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

Emanuele Franceschi, Chiara Osbat, Miles Parker
European Central Bank

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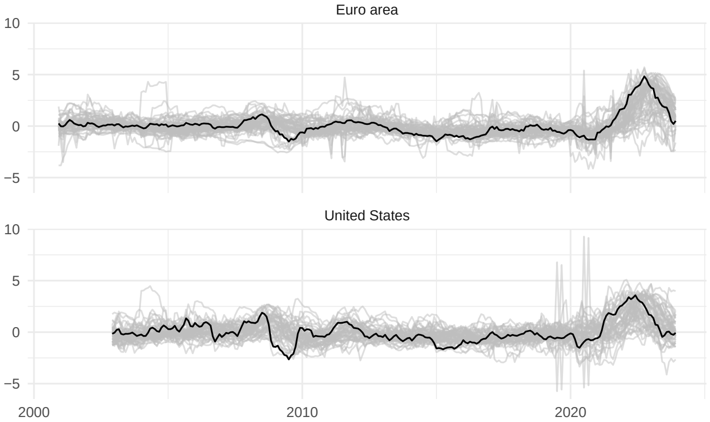
Aggregate and item inflation variability in HICPs



Headline HICP inflation and HICP item level inflation rates, rescaled year on year monthly rates.

Sectoral inflation rates

Pure inflation vs relative price changes

Research question:

- How to tell apart changes in relative prices from *pure* inflation?

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Policy relevance:

- How do sectoral and aggregate shocks affect pure inflation and relative prices?
- Should monetary policy respond to sectoral shocks?

Relation to existing literature

- **Aggregate inflation and relative prices:**
  - Old debate on relationship between aggregate inflation and higher moments of cross-sectional distribution: Ball and Mankiw 1995, Balke and Wynne 2000, Bryan and Cecchetti 1999
  - Explicitly disentangling "pure" inflation: Reis and Watson 2010, recently updated for USA by Ahn and Luciani 2021
- **Estimating the common trend or cyclical ("core") component of inflation:** Cristadoro et al. 2005, Mertens 2016, Stock and Watson 2016 (using dynamic factor models)
- **Diagnosing the sources of the post-2020 inflation surge:** Ruge-Murcia and Wolman 2022, Luo and Villar 2023, diGiovanni et al. 2023

An illustrative example of pure inflation

To fix ideas, consider a model with

i. multiple sectors, differing by price stickiness and productivity processes

ii. money growth rule and aggregate technological growth

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Then persistent shocks to (i) will move relative prices, persistent shocks to (ii) will move all *updating* prices in the same way:

An illustrative example of pure inflation

To fix ideas, consider a model with

i. multiple sectors, differing by price stickiness and productivity processes

ii. money growth rule and aggregate technological growth

Then persistent shocks to (i) will move relative prices, persistent shocks to (ii) will move all *updating* prices in the same way:

- absent other shocks, (ii) will progressively affect *all* prices in the same way

Detailed model & IRFs

Data and Method

Data

- Harmonised, CPI-basket item level data – 4-digit COICOP classes
- About 120 countries, average coverage of 55 classes each
- Monthly frequency, over 2000-2023

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Method

- Starting point: extract common components from large panel of time series
- Put restrictions on a Bayesian DFM to identify a "pure inflation" component
- Project inflation on this component, common relative prices and an idiosyncratic part

Why this approach

Building on Reis and Watson 2010:

- Estimate a dynamic factor model on many inflation sub-categories for the US – end of quarter on end of quarter
- Ad hoc factor: cross-sectional inflation
- Project factors into *pure inflation*, which loads uniformly, and *aggregate relative prices*.

Too many sample-specific specification choices to apply to 120 countries (our end goal).

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A more flexible approach:

- Monthly frequency and year-on-year inflation to account for heterogeneous price rigidity
- Loading restriction is a prior, so data can reject it

A Bayesian DFM with a "uniformity" restriction

Barebone state space representation of a dynamic factor model:

$$\pi_t = \Lambda F_t + \varepsilon_t$$
$$F_t = \Gamma F_{t-1} + \eta_t$$

where F_t is 5×1 and $\Lambda F_t = \mathbb{1} a_t + \gamma R_t$

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Factors identification restrictions follow Bai and Wang 2015

- Top $K \times K$ part of Λ is lower triangular and has strictly positive diagonal
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From 5 factors to pure (ν_t) and relative prices inflation (ρ_t)

$$\begin{aligned}
\nu_t =& a_t - E\left(a_t | F_{t-1}\right) \\
\rho_t =& E\left(F_t | R_{t-1}\right) \\
\text{so that} \quad \pi_t =& \nu_t + \beta \rho_t + u_t
\end{aligned}$$

BDFM Loadings ν, ρ details

Estimation details

$$
\begin{aligned}
\pi_t =& \Lambda F_t + \varepsilon_t \\
F_t =& \Gamma F_{t-1} + \eta_t
\end{aligned}
$$

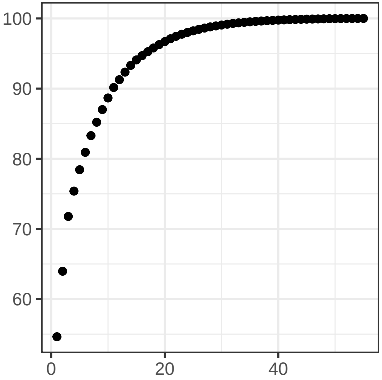
Priors

$$
\begin{aligned}
\boldsymbol{\pi_t} &\sim \boldsymbol{N}\left(\Lambda \boldsymbol{F_t}, \boldsymbol{Q_\epsilon}\right) \\
\boldsymbol{F_t} &\sim \boldsymbol{N}\left(\Gamma \boldsymbol{F_{t-1}}, \mathbb{1}_{\boldsymbol{K}}\right) \\
\Lambda &= \begin{bmatrix} \Lambda_{\boldsymbol{K}} \\ \Lambda_{\boldsymbol{N-K}} \end{bmatrix} \\
\Lambda_K &\sim \text{Chol. fact.} \\
\Gamma &\sim \boldsymbol{N}\left(0, 10\right)
\end{aligned}
$$

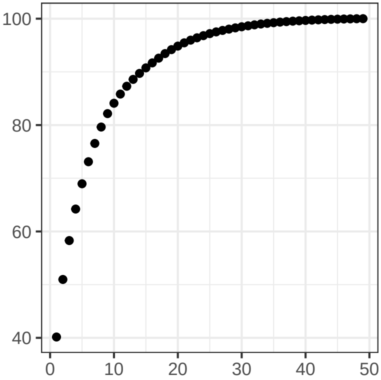
Setup

- NUTS sampler with mostly Gaussian priors
- 5000 total iterations, 50% burn-in inclusive of adaptation phase

Number of common factors



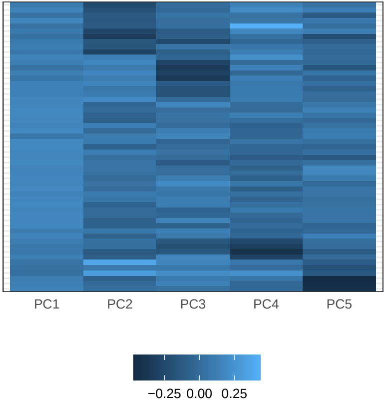
(a) EA



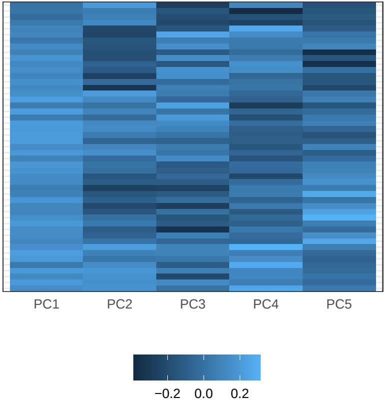
(b) US

Cumulative share of variance explained by principal components.

Uniform loading: Clustered PCA loadings



(a) EA, PCA

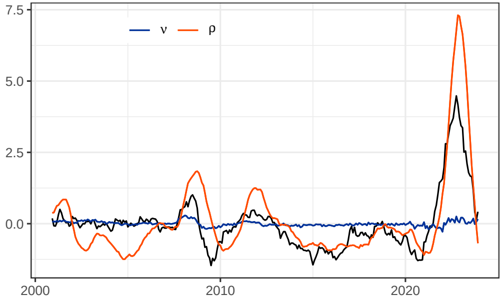


(b) US, PCA

Estimated loadings from PCA. Row-wise K-means clustering with 5 clusters.

Result 1: Separating pure inflation from relative price changes

$$\pi_t = \nu_t + \beta\rho_t + u_t$$



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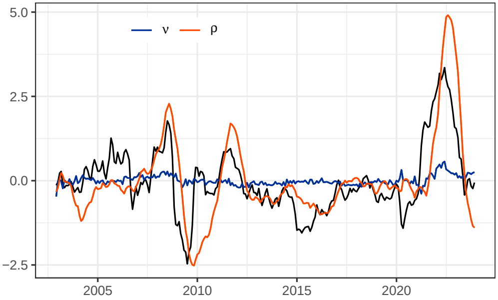


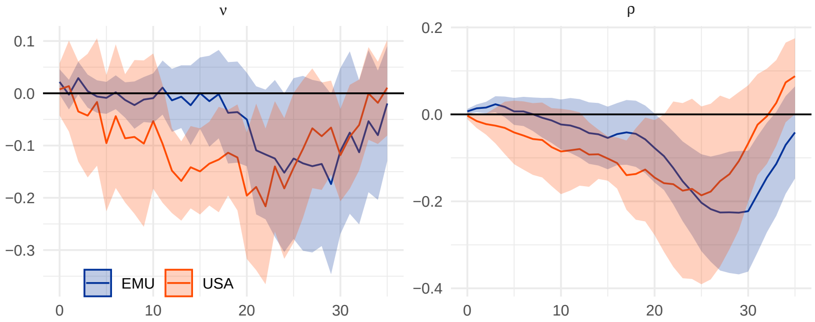
(b) US

Estimated ν_t (blue), ρ_t (red), and actual HICP (black)

Factors | Rob. two year π | Rob. synth data

Results 2: response to sectoral shocks: Global oil supply shocks

Figure: Cumulative impulse response function of ν_t and ρ_t to an oil supply shock

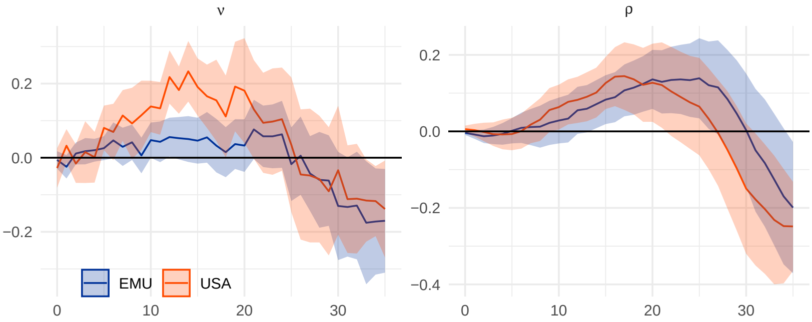


CIRFs after a **positive oil supply shock**. Shocks from Baumeister and Hamilton 2019, until December 2023. Shades mark 90% confidence intervals. Estimates from local projections.

Oil demand shock | Pre Covid sample | Kanzig 2021, news shocks | Kanzig 2021, production shocks

Results 2: response to aggregate shocks: traded/non-traded goods

Figure: Cumulative impulse response of ν_t and ρ_t to a global demand shock

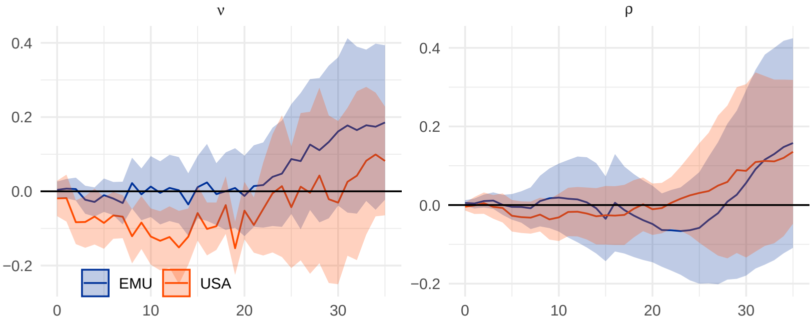


CIRFs after a **positive global demand shock** (economic activity shock from Baumeister and Hamilton 2019), until December 2023. Shades mark 90% confidence intervals. Estimates from local projections.

Pre Covid sample

Results 2: response to aggregate shocks: ECB monetary policy

Figure: Cumulative impulse response function of ν_t and ρ_t to an ECB mon. pol. shock

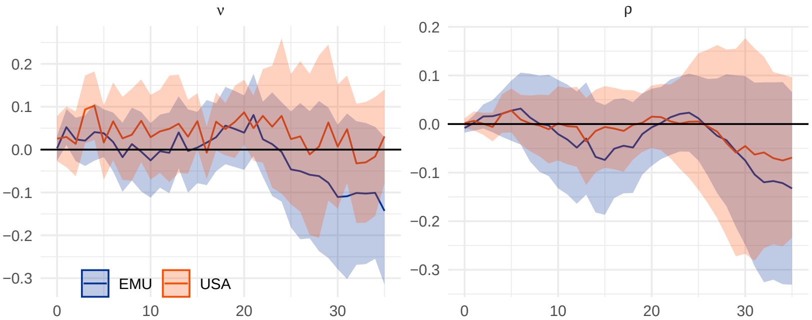


CIRFs after a **"poor man's" MP shock** from Jarociński and Karadi 2020, updated until June 2023. Shades mark 90% confidence intervals. Estimates from local projections.

Pre Covid sample

Results 2: response to aggregate shocks: Fed monetary policy

Figure: Cumulative impulse response function of ν_t and ρ_t to a Fed mon. pol. shock



CIRFs after a **"poor man's" MP shock** from Jarociński and Karadi 2020, updated until January 2024. Shades mark 90% confidence intervals. Estimates from local projections.

Fiscal spillover Pre Covid sample

Conclusions

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  - Enhance approach by Reis and Watson 2010 to accommodate heterogeneous price flexibility
- Do aggregate shocks only affect pure inflation or can they generate relative price changes?
  - Aggregate shocks are less relevant than sectoral ones
- What drives headline inflation in the euro area and the United States?
  - Relative prices are the bulk of inflation over the past $\sim$ 25 years
  - Even more so since 2021

The plan ahead

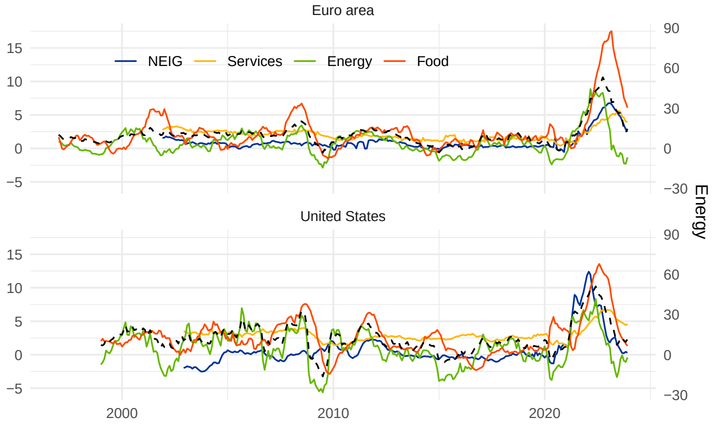
Current working areas:

- Documenting goodness of fit of alternative specifications
- Robustness to different numbers of factors and lag structures
- Incorporating model-based restrictions on IRF of pure and relative price inflation into estimation - how?
- US case study covering the '80s inflation
- Model with permanent shifts of expectations and money growth/monetary regime

Still work in progress, comments and suggestion are welcome!

Thank you!

A less granular view: HICP and its main components



Headline HICP inflation and sectoral inflation rates, year on year monthly rates. Energy rescaled on the right axis.

Back

Long run restriction

Intuition: the long-run effect of MP shocks is zero on pure inflation.

- Add an appropriate observed series, S, in the state equation $F_t = \Gamma F_{t-1} + \eta_t$
- for two factors, the first capturing pure inflation

$$\begin{bmatrix} S_t \\ F_{1,t} \\ F_{2,t} \end{bmatrix} = \Gamma \begin{bmatrix} S_{t-1} \\ F_{1,t-1} \\ F_{2,t-1} \end{bmatrix} + \begin{bmatrix} \eta_{S,t} \\ \eta_{F_1,t} \\ \eta_{F_2,t} \end{bmatrix}$$

- Then in the long run $F_{t,\infty} = (I - \Gamma)^{-1} \eta_t$ with the following restrictions

$$Q\eta_t = (I - \Gamma)^{-1} \eta_t = \begin{bmatrix} * & 0 & 0 \\ 0 & * & 0 \\ * & * & * \end{bmatrix} \begin{bmatrix} \eta_{S,t} \\ \eta_{F_1,t} \\ \eta_{F_2,t} \end{bmatrix}$$

- How to sample Q and ensure Γ makes the VAR stable?

Back

Model-based intuition

Consider a slightly modified version of Ghassibe 2021, which has

- Sectorally heterogeneous price rigidity
- Input/output intermediates supply network
- Consumption shares
- $M = PC$

Set of transitory/permanent shocks

- Money, aggregate TFP
- Sectoral TFP

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Set of transitory/permanent shocks

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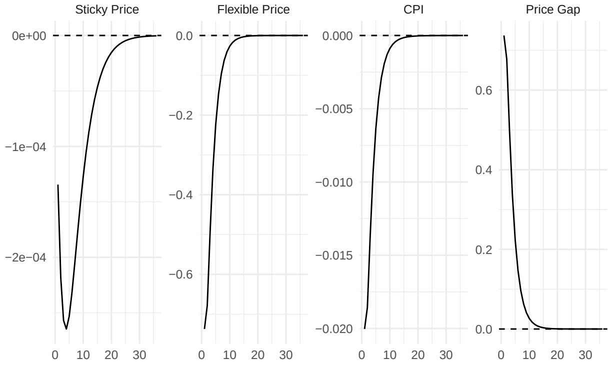
The model helps to

- Understand how not only sectoral, but also aggregate shocks show up in relative prices
- Test our empirical approach

Back

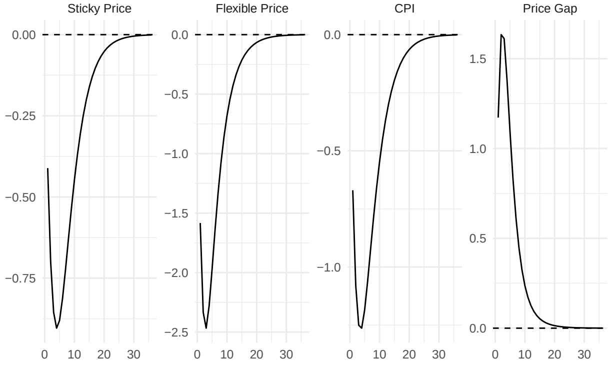
Temporary sectoral TFP shock



IRFs of a 1% SD sectoral TFP shock on the flexible and upstream sector. The price gap the log-difference between the sticky and flexible price.

Back

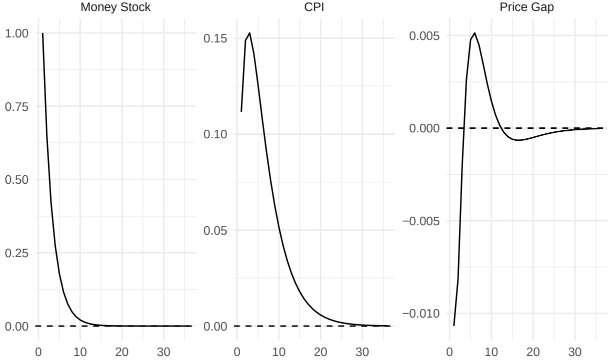
Temporary aggregate shocks – Technology



IRFs of a 1SD TFP shock. “Sticky Price” is a downstream sector whose prices adjust infrequently; “Flexible Price” is an upstream sector with very frequent price adjustment. The price gap is the log-difference between the sticky and flexible price.

Back

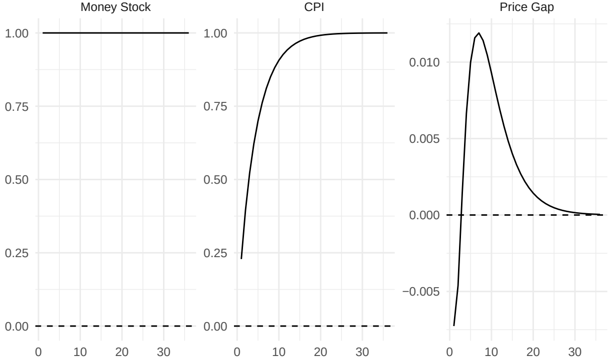
Temporary aggregate shocks – Monetary policy shock



IRFs of a 1% money stock increase from steady state. The price gap is the log-difference between the sticky and flexible price.

Back

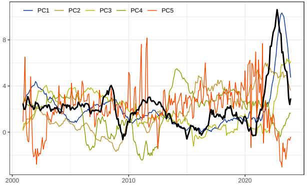
Persistent monetary shock



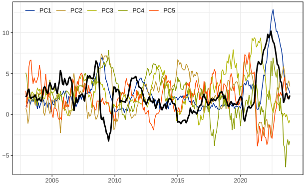
IRFs of a 1% persistent money stock increase from steady state. The price gap is the log-difference between the sticky and flexible price.

Back

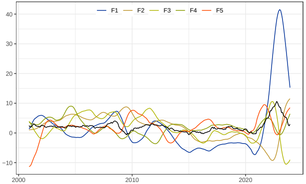
A look at the first 5 common factors using PCA and DFM



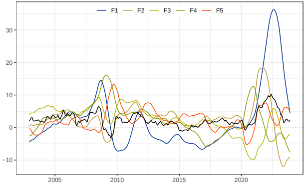
(a) EA, PCA



(b) US, PCA



(c) EA, DFM

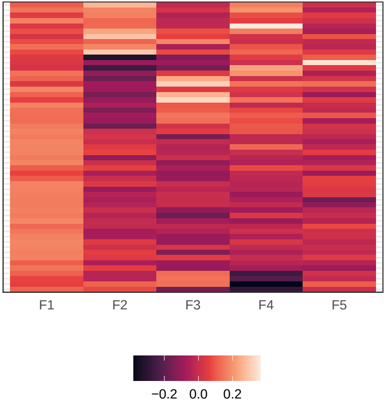


(d) US, DFM

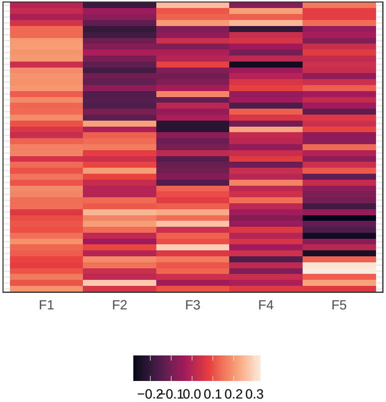
Principal Components and Dynamic Factors estimates.

Back

Clustered loadings – DFM



(a) EA, DFM

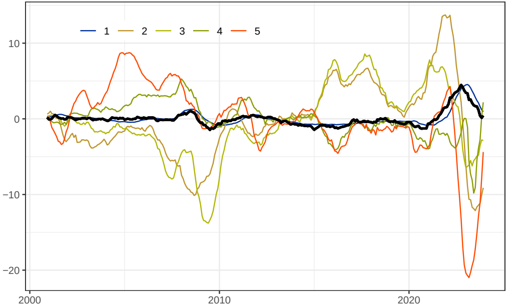


(b) US, DFM

Estimated loadings from DFM, using Doz, Giannone, and Reichlin 2012 approach. Row-wise K-means clustering with 5 clusters.

Back

Estimated Factors



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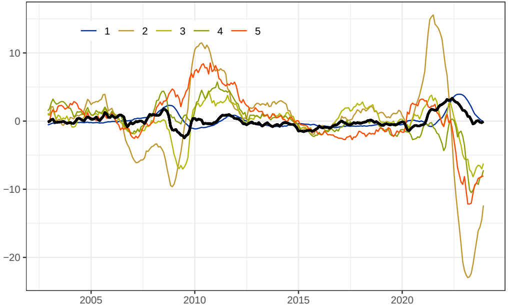
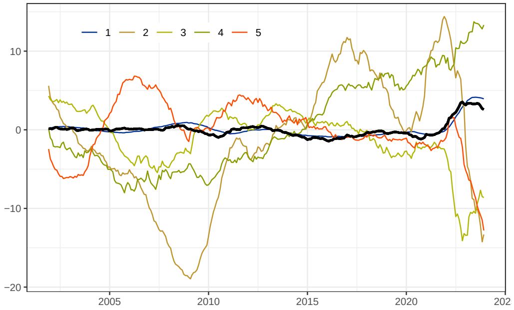


(b) US

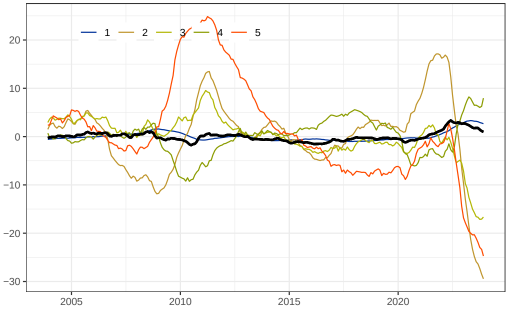
Estimated factors from the BDFM. First factor's loading restricted to be close to one.

Back

Estimated Factors



(a) EA

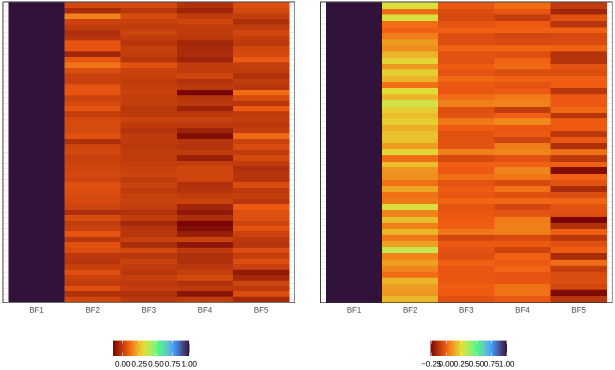


(b) US

Estimated factors from the BDFM on 2 years inflation rates. First factor's loading restricted to be close to one.

Back

Estimated loadings – BDFM

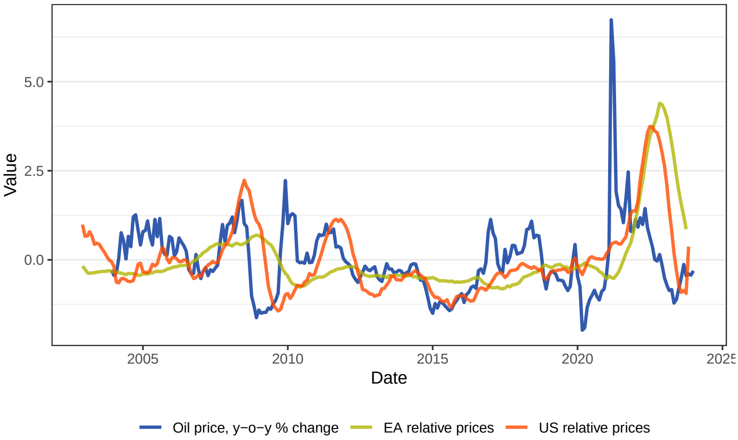


(a) EA (b) US

Loadings heatmap: median values of the posterior distributions.

Back

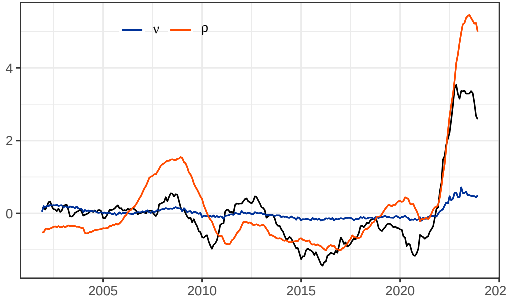
Oil price inflation and estimated relative price components



Oil price and estimated relative price components

Result 1: Robustness to a longer time lag

$$\pi_t = \nu_t + \beta \rho_t + u_t$$



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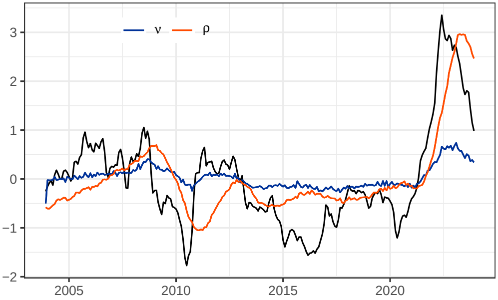
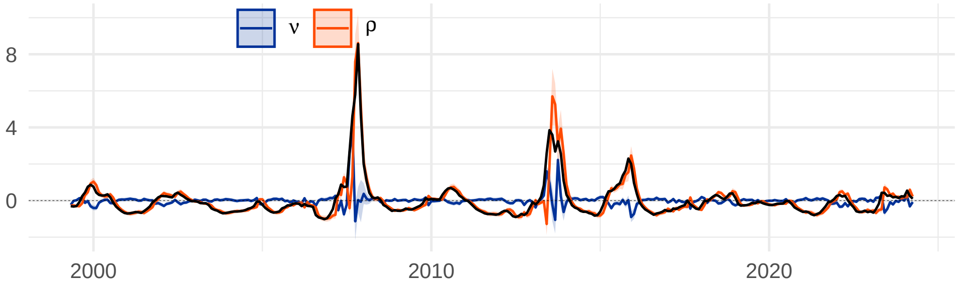


(b) US

Estimated ν_t (blue), ρ_t (red), and actual HICP (black)

Back Factors

Check on artificial data from the theoretical model

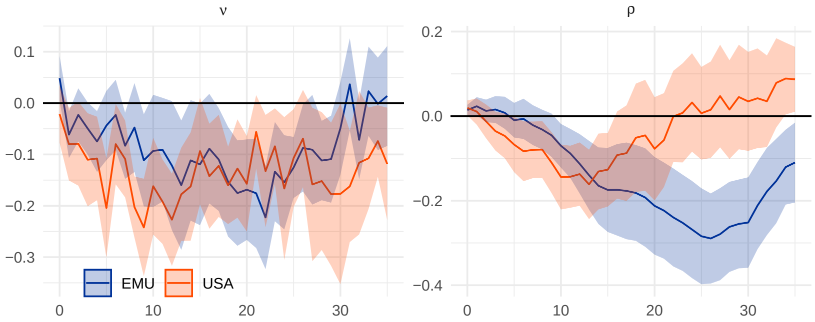


Estimates of ν (blue, pure inflation) and ρ (red, relative prices) on simulated data from Ghassibe 2021. Inflation data are centered and scaled.

Back Simulated HICP

Pre-Covid robustness: Global oil supply shocks

Figure: Cumulative impulse response function of ν_t and ρ_t to an oil supply shock



CIRFs after a **positive oil supply shock**. Shocks from Baumeister and Hamilton 2019, until December 2019. Shades mark 90% confidence intervals. Estimates from local projections.

Back

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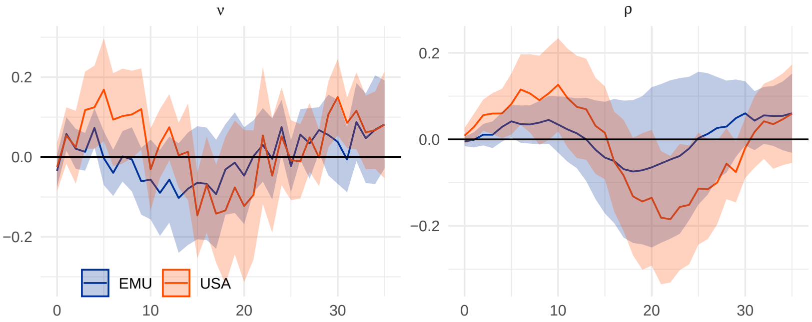

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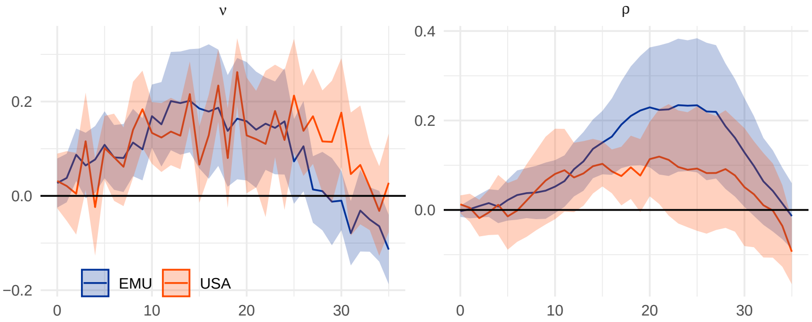
Back

Pre-Covid robustness: traded/non-traded goods

Figure: Cumulative impulse response of ν_t and ρ_t to a global demand shock



CIRFs after a **positive global demand shock** (economic activity shock from Baumeister and Hamilton 2019), until December 2019. Shades mark 90% confidence intervals. Estimates from local projections.

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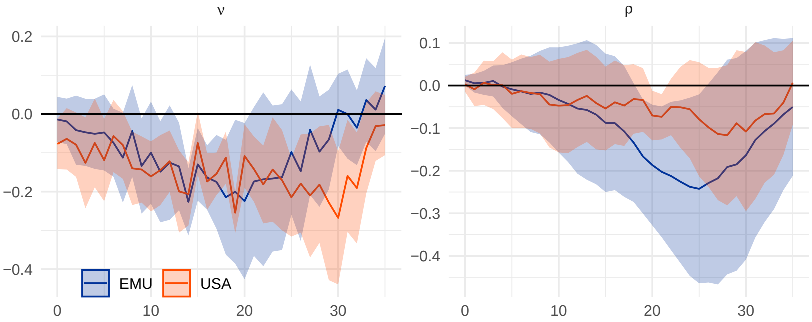
Pre-Covid robustness: ECB monetary policy

Figure: Cumulative impulse response function of ν_t and ρ_t to an ECB mon. pol. shock

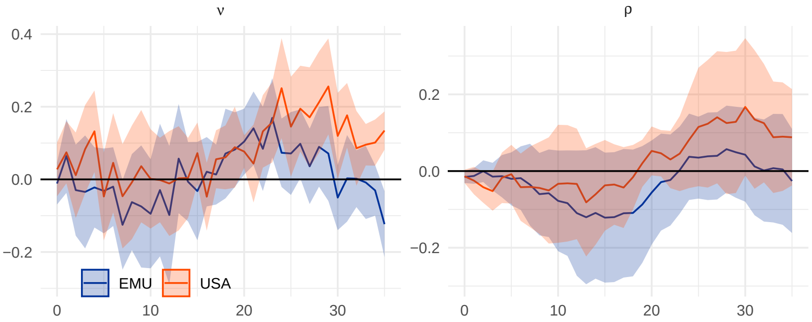


CIRFs after a **"poor man's" MP shock** from Jarociński and Karadi 2020, updated until December 2019. Shades mark 90% confidence intervals. Estimates from local projections.

Back

Pre-Covid robustness: Fed monetary policy

Figure: Cumulative impulse response function of ν_t and ρ_t to a Fed mon. pol. shock

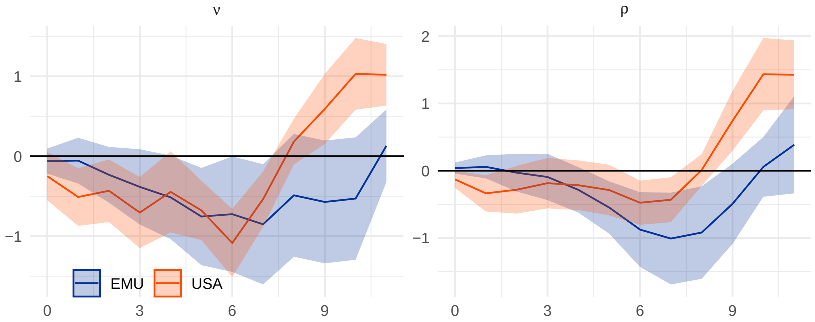


CIRFs after a **"poor man's" MP shock** from Jarociński and Karadi 2020, updated until December 2019. Shades mark 90% confidence intervals. Estimates from local projections.

Back

Results 2: shocks spillover: crude US fiscal policy

Figure: Cumulative impulse response function of ν_t and ρ_t to a US fiscal policy shock

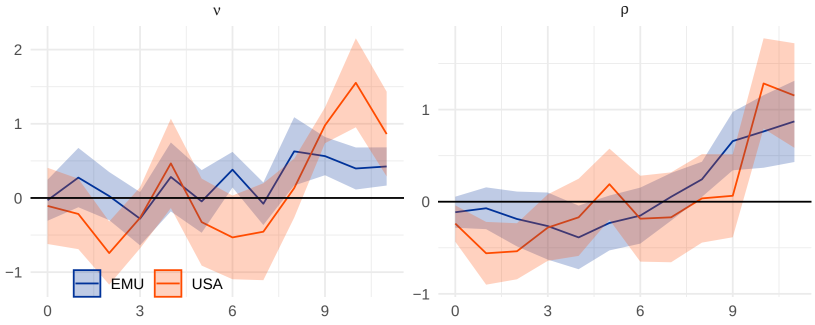


CIRFs after a "crude" US fiscal shock, computed as percentage deviation of local and federal spending from SPF estimates. Shades mark 90% confidence intervals. Estimates from local projections.

Back Pre Covid sample

Pre-Covid robustness: crude US fiscal policy

Figure: Cumulative impulse response function of ν_t and ρ_t to a US fiscal policy shock

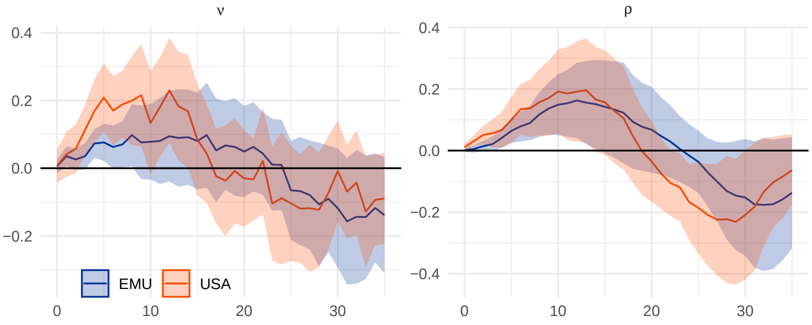


CIRFs after a "crude" US fiscal shock, computed as percentage deviation of local and federal spending from SPF estimates. Shades mark 90% confidence intervals. Estimates from local projections.

Back

Results 2: response to sectoral shocks: Global oil demand shocks

Figure: Cumulative impulse response function of ν_t and ρ_t to an oil demand shock

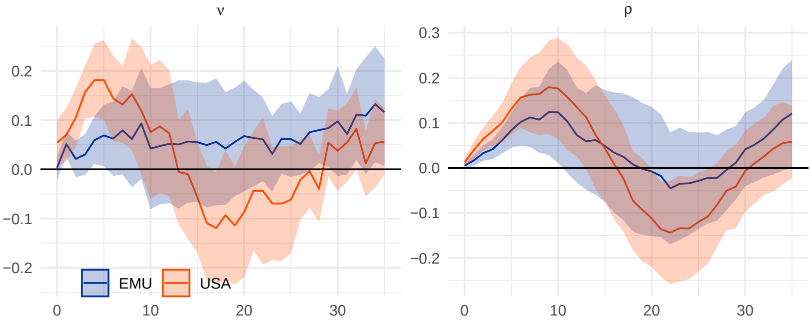


CIRFs after a **positive oil demand shock**. Shocks from Baumeister and Hamilton 2019, until December 2023. Shades mark 90% confidence intervals. Estimates from local projections.

Back
Pre Covid sample

Robustness: Oil supply news shocks

Figure: Cumulative impulse response function of ν_t and ρ_t to an oil supply news shock

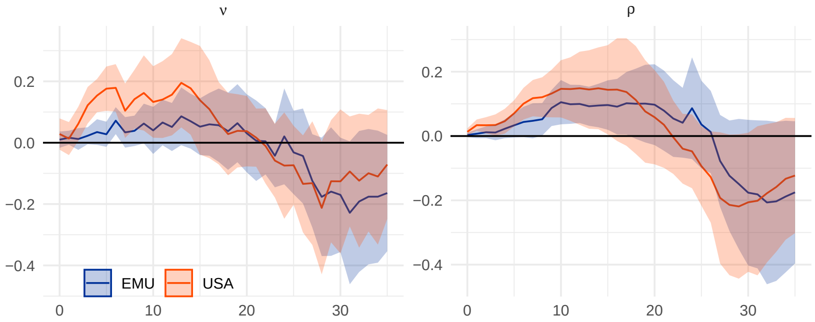


CIRFs after a **restrictive oil supply news shock**. Shocks from Kanzig 2021, until June 2023. Shades mark 90% confidence intervals. Estimates from local projections.

Back

Robustness: actual oil supply shock

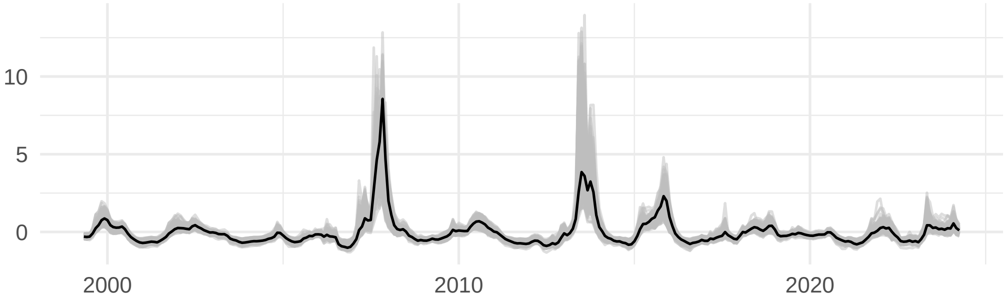
Figure: Cumulative impulse response function of ν_t and ρ_t to an oil supply shock



CIRFs after a **restrictive oil supply shock**. Shocks from Kanzig 2021, until June 2023. Shades mark 90% confidence intervals. Estimates from local projections.

Back

Check on artificial data from the theoretical model



Simulated data from Ghassibe 2021: 161 sectors with input/output intermediate goods network, three degrees of price rigidity, differing final consumption shares. 300 periods in total at monthly frequency. Black solid line is aggregate HICP, grey shaded lines are sector-level inflation rates.

Back

Computing ν and ρ

With the estimated factors f_k in F, the matrix Γ with elements γ_{ij}, and observed inflation π

$$\nu_t = f_{1,t} - \sum_{k=1}^{K} f_{k,t-1}\gamma_{1,k}$$

$$\rho_t = F_{-1}\hat{\beta} + \sum_{k=1}^{K} f_{k,t-1}\gamma_{1,k}$$

with

$$F_{-1} = (f_2' \quad f_3' \quad f_4' \quad f_5')'$$

and

$$\hat{\beta} = \left(F_{-1}'F_{-1}\right)^{-1} F_{-1}'(\pi - \nu)$$

Back