Cast out the pure? Inflation and relative prices on both sides of the Atlantic*

Emanuele Franceschi Chiara Osbat Miles Parker

March 20, 2025
PRELIMINARY AND INCOMPLETE: DO NOT CIRCULATE

Abstract

What drives inflation – domestic monetary policy or relative price shocks? After decades of low inflation in advanced economies, large relative price shocks – notably those related to energy prices – seem to have accounted for the bulk of inflation movements. We illustrate how even aggregate shocks can generate persistent relative price changes in the presence of heterogeneity in price flexibility. We then estimate the role of "pure" inflation versus relative prices, using a flexible Bayesian dynamic factor model on disaggregated, comparable price data for the euro area and the United States. We find that relative prices substantially explain the movements of inflation over the past 20 years, with an even more sizeable role since 2021. We also document the different responses of pure inflation and relative prices to various aggregate and sectoral shocks in both monetary areas, showing - as expected - that most shocks will affect inflation via relative prices in periods when inflation expectations are broadly anchored. Pure inflation was not a material cause of recent inflation dynamics, but it did show an unusual movement, albeit short-lived. Arguments to the extent that central banks should not be concerned with purely relative price changes should, we contend, be cast out.

JEL classification: E31, E52, E58
Keywords: Inflation, relative prices, monetary policy, commodity prices, supply shocks

*Emanuele Franceschi (European Central Bank): emanuele.franceschi@ecb.europa.eu, Chiara Osbat (European Central Bank): chiara.osbat@ecb.europa.eu, Miles Parker (European Central Bank): miles.parker@ecb.europa.eu.
We wish to thank Mishel Ghassibe, Marek Jarociński, Danilo Leiva-Leon, Michele Lenza, Catalina Martinez Hernandez, Giorgio Primiceri, Timo Reinelt, ECB internal seminars' audiences, and participants to the 14th RCEA ICEE, AFSE 2024, EEA 2024 for useful discussion and feedback on early versions. Alberto Lentini provided excellent research assistance. All errors remain solely the authors' own.

The views expressed are solely the authors' own and do not necessarily represent those of the European Central Bank nor its Governing Council.

1 Introduction

"We may regard price changes, therefore, as partly due to causes arising from the commodities themselves raising some, lowering others, and all different in degree, and, superimposed upon the changes due to these heterogeneous causes, a further change affecting all in the same ratio arising out of change on the side of money. This uniform ratio is the object of our investigations." (from The Collected Writing of John Maynard Keynes, volume XI, p. 106).

What is inflation? One definition, as laid out by Keynes above, is that inflation is a generalised increase in all prices, arising from changes in money. As Friedman, 1963 put it, "*Inflation is always and everywhere a monetary phenomenon.*" Yet since the adoption of inflation targeting starting with the Reserve Bank of New Zealand in 1990 and then more and more widely adopted throughout the world, central banks now commonly define their targets in terms of the annual change in the consumer price index. While this annual change does reflect price developments that are purely down to money, it also is driven by sharp divergences in relative prices that the former definition of inflation excludes. Yet the range of inflation rates across different consumption categories can be rather large, both when inflation is high and when it is low (see Figure 1). There can be two sources of variation in inflation rates across categories: sectoral shocks and different speed of adjustment to common shocks. Figure 2 shows that the price rigidity of different consumption categories is very heterogeneous, indicating that not only sectoral, but also common shocks will generate relative price changes, albeit temporary.

For inflation-targeting central banks, disentangling the pure inflation and relative prices components and their drivers is central to policy decisions. Our paper addresses this problem in a way that provides policymakers with an empirical tool to assess the respective contributions of each component to inflation without making assumptions on the exact sources of current shocks.

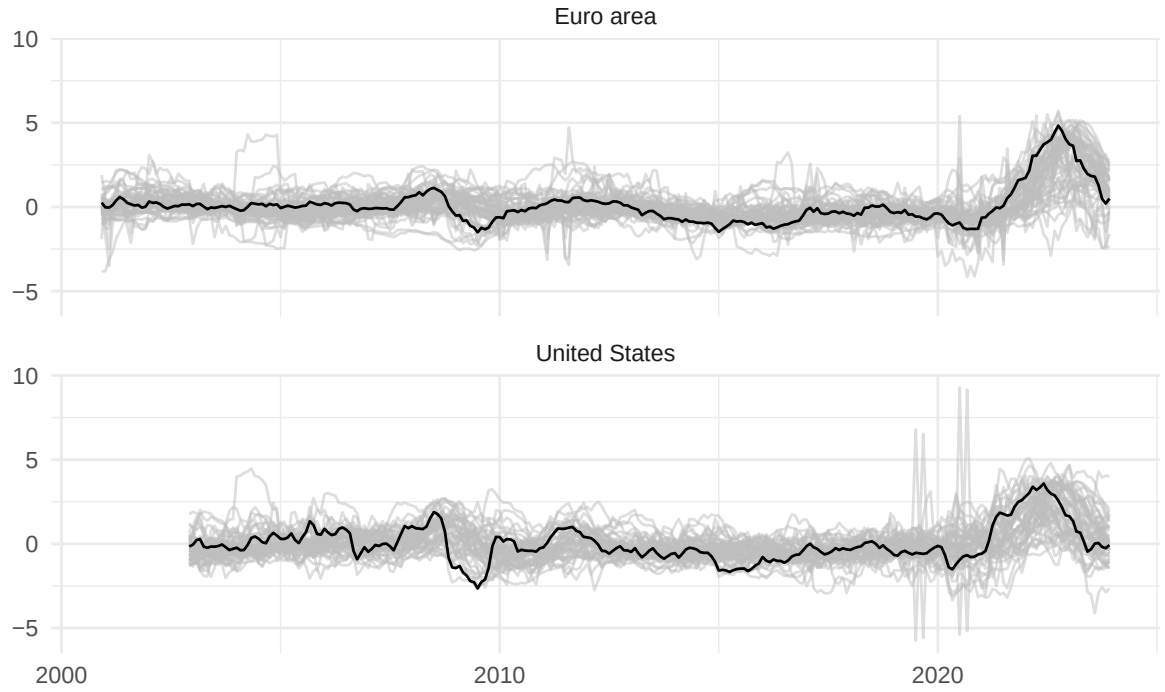
We use a model with both aggregate and sectoral shocks for a stylised illustration of the impact of aggregate and sectoral shocks on pure inflation and relative price changes. We then estimate the contributions of "pure inflation" and "relative prices" to headline inflation in the euro area and in the United States: Following Reis and Watson, 2010, we define "pure inflation" as the unobserved component that moves all prices in the same direction and by the same amount at the same time; relative prices inflation captures changes due to relative paths of prices. We adapt their econometric approach to take heterogeneous price rigidity into account.

Armed with this approach, we also contribute to the debate on the role of aggregate and sectoral shocks to the sharp spike in inflation at the start of the 2020s: was it driven by large relative price shocks due to supply disruptions, re-opening effects and soaring energy prices, or did pure inflation also rise, driven by monetary (and fiscal) policies, which had been extraordinarily accommodative in the year prior to the inflation surge?

We begin by using a modified version of the model in Ghassibe, 2021 to demonstrate how underlying shocks pass through input-output linkages to consumer prices. Even aggregate shocks that may ultimately affect all prices (including permanent money shocks), can affect relative prices for a number of periods as supply-chain linkages and sticky prices delay some price changes.

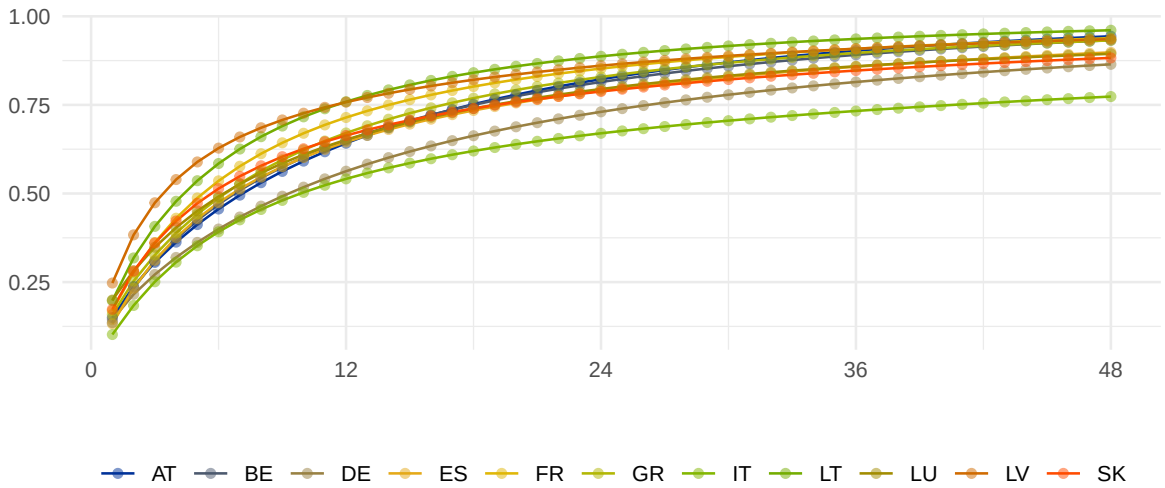
To add empirical bite to these findings, we modify the dynamic factor model proposed by Reis and Watson, 2010 in two ways, to take into account that different product categories respond at different speeds to aggregate shocks that would move pure inflation. First, we apply the model to year-on-year inflation rather than end-quarter-on-end-quarter, to acknowledge that the prices

Figure 1: COICOP-level inflation in the euro area and the United States



Note: the grey lines represent individual components of inflation; headline HICP/CPI inflation in solid black.

Figure 2: Weighted Share of Expected Price Changes Over 48 Months



Note: Each line shows what weighted proportion of categories is expected to have fully changed their prices by that month.

of different product categories have different nominal flexibility. This is illustrated in Figure 2, which uses the estimated frequency of consumer price changes for various euro area countries provided by Gautier et al., 2024: less than 50% of prices can be expected to have changed after 3 months in any country, while more than 70% will have changed by 12 months in most countries.[1] Second, we implement the identification restrictions in a Bayesian framework, which allows some "slack" to the restrictions pinning down pure inflation, as they are imposed as non-dogmatic priors on a subset of factor loadings. Based on this updated estimation approach we use comparable consumer price indices at detailed levels of the COICOP classification in the United States and the euro area to estimate the relative contributions of pure inflation and a common relative price factor to headline inflation.

We then analyse the response of the pure and relative inflation components to aggregate and sectoral shocks in the euro area and in the United States, comparing them to analogous shocks in the model. Our empirical results suggest that shifts in relative prices played a very substantial role in determining headline inflation during the low inflation period. During the inflation surge in 2021-2022, while relative price changes drove most of the inflation surge, we have evidence that pure inflation also edged up, especially in the United States.

The recent inflation surge in the euro area, therefore, looks to have arisen overwhelmingly from large shifts in relative prices following the pandemic and Russia's invasion rather than from a common, pure inflation, component. For the United States the very expansive fiscal and monetary policy mix may have contributed also to a temporary increase in pure inflaton.

The rest of the paper is structured as follows. In the rest of this section we give a brief overview of the relevant literature. Section 2 illustrates how not only sectoral, but also aggregate shocks can generate persistent changes in relative prices. Section 3 describes the econometric approach, Section 4 describes our dataset and how we transform the raw data. Sections 5 and 6 discuss our results and Section 7 concludes.

1.1 Related literature

In the paper that inspires our econometric approach, Reis and Watson, 2010 decompose the US PCE deflator into 187 individual categories over the period 1959-2006. They find that a pure measure of inflation – one where each category moves equally and independently from average relative price movements – accounts for just 15% of inflation volatility at business cycle frequency. By contrast, relative price changes account for three quarters of inflation volatility over the cycle.

In the following years the literature on global inflation, following from Ciccarelli and Mojon, 2010 also found an important role for relative prices at differing inflation rates. Ciccarelli and Mojon, 2010 showed that a common, "global", factor accounted for around 70% of the variance of inflation rates of OECD economies. Förster and Tillmann, 2014 found that for the same group of advanced economies, it was the global movements in energy and food prices that accounted for most of the co-movement. Parker, 2018 confirmed the role of energy prices in generating comovement in inflation across advanced economies. Conversely, the role played by global relative price factors diminishes substantially for less developed economies, which typically have less credible monetary policy and higher average inflation rates.

More recently, in the context of the global inflation surge, Borio et al., 2021 reprise the analysis of the relative importance of relative prices in driving inflation, again concentrating on the United States. They show that as aggregate inflation falls to low rates, relative price movements become

[1] To allow for even more prices to change we repeat the estimation on 24-month changes of HICP, with results shown in Figure A5 in Appendix A.

a much more dominant source of inflation variation than the pure component. They also show that monetary policy tends to affect the common component for the most part and that with the advent of low inflation, policy only affects a small number of prices, mainly in cyclical services.

Borio et al., 2023 extend this analysis to more countries and, among other exercises, look at the falling importance of the common component of inflation through time and use this "commonality" to characterise low- vs high-inflation regimes.

Our framework is substantially different, in that we look at two different common components of category-level inflation: one that we can associate with money - or the depreciation of the value of the currency *numéraire* - and one that arises from common relative price changes: either arising from common shocks and heterogeneous price flexibility, or from sectoral shocks that are large and "upstream" enough to affect all prices, albeit to different extents and at different speeds. This requires looking at more than the first principal component of inflation rates across consumption categories, or by high vs low inflation, to characterise inflation regimes: is high inflation driven "only" by a few relative price changes that are common to many categories, or also by monetary inflation, the tide that lifts all boats? Broadly speaking, as monetary policy successfully anchors the general trend at low rates, movements in relative prices become more prominent. Indeed, this is one of the textbook benefits of credible monetary policy — permitting agents to have a clearer view of the extent to which price movements reflect signals of demand and supply rather than changes in the value of the *numéraire*.

Recent studies that characterise inflation regimes in terms of the size of the shocks that hit the economy, with large shocks driving endogenous increases in price flexibility, and draw conclusions on the impact of monetary policy and on its optimality, offer a useful framework in this regard: see Karadi et al., 2024 and in particular Gerard, 2024, which introduce state-dependent pricing in a model with a production network.

These papers relate to the work by Pasten, Schoenle, and Weber, 2020, who highlighted the importance of heterogeneous price rigidity and its interaction with input-output linkages in determining the real effects of monetary policy shocks. Indeed, the strand of literature that looks at the impact of input-output linkages and sectoral heterogeneity in price rigidity has been very prolific in recent years, offering a more realistic framework to interpret the impact of both sectoral, especially supply, as well as monetary policy shocks on inflation. Other notable examples are La'O and Tahbaz-Salehi, 2022, Ferrante, Graves, and Iacoviello, 2023, Luo and Villar, 2023, Afrouzi and Bhattarai, 2023.

2 Insights on pure inflation and relative prices from an illustrative model

To better understand how aggregate and sectoral shocks affect individual prices, it is useful to look at a controlled environment. To this end, we slightly modify the model from Ghassibe (2021), which studies how input-output production networks and heterogeneity in price flexibility affect the transmission of monetary policy shocks.[2] It proposes a New Keynesian, multi-sector model where sectors differ by use of intermediate inputs and price adjustment frequency. The model also allows for a monetary policy rule that targets the quantity of money, rather than a policy rate, which is particularly useful to study how unexpected monetary injections percolate into relative prices or pure inflation. Besides switching to a monetarist policy rule, we further modify the model by adding an aggregate technological shock that impacts all sectors in the same

[2]We are thankful to Mishel Ghassibe for sharing his code.

way. In Ghassibe (2021) monetary policy is the only aggregate shock, while in Reis and Watson (2010) the theoretical model features aggregate productivity shocks, whose effects across sectors are heterogeneous. We work with the model by Ghassibe because introducing the production network aligns with the economic reality of production and allows sectoral shocks to generate common effects on inflation.

We use this modified model to both inform our expectations of how monetary and other shocks affect pure inflation and relative prices and to test our identification procedure. For an exhaustive overview of the model, we refer the reader to Ghassibe (2021).

2.1 Propagation of shocks through uniform and relative price movements

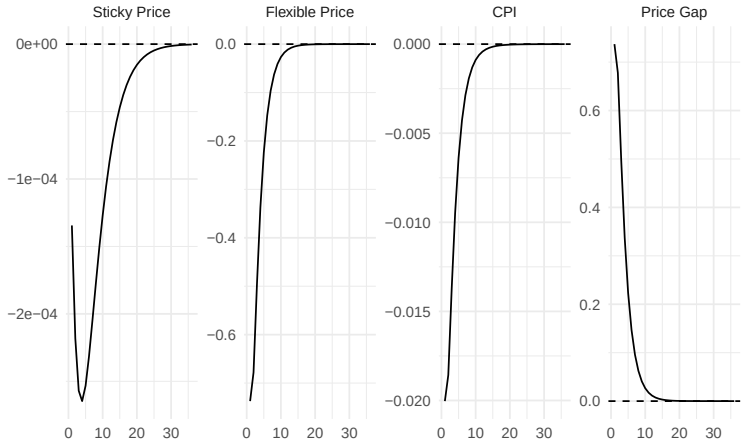
In this exercise we consider transitory shocks and price levels: the original model is log-linearised around a zero inflation steady state, therefore all values are in percentage deviation from such state. In single-sector New Keynesian models aggregate shocks affect inflation, as opposed to generating a one-off price change, because every period only a fraction of firms can adjust their price. This is equivalent to a multi-sector model where all sectors share the same price stickiness and firms face only aggregate shocks. Letting sectors differ by the degree of price rigidity implies that aggregate shocks will trigger relative prices dynamics, even in the absence of input-output linkages: in stickier sectors a smaller share of firms will adjust their prices, whereas more flexible sectors will transmit the shock quickly. The model uses the same calibration as in Ghassibe, 2021, to which we refer for details, with the exception of the sectoral price rigidity parameters, which are not currently publicly available; for that we relied on a judgmental adjustment to available estimates of price rigidity at CPI level from Gautier et al., 2024. The input-output network adds an extra channel of transmission, especially of sectoral shocks: industries producing inputs to many other sectors will pass on their shocks to the rest of the economy, while downstream sectors will not be as consequential. To capture this additional propagation channel, we focus on two opposite sectors. The first is an upstream sector with flexible prices: its prices adjust rapidly and its output serves as input to many other sectors, while also being relevant in the final consumption basket. The second sector is downstream and sticky: it features sluggish price adjustment and has a significant share in the final consumption basket. To provide an example, one can think of the first industry as the energy sector, and the second one as the health sector.

We first look at how sectoral shocks propagate to each sector, to aggregate consumer prices and to the gap between the two sectoral prices. Figure 3 shows the reaction to a sector-specific temporary technological shock in the flexible and upstream sector.[3] Given the weight of this sector in the input bundle of many other sectors, the effect is visible in both the sectoral price and the overall CPI. The sluggish, downstream sector is less affected and its price barely moves, therefore the price gap is driven almost exclusively by the dynamics of the flexible price sector. As the shock is temporary, the relative prices go back to their original level (see the right-most panel of Figure 3). While the duration is lower than the TFP shock, it is easy to see how sectoral shocks could have effects similar to aggregate shocks, and vice versa.

Next we turn our attention to aggregate shocks. Figure 4 shows the impulse response functions (IRFs) of the same variables to an aggregate total factor productivity (TFP) shock of one standard deviation. A positive, common technological shock has the expected effect of lowering all prices. However the more flexible price responds almost twice as much as the stickier one, so that the price gap also widens in this case. The gap is relatively persistent, as the stickier price takes some additional months to revert back to its steady state value. In other

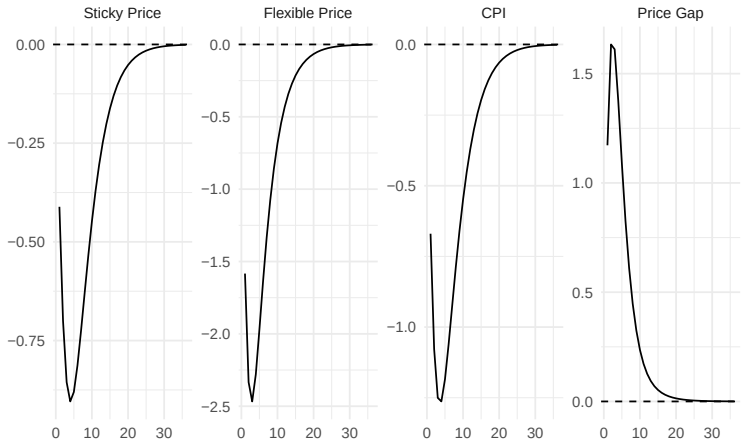
[3] All the temporary shocks were calibrated to follow $m_t = 0.65 m_{t-1} + e_t$

Figure 3: Sector-specific technology shock



Note: Impulse response functions of a sectoral technology shock of one standard deviation on the flexible and upstream sector. The price gap is computed as log difference between two representative prices: a sticky (log) price less a (log) flexible price.

Figure 4: Aggregate technology shock



Note: Impulse response functions of an aggregate technological shock of one standard deviation. From the left, ''Sticky Price'' is the reaction of a sector whose prices adjust infrequently; in contrast, ''Flexible Price'' is the reaction of a sector with very frequent price adjustments. The price gap is computed as log difference between the two prices.

words, a common supply shock leads to both temporary inflation and temporary relative price changes.

Figure 5 shows the reactions to a temporary monetary policy shock, when an extra unit of money is added to the stock of money. The CPI index jumps modestly on impact, while the price gap turns negative before oscillating around the steady state value. This last shock is remarkable as it affects all prices in a similar way. After a monetary expansion both prices move up, though at different speeds, opening a price gap that changes sign as the sectoral prices adjust in sequence. Even in a relatively parsimonious model, aggregate shocks can generate changes in relative prices.

The model allows for (limited) experiments with quasi-permanent shocks, by letting shocks be extremely persistent. Most interestingly for this paper, one can study how prices react after a permanent, unexpected increase of the stock of money. Figure 6 shows such IRFs: Individual prices increase and settle to their new level, while relative prices show a more persistent reaction to a temporary shock. This aggregate shock, closer to our concept of pure inflation, moves individual prices (and the CPI) to a new level, while also generating some temporary movements in terms of relative prices. Note that, as shown in Reis and Watson, 2010, only changes in the *expected* rate of money growth (or of tax rates) can generate a change in pure inflation, while all shocks discussed in this section can only generate an increase in relative prices. Another mechanism that could generate a (temporary) change in pure inflation could be via accommodated unfunded fiscal shocks, as in Bianchi, Faccini, and Melosi, 2023.

3 A Bayesian dynamic factor model to distinguish pure inflation from relative prices

As these examples from the model illustrate, aggregate shocks can affect relative prices and sectoral shocks can affect aggregate inflation in the near term, even when the long-run impact is neutral. This poses a challenge for monetary policymakers in their assessment of current economic conditions since the optimal policy response hinges on correctly identifying the risk of persistent aggregate inflation in the medium term. Distinguishing between relative price shifts that are sector-specific and those which presage more widespread inflationary pressures that will eventually affect all prices is vital to keep inflation anchored at target. We revive here the empirical framework proposed by Reis and Watson, 2010, adapting it to account for heterogeneous price rigidity and for less "dogmatic" restrictions, using a Bayesian implementation of the restricted dynamic factor model they proposed to help discern to what extent shocks are affecting the two common components of inflation: the pure and the relative prices one.

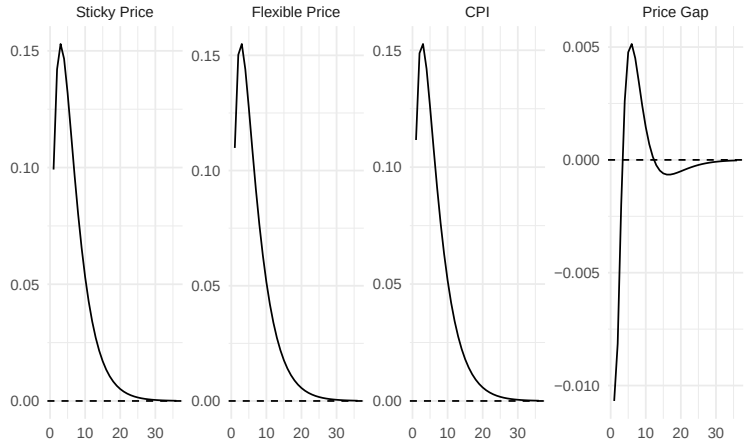
3.1 Method

We adapt the concept introduced by Reis and Watson, 2010 to decompose inflation in each country into three components: i) "pure inflation", i.e. the "change affecting all in the same ratio arising out of change on the side of money" in Keynes's terms, ii) the *common* component that summarises all relative price changes and iii) the part that is idiosyncratic to each component.[4]

We revisit this question for the United States and also look at the euro area. Unlike Reis and Watson, 2010, who measure inflation in quarter-on-quarter terms, taking log-differences between each end-of-quarter month, we use annual inflation. There are two reasons for this choice: the

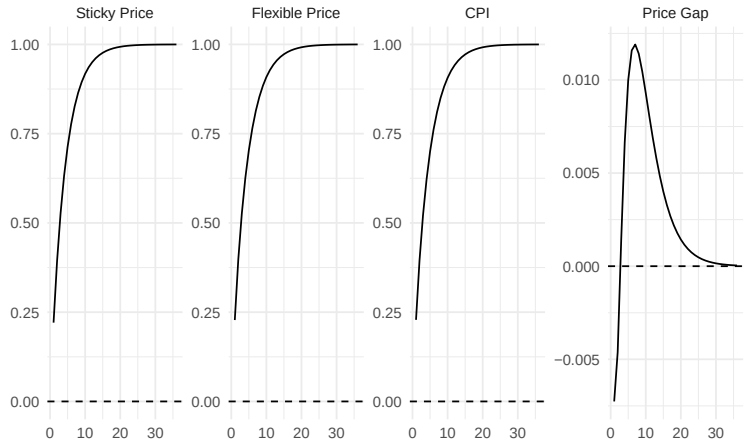
[4]The Reis and Watson approach has been recently applied also to the concept of "pure wage inflation" by Ahn, Cen, and Kister, 2024.

Figure 5: Temporary monetary policy shock



Note: Impulse response functions of an aggregate monetary policy shock of one percentage point from the steady state. From the left, ''Sticky Price'' is the reaction of a sector whose prices adjust infrequently; in contrast, ''Flexible Price'' is the reaction of a sector with very frequent price adjustments. The price gap is computed as log difference between the two prices.

Figure 6: Permanent monetary shock



Note: Impulse response functions of a permanent, aggregate monetary policy shock of one percentage point from the steady state. From the left, ''Sticky Price'' is the reaction of a sector whose prices adjust infrequently; in contrast, ''Flexible Price'' is the reaction of a sector with very frequent price adjustments. The price gap is computed as log difference between the two prices.

first, practical one is that we do not need to seasonally adjust every component.[5] The other is more fundamental: we want to account for the fact that not all goods and services have the same price flexibility and imposing an equi-proportional adjustment within a quarter is a stretch for categories, such as most services, whose prices tend to change less than four times a year (for an exhaustive review on price rigidity across consumption categories in the euro area and its countries see Gautier et al., 2024.

This methodology provides a way to identify the pure and relative prices components by imposing restrictions on the structure of a dynamic factor model. This approach extracts more information from the data than just looking at the loadings of the first principal component of the data, as done for example in the papers by Borio et al., 2021 and Borio et al., 2023 cited above; rather than studying the variation over time of the fraction of variance explained by the first principal component, we project the space of the most important principal components into a direction where the factor loads uniformly on all prices (the tide that lifts all boats) and a direction where they load differently (the choppy wakes).

We estimate the Bayesian factor model using a NUTS MCMC sampler implemented in Stan.[6]

Stan is a probabilistic programming language that employs a variant of the Hamiltonian Monte Carlo algorithm, called No U-Turn Sampler (NUTS). The advantage of Hamiltonian Monte Carlo in general, and NUTS in particular, is the adaptive exploration of the posterior space, drawing at once all parameters, thus leading to more reliable inference with shorter chains compared to a standard Gibbs sampler (see Carpenter et al., 2017; Gelman et al., 2014; Hoffman and Gelman, 2014).

For each country, we model the panel of year-on-year inflation rates as a linear factor model where each of $i \in N$ time series π_{it}, representing an inflation sub-category, is a function of $K \ll N$ factors F_t. In state-space representation, the measurement equation is:

$$\begin{aligned} \boldsymbol{\pi_t} &= \boldsymbol{\Lambda \mathbf{F}_t} + \boldsymbol{e_t} \\ \boldsymbol{e_t} &= \boldsymbol{\Psi e_{t-1}} + \boldsymbol{\varepsilon_t} \end{aligned} \tag{1}$$

Where $\boldsymbol{\pi_t}$ is a $N \times 1$ vector collecting all the category-level inflation rates at time t and the covariance of ε_t is diagonal. The state equation in K unobservable factors reads:

$$\boldsymbol{F_t} = \Xi \boldsymbol{F_{t-1}} + \boldsymbol{\eta_t} \tag{2}$$

where we assume that the distribution of the initial observation for the factor F_1 is known and normal and the two error processes are independently and identically distributed and uncorrelated with each other:

$$\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \sim \text{i.i.d.} \mathcal{N} \left[0, \begin{pmatrix} Q_\varepsilon & 0 \\ 0 & V_\eta \end{pmatrix} \right] \tag{3}$$

Also, for simplicity, we assume that the matrix Ψ containing the autoregressive parameters of the observation errors is diagonal. The structure of the model accounts for the moving average components induced by computing year-on-year inflation rates.[7]

[5] Unlike for the US, HICP data for the euro area at category level are only published in non-seasonally adjusted terms, requiring the researcher to make parameter choices for the seasonal adjustment of each inflation category.

[6] See https://github.com/stan-dev/stan, https://mc-stan.org/; also, see Geweke and Zhou, 1996 for an early application of Bayesian factor models.

[7] In fact the moving average parameter of the VARMA representation induced by the year-on-year transformation is known, while the lag-length of the underlying month-on-month autocorrelation structure is not; in practice, by estimating Ψ we aim at capturing the persistence of the residuals in a parsimonious manner.

Without additional restrictions, the factor model is not identified, since any non-singular matrix M such that $\Lambda M M^{-1} F_t$ would still be admissible. Our identification approach, thus, relies on a minimal set of restrictions derived by Bai and Wang, 2015. We restrict the covariance matrix of the factor innovations V_η to be diagonal (and normalised to 1), and restrict the K square top part of the loadings matrix Λ to be lower triangular with strictly positive diagonal elements. More formally

$$V_\eta = \mathbb{1}_K \tag{4}$$

$$\Lambda = \begin{bmatrix} \Lambda_K \\ \Lambda_{N-K} \end{bmatrix} \tag{5}$$

with $diag(\Lambda_K) > 0$ and its elements $\lambda^K_{i,j} = 0 \; \forall i < j$. This set of restrictions is sufficient to identify the factors and avoid label switching or sign permutations in the dynamic factor model, but is not innocuous for the interpretation of the estimated factors. Eq. 4 implies that the only source of co-movement between the factors is captured by the VAR structure of the state equation, while eq. 5 allows the first factor to load on all N inflation rates, while the second factors only loads on $N-1$, and so on until the last factor only affects $N-K$ series. Sorting the inflation rates within $\boldsymbol{\pi_t}$ thus imparts some block structure and somewhat tilts the factors towards clusters of category-level inflation rates.[8]

In addition to the identifying restrictions on Λ and V_η, we also need to ensure that one of the factors captures as closely as possible our concept of pure inflation. Along the lines of Reis and Watson, 2010, we identify pure inflation by separating the common factors into a factor that loads equiproportionally into all inflation categories and some relative price ones by specifying the factor structure as:

$$\Lambda F_t = \mathbb{1} a_t + \Gamma R_t, \tag{6}$$

where a_t is the pure inflation factor and R_t summarises the information from the remaining $K-1$ common factors. From a Bayesian perspective, the natural porting of this approach is to specify tight priors on one of the factors, thus imposing over-identifying assumptions. In a nutshell, while all the free elements $\lambda_{i,j}$ are given a fairly loose prior around 0, we assign to the first column of Λ a prior centered at 1 and with a tight variance. In this context, a Bayesian approach also allows for an assessment of the prior choice: if the posterior distribution shifts significantly far from the prior location, then the information contained in the data contradicts the starting assumption.[9]

After estimating the factors under these restrictions, we still need to decompose inflation into its pure and relative price components as captured by the factors. We thus compute the deviation of the restricted factor a_t from its expected value given R_t. For the relative prices, we obtain the aggregate relative price inflation from the fitted value of a regression of headline inflation "purged" from a_t on the remaining factors, plus the expected value $E(a_t|R_t)$ estimated in the previous step.[10] This results in the final decomposition of inflation into its pure component ν, the relative price component ρ, and an aggregate idiosyncratic component u_t:

[8] In practice we order the first four inflation components as follows: energy, food, services, non-energy industrial goods. Pure inflation precedes these components and loads on all inflation rates.

[9] Appendix C shows some checks along these lines.

[10] Note that Reis and Watson, 2010 use a Kalman smoother to estimate the expected value of a_t conditional on the whole sample of R_t, not just the contemporaneous and past values. Our counterpart in the Bayesian setting is the posterior distribution of a_t.

$$\begin{aligned}\nu_t &= a_t - E\left(a_t|R_t\right)\\ \rho_t &= E\left(F_t|R_t\right)\\ \pi_t &= \nu_t + \rho_t + u_t\end{aligned} \tag{7}$$

Our econometric approach keeps many of the parametric assumptions by Reis and Watson, 2010: besides the restrictions, we also allow a full VAR structure in the state equation: this is important to accommodate dynamic comovements among the factors. In economic terms, one can think of it as allowing relative price changes to spread into broader price dynamics. The post-pandemic bout of inflation, indeed, shows how sectoral price pressures can spread to other segments of the economy and spark a broad-based inflationary dynamic.

Differently from Reis and Watson, 2010, however, after exploratory analysis we impose five factors in total in our baseline specification. The number of common factors is central to finding whether much variation in inflation will be allocated to "aggregate" relative prices or to idiosyncratic factors, but not to whether the common pure inflation factor will show much variability through time. When letting the number of common factors be decided algorithmically for each country using. e.g., the Bai and Ng criteria, the estimated number of factors K tends to settle very close to the maximum number allowed, which in our exploratory analysis we parameterised to be one third of the number of COICOP categories included in the sample for that country. Experiments with standard dynamic factor models and principal components analysis also point to the need of using a relatively high number of factors to capture most of the variation in the data.

After experimentation we choose our baseline monthly specification to be the same for both countries, with $K = 5$ common factors. The results from this preliminary analysis based on principal components are presented in Section 4.2. Our setup for estimating the state-space model described by equations 1 and 2 relies on fourteen separate Markov chains that run individually until 5000 complete draws are generated for each chain – besides adaptation and warm-up phases. We discard the first half of these draws as burn-in. Once every chain converges to the selected number of draws, we combine all draws and perform inference on the posterior draws.

3.2 Parameterisation

A Bayesian approach allows the flexible introduction of restrictions in an otherwise standard dynamic factor model. As mentioned, by carefully selecting tight priors on some parameters, one can tell apart pure inflation while also letting the data speak about the appropriateness of such restrictions by comparing the posterior and prior distributions of the uniform loading parameters. Under the identification and restriction strategies outlined above, the Bayesian dynamic factor model is parameterised as follows, using fairly spread Gaussian distributions:

$$
\begin{aligned}
\boldsymbol{\pi_t} &\sim \boldsymbol{N}\left(\boldsymbol{\Lambda F_t}, \boldsymbol{Q_\epsilon}\right) \\
\boldsymbol{F_t} &\sim \boldsymbol{N}\left(\boldsymbol{\Xi F_{t-1}}, \mathbb{1}_{\boldsymbol{K}}\right) \\
\boldsymbol{\Lambda} &= \begin{bmatrix} \boldsymbol{\Lambda_K} \\ \boldsymbol{\Lambda_{N-K}} \end{bmatrix} \\
\lambda^K_{i,j} &= 0 \qquad\qquad \forall i < j \\
\lambda^K_{i,j} &\sim |N\left(0, 10\right)| \qquad \forall i = j \\
\lambda_{i,j} &\sim N\left(0, 10\right) \qquad \forall i > j \\
\lambda_{i,1} &\sim N\left(1, 0.1\right) \qquad \forall j \\
diag(\boldsymbol{Q_\epsilon}) &\sim |\boldsymbol{Cauchy}\left(\boldsymbol{0, 10}\right)| \\
\boldsymbol{\Gamma} &\sim \boldsymbol{N}\left(\boldsymbol{0, 10}\right)
\end{aligned}
\tag{8}
$$

Where $|x|$ means a positively truncated distribution for x. At the same time, for every iteration of the NUTS sampler, we also compute in parallel the values of our variables of interest, ν and ρ: doing so allows for parameter distributions that are internally consistent. As a byproduct, part of the contribution of this paper is a method applicable to a larger set of countries: in parallel work we have experienced that the Bayesian reformulation of a standard dynamic factor model can handle data from both mature and developing economies, for instance with different sensitivities to energy or commodity prices shocks, without ad-hoc restrictions or assumptions, for example on the number of cointegration vectors. Moreover, our estimation yields directly all the quantities of interest, affording the posterior checks on these, too.

4 Inflation data

In order to gauge the ability of our model to disentangle pure and relative price inflation, we apply it to synthetic data derived from the Ghassibe, 2021 model described in section 2 above, simulated under the assumption that aggregate inflation is only driven by shocks that affect relative prices. In other words, we should recover a flat nu_t hovering around zero. Our main exercise uses consumer price index data from the euro area and the United States. Finally, to compare the results with those by Reis and Watson, 2010, we also apply our framework to the US personal consumption expenditure deflator over a longer sample. We describe these three data sources below.

4.1 Simulating data to gauge the properties of the model

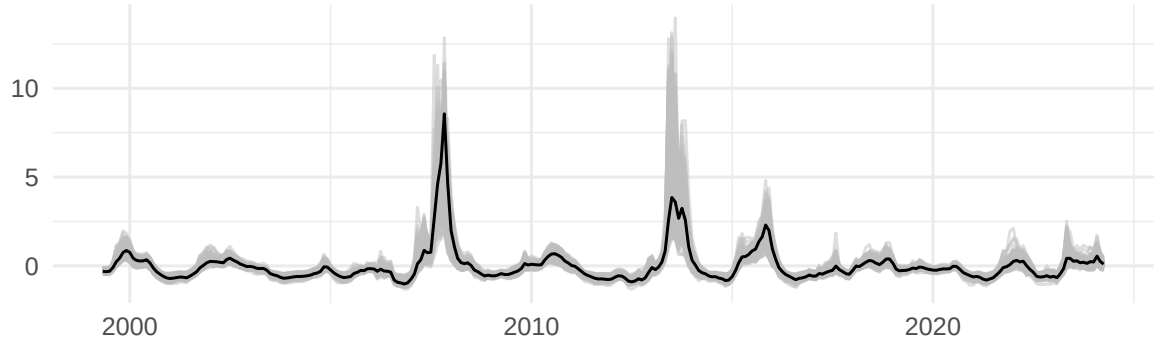
Simulating data from the model presented in Section 2 allows us to control the the data generating process and easily generate a sample with known properties. We draw about 400 observations from the model with standard calibration and compute inflation rates of the about 160 sectoral prices, dropping the first 100 observations.

Given the model structure, we can expect the following results. First, the model is linear and the shocks are unanticipated and transitory, so that no expected component can feed into pure inflation. That means that the series for pure inflation estimated by our framework should be close to zero. Second, each sector receives both sectoral (technology) and aggregate (monetary policy, TFP) shocks. Finally, while relative prices move in response to all shocks, the overall

impact may be reduced when the shock is indirect – such as when it occurs in an upstream sector.

We use the same input-output weights as in Ghassibe (2021) and calibrate price rigidity using Calvo parameters that can take the values of 0.25, 0.5, or 0.75 depending on whether the corresponding entry in the input-output matrix refers to a typically flexible or rigid inflation component. The simulated series, after rescaling, are comparable in range with actual inflation data, though we obtain a lower dispersion as shown by comparing Figure 7 with Figure 1.

Figure 7: Simulated Data



Note: the data are simulated from Ghassibe (2021), where we use about 160 sectors, aggregate and sectoral technological shocks, temporary shocks to the total stock of money. Dates are indicative only.

4.2 Consumer price indices

In order to compare consumer price indices across countries, it is necessary to both view indices at a more granular level than headline, and ensure that these categories are aligned in terms of the individual goods and services that are included in the index calculation. To do this, we have re-constructed the US national index and its subcomponents to match the structure used in EUROSTAT's Harmonised Index of Consumer Prices (HICP).

HICP is structured along the international standard Classification of Individual Consumption by Purpose (COICOP), which splits expenditure into 12 main divisions (2-digit COICOP),[11] such as clothing and footwear, health, and recreation. The divisions are in turn split into a total of 43 groups (3-digit COICOP) and further in 102 classes (4-digit COICOP).

The most notable changes are that imputed rents are included in the US national indices but excluded here to match HICP, and that the United States groups cafés and restaurants alongside food, but they fall under different divisions within COICOP. Even aligned to COICOP, there will be differences between economies based on consumption preferences and the choice of products used for price quotes.

We use the most disaggregated components available across countries rather than the most granular data available in each country. This means that in some cases we use 4-digit classes (e.g., "0112, Meat"), in others only 3-digit groups (e.g., "041, Actual rents paid by tenants").

[11] The 2018 version of COICOP has 13 divisions, which a handful of economies have now adopted.

When class-level data are not available for any components we use the corresponding group-level data. This maximises the coverage without causing overlap between components and leaves us with 49 inflation components for the United States and 54 for the euro area.

We use price indices at a monthly frequency and compute inflation year on year to jointly address seasonal adjustments and price rigidity. Seasonal analysis in general requires expert knowledge on the properties of each individual time series and became particularly difficult after 2020 since the pandemic restrictions affected seasonal patterns in many consumption categories. Price rigidity is important in light of the assumption needed to identify "pure inflation": to allow, in the words of J.M. Keynes quoted above, "a further change affecting all in the same ratio arising out of change on the side of money", enough time must be allowed to pass for the common monetary shock to feed to all consumer price categories to the same extent. More practically, the one-year window comprises enough price updates to better incorporate changes triggered by aggregate and sectoral shocks (Gautier et al., 2024, Pasten, Schoenle, and Weber, 2020).

Some time series are excluded from the database because of irregular missing values, samples that are too short (for example, through changing index composition) or that exhibit special characteristics. For example, we exclude prices that are usually regulated such as inpatient and outpatient medical services, postal services, and tobacco. This results in using 55 inflation subcomponents for euro area HICP and 49 for the United States.

The estimation sample starts in December 2000 for the euro area and in December 2002 for the United States, ending in October and November 2023 respectively.[12] Additionally, we rescale and centre every time series so that it has mean zero and unit variance.

We investigate the "commonality" of these consumer price indices using principal component analysis (PCA), to make an educated choice on the number of factors that we use in our empirical model in Section 5 below.

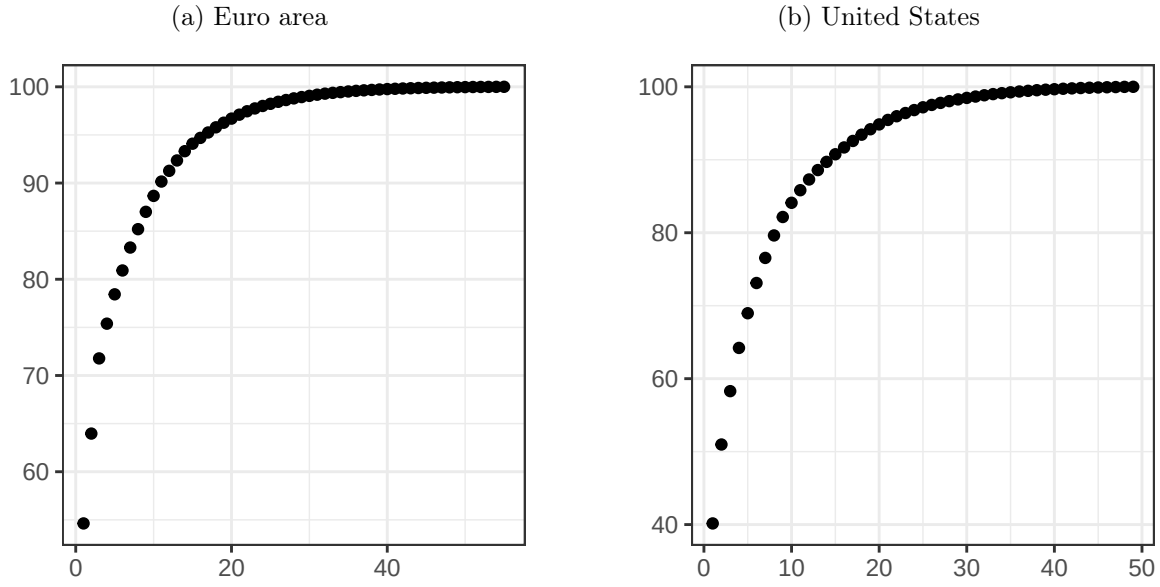
Figure 8 presents the cumulative percentage share of total variance explained by an additional factor, up to the point of saturating the principal component decomposition with $K = N$. In both the euro area and US cases, the first factor explains a rather large part of the the total variance in the data: about 39% and 53% respectively. Any additional factor, by design, captures less of the empirical variance. For the EA, the second and third factors add about 10% to the total variation explained, while for the US the second factor adds around 11% and the third about 8%. The marginal contribution of any additional factor beyond the third has a progressively lower explanatory power. Based on these results, in order to capture much of the common variation while keeping a parsimonious specification we set a conservative upper bound of five factors to represent the common drivers of all the inflation components: these capture a little less than 80% of the covariance for the euro area and about 70% for the USA.

4.3 Data covering a longer time span: US personal consumption expenditure deflator

The comparability across countries of the data in our baseline sample comes at the cost of a shorter time span, which covers a long period of quiet inflation and features only one high-inflation episode. Testing our methodology on multiple high-inflation episodes can shed light on the actual sensitivity of ν to several factors, such as inflation expectations and their degree of anchoring. Since longer euro area aggregate data would entail a cumbersome and possibly ad-hoc data manipulation, it is natural to look at disaggregated US personal consumption expenditure deflators. These data also permit a more direct comparison of our framework with the original

[12] Starting dates differ since we ensured a "rectangular" panel for both areas.

Figure 8: cumulative share of explained variance



Note: Cumulative share of variance explained by each principal component in a PCA decomposition of inflation components.

exercise of Reis and Watson (2010). The PCE sample covers 201 PCE components from January 1961 to September 2024.

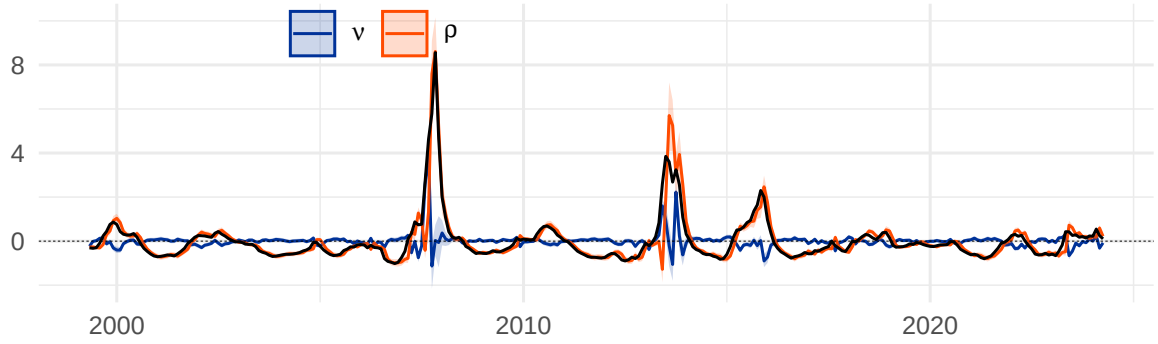
5 Results: decomposing inflation into pure and relative price components

We apply the econometric framework set out in Section 3 to the three datasets described in Section 4 with different questions in mind. The simulated data offer a controlled environment where we can check if the model recovers the properties of ν and ρ that we put in the data generation process (DGP). The central exercise is run on the US and EA consumer price indices, with a direct comparison with what we would get using the Reis and Watson, 2010 dynamic factor model (RW-DFM) approach. Finally, the US PCE data give us the chance to see the results over a longer time period, over some of which inflation expectations were arguably not as well anchored as in the 2000's. By the nature of the euro area, an analysis spanning many decades with markedly different monetary policy regimes is not possible.

5.1 Simulated data

The results from the simulated data derived from the modified Ghassibe, 2021 model are in line with our expectations given the DGP: Relative prices capture most of the movement in headline inflation, while pure inflation sits consistently close to zero. Pure inflation moves away from zero for very few periods, and only then briefly in presence of violent and sudden flares of inflation (see Figure 9).

Figure 9: Evaluating the BDFM on simulated data



Note: Results estimated from the restricted Bayesian dynamic factor model on simulated data. We feed the BDFM about 300 observations for each of the 160 sectors, plus headline HICP. The BDFM runs 14 chains with 5000 iterations of the NUTS sampler each, and discards the first half of these. ν represents pure inflation (in blue), ρ captures relative prices (in red). For both, lines are posterior medians and shaded areas cover the 10% to 90% credibility interval. The black solid line is headline HICP, the dashed line is the 0 intercept.

These results using simulated data are rather encouraging, for the model does precisely estimate a feeble to non-existent pure inflation, while assigning most of the variance to relative prices. Equipped with these results we now turn to actual data.

5.2 Consumer price indices

Starting from the estimated factors we decompose the headline CPI inflation in the euro area and in the United States into pure inflation (ν_t in Reis and Watson, 2010 terminology) and inflation due to average relative price changes, ρ_t.[13]

The period covered in our sample has for the most part been one of inflation stability. That stability ends at the end of the sample period, with inflation picking up sharply in 2021 and 2022, before falling in 2023 to rates more in line with the previous decades. According to our B-PIDFM the vast majority of the pick-up in inflation was driven by ρ_t, the relative price component, in both currency areas. At the same time, in both areas there were some signs of an increase in the pure inflation component, ν_t, which was unwound by the end of our sample. The two components together explain 76% of the variance of headline inflation in the euro area, but only explain 52% of its variation in the United States. Pure inflation explains about the same share of variation of headline inflation in the euro area and in the United States: between 12% and 14%, respectively (see Figures 10a and 10b). The rest can be ascribed to idiosyncratic components (or possibly to further, "local" common factors in the case of the United States).

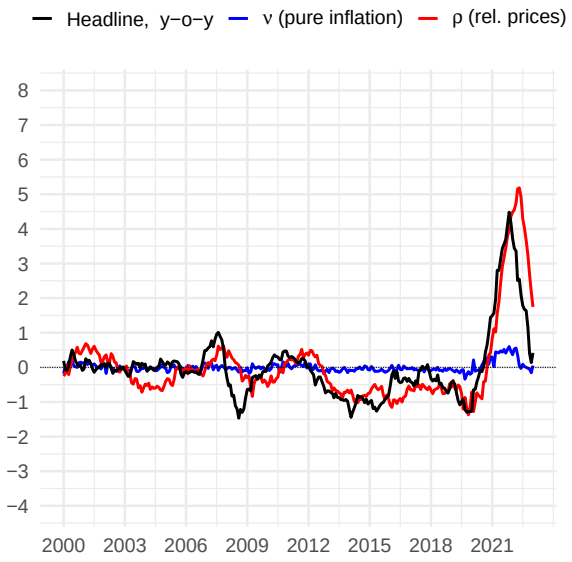
We have argued above that the B-PIDFM could be more accommodative with the data, because of the longer adjustment lag of annual inflation rates, as opposed to the end-of-quarter-on-end-of-quarter of RW-DFM, and because of the flexible implementation of the the uniformity restrictions on the loadings on the pure inflation. How compatible is this latter restriction with the data? As shown in Figure A4 and Tables A1 and A3, the posterior distributions for the restricted loadings shrink within the prior support, although the posterior medians tend to shift lower than 1 in most cases, but always in a rather narrow range of 0.8 to a little above 1. The IRQ of the posterior distributions also mostly overlap - with few exceptions - indicating a high degree of homogeneity in the loadings. All in all, most of the probability mass concentrates close enough to 1, which does not allow for a sharp rejection of the pure inflation restriction.

As a robustness check, we also apply our method on two-year inflation rates. As shown in Figure 2, a very large share of price rigidities unfold in the course of one year, but some take slightly longer, for instance some products within the service sector. The two-year inflation exercise allows even more time for price adjustments. In this set-up, relative prices still drive a sizeable share of the variation in headline inflation, while pure inflation is somewhat less stable. Pure inflation does contribute slightly more to the recent rise and fall of headline inflation, especially in the United States, where the rise of ν_t in 2021-22 is remarkable, but relative prices nonetheless still contribute the lion's share (see Figure A5 in the Appendix).

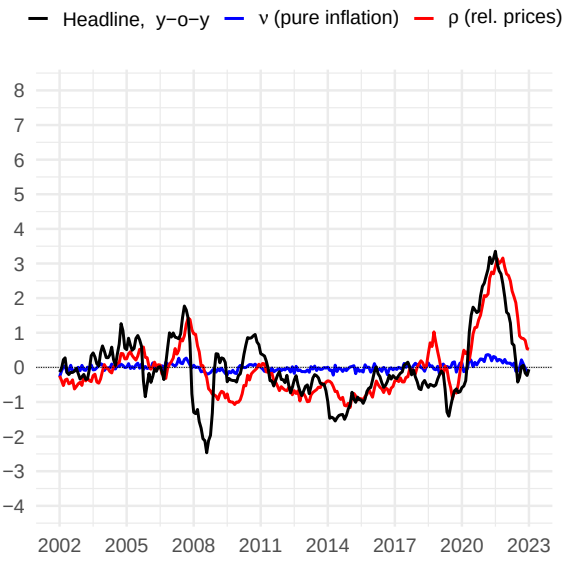
[13] The residual is the aggregate of the idiosyncratic terms. We omit it from the figures.

Figure 10: Inflation decomposition $\pi_t = \nu_t + \rho_t + u_t$

(a) Euro area



(b) United States



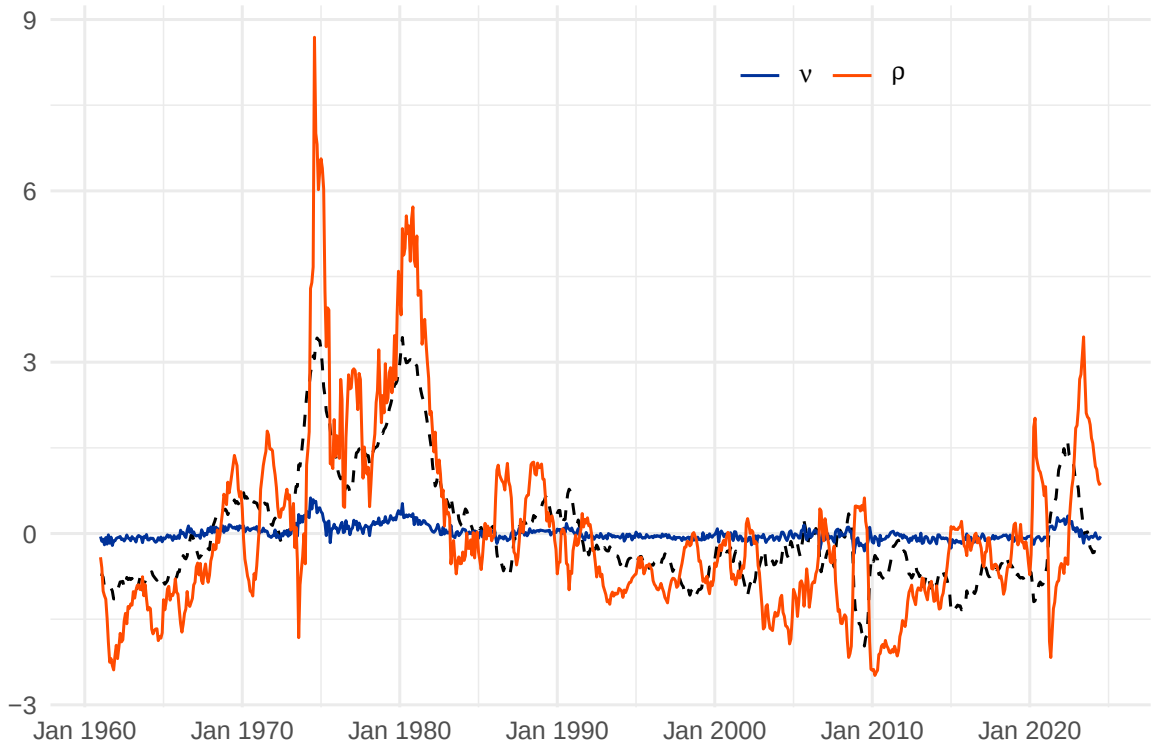
Note: headline inflation in black, pure inflation ν_t in blue and relative prices ρ_t in red. Results from a Bayesian dynamic factor model with static measurement equation and VAR(1) for the factors' state equation: ν and ρ are then derived as per eq. 7. The BDFM runs 14 chains with 5000 iterations of the NUTS sampler each, and discards the first half of these.

5.3 A longer-run perspective

Given the general stability of our estimates of pure inflation, it is useful to put the most recent episode into historical context. Previous inflationary episodes can provide useful yardsticks to gauge the magnitude of the recent pure inflation bump. Unfortunately, long-run HICP data does not exist for the euro area. But for the United States, we can use personal consumption expenditure (PCE) deflators. Crucially, US PCE data cover the high-inflation period of the 1970s and 1980s, when inflation expectations were not fully anchored and monetary policy accommodated price pressures, providing a fitting environment in which to evaluate the decomposition in terms of fitting the historical knowledge about that period.

Figure 11 shows the estimates for pure inflation and relative prices inflation. First off, the more recent dynamics of ν and ρ do not appear substantially different from our baseline results shown in Figures **??** and **??**. Similar to HICP in the last two decades, US PCE appears to have been mainly driven by relative prices over this longer sample, with some uptick in the contribution of pure inflation around the 2008 global financial crisis and during the 2021-2023 reflation and disinflation period.

Figure 11: US - ν and ρ estimates from PCE data



Note: estimates of ν (blue), ρ (red), and rescaled headline PCE (dashed, black) based on 201 US PCE item inflation rates, January 1961 to September 2024. Results based on a Bayesian dynamic factor model featuring a uniform restriction on the first factor, a static measurement equation, and a VAR(1) structure for the state equation, as described in Section 3.1. ν and ρ derived as per equation 7. The BDFM runs 14 chains with 5000 iterations of the NUTS sampler each, and discards the first half of these.

Second, the high-inflation episodes of the 1970s and 1980s also saw a larger contribution of pure inflation – around 1975 more than the early 1980s. During those years, inflation expectations were likely unanchored and monetary policy was more accommodating rather than aggressively responding to inflation.[14]

The bumps in pure inflation prior to the Great Moderation period, thus, corroborate our empirical methodology. Interestingly, the size of the latest increase of pure inflation in terms of the PCE in the United States is comparable to that of the early 1980s, though the level of headline inflation was not as high.

Between those two periods, Figure 11 also displays a smooth profile for pure inflation during the Great Moderation, when expectations, policy (and shocks) kept inflation in check.

[14]See results from Boivin (2006), Clarida, Galí, and Gertler (2000), Franceschi (2021), Primiceri (2005), and Sims and Zha (2006).

6 Impact of shocks

Having established our model as a useful way of identifying pure inflation and relative price shifts, we now turn our attention to how these components of inflation react to macroeconomic shocks.

Should central banks look through the sectoral shocks that drive relative price changes? The answer, unsurprisingly, is "it depends." For example, Nakov and Pescatori, 2010 show that the inflation stabilisation trade-off after a shock to the most volatile high-weight input price, oil, depends on market power within the oil sector. Costain and Nakov, 2011 discuss how identifying the contribution of sectoral shocks can be tricky as it depends on the firm distribution and on the econometric approach used to disentangle the contributions. Ruge-Murcia and Wolman, 2022 use a multi-sector New Keynesian model to disentangle the contribution of three types of shocks, namely sectoral relative price shocks and two kinds of aggregate shocks: monetary policy and real aggregate shocks. They find, in agreement with much of the literature including Reis and Watson, 2010, that relative price shocks contributed most to the variability of inflation, but remark that these results refer to a period when inflation was low and stable. Ferrante, Graves, and Iacoviello, 2023 also use a multi-sector model to disentangle the effects of relative price and aggregate shocks, but focus on the post-2019 period and consider a different aggregate shock – labour productivity – as well as two types of shocks that affect relative prices: sectoral TFP shocks and a preference shock that changes the relative demand for goods and services. They find that the imperfect substitutability of labour and intermediate goods in production and the heterogeneous price rigidity amplify the effects of the preference shocks and reverberate through the input-output network.

We contribute to the analysis of the impact of aggregate and sectoral shocks to inflation from a different angle: we look at the cumulated impulse response functions (CIRFs) of the relative price and pure inflation components to global (world economic activity and world demand), sectoral (oil supply, demand) and aggregate domestic (monetary policy), shocks.

To investigate the reaction of the pure and relative price inflation to shocks we use linear projections à la Jordà, 2005, using external, identified shocks. We look at a global aggregate shock meant to capture unexpected changes in global demand and global activity. We interpret the impact of these shocks on the euro area as coming from a sectoral foreign demand shock in favour of traded goods. We also include two sectoral shocks meant to capture innovations in global oil supply and demand, as identified in a Bayesian SVAR. To measure global economic activity, global oil demand, and global oil supply shocks we use the shocks produced by Baumeister and Hamilton, 2019. We also consider identified monetary policy shocks from Jarociński and Karadi (2020): in their contribution, they offer a suite of monetary policy shocks for the European Central Bank and the Federal Reserve.

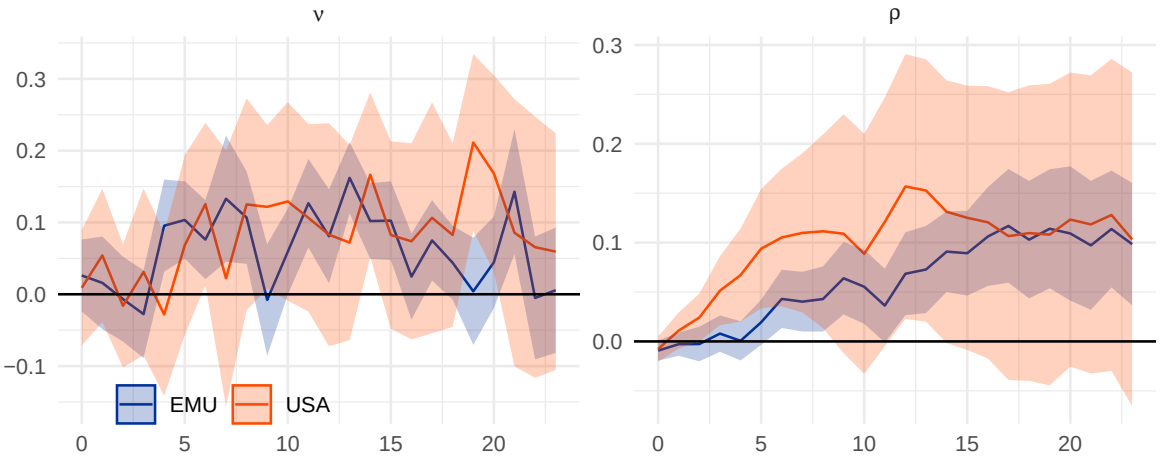
6.1 Global demand shock

As a premise to all our results, our estimated impulse response functions show the well-known issues associated with "plain vanilla" local projections: they have a jagged profile and their variance increases at longer horizons, as discussed in e.g., Li, Plagborg-Møller, and Wolf, 2024. The "economic activity" shock by Baumeister and Hamilton, 2019 captures a global demand shock, which would tend to lift all tradable goods prices. Our results, shown in Figure 12, indicate that it does indeed have an uneven impact across inflation categories, with the response of the relative price components ρ_t (right pane) peaking around between twelve and sixteen

months after the shock.[15] Two years out, the relative price component plateaus at a slightly higher level.

In addition to causing shifts in relative prices, the global economic activity shock also seem to lift all prices homogeneously in the euro area for some months, where the cumulative impulse response function (CIRF) of pure inflation ν_t (left pane) rises in the short term, for about ten months. The response of relative prices is more delayed in the euro area. One way to rationalise this would be to consider that it has been a net exporter in recent decades, whereas the United States has had a persistent trade deficit. In other words, an increase in global demand is likely to increase demand for euro area exports and in turn increase local inflationary pressures later than for the United States, which experience a quicker uptick of relative prices as they tend to be themselves an engine of global demand. After two years, both monetary areas settle on a slightly higher level of relative prices.

Figure 12: Cumulative IRF after a global economic activity shock



Note: Cumulative IRF of ν_t and ρ_t to a Baumeister and Hamilton, 2019 global economic activity shock. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance.

6.2 Oil supply and demand shocks

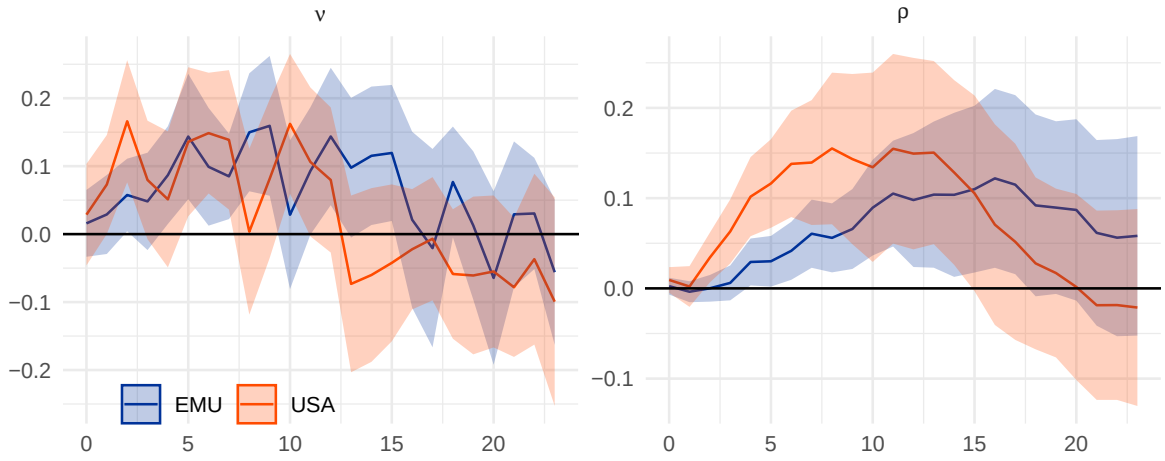
Turning to the sectoral shocks, the CIRF of pure inflation ν_t to an oil demand shock, shown in Figure 13 (left pane), are occasionally significant, especially for the United States where pure inflation picks up in the short run, then reverts back to baseline after about one year. By contrast, and as expected, the CIRF of European pure inflation is only significant for a very short period of time.

The CIRF of the relative price component ρ_t (right pane) shows that the impact of oil demand has a clear effect on relative prices, as one would expect given that it will tend to increase the price of oil relative to that of all other goods and services. The impact peaks slightly faster

[15] In all our local projection regressions we include lags of domestic unemployment, and local interest rates. All local projections we also include 12 lags of the dependent variable, as per Montiel Olea and Plagborg-Moller, 2021.

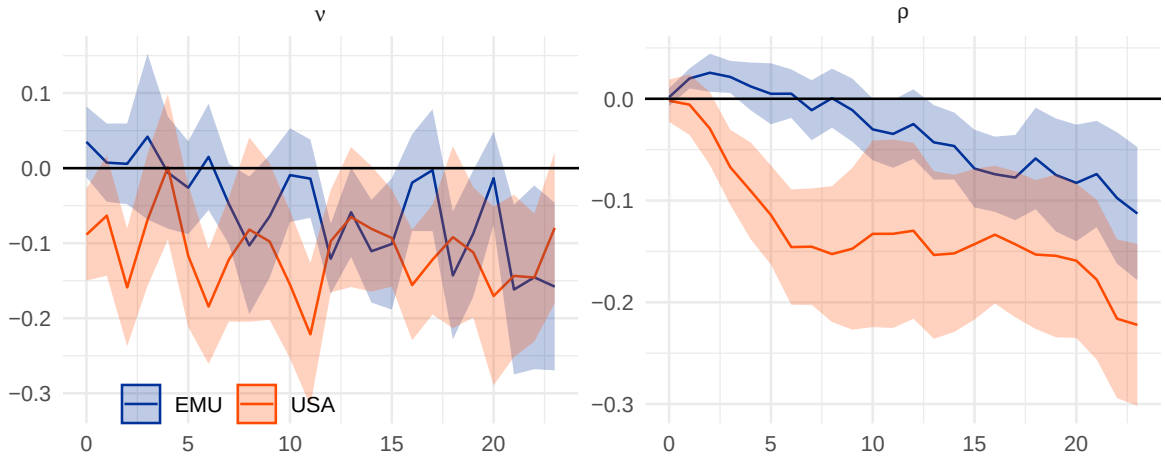
and higher in the United States, while the response of euro area relative prices is, similar to the case of global activity shocks, more delayed. One explanation for the shorter-lived impact in the United States could be that domestic oil production can be boosted in response to an increase in oil demand and price. Again, the longer-run responses show the expected increase in variance.

Figure 13: Cumulative IRF after a positive, global oil demand shock



Note: Cumulative IRF of ν_t and ρ_t to a Baumeister and Hamilton, 2019 positive, global oil demand shock. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance.

Figure 14: Cumulative IRF after a positive, global oil supply shock



Note: Cumulative IRF of ν_t and ρ_t to a Baumeister and Hamilton, 2019 positive, global oil supply shock. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance.

Baumeister and Hamilton (2019) also produce global oil supply shocks, measured in terms of increases in oil production.[16] For such shocks, in the US pure inflation falls, while in the EA the impact is significantly negative two years out, which is counterintuitive for a supply shock, unless understood through the lens of the production network, which can amplify the impact of upstream supply shocks and prolong their pass-through to other price components down the supply chain. Relative prices fall more slowly in the EA, with a significant impact happening about a year later than in the US. The larger, quicker impact in the US could be related to an indirect effect on domestic demand, as the US are a large oil producer, as well as to higher taxes on energy prices in the euro area, which can slow down and dampen the pass-through of commodity price shocks.

6.3 Monetary policy shocks

To investigate how ν and ρ react to monetary policy shocks we use updated shocks from Jarociński and Karadi (2020) for both the European Central Bank and the US Federal Reserve. Among the available flavours, we pick the shocks identified via the so-called "poor-man's sign restriction" identification setup. We homogenise the shocks' direction so that they are monetary restrictions.

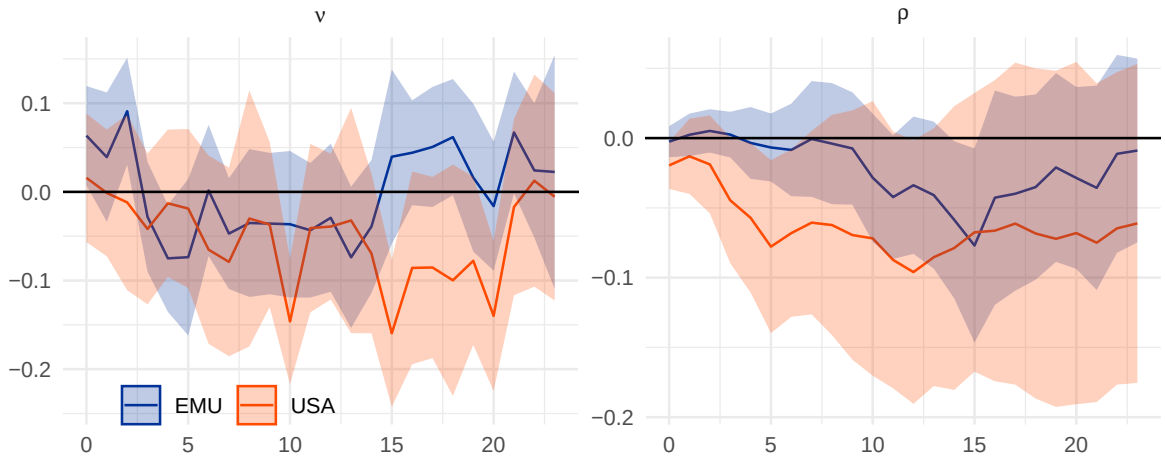
From the theory outlined in Section 2, we would expect monetary policy shocks to only affect relative prices.

We find that monetary policy shocks have no clearly significant effect on pure inflation: as shown in Figure 15, in the case of euro area "pure" monetary policy shocks, i.e., abstracting from the signalling about economic conditions as per the methodology, both pure inflation and relative prices impulse responses move sideways, with occasional short dips in significant territory. This applies to the response of euro area inflation as well as to the "spillover" of euro area monetary policy to US inflation components. A similar picture appears for the reactions to US monetary policy shocks. We do not find a significant response of relative prices, either, although directionally the effect is as expected.

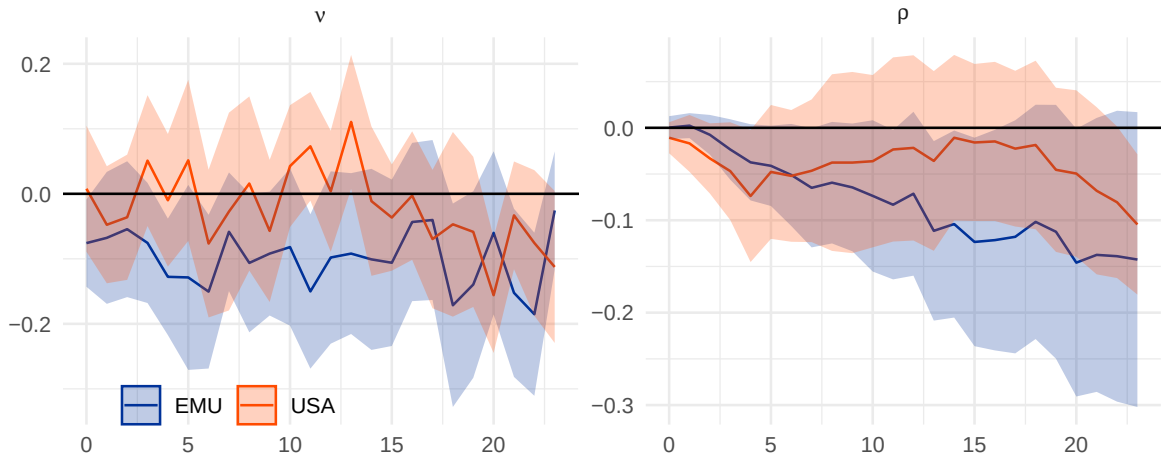
[16] Känzig (2021) further distinguishes between oil supply news and actual production shocks. For robustness, results with Känzig (2021) shocks are deferred to the Appendix D.2.

Figure 15: Cumulative IRFs to monetary policy shocks

(a) ECB "poor-man's" shock identification



(b) Fed "poor-man's" shock identification



Note: Cumulative IRF of ν_t and ρ_t to Jarociński and Karadi (2020) monetary policy shocks from the ECB and the US Fed. The shocks are identified via the "poor man's" restrictions and are a monetary tightening. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance.

7 Discussion and conclusions

Following several decades of low and stable inflation, the opening years of the present decade delivered the highest inflation rates for more than a generation in both the euro area and the United States. For central banks mandated to deliver price stability, it is crucial to understand the causes of these inflation spikes and what implications they may hold for the conduct of monetary policy. In particular, it is important to discern the extent to which the COVID-19 pandemic, the Russian war of aggression on Ukraine, and accommodative monetary policy in the previous decade may have contributed to inflation volatility.

To this end, we decompose the dynamics of disaggregated inflation for the euro area and the United States into a common, pure component and movements in relative prices, in the spirit of Reis and Watson, 2010. Similar to the previous research, we find a limited role for pure inflation in driving overall inflation dynamics: Pure inflation explains 12% of the variation of headline inflation in the euro area, and 14% in the United States over our entire sample.

We analyse the differential impact of sectoral and aggregate shocks on both the pure and relative price component of inflation, finding that, as expected, the latter tends to react more to both sectoral and aggregate shocks. Arguments that the surge in inflation was brought about mainly by sectoral shocks, find some support here for both the euro area and the United States. On the other hand, we find little effects of monetary policy shocks on both components of inflation, thus finding no support for a monetary-driven pure inflation component.

For the period of particular interest at the end of our sample, as expected given the large shocks following the COVID-19 lockdowns and their largely sectoral nature, the relative price component moves sharply and was the principal driver of inflation dynamics in both the euro area and the United States. Both the euro area and the United States witnessed modest shifts in the pure inflation component, which rapidly converged back to historical levels.

These results lend weight to arguments that inflation dynamics were driven primarily by relative price shocks arising from the pandemic and Russia's war of aggression on Ukraine in the euro area, but the extremely expansionary policy mix in the United States might have also temporarily lifted pure inflation. In this context the analysis of the impact of fiscal shocks, as well as the interactions of fiscal and monetary policy shocks with inflation expectations, is a particularly interesting direction of research.

References

Afrouzi, Hassan and Saroj Bhattarai (2023). *Inflation and gdp dynamics in production networks: A sufficient statistics approach*. Tech. rep. National Bureau of Economic Research (cit. on p. 5).

Ahn, Hie Joo, Han Cen, and Michael Kister (2024). "A New Indicator of Common Wage Inflation". In: *Journal of Money, Credit and Banking* n/a.n/a (cit. on p. 8).

Bai, Jushan and Peng Wang (2015). "Identification and Bayesian Estimation of Dynamic Factor Models". In: *Journal of Business & Economic Statistics* 33.2, pp. 221–240 (cit. on p. 11).

Baumeister, Christiane and James D. Hamilton (2019). "Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks". In: *American Economic Review* 109.5, pp. 1873–1910 (cit. on pp. 22–25, 39).

Bianchi, Francesco, Renato Faccini, and Leonardo Melosi (2023). "A Fiscal Theory of Persistent Inflation". In: *The Quarterly Journal of Economics* 138.4, pp. 2127–2179 (cit. on p. 8).

Boivin, Jean (2006). "Has U.S. Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data". In: *Journal of Money, Credit and Banking* 38.5, pp. 1149–1173 (cit. on p. 21).

Borio, Claudio et al. (2021). "Monetary policy, relative prices and inflation control: flexibility born out of success". In: *BIS Quarterly Review* (cit. on pp. 4, 10).

Borio, Claudio et al. (2023). *The two-regime view of inflation*. BIS Papers 133. Bank for International Settlements (cit. on pp. 5, 10).

Carpenter, Bob et al. (2017). "Stan: A probabilistic programming language". In: *Journal of statistical software* 76 (cit. on p. 10).

Ciccarelli, Matteo and Benoit Mojon (2010). "Global Inflation". In: *The Review of Economics and Statistics* 92.3, pp. 524–535 (cit. on p. 4).

Clarida, Richard, Jordi Galí, and Mark Gertler (2000). "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory". In: *The Quarterly Journal of Economics* 115.1, pp. 147–180 (cit. on p. 21).

Costain, James and Anton Nakov (2011). "Distributional dynamics under smoothly state-dependent pricing". In: *Journal of Monetary Economics* 58.6, pp. 646–665 (cit. on p. 22).

Doz, Catherine, Domenico Giannone, and Lucrezia Reichlin (2012). "A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models". In: *The Review of Economics and Statistics* 94.4, pp. 1014–1024 (cit. on p. 30).

Ferrante, Francesco, Sebastian Graves, and Matteo Iacoviello (2023). "The inflationary effects of sectoral reallocation". In: *Journal of Monetary Economics* 140. Inflation: Drivers and Dynamics 2022, S64–S81 (cit. on pp. 5, 22).

Förster, Marcel and Peter Tillmann (2014). "Reconsidering the International Comovement of Inflation". In: *Open Economies Review* 25.5, pp. 841–863 (cit. on p. 4).

Franceschi, Emanuele (2021). "Taylor Rules and Liquidity in Financial Markets". In: *Revue économique* 72.1, pp. 103–134 (cit. on p. 21).

Friedman, Milton (1963). *Inflation: Causes and Consequences*. Asia Publishing House, New York (cit. on p. 2).

Gautier, Erwan et al. (2024). "New Facts on Consumer Price Rigidity in the Euro Area". In: *American Economic Journal: Macroeconomics* 16.4, 386–431 (cit. on pp. 4, 6, 10, 15).

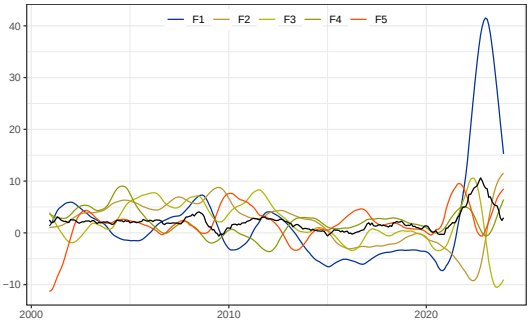
Gelman, Andrew et al. (2014). "Bayesian Data Analysis". In: *Bayesian Data Analysis* (cit. on p. 10).
Gerard, Hugo (Dec. 2024). *Business Cycles with Pricing Cascades*. Mimeo (cit. on p. 5).
Geweke, John and Guofu Zhou (1996). "Measuring the price of the Arbitrage Pricing Theory". In: *The Review of Financial Studies* 9.2, pp. 557–587 (cit. on p. 10).
Ghassibe, Mishel (2021). "Monetary policy and production networks: an empirical investigation". In: *Journal of Monetary Economics* 119, pp. 21–39 (cit. on pp. 2, 5, 6, 13, 14, 16).
Hoffman, Matthew D. and Andrew Gelman (2014). "The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo". In: *Journal of Machine Learning Research* 15.47, pp. 1593–1623 (cit. on p. 10).
Jarociński, Marek and Peter Karadi (2020). "Deconstructing Monetary Policy Surprises—The Role of Information Shocks". In: *American Economic Journal: Macroeconomics* 12.2, pp. 1–43 (cit. on pp. 22, 25, 26, 40).
Jordà, Òscar (2005). "Estimation and Inference of Impulse Responses by Local Projections". In: *American Economic Review* 95.1, pp. 161–182 (cit. on p. 22).
Känzig, Diego R. (2021). "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements". In: *American Economic Review* 111.4, 1092–1125 (cit. on pp. 25, 37, 38).
Karadi, Peter et al. (2024). *Strike while the iron is hot: optimal monetary policy with a nonlinear Phillips curve*. Mimeo (cit. on p. 5).
La'O, Jennifer and Alireza Tahbaz-Salehi (2022). "Optimal monetary policy in production networks". In: *Econometrica* 90.3, pp. 1295–1336 (cit. on p. 5).
Li, Dake, Mikkel Plagborg-Møller, and Christian K. Wolf (2024). "Local projections vs. VARs: Lessons from thousands of DGPs". In: *Journal of Econometrics* 244.2, p. 105722 (cit. on p. 22).
Luo, Shaowen and Daniel Villar (2023). "Propagation of shocks in an input-output economy: Evidence from disaggregated prices". In: *Journal of Monetary Economics* 137, pp. 26–46 (cit. on p. 5).
Montiel Olea, Jose Luis and Mikkel Plagborg-Moller (2021). "Local Projection Inference Is Simpler and More Robust Than You Think". In: *Econometrica* 89.4, pp. 1789–1823 (cit. on p. 23).
Nakov, Anton and Andrea Pescatori (2010). "Monetary Policy Trade-Offs with a Dominant Oil Producer". In: *Journal of Money, Credit and Banking* 42.1, pp. 1–32 (cit. on p. 22).
Parker, Miles (2018). "How global is "global inflation"?" In: *Journal of Macroeconomics* 58.C, pp. 174–197 (cit. on p. 4).
Pasten, Ernesto, Raphael Schoenle, and Michael Weber (2020). "The propagation of monetary policy shocks in a heterogeneous production economy". In: *Journal of Monetary Economics* 116, pp. 1–22 (cit. on pp. 5, 15).
Primiceri, Giorgio E. (2005). "Time Varying Structural Vector Autoregressions and Monetary Policy". In: *The Review of Economic Studies* 72.3, pp. 821–852 (cit. on p. 21).
Reis, Ricardo and Mark W. Watson (2010). "Relative goods' prices, pure inflation, and the Phillips correlation". In: *American Economic Journal: Macroeconomics* 2.3, pp. 128–157 (cit. on pp. 2, 4, 6, 8, 11–13, 16, 18, 22, 27).
Ruge-Murcia, Francisco J. and Alexander L. Wolman (May 2022). *Relative Price Shocks and Inflation*. Working Paper 22-07. Federal Reserve Bank of Richmond (cit. on p. 22).
Sims, Christopher A. and Tao Zha (2006). "Were There Regime Switches in U.S. Monetary Policy?" In: *American Economic Review* 96.1, 54–81 (cit. on p. 21).

A Explorative analysis: a simple dynamic factor model

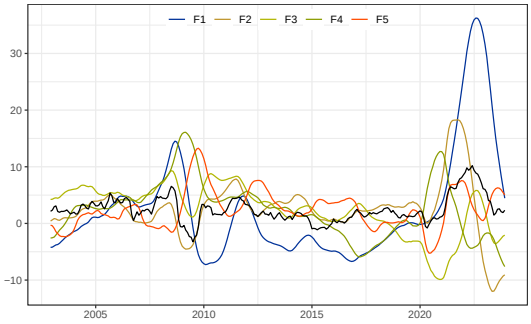
In this appendix we show the results of a standard dynamic factor model (DFM), using the well-established estimation methods from Doz, Giannone, and Reichlin, 2012. The factors are estimated via an Expectation-Maximisation algorithm, and we only restrict the covariance matrix of the factors to be an identity one. In line with the PCA analysis above, we use five factors.[17]

Figure A1: Dynamic factor model

(a) Euro area



(b) United States



Note: standard dynamic factor model for HICP components. Five factors estimated with EM algorithm from Doz, Giannone, and Reichlin, 2012, factors innovation are iid with unit variance. Kalman filter and smoother applied to the factors. Headline HICP in solid black. All data series are scaled and centered.

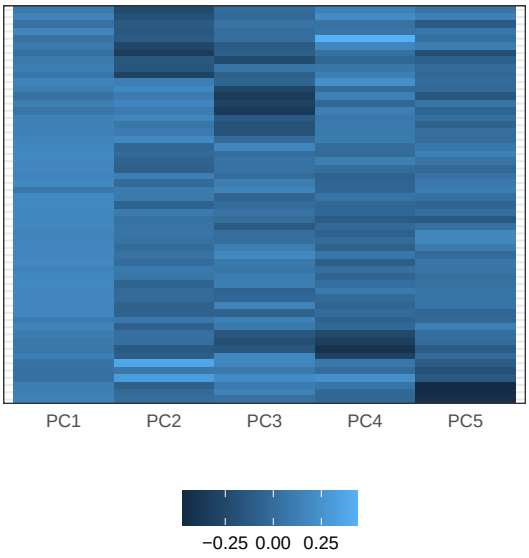
Figures A1a, A1b show that most of the action comes from the first factor, both in the euro area and the United States. Its dynamics would explain the low inflation in the euro area between the global financial crisis and the Covid pandemic. Other factors could potentially capture the effect of non-energy industrial goods and their long term slide in prices (F2), or energy (F3, sign flipped).

The pattern emerging from the dynamic factor model points to a clustering pattern in the loadings. Inspecting the estimated loadings of both PCA and the DFM points to the first factor having relatively homogeneous impact on all components, as visible in the panes of Figure A2.

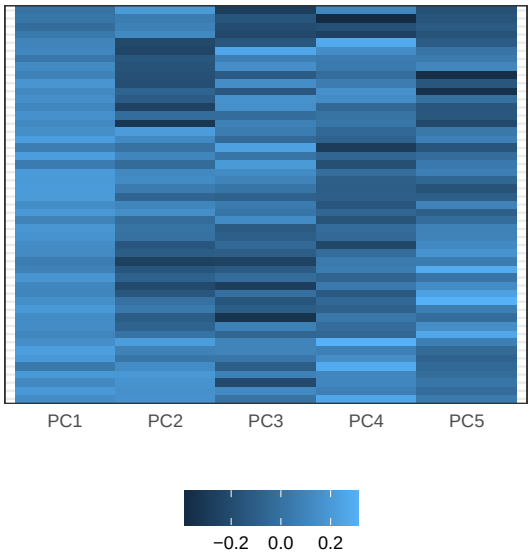
[17] Similar to the PCA case, diagnostics on the number of factors point to relatively high numbers, but the marginal explanatory power drops dramatically after the fifth factor, pointing rather to a contained number of common components.

Figure A2: Heatmaps of the loadings for PCA and DFM estimations

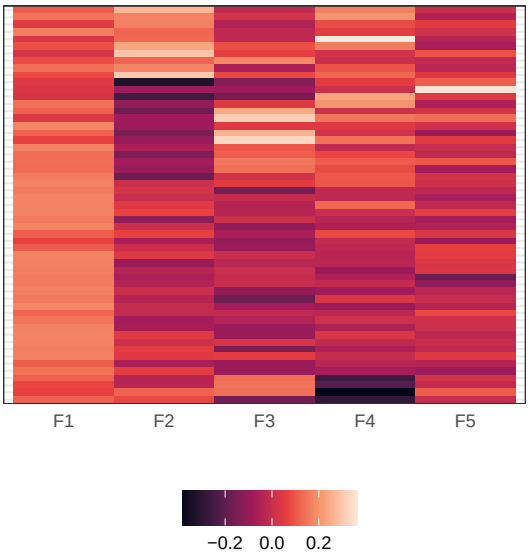
(a) Euro area - PCA



(b) United States - PCA



(c) Euro area - DFM



(d) United States - DFM

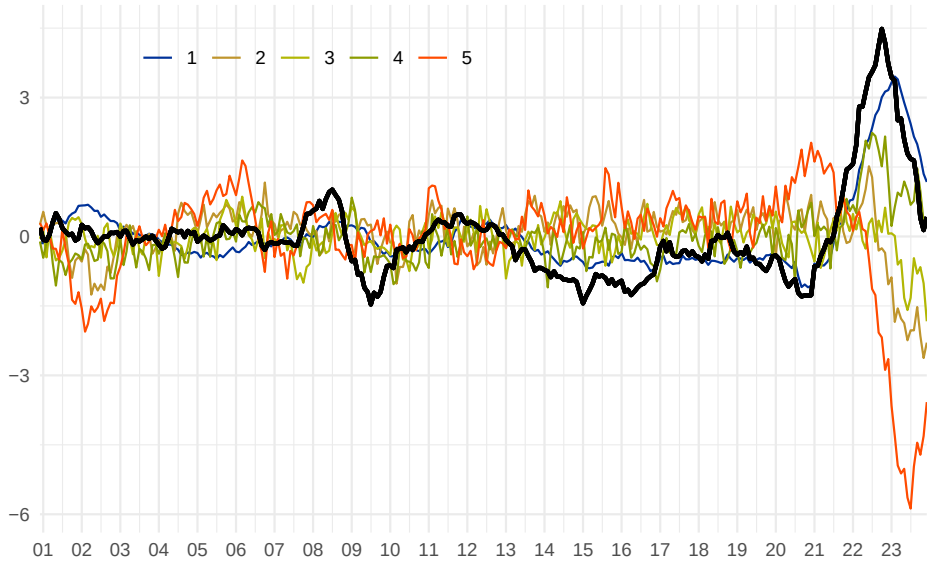


Note: each method has five components or factors: the loadings matrices' rows are grouped in five groups via a K-means algorithm. Loading values are not normalised and darker areas indicate smaller values.

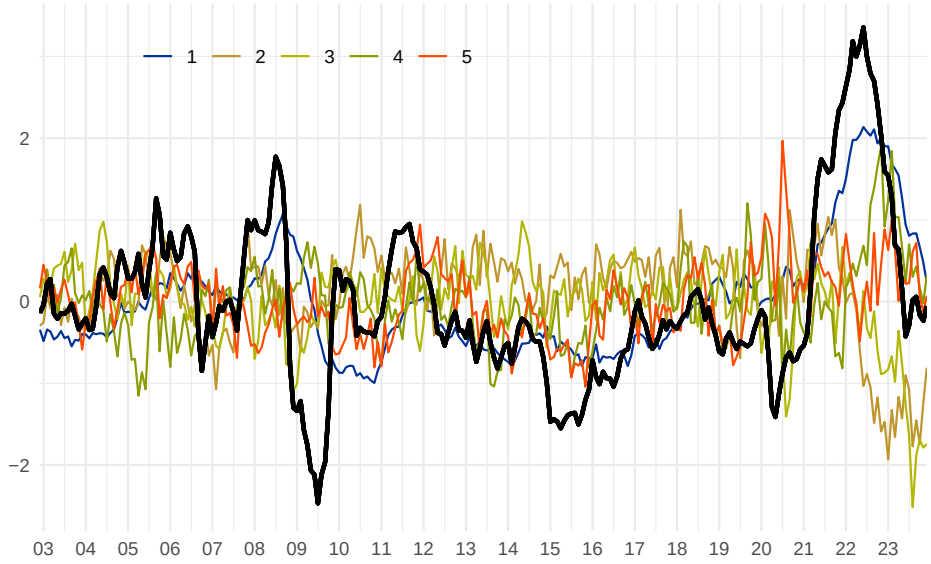
B Bayesian dynamic factor model with pure inflation restriction

Figure A3: Bayesian dynamic factor model – pure inflation restriction

(a) Euro area



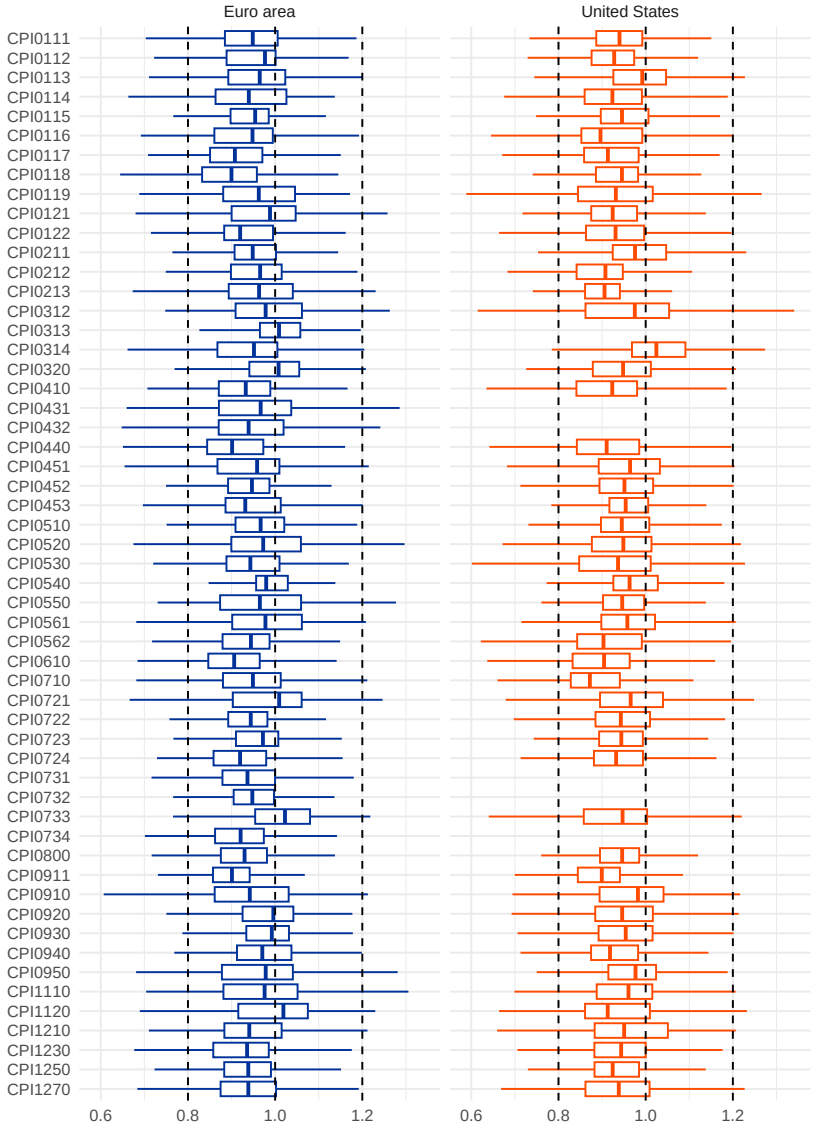
(b) United States



Note: Bayesian dynamic factor model for the US and EA HICP components. Five factors are estimated, with the first restricted to load equiproportionally on all items. $K \times K$ submatrix in the loadings matrix is also restricted to have positive elements on the diagonal, unrestricted elements on the lower triangular part, zero elements on the upper triangular part. The BDFM runs 14 chains with 5000 iterations of the NUTS sampler each, and discards the first half of these.

C Analysis of posterior distribution of the loadings to pure inflation

Figure A4: Distribution of posterior draws of restricted loadings $\lambda_{i,1}$



Note: Box plots based on posterior draws of the restricted loading $\lambda_{i,1}$ from the estimated Bayesian Dynamic Factor Model detailed in eq. 1, 2. In the boxplots, the central line marks the median, the outer edges of the box mark the first and third quartile, the outer lines cover observation 1.5 times the interquartile range above (below) the third (first) quartile. Dashed lines delimit the two-standard deviation area and the median of the normal prior for the restricted loadings, $\lambda_{i,1} \sim N(1, 0.1)$. The results are obtained by running 14 chains with 5000 iterations of the NUTS sampler each, discarding the first half.

Table A1: Posterior draws sorting – euro area

COICOP code	COICOP Label	Share
0111	Cereals	0.71
0112	Meat	0.73
0113	Fish	0.64
0114	Dairy and eggs	0.65
0115	Oils and fats	0.81
0116	Fruits and nuts	0.78
0117	Vegetables	0.84
0118	Sugar and sweets	0.85
0119	Other food	0.64
0121	Coffee, tea, cocoa	0.55
0122	Water, juices, soft drinks	0.76
0211	Spirits	0.73
0212	Wine	0.64
0213	Beer	0.61
0312	Garments	0.56
0313	Other clothing	0.46
0314	Cleaning and repair of clothing	0.73
0320	Footwear	0.45
0410	Rents	0.79
0431	Materials for dwelling maintenance and repair	0.61
0432	Services for dwelling maintenance and repair	0.71
0440	Water supply and other dwelling services	0.92
0451	Electricity	0.71
0452	Gas	0.81
0453	Liquid fuels	0.72
0510	Furniture	0.67
0520	Household textiles	0.61
0530	Household appliances	0.68
0540	Glassware, tableware etc	0.61
0550	Tools for house and garden	0.66
0561	Non-durable household goods	0.54
0562	Domestic and household services	0.79
0610	Medicines and health products	0.85
0710	Vehicles	0.68
0721	Parts for vehicles	0.47
0722	Fuels and lubricants for vehicles	0.78
0723	Maintenance and repair of personal vehicles	0.67
0724	Other services for personal vehicles	0.83
0731	Railway transport services	0.75
0732	Road transport services	0.76
0733	Air transport services	0.41
0734	Water transport services	0.81
0800	Communication	0.85
0911	Photo, audio and optical instruments	0.85
0910	Audio, video and information processing equipment	0.64
0920	Other recreational durables	0.52
0930	Recreational and garden products and pets	0.55
0940	Recreational services	0.65
0950	Newspapers, books	0.61
1110	Catering services	0.56
1120	Accommodation services	0.43
1210	Personal care	0.71
1230	Personal effects n.e.c.	0.80
1250	Insurance	0.79
1270	Other services	0.74

Notes: share of the posterior draws below 1 for the restricted loading $\lambda_{i,1}$. Perfect correspondence between prior and posterior median would give a 0.50 share. Draws are generated by 14 chains with 5000 iterations of the NUTS sampler each, with a 50% burn-in. Food, energy, NEIG and services are highlighted in different colors.

Table A3: Posterior draws sorting – United States

COICOP code	Label	Share
0111	Cereals	0.78
0112	Meat	0.85
0113	Fish	0.56
0114	Dairy and eggs	0.78
0115	Oils and fats	0.73
0116	Fruits and nuts	0.77
0117	Vegetables	0.78
0118	Sugar and sweets	0.83
0119	Other food	0.70
0121	Coffee, tea, cocoa	0.82
0122	Water, juices, soft drinks	0.76
0211	Spirits	0.58
0212	Wine	0.93
0213	Beer	0.92
0312	Garments	0.59
0314	Cleaning and repair of clothing	0.38
0320	Footwear	0.72
0410	Rents	0.81
0440	Water supply and other dwelling services	0.81
0451	Electricity	0.64
0452	Gas	0.72
0453	Liquid fuels	0.72
0510	Furniture	0.72
0520	Household textiles	0.68
0530	Household appliances	0.71
0540	Glassware, tableware etc	0.66
0550	Tools for house and garden	0.76
0561	Non-durable household goods	0.69
0562	Domestic and HH services	0.77
0610	Medicines and health products	0.88
0710	Vehicles	0.90
0721	Parts for vehicles	0.66
0722	Fuels and lubricants for vehicles	0.70
0723	Maint. and repair of personal vehicles	0.79
0724	Other services for personal vehicles	0.77
0733	Air transport services	0.74
0800	Communication	0.81
0911	Photo, audio and optical instruments	0.88
0910	Audio, video and information processing equipment	0.56
0920	Other recreational durables	0.68
0930	Recreational and garden products and pets	0.71
0940	Recreational services	0.79
0950	Newspapers, books	0.64
1110	Catering services	0.68
1120	Accommodation services	0.73
1210	Personal care	0.61
1230	Personal effects n.e.c.	0.75
1250	Insurance	0.81
1270	Other services	0.73

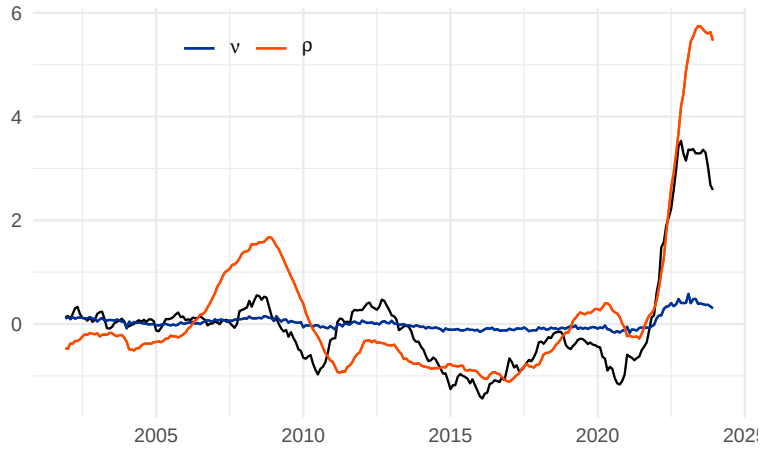
Notes: share of the posterior draws below 1 for the restricted loading $\lambda_{i,1}$. Perfect correspondence between prior and posterior median would give a 0.5 share. Draws are generated by 14 chains with 5000 iterations of the NUTS sampler each, with a 50% burn-in. Food, energy, NEIG and services are highlighted in different colours.

D Robustness checks

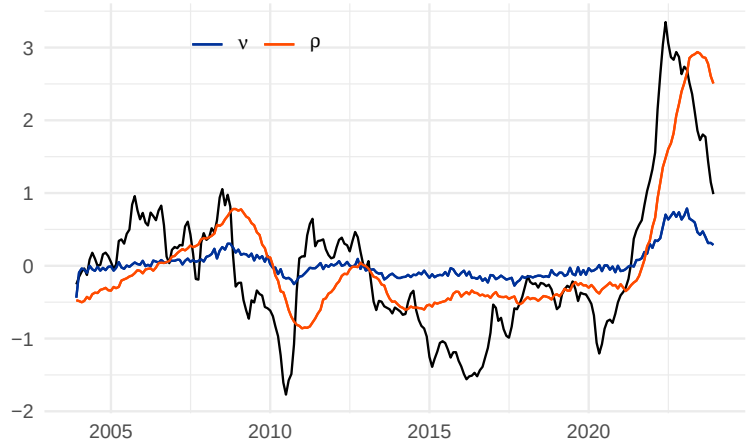
D.1 Impact of using two-year rather than year-on-year inflation rates

Figure A5: ν, ρ based on two-year inflation rates

(a) Euro area



(b) United States



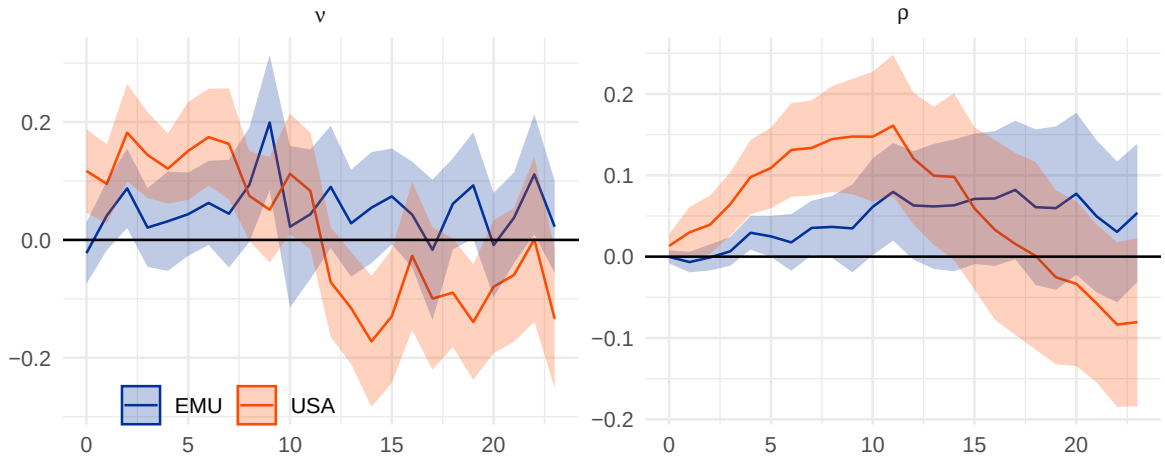
Note: headline inflation in black, pure inflation ν_t in blue and relative prices ρ_t in red. Results from a Bayesian dynamic factor model with static measurement equation and VAR(1) for the factors' state equation: ν and ρ are then derived as per eq. 7, on two-year inflation rates.

D.2 Känzig (2021) oil shocks

This appendix reports robustness results on the impact of oil shocks to using those produced by Känzig (2021). Crucially, Känzig (2021) focuses on supply shocks, and differentiate between news shocks – identified using high-frequency variation in oil future prices around OPEC announcements – and actual production shocks.

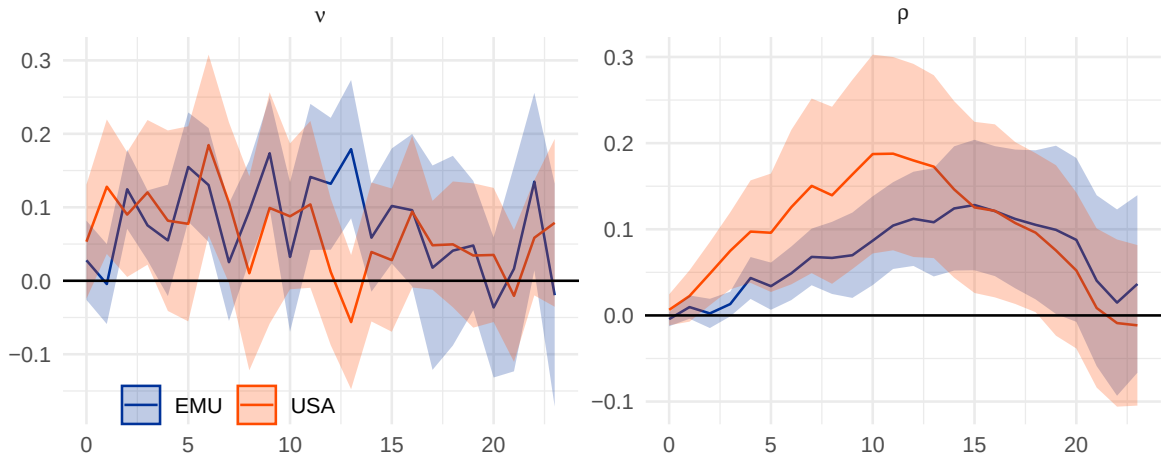
We test both negative shocks in Figures A6, A7: results do not change sensibly with respect to (mirrored) Figure 14 under these alternative shocks. With both shocks, US pure inflation shortly rises for about one year, then converges back to the baseline. EA pure inflation, on the other hand, does not react as much as its US equivalent, with fairly muted effects. Relative prices, similarly to Figure 14, are more reactive and rise quite significantly on impact, converging back to zero relatively quickly but with some heterogeneity. As in the baseline case, US ν and ρ rise and fall faster than their EA counterparts.

Figure A6: Cumulative IRF after an oil supply news shock



Note: Cumulative IRF of ν_t and ρ_t to a Känzig, 2021 oil supply news shock. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance.

Figure A7: Cumulative IRF after an oil supply shock



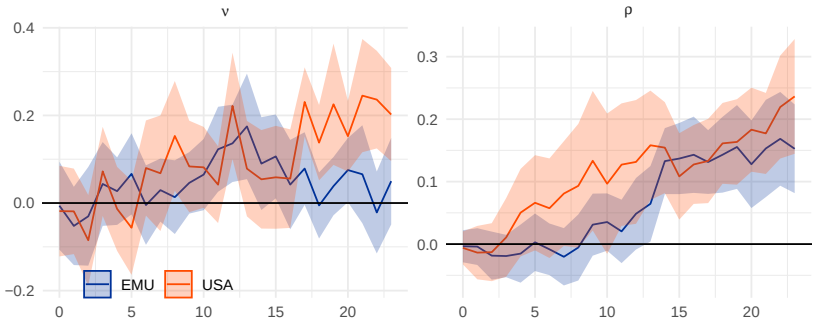
Note: Cumulative IRF of ν_t and ρ_t to a Känzig, 2021 oil supply shock. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance.

D.3 Pre-COVID sample

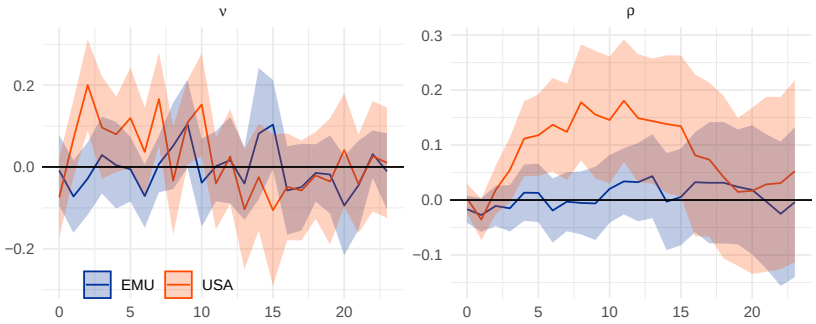
Our main sample covers the Covid period and the ensuing rise and fall of inflation, together with strong monetary and fiscal policy interventions. To assess the robustness of our results, this section presents results based only on data up to the end of 2019. The main message of our baseline results remains substantially unchanged.

Figure A8: CIRFs on pre-Covid sample – Baumeister and Hamilton (2019) shocks

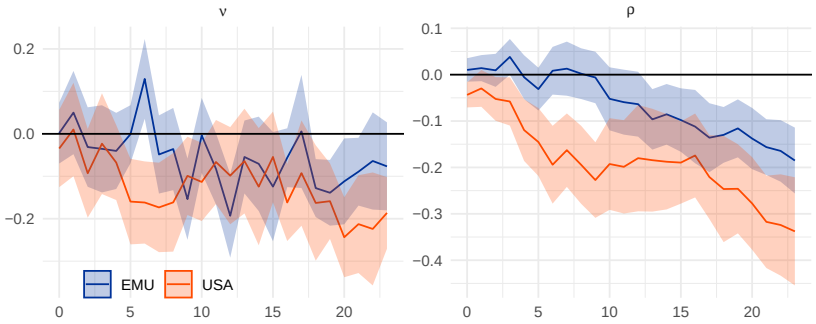
(a) Global activity



(b) Oil demand



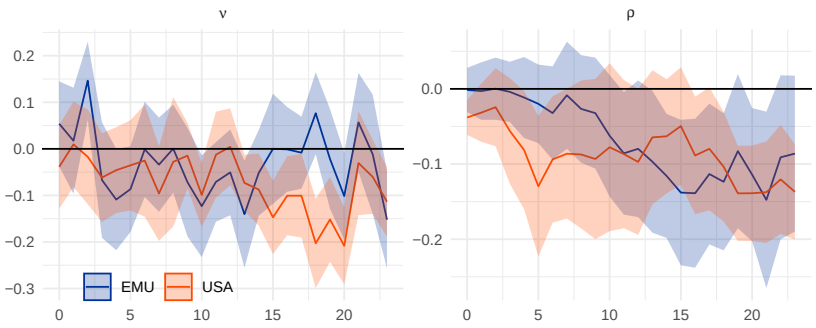
(c) Oil supply



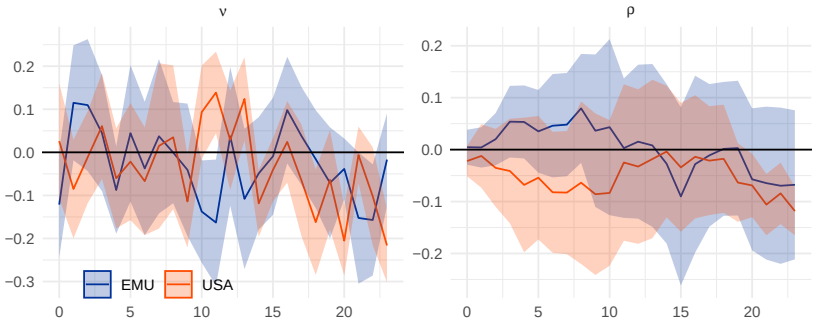
Note: Cumulative IRF of ν_t and ρ_t to a Baumeister and Hamilton, 2019 shocks. The bands indicate a 90% coverage. Shocks and series are rescaled to have zero mean and unit variance. ν and ρ estimated on the full sample, we then exclude observations later than December 2019

Figure A9: CIRFs on pre-Covid sample – monetary shocks

(a) ECB "poor-man's" shock identification – Jarociński and Karadi (2020)



(b) Fed "poor-man's" shock identification – Jarociński and Karadi (2020)



E Available COICOP classes

Code	**Divisions**	Groups	*Classes*
CPI0100	**Food and non-alcoholic beverages**		
CPI0110		Food	
CPI0111			*Bread and cereals*
CPI0112			*Meat*
CPI0113			*Fish and seafood*
CPI0114			*Milk, cheese and eggs*
CPI0115			*Oils and fats*
CPI0116			*Fruit*
CPI0117			*Vegetables*
CPI0118			*Sugar, jam, honey, chocolate and confectionery*
CPI0119			*Food products n.e.c.*
CPI0120		Non-alcoholic beverages	
CPI0121			*Coffee, tea and cocoa*
CPI0122			*Mineral waters, soft drinks, fruit and vegetable juices*
CPI0200	**Alcoholic beverages, tobacco and narcotics**		
CPI0210		Alcoholic beverages	
CPI0211			*Spirits*
CPI0212			*Wine*
CPI0213			*Beer*
CPI0220		Tobacco	
CPI0300	**Clothing and footwear**		
CPI0310		Clothing	
CPI0311			*Clothing materials*
CPI0312			*Garments*
CPI0313			*Other articles of clothing and clothing accessories*
CPI0314			*Cleaning, repair and hire of clothing*
CPI0320		Footwear	
CPI0400	**Housing, water, electricity, gas and other fuels**		
CPI0410		Actual rentals for housing	
CPI0430		Maintenance and repair of the dwelling	
CPI0431			*Materials for the maintenance and repair of the dwelling*
CPI0432			*Services for the maintenance and repair of the dwelling*
CPI0440		Water supply and miscellaneous services relating to the dwelling	
CPI0450		Electricity, gas and other fuels	
CPI0451			*Electricity*
CPI0452			*Gas*
CPI0453			*Liquid fuels*
CPI0454			*Solid fuels*
CPI0455			*Heat energy*
CPI0500	**Furnishings, household equipment and routine household maintenance**		
CPI0510		Furniture and furnishings, carpets and other floor coverings	
CPI0520		Household textiles	
CPI0530		Household appliances	
CPI0540		Glassware, tableware and household utensils	

CPI0550		Tools and equipment for house and garden
CPI0560		Goods and services for routine household maintenance
CPI0561		*Non-durable household goods*
CPI0562		*Domestic services and household services*
CPI0600	**Health**	
CPI0610		Medical products, appliances and equipment
CPI0620		Out-patient services
CPI0630		Hospital services
CPI0700	**Transport**	
CPI0710		Purchase of vehicles
CPI0720		Operation of personal transport equipment
CPI0721		*Spare parts and accessories for personal transport equipment*
CPI0722		*Fuels and lubricants for personal transport equipment*
CPI0723		*Maintenance and repair of personal transport equipment*
CPI0724		*Other services in respect of personal transport equipment*
CPI0730		Transport services
CPI0731		*Passenger transport by railway*
CPI0732		*Passenger transport by road*
CPI0733		*Passenger transport by air*
CPI0734		*Passenger transport by sea and inland waterway*
CPI0735		*Combined passenger transport*
CPI0736		*Other purchased transport services*
CPI0800	**Communications**	
CPI0810		Postal services
CPI0820		Telephone and telefax equipment
CPI0830		Telephone and telefax services
CPI0900	**Recreation and culture**	
CPI0910		Audio-visual, photographic and information processing equipment
CPI0911		*Equipment for sound and picture*
CPI0912		*Photographic and cinematographic equipment*
CPI0913		*Information processing equipment*
CPI0914		*Recording media*
CPI0915		*Repair of audio-visual, photographic, etc. equipment*
CPI0920		Other major durables for recreation and culture
CPI0930		Other recreational items and equipment, gardens and pets
CPI0940		Recreational and cultural services
CPI0950		Newspapers, books and stationery
CPI0960		Package holidays
CPI1000	**Education**	
CPI1100	**Restaurants and hotels**	
CPI1110		Catering services
CPI1120		Accommodation services
CPI1200	**Miscellaneous goods and services**	
CPI1210		Personal care
CPI1211		*Hairdressing salons and personal grooming establishments*
CPI1230		Personal effects n.e.c.
CPI1240		Social protection

CPI1250	Insurance
CPI1260	Financial services n.e.c.
CPI1270	Other services n.e.c.

Special aggregates

CPITOTL	**All-items HICP**
CPIGOOD	**Goods (overall index excluding services)**
CPINEIG	**Non-energy industrial goods**
CPIENRG	**Energy**
CPISERV	**Services (overall index excluding goods)**