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The Effects of Fiscal Policy Shocks: Evidence from a Bayesian SVAR Model With Uncertain Identifying Assumptions**

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Abstract

We explore the effects of fiscal policy shocks on aggregate output and inflation. We use the novel Bayesian econometric methodology of Baumeister and Hamilton applied to the fiscal structural vector autoregressive model to evaluate key elasticities and fiscal multipliers using U.S. data from 1947Q1 to 2023Q4. In our baseline specification, the government spending multiplier is equal to approximately 1.1 and tax multiplier is approximately -1.4 after one year. The short-term output elasticity of government spending is slightly negative and the output elasticity of taxes is approximately equal to 2.6.

Keywords: Fiscal policy, structural VAR, Bayesian inference, impulse-response functions.

JEL Classification: C11, C32, E62, E63, H50.

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1 Introduction

The effects of fiscal policy on the economy are the topic of continuing disagreements among Keynesian and neoclassical economists, as well as policy-makers. In contrast to monetary policy, the macroeconomic effects of fiscal policy are relatively more controversial. During the global financial crisis and the Covid-19 pandemic fiscal stimulus moved center-stage. The commonly used measure of fiscal policy effectiveness is the fiscal multiplier. It describes the effect of an exogenous change in a fiscal policy instrument, be it an unexpected government spending or tax change, on real GDP. The literature on empirical fiscal multipliers is extensive and inconclusive, as surveyed by Ramey (2019), multipliers generally range in value from 0.6 to 2 for government spending and -5 to 0 for tax changes (Ramey, 2019, Tables 1, p. 102, and Table 2, p.105, respectively). Multipliers may also depend on the state of the economy.

In regards to the identification of fiscal shocks in structural vector-autoregressive (SVAR) models, there are several common approaches in the empirical literature. The seminal study of Blanchard and Perotti (2002), as well as further work by Perotti (2004), relies on imposing contemporaneous restrictions on the structural coefficient matrices in an SVAR. Such restriction are based on externally calculated elasticities of government spending and taxes with respect to output and other variables included in the VAR.[1] More recently, several authors have relied on identification through sign restrictions with penalty function (Mountford and Uhlig, 2009), the use of narrative fiscal shocks derived from outside the SVAR (Ramey, 2011; Romer and Romer, 2010) or with narrative shocks used as external fiscal and non-fiscal instruments in so-called proxy-SVARs (Mertens and Ravn, 2014; Caldara and Kamps, 2017; Angelini et al., 2023). Moreover, Carriero et al. (2024) link sign restircted SVARs and proxy-SVARs to a regime-switching process for the variance of structural shocks that can point-identify (as opposed to set-identify).

The crucial point for our study is that the values of contemporaneous fiscal elasticities play a critical role for the size of the multipliers in the SVAR literature. Mertens and Ravn (2014) use a proxy-SVAR with narratively identified unanticipated tax shocks. They compare result from such a proxy-SVAR to a standard SVAR with externally imposed elasticities as in Blanchard and Perotti (2002). Mertens and Ravn (2014) show that the tax multiplier in standard SVARs can range from an absolute value near one (Blanchard and Perotti, 2002), to values of around two or three, depending on the size of the output

[1] Favero and Giavazzi (2012) present in their Footnote 3 (p. 74) a table with typical values used.

elasticity of tax revenues. They argue that lower tax multiplier values in previous studies can be explained by an imposed output elasticity of tax revenue value that is contradicted by empirical evidence. Caldara and Kamps (2017) demonstrate that the differences in fiscal multiplier estimates in SVARs can be analytically accounted for by different assumptions for the systematic response of tax and spending policies to output. Different fiscal rules lead to different identification schemes and different empirical multipliers. They propose instead a proxy-SVAR that uses non-fiscal external instruments to directly identify and estimate the parameters of alternative fiscal rules, without imposing external elasticities. Furthermore, Angelini et al. (2023) also use a proxy-SVAR and show the set of instruments used can crucially affect multiplier, as is the case for imposing or not imposing an orthogonality assumption between tax shocks and their factor productivity shock. Also, external instruments in proxy-SVARs may be weak (Stock and Watson 2018), or altogether not valid (Nguyen, 2022).

Baumeister and Hamilton (2015, 2018, 2019a) develop a novel approach for identifying structural relationships in a VAR model. The identification of structural shocks requires prior information about underlying economic relationships that are external and supplementary to the VAR model itself. Their methodology employs Bayesian priors to account for a researcher's uncertainty around imposed identifying assumptions. The traditional and most commonly used approaches to identifying structural shocks in SVARs are to impose zero restrictions on contemporaneous relationships among structural shocks, specific values for variables' elasticities to shocks, and/or sign restrictions. Instead of imposing such identifying restrictions as if they were know with certainty, Baumeister and Hamilton (2015) propose to explicitly account for the degree of uncertainty surrounding a researcher's prior information. As outlined in Baumeister and Hamilton (2019a), their approach allows for imposing varying degrees of a priori uncertainty about identifying values imposed, as well as for setting sign restrictions. In addition, it can deal with structural instability by assigning different weights to observations from different time periods. So far, the methodology has been applied to quantify the impact of monetary policy shocks in the U.S. economy (Baumeister and Hamilton, 2018) and to evaluate the elasticities on the U.S. oil and natural gas markets (Baumeister and Hamilton, 2019a; Rubaszek, Szafranek and Uddin, 2021). To the best of our knowledge, this framework has not been exploited to broaden the understanding of U.S. fiscal policy and pin down precisely fiscal elasticities.

In our paper we follow an alternative route to traditional SVARs and proxy-SVARs by estimating the size of fiscal elasticities and associated fiscal multipliers with the flexible Bayesian SAVR methodology of Baumeister and Hamilton (2015, 2018, 2019a). We consider a range of various identifying restrictions used in the previous fiscal literature in order to set up prior distributions that reflect the uncertainty around the identifying assumptions. Traditional SVAR estimates can be viewed as a special case of the Bayesian estimates with very strong prior beliefs about identifying restrictions.

We contribute to the existing literature across several margins. First, we provide direct estimates of fiscal and monetary policy elasticities, and fiscal multipliers, by applying Baumeister and Hamilton's methodology. Second, our model includes the Covid-19 period, ending with the fourth quarter of 2023, and produces sensible estimates that allow us to assess the effects of fiscal policy and also of monetary policy for the U.S. economy in recent turbulent years. We note a change in fiscal and monetary policy effects when we consider only pre-Covid-19 data, with generally smaller multipliers. Third, we find that monetary policy played an important role in bringing down recent inflation, whereas government transfer payments had the opposite effect.

The rest of the paper is structured as follows. In Section 2 we briefly review the related literature. Section 3 presents the Bayesian econometric model. Section 4 is dedicated to the data and the empirical specification, along with the choice of specific prior distributions. Empirical results are discussed in Section 5 and their sensitivity to modifications in the baseline model is explored in Section 6. Finally, Section 7 concludes the analysis.

2 Literature review of closely related fiscal SVAR models

Blanchard and Perotti's (2002) widely cited study forms the foundation for most subsequent empirical research on fiscal multipliers. In their approach fiscal shocks are identified by using institutional information about the tax and transfer systems to specify the automatic response of taxes and spending to economic activity and, then, by imposing externally calculated elasticities. Blanchard and Perotti (2002) use a trivariate SVAR model: the logarithms of quarterly government spending, GDP, and taxes, all in real and per capita terms.[2] Their main findings are the following. Government spending increases

[2] Many subsequent studies expand the model to include an interest and inflation rate to reflect the stance of monetary policy. Rossi and Zubairy (2011) show that fiscal and monetary policy shocks interact. Thus, neglecting one shock may lead to attributing its effects wrongly to another.

cause output to increase, while tax increases cause output to decrease. Spending multipliers are close to one and they depend on different components of output, meaning that private consumption increases following a government spending increase, while private investment is crowded out to some degree.

Mountford and Uhlig (2009) and Mertens and Ravn (2014) apply similar data as in Blanchard and Perotti (2002) but use a different methodology. Mertens and Ravn (2014) use a proxy-SVAR with unanticipated narrative tax shocks as an external proxy (instrument variable) and they allow for measurement error in the narrative tax shocks. On the other hand, Mountford and Uhlig (2009) set instead sign restrictions on VAR impulse responses to achieve identification. They use a so-called penalty function approach, that rewards large impulse responses in the right directions more than small responses and penalizes responses of the wrong sign. Their sample covers the period from 1955 to 2000 for U.S. data. Mountford and Uhlig (2009) consider three scenarios: deficit-spending, deficit-financed tax cuts and a balanced budget spending expansion.[3] They find that deficit-financed tax cuts are the most effective among the three scenarios with the largest present value multiplier equal to five after five years. Mountford and Uhlig (2009) also find that deficit spending weakly stimulates the economy, more precisely, it crowds out private investment but without interest rate increases and without real wage increases.

The two papers that are most closely related to ours are Caldara and Kamps (2017) and Caldara and Kamps (2008). They use a VAR model with five equations, as we do, including in addition to the three variables used by Blanchard and Perotti (2002) inflation and an interest rate.[4] Caldara and Kamps (2008) is a comparative study on using different approaches for fiscal shock identification in VAR models and in our view can be seen as an extended introduction to Caldara and Kamps (2017). Caldara and Kamps (2017) argue that the differences in fiscal multiplier estimates can be analytically accounted for by different assumptions for the systematic response of tax and spending policies to output (α_{gy} and α_{ty}, respectively). This is an important finding in the context of our analysis. It means that assumptions on α_{gy} and α_{ty} should strongly affect our results. Caldara and Kamps (2017) apply a proxy-SVAR model with various non-fiscal instruments. Their results show a positive and large systematic response of taxes to output (α_{ty}), and a small but negative systematic response of government spending to output (α_{gy}). They note that the implied government spending multipliers tend to be larger than government tax

[3]It is important to note that various subsequent studies follow this approach, including Caldara and Kamps (2008).
[4]Such a five-variable VAR specification is also used by Perotti (2004) and Favero and Giavazzi (2012).

multipliers. Mertens and Ravn (2014), however, find the opposite.

Mertens and Ravn (2014) and Caldara and Kamps (2017) agree on the crucial importance of the output elasticity of tax revenue. In their approach the short-term elasticities are estimated and no prior information for them is needed. Also Angelini et al. (2023) present a wide range of possible elasticities of government spending and tax responses to output, for fiscal and non-fiscal instruments in a proxy-SVAR. The output elasticity of government spending for detrended data ranges from -0.32 to 0.00 and the output elasticity of tax revenue ranges from 2.15 to 4.40, depending on the set of instruments used and whether imposing orthogonality between the tax shock and factor productivity shock (cf. Table A2 in Angelini et al., 2023). Angelini et al. (2023) use the sample between 1950Q1 and 2006Q4, which makes their results comparable with the study of Caldara and Kamps (2017) and enables them to use the publicly available proxies form Caldara and Kamps (2017), but it prevents full comparison with our study.

Carriero et al. (2024) extend the proxy-SVARs and sign/narrative restricted SVARs to using additionally heteroskedasticity for identification purposes. They assume that the variance of structural shocks follows a regime-switching process. It is further assumed that regime changes are either known or can be determined with change-point specifications, however, the contemporaneous shock-impact matrix is assumed to be time invariant. They apply, among other examples, a blended proxy-SVAR with narrative U.S. personal and corporate income tax shocks as external instruments to data spanning 1951Q1 to 2006Q4. Median responses in a proxy-SVAR with heteroskedasticity are largely similar to those with homoskedasticity. But, importantly, heteroskedasticity produces narrower confidence intervals and hence more precise estimates.

3 Methodology

In this section we outline the methodology for Bayesian estimation of parameters of the fiscal structural VAR, which will be specified in the next section. The form of the model is:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{u}_t,\ \mathbf{u}_t \sim N(\mathbf{0}, \mathbf{D}). \tag{1}$$

In this notation $\mathbf{y}_t = (y_{1t}, ..., y_{nt})'$ is an $n \times 1$ vector of endogenous variables, $\mathbf{A}$ is an $n \times n$ matrix containing contemporaneous structural relationships, $\mathbf{x}_{t-1}$ is a $k \times 1$ vector, $k = mn + 1$, consisting of

m lags for $\mathbf{y}_t$ and a constant, $\mathbf{x}_{t-1}^{'} = (\mathbf{y}_{t-1}^{'}, \ldots, \mathbf{y}_{t-m}^{'}, 1)'$, $\mathbf{B}$ is an $n \times k$ matrix of parameters of lagged variables, $\mathbf{u}_t$ is an $n \times 1$ vector of uncorrelated structural shocks and $\mathbf{D} = \text{diag}(d_{11}, \ldots, d_{nn})$ represents a diagonal matrix of size $n \times n$. We denote $\mathbf{a}_i$ row i of $\mathbf{A}$.

We estimate the parameters of model (1) with Baumeister and Hamilton's (2015, 2019a) Bayesian methodology. The key appealing feature of this approach is that it allows us to formulate identifying assumptions of the structural VAR in a very flexible fashion. Importantly, as discussed in Baumeister and Hamilton (2019b, 2022), we can robustly and properly quantify elasticities using this framework, which is the main focus of our study. In what follows, we shortly describe the methodology. We refer the reader to the source articles by Baumeister and Hamilton (2015, 2019a) for the detailed description and discussion. For the sake of transparency, we keep our notation almost identical to that in the source articles.

Prior We start by eliciting the prior for all unknown parameters included in model (1). The prior is decomposed into three parts:

$$p(\mathbf{A}, \mathbf{B}, \mathbf{D}) = p(\mathbf{B}|\mathbf{A}, \mathbf{D}) \times p(\mathbf{D}|\mathbf{A}) \times p(\mathbf{A}). \tag{2}$$

The prior for the covariance matrix, $p(\mathbf{D}|\mathbf{A})$, can be expressed as a product of priors for its elements:

$$\begin{aligned} p(\mathbf{D}|\mathbf{A}) &= \prod_{i=1}^{n} p(d_{ii}|\mathbf{A}) \\ d_{ii}^{-1}|\mathbf{A} &\sim \Gamma(\kappa_i, \tau_i(\mathbf{A})), \end{aligned} \tag{3}$$

with $x \sim \Gamma(\kappa, \tau)$, following a Gamma distribution with the shape and rate parameters κ and τ, respectively, where $E(x) = \kappa/\tau$ and $Var(x) = \kappa/\tau^2$; and d_{ii} is the (i, i) element of $\mathbf{D}$. The above notation stresses the fact that the rate parameter depends on the value of matrix $\mathbf{A}$.

The prior for the matrix of parameters of lagged variables, $p(\mathbf{B}|\mathbf{A}, \mathbf{D})$, is a product of priors for its individual rows $\mathbf{b}_i$:

$$\begin{aligned} p(\mathbf{B}|\mathbf{A},\mathbf{D}) &= \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{D},\mathbf{A}) \\ \mathbf{b}_i|\mathbf{A},\mathbf{D} &\sim N(\mathbf{m}_i, d_{ii}\mathbf{M}_i), \end{aligned} \tag{4}$$

with $N(\mu, \Sigma)$ representing the multivariate normal density function with the location and scale parameters μ and Σ.

Last, we set the prior for the contemporaneous relations matrix $p(\mathbf{A})$. By design, it should reflect the economic structure of the analyzed economic system. We will discuss in detail our approach towards eliciting $p(\mathbf{A})$ in Section 4.

Posterior We turn to explaining how observations collected within $\mathbf{Y}_T$, $\mathbf{Y}_T = (\mathbf{y}_1', \mathbf{y}_2', \ldots, \mathbf{y}_T')'$ affect our prior beliefs about unknown parameters $\mathbf{A}, \mathbf{B}$ and $\mathbf{D}$. We follow Baumeister and Hamilton (2019a) and divide the full sample into T_1 initial observations, labelled pre-sample, and T_2 last observations, labelled as the main sample, with $T_1 + T_2 = T$. In this way we downweight the impact of pre-sample observations on the posterior by a factor $0 \leq \mu \leq 1$. In order to derive the posterior distribution, it is decomposed into three parts:

$$p(\mathbf{A},\mathbf{B},\mathbf{D}|\mathbf{Y}_T) = p(\mathbf{B}|\mathbf{A},\mathbf{D},\mathbf{Y}_T) \times p(\mathbf{D}|\mathbf{A},\mathbf{Y}_T) \times p(\mathbf{A}|\mathbf{Y}_T). \tag{5}$$

The posterior of $\mathbf{A}$ is estimated using a Metropolis-Hastings algorithm with M draws from the posterior distribution after initial M^* burn-in draws ($M = M^* = 5e5$), while the posteriors of $\mathbf{B}$ and $\mathbf{D}$ are their respective natural conjugates.

First we present the equations for the contemporaneous relations matrix posterior, $p(\mathbf{A}|\mathbf{Y}_T)$, using the covariance matrices of the VAR model residuals estimated for the two subsamples, as well as their weighted average. The posterior marginal distribution for $\mathbf{A}$ is:

$$p(\mathbf{A}|\mathbf{Y}_T) = k_T p(\mathbf{A}) \left[\det(\mathbf{A}\widetilde{\mathbf{\Omega}}_T\mathbf{A}')\right]^{T^*} \prod_{i=1}^{n} \frac{[\tau_i(\mathbf{A})]^{\kappa_i}}{[\tau_i^*(\mathbf{A})/T^*]^{\kappa_i^*}}, \tag{6}$$

with $T^* = (\mu T_1 + T_2)/2$ and k_T a constant, ensuring that $p(\mathbf{A}|\mathbf{Y}_T)$ is a proper density function that integrates to unity.

Next, the posterior for the covariance matrix, $p(\mathbf{D}|\mathbf{A},\mathbf{Y}_T)$, is expressed as a product of the posterior for its diagonal elements:

$$\begin{aligned} p(\mathbf{D}|\mathbf{A},\mathbf{Y}_T) &= \prod_{i=1}^{n} p(d_{ii}|\mathbf{A},\mathbf{Y}_T) \\ d_{ii}^{-1}|\mathbf{A},\mathbf{Y}_T &\sim \Gamma(\kappa_i^*,\tau_i^*(\mathbf{A})). \end{aligned} \tag{7}$$

The posterior for the matrix of parameters of the lagged variables, $p(\mathbf{B}|\mathbf{A},\mathbf{D},\mathbf{Y}_T)$, is written as the product of the posterior for its individual rows:

$$\begin{aligned} p(\mathbf{B}|\mathbf{A},\mathbf{D},\mathbf{Y}_T) &= \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{D},\mathbf{A},\mathbf{Y}_T) \\ \mathbf{b}_i|\mathbf{A},\mathbf{D},\mathbf{Y}_T &\sim N(\mathbf{m}_i^*(\mathbf{A}), d_{ii}\mathbf{M}_i^*). \end{aligned} \tag{8}$$

Let

$$\begin{aligned} \widetilde{\mathbf{\Omega}}_1 &= (T_1)^{-1}\left(\sum_{t=1}^{T_1}\mathbf{y}_t\mathbf{y}_t' - \left(\sum_{t=1}^{T_1}\mathbf{y}_t\mathbf{x}_{t-1}'\right)\left(\sum_{t=1}^{T_1}\mathbf{x}_{t-1}\mathbf{x}_{t-1}'\right)^{-1}\left(\sum_{t=1}^{T_1}\mathbf{x}_{t-1}\mathbf{y}_t'\right)\right) \\ \widetilde{\mathbf{\Omega}}_2 &= (T_2)^{-1}\left(\sum_{t=T_1+1}^{T}\mathbf{y}_t\mathbf{y}_t' - \left(\sum_{t=T_1+1}^{T}\mathbf{y}_t\mathbf{x}_{t-1}'\right)\left(\sum_{t=T_1+1}^{T}\mathbf{x}_{t-1}\mathbf{x}_{t-1}'\right)^{-1}\left(\sum_{t=T_1+1}^{T}\mathbf{x}_{t-1}\mathbf{y}_t'\right)\right) \\ \widetilde{\mathbf{\Omega}}_T &= (\mu T_1 + T_2)^{-1}\left(\mu T_1\widetilde{\mathbf{\Omega}}_1 + T_2\widetilde{\mathbf{\Omega}}_2\right) \end{aligned} \tag{9}$$

$$\begin{aligned} \kappa_i^* &= \kappa_i + (\mu T_1 + T_2)/2 \\ \tau_i^*(\mathbf{A}) &= \tau_i(\mathbf{A}) + \zeta_i^*(\mathbf{A}). \end{aligned} \tag{10}$$

$\zeta_i^*(\mathbf{A}) = \left(\widetilde{\mathbf{Y}}_i'(\mathbf{A})\widetilde{\mathbf{Y}}_i(\mathbf{A})\right) - \left(\widetilde{\mathbf{Y}}_i'(\mathbf{A})\widetilde{\mathbf{X}}_i\right)\left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{X}}_i\right)^{-1}\left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{Y}}_i(\mathbf{A})\right)$ represents the sum of squared residuals from a regression of $\widetilde{\mathbf{Y}}_i(\mathbf{A})$ on $\widetilde{\mathbf{X}}_i$:

$$\begin{aligned} \underset{(T+k)\times 1}{\widetilde{\mathbf{Y}}_i(\mathbf{A})} &= \begin{bmatrix} \sqrt{\mu}\mathbf{y}_1'\mathbf{a}_i & \dots & \sqrt{\mu}\mathbf{y}_{T_1}'\mathbf{a}_i & \mathbf{y}_{T_1+1}'\mathbf{a}_i & \dots & \mathbf{y}_T'\mathbf{a}_i & \mathbf{m}_i'\mathbf{P}_i \end{bmatrix}' \\ \underset{(T+k)\times k}{\widetilde{\mathbf{X}}_i} &= \begin{bmatrix} \sqrt{\mu}\mathbf{x}_0 & \dots & \sqrt{\mu}\mathbf{x}_{T_1-1}' & \mathbf{x}_{T_1}' & \dots & \mathbf{x}_{T-1}' & \mathbf{P}_i \end{bmatrix}' \end{aligned} \tag{11}$$

$\mathbf{P}_i$ is the Cholesky factor of $\mathbf{M}_i^{-1} = \mathbf{P}_i\mathbf{P}_i'$, and

$$\begin{aligned} \mathbf{m_i^*}(\mathbf{A}) &= \left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{X}}_i\right)^{-1}\left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{Y}}_i(\mathbf{A})\right) \\ \mathbf{M_i^*} &= \left(\widetilde{\mathbf{X}}_i'\widetilde{\mathbf{X}}_i\right)^{-1}. \end{aligned} \tag{12}$$

4 The data and the empirical model

We describe the structural fiscal SVAR model that we apply to the U.S. economy. The choice of endogenous variables entering vector $\mathbf{y_t}$ is based on the setup considered by Caldara and Kamps (2017), whereas the prior information is elicited based on the survey of the literature on fiscal elasticities provided in Section 2. In what follows, we discuss both the data and the setup of our empirical model in more detail.

4.1 Data

In our baseline specification we consider the joint dynamics of five U.S. variables: real general government consumption and gross investment expenditures (G_t), real GDP (Y_t), inflation (π_t), real general government tax receipts (T_t), and the interest rate (r_t). We take G_t, Y_t and T_t in nominal, seasonally adjusted values from the U.S. Bureau of Economic Analysis's National Income and Product Accounts (NIPA) tables, deflate all the series with the implicit price deflator for GDP and express them in *per capita* terms. Next, we log the series G_t, Y_t, T_t and extract cycle estimates using Hamilton's (2018) filter.[5] In regards to the proxy for inflation, π_t, we source the CPI index from the FRED database and compute the year-on-year log rate of change. With respect to r_t, we construct a series based on data from Bernardini and Peersman (2018) and estimates of the shadow rate from Krippner (2013, 2015) for periods when the interest rate is near the zero lower bound. Consequently, the vector of endogenous variables is:

$$\mathbf{y}_t = \begin{bmatrix} \hat{g}_t & \hat{y}_t & \pi_t & \hat{t}_t & r_t \end{bmatrix}, \tag{13}$$

where $\hat{x}$ indicates the cyclical deviation of variable x from its stochastic trend estimate. All variables entering $\mathbf{y}_t$ are expressed in percent. Appendix A provides detailed sources of our data and lists all transformations.

Our sample covers quarterly data from the period 1947Q1-2023Q4, where the first observation is set

[5] Alternatively, one could remove a deterministic time trend from G, Y and T, as commonly done in the literature (e.g., Caldara and Kamps, 2017). We tested this approach and find it inferior due to flattening of the trend for recent data.

by data availability. For the sake of our analysis, we divide the sample into two subperiods. In our setup, the initial $T_1 = 160$ observations for the period 1947Q1-1986Q4 are treated as pre-sample observations. This choice is motivated by the fact that the output elasticity of tax revenues has increased after the Tax Reform Act of 1986, according to the studies of Mertens and Ravn (2014) or Follette and Lutz (2010).[6] For the above reasons, the information from this period is downweighted by a factor of 2 ($\mu = 0.5$). The subsequent $T_2 = 148$ observations for the period 1987Q1-2023Q4 are treated as the main sample. Given quarterly data, we set the maximum lag at $m = 4$, which is a frequent choice in the literature (e.g., Mertens and Ravn, 2014).[7]

Figure 1 illustrates time series for the dependent variables. Several observations follow. There is a strong cyclical pattern in both real general government consumption and gross investment expenditure, $\hat{g}_t$, and in real general government tax receipts, $\hat{t}_t$. Moreover, the patterns for both of these variables change markedly in the early 1950s. We note also that $\hat{t}_t$ is much more strongly correlated with $\hat{y}_t$ than $\hat{g}_t$, indicating an obvious link in the cyclicality of tax receipts to the tax base. In regards to $\hat{y}_t$, we observe several downturns, most recently related to the global financial crisis and the outbreak of the Covid-19 pandemic. We explore this issue further in section 6. Next, apart from several high inflation episodes (related to the removal of price controls, supply constraints and pent-up demand after World World II, oil shocks in the 1970s, and most recently the Covid-19 pandemic), the year-on-year inflation rate, π_t, evolves otherwise on a moderate level. Finally, following its peak in the 1980s, the nominal (shadow) interest rate decreased substantially and became negative after the global financial crisis and during the Covid-19 pandemic. By the end of the sample, along with a stark increase in inflation, the interest rate picked up considerably and moved away from its zero lower bound.

[6] The Tax Reform Act was signed into law by President Ronald Reagan on October 22, 1986.

[7] As a robustness check, we also estimate the model with $m = 1$. The impulse response functions become smoother, but the results do not change significantly. They are available from the authors on request.

4.2 Specification of the structural VAR model

The structure of contemporaneous relations among the endogenous variables is assumed to be as follows:

$$\hat{g}_t = \alpha_{gy}\hat{y}_t + \alpha_{gp}\pi_t + \alpha_{gt}\hat{t}_t + \alpha_{gr}r_t + \mathbf{b}_1^{'}\mathbf{x}_{t-1} + u_t^G \tag{14}$$

$$\hat{y}_t = \alpha_{yg}\hat{g}_t + \alpha_{yp}\pi_t + \alpha_{yt}\hat{t}_t + \alpha_{yr}r_t + \mathbf{b}_2^{'}\mathbf{x}_{t-1} + u_t^Y \tag{15}$$

$$\pi_t = \alpha_{pg}\hat{g}_t + \alpha_{py}\hat{y}_t + \alpha_{pt}\hat{t}_t + \alpha_{pr}r_t + \mathbf{b}_3^{'}\mathbf{x}_{t-1} + u_t^P \tag{16}$$

$$\hat{t}_t = \alpha_{tg}\hat{g}_t + \alpha_{ty}\hat{y}_t + \alpha_{tp}\pi_t + \alpha_{tr}r_t + \mathbf{b}_4^{'}\mathbf{x}_{t-1} + u_t^T \tag{17}$$

$$r_t = \alpha_{rg}\hat{g}_t + \alpha_{ry}\hat{y}_t + \alpha_{rp}\pi_t + \alpha_{rt}\hat{t}_t + \mathbf{b}_5^{'}\mathbf{x}_{t-1} + u_t^R \tag{18}$$

In the notation of equation (1) for the structural VAR model, the above system implies the following representation for matrix $\mathbf{A}$:

$$\mathbf{A} = \begin{bmatrix} 1 & -\alpha_{gy} & -\alpha_{gp} & -\alpha_{gt} & -\alpha_{gr} \\ -\alpha_{yg} & 1 & -\alpha_{yp} & -\alpha_{yt} & -\alpha_{yr} \\ -\alpha_{pg} & -\alpha_{py} & 1 & -\alpha_{pt} & -\alpha_{pr} \\ -\alpha_{tg} & -\alpha_{ty} & -\alpha_{tp} & 1 & -\alpha_{tr} \\ -\alpha_{rg} & -\alpha_{ry} & -\alpha_{rp} & -\alpha_{rt} & 1 \end{bmatrix}. \tag{19}$$

Below we discuss equations (14)-(18) and explain the most important short-term elasticities. Equation (14) can be interpreted as the government spending rule, where α_{gy} is the output elasticity of government spending. Equation (15) describes the aggregate demand equation, where α_{yg} is the government spending elasticity of output. Equation (16) constitutes the short-term Phillips curve, where α_{py} is the short term output elasticity of prices. Equation (17) is the tax rule with α_{ty} being the output elasticity of taxes, and α_{tp} being the price elasticity of taxes. Finally, the last equation, (18), can be interpreted as a short-term Taylor-type rule, where α_{ry} is the output elasticity of the interest rate and α_{rp} is the price elasticity of the interest rate. We discuss the choice for the prior for the elasticities in equations (14)-(18) in the next section.

Our system of equations implies that all endogenous variables are allowed to be affected by their past values, included in the vector $\mathbf{x}_{t-1}$. The dynamics of endogenous variables is also affected by five structural shocks. The first shock, u_t^G, can be perceived as an unexpected change in general government consumption and investment expenditures, hence we label it spending shock. The income shock u_t^Y reflects unexpected shifts in aggregate U.S. economic activity. The price shock, u_t^P, captures unanticipated changes to inflation. The fourth shock u_t^T accounts for unexpected changes in general government tax receipts, hence we label it tax shock. Finally, we account for the interest rate shock, u_t^R, which reflects unanticipated changes in the monetary policy stance.

4.3 The prior for the empirical model

Setting the prior distributions is of central importance for our model. In this subsection we describe our choices related to the parameters describing $p(\mathbf{A}, \mathbf{B}, \mathbf{D})$ for the empirical model.

Prior for A We start by describing our choices for the contemporaneous relations matrix prior, $p(\mathbf{A})$, which we summarize in the upper part of Table 2. We stress that while some elasticities are heavily researched in the literature (cf., Section 2), for others the provided evidence is scarce. This distinction is reflected in our choice of priors. We impose informative prior beliefs for the former parameters, while for the latter we use rather uninformative priors. We have chosen to use either symmetric or truncated Student t distributions for the elements of the $\mathbf{A}$ matrix or restrict them to zero.

First we discuss the government spending rule. The output elasticity of government spending (α_{gy}) is centered around 0 with the scale parameter equal to 0.2, which implie the confidence interval $(-0.47, 0.47)$, in accordance with the estimates presented in Table 1. For α_{gt} and α_{gr} we follow an agnostic approach and use rather uninformative distributions centered around 0, with the scale parameter 0.5. This is mostly motivated by the discussion in Blanchard and Perotti (2002), who claim that it typically takes longer than a quarter for discretionary fiscal policy to react to news at the quarterly frequency. It is important to underline that, concerning the output and interest rate elasticities of public spending, our definition of spending does not include unemployment benefits and interest payments. In regards to the price elasticity of public spending α_{gp} we center the prior at -0.5 following, for instance, Caldara and Kamps (2008), Favero and Giavazzi (2012) and Perotti (2008). The estimate is based on dividing spending into a non-wage and a wage components, where the non-wage component is indexed to the price level and the wage component shrinks proportionally to inflation.

Second, we discuss the aggregate demand curve. We follow Blanchard and Perotti (2002) and center the prior for α_{yg} at 1. The scale parameter, set at 0.2, resembles moderate uncertainty around our mode. In regards to α_{yt} we assume the mode prior is -0.9 and the scale parameter is 0.3, also in line with previous estimates provided by Blanchard and Perotti (2002). The assumed signs for α_{yg} and α_{yt}, imposed by using a truncated t distribution, are in accordance with Caldara and Kamps (2008) and Mertens and Ravn (2014). Hence, our one-sided 90% confidence interval for α_{yg} is $(0.00, 1.33)$ and for α_{yt} it is $(-1.40, 0.00)$, in line with the elasticity range reported in those studies. With no prior beliefs for α_{yp} and α_{yr}, we use symmetric Student t distributions centered at 0 and we set the scale parameter to 0.5.

Third, we move to the aggregate supply (Phillips) curve. We use a Student t distribution for α_{py}, truncated to be positive, with the mode at 0.03 and the scale parameter at 0.1. This is broadly in line with mean estimates from Gagliardone et al. (2023), Hazell et al. (2020) and Gali and Gertler (1999), ranging from 0.0062 to 0.05. For our prior, the corresponding one-sided 90% confidence interval is $(0.00, 0.24)$, which covers the elasticity ranges with a substantial margin. In turn α_{pg} and α_{pt} are restricted to zero, so we limit the possibility of fiscal variables affecting inflation on impact. We do not have any prior beliefs for α_{pr} and use symmetric Student t distributions centered at 0 and set the scale parameter to 0.5.

Fourth, we look at the tax rule equation. We base our prior beliefs mostly on previous estimates by Caldara and Kamps (2008), Favero and Giavazzi (2012), and Perotti (2008). Therefore, our prior belief for α_{ty} is represented by a Student t distribution, truncated to be positive, with the mode set at 1.85 and the scale parameter at 0.3. For α_{tp}, we use the same distribution, but we set the mode at 1.25. With this assumptions, our one-sided 90% confidence intervals for the priors are $(0.00, 2.34)$ and $(0.00, 1.75)$, respectively. For the remaining elasticities, we use rather uninformative, symmetric student t distributions with mean at 0.0 and scale parameter at 0.5.

Finally, for the Taylor-type (monetary policy) rule, we follow Baumeister and Hamilton (2018) and use a Student t distribution truncated to be positive for α_{ry} and α_{rp}. The means are set in accordance with Taylor (1993) and Baumeister and Hamilton (2018) at 0.5 and 1.5, respectively, while the scale parameters are equal to 0.4 and 0.3, respectively, with the difference resembling our slightly larger uncertainty surrounding the location parameter of α_{ry}. In regards to the remaining elasticities, α_{rg} and α_{rt} are restricted to zero to resemble our beliefs that monetary policy does not respond to changes in fiscal policy, at least on impact.

Taking into account the above considerations, we set the prior for the individual parameters of $\mathbf{A}$ as follows:

$$\begin{array}{llll}
\alpha_{gy} \sim t_3(0.00, 0.20) & \alpha_{gp} \sim t_3(-0.50, 0.50) & \alpha_{gt} \sim t_3(0.00, 0.50) & \alpha_{gr} \sim t_3(0.00, 0.50) \\
\alpha_{yg} \sim t_3^{+}(1.00, 0.20) & \alpha_{yp} \sim t_3(0.00, 0.50) & \alpha_{yt} \sim t_3^{-}(-0.90, 0.30) & \alpha_{yr} \sim t_3(0.00, 0.50) \\
 & \alpha_{py} \sim t_3^{+}(0.03, 0.10) & & \alpha_{pr} \sim t_3(0.00, 0.50) \\
\alpha_{tg} \sim t_3(0.00, 0.50) & \alpha_{ty} \sim t_3^{+}(1.85, 0.30) & \alpha_{tp} \sim t_3^{+}(1.25, 0.30) & \alpha_{tr} \sim t_3(0.00, 0.50) \\
 & \alpha_{ry} \sim t_3^{+}(0.50, 0.40) & \alpha_{rp} \sim t_3^{+}(1.50, 0.30), &
\end{array} \tag{20}$$

where $x \sim t_v(c, \sigma)$ denotes that a variable x follows the Student t distribution with mode c, scale parameter σ and v degrees of freedom, while superscripts "+" and "–" denote that the distribution is truncated to be either positive or negative, respectively. Our choice of t_3 distributions is the same as in Baumeister and Hamilton (2019a). We summarize the choice of our priors that affect the contemporaneous coefficients in $\mathbf{A}$ in the upper part of Table 2.

Having set prior distributions for individual parameters of matrix $\mathbf{A}$, we also use prior information for their interactions. Additionally, we introduce the prior belief on parameter $h_1 = \det(\mathbf{A})$, which governs how strongly endogenous variables react to structural shocks, with h_1 close to 0 resulting in substantial reactions of endogenous variables to structural shocks.

To this end, we assume that:

$$h_1 \sim At_3(2.9, 5.1, 2), \tag{21}$$

where $x \sim At_v(\mu, \sigma, \lambda)$ means that a variable x follows an asymmetric Student t distribution with v degrees of freedom, location μ, scale σ and skewness λ (see Baumeister and Hamilton, 2018, for details). In the case of the prior for h_1, we set the values for the location and scale parameters using the averages from 50 000 draws for $\theta_A = (\alpha_{gy}, \alpha_{gp}, \alpha_{gt}, \alpha_{gr}, \alpha_{yg}, \alpha_{yp}, \alpha_{yt}, \alpha_{yr}, \alpha_{pg}, \alpha_{py}, \alpha_{pt}, \alpha_{pr}, \alpha_{tg}, \alpha_{ty}, \alpha_{tp}, \alpha_{tr}, \alpha_{rg}, \alpha_{ry}, \alpha_{rp}, \alpha_{rt})'$, the skewness parameter is set to 2 and the degrees of freedom to 3 as in the Baumeister and Hamilton (2019a). This choice implies a 92.6 percent prior probability for h_1 being positive.

Priors for D given A The values of parameters τ_i and κ_i from equation (3) are set in line with the standard Bayesian VAR literature (Doan et al., 1984; Kadiyala and Karlsson, 1997; Sims and Zha, 1998). We choose $\kappa_i = 2$, which means that the weight of the prior for the posterior is equivalent to two full observations from the sample, as in Baumeister and Hamilton (2019a). Next, we set $\tau_i(\mathbf{A}) = \kappa_i \mathbf{a}_i' \widehat{\mathbf{S}} \mathbf{a}_i$, where $\widehat{\mathbf{S}} = \frac{1}{T_1} \sum_{t=1}^{T_1} \widehat{\mathbf{e}}_t \widehat{\mathbf{e}}_t'$ and $\widehat{\mathbf{e}}_t = (e_{it}, \ldots, e_{nt})'$ is a vector of residuals from an autoregressive AR(m) models fitted to the series of the i-th endogenous variable y_{it}, using the pre-sample set of observations, i.e., $t = 1, 2, \ldots, T_1$.

Priors for B given A and D The parameters from vectors $\mathbf{m}_i$ introduced in equation (4) are set to zero. In regards to the $\mathbf{M}_i$ matrices from equation (4), their values are set in a standard way and depend on three hyperparameters usually applied in Bayesian VAR analyses: overall tightness ($\lambda_0 = 0.5$), lag decay ($\lambda_1 = 1$), and tightness around the constant ($\lambda_3 = 1000$).

4.4 The definition of the fiscal multiplier

We follow the definition of the fiscal multiplier in Angelini et al. (2023). The multiplier is defined as the dollar response of GDP to an effective change in government spending or tax revenues of one dollar. Let IRF_{y_h} be the response of log-output at horizon h to a (one-standard deviation) fiscal policy shock; and IRF_{p_0} be the impact of the (one-standard deviation) fiscal policy shock to the corresponding fiscal variable, expressed in logs. The h periods ahead multiplier $\mathbf{M}_{Ph}$ is then expressed as:

$$\mathbf{M}_{Ph} = \frac{IRF_{y_h}}{IRF_{p_0}} \frac{1}{\frac{\overline{P}}{\overline{Y}}}, \tag{22}$$

where P is either government spending or government tax revenues, and $\frac{\overline{P}}{\overline{Y}}$ is the so-called scaling factor that converts elasticities to dollars. $\overline{P}$ denotes the mean across our sample of fiscal spending or tax revenues (not in logs) and $\overline{Y}$ denotes the mean across our sample of the level of output (nominal GDP, not in logs). In our baseline sample the scaling factor is equal to 0.2057 for government spending and 0.1977 for government tax revenues, in the pre-Covid sample the sacling factors are 0.207 and 0.130.[8] We do not discount impulse responses (use present values) as it has only marginal effects on the results. The definition (22) also corresponds to the definition in Blanchard and Perotti (2002) and the *alternative*

[8] For the pre-Covid sample we use a different definition of net taxes (see Section 6).

definition in Caldara and Kamps (2017).

5 Results for the baseline model

This section is devoted to presenting the results. We do it in three steps. First, we investigate the posterior distributions for contemporaneous elasticities. Second, we review the posterior impulse response functions and fiscal multipliers. Third, we quantify short-term and long-term effects of structural shocks on variables considered within our VAR system by calculating forecast error variance decompositions and the historical contributions of these shocks to the percentage deviation of the year-on-year CPI-inflation rate from its long-term mean.

5.1 Posterior of the empirical model

We compare the prior and posterior distributions for the contemporaneous relations matrix **A**. The results are presented in Table 2. We concentrate on the government tax rule and government spending rule. We are particularly interested in the response of fiscal variables to output (α_{ty} and α_{gy}) that likely strongly affect the value of fiscal multipliers (Blanchard and Perotti, 2002; Caldara and Kamps, 2017). We compare the results with those of the papers listed in Table 1. The most important findings are summarized below.

5.1.1 Government spending rule

We find a negative government spending output elasticity α_{gy} with a posterior median of -0.25 that lies in the range reported in the literature (cf. Table 1). As we indicated earlier, Angelini et al. (2023) report a government spending output elasticity between -0.32 and 0. The values reported in Table 1 are between -0.15 and 0.55. Our estimates in this regard are low. This indicates anti-cyclical behaviour of U.S. fiscal policy due to the Covid-19 related economic stimulus measures.

Our posterior estimates for α_{gp} are not statistically significantly different from zero, implying that real government spending does not change contemporaneously with an increase in inflation. Caldara and Kamps (2017), for comparison, report a negative estimate for the contemporaneous response of government spending to inflation (-0.75) for their general government spending rule model, but a positive relationship (0.41) for their penalty function model.

Finally, the median estimate of the contemporaneous response of government spending to the interest rate, α_{gr}, is not statistically significantly different from zero, which is consistent with the definition of spending that excludes government interest payments. Also, the impact response of government spending to taxes, α_{gt}, is not statistically significantly different from zero. The same results are found by Caldara and Kamps (2017).

5.1.2 Government tax rule

The output elasticity of taxes is the crucial short-term elasticity estimated in our model. Output represents a base for taxation to a large degree. Mertens and Ravn (2014), among others, establish that it significantly affects the size of fiscal multipliers. The posterior median for α_{ty} amounts to 2.65 and is higher than the assumed prior mode. It is also higher than the assumed upper prior bound. However, the median is lower than 3.13, which is the value for which Mertens and Ravn (2014) strongly argue. Angelini et al. (2023) provide a discussion on how sensible the assumption is that the output elasticity of taxes is equal to 3. As we indicate in Table 1, Blanchard and Perotti (2002) assume the output elasticity of net taxes is equal to 2.08. Perotti (2008), Favero and Giavazzi (2012), and Caldara and Kamps (2008) assume a value of 1.85. Caldara and Kamps (2017) prefer a value of 2.18, while Angelini et al. (2023) propose a range from 2.15 to 4.40. Our posterior median value for α_{ty} is somehow in-between.

We note that the posterior median estimate of the price elasticity of taxes, α_{tp}, is equal to 1.27, which is very close to the mode prior value of 1.25. The contemporaneous responses of taxes to government spending, α_{tg}, and of taxes to the interest rate, α_{tr}, are not economically meaningful. This is in accordance with the estimates of Caldara and Kamps (2017) for their general tax policy rule model.

5.1.3 Contemporaneous effects of government spending and tax revenue on output, and other parameter estimates

We first consider the contemporaneous effect of government spending on output. The posterior median for α_{yg} is 0.94 and is very close to the prior value of 1. Our estimated posterior value is similar to the corresponding c_2 coefficient (0.985) in Blanchard and Perotti's (2002) Table II for their stochastic model.

Next, we consider the impact effect of an increase in tax revenue on output. The posterior median value for α_{yt} is equal to -0.75 and is significantly higher than the assumed prior median of -0.90. It has the same sign as reported in the literature. It corresponds to the c_1 coefficient in Blanchard and Perotti's (2002) Table II, who report a value of -0.867 for their stochastic model. It is, however, lower than the values reported by Mertens and Ravn (2014) in Table 1. Overall, our estimates align relatively closely with those of Blanchard and Perotti (2002).

As far as other parameter estimates are concerned, the parameters that relate to a Phillips curve are of interest. The median posterior for α_{py} is well above our prior mode value and indicates a larger slope of the Phillips curve than assumed. However, the value of 0.22 is within the assumed prior confidence interval (from 0.00 to 0.24). Inoue et al. (2024) estimate time-varying coefficients of the Phillips curve and find evidence that the Phillips curve flattened over time. They report, however, some evidence that flattening of the curve reverted towards the end of their sample.

Furthermore, the coefficients that relate to a Taylor-type rule are of interest. The posterior median for α_{ry} amounts to 0.13 and is well below our prior value of 0.5. The posterior median for α_{rp} is 0.48 and is also lower than the assumed prior. This indicates a weaker reaction of the Federal Reserve to both the output gap and CPI inflation than assumed. Both of our posterior estimates are lower than the standard Taylor rule coefficients.

5.2 Impulse response functions and fiscal multipliers

In this section we describe impulse response functions for our baseline model. Figure 3 contains a panel of graphs, each one representing the non-cumulative response of an endogenous variable to a one standard deviation structural shock in a given quarter in terms of percentage changes. The median estimates are indicated by the blue solid lines and 68% (in dark grey) and 90% (in light grey) confidence intervals are denoted by gray shaded areas. Below, we focus on discussing the results for the 68% confidence intervals.

The first column shows the reaction of variables to a positive government spending shock of approximately 2%. As a result, we observe a real GDP increase of around 0.6%. This response slowly fades out, remaining statistically significant for 7 quarters.[9] Based on these responses, we estimate government spending multipliers in dollar-for-dollar terms according to the formula presented in equation (22) (see Figure 6). In the baseline model the multiplier is equal to 1.43 initially, 1.10 after a year, and is statistically insignificant after the seventh quarter. It reaches its peak value in the second quarter. Our estimates are a bit higher than the ones reported in the mainstream literature (Ramey, 2019), but, importantly, our sample includes the Covid-19 period. We do a robustness check for the sample that ends before the Covid-19 pandemic and these results are presented in Section 6. Kinda et al. (2022) report that cumulative fiscal multipliers one year after a health crisis are about twice as large as during normal times.

The government spending shock also leads to an increase in tax revenues, inflation, and the interest rate, which aligns with our expectations (see Figure 3). It is worth noting that the response of tax revenues is strong and statistically significant for 6 quarters and it reflects the increase in the taxation base (output). The responses of inflation and the interest rate are relatively weak, showing significance for the first 5 and 3 quarters, respectively.

The second column in Figure 3 presents the model variables' responses to a positive real GDP shock of about 0.9% initially, which is statistically significant for 9 quarters. As a result, we observe a sharp decline in government spending, reaching -1.2% initially, that is statistically significant for 5 quarters. This indicates that fiscal authorities in the U.S. act counter-cyclically, reducing spending during periods of economic expansion. The real GDP shock leads to inflationary pressures, with the strongest increase occurring in the fourth quarter, with a value of approximately 0.4%. One can also observe a significant increase in tax revenues and the interest rate, with the interest rate response being strongest in the 8th quarter.

A negative supply shock (third column in Figure 3) has a statistically significantly effect on inflation throughout the analyzed period (20 quarters) with the strongest impact in the third quarter. The CPI inflation response at time zero is 0.5%, peaking in the first quarter at 0.6%. As a result of increased inflation, the interest rate rises with the peak response in the 7th quarter, by 0.1%. This indicates that the central bank responds to inflation by raising the shadow interest rate, which is consistent with ex-

[9] The response of output to a government spending shock is similar to, for instance, Auerbach and Gorodnichenko's (2012) Figure 2 (bottom panel).

pectations. The rise in inflation leads to a decrease in GDP, with the strongest GDP response occurring in the 8th quarter. The decline in GDP is statistically significant until the 17th quarter. Government spending does not statistically significantly respond to the supply shock. However, tax revenues decline, statistically significantly from the 8th to the 15th quarter, which is likely associated with the decrease in real GDP.

The fourth column in Figure 3 presents the variables' responses to a tax shock. The tax shock is equal to 1.2% initially and statistically significant throughout the analyzed period (20 quarters). The tax shock primarily leads to a decrease in real GDP, with the strongest decline occurring on impact at -0.8%. The real GDP response is statistically significant for six quarters. The associated tax multiplier, showing by how many dollars GDP decreases with a \$1 increase in government taxes, is -3.64 initially, -1.39 after a year, and is statistically insignificant after seventh quarter (cf. Figure 6). A positive tax shock does not lead to statistically significant changes in government spending. It causes a decline in inflation with the peak impact of -0.2 after 6 quarters. The interest rate decreases, with the strongest response occurring in the 5th quarter at -0.3%.

The last fifth column in Figure 3 illustrates the variables' responses to an interest rate shock, i.e., to a monetary policy shock. The interest rate increases by 0.6% initially, and then its increase gradually diminishes but remains statistically significant throughout the analyzed period. Tax revenues and real GDP do not respond to the interest rate impulse. CPI inflation decreases by 0.2% initially. The increase in the interest rate leads to a decrease in government spending, with the strongest response occurring in the third quarter at -0.6%. This could indicate that the fiscal authority coordinates its policy with the monetary authority's to cool the economy.

5.3 Forecast error variance decomposition

Baumeister and Hamilton (2018) present formulas for h-period ahead forecast error variance decompositions in terms of their mean squared errors (MSEs). We follow their procedures and report in Table 3 the average percentage contribution of each structural shock to the h-period ahead MSE of the variance for each variable in our model. We show results for the baseline model.

We are mostly interested in forecast error variance decomposition for economic activity, because it informs us to what extent fiscal policy shocks are transmitted to future output fluctuations. The results presented in Table 3 show that the variance decomposition of output is driven to a large extend by government spending shocks, with relative contributions ranging form 20% to 23%. This reflects a major role of active fiscal policy, government spending in this case, over the sample period. Aggregate demand shocks, after having controlled for government spending shocks, are the main driver and account for 41% to 47%, whereas tax shocks contribute 18% to 33%. Supply shocks and especially monetary policy shocks matter much less for the fluctuations in aggregate output. This finding implies that monetary policy shocks have a relatively small impact on output, ranging from 2% to 4%.

Also the results from Table 3 show that the variance of government spending is driven mostly by government spending and aggregate demand shocks. This means that government consumption expenditures and government investment, the two components of our measure of government spending, are quite sensitive to business cycle fluctuations, to the tune of 26% to 16% as we move from h=1 to h=20. Government spending shocks account for 60% to 70% of the variance in government spending across the horizons considered in Table 3. Supply, tax and monetary policy shocks play in comparison a rather minor role in the explanation of the variance of government spending.

Staying with fiscal policy, the variance of tax revenues in the baseline model is explained mainly by demand shocks over the various horizons. This is due to the nature of the tax system so that tax revenue changes directly fluctuate with shocks to aggregate economic activity. The contributions to the variance range from 56% to 65%. Tax shocks contribute from 8% to 14% and government spending shocks from 21% to 23%. Otherwise, supply and monetary policy shocks contribute less than 8% and 4%, respectively.

Next, we consider inflation. Its variance is determined mostly by supply shocks (56% to 73%). Aggregate demand shocks matter much less, contributing 6% to 18%. The influence of government spending and tax shocks is each below 10% across horizons. Monetary policy is most effective at h=1 with an impact of 13%, levelling off afterwards and fluctuating around the 9% mark.

Last, we discuss the decomposition of forecasts of interest rate variances. Table 3 shows that the main driver is monetary policy. Monetary policy shocks account for 63% at h=1, falling steadily to 29% at h=20. The next most important factors are demand shocks (8% to 35%) and supply shocks (14% to

18%). In contrast, government spending shocks and tax shocks play a minor role (4% to 15%). This may indicate that government fiscal policy likely has moderate crowding out effects in regards to private sector spending, because a positive government spending shock drives up interest rates only moderately.

5.4 Historical decomposition

The period with the recent resurgence of U.S. inflation starting in the year 2021 (and peaking in June of 2022 with 9.1% for year-on-year CPI-based inflation) is covered in our main sample and calls for a more detailed analysis. Figure 4 shows the historical contribution of each identified structural shock to the deviation of the year-on-year CPI inflation rate from its long-term sample mean for every quarter. A historical decomposition allows us to gauge the relative roles of fiscal and monetary policy shocks at each point in time relative to the other structural shocks, instead of looking at the average contribution of each shock to the variance of inflation over the whole sample period, as we did in the previous Section.

Monetary and fiscal policies are not independent of each other. An aggressive monetary policy reaction to a fiscal stimulus may moderate the stimulus effects on output and its upward pressure on inflation. On the other hand, monetary accommodation could lead to amplified effects of a fiscal expansion, say when interest rates are near their zero lower bound (e.g., Ramey and Zubairy, 2018; Wolf, 2023).

The two main drivers in Figure 4 for large deviation of the inflation rate from its mean are aggregate demand and supply shocks. The most recent spike in inflation is mostly due to supply shocks (in grey), and to a lesser extend to demand shocks (in yellow) and government spending shocks (in red). This shows that general government spending contributed to the resurgence of inflation in recent years. However, our measure of government spending does not include government transfer payments, which were relatively large during the COVID-19 period. We show in Figure 5 the effects of using a measure of government spending that includes all general government expenditures, including transfer payments to the private sector. In this graph the recent contribution of government expenditure shocks to inflation is substantial, dominating any other shocks in the early quarters of the pandemic, whereas for the post-2007 period prior to COVID-19 the opposite is the case for the years from 2009 to 2015, with negative contributions to the mean of inflation of around 1/2. On the other hand, tax revenue had a noticeable negative contribution to inflation in Figure 4 for the post-2011 period, with much smaller positive and negative contributions in earlier years. Monetary policy shocks contribute much less but have at times accentuated both positive and negative peaks in inflation, suggesting that the Federal Reserve occasionally made matters worse with its monetary policy, whereas at other time it managed to dampen inflation rates. This is particularly notable in the last four quarters of our sample, when the contributions of monetary policy shocks to inflation are negative and thus monetary policy brought down high inflation.

One other period of interest in the literature on monetary policy is the period of the so-called Great Moderation from 1986Q1 to 2008Q3, which is the focus of Baumeister and Hamilton's (2019) study. Our findings basically agree with their results. The rising inflation in the 1980s was mostly due to aggregate demand shocks, whereas the moderation of inflation in the late 1990s in Figure 4 was driven mostly by the negative contributions of supply side shocks. Taxes and government spending shocks had only relatively small effects on inflation in this time period.

6 Sensitivity check - the pre-Covid sample

We estimate the model for the pre-Covid sample that ends in 2019Q4. In this model net taxes are defined as nominal general government current receipts minus current transfer payments and minus interest payments. This definition is often used in the literature (see the data section in Blanchard and Perotti (2002)). We were not able to use this series in the baseline model, because it takes negative value during the Covid pandemic (in 2020). We concentrate on the results for contemporaneous relations presented in Table 2 and fiscal multipliers presented in Figures 6 and 7. Other results for the pre-Covid model are available upon request. Below we describe the most important differences between pre- Covid and post-Covid (baseline) models.

First of all, in the pre-Covid model we obtain a negative government spending output elasticity α_{gy} with a posterior median of -0.06, that is higher than in the baseline model (-0.25). It implies a lower degree of fiscal policy anti-cyclicality before pandemic. Second, the posterior median for α_{yg} is 0.68 and is lower than the posterior median in the baseline model (0.94). Thus the impact effect of government spending on output is lower before the pandemic. Third, in the pre-Covid model α_{yt}, the government tax revenue output elasticity, is statistically insignificant. In the post-Covid model it was equal to approximately -0.75. Similarly, the impact effect of tax revenue on output is lower before the pandemic. Fourth, we note that in the pre-Covid model we get a slightly lower value for the output elasticity of taxes, the posterior median for α_{ty} amounts to 2.15 versus 2.65 in the baseline model. The above mentioned short term elasticities are of crucial importance for calculating fiscal multipliers. So it is not a surprise that we obtain different values of fiscal multipliers for pre-Covid sample (see Figure 6).

Before the pandemic the government spending multiplier is equal to 1.04 on impact, 0.65 after one year and it gets statistically insignificant after 5 quarters. The values are lower than in the baseline specification. On the other hand, we obtain statistically insignificant government tax revenue multiplier for the pre-Covid model. In the baseline post-Covid model the spending multiplier is smaller in the absolute terms than the tax multiplier. But in the pre-Covid sample the government spending multiplier is larger than the tax multiplier. The result is consistent with the findings of Caldara and Kamps (2017) and indicates that increasing government spending was a more effective fiscal policy tool than reducing taxes before the pandemic.

Lastly, the two models differ in terms of the short term Taylor rule coefficients α_{ry} and α_{rp}. Both of them are higher for the pre-Covid model taking the values 0.61 and 0.98 respectively. This indicates a stronger response of the central bank to price and output fluctuations before the pandemic.

7 Conclusion

The paper offers a first application of Baumeister and Hamilton's (2015, 2018, 2019a) Bayesian method with uncertain identifying assumptions to a structural fiscal policy VAR model for the United States. This approach allows us to incorporate a researcher's uncertainty regarding the sign and magnitude of short-term elasticities used for model identification. It is worth emphasizing that the model is estimated using data from the period 1947Q1 to 2023Q4, encompassing the entire Covid-19 pandemic period.

The literature disagrees on the size of fiscal multipliers, which crucially depend on certain contemporaneous elasticities. Mertens and Ravn (2014), Caldara and Kamps (2017) and Angelini et al. (2023), inter alia, point to the crucial role of the output elasticities of taxes, but no consensus has emerged. Angelini et al. (2023) also uncover substantial uncertainties around tax multipliers that we try to account for. Our results produce an output elasticity of taxes of around 2.65. This value is above the value of 2.08 in the seminal paper of Blanchard and Perotti (2002) and also above the values reported in Caldara and Kamps (2008) and Favero and Giavazzi (2012). But, it is below the value of 3.13 in Mertens and Ravn (2014), and within the range suggested by Angelini et al. (2023) of 2.15 to 4.40.

Our estimates indicate a negative output elasticity of government spending (-0.25). This result suggests countercyclical fiscal policy actions driven by large pandemic related economic stimulus programs. Additionally, we obtained an estimate for the price elasticity of tax revenue (1.27), as well as a statistically insignificant price elasticity of government revenue, consistent with the literature. The short-term output elasticities of government spending (positive) and of tax revenue (negative) closely resemble those found in Blanchard and Perotti (2002).

Having estimated the various structural elasticities allows us to calculate dollar-for-dollar fiscal multipliers. The government spending multiplier over our main sample is equal to 1.43 on impact, 1.10 after one year, and is statistically insignificant after two years. The tax multiplier is equal to -3.64 on impact, -1.39 after one year, and is statistically insignificant after two years. Based on Ramey's (2019, p. 102 and p. 105) our government spending and tax revenue multipliers are at the higher end of values reported in the literature, however, when we remove the pandemic period from our sample, we get values lower than unity after the first quarter for government spending and statistically insignificant values for tax revenue.

Our study allows us to draw several interesting additional conclusions. In the model that includes government transfer payments to the private sector, we observe a significant impact of government spending on year-on-year CPI-based inflation, particularly in the post-Covid period. In addition, our research indicates a slightly steeper short-term Phillips curve than recently found in the literature, specifically, the short-term output elasticity of prices is 0.22. Furthermore, the results suggest coefficients that differ from those typically assumed in a Taylor-type rule for monetary policy. The short-term impact (in percent) of the output gap on the interest rate is 0.13, while the short-term impact of inflation on the interest rate is 0.48. Finally, a historical decomposition for CPI-based inflation confirms the important role of monetary policy in bringing down inflation towards the end of our sample period. In contrast, monetary policy has occasionally strengthened at other times (positive and negative) spikes of the deviations of inflation from its long-run mean.

References

Angelini, G., Caggiano, G., Castelnuovo, E., Fanelli L., 2023. Are Fiscal Multipliers Estimated with Proxy-SVARs Robust? Oxford Bulletin of Economics and Statistics 85 (1), 95–122.

Auerbach, A., Gorodnichenko, Y., 2012. Measuring the Output Responses to Fiscal Policy. American Economic Journal: Economic Policy 4 (2), 1–27.

Baumeister, C., Hamilton, J. D., 2015. Sign Restrictions, Structural Vector Autoregressions, and Useful Prior Information. Econometrica 83 (5), 1963–1999.

Baumeister, C., Hamilton, J. D., 2018. Inference in Structural Vector Autoregressions When the Identifying Assumptions are Not Fully Believed: Re-evaluating the Role of Monetary Policy in Economic Fluctuations. Journal of Monetary Economics 100, 48–65.

Baumeister, C., Hamilton, J. D., 2019a. Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. American Economic Review 109 (5), 1873–1910.

Baumeister, C., Hamilton, J. D., 2019b. Structural Interpretation of Vector Autoregressions with Incomplete Identification: Setting the Record Straight. Manuscript, University of California, San Diego.

Baumeister, C., Hamilton, J. D., 2022. Structural Vector Autoregressions with Imperfect Identifying Information. American Economic Association Papers and Proceedings 112, 466–70.

Bernardini, M., Peersman, G., 2018. Private Debt Overhang and the Government Spending Multiplier: Evidence for the United States. Journal of Applied Econometrics 33, 485–508.

Blanchard, O., Perotti, R., 2002. An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output. Quarterly Journal of Economics 117, 1329–1368.

Caldara, D., Kamps, C., 2008. What are the Effects of Fiscal Policy Shocks? A VAR-based Comparative Analysis. European Central Bank Working Paper No. 877.

Caldara, D., Kamps, C., 2017. The Analytics of SVARs: A Unified Framework to Measure Fiscal Multipliers. Review of Economic Studies 84(3), 1015–1040.

Carriero, A., Marcellino, M., Tornese, T., 2024. Blended Identification in Structural VARs. Journal of Monetary Economics 146, 103581.

Doan, T., Litterman, R., Sims, C., 1984. Forecasting and Conditional Projection Using Realistic Prior Distributions. Econometric Reviews 3 (1), 1–100.

Favero, C., Giavazzi, F., 2012. Measuring Tax Multipliers: The Narrative Method in Fiscal VARs. American Economic Journal: Economic Policy 4, 69–94.

Follette, G. R., Lutz, B. F., 2010. Fiscal Policy in the United States: Automatic Stabilizers, Discretionary Fiscal Policy Actions, and the Economy. Federal Reserve Board Working Paper No. 2010–43.

Gagliardone, L., Gertler, M., Lenzu, S., Tielens, J., 2023. Anatomy of the Phillips Curve: Micro Evidence and Macro Implications. NBER Working Paper No. 31382.

Gali, J., Gertler, M., 1999. Inflation Dynamics: A Structural Econometric Analysis. Journal of Monetary Economics 44(2), 195–222.

Hamilton, J.D., 2018. Why you should never use the Hodrick-Prescott filter. Review of Economics and Statistics 100(5), 831-843.

Hazell, J., Herreño, J., Nakamura, E., Steinsson, J., 2020. The Slope of the Phillips Curve: Evidence from U.S. States. NBER Working Papers No. 28005.

Hooper, P., Mishkin, F. S., Sufi, A., 2020. Prospects for Inflation in a High Pressure Economy: Is the Phillips Curve Dead or is it Just Hibernating?. Research in Economics 74(1), 26–62.

Inoue, A., Rossi B., Wang Y., 2024. Has the Phillips Curve Flattened? CEPR Discussion Paper No. 18846.

Kadiyala, K. R., Karlsson, S., 1997. Numerical Methods for Estimation and Inference in Bayesian VAR Models. Journal of Applied Econometrics 12 (2), 99–132.

Kinda, T., Lengyel, A., Chahande K., 2022. Fiscal Multipliers During Pandemics. IMF Working Papers 2022/149.

Krippner, L., 2013. Measuring the Stance of Monetary Policy in Zero Lower Bound Environments. Economics Letters 118, 135–138.

Krippner, L., 2015. Zero Lower Bound Term Structure Modeling: A Practitioner's Guide. Palgrave Macmillan, New York, N.Y.

Leeper, E. M., Sims, C., Zha T., 1996. What Does Monetary Policy Do? Brookings Papers on Economic Activity 1996(2), 1-78.

Lubik, T., Schorfheide, F., 2004. Testing for Indeterminacy: An Application to U.S. Monetary Policy. American Economic Review 94(1), 190–217.

Mertens, K., Ravn, M. O., 2014. A Reconciliation of SVAR and Narrative Estimates of Tax Multipliers. Journal of Monetary Economics 68(S), 1–19.

Mountford, A., Uhlig, H., 2009. What are the Effects of Fiscal Policy Shocks? Journal of Applied Econometrics 24, 960–992.

Nguyen, L., 2022. Bayesian Inference in Structural Vector Autoregression with Sign Restrictions and External Instruments. Available at https://ssrn.com/abstract=4680099.

Perotti, R., 2004. Estimating the Effects of Fiscal Policy in OECD Countries. IGIER Working Paper No. 276.

Perotti, R., 2008. In Search of the Transmission Mechanism of Fiscal Policy. In: NBER Macroeconomics Annual 2007, edited by D. Acemoglu, K. Rogoff, and M. Woodford. University of Chicago Press, Chicago, vol.22, pp. 169–226.

Ramey, V. A., 2011. Identifying Government Spending Shocks: It's All in the Timing. Quarterly Journal of Economics 126, 1–50.

Ramey, V. A., Zubairy, S., 2018. Government Spending Multipliers in Good Times and in Bad: Evidence from U.S. Historical Data. Journal of Political Economy 126, 850–901.

Ramey, V. A., 2019. Ten Years After the Financial Crisis: What Have We Learned From the Renaissance in Fiscal Research? Journal of Economic Perspectives 33(2), 89–114.

Romer, C. D., Romer, D. H., 2010. The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks. American Economic Review 100(3), 763–801.

Rossi, B., Zubairy, S., 2011. What Is the Importance of Monetary and Fiscal Shocks in Explaining U.S. Macroeconomic Fluctuations? Journal of Money, Credit and Banking 43, 1247–1270.

Rubaszek, M., Szafranek, K., Uddin, G. S., 2021. The Dynamics and Elasticities on the U.S. Natural Gas Market. A Bayesian Structural VAR Analysis. Energy Economics 103, Article 105526.

Rubio-Ramírez, J., Waggoner, D. F., Zha, T., 2010. Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference. Review of Economic Studies 77(2), 665–696.

Sims, C. A., Zha, T., 1998. Bayesian Methods for Dynamic Multivariate Models. International Economic Review 39 (4), 949–968.

Stock, J. H., Watson, M. W., 2018. Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments. Economic Journal 128 (610), 917-948.

Taylor, J. B., 1993. Discretion versus Policy Rules in Practice. Carnegie-Rochester Conference Series on Public Policy 39, 195–214.

Wolf, C. K., 2023. Fiscal Stimulus and the Systematic Response of Monetary Policy. American Economic Association Papers and Proceedings 113, 388–393.

Wu, J. C., Xia, F. D., 2016. Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. Journal of Money, Credit and Banking 48, 253–291.

Tables and Figures

Table 1: Contemporaneous elasticities for the fiscal policy rules

	α_{tg}	α_{ty}	α_{tp}	α_{tr}	α_{gy}	α_{gp}	α_{gt}	α_{gr}
BP2002		2.08			0.00			
MR2014		3.13			0.06			
		[2.73 3.55]			[-0.06 0.17]			
CK2008	0.00	1.85	1.25	0.00	0.00	-0.50	0.00	0.00
FG2012 & P2008								
Entire sample		1.85	1.25	0.00	0.00	-0.50		0.00
1960:1-1979:4		1.75	1.09	0.00	0.00	-0.50		0.00
1980:1-2006:2		1.97	1.40	0.00	0.00	-0.50		0.00
CK2017								
BP	-0.14	1.70	1.25	0.00	0.00	-0.50		0.00
	[-0.17 -0.10]							
penalty	0.01	3.24	0.48	-0.42	0.55	0.41	0.00	-0.36
function	[-0.15 0.18]	[3.04 3.45]	[0.23 0.74]	[-0.65 -0.20]	[0.44 0.66]	[0.30 0.52]		[-0.45 -0.26]
proxy	-0.29	3.58	2.41	-0.01				
SVAR	[-0.50 -0.09]	[3.22 3.98]	[1.95 2.91]	[-0.42 0.39]				
general	-0.23	2.18	1.06	0.56	-0.13	-0.75	0.01	0.00
fiscal rule	[-0.46 -0.02]	[1.96 2.41]	[0.09 2.10]	[0.39 0.73]	[-0.28 0.01]	[-1.65 -0.08]	[-0.09 0.13]	
simple		2.43			-0.15			
fiscal rule		[2.21 2.66]			[-0.27 -0.03]			

Notes: The table gathers estimates of contemporaneous elasticities for fiscal policies. Point estimates and confidence intervals (in square brackets) are reported. Abbreviations used: BP2002 – Blanchard and Perotti (2002), MR2014 – Mertens and Ravn (2014), CK2008 – Caldara and Kamps (2008), FG2012 – Favero and Giavazzi (2012), P2009 – Perotti (2008), and CK2017 – Caldara and Kamps (2017). BP refers to Blanchard and Perotti's (2002) model specification.

Table 2: Priors and posteriors for contemporeaneous relations matrix **A**.

		Reported statistic	α_{gy}	α_{gp}	α_{gt}	α_{gr}	α_{yg}	α_{yp}	α_{yt}	α_{yr}	α_{py}	α_{pr}	α_{tg}	α_{ty}	α_{tp}	α_{tr}	α_{ry}	α_{rp}	h_1
Prior	Type		t	t	t	t	t^+	t	t^-	t	t^+	t	t	t^+	t^+	t	t^+	t^+	At
	Location		0.00	-0.50	0.00	0.00	1.00	0.00	-0.90	0.00	0.03	0.00	0.00	1.85	1.25	0.00	0.50	1.50	2.95
	Scale		0.20	0.50	0.50	0.50	0.20	0.50	0.30	0.50	0.10	0.50	0.50	0.30	0.30	0.50	0.40	0.30	5.10
	D.o.f.		3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	Skew		—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	2
	90% LB		-0,471	-1,427	-1.18	-1.18	0.00	-1.18	-1.40	-1.18	0.00	-1.18	-1.18	0.00	0.00	-1.18	0.00	0.00	0.00
	90% UB		0,471	0,427	1.18	1.18	1.33	1.18	0.00	1.18	0.24	1.18	1.18	2.34	1.75	1.18	1.22	1.99	13.11
Posterior	Baseline	5%	-1.410	-0.703	-0.61	-0.72	0.38	-0.80	-1.26	-1.29	0.10	-1.10	-0.59	1.86	0.75	-0.27	0.02	0.05	3.40
		50%	**-0.247**	**-0.073**	**-0.28**	**-0.10**	**0.94**	**0.03**	**-0.75**	**-0.04**	**0.22**	**-0.28**	**-0.05**	**2.65**	**1.27**	**0.42**	**0.13**	**0.48**	**5.89**
		95%	0.155	0.534	0.04	0.43	1.34	0.84	-0.25	0.73	0.42	0.19	0.36	3.57	1.84	1.43	0.30	1.16	10.91
		mean	-0.382	-0.078	-0.28	-0.11	0.92	0.03	-0.75	-0.13	0.24	-0.34	-0.08	2.67	1.28	0.48	0.14	0.53	6.35
	Pre-Covid	5%	-0.977	-0.954	-0.14	-5.33	0.07	-0.80	-0.09	-3.64	0.04	-1.69	-1.00	1.69	0.78	-0.68	0.07	0.12	1.60
		50%	**-0.056**	**-0.075**	**-0.01**	**-1.68**	**0.68**	**-0.01**	**-0.02**	**-1.25**	**0.25**	**-0.23**	**-0.27**	**2.15**	**1.29**	**0.11**	**0.61**	**0.98**	**5.55**
		95%	0.332	0.687	0.12	0.13	1.19	0.87	0.00	0.25	0.67	0.22	0.42	3.06	1.86	1.18	1.11	1.64	12.91
		mean	-0.141	-0.095	-0.01	-1.86	0.61	0.01	-0.03	-1.43	0.30	-0.44	-0.28	2.25	1.30	0.16	0.59	0.93	6.09

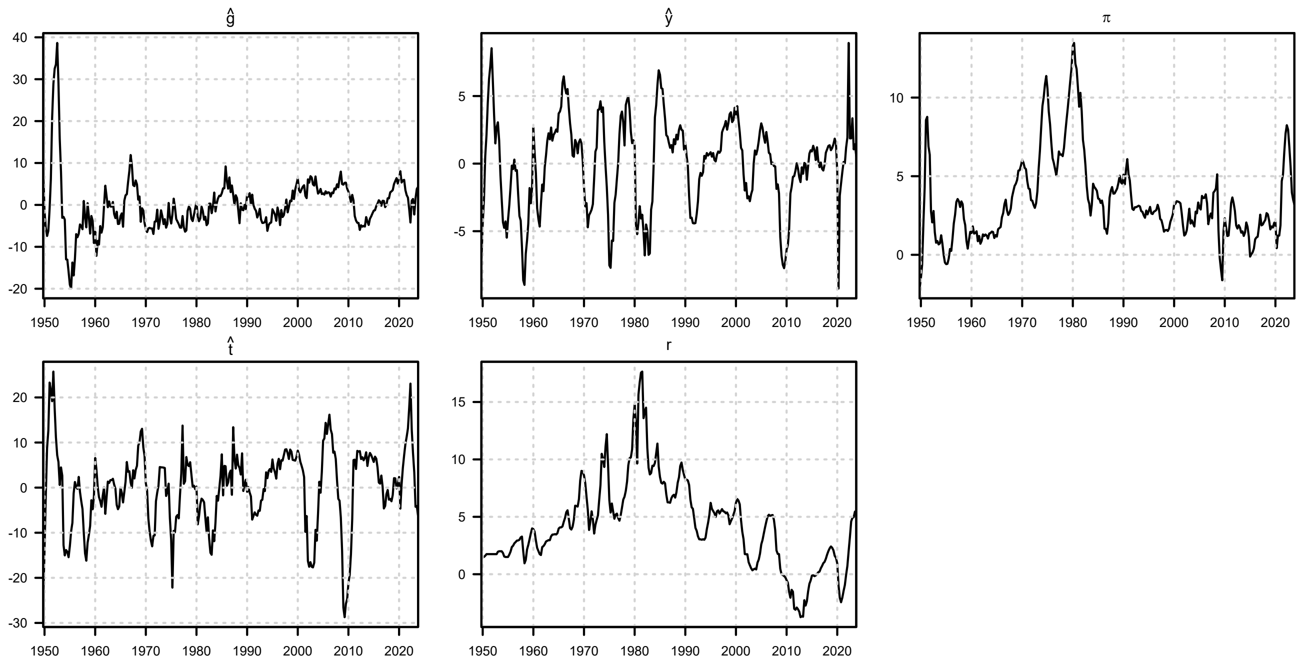
Notes: In the table t denotes a Student t distribution and At denotes an asymmetric Student t distribution proposed by Baumeister and Hamilton (2018). Signs + and − indicate that the distribution is truncated to be either positive or negative, respectively. D.o.f stands for degrees of freedom for each distribution. 90% LB and UB denote the lower and upper bounds for the confidence intervals (for truncated distributions, one-sided confidence sets are reported). For the posterior distributions the coefficients for the 5th percentile, the median, the 95th percentile and the mean are reported.

Table 3: Forecast error variance decomposition.

	Government spending					Economic activity					Inflation					Taxes					Interest rate				
	u^G	u^Y	u^P	u^T	u^R	u^G	u^Y	u^P	u^T	u^R	u^G	u^Y	u^P	u^T	u^R	u^G	u^Y	u^P	u^T	u^R	u^G	u^Y	u^P	u^T	u^R
h=1	69.9	26.3	0.4	3.0	0.4	19.6	41.4	4.0	33.1	1.9	2.7	5.8	73.9	4.3	13.3	21.8	62.7	1.2	13.5	0.7	3.8	8.5	18.1	6.2	63.4
h=4	69.6	20.3	2.2	3.9	3.9	23.3	47.3	5.4	21.7	2.4	3.9	14.0	69.8	3.7	8.6	23.1	65.4	1.6	8.5	1.4	4.5	22.9	13.5	10.9	48.3
h=8	68.1	15.9	3.2	5.8	7.0	22.2	46.8	8.7	19.2	3.1	4.7	18.2	63.1	5.6	8.3	22.4	63.2	2.9	9.4	2.1	4.7	32.8	13.5	12.6	36.5
h=12	64.5	16.1	4.5	7.4	7.4	21.5	44.2	12.0	18.5	3.7	5.5	18.1	59.8	7.5	9.1	21.7	59.2	5.3	11.1	2.7	5.1	35.5	14.1	13.4	31.9
h=16	62.0	16.3	5.9	8.1	7.6	21.5	42.8	13.5	18.2	4.1	6.1	17.8	57.6	8.8	9.7	21.3	56.8	6.7	11.9	3.2	5.6	35.3	14.7	14.1	30.2
h=20	60.6	16.5	6.8	8.4	7.7	21.4	42.3	13.9	18.1	4.3	6.3	17.9	56.1	9.7	10.0	21.0	55.8	7.2	12.5	3.6	6.0	34.6	15.3	14.7	29.4

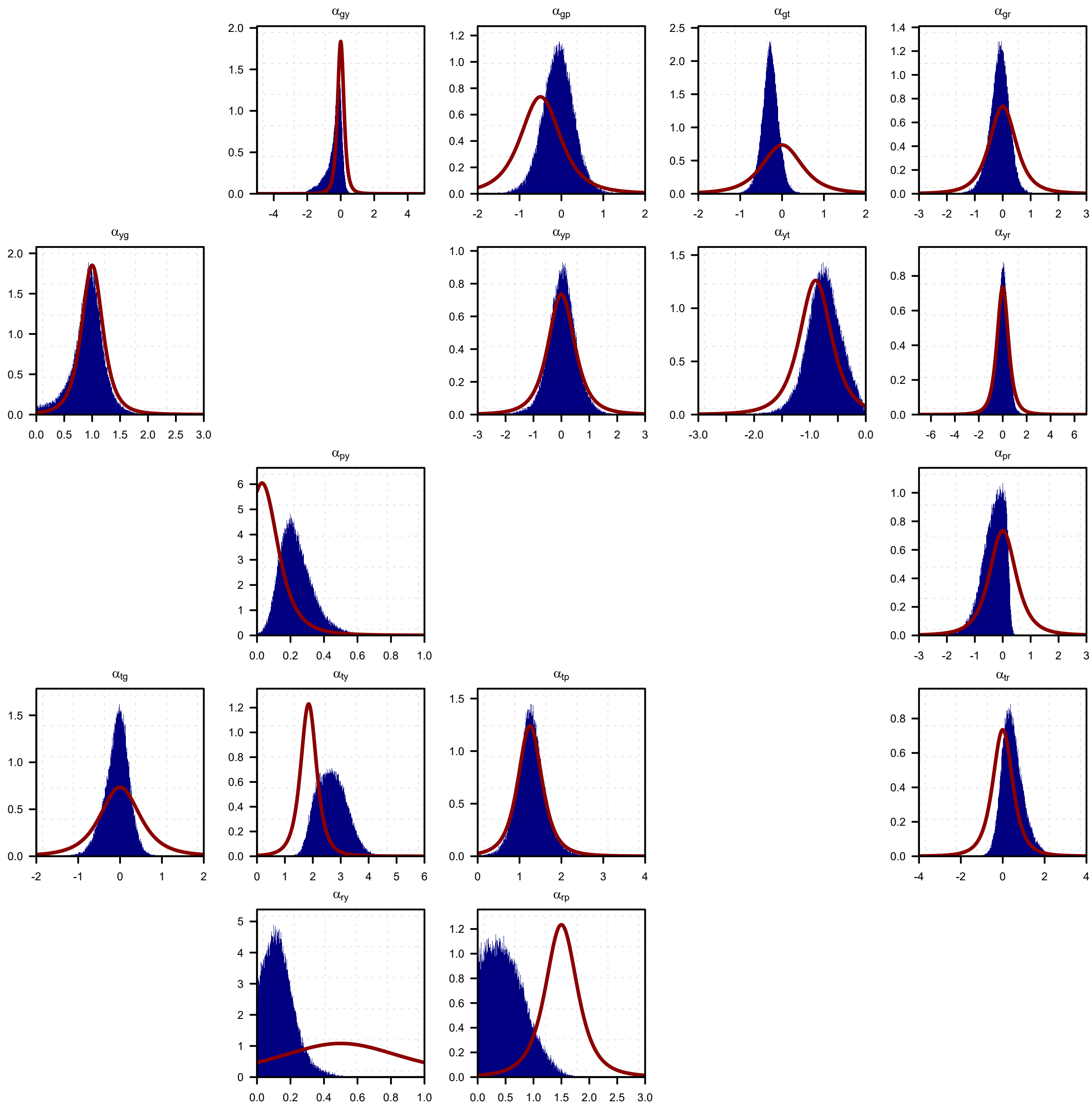
Notes: In the table u^G, u^Y, u^P, u^T and u^R denote the contributions of government spending, aggregate demand (income), aggregate supply (price), tax and monetary policy (interest rate) shocks (in %) to the overall variability to each of the endogenous variables entering the SVAR model.

Figure 1: Time series for the endogenous variables.



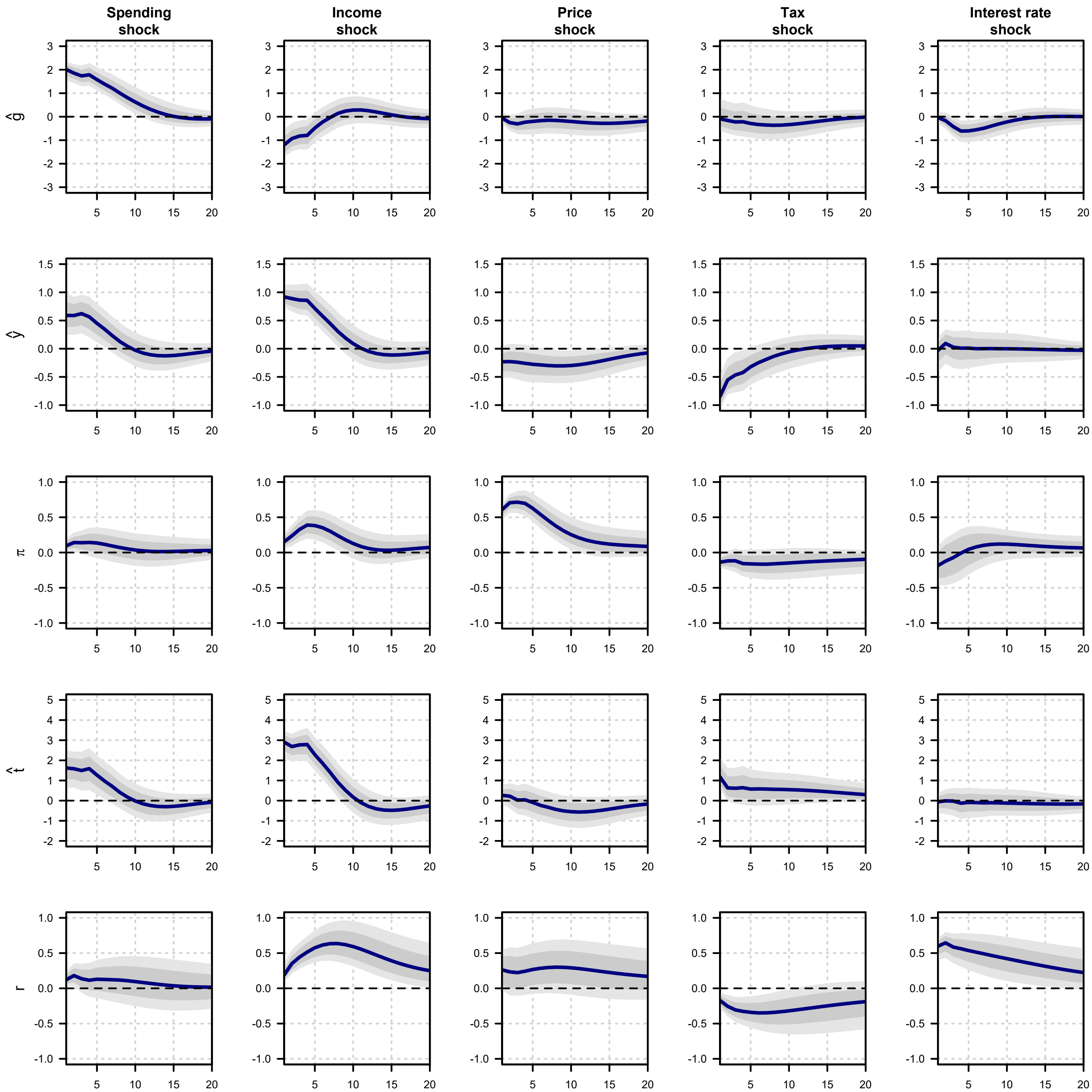
Notes: The figure presents the endogenous variables used in the baseline model. For variable definitions and their transformations the reader is referred to Section 4.1.

Figure 2: Prior and posterior distributions of contemporaneous elasticities in the baseline model.



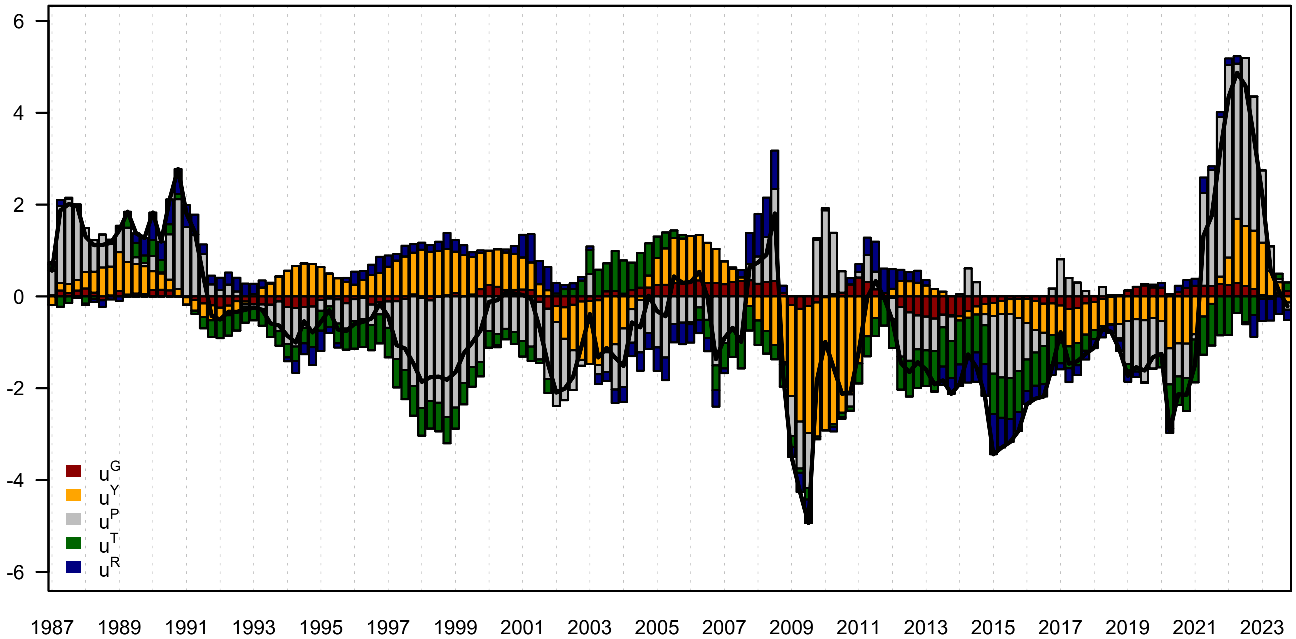
Notes: The baseline prior is represented using solid red lines, whereas the posterior is depicted using blue histograms. These distributions concern the contemporaneous elasticities in matrix **A** in the baseline model. The location of each plot corresponds to the location of the respective parameter in matrix **A**.

Figure 3: Impulse response functions for the baseline model.



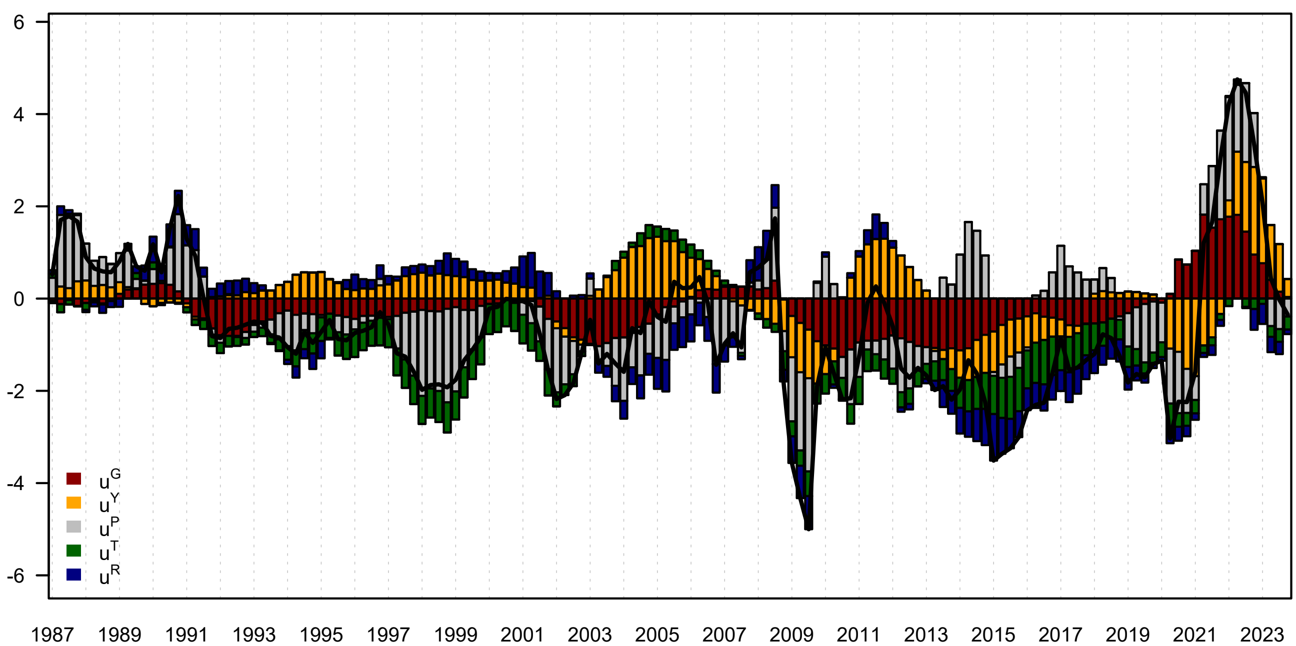
Notes: The blue solid lines represent the Bayesian median posterior response. The grey areas denote the 68 (dark grey) and 90 (light grey) percent posterior credible sets, respectively. Spending, income, price, tax and interest rate shocks correspond to government spending, aggregate demand, supply, tax and monetary policy shocks, respectively. For variable and shock definitions the reader is referred to Section 4.

Figure 4: Historical decomposition for inflation from the baseline model.



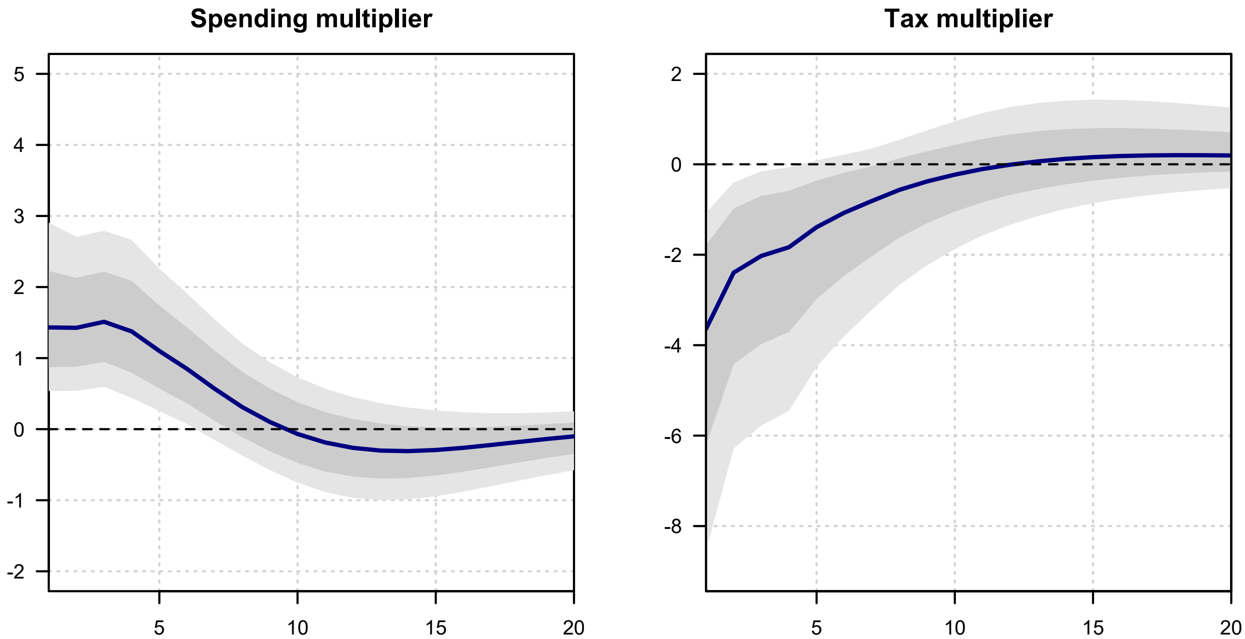
Notes: Black solid lines represent the deviation of the year-on-year inflation rate from the long-term mean implied by the model (in %). In turn, u^G, u^Y, u^P, u^T and u^R denote the contribution (in %) of the government spending, aggregate demand, supply, tax and monetary policy shocks, respectively.

Figure 5: Historical decomposition for inflation from the model including government transfer payments to the private sector.



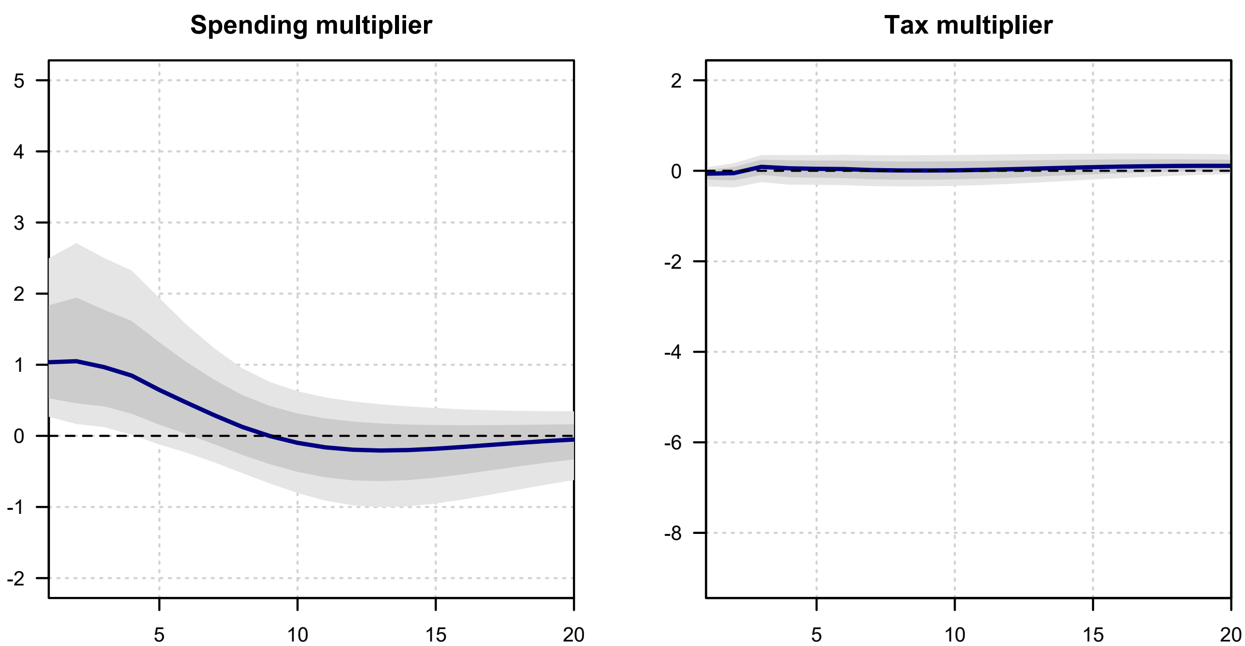
Notes: See Figure 4

Figure 6: Fiscal multipliers from the baseline model.



Notes: The blue solid lines represent the Bayesian median posterior response. The grey areas denote the 68 (dark grey) and 90 (light grey) percent posterior credible sets, respectively.

Figure 7: Fiscal multipliers from the pre-Covid model.



Notes: See Figure 6

A Appendix – data transformation and sources

Table 4: Variable definitions, transformation and sources

Variable	Description	Transformations	Model version	Source	Reported
G	Nominal general government consumption and gross investment expenditures	defl, pc, $\hat{x}$	Baseline	NIPA Table 3.9.5, line 1	Yes
Y	Nominal GDP	defl, pc, $\hat{x}$	Baseline	NIPA Table 1.1.5, line 1	Yes
π	Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, Index 1982-1984=100	Δ^4log	Baseline	FRED Economic Data (`CPIAUCSL`)	Yes
T	Nominal general government current tax receipts	defl, pc, $\hat{x}$	Baseline	NIPA Table 3.1, line 2	Yes
T	Nominal general government current receipts (all) minus current transfer payments and minus government interest payments	defl, pc, $\hat{x}$	Robustness check	NIPA Table 3.1, line 1 minus line 22 minus line 27	Yes
r	Interest rate	—	Baseline	Krippner (2013, 2015) for period 1995Q1-2023Q3, Bernardini and Peersman (2018) for period 1947Q1-1994Q4	Yes

Notes: The table provides information on variable definitions, transformations and sources. *Defl* means that the series has been deflated with the implicit GDP deflator (from NIPA Table 1.1.9, line 1), *pc* denotes per capita values using the US population series from the FRED Economic Database (series `B230RC0Q173SBEA`), $\hat{x}$ indicates that a cycle estimate is extracted from the log level of the series (either using the Hamilton (2018) filter (removing a stochastic time trend) for the baseline sample or using the Caldara and Kamps (2017) approach (removing a deterministic time trend) for one of the robustness checks), Δ^4log denotes the year-on-year log rate of change. Following transformations, all variables are expressed in per cent. We note that such a specification is appropriate because our data do not support cointegration among variables that are integrated of order one in log levels. For the sake of brevity, some robustness checks (with respect to variable definitions and transformations) have not been reported in the paper. They are marked in the last column of the table and the results are available on request from the authors, along with results for unit root and cointegration testing.