What drives the recent surge in inflation?

The historical decomposition roller coaster.

Drago Bergholt[†], Fabio Canova[‡,⋆],

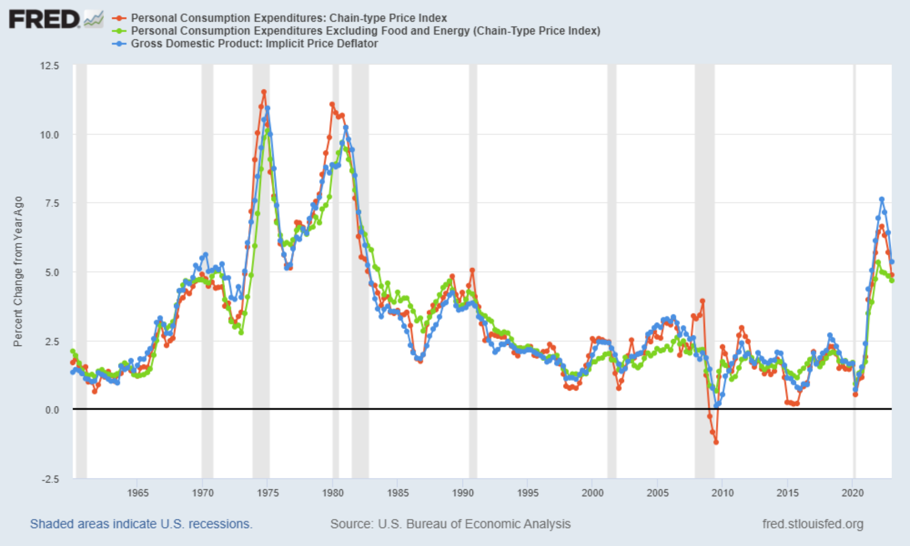
Francesco Furlanetto[†,‡], Nicolò Maffei-Faccioli[†], Pål Ulvedal[†,∗]

[†]Norges Bank, [‡]BI Norwegian Business School, [⋆]CEPR, [∗]Nord University

Structural Changes and the Implications for Inflation
May 7-8, 2024

Disclaimer: the views expressed in this presentation are those of the authors and do not necessarily reflect those of Norges Bank

The surge in US inflation: unseen in the last 40 years



Motivation I

What drives the recent inflation surge?

- Supply vs. demand factors
- Important policy implications

Rapidly growing literature:

- Bernanke and Blanchard (2024), Benigno and Eggertsson (2024), Shapiro (2023), Eickmeier and Hofmann (2022), Ascari et al. (2023), Friis et al. (2023), Cerrato and Gitti (2022), Mori (2024)
- Most analyses use:
    - Structural Vector Autoregressive (SVAR) models
    - Historical shock decompositions

Motivation II

This paper: Important pitfall in computing historical decompositions in standard SVARs

- The **large uncertainty** around the deterministic components of the VAR make inference whimsical
- Point related to Sims (1993, 1996 and 2000) and Giannone, Lenza and Primiceri (GLP) (2019)
- We highlight a new aspect of the problem

Road map

- Describe the nature of the problem. Independent of:
  - The identification scheme
  - The prior selection
  - The VAR dimension, see Canova and Ferroni (2022)
  - The sample size
- Propose solutions:
  - Single-unit-root prior, see Sims (1993)
  - Data treatment pre-estimation
  - Median historical decomposition
- Answer the question “what drives US post-Covid inflation?”
- Look at evidence from other countries

The problem

A Baseline SVAR

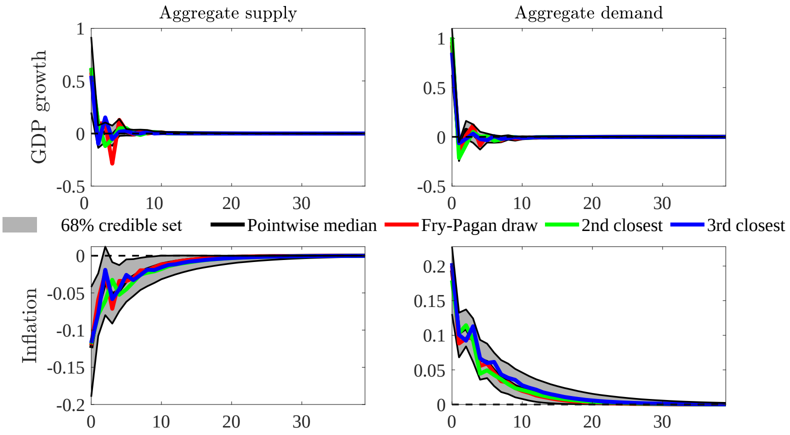
$$Y_t = C + \sum_{i=1}^{p} A_i Y_{t-i} + u_t,$$

- $Y_t = \begin{bmatrix} \Delta y_t & \pi_t \end{bmatrix}$ where Δy_t is Real GDP growth; π_t is GDP deflator inflation
- US data; sample 1983Q1-2022Q4
- $p = 4$ lags; diffuse prior

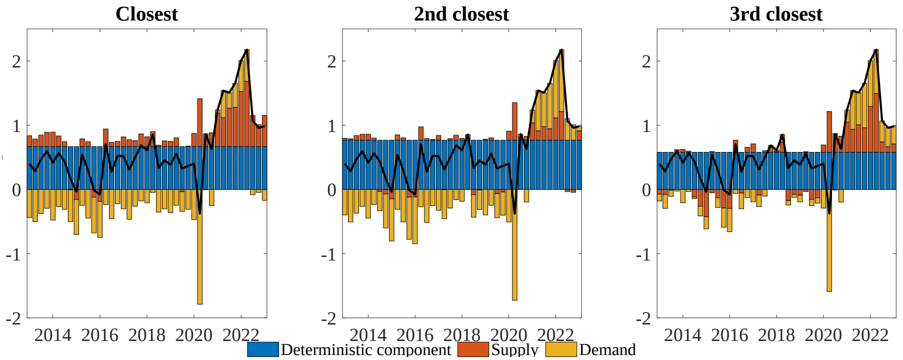
Contemporaneous sign restrictions

	Supply	Demand
Δ GDP	+	+
Inflation	-	+

IRFs: pointwise median and 3 (Fry-Pagan) draws



HDs of inflation based on the same 3 draws



- Indistinguishable IRFs, but different HDs! Why?

Deterministic and stochastic components in VARs

A (companion form) VAR(1):

$$Y_t = C + AY_{t-1} + u_t$$

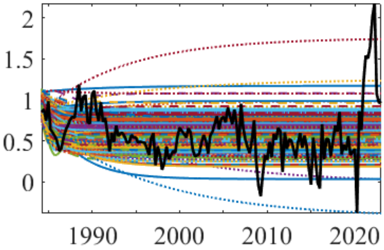
Iterating backwards:

$$\begin{aligned} Y_t &= \underbrace{(I + A + A^2 + \cdots + A^{t-1})C + A^t Y_0}_{\text{Deterministic components}} \\ &+ \underbrace{A^{t-1}u_1 + \cdots + Au_{t-1} + u_t}_{\text{Stochastic components}} \\ &\equiv DC_t + SC_t \end{aligned}$$

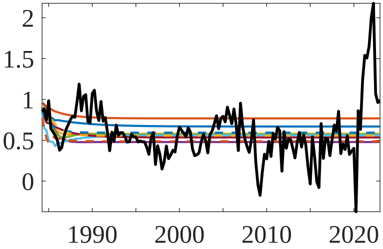
- DC_t is the component of Y_t predictable at time 0.
- $u = Fe_t$, F identification matrix.

The deterministic component of inflation

All posterior draws

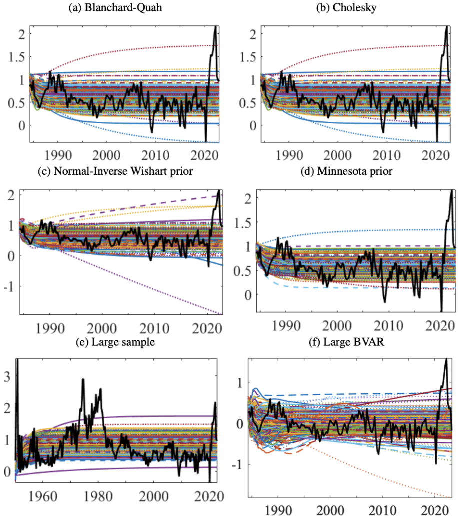


10 models closest to median IRFs



Deterministic components dispersed! They settle to a different level!

Different specifications, same issue



Takeaways

- Need HDs to shed light on the sources of the recent inflation surge.
- Similar IRFs may generate vastly different HDs!
  - Large dispersion in DC $\rightarrow$ large dispersion in SC

Conclusions independent of:

- identification assumptions
- VAR priors
- the dimensionality of the VAR
- the sample size (a larger sample may include a break)

Q1: Why are deterministic components dispersed?

Q2: How can we solve the problem?

A simulation exercise

Simulate data from two bivariate VAR(1) models:

$$Y_t = C + AY_{t-1} + u_t$$

Less persistent

$$A = \begin{pmatrix} 0.6 & -0.3 \\ 0.3 & 0.4 \end{pmatrix}$$

$$C = \begin{pmatrix} 0.4 \\ 0.5 \end{pmatrix}$$

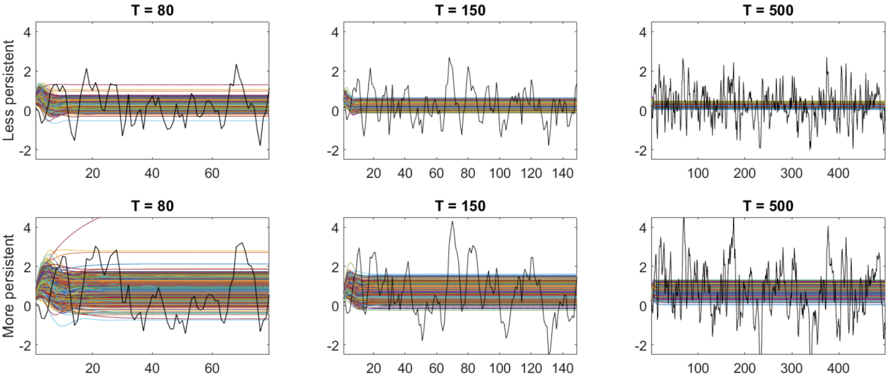
More persistent

$$A = \begin{pmatrix} 0.95 & -0.3 \\ 0.3 & 0.4 \end{pmatrix}$$

$$C = \begin{pmatrix} 0.4 \\ 0.5 \end{pmatrix}$$

- Use T=500, 150, and 80.
- Study the properties of estimates of deterministic components.

Deterministic components of y_1: Diffuse prior



- Problem more relevant for small T and persistent process.

Solutions

A single-unit-root prior á la Sims (1993)

Add artificial observation to the beginning of the sample: both current and lagged data given by $\frac{1}{\delta}\bar{Y}_0$, intercept set to $\frac{1}{\delta}$

- $\bar{Y}_0$ is set to the sample mean.
- δ set maximizing the marginal likelihood.

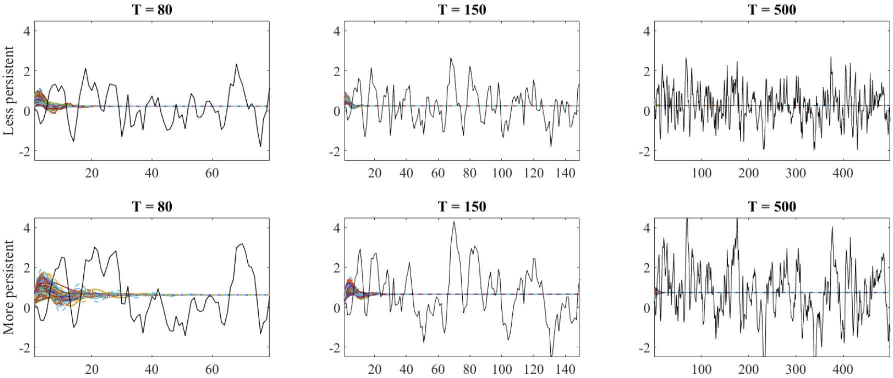
The stochastic constraint imposed by artificial observation on the VAR model

$$[I - A]\,\bar{Y}_0 - C = \delta u_0$$

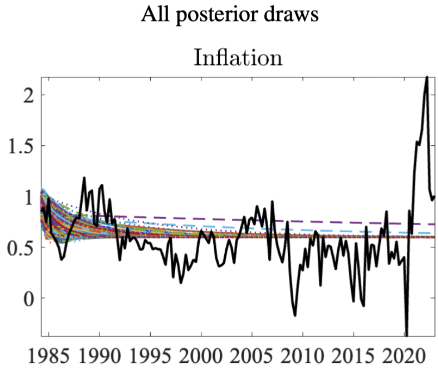
Implying

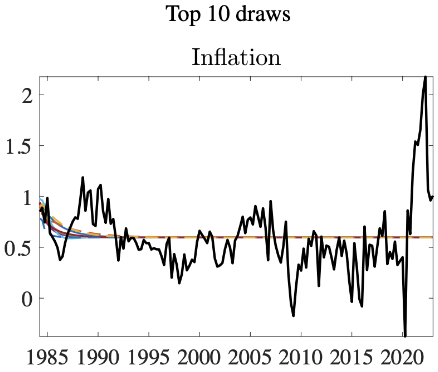
$$DC_t = (A^t(Y_0 - \bar{Y}_0 + (I - A)^{-1}\delta u_0) + \bar{Y}_0 - (I - A)^{-1}\delta u_0))$$

SUR prior in the simulation exercise revisited

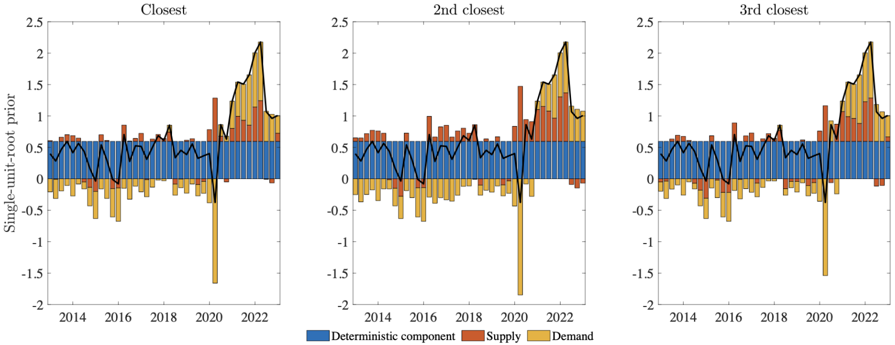


SUR prior applied to US inflation data





HD of US inflation with SUR prior



- Similar deterministic components imply similar HD
- About 2/3 of the recent inflation surge due to demand factors

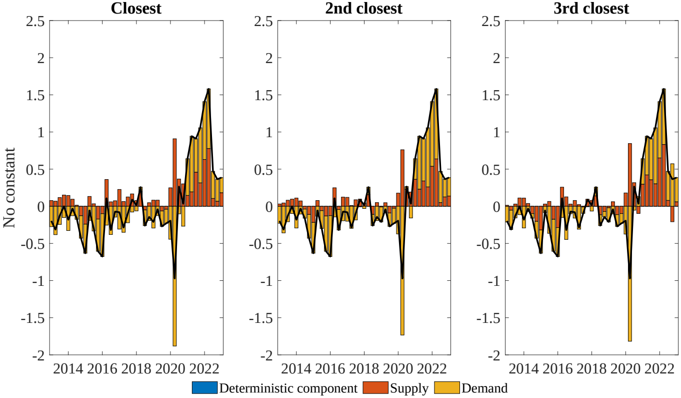
Alternative I: De-meaning of the VAR

By de-meaning the data and estimating the VAR without a constant:

$$\hat{Y}_t = \underbrace{A^t \hat{Y}_0}_{\text{Deterministic components}} + \underbrace{A^{t-1} u_1 + \cdots + A u_{t-1} + u_t}_{\text{Stochastic components}}$$

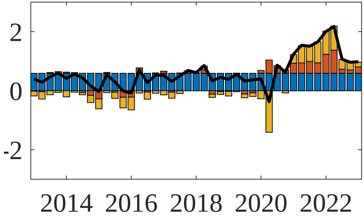
The term $(I + A + A^2 + \cdots + A^{t-1})C$ disappears!

HD of inflation: de-meaned data

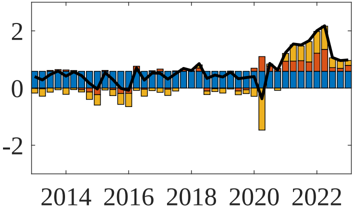


Alternative II: median historical decomposition

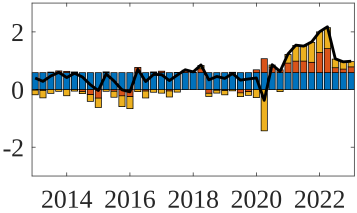
Diffuse prior



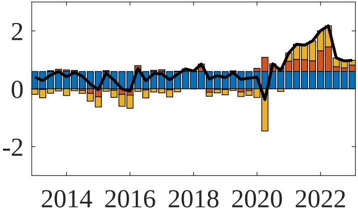
Normal-Inverse Wishart prior



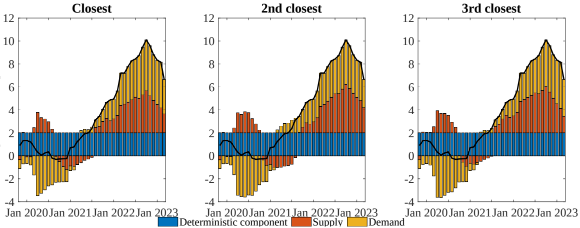
Minnesota prior



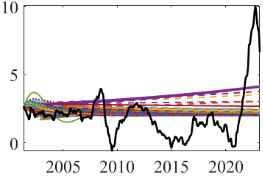
Single-unit-root prior



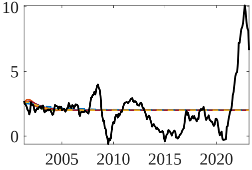
Euro area: SVAR estimated using the single-unit-root prior



All posterior draws



Top 10 draws



Overfitting vs. excess volatility

Overfitting: flat-prior VARs attribute an implausibly large share of the variation in observed time series to their deterministic components

- problem arises with stationary variables when initial values are distant from their steady state
- leads to marked temporal heterogeneity

Excess volatility: *uncertainty* around the estimated deterministic components, not to their *level*.

Important: excess volatility can easily manifest itself even when the overfitting problem is relatively minor

Insight: SUR prior, initially designed for overfitting, is even more effective at dealing with excess volatility

Conclusions

- Large dispersion in estimates of the deterministic component. Problem more relevant for persistent variables and small samples.
- Posterior draws with similar IRFs may generate different HDs.
- Potential solutions:
  - Add single-unit-root prior
  - Demean the data and estimate a VAR without a constant
  - Compute median historical decomposition
- Around 2/3 of the recent US inflation surge is driven by demand factors and 1/3 by supply factors.
- Demand factors are also important drivers of the surge in inflation in many other countries.

EXTRA SLIDES

Sign restrictions

- Why sign restrictions?
    - Meaningful and mutually exhaustive distinction between supply and demandshocks.
    - Cholesky: no structural interpretation.
    - Blanchard-Quah: problematic when demand shocks may have long run effects, Furlanetto, et al. (2023).

Different identification schemes

- Sign-restricted SVARs are set identified. Use point identification schemes to eliminate additional layer of uncertainty.
- Blanchard-Quah decomposition, restriction on the cumulative response.

	Supply	Demand
Δ GDP	x	0
Inflation	x	x

- Cholesky decomposition, restriction on impact.

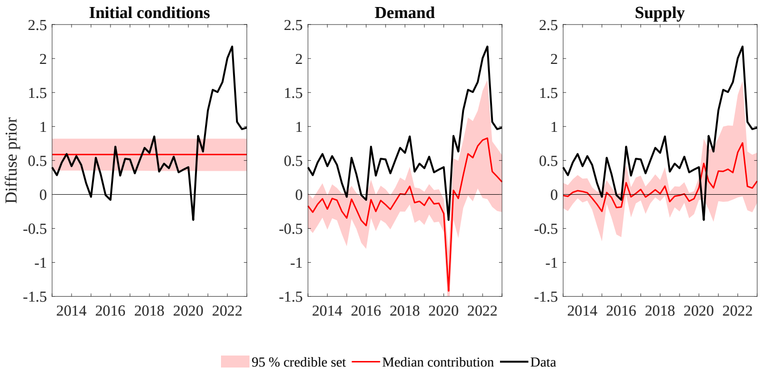
	Supply	Demand
GDP	x	0
Inflation	x	x

Informative priors

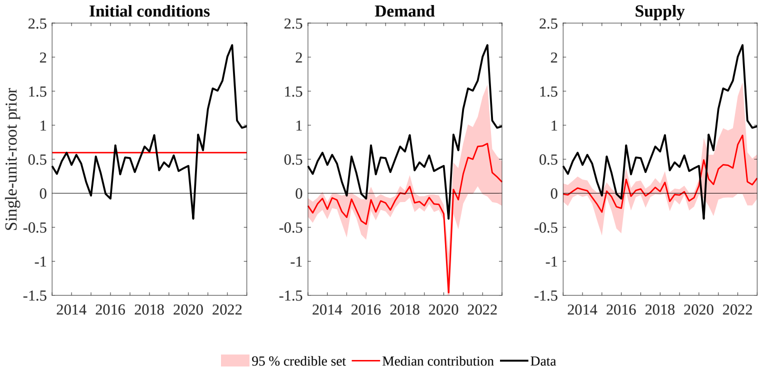
- Informative priors helps to reduce estimation uncertainty.
- Do they also help to reduce historical decomposition uncertainty?

1. Normal-Inverse Wishart prior
   - A normal prior for the AR parameters centered at zero with a diagonal covariance matrix of 10.
   - A inverse Wishart prior for the covariance matrix of the residuals with a unitary diagonal matrix as scale and n+1 degrees of freedom.
2. Minnesota prior
   - A normal prior centered at zero for all AR coefficients, including the variables' first own lag
   - The overall tightness is optimized, as in Giannone et al. (2015)

Uncertainty surrounding historical decomposition for diffuse prior

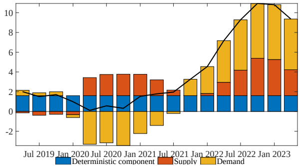


Uncertainty surrounding the historical decomposition of inflation, SUR prior

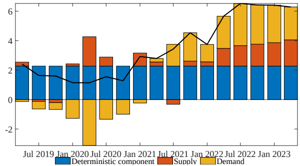


Historical decompositions in selected countries

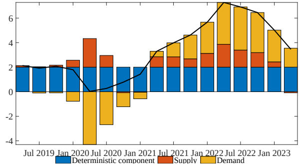
Sweden



Norway



Canada



Australia