Business Cycles and Fiscal Policy in the United States: A Bayesian Proxy-FAVAR Model*

Anna Sznajderska† Lukas Berend‡ Alfred A. Haug§

Abstract
This paper studies the transmission of U.S. fiscal policy shocks by decomposing their effects into common business and inflation cycles and their idiosyncratic component-specific channels. We estimate a restricted Bayesian proxy factor-augmented vector-autorgressive (FAVAR) model in which output and inflation factors are identified as economically interpretable common cycles from a large set of macroeconomic variables. Using external instruments for government spending, tax revenue, monetary policy, productivity, and price shocks, we trace the effects of fiscal policy on aggregate output and its dominant components. The main contribution of the paper is to show that the aggregate effects of fiscal policy are transmitted both through the common output cycle and through idiosyncratic component-level dynamics. Positive government spending shocks increase output, private consumption, and employment, but crowd out private investment. Positive tax revenue shocks reduce economic activity mainly in the short run. The cumulative fiscal multiplier after one year equals 0.87 for government spending and -0.62 for tax revenues. Also, the idiosyncratic channel matters mainly for the composition of fiscal transmission, especially for investment, trade, and inventories. The estimated multipliers and the dominance of the common channel are robust to relaxing selected orthogonality assumptions between proxies and structural shocks.

Keywords: Proxy FAVAR model, fiscal multipliers, monetary and fiscal policy interactions

JEL classification: E31, E32, E52, E62, E63

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†Corresponding author. Econometrics Institute (Financial Markets Modelling Unit), SGH Warsaw School of Economics, 02-513 Warsaw, Poland. E-mail: `asznajd@sgh.waw.pl`.

‡Faculty of Business Administration and Economics (Department of Macroeconomics), FernUniversität in Hagen, 58097 Hagen, Germany. E-mail: `lukas.berend@fernuni-hagen.de`.

§Department of Economics, University of Otago, New Zealand. E-mail: `alfred.haug@otago.ac.nz`.

1 Introduction

Fiscal policy is a central tool for stabilizing economic activity and influencing the allocation of resources over the business cycle. Changes in government spending and tax revenues affect aggregate demand, private consumption and investment, labor markets, external balances, and public debt dynamics. The magnitude and persistence of these effects are commonly summarized by fiscal multipliers. Despite decades of empirical research, however, there remains substantial disagreement about the size of fiscal multipliers and about the mechanisms through which fiscal shocks are transmitted to the economy.

Vector autoregressions (VARs) are a widely used modelling framework to study the effects of monetary and fiscal policy (Ramey, 2016, 2019). Typical macro-level VARs include only a small number (often only a handful or less) of variables to preserve degrees of freedom, even though fiscal policy may affect the economy through many channels at once. On the other hand, policy makers consider much larger sets of variables (e.g., B. S. Bernanke and Boivin (2003)). Therefore, such VARs may suffer from omitted variable bias and lead to flawed impulse response (policy shock) analysis. B. Bernanke et al. (2005) suggest combining the VAR with a few so-called factors (principal components) that are estimated from a large set of macroeconomic time series. They (p. 387) find that a monetary (not fiscal) VAR with monthly observations and three variables plus one factor extracted from 120 time series provides "a comprehensive and coherent picture for effects of monetary policy on the economy."[1] Stock and Watson (2016) provide a detailed discussion of dynamic factors and their use in VARs for structural shock identification and impulse response analysis. Furthermore, the seminal paper by Stock and Watson (2012) demonstrates the usefulness of the dynamic factor model when disentangling the contributions of various macroeconomic shocks to the 2007-09 recession in the U.S. All of these models require the identification of structural shocks that have an economically meaningful interpretation so that one can study their effects on the variables that enter the VAR and/or are being used in estimating the factors. Stock and Watson (2012) introduced a novel way of identifying shocks in dynamic factor models with external instruments, or

[1] See also Grigoli et al. (2026) for a recent study of the channels for monetary policy changes to household portfolio reallocations.

equivalently, proxy variables, constructed by other researchers.

This paper augments a standard fiscal VAR with a relatively large set of additional variables that enter the VAR through (unobservable) factor augmentations (FAs). Also, our VAR includes variables that account for monetary policy. Parallel to B. Bernanke et al. (2005)'s monetary FAVAR, our fiscal FAVAR provides a detailed explanation of the effects of fiscal policy actions on various macroeconomic variables relevant to policy makers, beyond the limited set of time series usually included in a standard fiscal VAR. In particular, we study the effects of government spending and tax shocks within a state-of-the-art restricted Bayesian FAVAR model, adopting Bayesian techniques developed by Belviso and Milani (2006) to jointly estimate the factors and parameters of the fiscal VAR. Our (two) factors have an economic interpretation as a real factor and a price factor. These latent factors capture broad movements in real activity and inflation. However, in contrast to Belviso and Milani (2006), we use proxy variables presented elsewhere in the literature and sign restrictions to achieve identification in our proxy FAVAR model, following Bruns (2021) and Berend and Prüser (2024).

Our identification strategy combines multiple external instruments with sign restrictions. We use updated fiscal and non-fiscal proxies to identify five structural shocks: government spending, tax revenue, output, inflation, and monetary policy shocks. Government spending shocks are instrumented using military spending news shocks based on Ramey (2011) and a measure of government spending news constructed from the Survey of Professional Forecasters' revisions as in Caggiano et al. (2015). Tax shocks are identified using the personal and corporate income tax shock proxies of Mertens and Ravn (2014), extended with the estimates of Hanson et al. (2021). Output shocks are instrumented using utilization-adjusted total factor productivity from Fernald (2014). Inflation shocks are instrumented using oil-price-related proxies, and monetary policy shocks are identified using high-frequency monetary policy surprises from Bauer and Swanson (2023) and Jarocinski and Karadi (2020). This multi-proxy structure allows us to identify fiscal shocks while controlling for other important macroeconomic disturbances.

The paper makes three main contributions. First, to the best of our knowledge, this is the first application of a restricted Bayesian proxy FAVAR model with multiple proxies to study the effects of fiscal policy shocks in the United States. This framework allows us to estimate fiscal multipliers in a data-rich environment and to examine the responses of many output components within a single structural FAVAR model. In this respect, our analysis extends the fiscal proxy SVAR literature by combining external instruments with the information advantages of factor-augmented models.

Second, we assess the robustness of fiscal multipliers to alternative assumptions about the orthogonality between proxies and structural shocks. This issue is central to recent debates in the fiscal VAR literature. Angelini et al. (2023) argue that the assumption of orthogonality between total factor productivity and tax shocks is important for explaining the heterogeneity of tax multiplier estimates. Ben Zeev and Pappa (2015), in contrast, emphasize the role of orthogonality between total factor productivity and government spending shocks. We examine both concerns within the same proxy FAVAR framework by relaxing the relevant orthogonality restrictions and evaluating how the estimated spending and tax multipliers change.

Third, we distinguish between idiosyncratic and common cycles for the real (output) factor and for the price factor, and their transmission to the time series considered. The factor analysis separates each time series into two components, a common component or factor that is shared with the other variables that form a factor, and a series-specific (idiosyncratic) random shock (Stock & Watson, 2012). We refer to the common factor as a common cycle. For example, private investment may increase simply as a result of a broad-based expansion in economic activity, but it may also exhibit a distinct response due to characteristics specific to this output component. It therefore provides evidence on whether fiscal policy mainly affects GDP through economy-wide movements or through sector- and component-specific responses.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the econometric framework. Section 4 describes the data and the structural identification strategy. Section 5 discusses the empirical results and Section 6 concludes. Additional material is provided in an online appendix.

2 A Brief Overview of Closely Related Literature

Our paper is related to a few strands of literature. First, there are the studies that use FAVAR models. Some authors argue that the small number of variables in the VAR models should be increased to account for rich datasets to bring more relevant information to bear and avoid misspecification (Stock & Watson, 2005; Bruns, 2021). B. Bernanke et al. (2005) introduce a FAVAR model to examine monetary policy transmission in the U.S. and Belviso and Milani (2006) show how to give economic interpretations to the factors. Bruns (2021) exploits external instruments in a proxy VAR model with latent factors to examine the reaction of financial spreads with different maturities to monetary policy shocks, as well as to trace the reaction of U.S. macroeconomic variables to oil price shock.

Second, our study relates to fiscal proxy SVAR models (Mertens and Ravn, 2014; Caldara and Kamps, 2017), to efficient sampling for missing observations in dynamic factor models and Bayesian VARs (Chan et al., 2023), and to Bayesian estimation of proxy SVARs with linear and inequality resrictions (Hou, 2024), as well as to proxy FAVAR models (Bruns, 2021). Proxy SVAR models are a popular tool for assessing the role of fiscal policy. Klein and Linnemann (2019), for example, apply a proxy fiscal SVAR model to show that tax decreases cause increases in demand for imports (i.e. a reduction in current account of the U.S. balance of payments, ceteris paribus). There are also studies that focus on contemporaneous relations of structural shocks and the size of the fiscal multiplier; these include Mertens and Ravn (2014), Caldara and Kamps (2017) and Angelini et al. (2023). Mertens and Ravn (2014) state that important differences in the estimates of fiscal multipliers in some of this literature are due to different assumptions about the cyclical sensitivity of tax revenues or the failure to account for measurement error in narrative series of tax shocks.

Third, our study is connected to research on potentially endogenous proxies in fiscal VAR models, that is explored by, for example, Keweloh et al. (2023) and Angelini et al. (2023). Angelini et al. (2023) state that the key reason for different tax multiplier estimates is the assumption of orthogonality between total factor productivity (a non-fiscal proxy, denoted TFP) and the tax shock. Whereas Ben Zeev and Pappa (2015) show that the spending multiplier crucially depends on the assumption of orthogonality between TFP and the government spending shock. They show that when the unanticipated government defense spending shock is orthogonalized with respect to TFP, the multiplier is equal to zero. Keweloh et al. (2023) follow a different route and propose to correct proxies for endogeneity.

Interestingly, Carriero et al. (2024) enhance proxy-SVARs with sign and narrative restrictions by incorporating heteroskedasticity for identification purposes. Among others, they apply a blended proxy-SVAR with narrative U.S. personal tax shocks and corporate income tax shocks as external instruments to U.S. data from 1951Q1 to 2006Q4. Following both types of tax shocks output decreases, which is in contrast to the results of Mertens and Ravn (2013) for corporate income taxes. Further, the credible bands for the heteroskedastic model are narrower than for the homoskedastic model.

3 A Sign-Restricted Proxy FAVAR Model

In this section, we present and discuss our Bayesian sign-restricted proxy FAVAR model. We use the model to estimate the US common cycles for output and inflation. The factors have a clear economic interpretation as common cycles. Additionally, the model allows us to examine how each variable is influenced by these cycles and how fiscal and monetary policy shocks are propagated via these cycles. Following Burns (2021), our model consists of a factor equation $\boldsymbol{x}_t$ and a structural VAR equation and thus departs from the standard FAVAR model:

$$\begin{aligned} \boldsymbol{x}_t &= \boldsymbol{\Lambda} \boldsymbol{f}_t + \boldsymbol{\Lambda}^{\boldsymbol{z}} \boldsymbol{z}_t + \boldsymbol{e}_t && (1) \\ \begin{bmatrix} \boldsymbol{f}_t \\ \boldsymbol{z}_t \end{bmatrix} &= \boldsymbol{A} \begin{bmatrix} \boldsymbol{f}_{t-1} \\ \boldsymbol{z}_{t-1} \end{bmatrix} + \ldots + \boldsymbol{B}\boldsymbol{\epsilon}_t, && (2) \end{aligned}$$

3.1 The Restricted Dynamic Factor Equation

In the factor equation, we assume the various macroeconomic variables in the factor space to depend on a common cycle for output and for prices and the endogenous variables that also enter the structural VAR equation below. More specifically, we can write (2) as:

$$x_{i,t} = \sum_{p=0}^{P} \lambda_{i,p}^{j} f_{t-p}^{j} + \sum_{p=0}^{P} \sum_{k \in \{1,2,3\}} \lambda_{i,p}^{k} z_{i,t-p}^{k} + e_{i,t}, \tag{3}$$

where $x_{i,t}$ represents the variable i of the factor space, f_t^j the common cycle for output or for prices that $x_{i,t}$ belongs to, and $z_{i,t}^k$ the endogenous variables of the structural VAR. The error terms $e_{i,t}$ depict the variable-specific time-varying idiosyncratic components. In (3), we restrict the factor loadings $\lambda_{i,p}^j$ such that the variables related to output and price are exclusively affected by the corresponding cycle f_t^j. We introduce the variables in the data section and list them in more detail in the appendix.

In line with Del Negro and Otrok (2007), Antolin-Diaz (2024) and Korobilis and Schröder (2024), it is crucial to note that the restriction of the loadings enables us to economically interpret f_t^j as common cycles for output and inflation. In order to achieve statistical identification, we normalize the factor loadings $\lambda_{i,0}^j$ of real GDP and GDP deflator to 1. In this regard, our model resembles Karadimitropoulou and Leon-Ledesma (2013) and Beck (2021), which allows us to interpret the loadings of the remaining variables in relation to the two variables.[2] Importantly, the above zero restrictions on the factor loadings to identify the two cycles do not prevent cross-factor dynamics as the structural shocks identified in the below SVAR are transmitted via the contemporaneous impact matrix $\boldsymbol{B}$ (see below).[3]

In our baseline model, we set $p = 2$ and thereby, allow for disproportionate impulse responses in terms of persistence and peaks across the variables in the factor space (Korobilis & Schröder, 2024; Antolin-Diaz et al., 2024). Economically, the inclusion of lags of the

[2]Naturally, this normalization closely links the common cycles to real GDP and GDP deflator respectively. However, as these variable can be regarded as main indicators with respect to the dynamic of economic activity and prices, we motivate the assumption to be reasonable.

[3]Following Antolin-Diaz (2024), this ensures that structural shocks can impact both factors simultaneously. Therefore, we do not impose any orthogonality between the output and inflation cycle. In the online appendix, we outline the cross-cycle interaction via the impact matrix $\boldsymbol{B}$ and the factor loadings in more detail.

common cycles is motivated by the delayed exposure of some variables to the cycles.

We allow for stochastic volatilities of output and inflation components. The extent to which common cycles account for fluctuations in the variables may undergo changes over time. In particular, and with $e_{i,t} \sim N(0, \sigma_{i,t})$, $\sigma_{i,t}$ is allowed to vary over time according to geometric random walks:

$$h_{i,t} = h_{i,t-1} + \xi^j_{i,t}, \quad \xi_{i,t} \sim N(0, V_{h_{i,t}}), \tag{4}$$

where $\sigma_{i,t} = exp(h_{i,t})$. The variance $V_{h_{i,t}}$ determines the degree of time variation. We estimate $V_{h_{i,t}}$ using a hierarchical horseshoe prior which comprises a global and a local shrinkage component to allow for smooth as well as sudden changes in the idiosyncratic part of the model (Prüser, 2021). This allows us to study if any disconnection of one variable from the common cycle occurs abruptly or more gradually. The prior specifications for the factor equation are presented in next Appendix C.

3.2 Proxy-Augmented SVAR

Next, the second equation is the structural proxy VAR model following the implementation by Hou (2024) and which draws upon the concept of Braun and Bruggemann (2023). In more detail, we augment (2) by adding proxies so that we can write:

$$\boldsymbol{y}_t \quad = \quad \boldsymbol{c} + \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{A}_L \boldsymbol{y}_{t-L} + \boldsymbol{B}\boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{I}_n), \tag{5}$$

where $\boldsymbol{y}_t$ contains the common cycles for output and prices, f^j_t, the endogenous variables, $\boldsymbol{z}_t$ and the proxies, $\boldsymbol{m}_t$ such that $\boldsymbol{y}_t = (f^j_t, \boldsymbol{z}'_t, m_t)'$. The $n \times 1$ vector $\boldsymbol{y}_t$ is modeled by a structural proxy VAR model, where $n = r + k$. In this context, r denotes the sum of the factors and the variables in $\boldsymbol{z}_t$, while k denotes the number of external instruments. $\boldsymbol{A}_1, \ldots, \boldsymbol{A}_L$ are $n \times n$ and contain the autoregressive VAR coefficient matrices and $\boldsymbol{B}$ denotes the (invertible) contemporaneous impact matrix of the structural shocks $\boldsymbol{\epsilon}_t$. In our baseline model, we set $L = 4$.

The shocks $\boldsymbol{\epsilon}_t$ comprise the structural shocks of the endogenous variables $\boldsymbol{\epsilon}^{r'}_t$ and the shocks of the instrumental variables $\boldsymbol{\epsilon}^{k'}_t$. Since the shocks of instrumental variables lack information for the variables in $\boldsymbol{y}_t$, the coefficient matrices in (5) read as follows:

$$\boldsymbol{A}_l = \begin{bmatrix} \boldsymbol{\Gamma}_l & \mathbf{0}_{r\times k} \\ \boldsymbol{\Phi}_{l,1} & \boldsymbol{\Phi}_{l,2} \end{bmatrix}, \ \boldsymbol{B} = \begin{bmatrix} \boldsymbol{\Gamma}_0 & \mathbf{0}_{r\times k} \\ \boldsymbol{\Phi}_{0,1} & \boldsymbol{\Phi}_{0,2} \end{bmatrix}, \ l = 1, \ldots, L, \tag{6}$$

where $\boldsymbol{\Gamma}_l$ is $r \times r$, $\boldsymbol{\Phi}_{l,1}$ is $k \times r$ and $\Phi_{l,2}$ is $k \times k$ for $0 \leq l \leq L$. In $\boldsymbol{A}_l$, $\boldsymbol{\Phi}_{l,1}$ and $\Phi_{l,2}$ are set to 0, thereby ensuring that the instrument variable m_t does not exert a lagged effect on the endogenous variables. The autoregressive parameters in $\boldsymbol{\Gamma}_l$ are subject to adaptive asymmetric Minnesota-type shrinkage priors. In the following, we outline $\boldsymbol{B}$ for the baseline model in more detail as it encompasses the identification of our structural shocks:

$$\boldsymbol{B} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & 0 & & \cdots & & 0 \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} & \gamma_{25} & & & & & \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} & \gamma_{35} & \vdots & & \ddots & & \vdots \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} & \gamma_{45} & & & & & \\ \gamma_{51} & \gamma_{52} & \gamma_{53} & \gamma_{54} & \gamma_{55} & 0 & & \cdots & & 0 \\ \Phi_{1,1} & 0 & \Phi_{1,3} & \Phi_{1,4} & 0 & \Phi_{1,6} & 0 & \cdots & & 0 \\ 0 & \Phi_{2,2} & 0 & \cdots & 0 & 0 & \Phi_{2,7} & & & 0 \\ 0 & \Phi_{3,2} & 0 & \cdots & 0 & & & \Phi_{3,8} & & 0 \\ \vdots & \vdots & & & \vdots & \vdots & \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & \Phi_{9,5} & 0 & & \cdots & & \Phi_{9,14} \end{bmatrix} \tag{7}$$

In the baseline specification, matrix $\boldsymbol{B}$ has 14 columns. The first five correspond to the endogenous variables: output factor, price factor, government spending, tax revenues, and the interest rate. The remaining nine columns are associated with our proxy variables. We allow for $\Phi_{1,3}$ and $\Phi_{1,4}$ being different from zero in robustness check estimations.

In $\boldsymbol{B}$, $\boldsymbol{\Phi}_{0,1}$ is composed of a row of zeros, with the exception of coefficients that describe the relationship between the instrument variable m_t and the relevant structural shock.[4] In our baseline model, $\boldsymbol{\Phi}_{0,2}$ is a diagonal identity matrix following Caldara and Herbst (2019) (see our section 4.3). As in Hou (2024), the non-zero elements of $\boldsymbol{B}$ are assumed

[4]Hou (2024) discusses the structural proxy VAR in more depth.

to follow independent (sign-restricted) Gaussian priors. A comprehensive discussion of the prior specifications for the Proxy SVAR can be found in appendix Appendix C. The sign restrictions in the contemporaneous impact matrix $\boldsymbol{B}$ are jointly presented with the external instrument in section 3.2. The autoregressive coefficients in $\boldsymbol{A}_l$ are estimated following Carriero et al. (2019) and Carriero et al. (2022). The estimation of the impact matrix $\boldsymbol{B}$ is implemented as in Hou (2024), employing a parameter transformation scheme that avoids the computationally inefficient Metropolis Hastings algorithm (see Fu, Hou, and Prüser (2025) and Berend and Prüser (2024)).

3.3 The Gibbs Sampler

We employ a fully Bayesian framework to estimate the FAVAR model with proxy variables and sign restrictions using the Gibbs sampler. In this section, we provide a brief overview of our proposed sampler, which incorporates the sampling algorithms of B. Bernanke et al. (2005), Prüser (2021), Berend and Prüser (2024), and Hou (2024). In contrast to a principal component analysis, our novel Gibbs sampler takes the uncertainty of the dynamic factor model into account, resulting in posterior distributions for both the factors and their loadings. Furthermore, we address the issue of over-parameterization and estimate the scaling parameters for the stochastic volatilities in the factor equation and the VAR parameters within the sampler in a data-driven approach. In addition, our proposed sampler incorporates sign restrictions on the contemporaneous impact matrix $\boldsymbol{B}$ as well as external instruments for the purpose of identifying structural shocks to the VAR. This is achieved in an efficient manner that minimizes the computational costs substantially in comparison to other more recent attempts to combine sign restrictions and instruments (Hou, 2024). We simulate 18,000 iterations and reject the first 3,000 as burn-in and retain every fifth draw. In the online appendix, we describe the Gibbs sampler in detail.

Step 1 Draw factor loadings from the conditional posterior of λ_i^j.

Step 2 Draw stochastic volatilities $h_{i,t}^j$ using the auxiliary mixture sampler of Kim et al. (1998) in combination with the precision sampler of Chan and Jeliazkov (2009).

Step 3 Draw the initial conditions for $h_{i,0}^j$ using the precision sampler of Chan and Jeliazkov

(2009).

Step 4 Draw the local and global shrinkage components $\lambda_{h^j_{i,t}}$ and $\tau_{h^j_i}$ of the stochastic volatilities $h^j_{i,t}$ using the sampler for half-Cauchy distributions of Makalic and Schmidt (2016).

Step 5 Draw the VAR coefficients $\boldsymbol{A} = (\boldsymbol{c}, \boldsymbol{A}_1, \ldots, \boldsymbol{A}_L)'$ using the equation-by-equation approach of Carriero et al. (2019).

Step 6 Draw the contemporaneous impact matrix $\boldsymbol{B}$ with zero and sign restrictions using the parameter transformation scheme of Hou (2024).

Step 7 Draw the shrinkage components κ_1 and κ_2 of the VAR coefficients $\boldsymbol{A} = (\boldsymbol{c}, \boldsymbol{A}_1, \ldots, \boldsymbol{A}_L)'$ from truncated inverse Gamma distributions.

Step 8 Draw the common factors f^j_t using the algorithm of Carter and Kohn (1994) and following B. Bernanke et al. (2005).

4 Data and Structural Identification

4.1 Data

We use quarterly series from 1959 Q1 to 2023 Q4. Our dataset contains 32 variables (see Table A.3) for an output factor and 30 variables for a price factor (see Table A.4). The data are from the McCracken and Ng (2020) database. Similar large datasets were used by B. Bernanke et al. (2005), Belviso and Milani (2006), or Bruns (2021).

We study the joint dynamics of five variables, including the output and price factors, real government spending, real tax revenues, and the short term interest rate. Real government spending is the sum of general government consumption expenditures and gross investment from NIPA Table 3.9.5. Real tax revenues are tax revenues of the general government from NIPA Table 3.1. The series are deflated using implicit price deflators (see Table A.1). The short term interest rate is measured using the 3-month Treasury Bill rate (in percent).

Price indices are computed as year-on-year log changes. Output indices, together with government spending and tax revenues, are expressed in logs, following the seminal empirical study on fiscal policy effects by Blanchard and Perotti (2002), among many subsequent studies. Caldara and Kamps (2017) and Angelini et al. (2023) remove a linear deterministic time trend from the latter set of variables. We entertain instead the possibility of stochastic trends (unit roots), as Blanchard and Perotti (2002) do.[5] Instead of using first differences, we apply a modified Beveridge-Nelson filter suggested by Kamber et al. (2025). It removes the nonstationary stochastic trend from the time series and produces covariance stationary time series. We remove a very smooth stochastic trend, i.e., a low frequency trend, by minimizing the variance of the change in trend. [6]

4.2 External Proxies

We use nine time series as proxies to identify five shocks of interest. Thus, we follow Hou (2024) and use multiple proxies to identify five structural shocks. The data sources for the proxies can be found in Table A.2.

Specifically, for the government spending shock, we use two proxies. The first is based on news shocks about military spending from Ramey (2011), representing an unexpected fiscal spending shock. It is worth noting that Ramey (2011) focuses on anticipated shocks. Following Auerbach and Gorodnichenko (2012) and Angelini et al. (2023), we construct the proxy by purging the residuals from a regression of fiscal spending on a set of macroeconomic indicators, using Ramey's (2011) measure of spending shocks. The rationale is to exclude the component of the one-step-ahead fiscal spending forecast error that can be anticipated based on narrative records. More precisely, we use the residuals from an OLS regression of the log of fiscal spending on a linear trend, Ramey's spending news shock series, and three lags of output, fiscal spending, tax revenues (all in logs), and Ramey's series. The second proxy for government spending shocks is based on revisions in expectations from the Survey of Professional Forecasters' forecasts of government spending, constructed exactly as in Caggiano et al. (2015). This proxy is used because Ramey's series covers only the period from 1959 Q4 to 2015 Q4. The key idea behind the Caggiano et

[5]They report fiscal multipliers for two specifications, one with deterministic time trends removed and another with variables in log-differences after establishing that variables with unit roots are not cointegrated with each other.

[6]We explore alternative approaches, such as applying other filters (the Hodrick-Prescott filter and also the Hamilton filter) suggested in the literature or removing a deterministic time trend, and find them all inferior due to large shocks in recent years that cause a mechanical spike in the log of real GDP and its components after the covid-19 period or flattening of the trend, respectively, as also demonstrated by Kamber et al. (2025).

al. (2015) measure is that forecast errors reflect changes in government spending that are independent of broader economic news and, therefore, are unexpected by private agents.

We use the proxies of Mertens and Ravn (2014) for tax shocks to personal income taxes and tax shocks to corporate income taxes, which are an extension of original series by Romer and Romer (2010).[7] We follow Breitenlechner et al. (2024) and extend the proxies in Mertens and Ravn (2014) with the estimates from Hanson et al. (2021). Furthermore, we instrument the output shock using the total utility adjusted factor productivity proxy from Fernald (2014), as applied in Caldara and Kamps (2017) and Angelini et al. (2023).

Monetary policy shocks are instrumented using the proxies calculated from high-frequency changes in interest rates around FOMC announcements as in Bauer and Swanson (2023) and Jarocinski (2022). In regards to the first proxy, Bauer and Swanson (2023), we follow Nakamura and Steinsson (2018) and employ the first principal component of eurodollar futures (ED1-ED4) as a monetary policy surprise. To purge any *FED response to macroeconomic news* effect, the authors regress the principal component on various economic indicators, such as employment growth, stock and commodity prices etc. The proxy proposed by Jarocinski (2022) estimates the first principal component of the above mentioned eurodollar futures and the current month and 3-month FED funds futures. Differing from Bauer and Swanson (2023), Jarocinski (2022) then purges the *pure* monetary policy shocks from central bank information shocks using changes in the S&P500 around the FOMC announcements.[8] Naturally, the proxies are only available for days of FOMC announcements and to aggregate them to a quarterly frequency, we resort to Corsetti et al. (2022) and for each day in the sample calculate the cumulative surprise over the last 93 days. The resulting time series is then averaged for every quarter.[9]

The inflation shock is instrumented using the oil price shock from Hamilton (2003) and the oil supply news shock from Känzig (2021). The former is also employed in Caldara and Kamps (2017) and available on a quarterly frequency, while the latter is based on high-frequency changes of oil future prices around OPEC announcement dates. Since in

[7]Mertens and Ravn (2012) improve the narrative measures in Romer and Romer (2010) by splitting their series into anticipated and unanticipated tax changes

[8]Recently, Jarocinski and Karadi (2025) merge the two approaches.

[9]In a robustness check, we follow Geiger et al. (2023) and weight the daily proxies by the day of the quarter in order to control for the timing of the FOMC announcements.

most cases OPEC announcements did not take place more than once in a quarter, we sum the daily events.

Some of the proxy variables that we employ do not cover our full sample range. Following Känzig (2021), Breitenlechner et al. (2024) and others, we treat the missing observations conservatively and set them to zero. In the robustness analysis, we estimate the missing observations as in Hou (2024) and Chan et al. (2023).

4.3 Structural Identification

For the proxy variables $m_{k,t}$ to be valid instruments, they should satisfy the relevance and the exogeneity conditions. The relevance condition requires them to be correlated with the corresponding structural shock. The exogeneity condition posits that the instruments are uncorrelated with other structural shocks. In particular, the structural shocks $\boldsymbol{\epsilon}_t^{r'}$ can be split into $\epsilon_{1,t}^{r'}$ and $\boldsymbol{\epsilon}_{2,t}^{r'}$. Let the former represent one structural shocks, and the latter encompass all other shocks. Furthermore, let k be the related proxy (or proxies) for the structural shock $\epsilon_{1,t}^{r'}$. In accordance with Hou (2024), the relevance and exogeneity assumptions can be summarized as follows:

$$\mathbb{E}(m_{k,t}\boldsymbol{\epsilon}_t^{r'}) = \begin{pmatrix} \mathbb{E}(m_{k,t}\epsilon_{1,t}^{r'}) & \mathbb{E}(m_{k,t}\boldsymbol{\epsilon}_{2,t}^{r'}) \end{pmatrix} = \begin{pmatrix} \mathbb{E}(m_t\epsilon_{1,t}^{r'}) & 0 \end{pmatrix}. \tag{8}$$

Following (8), we implement the relationship between the structural shocks and the instruments $m_{k,t}$ via the proxy equations as in Caldara and Herbst (2019). From (6) and (7), we obtain:

$$m_{k,t} \;=\; \Phi_{r+k,r}\epsilon_{1,t}^{r'} + \Phi_{r+k,r}\epsilon_t^{k'}, \quad \epsilon_t^{k'} \sim N(0,1) \text{ and } \epsilon_{1,t}^{r'} \perp \epsilon_t^{k'}. \tag{9}$$

In order to incorporate our prior beliefs regarding the relevance of the proxy, we set a tight prior variance on $\Phi_{r+k,r+k}$ (see appendix Appendix C).

We enhance the identification strategy and integrate sign restrictions into the contemporaneous impact matrix $\boldsymbol{B}$ as proposed by Hou (2024). We assume that contractionary policy shock raises short-term interest rate (γ_{55} positive in equation 7) and lowers inflation and output factors on impact (γ_{51} and γ_{52} positive). Positive government spending shock increases real government spending and output factor (γ_{33} and γ_{13} positive), whereas positive tax revenue shock increases tax revenues and lowers output factor (γ_{44} positive and γ_{14} negative). Most importantly, these sign restrictions do not have much impact on our results. However, they provide additional information for the identification of structural shocks.

4.4 Fiscal Multiplier Definition

The fiscal multiplier is defined as the dollar response of GDP (or the chosen output component) to an effective change in government spending or tax revenues of one dollar. We calculate cumulative fiscal multipliers (cf. Ramey, 2019). Let IRF_{y_h} be the response of log-output at horizon h to a (one-standard deviation) fiscal policy shock; and IRF_{p_h} be the response of the log of the corresponding fiscal variable to the same fiscal policy shock. The h periods ahead cumulative multiplier $\mathbf{M}_{Ph}$ is then expressed as:

$$\mathbf{M}_{Ph} = \frac{\sum_{i=1}^{h} IRF_{y_h}}{\sum_{i=1}^{h} IRF_{p_h}} \frac{\overline{Y}}{\overline{P}}, \tag{10}$$

where P is either government spending or government tax revenues, and $\frac{\overline{Y}}{\overline{P}}$ is the so-called conversion factor that converts elasticities to dollars.[10] $\overline{P}$ 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) or the chosen output component. In our baseline sample, the conversion factor for GDP is equal to 5.26 for both, government spending and government tax revenues, or 0.19 for the inverse, similar to Angelini et al. (2023), who report values of .20 and 0.18, respectively). However, conversion factors vary across different components of output.

[10] See for example Blanchard and Perotti (2002), Caldara and Kamps (2017), and Angelini et al. (2023).

5 Empirical Results

5.1 Common Cycles

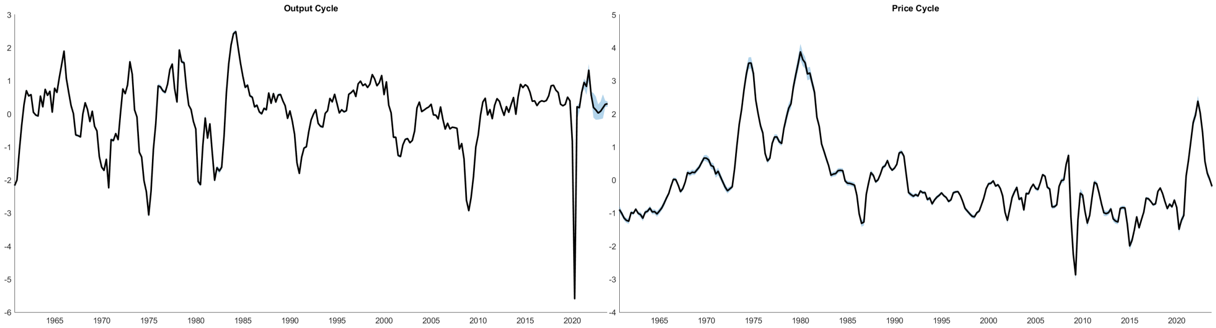
Dating peaks and troughs of business cycles generally involves assessing several indicators of real economic activity (e.g., https://www.nber.org/research/business-cycle-dating). In this section, we explore the common components of real factors or the output cycle and the common components of price factors or the price cycle. This allows us to judge the importance of common cycles in the movement of various variables (or sectors in the economy) relative to idiosyncratic or variable specific shocks that are not shared across sectors. In other words, are there common cycles that drive aggregate output or is there one or more sector specific shocks? Following Stock and Watson (2012), we compare cycles across components of each of the two factors in our analysis, period by period. We identify common cycles for output and inflation with credible bands (Figure 1) that capture common comovements of the variables that we use in our analysis to extract output and price factors (see Table A.3 and Table A.4).

The left panel of Figure 1 presents the output cycle. The identified cycle has a clear economic interpretation. We observe several downturns, the most significant is the one related to the outbreak of the covid-19 pandemic in 2020. The other major downturns are related to global financial crisis in 2009, dot-com bubble and terrorist attacks in 2001, real estate market crisis in 1990, energy crisis in 1979 and oil crisis in 1975.

The right panel of Figure 1 presents the price cycle. It nicely corresponds with the identified output cycle. The major price spikes are related to skyrocketing oil prices in 1973–1975, and increased demand for goods due to supply chain disruptions during the covid-19 pandemic.

Figure 2 presents individual exposure of the chosen variables to the common cycle. The output cycle accounts for more than 70% of the variation in private consumption and private investment. It is, however, weakly related to exports or inventories cycles with the R-squared coefficient (as defined in Stock and Watson, 2012) lower than 15% (as defined in Stock and Watson, 2012). Turning to the price cycle, it accounts for more than 70% of the variation in the GDP deflator, PCE, CPI, and PPI indices. But it is not related to earnings in construction and manufacturing.

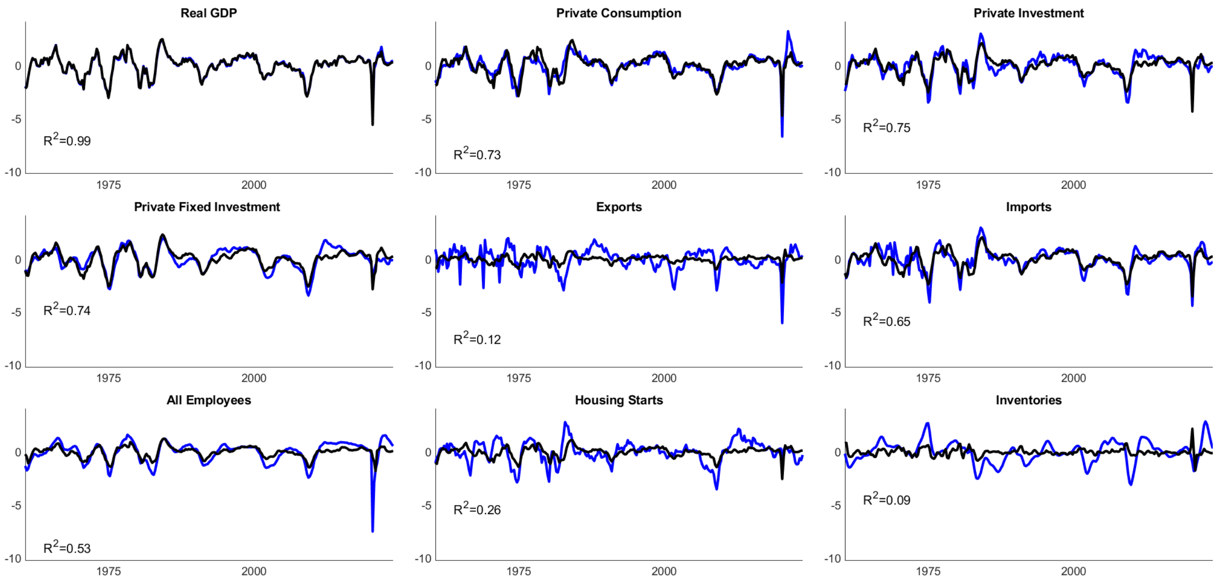
Figure 1: Output and Price Cycle



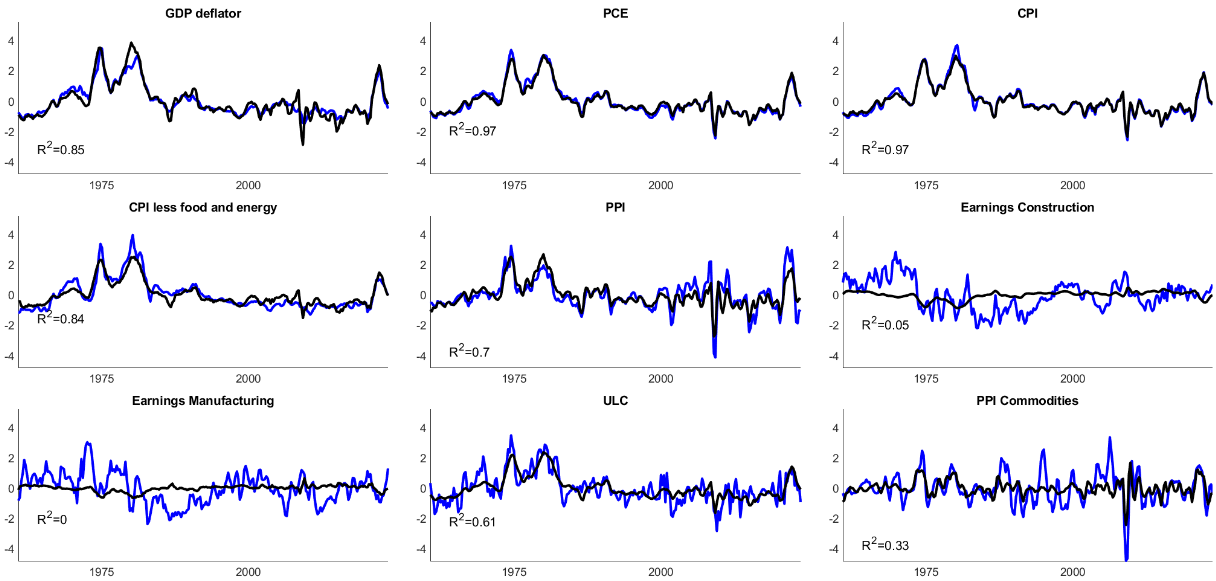
Note: The figures show the posterior medians of the standardized output and price cycles. The light blue shaded areas display the 16^{th} and 84^{th} percentiles of the posterior distribution. The sample period spans from 1959 to 2023.

Figure 2: Individual Exposure to Common Cycles

(a) Output Cycle.



(b) Price Cycle.



Note: The figures show the exposures of selected output and price components to the corresponding common cycles. The solid blue lines depict the actual time series and solid black lines display the product the $\sum_{p=0}^{P} \lambda_{i,p}^{j} f_{t-p}^{j}$. R^2 denotes the R-squared.

5.2 Response to Fiscal Shocks: Effects on Output and Price Components

We follow Blanchard and Perotti (2002) and trace the effects of fiscal shocks on output components. A positive government spending shock leads to an increase in real GDP and private consumption (see Figure 3).[11] Private investment and private fixed investment

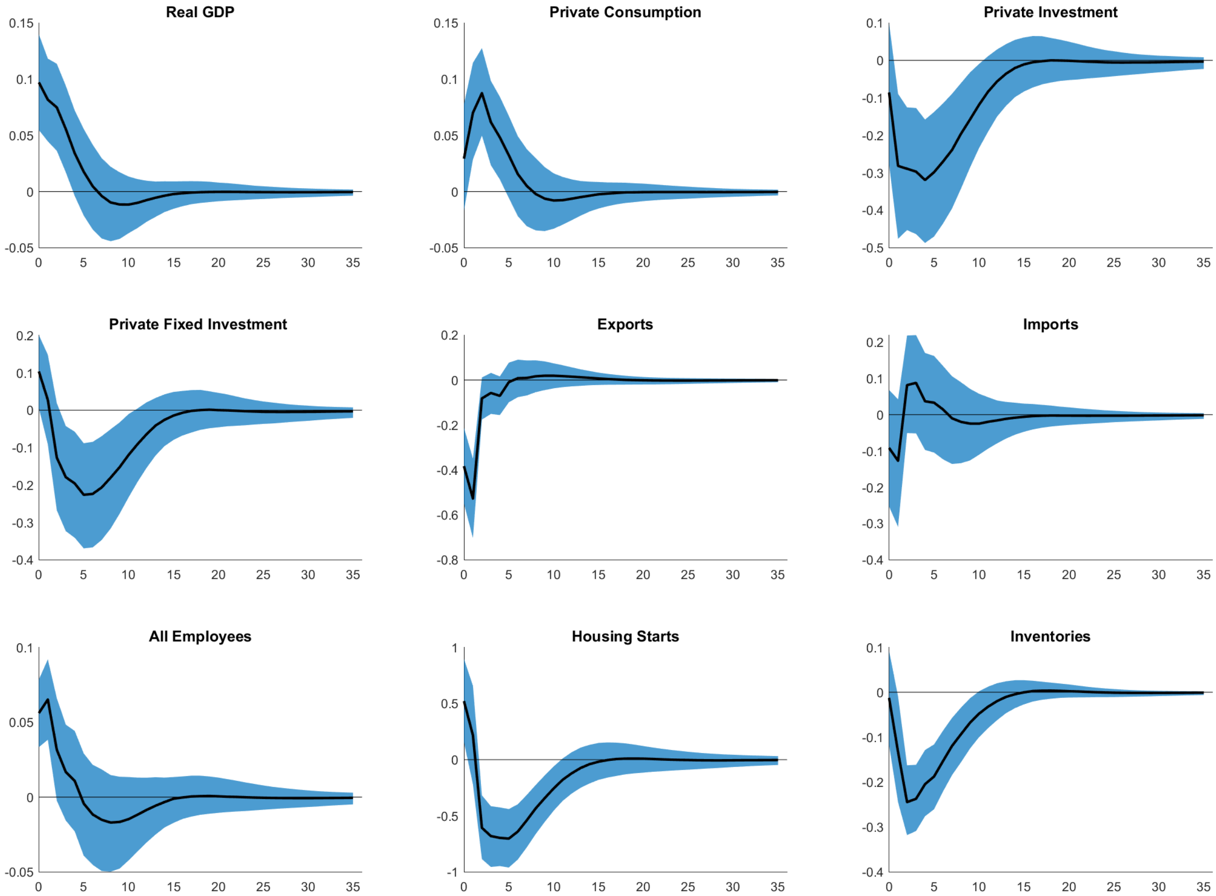
[11] Impulse response functions for the main variables in the model are presented in Figures B.3–B.6.

are crowded out by the increase in government spending. Exports decrease, reaching their lowest point after two quarters, whereas the response of imports is insignificant. This result is consistent with the twin deficit hypothesis, because the current account deteriorates while the fiscal deficit increases. In this respect, we confirm the result found by Klein and Linnemann (2019), who state that identified fiscal shocks that increase the fiscal deficit are typically followed by protracted current account deficits over time. Moreover, in accordance with our expectations, we observe an increase in employment, which is a consequence of higher levels of economic activity. Finally, a positive government spending shock causes a decrease in inventories. Due to initially limited production capacity, firms reduce inventories in the first two periods following the shock to meet the demand for their products before replenishing inventories afterwards.

Next, we move to the effects of tax increases (see Figure B.4). The output cycle factor falls in response to increase in tax revenues. The negative response of prices is statistically insignificant and government spending increases slightly. The response of interest rate to tax shock is insignificant.

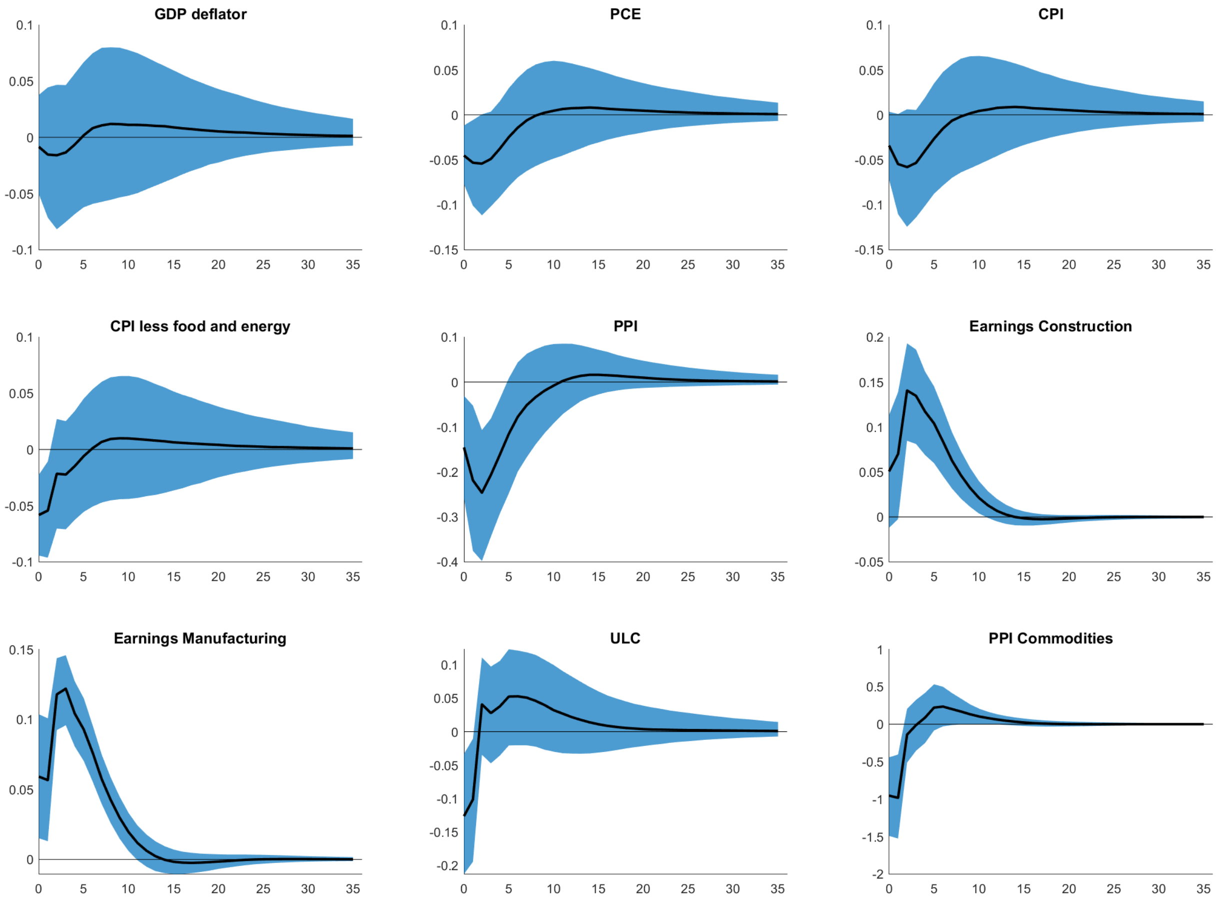
Increases in taxes reduce both private consumption and private investment (see Figure 5). The effect on exports is statistically insignificant. The negative effect on imports is small and statistically significant only at horizon two. In response to a positive tax shock, we observe a significant increase in inventories.

Figure 3: Impulse response functions (positive government spending shock) chosen output components



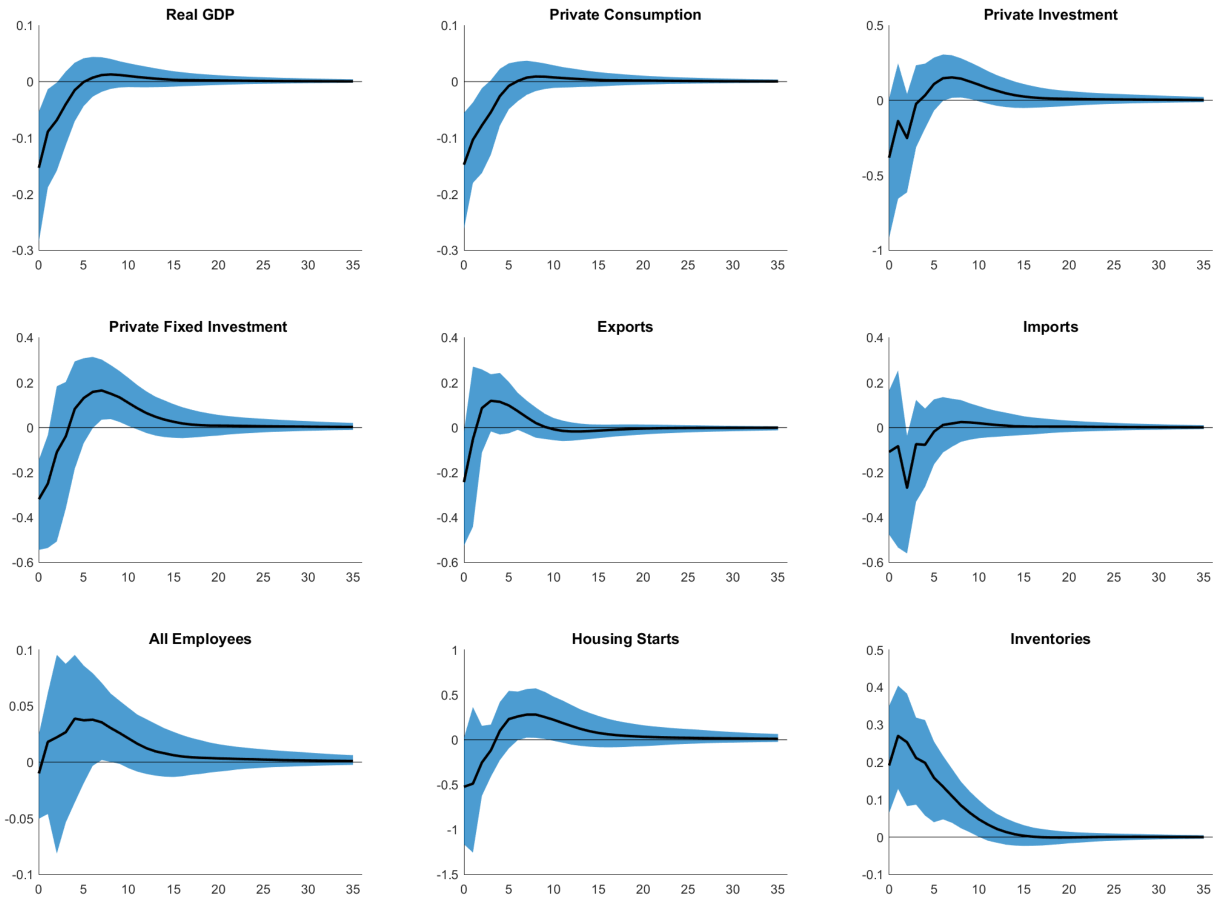
Note: The figure shows the median responses of selected output components to a positive government spending shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure 4: Impulse response functions (positive government spending shock) chosen price components



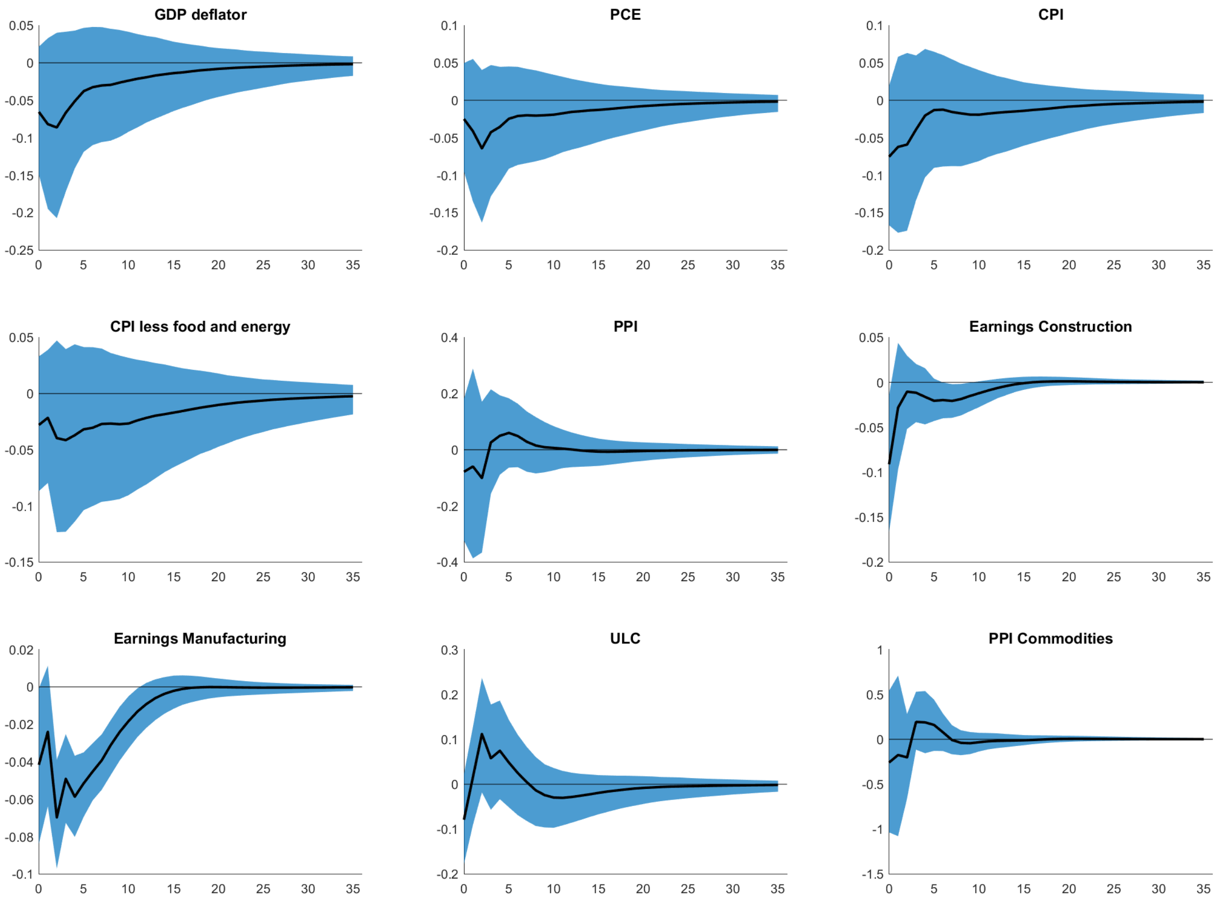
Note: The figure shows the median responses of selected price components to a positive government spending shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure 5: Impulse response functions (positive tax shock) chosen output components



Note: The figure shows the median responses of selected output components to a positive tax revenue shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure 6: Impulse response functions (positive tax shock) chosen price components



Note: The figure shows the median responses of selected price components to a positive tax revenue shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

5.3 Fiscal Multipliers

The remainder of the paper is devoted to the analysis of fiscal multipliers. Figure 7 depicts government spending multiplier for the baseline model. We obtain a spending multiplier within the range of values found in the literature. It is equal to 1.03 on impact and then steadily decreases to become statistically insignificant after 14 quarters. The spending multiplier amounts to 0.87 after one year and 0.67 after two years. According to Ramey (2019), cumulative fiscal multipliers generally range from about 0.6 to 2 for government spending. For instance, Kapetanios, Koutroumpis, Tsoukis, and Glebkina (2025) report that spending multipliers are almost always above one, while Caldara and Kamps (2017) find peak values between 1 and 1.3.

We only note that many studies (i.e. Mertens and Ravn, 2014; Caldara and Kamps, 2017) agree that the differences in fiscal multiplier estimates stem from different assumptions concerning the level of contemporaneous output elasticities. The posterior median for the output elasticity of government spending is equal to 0.16. Whereas the posterior median for the output elasticity of tax revenues is equal to 1.14 (see Appendix Figure B.8).

Figure 7: Spending multiplier

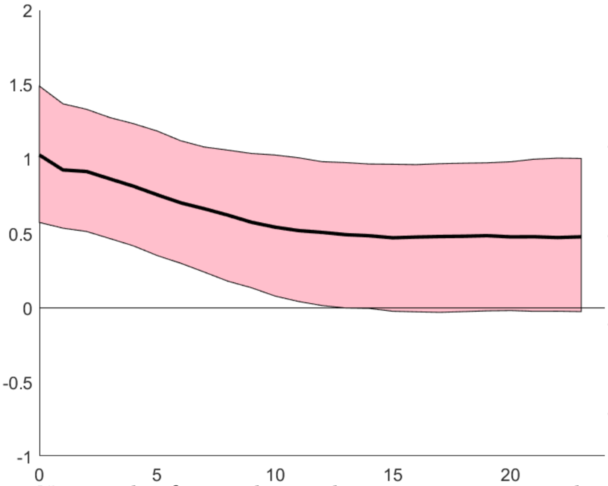
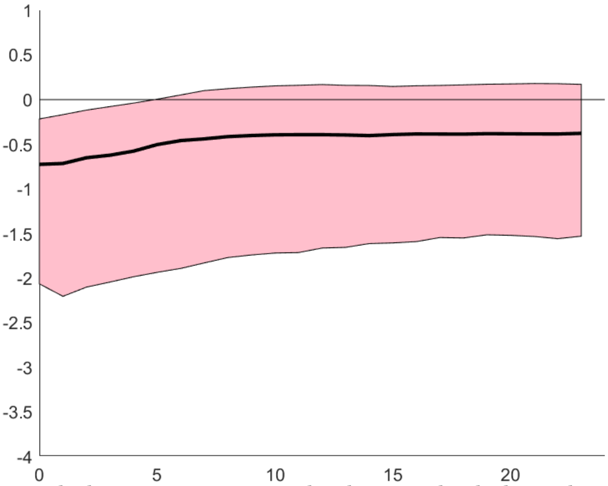


Figure 8: Tax revenues multiplier



Note: The figure shows the government spending and the tax revenue multipliers. The light red shaded areas in the left figure depicts the 68% credible bands.

Tax multiplier for the baseline model is presented in the left panel in Figure 8. It is equal to -0.72 on impact, -0.62 after one year, and is statistically insignificant afterwards. Thus, the baseline tax multiplier is lower than the values often found in literature (see Ramey (2019) Table 2).

5.4 Fiscal multipliers - Common and Idiosyncratic Transmission

Figures 9 and 10 decompose the fiscal multipliers for selected output components into common and idiosyncratic transmission channels. In the FAVAR framework, each output component can respond to fiscal shocks through the common output cycle, which captures the part of the response shared across macroeconomic aggregates, and through an idiosyncratic component, which captures component-specific deviations from the common cycle. We compute the corresponding multipliers using the same scaling factors as in Equation (10), replacing the total impulse response of each output component with either its common or idiosyncratic response. By construction, the total multiplier is the sum of the common and idiosyncratic multipliers.

The transmission appears to occur through both the common and the idiosyncratic output transmission channel (see Figure 11). While government spending expands aggregate activity, its effects across GDP components are uneven.The idiosyncratic channel often operates in the opposite direction to the common channel and is quantitatively significant. It accounts for a large share of overall transmission and is even dominant for some components.

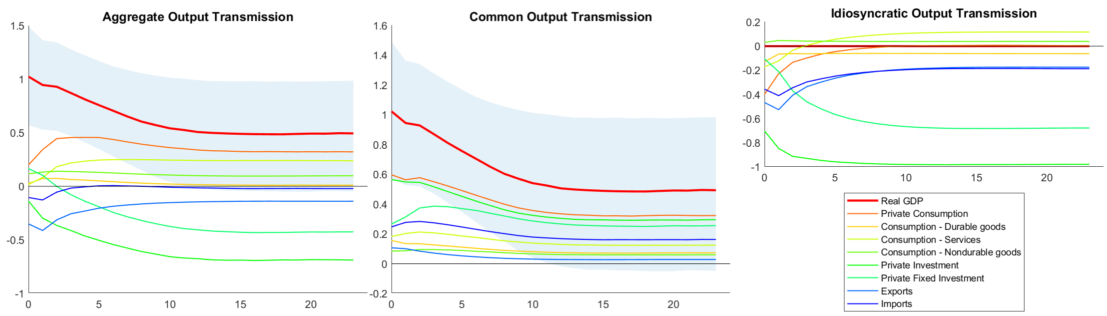
For spending multipliers, the common transmission is predominantly positive and ranges approximately from 0.1 to 1 across variables and horizons. In contrast, the idiosyncratic component ranges roughly from -1 to 0.1, indicating mostly negative or close-to-zero responses. The common channel therefore appears to be the main driver of the aggregate response to spending shocks, especially for private consumption. The idiosyncratic component is much weaker for consumption aggregates, but it is more relevant for investment and trade variables, where responses are negative and persistent.

The idiosyncratic channel has the strongest effect on private investment, generating a crowding-out effect on private investment. As shown in Figure 3, this is mainly driven by a sharp decline in inventories, accompanied by a somewhat smaller decline in fixed investment. Another group for which idiosyncratic output transmission plays an important role is exports and imports. Both categories appear to decline slightly in response to a positive government spending shock. This points to the low import intensity of government spending in the United States. Such spending appears to increase employment in the domestic economy (Figure 3) and to raise wages in construction and manufacturing. This, in turn, contributes to higher private consumption.

Figure 12 presents the corresponding decomposition for a positive tax revenue shock. For tax multipliers, the common transmission is mostly negative, ranging approximately from -3.1 to -0.2. By contrast, the idiosyncratic component ranges from about -0.2 to 2.4, with several variables displaying sizeable positive responses. The offset between the two channels is particularly visible for investment-related and trade variables: these variables react negatively through the common component but positively through the idiosyncratic component. Private consumption, however, shows only limited idiosyncratic responses. Overall, tax multipliers display larger absolute effects and stronger heterogeneity across variables than spending multipliers, suggesting that tax shocks operate more through compositional adjustments across output components.

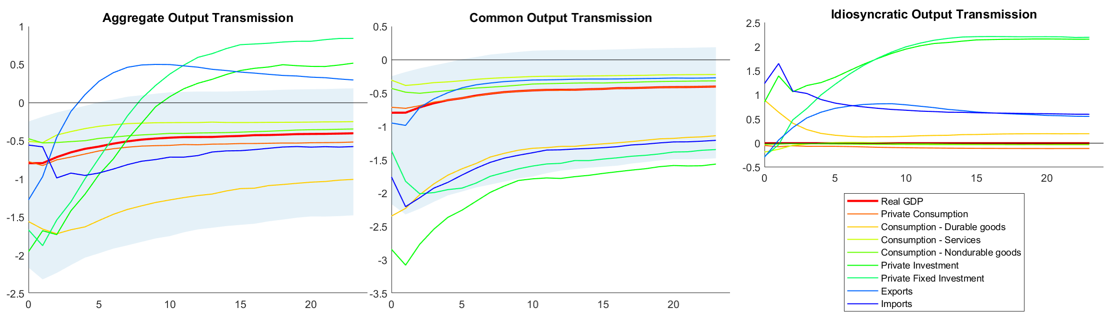
It is worth noting that the idiosyncratic output transmission channel has a strongly positive effect on private investment, exports, imports, and consumption of durable goods. The positive impact on private investment may be related to a decline in interest rates and prices (Figure B.4). Our results also indicate that an increase in tax revenues is associated with a subsequent decline in government spending, which limits the crowding-out effect on private investment.

Figure 9: Spending multipliers



Note: The figure shows the total spending multipliers for selected output components, together with their decomposition into common and idiosyncratic components.

Figure 10: Tax multipliers



The figure shows the total tax multipliers for selected output components, together with their decomposition into common and idiosyncratic components.

5.5 Fiscal Multipliers - Relaxing Orthogonality Conditions

Next, following Angelini et al. (2023), we examine how the results change when relaxing the assumption of orthogonality between total factor productivity and the tax shock—a modification we refer to as the Angelini correction.

Alternatively, following Ben Zeev and Pappa (2015), we assess how relaxing the assumption of orthogonality between total factor productivity and the government spending shock affects the results—a modification we refer to as the Ben Zeev correction.

Mathematically, this corresponds to allowing $\Phi_{1,4}$ in Equation 7 to differ from zero for the Angelini correction, and $\Phi_{1,3}$ for the Ben Zeev correction.

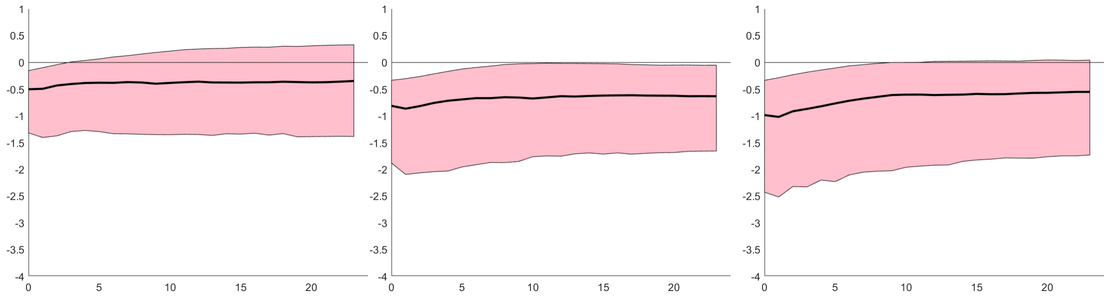
Moreover, we test how the results change if we allow for proxy interaction (correlation). In mathematical terms it is equivalent to allowing for $\Phi_{3,7}, \Phi_{2,8}, \ldots, \Phi_{9,13}, \Phi_{8,14}$ in Equation 7 being different than zero.

Figures 11 and 12 show that the changes in orthogonality conditions do not have much impact on fiscal multipliers.

Figure 11, middle panel, shows that the posterior median tax multiplier is lower in absolute terms when the Angelini correction is applied. The right panel further demonstrates that the multiplier decreases even more with the Ben Zeev correction. In contrast, allowing for proxy correlation does not affect the value of the tax multiplier.

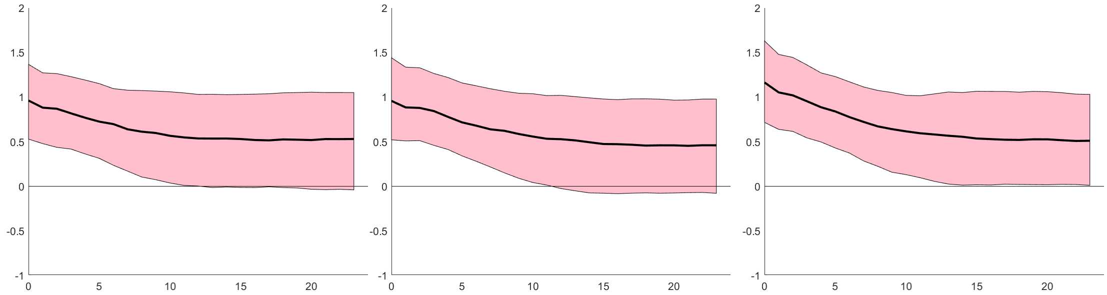
Therefore, we confirm that relaxing the assumption of orthogonality between TFP and tax shock affects the level of tax multiplier. In terms of spending multiplier we end with almost exactly the same values for the baseline and other model specifications (cf. Figure 12).

Figure 11: Tax multiplier - left panel model with proxy interaction, middle panel - Angelini correction, right panel - Ben Zeev correction



Note: The figure shows the tax multipliers for the baseline model, the model that allows for the correlation of proxies and the model that follows the specification of Angelini et al. (2023) and the model that follows the specification of Ben Zeev and Pappa (2015). The light red shaded areas in the left figure depicts the 68% credible bands.

Figure 12: Spending multiplier - left panel model with proxy interaction, middle panel - Angelini correction, right panel - Ben Zeev correction



Note: The figure shows the spending multipliers for the baseline model, the model that allows for the correlation of proxies and the model that follows the specification of Angelini et al. (2023) and the model that follows the specification of Ben Zeev and Pappa (2015). The light red shaded areas in the left figure depicts the 68% credible bands.

5.6 Robustness Checks

We perform a few additional robustness checks and test how they affect the level of fiscal multipliers. These changes include looking at the sample that ends before the covid-19 pandemic and the sample that starts in 1983 (when Fed Chair Paul Volcker started combating high inflation with tight monetary policy), as well as setting to zero missing proxy observations instead of estimating them or estimating the model without sign restrictions. Also, we test how the results change when we include corporate credits spreads (as suggested by Caldara and Herbst (2019)). Most importantly, across all robustness checks, the median posterior fiscal multipliers from the baseline model remain within the 68% credible intervals. These are depicted as blue dashed lines in Figures 13–17.

First, Figures B.13 and B.12 show that estimating the model without sign restrictions and setting to zero missing proxy observations do not affect the level of spending and tax multipliers. Second, changing the time period for estimation has significant effects for fiscal multipliers (see Figures B.9, B.10, and B.11).

In the pre-covid period we observe a higher cumulative spending multiplier than in baseline, reaching a peak value of 1.11 after six quarters (cf. Figure B.9). In contrast, the tax multiplier is lower in absolute terms during the same period, with a peak value of -0.34 after six quarters. However, the 68% credible interval for the tax multiplier includes zero from the fourth quarter onwards.

On the other hand, for the post-1983 sample, we obtain lower spending multiplier and a higher tax multiplier in absolute terms compared to the baseline model. The impact multipliers—which also represent the peak values in the post-1983 model—are equal to 0.70 for spending and −1.58 for tax revenues, respectively (cf. Figure B.11).

Figure B.10 shows how the results change if we include in the model corporate credit spreads and estimate the model for the sample beginning in 1973 (due to excess bond premium data availability). The inclusion of additional variables significantly affects the level of fiscal multipliers. It leads to lower tax multipliers (in absolute terms) that equal −1.40 on impact in comparison to −0.72 in the baseline specification. The posterior median for the spending multiplier is similar to the baseline model and is equal to 1.11 on impact (vs. 1.03 in the baseline model).

6 Conclusion

Our findings for the United States suggest that government spending and tax shocks have relatively large output effects. We use a state-of-the-art Bayesian proxy factor-augmented VAR model with five variables in the baseline model that includes monetary policy. We obtain a median posterior cumulative spending multiplier of 1.03 on impact, 0.87 after one year, and 0.67 after two years, similar to recent estimates in related models (Ramey, 2019). In contrast, the tax multiplier is −0.72 on impact, −0.62 after one year, and becomes not different from zero thereafter. These tax multiplier estimates are much smaller than what is reported in the empirical literature with time series models, however, they align with estimates from New Keynesian dynamic stochastic general equilibrium (DSGE) models (Ramey, 2019, Table 2, p. 105).

In addition, in contrast to most previous empirical time-series studies, we present fiscal multipliers for different components of GDP and decompose the transmission of fiscal policy into common and idiosyncratic parts, which has not been explored in the existing literature, as far as we know. We find that both spending and tax shocks affect GDP through both common and idiosyncratic channels. A positive spending shock has a strong positive impact on private consumption and employment but a negative effect on private investment, inventories, and exports. A positive tax shock has a negative or statistically insignificant effect on almost all components of output, with the exception of inventories.

We test various identification schemes within the proxy VAR framework. Our analysis primarily focuses on the approaches proposed by Angelini et al. (2023) and Ben Zeev and Pappa (2015), while also allowing for proxy correlations. We find that different assumptions regarding the orthogonality conditions between total factor productivity and fiscal variables have only a minor impact on the estimated fiscal multipliers. The most notable differences are observed in the tax multiplier when applying a correction that relaxes the assumption of orthogonality between total factor productivity shocks and government spending shocks.

Furthermore, we conduct a series of robustness checks. The results indicate that neither the treatment of missing proxy observations nor the inclusion of sign restrictions significantly alters our baseline findings. However, we observe notable differences when analyzing sub-samples, particularly the pre-covid period and the post-1983 sample. For the pre-covid period, we obtain a larger spending multiplier, reaching 1.11 after six quarters. In contrast, for the post-1983 sample, the spending multiplier is lower, with a peak value of 0.70 on impact. It is also worth noting that the tax multiplier is subject to greater uncertainty. For instance, the model that includes a risk premium shows a median value of -1.40, and the 68% credible interval ranges from -4.6 to -0.42.

The fiscal multipliers that we report are averages over economic expansions and recessions. Multipliers may be non-linear in the sense that periods of economic slack or tight private sector credit conditions affect its size. However, Ramey (2019, p. 103) assesses the evidence in favor of state-dependent fiscal multipliers as follows:"The more robust methods generally fail to produce multipliers above one during recessions or times of slack." A nonlinear Bayesian proxy factor-augmented VAR could be a suitable and robust vehicle for further explorations.

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Appendix A Additional Tables

Table A.1: Variables used to calculate scaling factors for fiscal multipliers and endogenous variables for fiscal and monetary policy

Y	Nominal GDP (SA, Billions of dollars)	NIPA Table 1.1.5, line 1
G	Nominal Government Consumption Expenditures & Gross Investment (SA, Billions of dollars)	NIPA Table 3.9.5, line 1
T	Nominal Tax Receipts (SA, Billions of dollars)	NIPA Table 3.1 line 2
p	Implicit Price Deflators for Government consumption expenditures and gross investment	NIPA 1.1.9, line 22
r	3-Month Treasury Bill: Secondary Market Rate (Percent)	FRED TB3MS
EBP	Excess Bond Premium	Gilchrist and Zakrajšek (2012), Favara et al. (2016)

Table A.2: Proxies

Proxy	**Shock**	**Source**	**Data availability**
gs_proxy1	Government spending	proxy based on Ramey (2011), updated by Ramey and Zubairy (2018) and used in Zeev et al. (2014)	1959Q1 - 2015Q4
gs_proxy2	Government spending	News13 variable from Caggiano et al. (2015), sum of revisions of expectations from the Survey of Professional Forecasters	1981Q4 - 2024Q3
tfp_proxy	Income shock	utilization-adjusted series on total factor productivity from `https://www.johnfernald.net/TFP`	1959Q1 - 2024Q3
oil_proxy1	Price shock	oil price shock from Caldara and Kamps (2017)	1959Q1 - 2006Q4
oil_proxy2	Price shock	Diego Kanzig, oil supply surprise series, `https://www.diegokaenzig.com/data`	1975Q1 - 2023Q4
tax_proxy1	Tax shock	shocks to personal income taxes from Mertens and Ravn (2014) updated by Hanson et al. (2021)	1959Q1 - 2019Q4
tax_proxy2	Tax shock	shocks to corporate income taxes from Mertens and Ravn (2014) updated by Hanson et al. (2021)	1959Q1 - 2019Q4
mp_proxy1	Monetary policy shock	proxy based on daily data from Bauer and Swanson (2023), rolling/weighted sum of last 93 days and then the average of Corsetti et al. (orthogonalized)	1988Q2 - 2023Q4
mp_proxy2	Monetary policy shock	proxy based on Jarocinski (2022)	1990Q2 - 2023Q4

Table A.3: Output factor

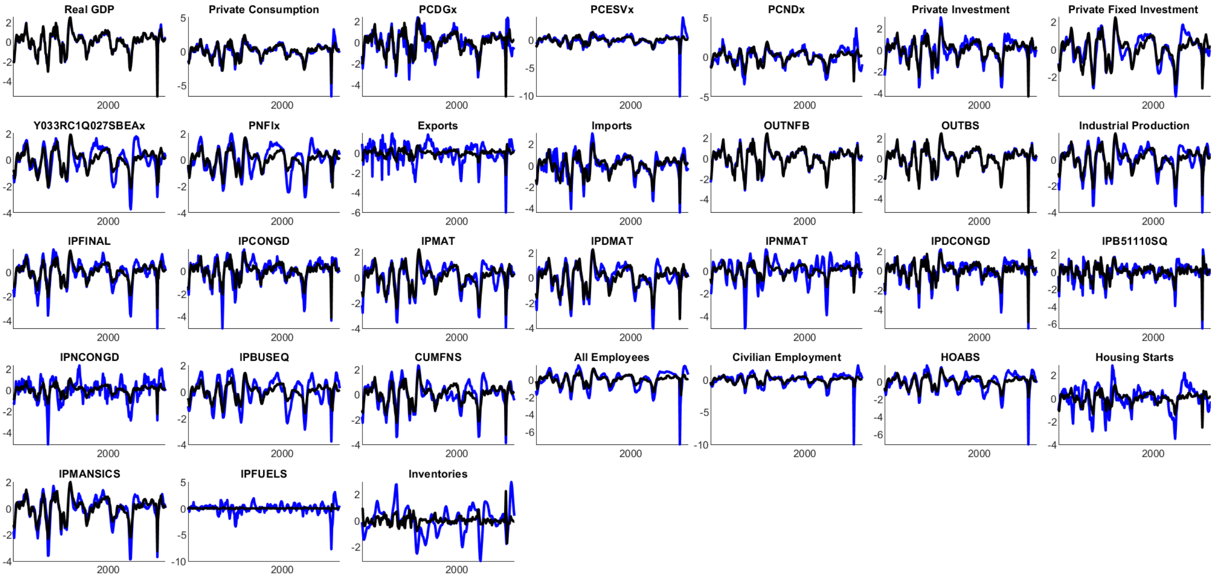
1	GDPC1	Real Gross Domestic Product, 3 Decimal (Billions of Chained 2012 Dollars)
2	PCECC96	Real Personal Consumption Expenditures (Billions of Chained 2012 Dollars)
3	PCDGx	Real personal consumption expenditures: Durable goods (Billions of Chained 2012 Dollars), deflated using PCE
4	PCESVx	Real Personal Consumption Expenditures: Services (Billions of 2012 Dollars), deflated using PCE
5	PCNDx	Real Personal Consumption Expenditures: Nondurable Goods (Billions of 2012 Dollars), deflated using PCE
6	GPDIC1	Real Gross Private Domestic Investment, 3 decimal (Billions of Chained 2012 Dollars)
7	FPIx	Real private fixed investment (Billions of Chained 2012 Dollars), deflated using PCE
8	Y033RC1Q027SBEAx	Real Gross Private Domestic Investment: Fixed Investment: Nonresidential: Equipment (Billions of Chained 2012 Dollars), deflated using PCE
9	PNFIx	Real private fixed investment: Nonresidential (Billions of Chained 2012 Dollars), deflated using PCE
16	EXPGSC1	Real Exports of Goods & Services, 3 Decimal (Billions of Chained 2012 Dollars)
17	IMPGSC1	Real Imports of Goods & Services, 3 Decimal (Billions of Chained 2012 Dollars)
19	OUTNFB	Nonfarm Business Sector: Real Output (Index 2012=100)
20	OUTBS	Business Sector: Real Output (Index 2012=100)
22	INDPRO	Industrial Production Index (Index 2012=100)
23	IPFINAL	Industrial Production: Final Products (Market Group) (Index 2012=100)
24	IPCONGD	Industrial Production: Consumer Goods (Index 2012=100)
25	IPMAT	Industrial Production: Materials (Index 2012=100)
26	IPDMAT	Industrial Production: Durable Materials (Index 2012=100)
27	IPNMAT	Industrial Production: Nondurable Materials (Index 2012=100)
28	IPDCONGD	Industrial Production: Durable Consumer Goods (Index 2012=100)
29	IPB51110SQ	Industrial Production: Durable Goods: Automotive products (Index 2012=100)
30	IPNCONGD	Industrial Production: Nondurable Consumer Goods (Index 2012=100)
31	IPBUSEQ	Industrial Production: Business Equipment (Index 2012=100)
34	CUMFNS	Capacity Utilization: Manufacturing (SIC) (Percent of Capacity)
35	PAYEMS	All Employees: Total nonfarm (Thousands of Persons)
57	CE16OV	Civilian Employment (Thousands of Persons)
74	HOABS	Business Sector: Hours of All Persons (Index 2012=100)
81	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started (Thousands of Units)
192	IPMANSICS	Industrial Production: Manufacturing (SIC) (Index 2012=100)
194	IPFUELS	Industrial Production: Fuels (Index 2012=100)
220	BUSINVx	Total Business Inventories (Millions of Dollars)

Table A.4: Price factor

97	GDPCTPI	Gross Domestic Product: Chain-type Price Index (Index 2012=100)
98	GPDICTPI	Gross Private Domestic Investment: Chain-type Price Index (Index 2012=100)
99	IPDBS	Business Sector: Implicit Price Deflator (Index 2012=100)
95	PCECTPI	Personal Consumption Expenditures: Chain-type Price Index (Index 2012=100)
96	PCEPILFE	Personal Consumption Expenditures Excluding Food and Energy (Chain-Type Price Index) (Index 2012=100)
101	DDURRG3Q086SBEA	Personal consumption expenditures: Durable goods (chain-type price index)
102	DSERRG3Q086SBEA	Personal consumption expenditures: Services (chain-type price index)
103	DNDGRG3Q086SBEA	Personal consumption expenditures: Nondurable goods (chain-type price index)
122	WPSFD49207	Producer Price Index by Commodity for Finished Goods (Index 1982=100)
123	PPIACO	Producer Price Index for All Commodities (Index 1982=100)
124	WPSFD49502	Producer Price Index by Commodity for Finished Consumer Goods (Index 1982=100)
125	WPSFD4111	Producer Price Index by Commodity for Finished Consumer Foods (Index 1982=100)
126	PPIIDC	Producer Price Index by Commodity Industrial Commodities (Index 1982=100)
127	WPSID61	Producer Price Index by Commodity Intermediate Materials: Supplies & Components (Index 1982=100)
120	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items (Index 1982-84=100)
121	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy (Index 1982-84=100)
205	CPIAPPSL	Consumer Price Index for All Urban Consumers: Apparel (Index 1982-84=100)
206	CPITRNSL	Consumer Price Index for All Urban Consumers: Transportation (Index 1982-84=100)
207	CPIMEDSL	Consumer Price Index for All Urban Consumers: Medical Care (Index 1982-84=100)
208	CUSR0000SAC	Consumer Price Index for All Urban Consumers: Commodities (Index 1982-84=100)
209	CUSR0000SAD	Consumer Price Index for All Urban Consumers: Durables (Index 1982-84=100)
210	CUSR0000SAS	Consumer Price Index for All Urban Consumers: Services (Index 1982-84=100)
211	CPIULFSL	Consumer Price Index for All Urban Consumers: All Items Less Food (Index 1982-84=100)
212	CUSR0000SA0L2	Consumer Price Index for All Urban Consumers: All items less shelter (Index 1982-84=100)
213	CUSR0000SA0L5	Consumer Price Index for All Urban Consumers: All items less medical care (Index 1982-84=100)
140	ULCBS	Business Sector: Unit Labor Cost (Index 2012=100) - note that Belviso and Milani (2005) use manufacturing sector here
132	CES2000000008x	Real Average Hourly Earnings of Production and Nonsupervisory Employees: Construction (2012 Dollars per Hour), deflated by Core PCE
133	CES3000000008x	Real Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing (2012 Dollars per Hour), deflated by Core PCE
203	WPSID62	Producer Price Index: Crude Materials for Further Processing (Index 1982=100)
204	PPICMM	Producer Price Index: Commodities: Metals and metal products: Primary nonferrous metals (Index 1982=100)
177	USSTHPI	All-Transactions House Price Index for the United States (Index 1980 Q1=100)

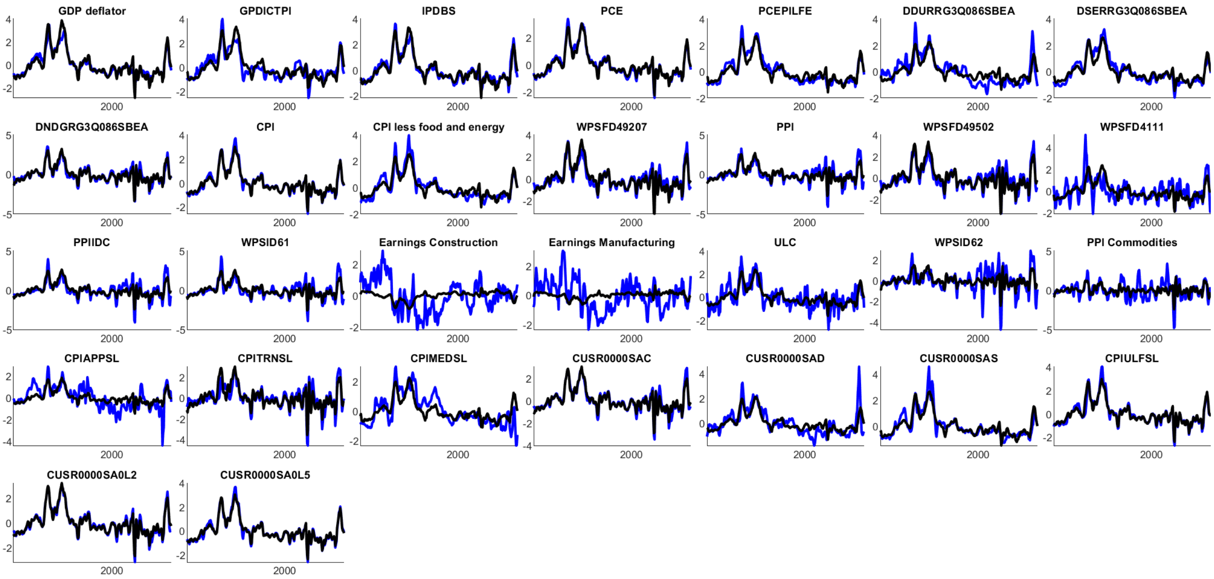
Appendix B Additional Figures

Figure B.1: Output Cycle



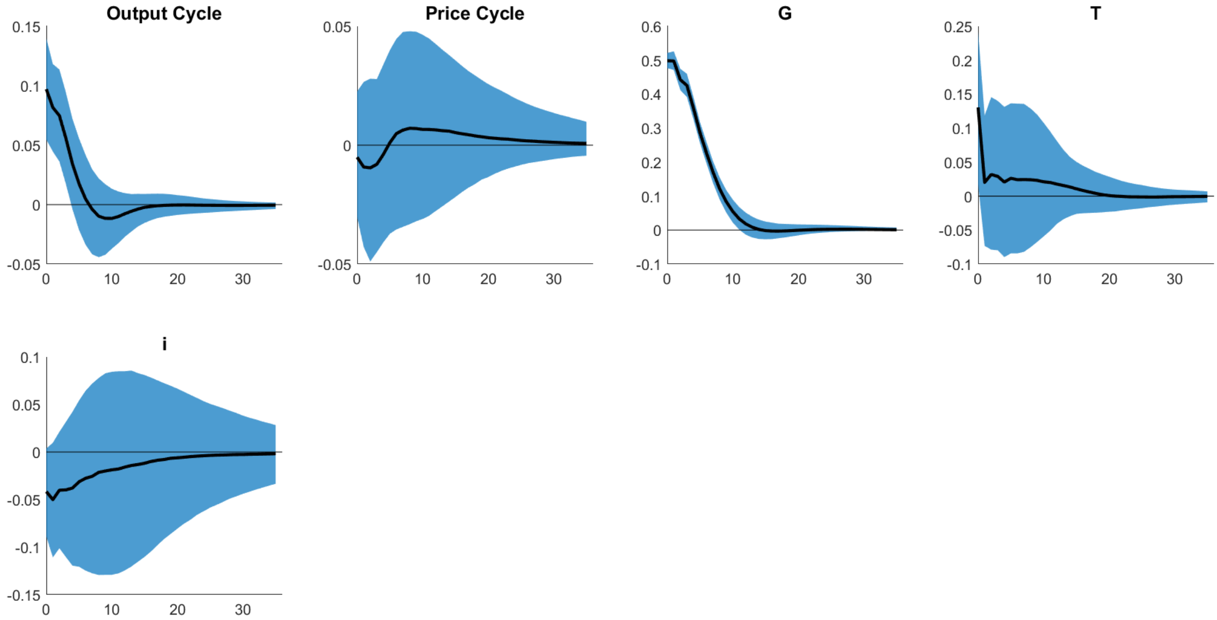
Note: The figures show the exposures of all output components to the corresponding common cycles. The solid blue lines depict the actual time series and solid black lines display the product the $\sum_{p=0}^{P} \lambda_{i,p}^{j} f_{t-p}^{j}$.

Figure B.2: Price Cycle



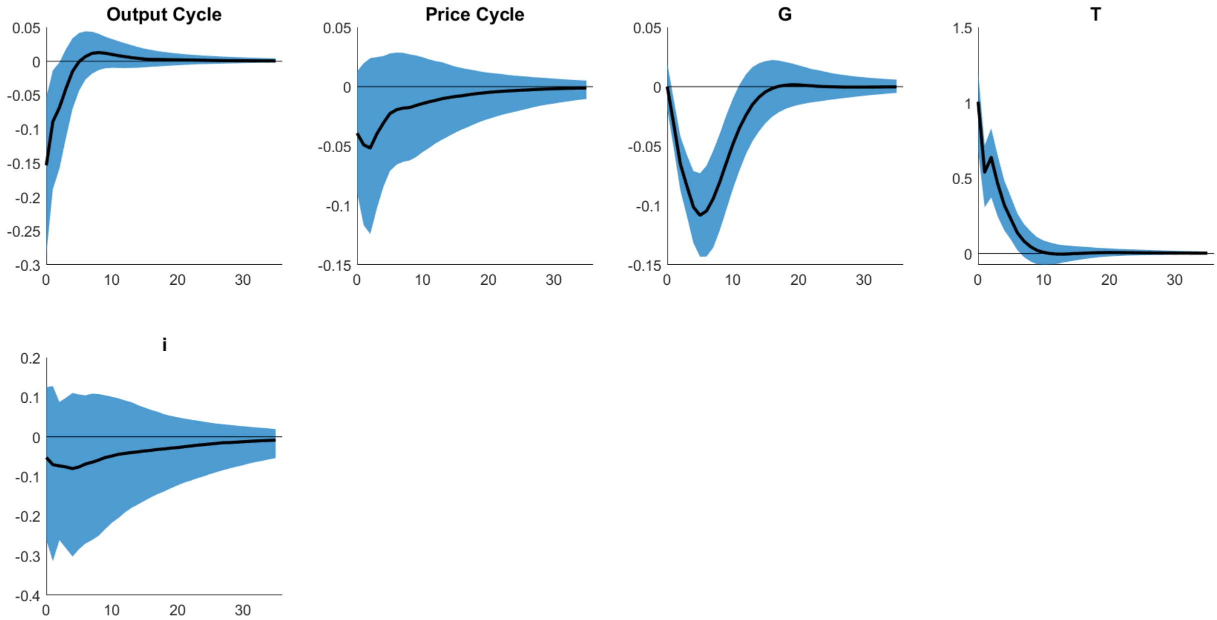
Note: The figures show the exposures of all price components to the corresponding common cycles. The solid blue lines depict the actual time series and solid black lines display the product the $\sum_{p=0}^{P} \lambda_{i,p}^{j} f_{t-p}^{j}$.

Figure B.3: Impulse response functions (G shock)



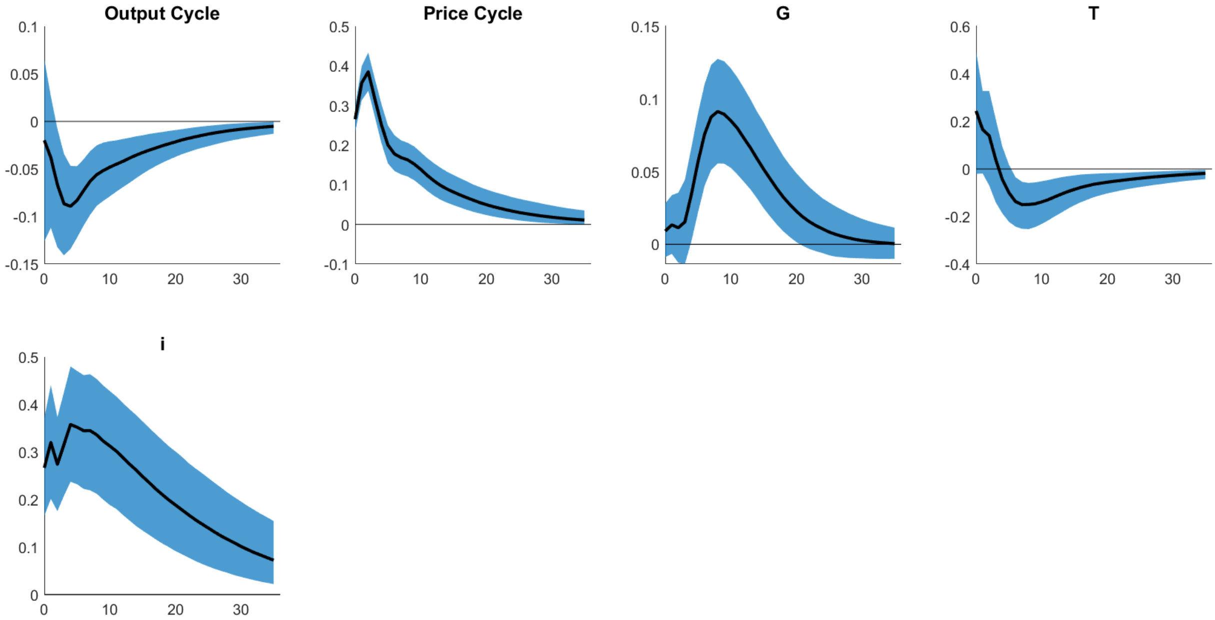
Note: The figure shows the median responses to a positive government spending policy shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure B.4: Impulse response functions (T shock)



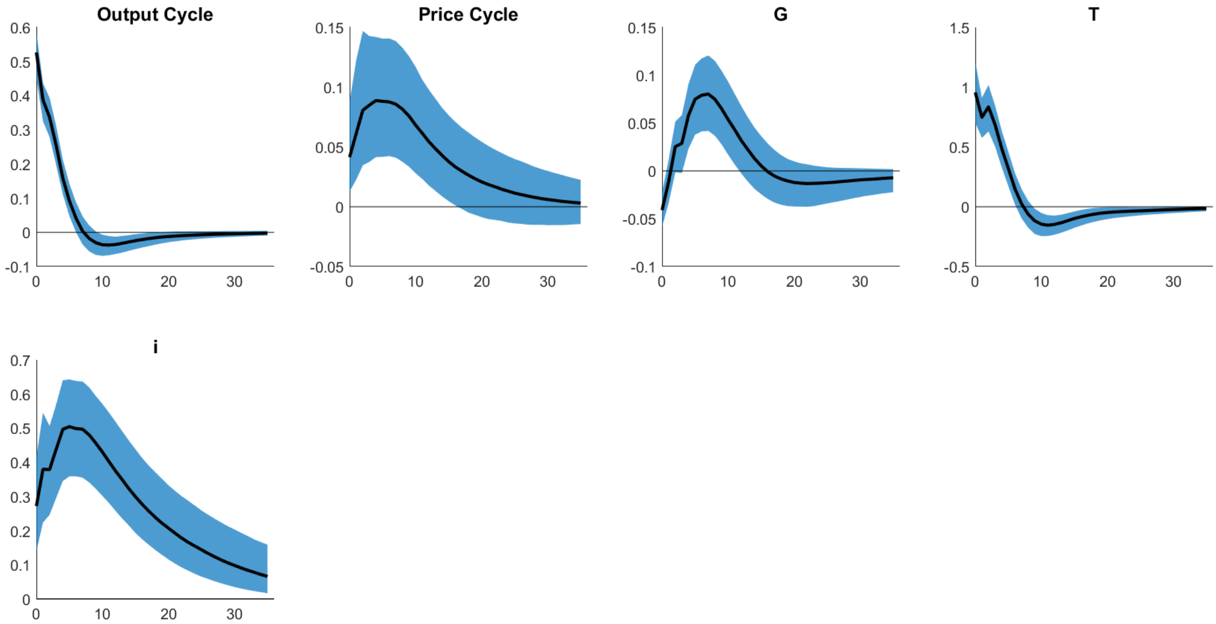
Note: The figure shows the median responses to a positive tax revenue policy shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure B.5: Impulse response functions (P shock)



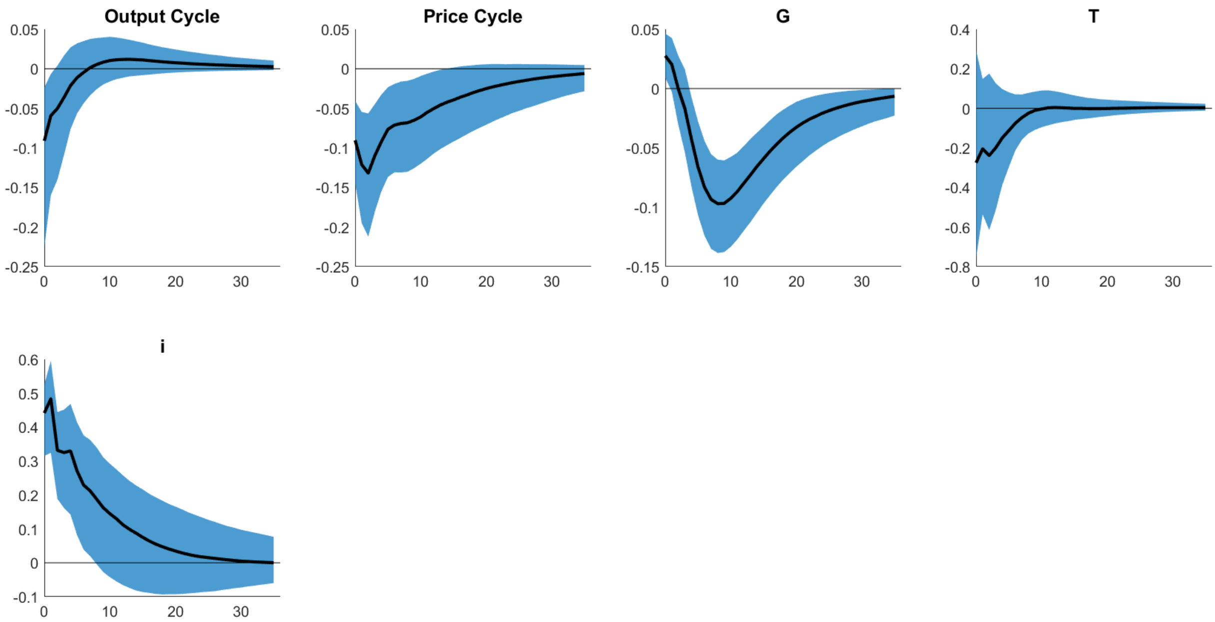
Note: The figure shows the median responses to a contractionary price shock induced by the oil price. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure B.6: Impulse response functions (Y shock)



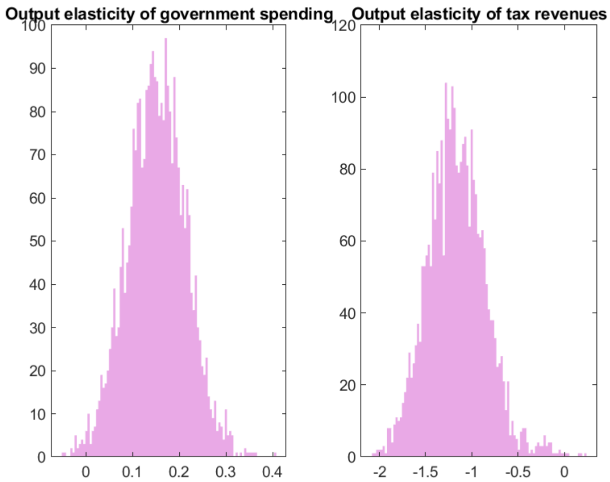
Note: The figure shows the median responses to a positive demand shock induced by the utilization-adjusted total factor productivity. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure B.7: Impulse response functions (MP shock)



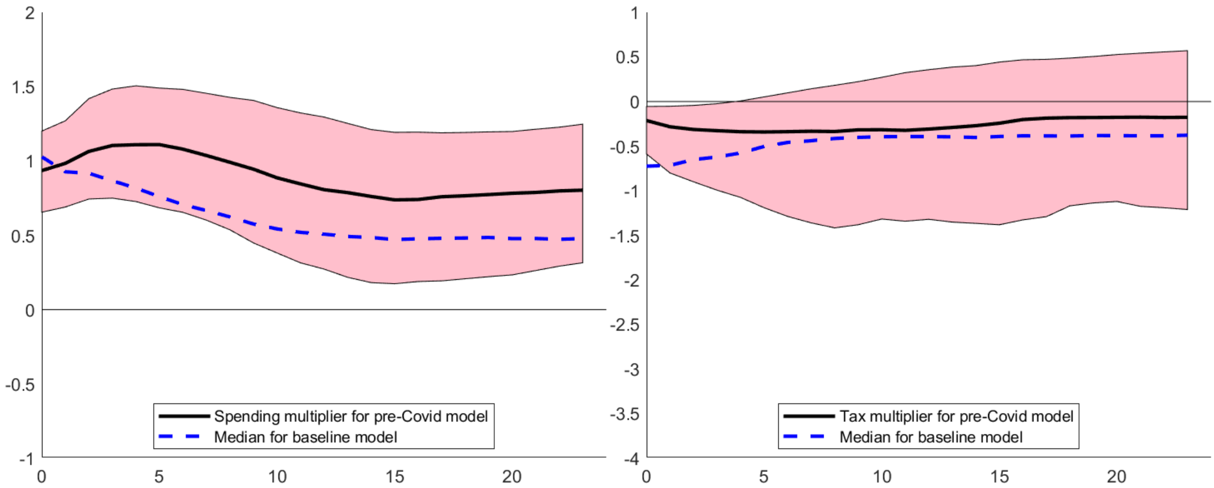
Note: The figure shows the median responses to a contractionary monetary policy shock. The solid black line depicts the median and the shaded blue area the 68% credible bands.

Figure B.8: Contemporaneous elasticities



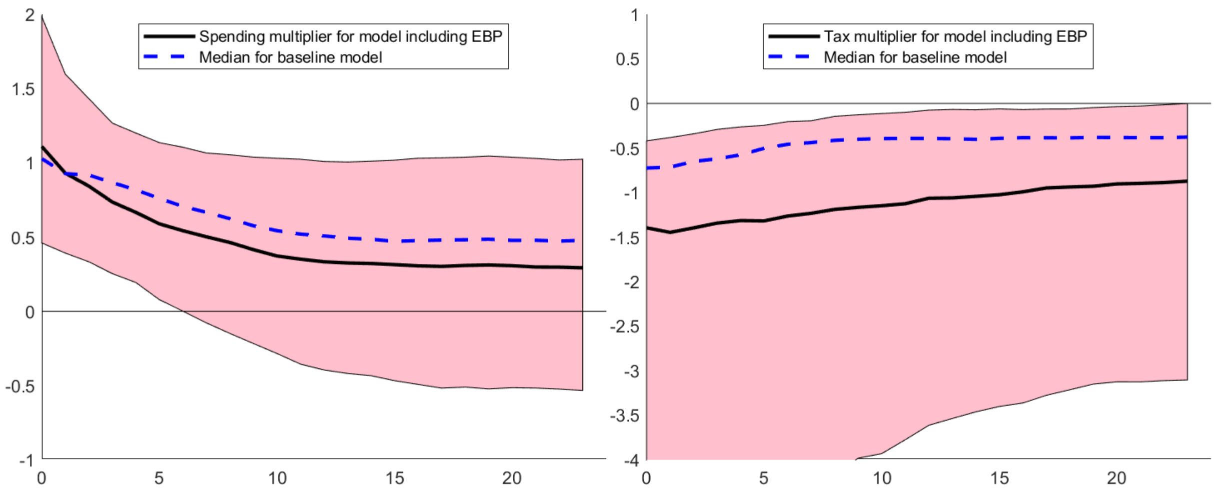
Note: The figures show posterior distribution of the elasticities of output with respect to government spending and tax revenues.

Figure B.9: Fiscal multipliers for pre-covid period



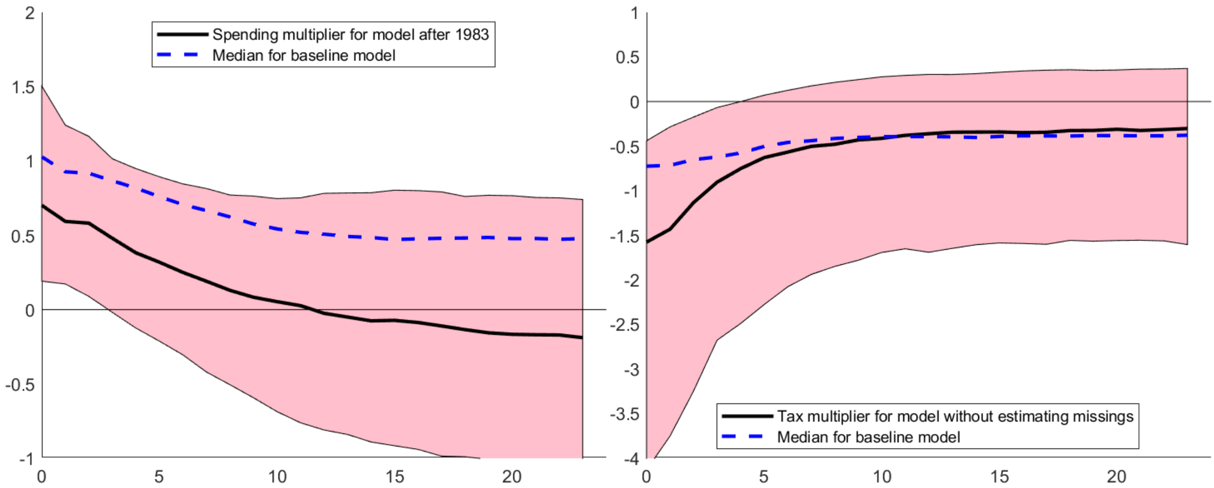
Note: The figure shows the government spending and the tax revenue multipliers with respect to the output cycles of the alternative model specification. The light red shaded areas in the left figure depicts the 68% credible bands.

Figure B.10: Fiscal multipliers for EBP model



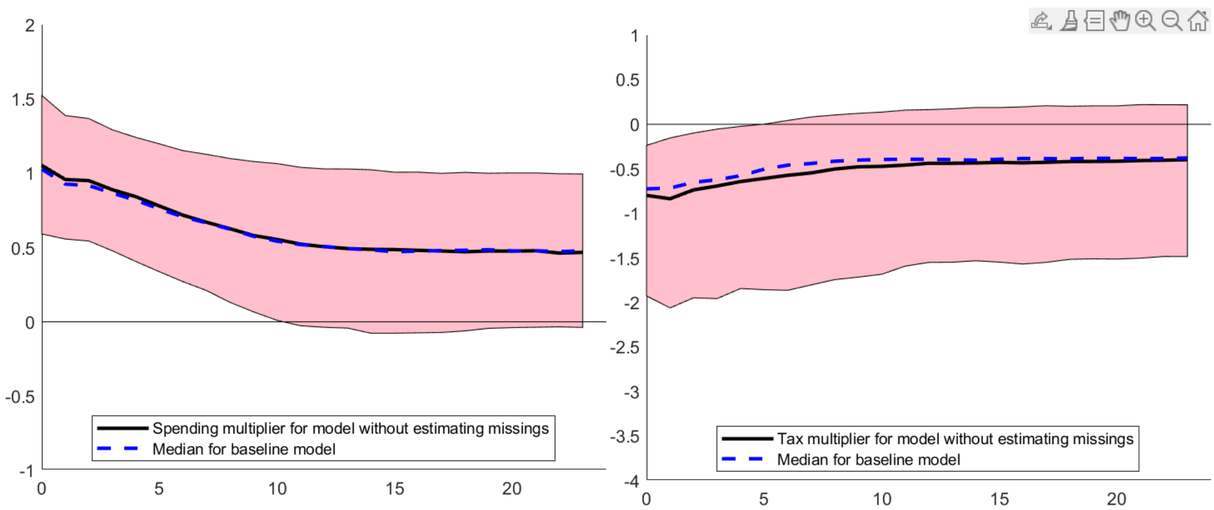
Note: The figure shows the government spending and the tax revenue multipliers with respect to the output cycles of the alternative model specification including EBP. The light red shaded areas in the left figure depicts the 68% credible bands.

Figure B.11: Fiscal multipliers model after 1983



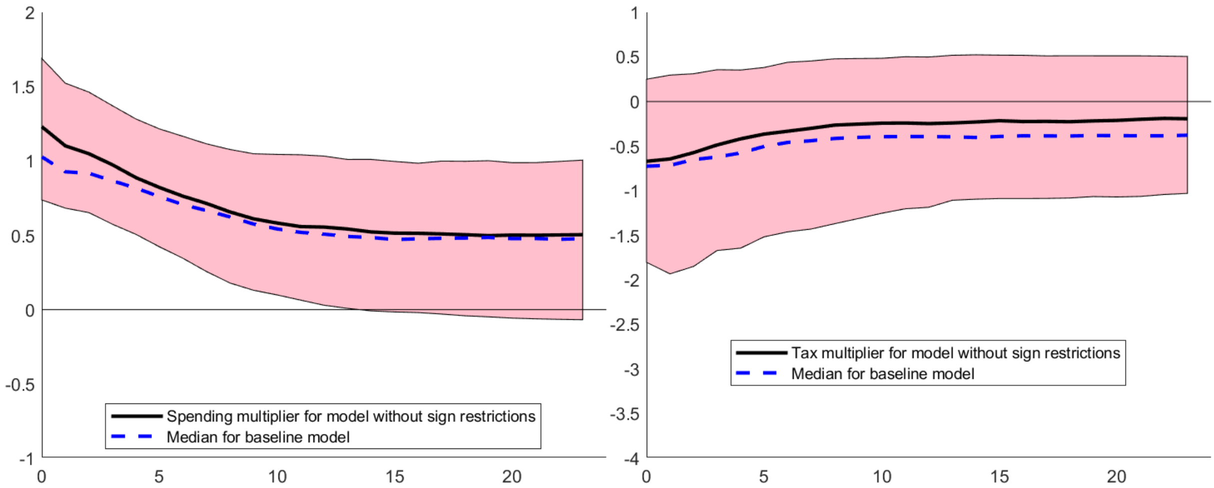
Note: The figure shows the government spending and the tax revenue multipliers with respect to the output cycles of the alternative model specification. The light red shaded areas in the left figure depicts the 68% credible bands.

Figure B.12: Fiscal multipliers without estimating missings



Note: The figure shows the government spending and the tax revenue multipliers with respect to the output cycles of the alternative model specification. The light red shaded areas in the left figure depicts the 68% credible bands.

Figure B.13: Fiscal multipliers without sign restrictions



Note: The figure shows the government spending and the tax revenue multipliers with respect to the output cycles of the alternative model specification. The light red shaded areas in the left figure depicts the 68% credible bands.

Appendix C Prior Specification

In this section, we discuss the specification of the prior distributions. First, we present the priors for the factor equation in (3). The priors of the factor loadings $\lambda_{i,p}^{j}$ with $i = 1, \ldots, N, p =, \ldots, P$ and j for both the common cycles and macro-financial variables are kept loose and follow:

$$\begin{aligned} \lambda_{i,p}^{j} &\sim N(\mu_{\lambda_{i,p}^{p}}, \Sigma_{\lambda_{i,p}^{j}}), \quad \forall i = 1, \ldots, N, \quad \forall p = 0, \ldots, P, & (11) \\ \lambda_{i,p}^{j,\boldsymbol{z}_t} &\sim N(\mu_{\lambda_{i,p}^{j,\boldsymbol{z}_t}}, \Sigma_{\lambda_{i,p}^{j,\boldsymbol{z}_t}}), \quad \forall i = 1, \ldots, N, \quad \forall p = 0, \ldots, P, & (12) \end{aligned}$$

with $\mu_{\lambda_{i,p}^{j}}$ and $\mu_{\lambda_{i,p}^{j,\boldsymbol{z}_t}} = 0$ and $\Sigma_{\lambda_{i,p}^{j}}$ and $\Sigma_{\lambda_{i,p}^{j,\boldsymbol{z}_t}} = 10$.

The prior variances of the stochastic volatilities $V_{h_{i,t}^{j}}$ in (4) read as:

$$V_{h_{i,t}^{j}} = \tau_{h_i^j} \lambda_{h_{i,t}^{j}}, \tag{13}$$

for $j = (OUT, INF)$ and where $\tau_{h_i^j}$ and $\lambda_{h_{i,t}^{j}}$ depict the global and the local shrinkage components. We follow Carvalho et al. (2010) and assume a half-Cauchy prior for the components:

$$\sqrt{\tau_{h_i^j}} \sim C^{+}(0,1), \quad \sqrt{\lambda_{h_{i,t}^{j}}} \sim C^{+}(0,1). \tag{14}$$

These hierarchical priors define the horseshoe prior and allow for both gradual changes and larger breaks in $V_{h_{i,t}^{j}}$ and therefore, half-Cauchy distributions can depict a more suitable prior than inverse Gamma distributions (Gelman (2006), Prüser (2021)).

Further, we avoid overfitting in the VAR model by implementing an adaptive asymmetric Minnesota-type shrinkage prior for the parameters $\boldsymbol{\Gamma} = (\boldsymbol{\Gamma}_1, \ldots, \boldsymbol{\Gamma}_L)$ in (5) and (**??**) (Cross et al. (2020), Chan (2021) and Hou (2024)). This prior combines the strengths of both the commonly employed Minnesota prior (see Litterman (1986) and Bańbura et al. (2010)) and more recent hierarchical priors (see Chan (2021)). Briefly, the Minnesota prior places more weight to coefficient of own recent lags, while the other coefficients are shrunk to zero. The hierarchical priors which control the degree of shrinkage are obtained in a data-driven fashion instead of being selected a priori.

More precisely, let $\boldsymbol{\Gamma}_{ij,l}$ be the (i,j)-th entry $\boldsymbol{\Gamma}_l$ which follows an independent normal prior:

$$\boldsymbol{\Gamma}_{ij,l} \sim N(\gamma_{ij,l}, V_{ij,l}), \quad l = 1, \ldots, L, \tag{15}$$

where

$$\gamma_{ij,l} = \begin{cases} 1, & l=1, i=j \text{ and } i, \neq 1,2, \\ 0, & \text{otherwise}, \end{cases} \qquad V_{ij,l} = \begin{cases} \frac{\kappa_1}{l^2}, & i=j, \\ \frac{\kappa_1 \kappa_2 \sigma_i^2}{l^2 \sigma_j^2}, & i \neq j, \end{cases}$$

and where σ_i^2 is a scale parameter and equal to the residual variance of an AR(L) model for variable $i = 1, \ldots, r$. Note that for $i = 1, 2$ we assume $\gamma_{11,1}$ and $\gamma_{22,1}$ to be 0 since the factors f_t^{OUT} and f_t^{INF} depict growth rates (Chan et al., 2021). The remaining variables in $\boldsymbol{z}_t$ are assumed to follow a random walk. The constants $\boldsymbol{c}$ follow a normal prior with $N(0, 100^2)$. The prior for shrinkage parameters κ_1 and κ_2 follow an uninformative prior:

$$p(\kappa_1) \propto c_1, \quad p(\kappa_2) \propto c_2. \tag{16}$$

As noted in the previous subsection, the non-zero elements in $\boldsymbol{B}$ follow independent (sign-restricted) normal priors. Let $b_{i,j}$ be the (i,j)-th element $\boldsymbol{\Gamma}_0$ in $\boldsymbol{B}$ such that

$$b_{i,j} = \begin{cases} N(\beta_{i,j}, v_{i,j}), & \text{if } b_{i,j} \text{ is unrestricted}, \\ N(\beta_{i,j}, v_{i,j}) \mathbb{1}(b_{i,j} > 0), & \text{if } b_{i,j} > 0 \\ N(\beta_{i,j}, v_{i,j}) \mathbb{1}(b_{i,j} < 0), & \text{if } b_{i,j} < 0 \\ \delta_0(b_{i,j}), & \text{if } b_{i,j} = 0, \end{cases} \tag{17}$$

where $\mathbb{1}$ denotes a indicator function and $\delta_0(\cdot)$ the Dirac delta function at zero. We set $\beta_{i,j} = 0$ and $\nu_{i,j} = 1$.

The (non-zero) parameters in the proxy variable equation ($\Phi_{0,1}$, $\Phi_{0,2}$) are assumed to be independently normal distributed:

$$\Phi_{r+k,r} \sim N(\phi_{r+k,r}, V_{r+k,r}), \quad \Phi_{r+k,r+k} \sim N(\phi_{r+k,r+k}, V_{r+k,r+k}). \tag{18}$$

We set $\phi_{r+k,r} = 0.5, \phi_{r+k,r+k} = 0, V_{r+k,r} = 1/10$ and $V_{r+k,r+k} = 1/10$. Doing so, we mostly resemble Caldara and Herbst (2019), Arias et al. (2021) and Breitenlechner et al. (2022) and impose our prior belief that our proxy variable depicts a relevant instrument. More specifically, with $\phi_{r+k,r+k} = 0$ and $V_{r+k,r+k} = 1/10$ we assume that the noise does not drive the variation in our proxy m_t as we set the prior variance to be very tight. Further, by setting a very loose variance and a positive prior on $\phi_{r+k,r}$ to state our belief in the proxies and still allow the data to drive the posterior mean.