Kouvavas, O., Bodnar, K., and Koester, G. (2024). Decomposing HICPX inflation into energy-sensitive and wage-sensitive items. *European Central Bank Economic Bulletin Issue 3, Box 6*.

Gautier, E., Conflitti, C., Faber, R. P., Fabo, B., Fadejeva, L., Jouvanceau, V., Menz, J.-O., Messner, T., Petroulas, P., Roldan-Blanco, P., Rumler, F., Santoro, S., WIeland, E., and Zimmer, H. (2024). New facts on consumer price rigidity in the euro area. *American Economic Journal: Macroeconomics*, Forthcoming.

Grigoli, F. and Sandri, D. (2023). Monetary policy and credit card spending. BIS Working Papers 1064, Bank for International Settlements.

Ho, P., Lubik, T. A., and Matthes, C. (2024). Averaging impulse responses using prediction pools. *Journal of Monetary Economics*, page 103571.

Hong, G. H., Klepacz, M., Pasten, E., and Schoenle, R. (2023). The real effects of monetary shocks: Evidence from micro pricing moments. *Journal of Monetary Economics*, 139:1–20.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Jordà, Ò. (2023). Local projections for applied economics. *Annual Review of Economics*, 15:607–631.

Kadiyala, K. R. and Karlsson, S. (1997). Numerical methods for estimation and inference in bayesian var-models. *Journal of Applied Econometrics*, 12(2):99–132.

Mankiw, N. G. (1985). Consumer Durables and the Real Interest Rate. *The Review of Economics and Statistics*, 67(3):353–362.

Noh, E. (2024). Revisiting the effects of conventional and unconventional monetary policies. *Journal of Applied Econometrics*.

Orchard, J. (2022). Cyclical Demand Shifts and Cost of Living Inequality. *manuscript*.

Parker, J. A. (1999). The Reaction of Household Consumption to Predictable Changes in Social Security Taxes. *American Economic Review*, 89(4):959–973.

Paul, P. (2020). The time-varying effect of monetary policy on asset prices. *Review of Economics and Statistics*, 102(4):690–704.

Peersman, G. and Smets, F. (2005). The industry effects of monetary policy in the euro area. *The Economic Journal*, 115(503):319–342.

Plagborg-Møller, M. and Wolf, C. K. (2021). Local projections and vars estimate the same impulse responses. *Econometrica*, 89(2):955–980.

Plagborg-Møller, M. and Wolf, C. K. (2022). Instrumental variable identification of dynamic variance decompositions. *Journal of Political Economy*, 130(8):2164–2202.

Ramey, V. A. (2011). Identifying government spending shocks: It's all in the timing. *The Quarterly Journal of Economics*, 12(1):1–50.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. *Handbook of macroeconomics*, 2:71–162.

Rostagno, M., Altavilla, C., Carboni, G., Lemke, W., Motto, R., Saint Guilhem, A., and Yiangou, J. (2019). A tale of two decades: the ECB's monetary policy at 20. Working Paper Series 2346, European Central Bank.

Slacalek, J., Tristani, O., and Violante, G. L. (2020). Household balance sheet channels of monetary policy: A back of the envelope calculation for the euro area. *Journal of Economic Dynamics and Control*, 115:103879.

Stock, J. H. and Watson, M. W. (2016). Core inflation and trend inflation. *Review of Economics and Statistics*, 98(4):770–784.

Tobin, J. (1983). Monetary Policy: Rules, Targets, and Shocks. *Journal of Money, Credit and Banking*, 15(4):506–518.

Wright, J. H. (2024). Comment on “the long and variable lags of monetary policy: Evidence from disaggregated price indices” by s. borağan aruoba and thomas drechsel. *Journal of Monetary Economics*, page 103653.

Zlobins, A. (2024). Monetary policy transmission in the euro area: is this time different? chapter i: lags and strength. *Mimeo*.

A Data description

Table 6: Data description

Variable	Description	Source	Trans.
HICP headline	Total HICP	Eurostat	Log
HICP core	HICP excluding energy and food	Eurostat	Log
IP	Industrial production, total excluding construction	Eurostat	Log
UR	Unemployment rate, total, age 15-74	European Labour Force Survey	None
Euribor 3M	Euribor 3 months maturity, historical close, average of observations through period	Refinitiv	None
German Bund 1Y	Yields on Outstanding Debt Securities	Haver	None
BBB spread	ICE BofA ML Euro area High Yield Bond Index	ICE & Haver	None
EUROSTOXX	EURO STOXX 50 Equity Index, historical close, average of observations through period	DataStream	Log
NEER	Nominal effective exch. rate of the Euro against extended EER group of trading partners	ECB	None
Oil Brent	Brent spot, historical close, US dollar	Refinitiv	Log
PPI	Producer Price Index, domestic sales, Total Industry (excluding construction)	Eurostat	Log
PMI supplier delivery	Purchasing Managers' Index, manuf., supplier delivery times	S&P Global	None
GSCPI	Global Supply Chain Pressure Index	NY Fed	None
Neg. wages	Negotiated wages excluding one-off payments (year-on-year)	ECB	None

Note: HICPs, PPI, IP, and UR were retrieved from Eurostat/Labour Force Survey in their seasonally adjusted version.

Table 7: COICOP-4 Items

Bread and cereals	Hospital services
Meat	Motor cars
Fish	Motor cycles, bicycles and animal drawn vehicles
Milk, cheese and eggs	Spare parts and accessories for personal transport equipment
Oils and fats	Fuels and lubricants for personal transport equipment
Fruit	Maintenance and repair of personal transport equipment
Vegetables	Other services in respect of personal transport equipment
Sugar, jam, honey, chocolate and confectionery	Passenger transport by railway
Food products n.e.c.	Passenger transport by road
Coffee, tea and cocoa	Passenger transport by air
Mineral waters, soft drinks, fruit and vegetable juices	Passenger transport by sea and inland waterway
Spirits	Combined passenger transport
Wine	Other purchased transport services
Beer	Postal services
Tobacco	Telephone and telefax equipment and tel. and telefax services
Clothing materials	Equip. for reception, recording and reprod. of sound and pictures
Garments	Photographic and cinematographic equip. and optical instruments
Other articles of clothing and clothing accessories	Information processing equipment
Cleaning, repair and hire of clothing	Recording media
Footwear	Repair of audio-visual, photographic, info. processing equip.
Actual rentals for housing	Major durables for in/outdoor recreation incl. musical instr.
Materials for the maintenance and repair of the dwelling	Mainten. and repair of other major durab. for recreat. and culture
Services for the maintenance and repair of the dwelling	Games, toys and hobbies
Water supply	Equipment for sport, camping and open-air recreation
Refuse collection	Gardens, plants and flowers
Sewerage collection	Pets and related prod. incl. veterinary and other serv. for pets
Other services relating to the dwelling n.e.c.	Recreational and sporting services
Electricity	Cultural services
Gas	Books
Liquid fuels	Newspapers and periodicals
Solid fuels	Misc. printed matter and stationery and drawing materials
Heat energy	Package holidays
Furniture and furnishings	EDUCATION
Carpets and other floor coverings	Restaurants, cafes and the like
Repair of furniture, furnishings and floor coverings	Canteens
Household textiles	Accommodation services
Major household appliances, small electric hous. appl.	Hairdressing salons and personal grooming establishments
Repair of household appliances	Electric appliances and other appliances etc. for pers. Care
Glassware, tableware and household utensils	Jewellery, clocks and watches
Tools and equipment for house and garden	Other personal effects
Non-durable household goods	Social protection
Domestic services and household services	Insurance connected with the dwelling
Pharmaceutical products	Insurance connected with health
Other medical products, therapeutic appliances and equipment	Insurance connected with transport
Medical and paramedical services	Other insurance
Dental services	Financial services n.e.c.
	Other services n.e.c.

Note: all variables are seasonally adjusted and transformed to log levels.

B Classifying items by monetary policy sensitivity

Table 8: Consumption items and monetary policy sensitivity

Highly sensitive	**Moderately sensitive**	**Not sensitive**
Clothing materials	Cleaning, repair and hire of clothing	Other articles of clothing and clothing accessories
Materials for the maintenance and repair of the dwelling	Services for the maintenance and repair of the dwelling	Actual rentals for housing
Sewerage collection	Water supply	Refuse collection
Non-durable household goods	Repair of furniture, furnishings and floor covering	Other services relating to the dwelling n.e.c.
Motor cars	Repair of household appliances	Furniture and furnishing
Passenger transport by air	Glassware, tableware and household utensils	Books
Passenger transport by sea and inland waterway	Other services in respect of personal transport equipment	Household textiles
Combined passenger transport	Passenger transport by railway	Major household appliances, small electric hous. appl.
Information processing equipment	Passenger transport by road	Tools and equipment for house and garden
Recording media	Games, toys, and hobbies	Domestic services and household services
Mainten. and repair of other major durab. for recreat. and culture	Gardens, plants and flowers	Carpets and other floor coverings
Pets and related prod. incl.veterinary and other serv. for pets	Recreational and sporting services	Other purchased transport services
Package holidays	Cultural services	Repair of audio-visual, photographic, info. processing equip.
Canteens	Newspapers and periodicals	Education
Accommodation services	Misc. printed matter and stationery and drawing materials	Insurance connected with transport
Electric appliances and other appliances etc. for pers. Care	Insurance connected with the dwelling	Pharmaceutical products
Jewellery, clocks and watches		Other medical products, therapeutic appliances and equipment
		Medical and paramedical services
		Dental services
		Hospital services
		Motor cycles, bicycles and animal drawn vehicles
		Spare parts and accessories for personal transport equipment
		Maintenance and repair of personal transport equipment
		Garments
		Postal services
		Telephone and telefax equipment and tel. and telefax services
		Equip. for reception, recording and reprod. of sound and pictures
		Photographic and cinematographic equip. and optical instruments
		Footwear
		Major durables for in/outdoor recreation incl. musical instr.
		Restaurants, cafes and the like
		Equipment for sport, camping and open-air recreation
		Other personal effects
		Insurance connected with health
		Other insurance
		Hairdressing salons and personal grooming establishments
		Social protection
		Financial services n.e.c.
		Other services n.e.c.

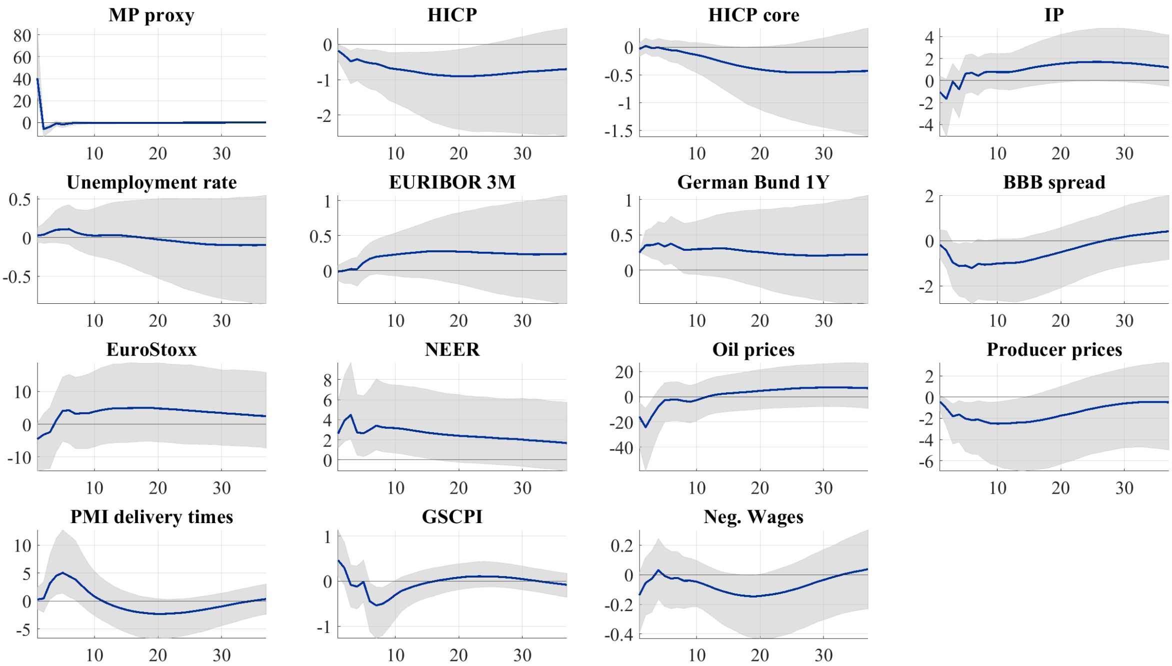
Note: The table shows classification of euro area COICOP-4 HICPX items into sensitive and non-sensitive to monetary policy shocks, based on the item-by-item estimation of equation (5).

Figure 7: Items sensitive to monetary policy shocks across time

Note: The heatmap shows the items classified as sensitive to monetary policy based on the item-by-item estimation of equation (9). A black (white) cell represents that the item is (not) selected for the sample ending in the time period shown in the x-axis.

C Additional Tables and Figures

Figure 8: Impulse responses of full set of variables to a monetary policy shock.



Notes: The figure shows the median of the posterior distribution of impulse responses to a monetary policy shock (blue lines) normalised to a 25 basis points increase in the German Bund 1Y. The shaded areas correspond to the 68% credibility bands.

Table 9: Difference in the share of consumption baskets spent on COICOP-3 items by their monetary policy sensitivity: Low-skilled workers versus unemployed (%).

	2010		2015		2020	
	Non-sens.	Sensitive	Non-sens.	Sensitive	Non-sens.	Sensitive
EA	-6.5	22.9				
BE	-13.3	25.6	-11.7	77.8	-17.8	28.2
DE	-18.3	55.0	-19.3	54.6	-17.9	47.5
ES	4.9	18.0	12.5	24.6	6.4	35.1
FR	1.2	2.4	-3.0	10.8	-3.0	10.8
IT			14.5	31.2	5.8	24.5
No. items	21	13	21	13	21	13

Notes: The table shows the percentage differences in the share of consumption baskets spent on items sensitive and nonsensitive to monetary policy shocks by manual workers compared to unemployed respondents, based on HBS.

Table 10: Difference in the share of consumption baskets spent on COICOP-3 items by their monetary policy sensitivity: High-skilled versus low-skilled workers(%).

	2010		2015		2020	
	Non-sens.	Sensitive	Non-sens.	Sensitive	Non-sens.	Sensitive
EA	3.9	12.7				
BE	2.6	10.9	5.9	-2.2	-2.2	2.7
DE	13.6	6.9	8.1	11.3	10.2	6.9
ES	-2.2	28.2	1.8	21.0	2.0	16.2
FR	-3.7	10.7	-5.5	15.0	-5.5	15.0
IT			-5.1	21.3	-3.1	22.6
No. items	21	13	21	13	21	13

Notes: The table shows percentage differences in the share of consumption baskets spent on items sensitive and nonsensitive to monetary policy shocks by non-manual workers compared to manual workers, based on HBS.

Table 11: Average difference in expenditure share between high-income and low-income households by monetary policy sensitivity of COICOP-3 items (%).

	2010		2015		2020	
	Non-sens.	Sensitive	Non-sens.	Sensitive	Non-sens.	Sensitive
EA	37.3	67.8				
BE	36.3	69.4	37.8	89.6*	61.1	114.0
DE	69.2	93.2	75.2	81.9	48.8	69.7
ES	32.2	92.6*	26.9	89.2**	33.6	86.3*
FR	21.3	48.1	36.5	63.0	36.5	63.0
NL	28.8	38.8	99.6	64.0	95.9	65.1
No. items	18-21	12-13	16-21	12-13	19-21	12-13

Notes: The table shows the average percentage differences in the share of consumption baskets across items sensitive and non-sensitive to monetary policy shocks between households in the 5th quintile of income distribution versus 1st income quintile households, based on HBS. For the sensitive items, the Table also reports significance level for the t-test for equality of means (H0: sample means are qual) compared to the non-sensitive category ($^{***} - p < 0.01$, $^{**} - p < 0.05$ and $^{*} - p < 0.1$). The number of items varies across countries and years depending on survey data.

Table 12: Average difference in expenditure share between low-skilled workers and unemployed workers by monetary policy sensitivity of COICOP-3 items (%).

	2010		2015		2020	
	Non-sens.	Sensitive	Non-sens.	Sensitive	Non-sens.	Sensitive
EA	12.6	22.5				
BE	2.3	31.9*	28.1	98.7*	30.6	36.3
DE	26.5	79.5	24.8	74.4*	30.0	47.5
ES	11.5	17.8	11.7	26.0*	12.5	38.1*
FR	29.4	-5.5	6.8	13.9	6.8	13.9
IT			36.9	277.6*	6.1	28.1*
No. items	17-21	12-13	17-20	12-13	17-21	12-13

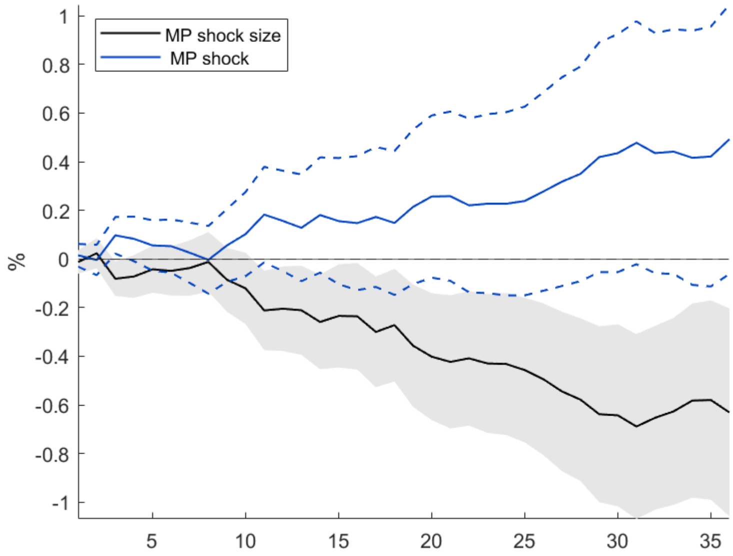
Notes: The table shows the average percentage differences in the share of consumption baskets across items sensitive and non-sensitive to monetary policy shocks between manual workers and unemployed respondents, based on HBS. For sensitive items, the Table also reports significance level for the t-test for equality of means (H0: sample means are qual) compared to the non-sensitive category ($^{***} - p < 0.01$, $^{**} - p < 0.05$ and $^{*} - p < 0.1$). The number of items varies across countries and years depending on survey data.

Table 13: Average difference in expenditure share between high-skilled and low-skilled workers by monetary policy sensitivity of COICOP-3 items (%).

	2010		2015		2020	
	Non-sens.	Sensitive	Non-sens.	Sensitive	Non-sens.	Sensitive
EA	14.8	22.4				
BE	11.4	20.5	11.1	18.2	25.8	34.6
DE	20.4	22.0	22.3	17.0	21.8	22.3
ES	23.0	38.0	9.0	28.8*	6.6	23.8
FR	2.0	27.8**	2.5	25.5**	2.5	25.5**
IT			9.8	30.6*	11.6	34.1*
No. items	19-21	12-13	17-21	12-13	19-21	12-13

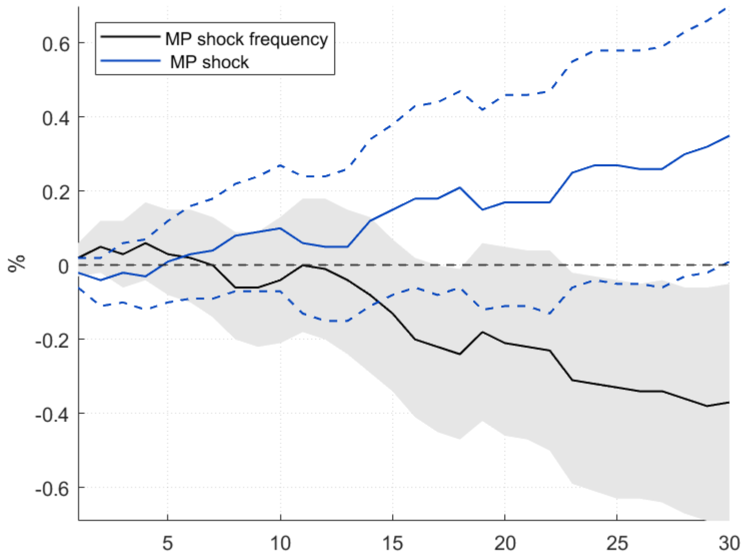
Notes: The table shows the average percentage differences in the share of consumption baskets across items sensitive and non-sensitive to monetary policy shocks between non-manual workers and manual workers, based on HBS. See notes to Table 10 for more details. For -sensitive items, the Table also reports significance level for the t-test for equality of means (H0: sample means are qual) compared to the non-sensitive category ($^{***} - p < 0.01$, $^{**} - p < 0.05$ and $^{*} - p < 0.1$). The number of items varies across countries and years depending on survey data.

Figure 9: Impulse responses of COICOP-4 HICPX prices to a monetary policy shock.



Notes: The figure shows impulse responses to a monetary policy shock (blue lines) and the coefficient on the interaction term of monetary policy shock with the size of price changes from equation (8) (black lines), estimated on a sample ending in December 2019. Grey areas and dashed blue lines correspond to 90% confidence bands.

Figure 10: Impulse responses of COICOP-4 HICP prices to a monetary policy shock.



Notes: The figure shows impulse responses to a monetary policy shock (blue lines) and the coefficient on the interaction term of monetary policy shock with the frequency of price changes from equation (8) (black lines), estimated on a sample of 66 HICP COICOP-4 items, ending in December 2019. Grey areas and dashed blue lines correspond to 90% confidence bands.

D SLP evidence

In this section we present evidence based on a complementary univariate framework of Smooth Local Projections (SLP).

We pin down HICPX items sensitive to monetary policy through local projections as in Jordà (2005) and Jordà (2023). In this case, the equations take the following form:

$$y_{i,t+h} - y_{i,t} = \alpha_{0,i}^{(h)} + \beta_i^{(h)} MP_t + \sum_{j=1}^{M} \gamma_{i,j}^{h} X_{i,t-j} + u_{t+h}, \tag{9}$$

where $y_{i,t+h}$ is the log-price of the i-th HICPX item at time $t+h$, h is the forecasting horizon; MP_t is a measure of monetary policy shocks; and $X_{i,t-j}$ is a vector of controls. Our dependent variable is the inflation rate between periods t and $t+h$. The key parameter of interest is $\beta_i^{(h)}$, which corresponds to the response of inflation of the i-th core HICP item to monetary policy shocks. When $\beta_i^{(h)} < 0$, a positive, contractionary monetary policy shock has a negative impact on the change in price of item i between t and $t+h$.

Given the well-known problem of the erratic variability of traditional least squares estimates of local projections (LP), we estimate equation (9) following the smooth local projection (SLP) algorithm of Barnichon and Brownlees (2019). Specifically, this methodology estimates impulse responses based on a penalised combination of B-splines and the selected impulse responses are the results from shrinking the estimator towards a polynomial. Impulse responses based on SLP are easier to interpret and have a more regular shape relative to those stemming from vector autoregressions.[21]

Barnichon and Brownlees (2019) propose to adopt generalised ridge estimation techniques in order to estimate SLP. This methodology critically depends on a shrinkage parameter (denoted by λ in the original paper) which determines the bias-variance trade-off. We follow the recommendation provided in the original paper and select the degree of shrinkage using k-fold cross validation. Furthermore, to alleviate serial autocorrelation of the residuals in equation (9) - a known issue in local projections - the framework by Barnichon and Brownlees (2019) allows the estimation of the variance of the parameters following a modified Newey-West estimator corrected for the penalty parameter.[22]

The aggregated impulse responses constructed based on the SLP framework are shown in Figure 11. For comparison purposes, the choice of controls and lags, as well as the classification criteria, are identical to the baseline BVAR model. To reflect the uncertainty around the weighted impulse responses, shaded areas capture the 30% and 70% percentiles across the consumption items within each category. As such, communication of uncertainty surrounding the aggregated impulse responses in this specific context should be interpreted with caution. Nonetheless, the overall profile of highly and moderately-sensitive categories confirms the substantial heterogeneity across categories previously documented using the BVAR model, with monetary policy shocks having approximately three times larger impact on highly-sensitive items relative to moderately-sensitive ones.

Turning to the items classified as sensitive, Table 14 presents an overview of all consumption items picked-up by the SLP algorithm, and their corresponding overall time profile. Despite some differences in the selection of items, most items that have been classified as sensitive based on the SLP classification overlap with items also identified as sensitive using the baseline Bayesian multivariate framework (underlined items in Table 14).[23] For example, out of the 12 highly-sensitive items, 9 have also been classified as

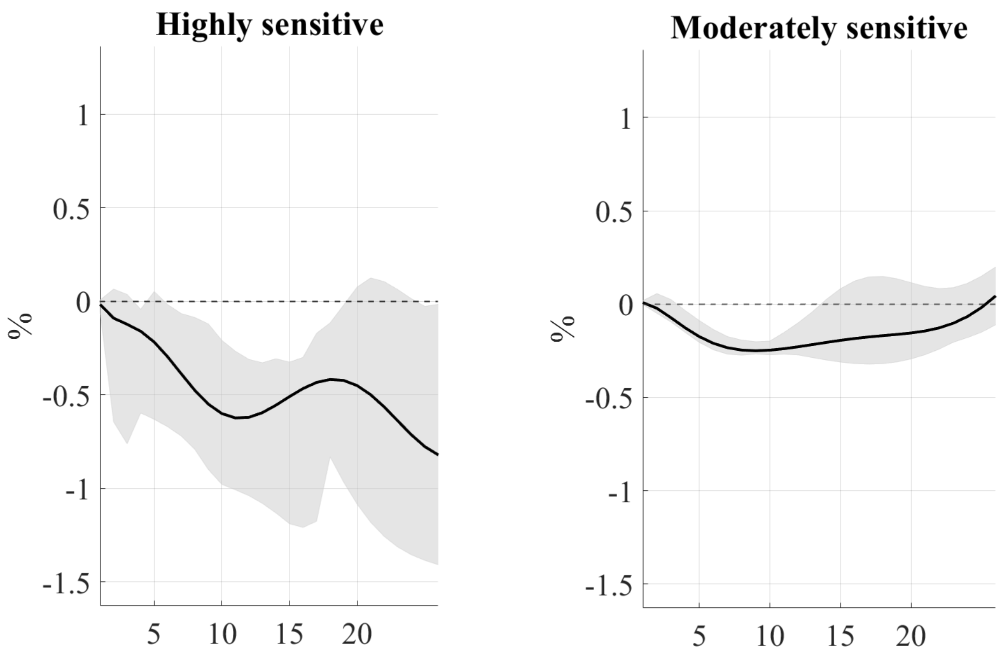
[21] Some caveats associated with the SLP methodology include the construction of confidence bands, especially when the exercise involves small-sample concerns. Although the proposed procedure requires some ad-hoc choices, Barnichon and Brownlees (2019) show in the context of a simulation exercise that the LP and SLP confidence interval procedures exhibit similar performance.

[22] As highlighted by Jordà (2005), the forecast error in the local projections regression is a moving average of forecast errors of past horizons.

[23] Differences across econometric methods are to be expected, with prior literature showing that results on the effects of monetary policy on the price level crucially depend on the identification methodology and

sensitive (either highly-, or moderately-sensitive) in the context of the baseline BVAR: These items include, for example, durable goods and services related to transport.

Figure 11: Monetary policy pass-through in highly vs moderately sensitive items: SLP model



Note: The figure shows the responses of the highly and moderately sensitive items to monetary policy shocks. The black lines represent the weighted average based on their weights on the core HICP basket and the shaded areas are the 30% and 70% percentiles across the core items in each category.

choice of controls. Most recently. Plagborg-Møller and Wolf (2021) and Wright (2024) discuss relevant concerns and empirical applications.

Table 14: Items sensitive to monetary policy: Smooth Local projection

Highly sensitive	**Moderately sensitive**
1. <u>Clothing material</u>	1. Other services relating to the dwelling n.e.c.
2. Medical and paramedical services	2. <u>Motor cars</u>
3. Dental services	3. <u>Electric appliances and other appliances etc. for personal care</u>
4. <u>Passenger transport by road</u>	4. Other personal effects
5. <u>Combined passenger transport</u>	5. Insurance connected with health
6. <u>Information processing equipment</u>	
7. <u>Recording media</u>	
8. <u>Mainten. and repair of other major durables for recreation and cutlure</u>	
9. <u>Misc. printed matter and stationery and drawing materials</u>	
10. <u>Canteens</u>	
11. <u>Jewellery, clocks and watches</u>	
12. Insurance connected with transport	

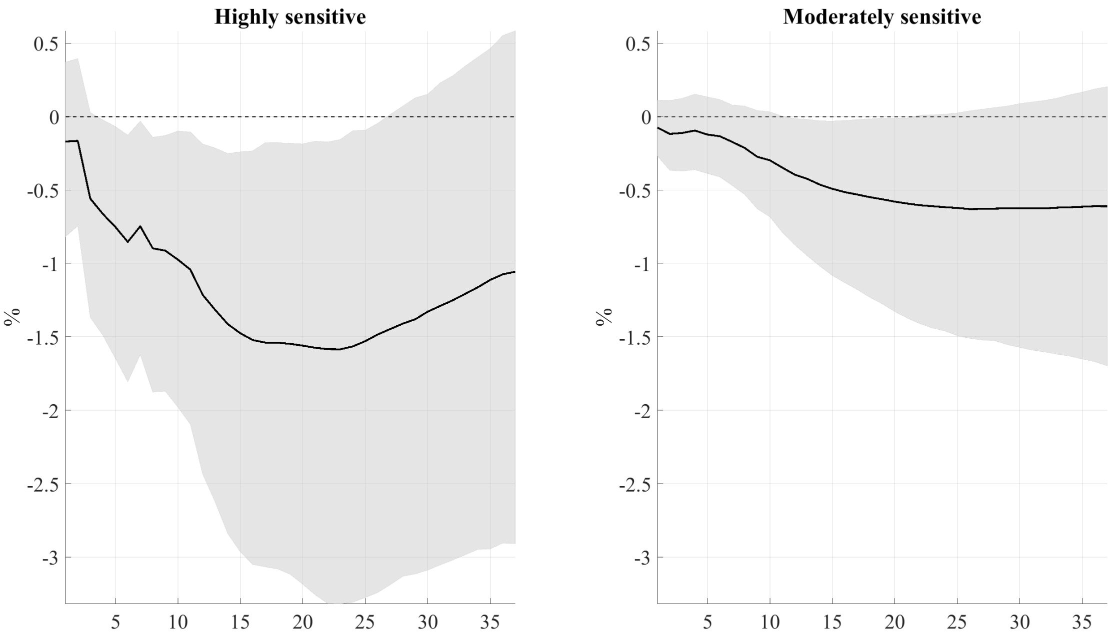
Note: Underlined items are items that are selected as sensitive (either highly- or moderately-sensitive) using both the baseline Bayesian VAR and the SLP specification.

E BVAR robustness checks

This section evaluates the robustness of the main findings obtained from the BVAR model related to the inclusion of additional lags (Figure 12 and Table 15), and to controlling for a restricted information set that excludes information from labour markets, and short-term interest rates (Figure 13 and Table 16).

Our additional checks confirm the robustness of our results originated from the BVAR. The overall response of highly- and moderately- sensitive items is preserved. The selection of items slightly differs across specifications, but the vast majority of items is consistently being selected, further corroborating the robustness of our empirical framework.

Figure 12: Monetary policy pass-through in highly vs moderately sensitive items: BVAR model with 12 lags



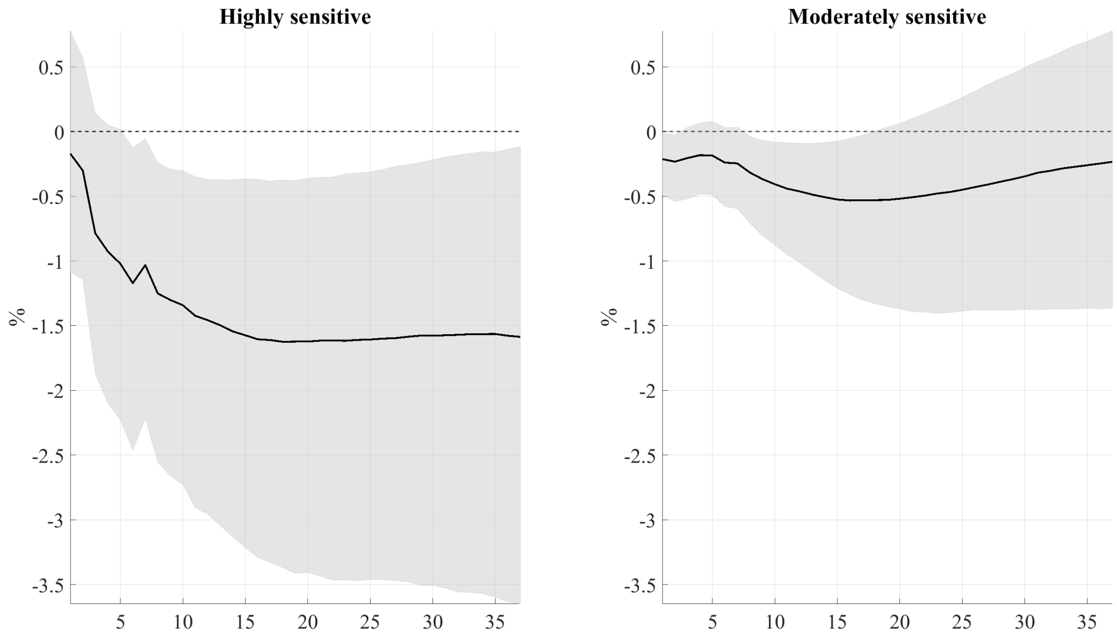
Note: The figure shows the responses of the highly and moderately sensitive items to monetary policy shocks. The black lines represent the weighted average based on their weights on the core HICP basket and the shaded areas are 68% credibility bands of the IRFs.

Table 15: Items sensitive to monetary policy: BVAR model with 12 lags

Highly sensitive	**Moderately sensitive**
1. Materials for the maintenance and repair of the dwelling	1. Cleaning, repair and hire of clothing
2. Services for the maintenance and repair of the dwelling	2. Sewerage collection
3. Repair of furniture, furnishings and floor coverings	3. Repair of household appliances
4. Motor cars	4. Maintenance and repair of personal transport equipment
5. Passenger transport by air	5. Other services in respect of personal transport equipment
6. Combined passenger transport	6. Passenger transport by railway
7. Recording media	7. Passenger transport by road
8. Mainten. and repair of other major durables for recreation and culture	8. Recreational and sporting services
9. Games, toys and hobbies	9. Newspapers and periodicals
10. Pets and related prod. incl. veterinary and other services for pets	10. Misc. printed matter and stationery and drawing material
11. Package holidays	11.Canteens
12. Accommodation services	12. Other personal effects
13. Electric appliances and other appliances etc.	13. Other services n.e.c.
14. Jewellery, clocks and watches	

Note: Underlined items are items that are selected as sensitive (either highly- or moderately-sensitive) using both the baseline Bayesian VAR and the one based on longer lags.

Figure 13: Monetary policy pass-through in highly vs moderately sensitive items: BVAR model with alternative control set



Note: The figure shows the responses of the highly and moderately sensitive items to monetary policy shocks. The black lines represent the weighted average based on their weights on the core HICP basket and the shaded areas are 68% credibility bands of the IRFs.

Table 16: Items sensitive to monetary policy: BVAR model with alternative control set

Highly sensitive	**Moderately sensitive**
1. Clothing materials	1. Repair of household appliances
2. Motor cars	2. Games, toys and hobbies
3. Passenger transport by air	3. Pets. and related products transport equipment
4. Passenger transport by sea and inland waterway	4. Newspapers and periodicals
5. Combined passenger transport	5 Insurance connected with the dwelling
6. Recording media	
7. Maintenance and repair of other major durables for recreation and culture	
8. Package holidays	
9. Jewellery, clocks and watches	

Note: Underlined items are items that are selected as sensitive (either highly- or moderately-sensitive) using both the baseline Bayesian VAR and the one using an alternative control set.

Acknowledgements
We are grateful to Bruno Fagandini for excellent research assistance. We would like to thank Carlo Altavilla, Fernando Álvarez, Christiane Baumeister, Florin Bilbiie, Elena Bobeica, Miguel Boucinha, Andrea De Polis, Jordi Galí, Erwan Gautier, Mishel Ghassibe, Refet Gürkaynak, Andrew Hannon, Gee Hee Hong, Marek Jarociński, Bartosz Maćkowiak, Carlos Montes-Galdón, Philip Lane, Evi Pappa, Theódore Renault, Ieva Rubene, Raphael Schoenle, Frank Smets, Silvana Tenreyro, and the participants at the IMF and CREI seminars, ESCB ChaMP Workstream 2 workshop, Barcelona GSE Summer Forum 2024, IAAE 2024 Greece Meeting, GRAPE Summer Workshop on Macro & Finance 2024, CEBRA annual meeting 2024, Bank of Finland and CEPR Joint Conference on Back to Basics and Beyond: New Insights for Monetary Policy Normalisation, CEPR Annual Monetary Economics and Fluctuations Symposium 2024, ECB-Cleveland Fed's Inflation: Drivers and Dynamics Conference 2024 for useful discussions and suggestions.

Anastasia Allayioti
European Central Bank, Frankfurt am Main, Germany; email: anastasia.allayioti@ecb.europa.eu

Lucyna Górnicka
European Central Bank, Frankfurt am Main, Germany; email: lucyna_anna.gornicka@ecb.europa.eu

Sarah Holton
European Central Bank, Frankfurt am Main, Germany; email: sarah.holton@ecb.europa.eu

Catalina Martínez Hernández
European Central Bank, Frankfurt am Main, Germany; email: catalina.martinez_hernandez@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-6893-5 ISSN 1725-2806 doi:10.2866/9983000 QB-01-24-020-EN-N