# What drives the Recent Surge in Inflation? The historical decomposition roller coaster*

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**Abstract:** What drives the inflation surge in the post Covid period? To answer this question, one must decompose observable fluctuations into the contributions due to structural shocks. We document how whimsical an *historical shock decomposition* can be in standard vector autoregressive models. Neglecting the uncertainty surrounding the deterministic component of the model implies implausible behavior for shocks over history under general conditions. Our favorite approach to solve the problem, the single unit prior, shrinks the massive uncertainty around the deterministic components toward their sample mean values. With such a prior and a standard sign-identified VAR, demand shocks are the main drivers of the current inflation surge, both in the United States and in the euro area.

**Keywords:** *Bayesian vector autoregression, initial conditions, single unit root prior, inflation dynamics.*
**JEL Classification:** *C11, C32, E32.*

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# 1 Introduction

Motivation After a long period of low and stable inflation, the outlook has suddenly changed in the aftermath of the COVID pandemic and most countries have seen inflation rates reaching unprecedented levels since the late 1970s. In the US, the GDP deflator started rising at the end of 2020 and peaked at 9.1 percent in 2022:Q2. In the euro area, inflation was in negative territory at the end of 2020 before rising sharply in 2021 and 2022, and peaking around 10 percent on an annual basis. In some European countries the annual inflation rate exceeded 15 percent in 2022. Initially, supply disruptions associated with the pandemic-induced reallocation of economic activity across sectors were thought to be the cause of the rise in inflation. However, the emergence of a historically tight labor market (as measured, e.g., by the vacancy-to-unemployment rate) and the fast recovery in the employment-to-population ratio have shifted the attention towards demand factors, in particular, as the result of the massive monetary and fiscal stimulus implemented by central banks and national governments. Needless to say, disentangling demand and supply factors is crucial since a proper policy response may be highly dependent on the nature of the impulses driving the inflation surge.

A natural way to disentangle demand and supply shocks is to rely on flexible time-series models such as Vector Autoregressions (VAR). These models are routinely employed for understanding key features of the data and for evaluating the state of the macroeconomic environment, both retrospectively and prospectively (see Crump et al. (2021)). Equipped with some identification assumptions, these models are also used to disentangle structural shocks with the most natural partitioning, in this case, being between demand and supply shocks. With the resulting structural shocks one can decompose fluctuations in macroeconomic variables over histories. Thus, structural VAR (SVAR) models deliver a decomposition that allows one to quantify the relative importance of demand and supply shocks for the recent inflation surge.

Contribution This paper highlights an important pitfall when computing historical decompositions which, as far as we know, has not been discussed in literature. Suppose that a researcher wishes to quantify the role of demand and supply factors for inflation in the post-COVID period. A SVAR decomposes inflation into a deterministic and a stochastic component. The deterministic component represents the counterfactual evolution of inflation absent shocks and is regulated by the parameters of the reduced-form model and by the initial values of the variables of the VAR.[1] The stochastic component, in contrast, represents the component of inflation fluctuations due to realized demand and supply shocks. Historical shock decompositions are routinely computed using median estimates of the parameters and the exclusive focus of applied researchers is on the drivers of the deviations of the series from the estimated deterministic component. Our key contribution is to show that there is considerable uncertainty around the point estimate of thedeterministic component which crucially translates into large uncertainty in historical decompositions. This specific type of uncertainty is largely ignored in the literature and may make the economic interpretation whimsical.

Most empirical applications of SVAR models focus on uncertainty present in the

[1]The deterministic component is often referred as "the initial conditions" in the literature, see Giannone et al. (2019).

impulse-response functions, which is routinely reported. When computing impulse responses, it is common to focus attention on the dynamics induced by one draw from the posterior distribution to provide a measure of central tendency; for example, Fry and Pagan (2011) select the posterior draw which is closest to the point-wise median. However, posterior draws that exhibit "good" impulse responses (meaning impulse responses close to the pointwise median) may feature extreme deterministic components and thus provide a distorted historical decomposition because shocks have to match the gap between the inflation series and the estimated deterministic component. To put this result in another way, there is no guarantee that "good" impulse response functions are associated with "good" historical decompositions.

We show that the problem is pervasive and is present in SVAR models featuring different dimensions, different prior distributions, different identification assumptions and different sample sizes. In fact, the uncertainty in the deterministic component we highlight is associated with the estimation of the reduced-form parameters and is therefore completely independent, e.g., from the identification scheme used to transform reduced-form residuals into structural shocks. The issue appears in a largely homogeneous sample like our baseline (1983-2023) for the United States and it is exacerbated if we use a longer sample (1949-2022), which is subject to considerable instabilities.

After highlighting the pitfall in the computation of historical decompositions, and showing with a simple Monte Carlo exercise that sample size and the persistence of the process matter for the uncertainty we highlight, we turn our attention to potential solutions. We show that standard prior assumptions about the parameters of the VAR are unable to solve the problem. Our favorite approach consists in using a specific prior distribution, the single-unit-root prior, also known as the "dummy initial observations prior", introduced by Sims (1993). Such a prior shrinks the deterministic component of each variable of the VAR to resemble its sample mean. We estimate the tightness of such a prior using the approach of Giannone et al. (2015) and obtain a rather small value, implying tight prior restrictions. As a result, a SVAR estimated with the single-unit prior features almost no uncertainty around the deterministic component. Hence, draws featuring similar impulse-response functions will also feature similar historical decompositions. While the use of the single-unit-root prior is not new, Its ability to reduce the massive uncertainty around the historical decomposition has not been highlighted in the literature.

For those researchers who are reluctant in using a prior for inferential purposes, we offer two alternative pragmatic solutions. The first is demeaning the data before estimation. Such an approach in part addresses the problem since poor estimates of the VAR constant contribute to making the problem important. The second alternative is to construct a *median* historical decomposition along the lines of Fry and Pagan (2011), thus taking account the entire set of historical decompositions as in Bergholt et al. (2023). Such an approach will not solve the problem of uncertainty related to initial conditions but will, at least, take into account such uncertainty when computing the summary measure for the historical decomposition.

We apply our solutions to analyze the drivers of the current inflation boom. When we estimate the SVAR on US data with diffuse priors, we find substantial uncertainty around the deterministic component of inflation. In addition, the Fry-Pagan draw and the next two closest draws deliver three totally different historical decompositions despite exhibiting almost identical impulse responses: one draw implies a prevalent role for supply shocks, one a prevalent role to demand shocks and one a balanced role for both shocks. When we apply the single unit prior to the same SVAR, the uncertainty around the deterministic component shrinks dramatically and draws leading to similar impulse responses are also associated with similar historical decompositions of inflation. Notably, demand shocks are prevalent over the sample and more so over the last few years. In the US, demand shocks account for 56 percent of inflation fluctuations in 2021 and 77 percent in 2022; in the euro area demand shocks account for 55 percent of inflation fluctuations in 2022. This result is remarkable since the euro area is substantially more exposed than the US to the Ukraine war, an important supply shock.

RELATED LITERATURE Our work contributes to two separate strands of the literature. First, we complement existing work warning about the mechanical use of SVARs, see e.g. Canova and Ferroni (2022) for a recent contribution.

While other papers have studied the role of the initial conditions (and their pathological behavior, see e.g. Sims (1996) and Sims (2000)), we believe that our point is novel. One common problem discussed in the literature is that initial conditions tend to explain an implausibly large share of the low frequency variation of the data (the so-called overfitting problem), yielding inaccurate out-of-sample forecasts. Giannone et al. (2019) discuss the issue in detail and propose a prior (the prior for the long run) based on long-run theoretical predictions of macroeconomic models that addresses the overfitting problem. While such solution relates to a measure of central tendency of the initial conditions, the problem of their high dispersion is still present, making interpretation of historical shock decomposition problematic, even within this framework.

We also contribute to the recent debate on the drivers of the inflation boom. Shapiro (2022) provides a decomposition of demand-driven and supply-driven inflation based on sectorial data without, however, identifying structural shocks. Eickmeier and Hofmann (2022) estimate a factor model using a large number of inflation and real activity series and find that the recent inflation dynamics in the US are driven mainly by strong demand and to a lesser extent also by tight supply factors. Ascari et al. (2023) estimate a Bayesian SVAR on Euro area data and find a crucial role for demand factors since the fall 2020. Rubbo (2023) disentangles cross-sectional demand and supply disruptions from aggregate stimulus policies and finds that three quarters of the increase in CPI since 2021 is driven aggregate demand. Cerrato and Gitti (2022) rely on data from metropolitan statistical areas to derive a cross-sectional estimate of the slope of the Phillips curve during, before and after COVID and find that the Phillips curve has steepened substantially after COVID. di Giovanni et al. (2023) focus on the impact of fiscal policy on current inflation in a multi-sector model with a network structure while Gagliardone and Gertler (2023) emphasize the role of oil shocks and accommodative monetary policy in a New Keynesian model. Ball et al. (2022) find that the very high levels of labor market tightness over 2021–2022 can explain much of the rise in monthly core inflation, especially during 2022. The rest of the rise is explained by a substantial pass-through of headline inflation shocks into core inflation. All in all, our emphasis on demand factors is consistent with the findings of these papers. We contribute with a methodological point on the importance of obtaining a more robust interpretation of the historical decomposition of inflation.

OUTLINE The paper proceeds as follows: Section 2 illustrates the problem. Section 3 proposes our solution based on the single unit prior and Section 4 presents two alternative pragmatic solutions. Finally, Section 5 concludes.

# 2 ILLUSTRATING THE PROBLEM

This section discusses how large uncertainty present in the initial conditions may arise in a VAR model, and demonstrates the implications for estimated historical decompositions. We also present evidence that the issue may be pervasive when VAR models are fitted to commonly used macroeconomic data.

## 2.1 VAR MODEL

Consider the following reduced-form VAR model:

$$Y_t = C + A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + u_t \tag{1}$$

where $u_t \sim N(0_n, \Sigma)$ is a $n \times 1$ vector of the reduced-form innovations, $Y_t$ is a $n$ x 1 vector of the $n$ endogenous variables, $A_1, ..., A_p$ are $n$ x $n$ matrices of coefficients associated to the $p$ lags of the dependent variable $Y_t$ and $C$ is a $n$ x 1 vector of constants.

We can transform model (1) into a VAR(1) by using the companion form representation. Define $\mathbf{Y_t} = (Y_t, Y_{t-1}, ..., Y_{t-p+1})'$, $\mathbf{u_t} = (u_t, 0, ..., 0)'$, $\mathbf{C} = (c_1, ..., c_n, 0, ..., 0)'$ and construct the following $np$ x $np$ companion matrix:

$$\mathbf{A} = \begin{bmatrix} A_1 & A_2 & ... & ... & A_p \\ I_n & \mathbf{0}_n & ... & ... & \mathbf{0}_n \\ \mathbf{0}_n & I_n & ... & ... & \mathbf{0}_n \\ \mathbf{0}_n & \mathbf{0}_n & I_n & ... & \mathbf{0}_n \\ . & . & . & ... & . \\ . & . & . & ... & . \\ . & . & . & ... & . \\ \mathbf{0}_n & \mathbf{0}_n & ... & I_n & \mathbf{0}_n \end{bmatrix} \tag{2}$$

Then $(1)$ can be rewritten as:

$$\mathbf{Y_t} = \mathbf{C} + \mathbf{A}\mathbf{Y_{t-1}} + \mathbf{u_t} \tag{3}$$

Substituting backwards, we obtain:

$$\mathbf{Y_t} = (I + \mathbf{A} + \mathbf{A}^2 + \cdots + \mathbf{A}^{t-1})\mathbf{C} + \mathbf{A}^t\mathbf{Y_0} + \mathbf{A}^{t-1}\mathbf{u_1} + \cdots + \mathbf{A}\mathbf{u_{t-1}} + \mathbf{u_t}$$

where $\mathbf{A}^t\mathbf{Y_0}$ are the initial conditions, and together with $(I + \mathbf{A} + \mathbf{A}^2 + \cdots + \mathbf{A}^{t-1})\mathbf{C}$ constitute the **deterministic component** of the model. $\mathbf{A}^{t-1}\mathbf{u_1} + \cdots + \mathbf{A}\mathbf{u_{t-1}} + \mathbf{u_t}$ is instead the **stochastic component** of the model, i.e. the part explained by the different shocks. The deterministic component can be interpreted as the forecast made at time $t = 0$, of $\mathbf{Y_t}$ given $Y_0$ and values for $\mathbf{C}$, $\mathbf{A}$.

To illustrate the problem of interest it is convenient to use a simple bi-variate VAR(4) estimated on US data on Real GDP growth and the growth rate of the GDP deflator over

Table 1: Sign restrictions imposed on impact

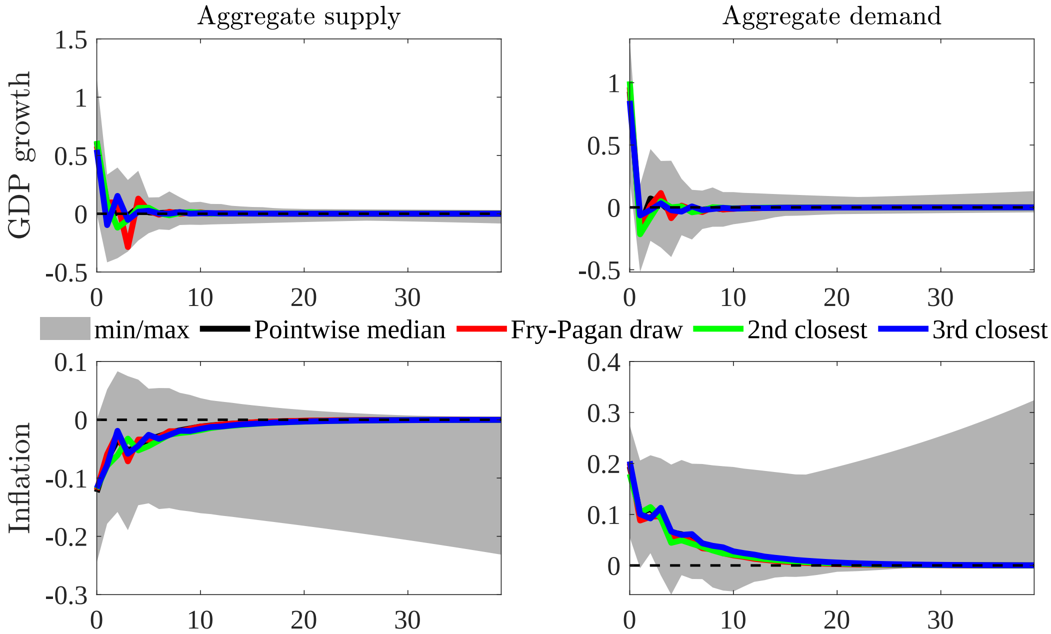
| | Aggregate supply | Aggregate demand |
|---|---|---|
| $\Delta$ GDP | + | + |
| Inflation | - | + |

the sample 1983:Q1 to 2022:Q4. We use Bayesian techniques and a diffuse prior (Jeffreys, 1946) to obtain posterior estimates of the VAR parameters and the covariance matrix $\Sigma$.

Two structural shocks are identified using impact standard sign restrictions as in Canova and DeNicolo (2002): an aggregate supply shock contemporaneously drives GDP growth and inflation in different directions, while an aggregate demand shock contemporaneously drives the two variables in the same direction, see Table 1. All the results we report are generated using 1000 draws from the posterior distributions.

Figure 1: IRFs of an aggregate demand and an aggregate supply shock

Pointwise median and three draws closest to the pointwise median




*Note:* The black line is the pointwise median and the shaded areas the min-max identified set. The red line is the IRF for the draw that is closest to the pointwise median; the green and blue lines are IRFS for 2nd and 3rd draws closest to the pointwise median, respectively.

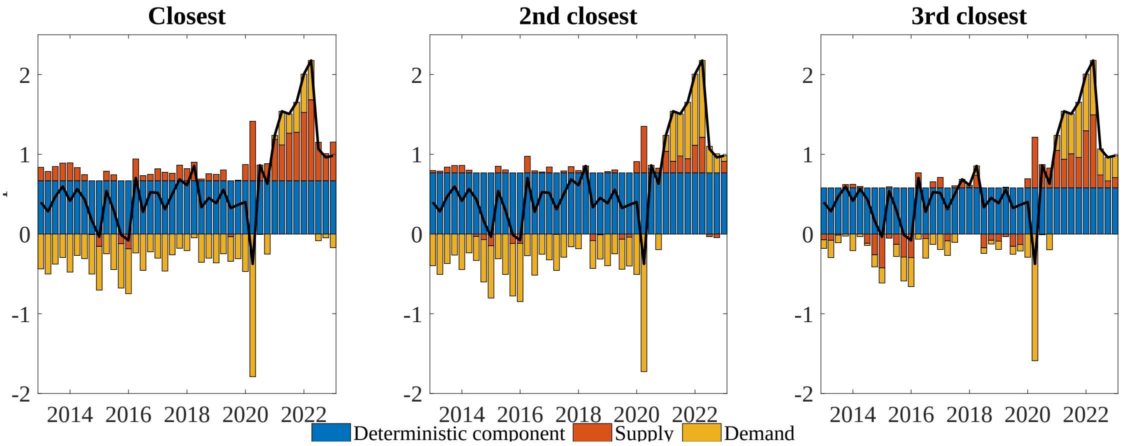
Figure 1 shows the impulse response functions (IRFs) to the two shocks. The black line is the pointwise median, while the shaded area represents the min-max identified set.[2] The red line is the IRF for the draw that is closest to the pointwise median, as in Fry and Pagan (2011), while the green and blue lines are the draws that are the IRFs for the 2nd and 3rd closest draw to the poinwise median, respectively. Clearly, the dynamics produced by these three draws are very close to the dynamics produced by the pointwise median.

However, even if the IRFs are almost identical, the three draws tell a very different story regarding the drivers of inflation in the post-COVID period, as illustrated in the upper panel of Figure 2. The draw closest to the pointwise median attributes most of the recent inflation surge in the US to the supply shock, the second closest draw attributes most of it to the demand shock, while the third closest draw indicates that both shocks are roughly equally important. An important reason for these differences is that the deterministic components are rather different, as shown by the blue areas in each panel. Furthermore, as shown in the bottom panel of Figure 2, the dispersion in the posterior estimates of deterministic components is very large, andceven the 10 draws closest to the pointwise median IRFs, stabilize at very different levels.

[2]Note that by reporting the full min-max set as recommended by Baumeister and Hamilton (2015), uncertainty is obviously large. It can be reduced by imposing narrative restrictions as in Antolín-Díaz and Rubio-Ramírez (2018) or by imposing the restrictions over a longer horizon.

Figure 2: Historical decompositions and deterministic components of US inflation

(a) Historical decomposition of inflation for the 3 models closest to the pointwise median IRFs




(b) Deterministic components of inflation

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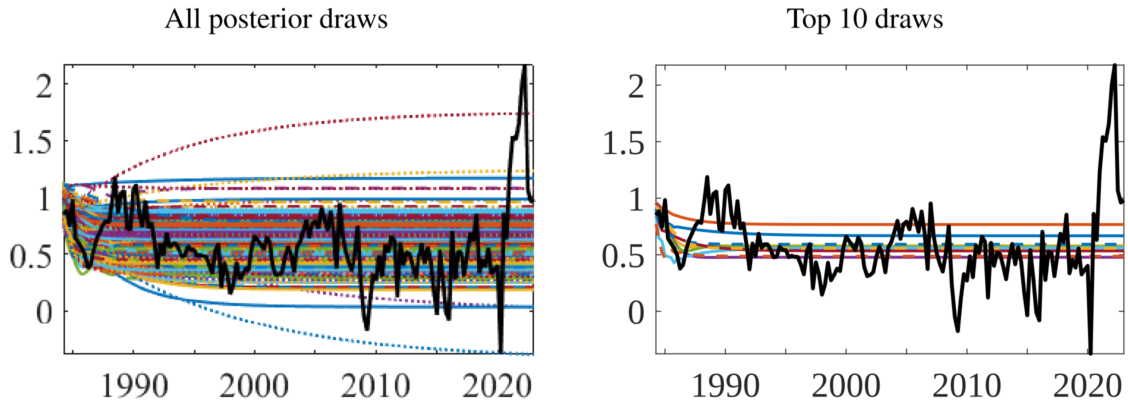


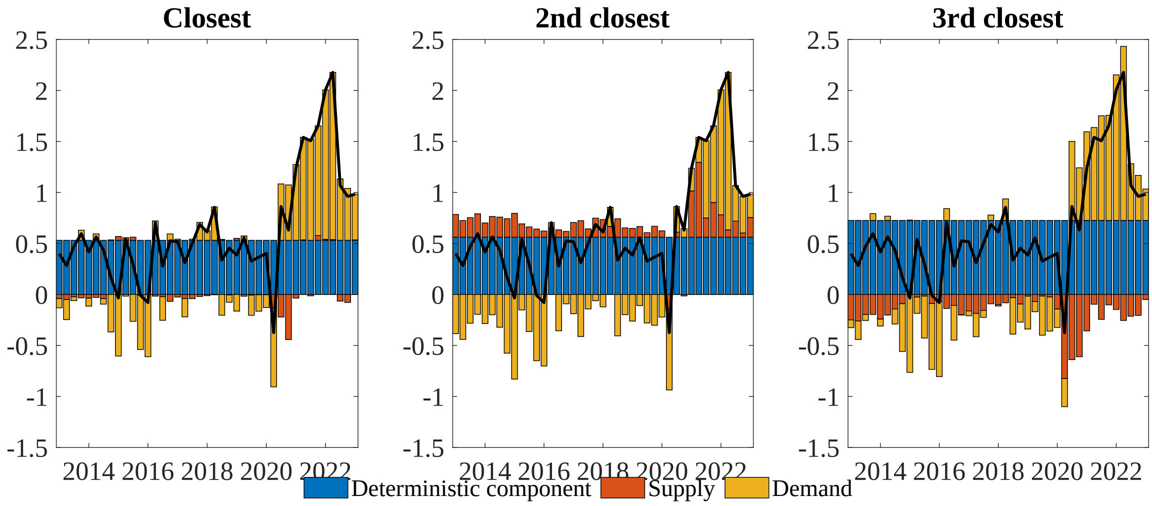

## 2.2 Different identification schemes

As SVARs identified with sign restrictions are set-identified, meaning that there is not one single model that satisfies the restrictions but rather a set, it is interesting to investigate whether the dispersion of historical decompositions is less of a problem for identification schemes where zero restrictions are imposed. We consider two among the most popular identification strategies: the Blanchard-Quah decomposition, which imposes zero restrictions on the long run cumulative sum of the IRF (Blanchard and Quah, 1989), and the Cholesky decomposition, which imposes zero restrictions on impact (see, Sims et al., 1986).

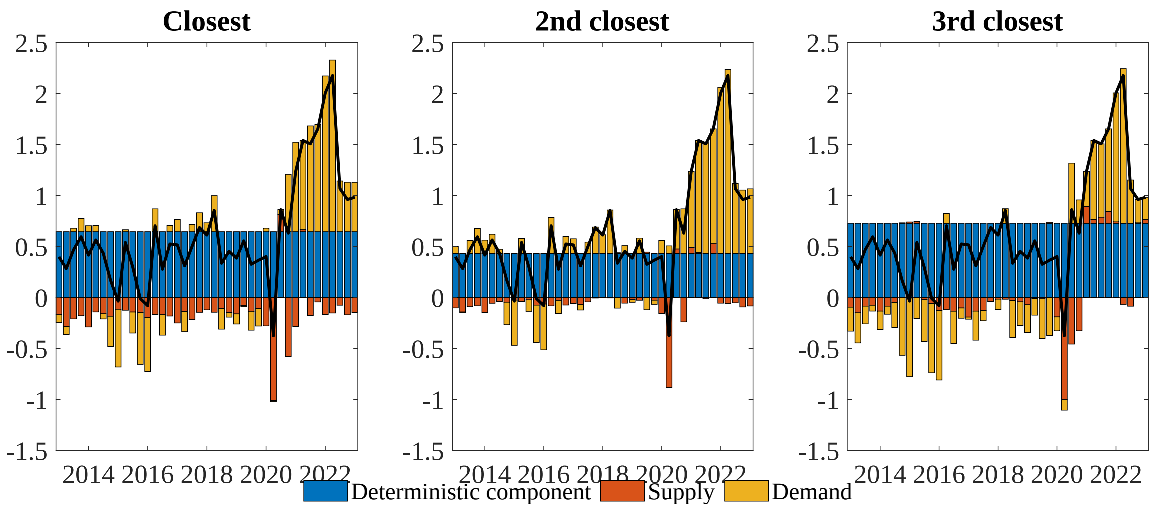
The Blanchard-Quah decomposition is commonly used to separate demand shocks from supply shocks under the assumption that demand shocks cannot affect the level of output in the long-run. Therefore, the transitory shock is interpreted as a demand shock while the unrestricted shock, which can affect output in the long run, is interpreted as a supply shock. However, these restrictions do not necessarily guarantee that the identified shocks will generate the right contemporaneous co-movement between output growth and inflation in practice. In our sample, the unrestricted shock looks like a second demand shock, as it implies a positive contemporaneous co-movement of output growth

Figure 3: Historical decompositions and deterministic components of US inflation, different identification schemes

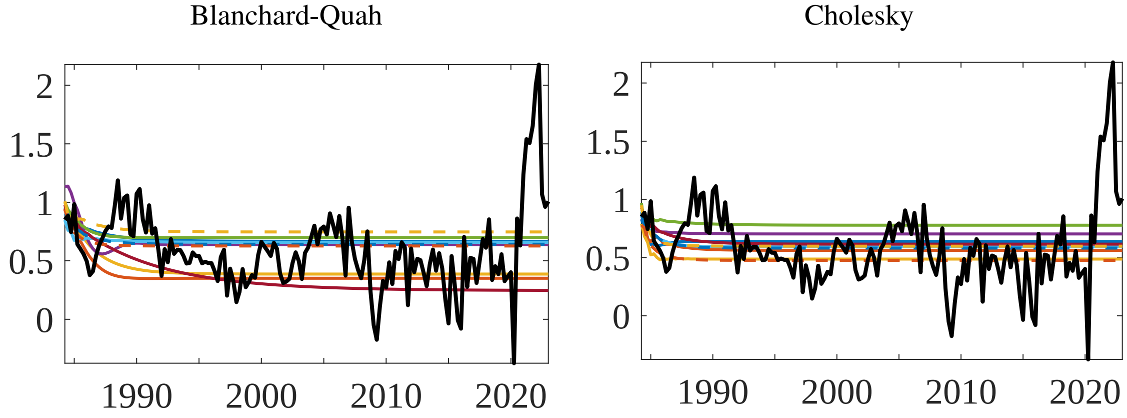
(a) Blanchard-Quah decomposition




(b) Cholesky decomposition




(c) Deterministic components of inflation



and inflation, see Figure A-1 in the Appendix. As shown by Furlanetto et al. (2021), the unrestricted shock commingles supply shocks and demand shocks generating hysteresis effects.

Using Cholesky decompositions to identify supply and demand shocks in a VAR with output growth and inflation leads to the same problem: there is no guarantee that the two shocks will generate the right contemporaneous co-movements between output and prices. We restrict one of the shocks to have a zero effect on GDP growth on impact, while the other shock is unrestricted. As in the previous case, both shocks lead to a positive comovement between output and inflation, as shown in Figure A-1.

Thus while both identification strategies are not appropriate to disentangle demand and supply shocks, they can nevertheless used to investigate how much uncertainty there is in the historical decomposition of inflation, which constitutes the main focus of our paper. The historical decompositions for inflation from the three draws closest to the pointwise median IRFs for both identification schemes are presented in Figure 3. While the relative importance of the two identified shocks in explaining the variation in inflation changes relative to the sign restricted case (see Figure 2), it is still clear that there are notable differences between the historical decompositions for the three draws in both cases. This is mainly due to the largely different levels the deterministic components take across the draws. Notably, the Blanchard-Quah decomposition, the Cholesky decomposition and the sign-restricted model share the same 1000 draws from the reduced form. Therefore, the large uncertainty around the deterministic component presented in Figure 2 is a feature of all identification schemes. This is crucial: the type of uncertainty that we are documenting originates in the estimation of the reduced form model. Any Bayesian VAR is in principle susceptible to the problem highlighted here. In contrast, the ten draws closest to the median are different for each identification scheme because they are based on impulse response that are different for each identification scheme. In both cases, we find large differences in the deterministic components across the ten draws, as shown in the bottom panel of Figure 3.

### 2.3 A LONGER SAMPLE

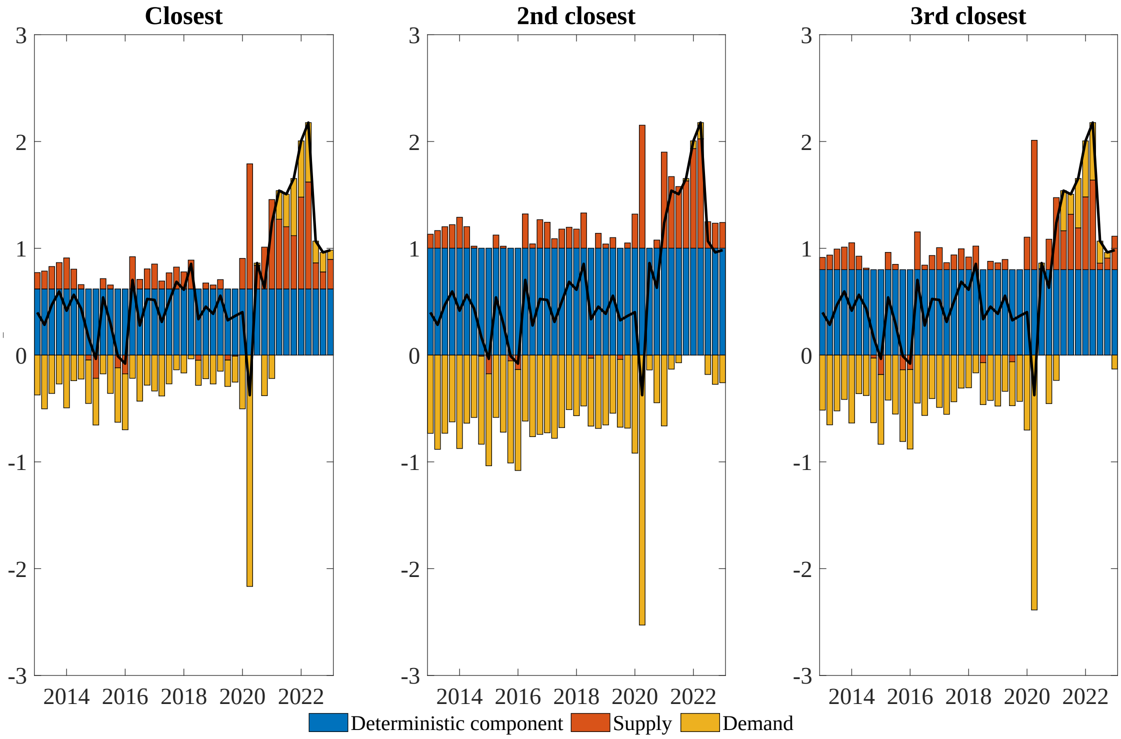
In our baseline estimation we consider a relatively homogeneous sample period starting in 1983. We now re-estimate the model over the period 1949:Q1 - 2022:Q4 with diffuse priors and identify shocks with the same sign restrictions. We present results in Figure 4. The dispersion of both the historical decompositions and the deterministic components is substantially larger over this less homogeneous sample. Note that the large uncertainty around the deterministic component is an additional argument for not using a long and dis-homogeneous sample to estimate a SVAR model (see e.g. Furlanetto et al. (2021) for a detailed discussion of this point).

### 2.4 A LARGER SCALE VAR

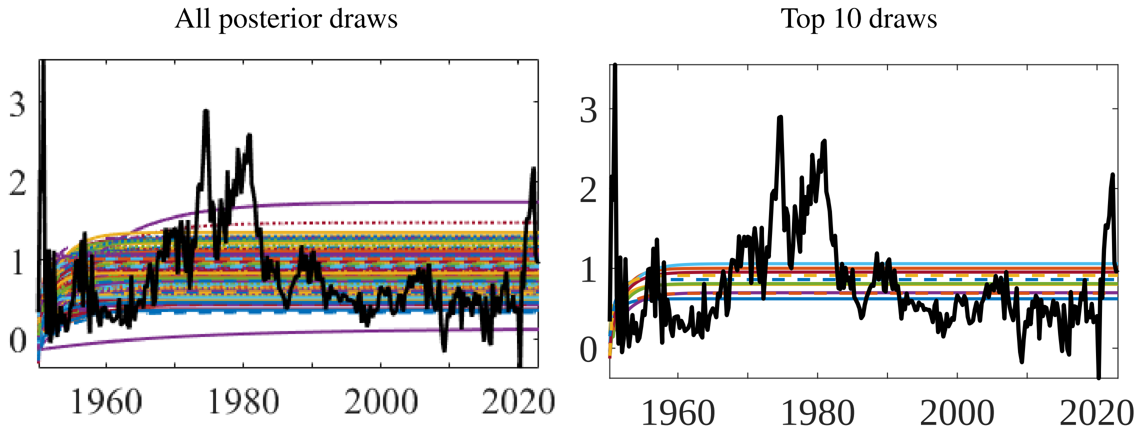
Canova and Ferroni (2022) have shown that the dimensionality of an estimated VAR is important to make sense of the estimated impulse responses and that small-scale VARs are prone to deformation problems. This subsection shows that the large uncertainty in the posterior estimates of initial conditions is independent of the dimension of the VAR.

Figure 4: Longer sample: 1949:Q1 - 2022:Q4

(a) Historical decomposition of inflation for top 3 draws

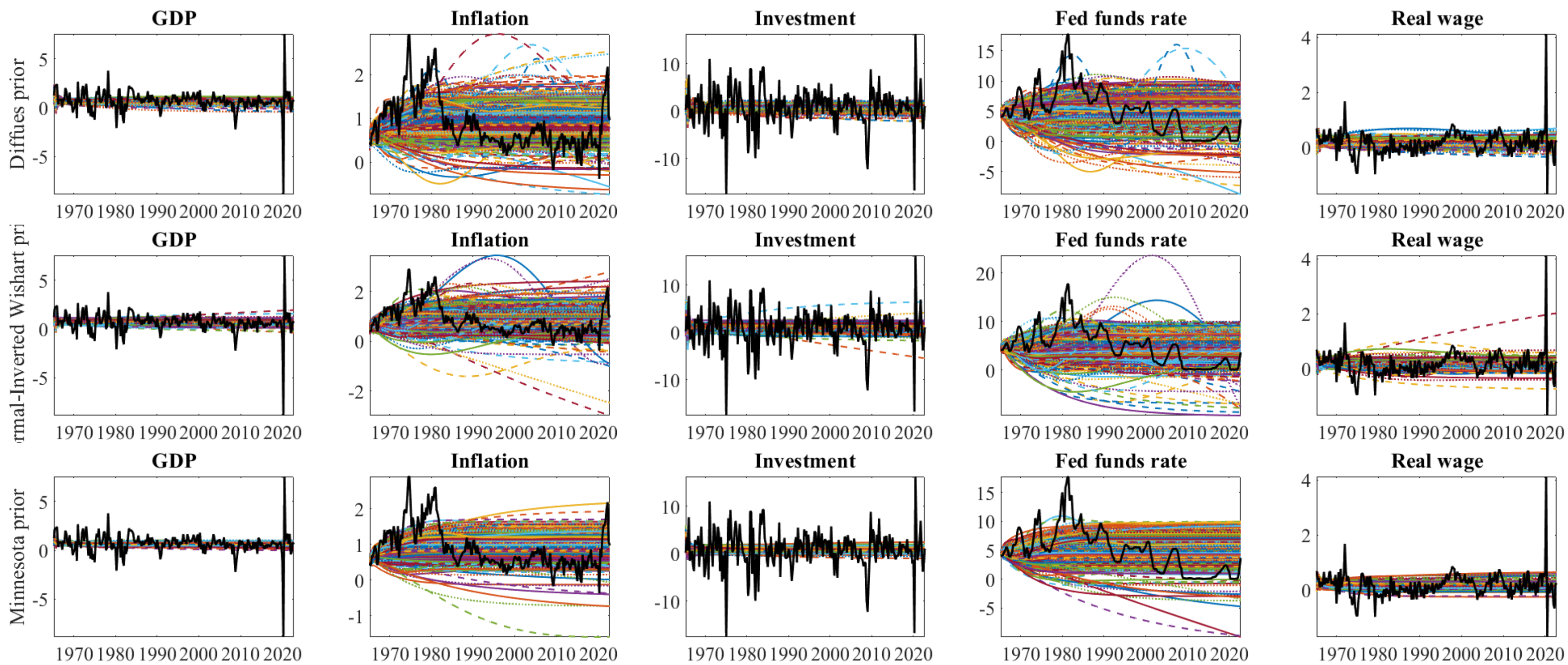



(b) Deterministic components of inflation




For that purpose we estimate a VAR with five variables (real GDP growth, GDP deflator growth, real gross private domestic investment growth, federal funds rate, and real wage growth, measured as Average Hourly Earnings of Production and Nonsupervisory employees deflated with the GDP deflator) on the sample 1964:Q1-2022:Q4 using the sign restrictions described in table 2. We identify three demand shocks: a monetary policy shock, an investment shock (that bundles investment-specific technology shocks and financial shocks) and a residual demand shock (that bundles discount factor shocks, government spending shocks and foreign shocks). In addition we disentangle two supply shocks: a standard technology shock and a labor supply shock. The identification as-

Figure 5: Deterministic components from the large model for different priors



| | Residual demand | Investment | Monetary | Labor supply | Technology |
|---|---|---|---|---|---|
| GDP | + | + | + | + | + |
| Inflation | + | + | + | - | - |
| Investment | + | + | + | | |
| Interest rate | + | + | - | | |
| Real wage | | | | - | + |
| *Investment/GDP* | - | + | | | |

Table 2: Sign restrictions imposed on the large model

sumptions are standard in the literature (for example, they are satisfied in the Smets and Wouters (2007) model). The deterministic components for a few variables are reported in Figure 5. Clearly, the problem remains even when the estimated system is larger and one tries to identify different types of demand and supply shocks. In fact, the problem seems exacerbated and becomes dramatic for variables like inflation or the federal funds rate.

### 2.5 A SIMULATION EXERCISE

In order to gain some intuition on the factors which may affect the dispersion of the estimates of the deterministic components of a VAR, we run a simple simulation exercise. We estimate a SVAR on simulated data and analyze how the sample size and persistence of variables affect on the dispersion of the estimate of the deterministic components. We simulate data from the following bi-variate VAR(1) with two different parameterizations:

$$Y_t = C + AY_{t-1} + u_t \tag{4}$$

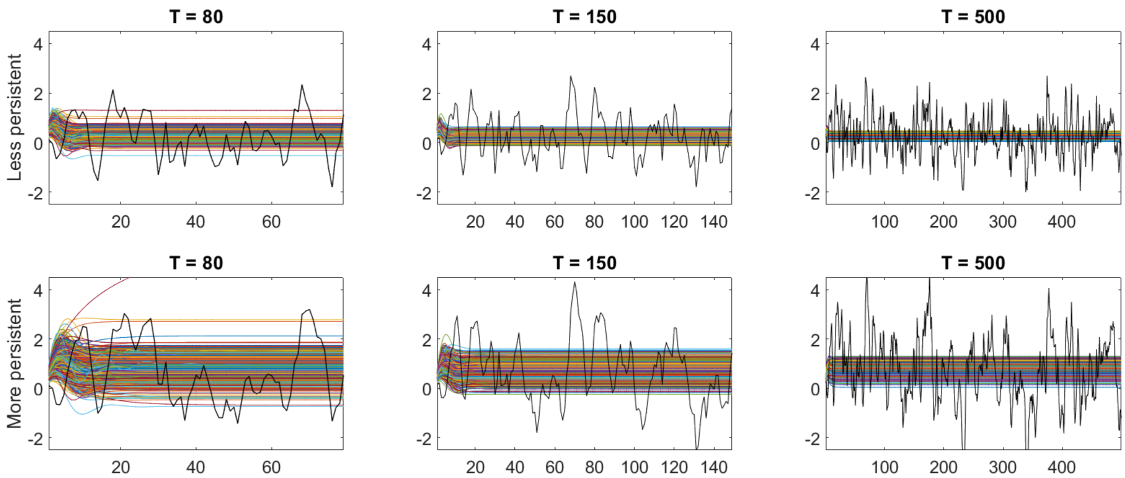
First, we simulate data from a version of the model with little persistence in the variables, with the parameters labeled *less persistent*. Then, we simulate data from a version of the model where one of the variables in the system is made more persistent. This is done by changing the value of the coefficient of the first own lag of variable 1. The parameters used in the less persistent case is denoted $A_1$, while the more persistent case is denoted $A_2$. $C$ is the same in both cases.

$$C = \begin{pmatrix} 0.4 \\ 0.5 \end{pmatrix}, \quad A_1 = \begin{pmatrix} 0.6 & -0.3 \\ 0.3 & 0.4 \end{pmatrix}, \quad A_2 = \begin{pmatrix} 0.95 & -0.3 \\ 0.3 & 0.4 \end{pmatrix} \tag{5}$$

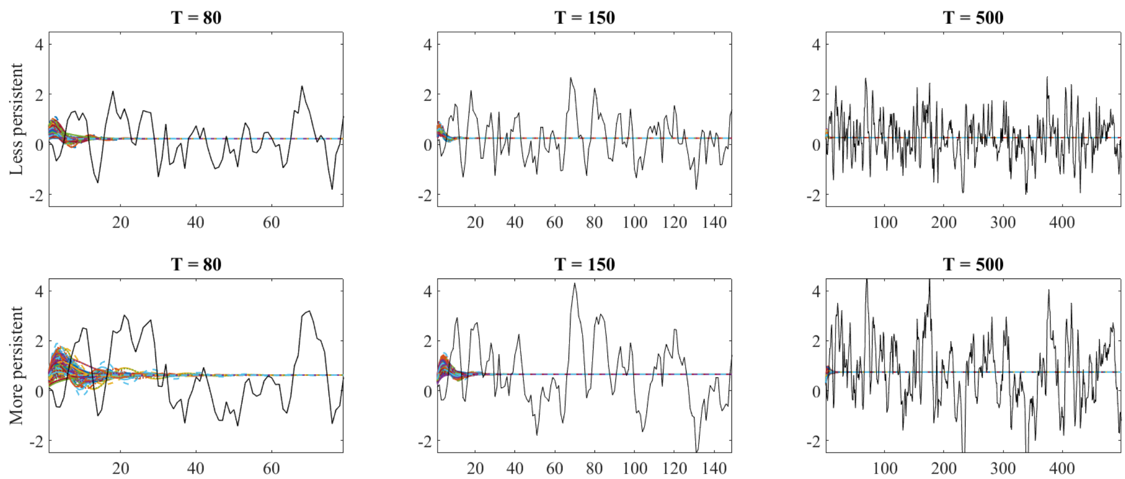
We simulate data over 80, 150 and 500 periods and estimate a VAR(1) on the simulated data using a diffuse prior. The estimated deterministic components of variable 1 are plotted in Figure 6a. The dispersion is larger for small samples than for large samples. It is also clear that the dispersion is larger for more persistent variables than for less persistent variables.

Figure 6: Deterministic components of $y_1$

(a) Diffuse prior




(b) Single-unit-root prior




# 3 Solving the problem

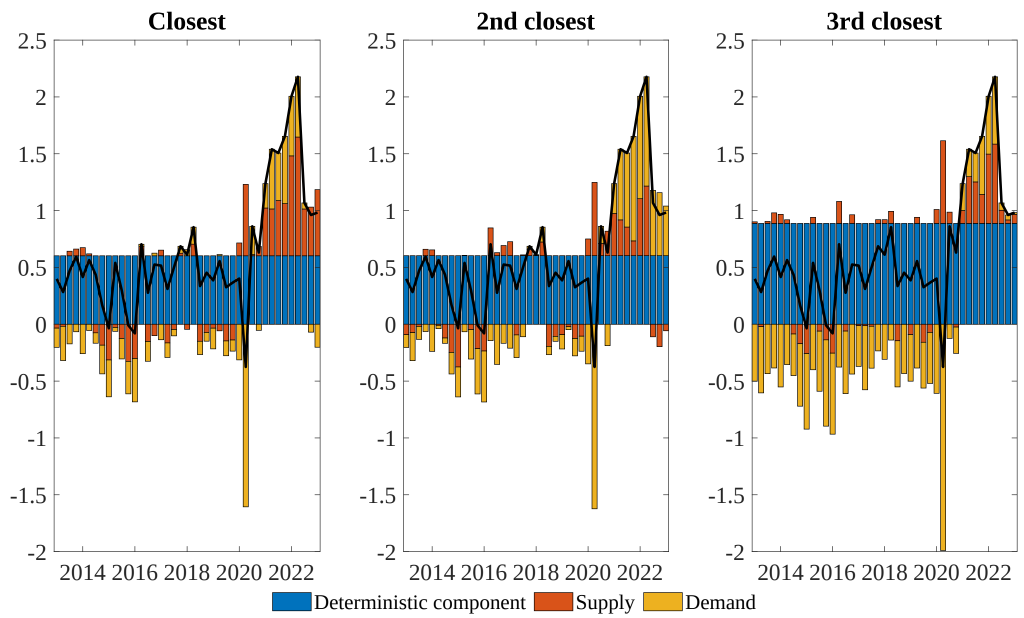
In this Section we propose a few alternatives to resolve the problem we have highlighted in the previous section.

## 3.1 Adding prior restrictions

Our baseline bivariate VAR is estimated using the diffuse prior. One question of interest is whether adding standard prior assumptions is sufficient to make the uncertainty problem less important. In particular, one would like to know nwhether priors that are commonly used to reduce parameter uncertainty can also reduce the uncertainty around historical decompositions. Here we consider a Normal-Inverse Wishart prior and a Minnesota-like prior (see Doan et al. (1984)).

Figure 7: Historical decompositions of US inflation for top 3 model draws for different priors

(a) Normal-Inverse Wishart prior




(b) Minnesota prior

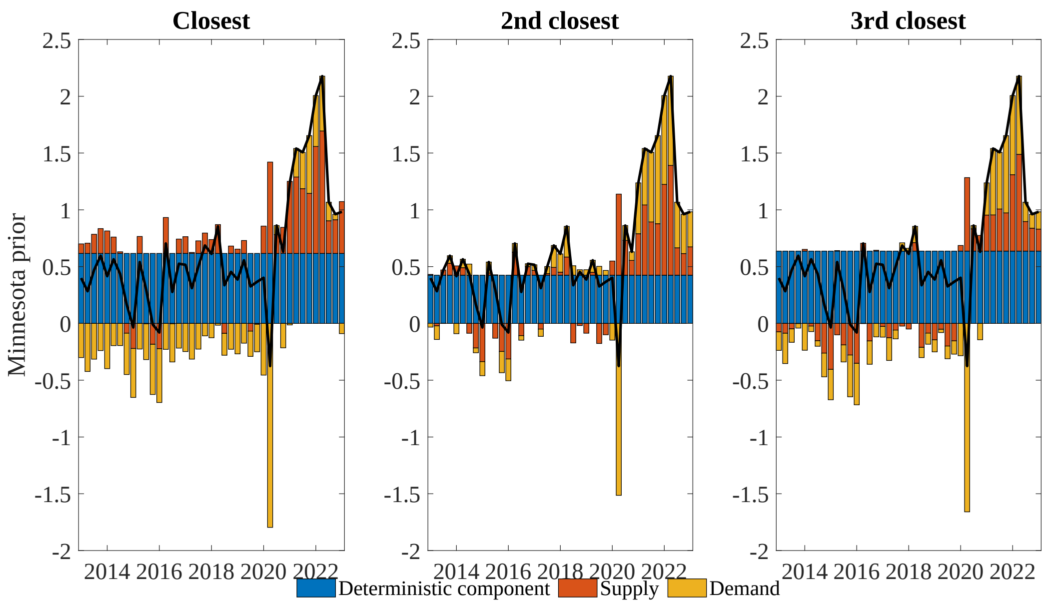
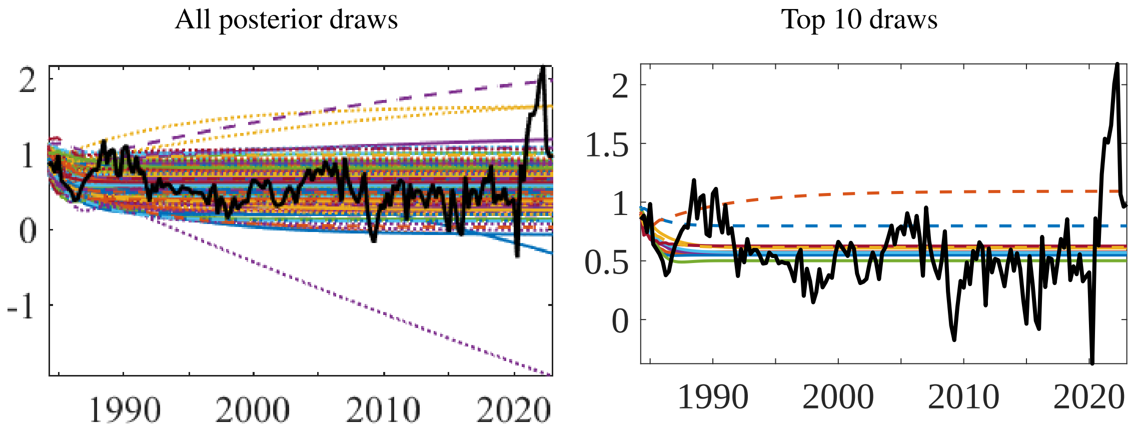
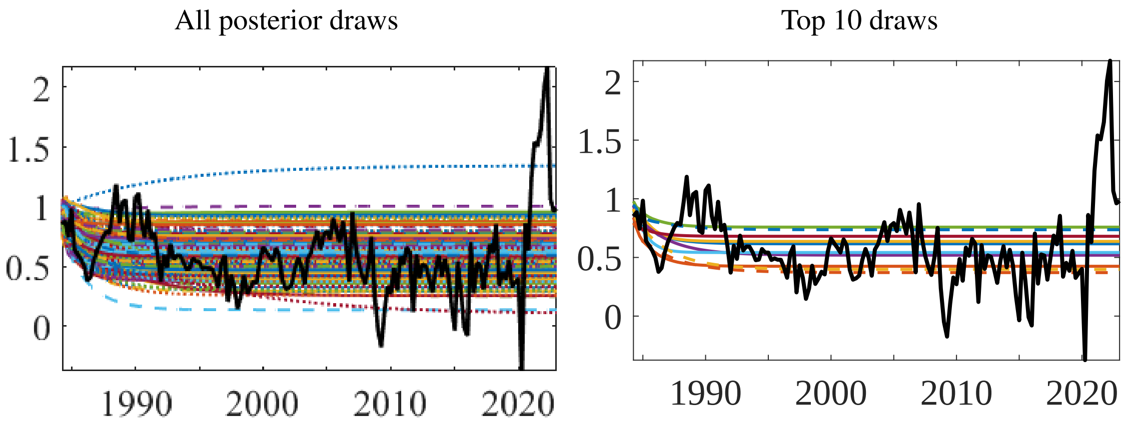


Figure 8: Deterministic components of US inflation

(a) Normal-Inverse Wishart prior




(b) Minnesota prior




In the Normal-Inverse Wishart case, the prior for the autoregressive (AR) coefficients is normal and centered at zero with a diagonal covariance matrix of 10, while the prior for the covariance matrix of the residuals is inverse Wishart with a unitary diagonal matrix as scale and n+1 degrees of freedom.

The Minnesota-like prior is also normally distributed for all AR coefficients is centered around zero for all parameters, including the variables' first own lag, as we have the variables in growth rates. The lag-decaying parameter is set to 2. Rather than fixing the tightness parameter, we treat it as random variable. The posterior distribution appears in Figure A-2 in the Appendix. The diagonal elements of the scale matrix of the inverse Wishart prior on the covariance of the residuals are set to the residual variance of an AR(1) process for each of the two variables. In all cases, identification is achieved using sign restrictions.

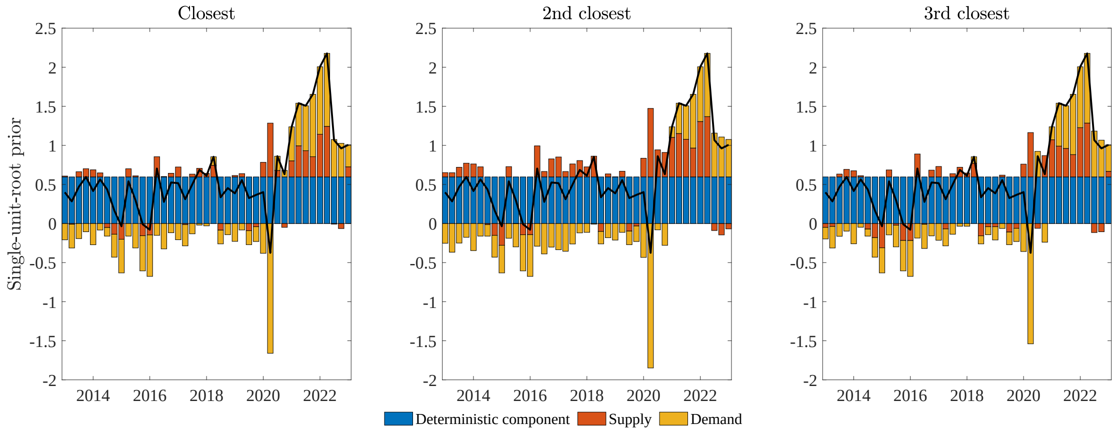
The historical decompositions of US inflation for the different priors are in Figure 7. There are large differences among the 3 draws closest to the pointwise median IRFs for both priors, indicating that these priors do not contribute significantly to reducing the uncertainty surrounding the historical decompositions. As shown in Figure 8, the dispersion of deterministic components is large also for these priors.

The question is then: are there prior restrictions which, when used in addition to a standard prior for the VAR parameters, are able to reduce the uncertainty in the deterministic components?

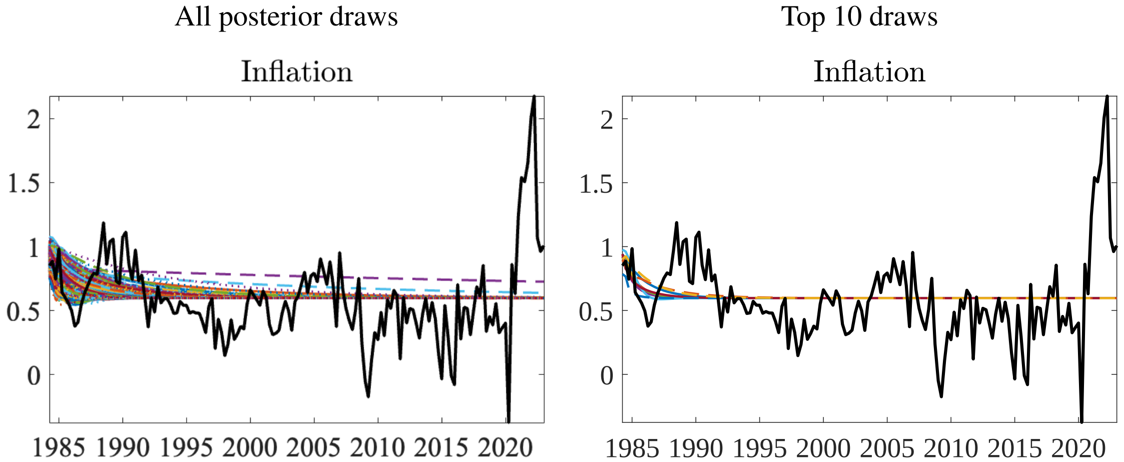
## 3.2 The single-unit-root prior

Figure 9: US: SVAR estimated using the single-unit-root prior

(a) Historical decomposition of inflation for top 3 draws




(b) Deterministic components of inflation




The single-unit-root prior, also known as the "dummy initial observations prior", was first introduced by Sims (1993). It is implemented by adding the following dummy observations to the data:

$$y^+ = \frac{\bar{y}_0}{\delta}$$
$$x^+ = [\frac{1}{\delta}, y^+, \vdots, y^+]$$

The prior states that $\bar{y}_0$ is a good forecast for variables in the model. $\bar{y}_0$ is set to the sample mean, while $\delta$, which governs the tightness of the prior is set optimally, following Giannone et al. (2015). The value of $\delta$ returned from the algorithm is at the lower bound, which is set to 0.0001. Thus, the single-unit-root prior is very tight. We combine this prior with the Minnesota prior and use the same sign identification restrictions described before.

Figure 9 present the main result of the paper. In the model estimated with the single unit prior, draws featuring similar impulse responses feature also similar historical decompositions. In fact, the deterministic component stabilizes now at the same level for the overwhelming majority of draws. Therefore, all draws close to the pointwise median IRF produce a similar story for post-COVID inflation: while supply factors were important in the initial phase, demand factors are the main drivers since 2021. On average over the recent period, demand factors explain from one half to two thirds of the inflation surge. More precisely, the Fry-Pagan historical decomposition implies that demand shocks drive 56 percent of inflation fluctuations in 2021 and 77 percent in 2022. This result is broadly consistent with Eickmeier and Hofmann (2022) who stress the role of demand factors using a factor model estimated using more than 140 quarterly time series for the US. While their model exploits information from a much larger data set, their decomposition is not jointly exaustive since demand ans supply factors do not explain the entire variation data. Relying on a bivariate model is jointly exahustive by construction.

It is important to note that a SVAR with a single unit root prior still implies quite a lot of uncertainty around historical decompositions. However, it is the same type of uncertainty associated with the impulse response functions. In contrast, the specific kind of uncertainty associated to the initial conditions becomes largely irrelevant, see panel b) of Figure 9.

We have also estimated the same SVAR model for the euro area. Since the estimation sample is shorter than for the US, we use data on industrial production (and not on GDP) and HICP inflation at a monthly frequency. As in the case of the US, the model features a large dispersion of deterministic components across draws (see Appendix 5) when using diffuse priors. However, when estimated with the single unit root prior, the historical shock decompositions for the euro area look similar across draws as shown in figure 10. Demand and supply factors contributed more or less equally to the recent surge in euro area inflation with a more prevalent role for demand factors in 2022. This is in line with the findings of Ascari et al. (2023).

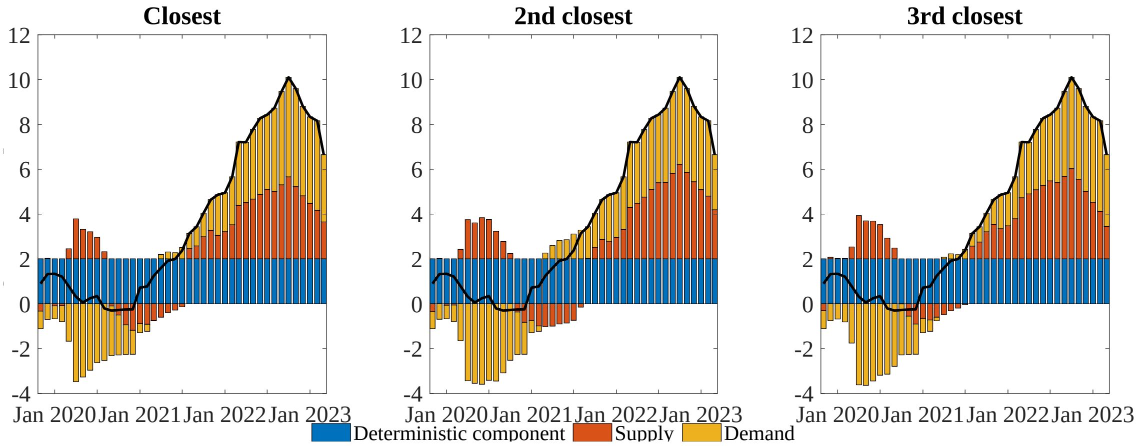
To confirm the results we obtained with real data we impose the single-unit-root prior on the data we have simulated in the samll Monte Carlo exercise. The results presented in Figure 6b confirm that the dispersion of the estimated deterministic components is drastically reduced, regardless of the persistence of the variables and the sample size one has available.

It is important to stress that we are not the first using the single unit root prior in empirical applications. One example among others is Rubio-Ramírez et al. (2021) who use the single-unit-root prior to investigate the role of persistence in dividends for stock returns predictability in a SVAR. However, while the use of this prior is not new, its ability to shrink the uncertainty around the estimated deterministic component has not been discussed in the literature so far.

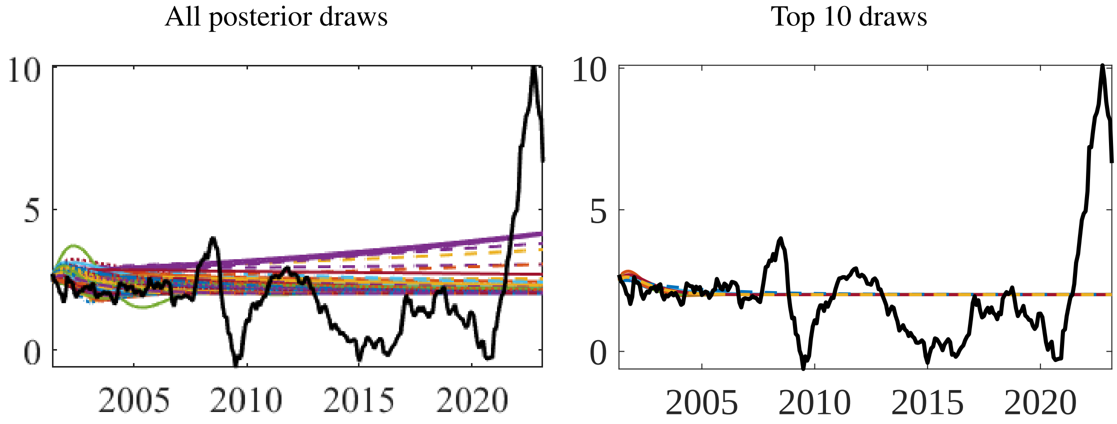
Finally, we reiterate that the problem emphasized in this paper, the uncertainty around the estimated deterministic component, is different from the overfitting problem discussed in Giannone et al. (2019). The overfitting problem appears when the deterministic component explain an implausibly large share of the low-frequency variation in the data. In that

Figure 10: Euro area: SVAR estimated using the single-unit-root prior

(a) Historical decomposition of inflation for top 3 draws




(b) Deterministic components of inflation




context, the deterministic component is a measure of central tendency across all draws and the uncertainty around such a measure is ignored. In this paper, we highlight the uncertainty around the deterministic component that appears even in absence of the overfitting problem. Nonetheless, both pathologies distort historical decompositions and should be a concern for applied researchers.

### 3.3 A measure of dispersion for the historical decompositions

Since it is hard to visually determine to what extent historical decompositions across draws are different, we propose next a simple measure of dispersion of the historical decompositions using the 100 draws that are closest to the pointwise median IRFs (from now on referred to as the top 100 draws). Let $C_{i,j,t}$ is the contribution from the shock $j$ to variable $i$ in period $t$. Then

$$D_{i,j,t} = \max\left(C_{i,j,t}\right) - \min\left(C_{i,t}\right) \tag{6}$$

$$M_{i,j} = \frac{1}{T} \sum_{t=1}^{T} D_{i,j,t} \tag{7}$$

$D_{i,j,t}$ is the difference between the maximum and minimum value of $C_{i,j,t}$ among the top 100 draws for variable $i$ and shock $j$, and $M_{i,j}$ is the time average dispersion. We focus on the dispersion in the contribution from the demand shock to inflation for the period 2020:Q2 to 2022:Q4. Table 3 reports this statistics for the four different priors, and the 3 different identification schemes. There are considerable differences among the historical decompositions among the top 100 draws for all priors. However, the dispersion becomes smaller when the single-unit-root prior is imposed, as the deterministic components are similar across draws.

| | **Sign** | **Blanchard-Quah** | **Cholesky** |
|---|---|---|---|
| **Diffuse** | 1.07 | 0.88 | 2.33 |
| **Normal-Inverse Wishart** | 1.53 | 1.20 | 0.91 |
| **Minnesota** | 0.87 | 0.71 | 0.61 |
| **Single-unit-root** | 0.68 | 0.48 | 0.54 |
| **Diffuse, demeaned** | 0.79 | 0.69 | 0.69 |

Table 3: Dispersion of historical decompositions for different priors and identification schemes

*Note:* The numbers report a the measure of dispersion in the historical decompositions among the 100 draws closest to the pointwise median IRF, see Equation 7.

# 4 ALTERNATIVE APPROACHES

For those researchers who are reluctant in using our prior for inferential purposes, we offer two alternative pragmatic solutions. The first is demeaning the data prior to estimation. Such an approach in part addresses the problem, since poor estimates of the VAR constant contribute to making the problem important. The second alternative is to construct a *median* historical decomposition a-la Fry and Pagan.

## 4.1 DEMEANING THE DATA

As discussed in Section 2, the deterministic component consists of two terms:

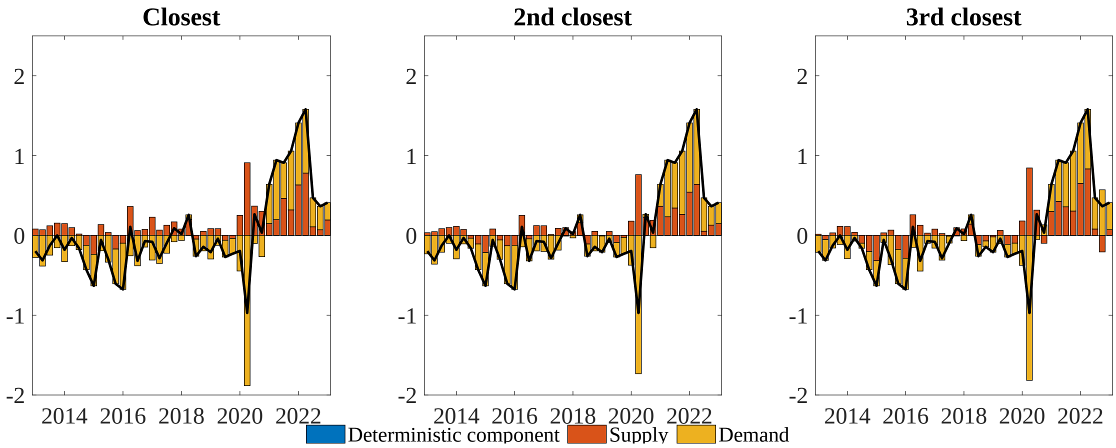
$$(I + \mathbf{A} + \mathbf{A}^2 + \cdots + \mathbf{A}^{t-1})\mathbf{C} + \mathbf{A}^t\mathbf{Y_0} \tag{8}$$

If the constant in the VAR is zero, the first term disappears. As $t$ increases the last term goes towards zero, as long as the data is ergodic. Thus, a simple way to impose the deterministic component is similar across draws in finite samples, is to demean the data, and estimate the VAR without a constant.

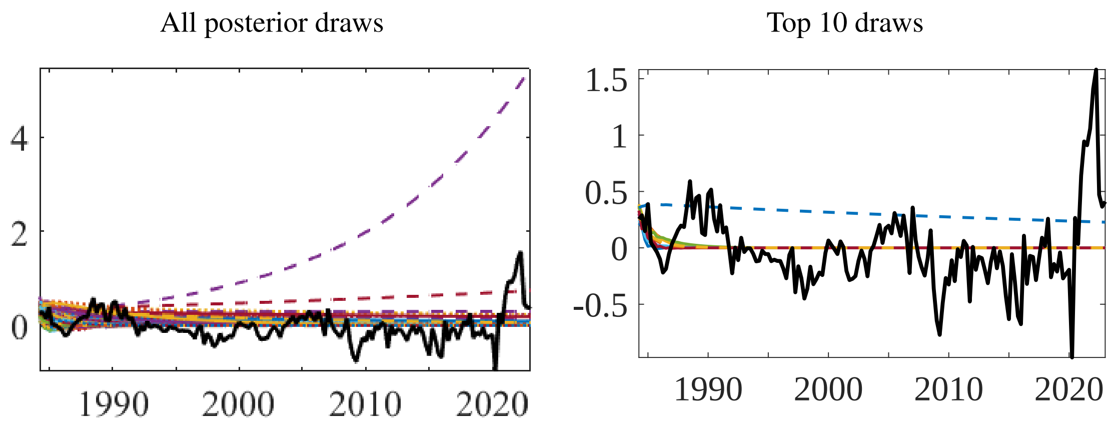
We present the results on Figure 11. In this specification, the role of demand shocks is slightly more prevalent and draws generating similar IRFs generate also relatively similar historical decompositions. Note, however, that the uncertainty is still substantially larger than in Figure 9, where we use the single-unit-root prior. By demeaning and estimating the VAR without a constant, the deterministic component is forced to be on the path described by $A^tY_0$. Thus, draws that implies similar A's will force the estimated shocks to take different values and thus altering their contribution in a given historical episode.

Figure 11: US: Estimated without constant (demeaned data) with a diffuse prior

(a) Historical decomposition of inflation for top 3 draws




(b) Deterministic components of inflation

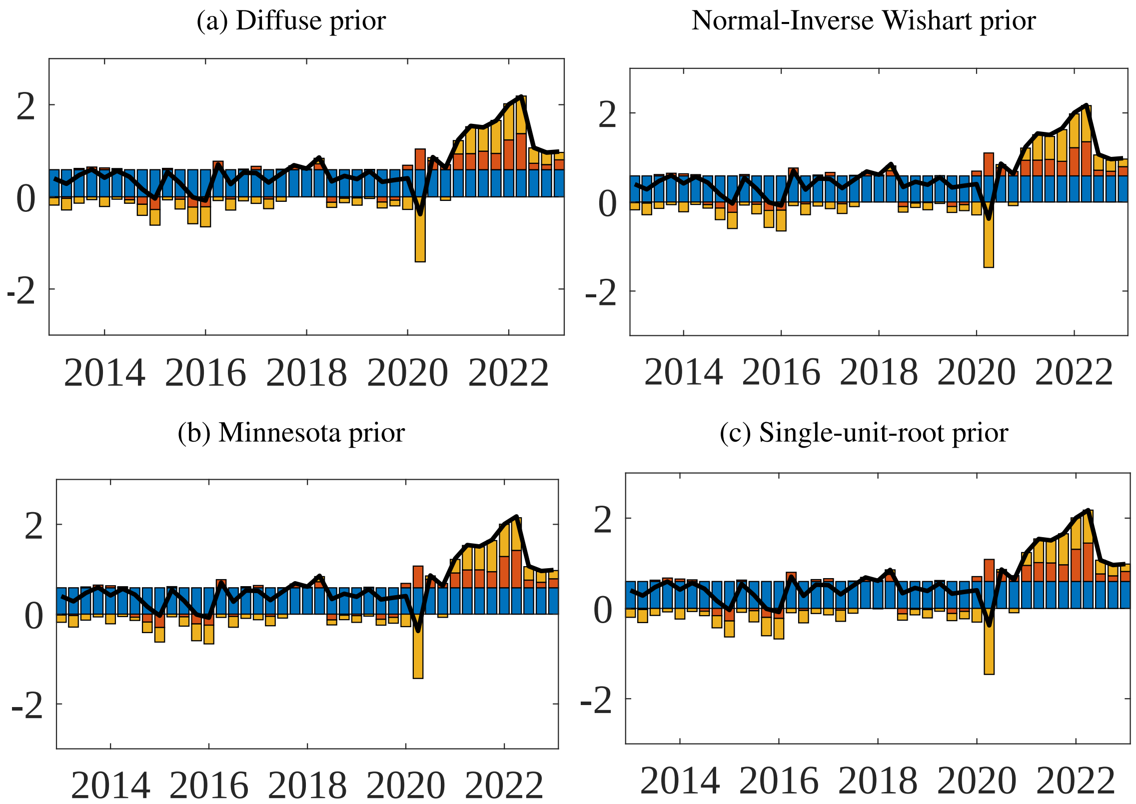



## 4.2 Computing the median historical decomposition

Another pragmatic approach consists in acknowledging the uncertainty present in the initial conditions and computing the historical decomposition for the draw that minimizes the distance from the median (as in Fry and Pagan (2011)). We call this "median" historical decomposition. Thus, at each quarter the data is decomposed into the median contribution of demand shock, the median contribution of supply shock and a residual deterministic component that absorbs the difference between data and the two median stochastic components. While such a summary measure is arbitrary it features the non-negligible advantage of considering uncertainty around the deterministic component into the inferential process. Bergholt et al. (2023) use such an approach when studying the causes of the reduced sensitivity of inflation to measures of economic slack in the pre-COVID period.

Figure 12 computes the median historical decomposition for the four prior distributions we considered. In all cases, we find an important role for demand shocks during the current inflation surge. The comparison between the four panels in Figure 12 and panel a) in Figure 9 is of particular interest. All in all, the median historical decompositions and our favorite setup with the single unit prior provide a similar reading of the current inflation surge with a prevalent role for demand factors.

Figure 12: Historical decomposition of inflation, pointwise median




# 5 Concluding remarks

Most empirical applications of SVAR models report the uncertainty around impulse-response functions. We show that it is important to consider also the uncertainty around historical decompositions. This kind of uncertainty is heavily affected the uncertainty around the deterministic component of the VAR. Posterior draws that exhibit ”good” impulse responses (meaning impulse responses close to the pointwise median) can feature extreme initial conditions and thus exhibit a distorted historical decomposition because shocks have to match the gap between the series of interest and the estimated deterministic component. According to the same logic, draws that feature a ”good” deterministic component, and thus a ”good” historical decomposition, can be associated with extreme impulse-response functions. There is no guarantee that ”good” impulse response functions provide ”good” historical decompositions and vice-versa. We have provided one solution to the problem based on the use of the single unit prior and two pragmatic alternatives based on demeaning the data and on computing an median historical decomposition. Our results show that the current inflation surge is mainly driven by demand factors both in the US and in the euro area.

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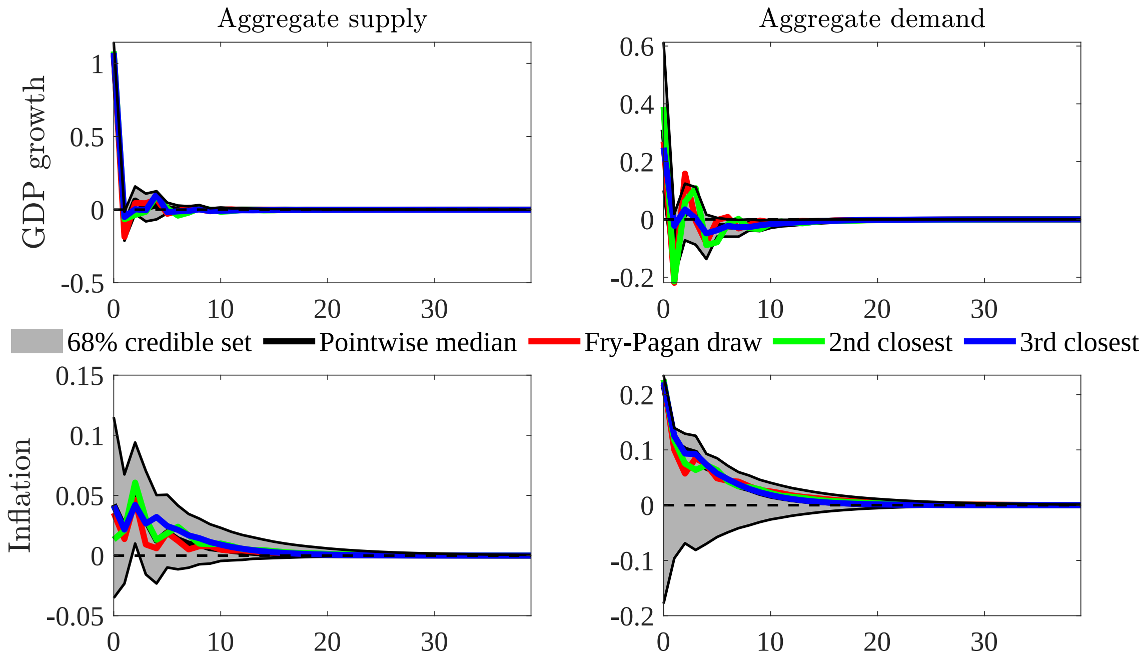
# Appendix 1: Additional results for the US

Figure A-1: IRFs of an aggregate demand and an aggregate supply shock, different identification schemes. US

(a) Blanchard-Quah




(b) Cholesky

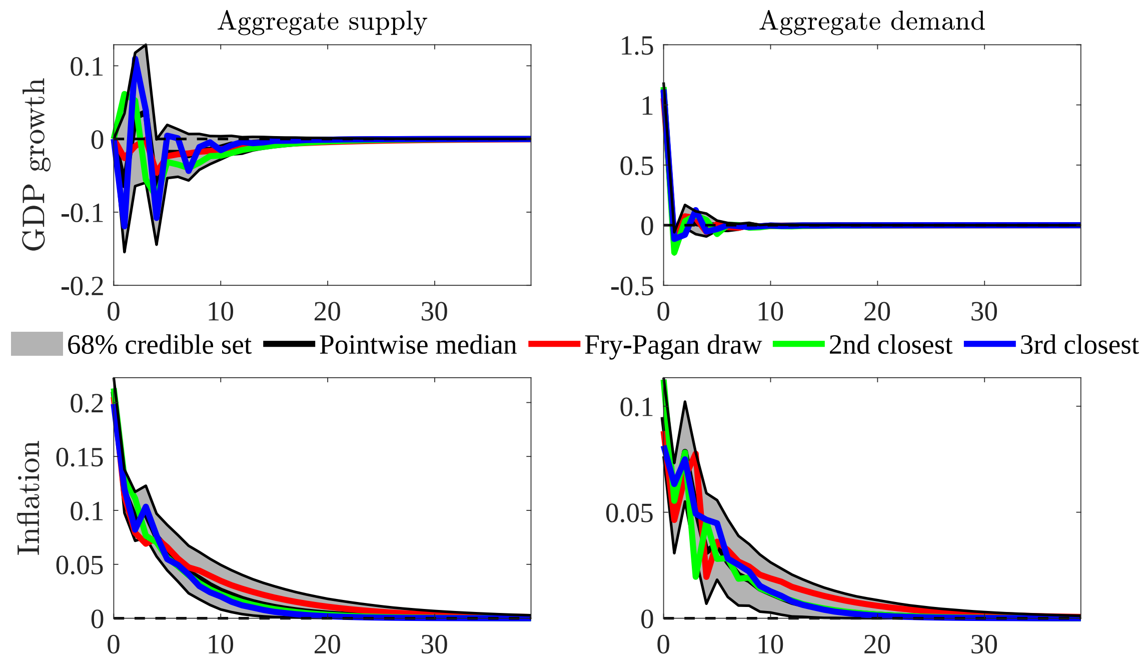


Figure A-2: Overall tightness of the Minnesota prior

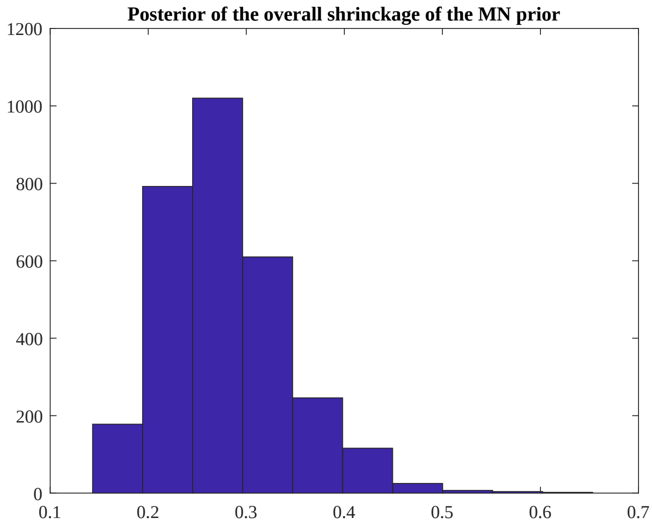
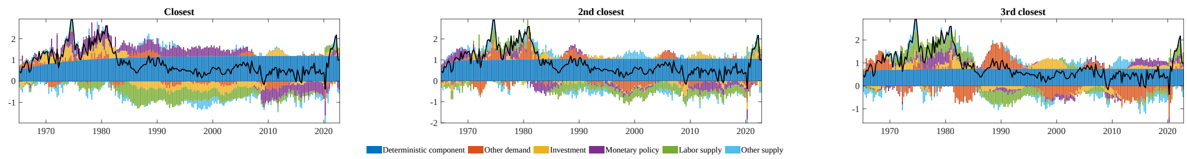
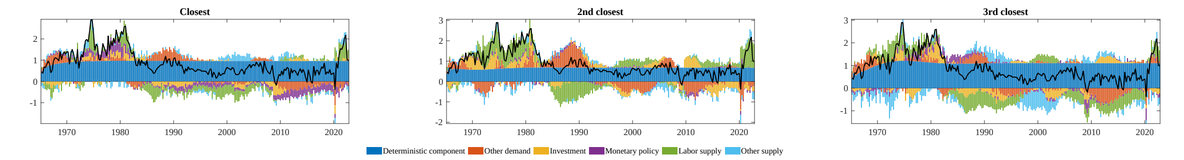



Figure A-3: Historical decompositions of US inflation from the large model, top 3 draws

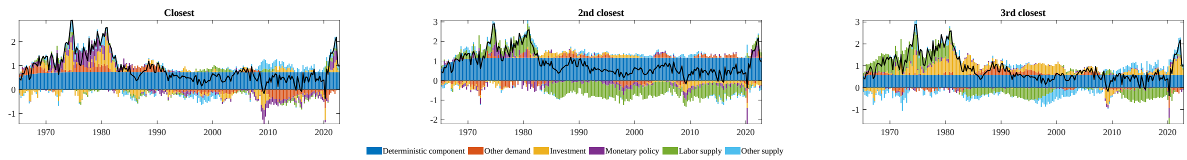
(a) Diffuse prior




(b) Normal-Inverse Wishart prior




(c) Minnesota prior

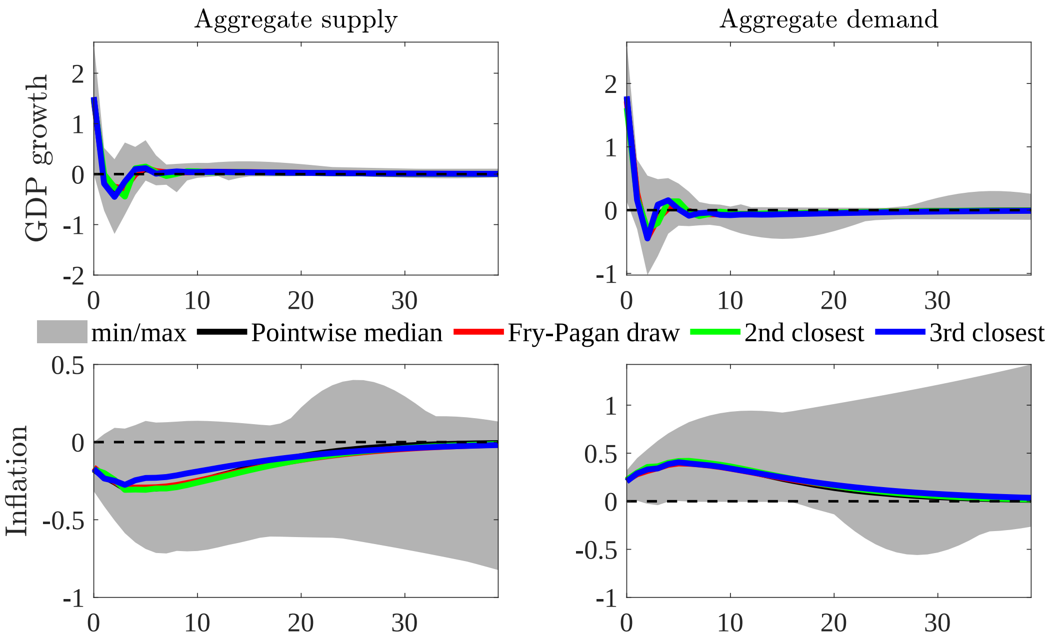


# Appendix 2: Additional results for the euro area

Figure A-4: IRFs of an aggregate demand and an aggregate supply shock

Pointwise median and three draws closest to the pointwise median

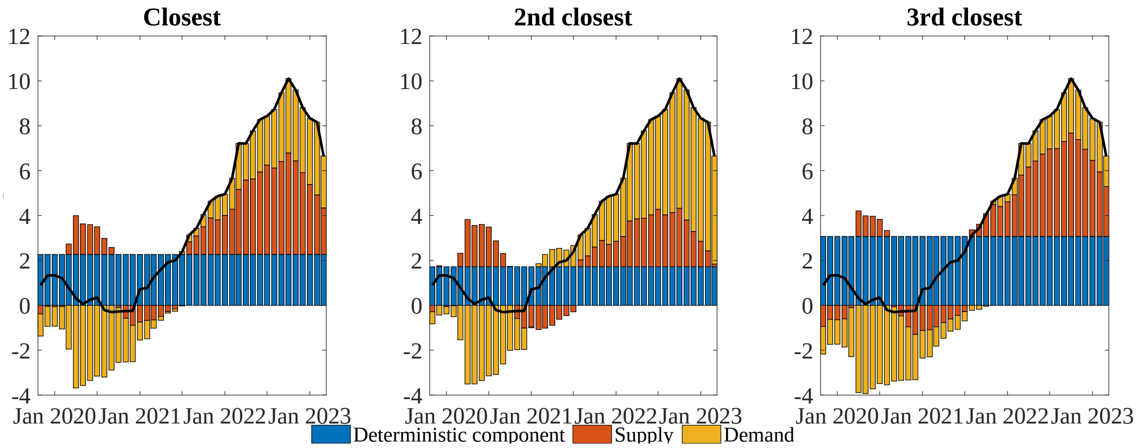
(a) Euro Area




*Note:* The black line is the pointwise median and the shaded areas the min-max identified set. The red line is the IRF for the draw that is closest to the pointwise median; the green and blue lines are IRFS for 2nd and 3rd draws closest to the pointwise median, respectively.

Figure A-5: Historical decompositions and deterministic components of euro area inflation. Diffuse prior

(a) Historical decomposition of inflation for the 3 draws closest to the pointwise median IRFs




(b) Deterministic components of inflation

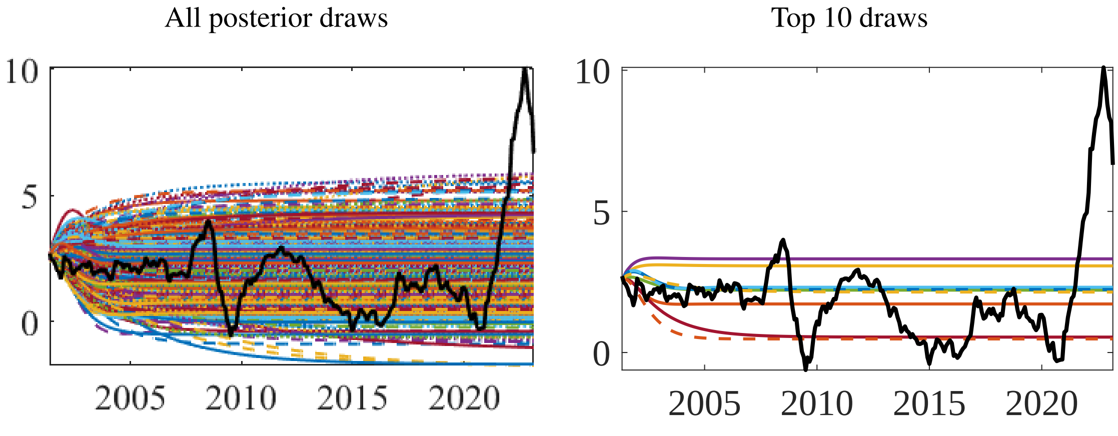
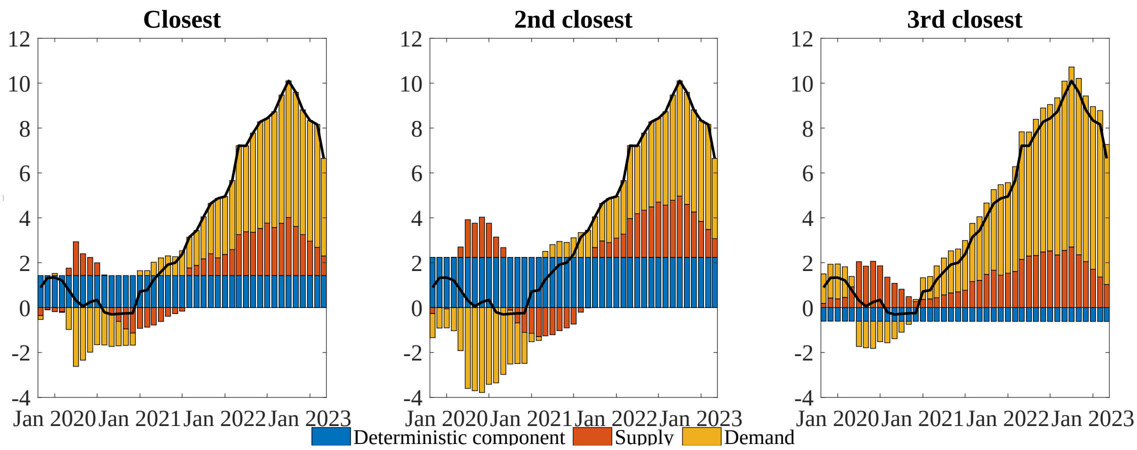
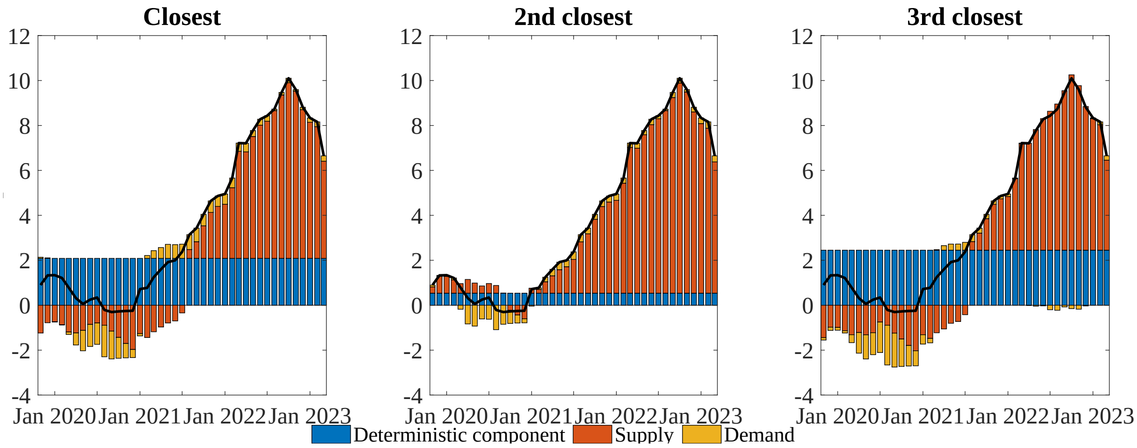


Figure A-6: Historical decompositions and deterministic components of euro area inflation, different identification schemes. Diffuse prior

(a) Blanchard-Quah decomposition: Historical decomposition, top 3 model draws




(b) Cholesky decomposition: Historical decomposition, top 3 model draws




(c) Deterministic components of inflation

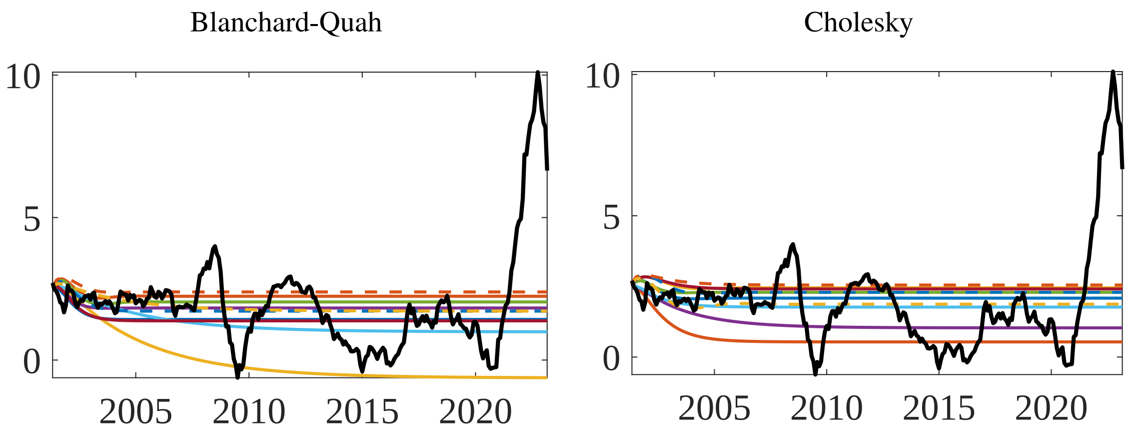
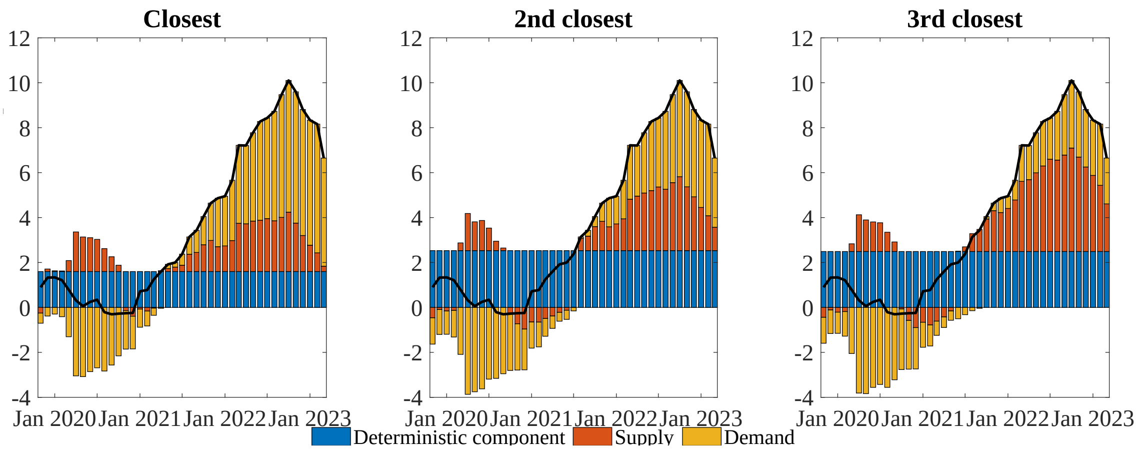


Figure A-7: Historical decompositions of euro area inflation for top 3 model draws for different priors

(a) Normal-Inverse Wishart prior




(b) Minnesota prior

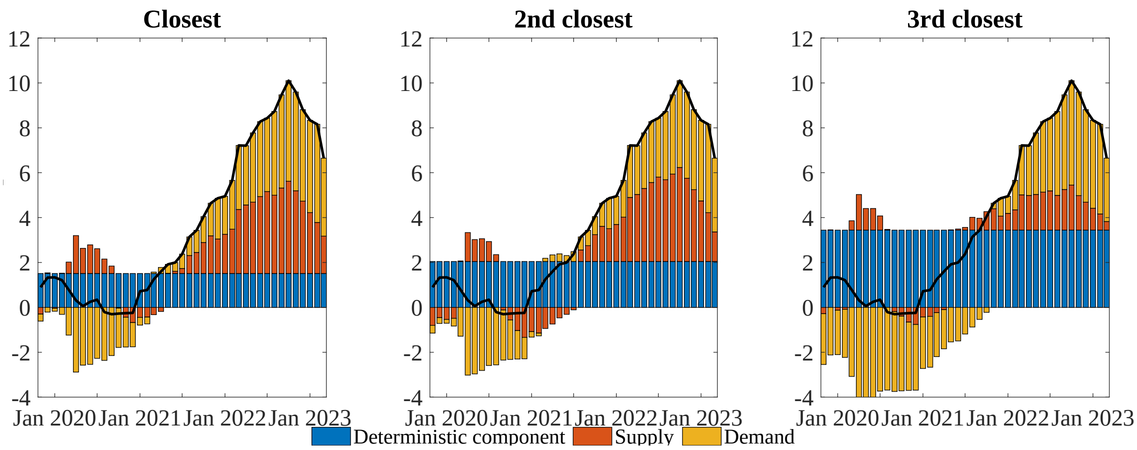
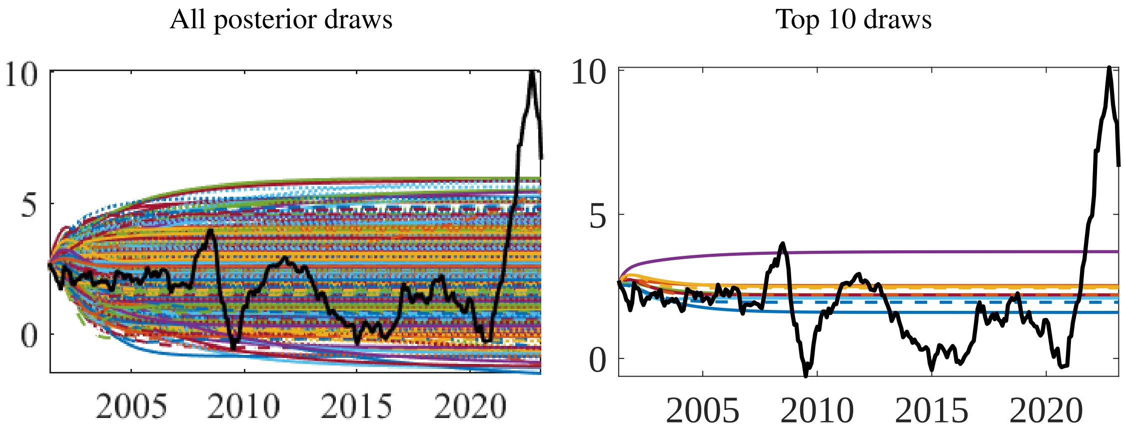


Figure A-8: Deterministic components of euro area inflation

(a) Normal-Inverse Wishart prior




(b) Minnesota prior

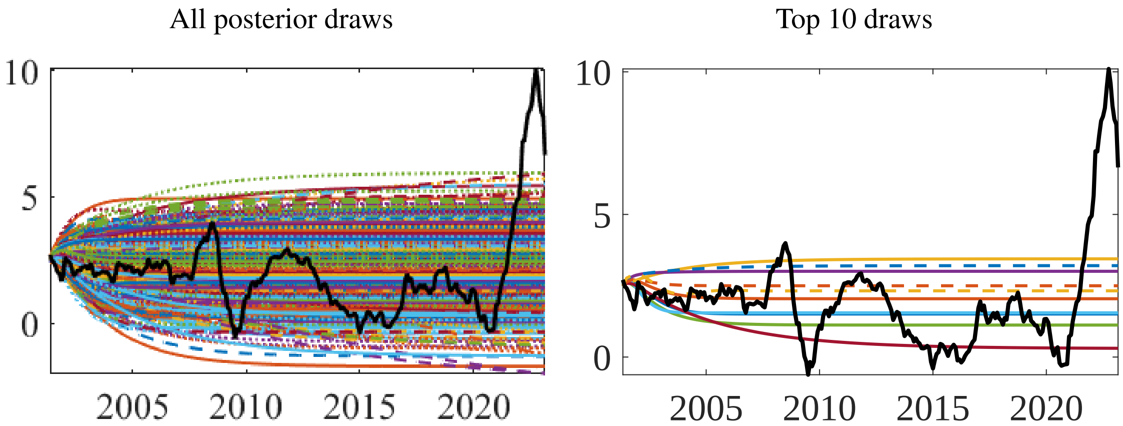
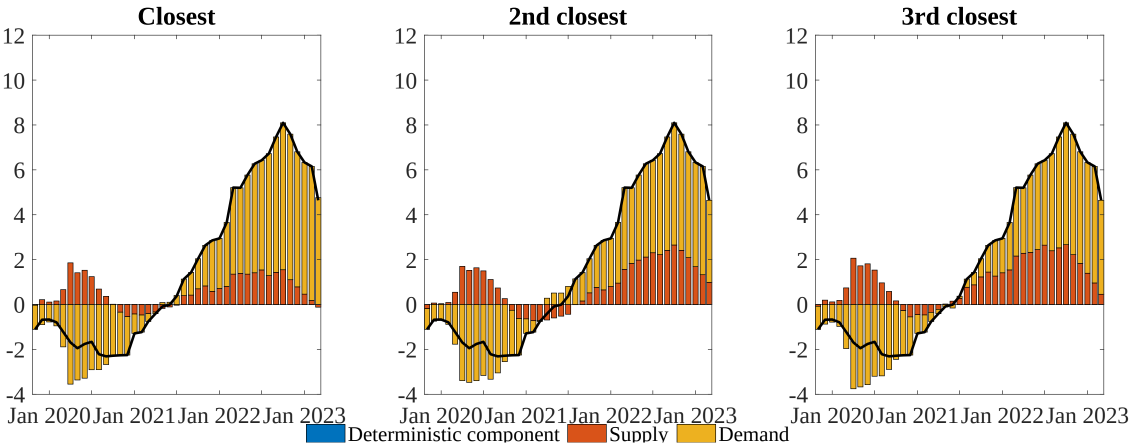


Figure A-9: Euro area: Estimated without constant (demeaned data) with a diffuse prior

(a) Historical decomposition of inflation for top 3 draws




(b) Deterministic components of inflation

All posterior draws

Top 10 draws

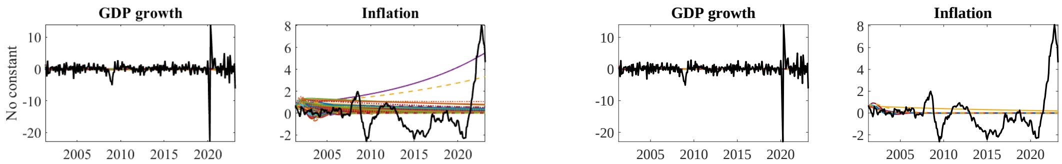
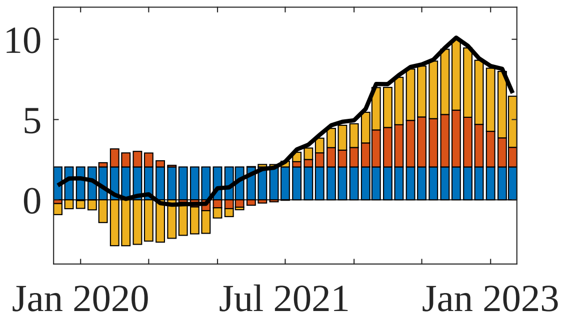
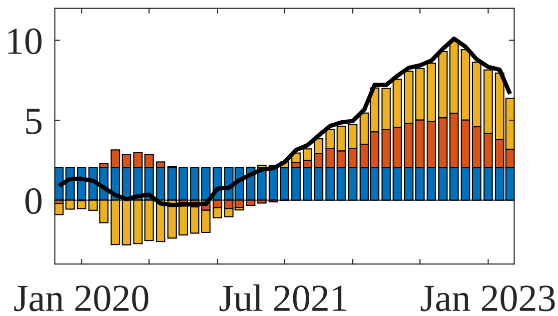



Figure A-10: Euro area: Historical decomposition of inflation, pointwise median

(a) Diffuse prior

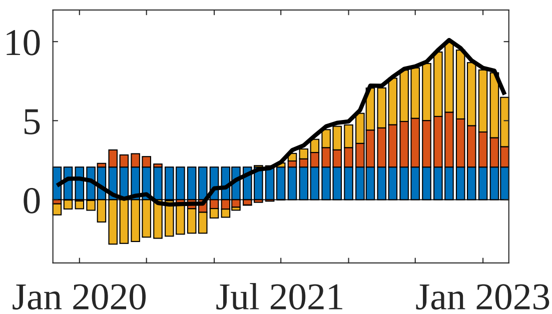
Normal-Inverse Wishart prior

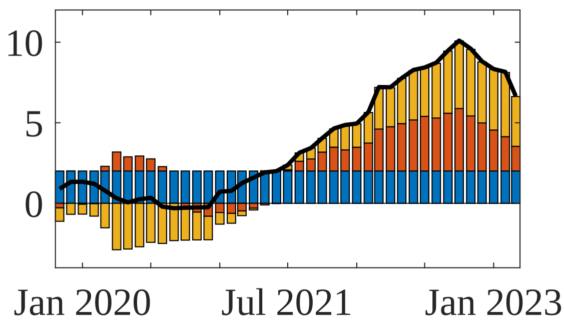



(b) Minnesota prior

(c) Single-unit-root prior

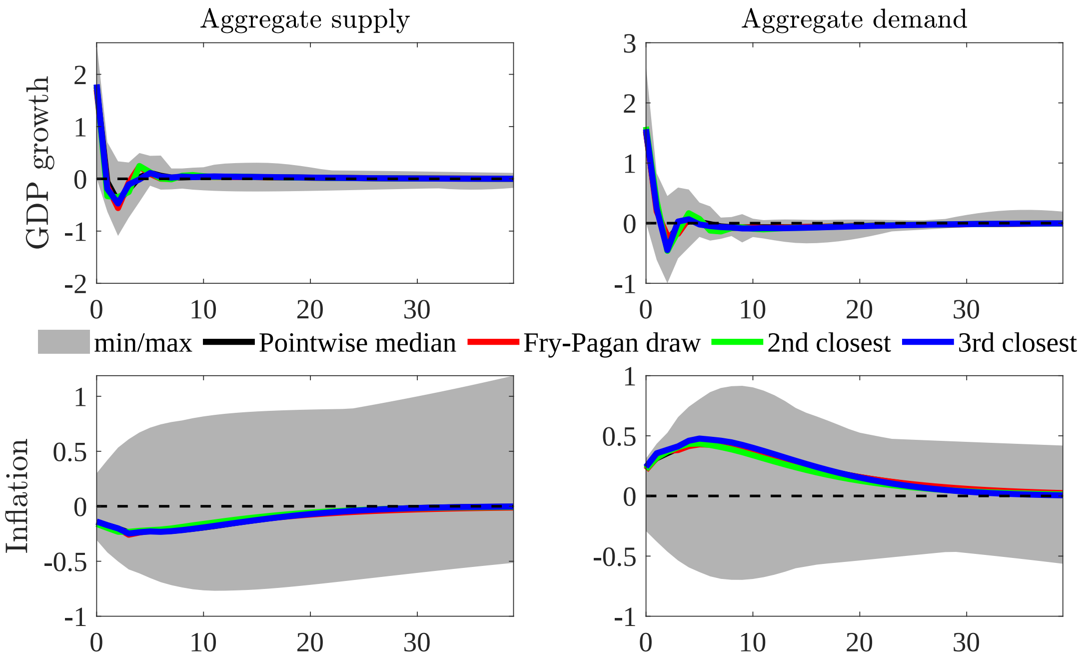



*Note:*

Figure A-11: IRFs of an aggregate demand and an aggregate supply shock, different identification schemes. Euro area

(a) Blanchard-Quah




(b) Cholesky