

# Measuring the Effects of Fiscal Policy Shocks on U.S. Output in a Markov-Switching Bayesian VAR\*

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## Abstract

This paper measures the effects of government spending and tax shocks on U.S. output in a Markov-switching Bayesian vector autoregression (MS-BVAR). Motivation for estimating an MS-BVAR rests on the idea that MS-BVARs account for anticipation effects caused by households, workers, firms, and investors reacting to announcements of future fiscal policy changes. The best-fit MS-BVAR produces several interesting results about government spending and tax multipliers. First, the government spending multiplier is near one during expansions but is between 1.5 to 2 during recessions. Second, there is no strong evidence of a negative tax multiplier. This finding is at odds with a number of studies reporting large tax multipliers ranging from -2 to -3. Comparing the estimated fiscal multipliers lends support to traditional Keynesian theory, which predicts U.S. output responds more to government spending shocks than to tax shocks.

**JEL Classification:** E62, H30, C32.

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# 1. Introduction

In response to the 2007-2009 financial crisis and COVID-19 pandemic, U.S. fiscal authorities implemented policies aimed at stimulating the economy and stabilizing the business cycle. These events have renewed interest in the effects of fiscal policy on real economic activity in the U.S. Much of the empirical research in this area works in the tradition of [Blanchard and Perotti \(2002\)](#). They rely on structural vector autoregressions (SVARs) to measure the response of output to an exogenous government spending or tax shock. These measures are often referred to as fiscal multipliers. Despite the vast size of the Blanchard-Perotti literature, there is still no consensus about the size or, in several cases, the sign of fiscal multipliers.

[Leeper, Walker, and Yang \(2013\)](#) (LWY) offer one possible explanation for the disparate fiscal multiplier estimates across the Blanchard-Perotti literature. They argue SVARs are unable to properly identify fiscal policy shocks due to the legislative and implementation lags of fiscal policymaking. While agents react to the announcement of future policy changes, the econometrician only observes fiscal policy shocks when these new policies occur. LWY show this phenomenon, known as fiscal foresight, generates non-fundamentalness in a VAR. Non-fundamentalness in a VAR implies the structural shocks of interest cannot be recovered from current and past observable data. Thus, according to LWY, fiscal foresight invalidates estimates obtained from conventional SVARs.

One approach to account for fiscal foresight relies on using established tools that address the problem of non-fundamentalness. For example, [Lippi and Reichlin \(1994\)](#) develop an empirical strategy using Blaschke matrices to handle non-fundamentalness in a VAR. [Mertens and Ravn \(2010\)](#) implement this strategy to recover anticipated fiscal policy shocks from an SVAR estimated on U.S. data.

This paper contributes to the Blanchard-Perotti literature by estimating Markov-switching Bayesian VARs (MS-BVARs). A MS-BVAR is another empirical tool that addresses the identification issue caused by fiscal foresight. Motivation for estimating MS-BVARs comes from

[Davig and Leeper \(2007b\)](#). Using a small-scale new Keynesian DSGE model, Davig and Leeper show a central bank can temporarily violate the Taylor principle without destabilizing the economy as long as agents believe there is a positive probability of moving back to the stable Taylor rule regime. This reasoning can be applied to the current case of fiscal foresight. With fiscal foresight at play, agents construct probability distributions over future fiscal policy regimes and from those distributions form rational expectations. A MS-BVAR captures these probability distributions during the estimation process. If a MS-BVAR finds agents attach a positive probability to these probability distributions, it implies agents within the MS-BVAR anticipate switching between future policy regimes.

Another motivation for estimating MS-BVARs is to study changes in U.S. fiscal, macroeconomic, and financial conditions over the last 60 years. [Steuerle \(2006\)](#) and [Davig and Leeper \(2007a\)](#) document postwar U.S. fiscal policy behavior falls under two policy regimes. One fiscal policy regime is associated with increases in government spending and tax cuts. The other is characterized as periods during which the government aims at balancing its budget or stabilizing its debt-to-GDP ratio. U.S. business and financial cycles are associated with expansionary or recessionary states. This paper builds a model space of MS-BVARs reflecting these assumptions.

The MS-BVARs are estimated on quarterly U.S. per capita real government spending, per capita real tax revenue, per capita real GDP, inflation, and short- and long-term government interest rates from 1960 to 2019. This information set extends [Blanchard and Perotti \(2002\)](#) by including inflation and interest rates.<sup>1</sup> The goal is to study the transmission of fiscal policy shocks to the nominal, financial, and real sides of the economy.

Identification of the MS-BVARs builds on [Blanchard and Perotti \(2002\)](#). Fiscal policy shocks are identified using a non-recursive identification strategy that is grounded in three assumptions. First, government spending only responds to its own shock within the same period. Changing spending decisions often takes time for state and federal governments

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<sup>1</sup>[Perotti \(2005\)](#) and [Caldara and Kamps \(2017\)](#) also add inflation and the long-term government interest rate to the [Blanchard and Perotti \(2002\)](#) information set.

because of legislative and implementation lags inherent in the political process. Second, tax revenue only responds to its own and aggregate supply shocks at impact. By extension, government spending shocks have a lagged effect on net taxes. Third, the fiscal policy block is placed above the macro/financial block. This implies government spending and tax shocks have an immediate effect on the macro and financial variables.

The recursive ordering within the macro/financial block allows me to identify four additional shocks. Ordering output before inflation assumes aggregate supply shocks drive price fluctuations at impact, while output responds to aggregate demand shocks with a lag. The interest rates respond to aggregate supply and demand shocks at impact. Following [Favero and Giavazzi \(2007\)](#), unanticipated movements in the short-term interest rate represent changes to the cost of financing government debt. Finally, having the long rate immediately respond to shocks to the short rate embeds a rational expectations term structure in the MS-BVAR.

Two recursive identification schemes are also considered as a robustness check. The first recursive identification orders government spending before net taxes. The implication is the fiscal authority follows a tax rule in which net taxes passively adjust to satisfy the government budget constraint. The second recursive identification adopts a government spending rule by ordering net taxes before government spending. This policy rule assumes shocks to net taxes have an immediate effect on government spending, implying tax policy decisions take precedence over government spending decisions. As a result, the government adjusts its spending when tax shocks occur to ensure the government budget constraint is satisfied.

Estimation of the MS-BVARs relies on the Metropolis-within-Gibbs MCMC sampler developed by [Sims, Waggoner, and Zha \(2008\)](#). Their MCMC sampler sequentially samples from several conditional posterior distributions to construct the posteriors of the MS-BVARs. Marginal data densities (MDDs) are then computed from the constructed posteriors to recover the MS-BVAR favored by the data.

The best-fit MS-BVAR is non-recursive and imposes two distinct Markov chains on the structural coefficients of the fiscal policy block regressions, two more on the structural co-

efficients of the macro/financial block, and assumes two stochastic volatility (SV) regimes. One SV regime exhibits high degrees of SV in aggregate supply, debt, and debt financing costs coinciding with NBER dated recessions. However, there is uncertainty of the scale of fiscal policy and term premium shocks in the other SV regime.

There is also evidence of frequent regime switching in the structural coefficients of the fiscal policy and macro/financial block regressions. One fiscal policy regime occurs during historical episodes of tax cuts and expansions in government spending. During these episodes, taxes are only responsive to aggregate supply shocks. Tax and aggregate supply shocks produce a larger response in the other fiscal policy regime. The macro/financial regimes resemble the U.S. business and financial cycles. Output has a larger response to fiscal policy shocks at impact during recessions compared to expansions.

Generalized impulse response functions (GIRFs) and present-value fiscal multipliers are calculated from the posterior of the best-fit MS-BVAR. These measures are used to assess the output effects of government spending and tax shocks in the U.S. Output responds positively to a government spending shock regardless of the concurrent regime. In addition, output is permanently higher following the shock. However, the government spending multiplier is state-dependent. The government spending multiplier ranges from 1.5 to 2 during recessions and is near one during expansions. This result mirrors those found by [Auerbach and Gorodnichenko \(2012\)](#) and [Ramey and Zubairy \(2018\)](#).

Tax shocks have a relatively small negative effect on U.S. output. GIRFs conditioning on the second macro/financial block regime indicate a TAX shock permanently lowers output. However, there is no strong evidence of a large tax multiplier. This is at odds with multiple studies reporting large tax multipliers ranging from -2 to -3.<sup>2</sup> Comparing government spending and tax multipliers indicate the results in this paper are consistent with traditional Keynesian theory, which predicts U.S. output responds more to government spending shocks than to tax shocks.

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<sup>2</sup>[Ramey \(2019\)](#) provides an extensive summary of the government spending and tax multiplier literature.

The remainder of this paper is organized as follows. Section 2 outlines the identification strategy. Section 3 describes the MS-BVARs and estimation procedure. Results of the best-fit MS-BVAR are discussed in section 4. Section 5 measures the effects of government spending and tax shocks on U.S. output. Section 6 concludes.

## 2. Identifying Fiscal Policy Shocks

This section describes my identification strategy. I begin by mapping Blanchard and Perotti's (2002) fiscal policy SVAR to Sims and Zha's (1998) SVAR. As will be seen later, MS-BVARs resemble the Sims-Zha constant coefficient SVAR. I then extend the Blanchard-Perotti SVAR to identify fiscal policy shocks in a setting with fiscal, macroeconomic, and financial variables.

### 2.1. A Constant Coefficient SVAR

Consider the constant coefficient SVAR of Sims and Zha (1998) (SZ)

$$y'_t A_0 = \sum_{j=1}^p y'_{t-j} A_j + c + \varepsilon'_t, \quad \varepsilon_t \sim \mathcal{N}(0_{n \times 1}, I_n), \quad (2.1)$$

where  $y_t$  is an  $n \times 1$  vector of observable variables,  $\varepsilon_t$  is an  $n \times 1$  vector of structural shocks,  $A_j$  is an  $n \times n$  matrix of structural coefficients for  $j = 0, \dots, p$  with  $A_0$  invertible,  $c$  is an  $1 \times n$  vector of intercept terms,  $p$  is the lag length, and  $T$  is the sample size.

The SZ-SVAR (2.1) can be written as a simultaneously equations model (SEM)

$$y'_t A_0 = x'_t A_+ + \varepsilon'_t, \quad \varepsilon_t \sim \mathcal{N}(0_{n \times 1}, I_n), \quad (2.2)$$

where  $x_t = [y'_{t-1} \cdots y'_{t-p} 1]'$  and  $A_+ = [A'_1 \cdots A'_p c]'$ . Furthermore, the SEM (2.2) can be written as the system of reduced regressions

$$y'_t = x'_t \Phi + u'_t, \quad u_t \sim \mathcal{N}(0_{n \times 1}, \Sigma_u), \quad (2.3)$$

where  $\Phi = A_+ A_0^{-1}$ ,  $u_t = A_0'^{-1} \varepsilon_t$ , and  $\Sigma_u = (A_0 A_0')^{-1}$ .

## 2.2. The Fiscal Policy SVAR of Blanchard and Perotti (2002)

My identification strategy builds on Blanchard and Perotti's (2002) identifying assumptions. Blanchard and Perotti (BP) assess the effects of fiscal policy on U.S. output using the SVAR

$$y_t' A = \sum_{j=1}^p y_{t-j}' A_j + c + \varepsilon_t' B, \quad \varepsilon_t \sim \mathcal{N}(0_{n \times 1}, I_n). \quad (2.4)$$

where  $y_t \equiv [\text{GOV}_t \text{ TAX}_t \text{ RGDP}_t]'$ ,  $\text{GOV}_t$  is the log of per capita real government spending,  $\text{TAX}_t$  is the log of per capita real tax revenue, and  $\text{RGDP}_t$  is the log of per capita real GDP.

Note the BP-SVAR (2.4) differs from the SZ-SVAR (2.1) in two ways. First, the diagonal elements of the impact matrix  $A$  in (2.4) are equal to one. The SZ-SVAR (2.1) leaves these coefficients unrestricted. Second, the BP-SVAR (2.4) allows one to place restrictions on the response matrix of the structural shocks  $B$ . The SZ-SVAR (2.1) restricts  $B = I_n$ .

Mapping the BP-SVAR (2.4) to the SZ-SVAR (2.1) begins by revisiting BP's mapping between the reduced-form errors  $u_t$  to the structural shocks  $\varepsilon_t$ . BP posit this mapping can be expressed as  $A' u_t = B' \varepsilon_t$  such that

$$u_t^{GOV} = b_1 u_t^{RGDP} + b_2 \varepsilon_t^{TAX} + \varepsilon_t^{GOV}, \quad (2.5)$$

$$u_t^{TAX} = a_1 u_t^{RGDP} + a_2 \varepsilon_t^{GOV} + \varepsilon_t^{TAX}, \quad (2.6)$$

and

$$u_t^{RGDP} = c_1 u_t^{TAX} + c_2 u_t^{GOV} + \varepsilon_t^{RGDP}. \quad (2.7)$$

Equation (2.5) states GOV shocks,  $\varepsilon_t^{GOV}$ , are driven by forecast innovations in GOV and RGDP,  $u_t^{GOV}$  and  $u_t^{RGDP}$ , and TAX shocks,  $\varepsilon_t^{TAX}$ . A similar interpretation applies to TAX shocks in equation (2.6). Equation (2.7) states aggregate supply shocks,  $\varepsilon_t^{RGDP}$ , are driven by the three forecast innovations  $u_t^{GOV}$ ,  $u_t^{TAX}$ , and  $u_t^{RGDP}$ . Aggregate supply shocks also do not directly affect GOV and TAX shocks. Writing equations (2.5)-(2.7) in matrix form yields

$$\begin{bmatrix} 1 & 0 & -b_1 \\ 0 & 1 & -a_1 \\ -c_2 & -c_1 & 1 \end{bmatrix} \begin{bmatrix} u_t^{GOV} \\ u_t^{TAX} \\ u_t^{RGDP} \end{bmatrix} = \begin{bmatrix} 1 & b_2 & 0 \\ a_2 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{GOV} \\ \varepsilon_t^{TAX} \\ \varepsilon_t^{RGDP} \end{bmatrix}. \quad (2.8)$$

The next step is to impose the identifying restrictions of (2.8) on the impact matrix  $A_0$  in (2.1). After normalizing the diagonal elements of  $A'_0$  to one, the result is

$$\begin{bmatrix} 1 & 0 & \frac{A_{0,13}}{A_{0,11}} \\ 0 & 1 & \frac{A_{0,23}}{A_{0,22}} \\ \frac{A_{0,31}}{A_{0,33}} & \frac{A_{0,32}}{A_{0,33}} & 1 \end{bmatrix} \begin{bmatrix} u_t^{GOV} \\ u_t^{TAX} \\ u_t^{RGDP} \end{bmatrix} = \begin{bmatrix} 1 & \frac{B_{12}}{A_{0,11}} & 0 \\ \frac{B_{21}}{A_{0,22}} & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{GOV} \\ \varepsilon_t^{TAX} \\ \varepsilon_t^{RGDP} \end{bmatrix}, \quad (2.9)$$

where  $\frac{A_{0,13}}{A_{0,11}} = -b_1$ ,  $\frac{A_{0,23}}{A_{0,22}} = -a_1$ ,  $\frac{A_{0,31}}{A_{0,33}} = -c_2$ ,  $\frac{A_{0,32}}{A_{0,33}} = -c_1$ ,  $\frac{B_{12}}{A_{0,11}} = b_2$ , and  $\frac{B_{21}}{A_{0,22}} = a_2$ .

Finally, pre-multiplying both sides of (2.9) by the normalized inverted  $B$  matrix yields

$$\frac{A_{0,11}A_{0,22}}{A_{0,11}A_{0,22} - B_{12}B_{21}} \begin{bmatrix} 1 & -\frac{B_{12}}{A_{0,11}} & \frac{A_{0,13}}{A_{0,11}} - \frac{A_{0,23}B_{12}}{A_{0,11}A_{0,22}} \\ -\frac{B_{21}}{A_{0,22}} & 1 & \frac{A_{0,23}}{A_{0,22}} - \frac{A_{0,13}B_{21}}{A_{0,11}A_{0,22}} \\ \frac{A_{0,31}}{A_{0,33}} \left( \frac{A_{0,11}A_{0,22} - B_{12}B_{21}}{A_{0,11}A_{0,22}} \right) & \frac{A_{0,32}}{A_{0,33}} \left( \frac{A_{0,11}A_{0,22} - B_{12}B_{21}}{A_{0,11}A_{0,22}} \right) & \frac{A_{0,11}A_{0,22} - B_{12}B_{21}}{A_{0,11}A_{0,22}} \end{bmatrix} \begin{bmatrix} u_t^{GOV} \\ u_t^{TAX} \\ u_t^{RGDP} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{GOV} \\ \varepsilon_t^{TAX} \\ \varepsilon_t^{RGDP} \end{bmatrix}. \quad (2.10)$$

BP impose two zero restrictions. First, they set  $b_1 = 0$  by arguing government spending decisions are often made in advance and require time to change due to legislative and implementation lags. Thus, GOV does not respond to forecast innovations in RGDP within the quarter. Second, BP set  $b_2 = 0$  on the assumption that government decisions on spending are taken before decisions on revenue. This implies structural TAX shocks do not affect GOV at impact. These two restrictions are equivalent to setting  $\frac{A_{0,13}}{A_{0,11}} = \frac{B_{12}}{A_{0,11}} = 0$ . However, one more restriction is necessary to identify the SVAR. I set  $\frac{B_{21}}{A_{0,22}} = 0$ . This identifying restriction is motivated by [Blanchard and Perotti's \(2002\)](#) finding that the (asymptotic) 95% confidence interval of  $a_2$  contains zero. As a result, (2.10) reduces to

$$A_0^* \begin{bmatrix} u_t^{GOV} \\ u_t^{TAX} \\ u_t^{RGDP} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{GOV} \\ \varepsilon_t^{TAX} \\ \varepsilon_t^{RGDP} \end{bmatrix}, \quad (2.11)$$

where

$$A_0^* = \frac{A_{0,11}A_{0,22}}{A_{0,11}A_{0,22} - B_{12}B_{21}} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & \frac{A_{0,23}}{A_{0,22}} \\ \frac{A_{0,31}}{A_{0,33}} & \frac{A_{0,32}}{A_{0,33}} & 1 \end{bmatrix} = \begin{bmatrix} A_{0,11}^* & 0 & 0 \\ 0 & A_{0,22}^* & A_{0,23}^* \\ A_{0,31}^* & A_{0,32}^* & A_{0,33}^* \end{bmatrix}.$$

The modified impact matrix  $A_0^*$  maps the BP-SVAR (2.4) to the SZ-SVAR (2.1).<sup>3</sup>

<sup>3</sup>Attempts to estimate three-variable MS-BVARs with this identification failed due to non-convergence of the Metropolis-within-Gibbs MCMC sampler in section 3.5.

### 2.3. Extending the Blanchard-Perotti Fiscal Policy SVAR

This section extends the Blanchard-Perotti fiscal policy SVAR to include fiscal, macroeconomic, and financial variables. A fiscal policy ( $\mathcal{FP}$ ) block consisting of  $\text{GOV}_t$  and  $\text{TAX}_t$  is placed before a macro/financial ( $\mathcal{MF}$ ) block that includes  $\text{RGDP}_t$ , the GDP deflator inflation rate ( $\pi_t$ ), the three-month U.S. Treasury bill rate ( $\text{R}_{3\text{m},t}$ ), and the constant maturity yield on ten-year U.S. Treasury bonds ( $\text{R}_{10\text{yr},t}$ ).<sup>4</sup> This redefines  $y_t$  as the  $6(=n) \times 1$  vector

$$y_t \equiv \left[ \underbrace{[\text{GOV}_t \ \text{TAX}_t]}_{\text{Fiscal Policy}} \underbrace{[\text{RGDP}_t \ \pi_t \ \text{R}_{3\text{m},t} \ \text{R}_{10\text{yr},t}]}_{\text{Macro/Financial}} \right]'$$

The sample runs from 1960Q1 to 2019Q4,  $T = 240$ . Data for the fiscal and macro variables are drawn from the National Income and Product Accounts (NIPA) tables published by the Bureau of Economic Analysis (BEA). The short- and long-term government interest rates come from the Federal Reserve Bank of St. Louis's FRED database. The quantity variables are expressed in natural logs and scaled by 100. Inflation and the interest rates are in percents. Additional details of the data construction and sources are in the Data Appendix.

Enlarging the information set  $y_t$  allows me to study how fiscal policy shocks are transmitted to the nominal, financial, and real sides of the economy. Inflation and the interest rates also provide information about expectations of future fiscal policy and term premiums, according to [Yong and Dingming \(2019\)](#).

### 2.4. Identifying the Fiscal Policy Transmission Mechanism

This section presents three identifications of the fiscal policy transmission mechanism. Identification is achieved by imposing short-run zero restrictions on the impact matrix  $A'_0$ . I adapt [Blanchard and Perotti's \(2002\)](#) assumptions about tax, transfer, and spending programs to construct one non-recursive identification scheme. I also consider two recursive identifications as an easy robustness check.

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<sup>4</sup>Separating the  $\mathcal{MF}$  block into a macro ( $\mathcal{M}$ ) and financial ( $\mathcal{F}$ ) block was considered. However, estimating MS-BVARs with discrete Markov chains on the  $\mathcal{FP}$ ,  $\mathcal{M}$ , and  $\mathcal{F}$  block regressions proved unsuccessful. Future work will revisit this issue.

#### 2.4.1. Non-Recursive Impact Matrix: Extended Blanchard-Perotti

The first identification is non-recursive.<sup>5</sup> The mapping between the reduced-form regression errors of the system (2.3) to the errors of the SEM (2.2) is

$$\begin{bmatrix} A_{0,11} & 0 & 0 & 0 & 0 & 0 \\ 0 & A_{0,22} & A_{0,23} & 0 & 0 & 0 \\ A_{0,31} & A_{0,32} & A_{0,33} & 0 & 0 & 0 \\ A_{0,41} & A_{0,42} & A_{0,43} & A_{0,44} & 0 & 0 \\ A_{0,51} & A_{0,52} & A_{0,53} & A_{0,54} & A_{0,55} & 0 \\ A_{0,61} & A_{0,62} & A_{0,63} & A_{0,64} & A_{0,65} & A_{0,66} \end{bmatrix} \begin{bmatrix} u_t^{GOV} \\ u_t^{TAX} \\ u_t^{RGDP} \\ u_t^\pi \\ u_t^{R_{3m}} \\ u_t^{R_{10yr}} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{GOV} \\ \varepsilon_t^{TAX} \\ \varepsilon_t^{RGDP} \\ \varepsilon_t^\pi \\ \varepsilon_t^{R_{3m}} \\ \varepsilon_t^{R_{10yr}} \end{bmatrix}. \quad (2.12)$$

The identifying restrictions on the  $\mathcal{FP}$  block mirror ones imposed by [Blanchard and Perotti \(2002\)](#). The fiscal policy variables, GOV and TAX, do not respond to the other fiscal policy shock at impact. Allowing TAX to immediately respond to RGDP shocks assumes the fiscal authority follows a policy rule which adjusts TAX to accommodate aggregate supply shocks.

The  $\mathcal{MF}$  block comes after the  $\mathcal{FP}$  block. Therefore, the macro and financial variables respond to fiscal policy shocks at impact. Placing RGDP before  $\pi$  assumes aggregate supply shocks immediately affect prices, while aggregate demand shocks affect RGDP with a lag.

Interest rates are ordered last and respond to fiscal policy and macro shocks in the same quarter. [Favero and Giavazzi \(2007\)](#) argue an unanticipated increase in  $R_{3m}$  raises the cost of financing government debt. Thus, shocks to  $R_{3m}$  are identified as debt financing shocks. Ordering  $R_{3m}$  before  $R_{10yr}$  embeds a rational expectations term structure in the SVAR. This identifies an unanticipated change in  $R_{10yr}$  as a term premium shock.

#### 2.4.2. Recursive Impact Matrix: Tax Rule

The next identification scheme relies on the recursive ordering of the variables in  $y_t$  as shown

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<sup>5</sup>Global identification of the non-recursive SVAR is verified using the tools provided by [Rubio-Ramírez, Waggoner, and Zha \(2010\)](#). The necessary and sufficient conditions appear in Appendix B.

in section 2.3. This identification restricts  $A'_0$  to be lower-triangular such that

$$\begin{bmatrix} A_{0,11} & 0 & 0 & 0 & 0 & 0 \\ A_{0,21} & A_{0,22} & 0 & 0 & 0 & 0 \\ A_{0,31} & A_{0,32} & A_{0,33} & 0 & 0 & 0 \\ A_{0,41} & A_{0,42} & A_{0,43} & A_{0,44} & 0 & 0 \\ A_{0,51} & A_{0,52} & A_{0,53} & A_{0,54} & A_{0,55} & 0 \\ A_{0,61} & A_{0,62} & A_{0,63} & A_{0,64} & A_{0,65} & A_{0,66} \end{bmatrix} \begin{bmatrix} u_t^{GOV} \\ u_t^{TAX} \\ u_t^{RGDP} \\ u_t^\pi \\ u_t^{R3m} \\ u_t^{R10yr} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{GOV} \\ \varepsilon_t^{TAX} \\ \varepsilon_t^{RGDP} \\ \varepsilon_t^\pi \\ \varepsilon_t^{R3m} \\ \varepsilon_t^{R10yr} \end{bmatrix}.$$

Ordering GOV first assumes GOV does not respond to TAX and  $\mathcal{MF}$  block shocks at impact. BP justify this assumption by arguing spending decisions are predetermined. TAX is ordered second. The reason is the government employs a tax rule in which TAX adjust to balance or accommodate the government spending constraint. However, TAX does not respond to aggregate supply shocks at impact. Shocks in the  $\mathcal{MF}$  block are identified as before.

#### 2.4.3. Recursive Impact Matrix: Government Spending Rule

Switching the order of GOV and TAX in  $y_t$  delivers the second recursive identification

$$\begin{bmatrix} A_{0,11} & 0 & 0 & 0 & 0 & 0 \\ A_{0,21} & A_{0,22} & 0 & 0 & 0 & 0 \\ A_{0,31} & A_{0,32} & A_{0,33} & 0 & 0 & 0 \\ A_{0,41} & A_{0,42} & A_{0,43} & A_{0,44} & 0 & 0 \\ A_{0,51} & A_{0,52} & A_{0,53} & A_{0,54} & A_{0,55} & 0 \\ A_{0,61} & A_{0,62} & A_{0,63} & A_{0,64} & A_{0,65} & A_{0,66} \end{bmatrix} \begin{bmatrix} u_t^{TAX} \\ u_t^{GOV} \\ u_t^{RGDP} \\ u_t^\pi \\ u_t^{R3m} \\ u_t^{R10yr} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{TAX} \\ \varepsilon_t^{GOV} \\ \varepsilon_t^{RGDP} \\ \varepsilon_t^\pi \\ \varepsilon_t^{R3m} \\ \varepsilon_t^{R10yr} \end{bmatrix}.$$

Placing TAX ahead of GOV indicates TAX shocks have contemporaneous effects on GOV. The implication is the government follows a spending rule to accommodate changes in tax policy. Therefore, tax policy decisions are taken before spending decisions.

## 3. A Fiscal Policy MS-BVAR

This section reviews the tools developed by [Sims, Waggoner, and Zha \(2008\)](#) (SWZ) to estimate MS-BVARs.

### 3.1. A Markov-Switching BVAR

SWZ write the structural MS-BVAR

$$y_t' A_0(s_t) = x_t' A_+(s_t) + \varepsilon_t' \Xi^{-1}(s_t), \quad \varepsilon_t \sim \mathcal{N}(0_{n \times 1}, I_n), \quad (3.1)$$

where  $s_t$  denotes an unobservable state (regime) variable and  $\Xi(s_t)$  denotes an  $n \times n$  diagonal matrix of factor loadings scaling the degree of SV of the structural shocks in  $\varepsilon_t$ . The values of  $s_t$  are elements of the finite set  $\{1, \dots, H\}$ , where  $H$  denotes the number of regimes. Collect all the parameters across each state together to form  $A_0 \equiv \{A_0(h)\}$ ,  $A_+ \equiv \{A_+(h)\}$ , and  $\Xi \equiv \{\Xi(h)\}$  for  $h = 1, \dots, H$ . Define  $\theta \equiv \{A_0, A_+, \Xi\}$  and  $Y_T \equiv \{y_1, \dots, y_T\}$ .

SWZ assume  $s_t$  evolves according to a first-order Markov process governed by the transition matrix  $Q = [q_{i,j}]$ , where  $q_{ij} = \text{Prob}[s_t = i | s_{t-1} = j]$  for  $i, j = 1, \dots, H$ . They restrict the transition to only adjacent cells in  $Q$  to reduce the number of free parameters. Thus,

$$Q = \begin{bmatrix} q_{11} & (1 - q_{22})/2 & \cdots & 0 & 0 \\ 1 - q_{11} & q_{22} & \ddots & \vdots & \vdots \\ 0 & (1 - q_{22})/2 & \ddots & (1 - q_{H-1, H-1})/2 & 0 \\ \vdots & \vdots & \ddots & q_{H-1, H-1} & 1 - q_{H, H} \\ 0 & 0 & \cdots & (1 - q_{H-1, H-1})/2 & q_{H, H} \end{bmatrix}.$$

The MS-BVAR (3.1) has the likelihood function

$$p(Y_T | \theta, Q) = \prod_{t=1}^T \left[ \sum_{s_t \in H} p(y_t | Y_{t-1}, \theta, Q, s_t) p(s_t | Y_{t-1}, \theta, Q) \right]. \quad (3.2)$$

where  $p(s_t | Y_{t-1}, \theta, Q)$  is the density used to sample the probability of being in regime  $i$  at date  $t$  given the information available at date  $t - 1$ . The probability terms are updated using the filtering algorithm described in Appendix A of [Sims, Waggoner, and Zha \(2008\)](#). This algorithm employs backward recursion to integrate out the regime sequence  $S_T \equiv \{s_1, \dots, s_T\}$  from the likelihood (3.2).

The joint posterior distribution of  $\theta$  and  $Q$  is calculated using Bayes' rule

$$p(\theta, Q|Y_T) \propto p(Y_T|\theta, Q)p(\theta, Q), \quad (3.3)$$

where  $p(\theta, Q)$  denotes the priors for  $\theta$  and  $Q$ .

### 3.2. Accounting for Fiscal Foresight in MS-BVARs

My identification strategy assumes the fundamental shocks can be recovered from current and past information in  $y_t$ . [Ramey \(2011\)](#) and [Leeper, Walker, and Yang \(2013\)](#) contend this is not possible when one attempts to identify a conventional fiscal policy SVAR. They argue GOV and TAX shocks estimated by the econometrician are likely to be anticipated by households, workers, firms, and investors. Current expectations of future changes in spending and tax policy is often referred to as fiscal foresight. Fiscal foresight is the result of legislative and implementation lags associated with fiscal policymaking. This causes a misalignment between the information sets of the econometrician and the agents in the SVAR.

[Lippi and Reichlin \(1994\)](#) offer one empirical approach to address fiscal foresight. It starts from the observation that anticipated shocks are the source of forward-looking non-fundamental MA components in VARs. When non-fundamental MA components exist, there is no direct mapping from the reduced-form regression errors of the system [\(2.3\)](#) to the errors of the SEM [\(2.2\)](#). This is a direct violation of the Wold Decomposition theorem. As a result, the econometrician cannot recover the fundamental shocks of interest from current and past information in  $y_t$ .

[Lippi and Reichlin's \(1994\)](#) empirical strategy relies on Blaschke matrices to address the problem of non-fundamentalness of a VAR. Their approach uses Blaschke matrices to discount the forward-looking MA components of VARs subject to anticipated shocks. [Mertens and Ravn \(2010\)](#) employ the [Lippi and Reichlin \(1994\)](#) estimation strategy to recover anticipated fiscal policy shocks by discounting the discount factor implicit in Blaschke matrices

in a SVAR.

A MS-BVAR is another empirical approach to address fiscal foresight. Motivation for considering MS-BVARs comes from the insights of [Davig and Leeper \(2007b\)](#). Using a small-scale new Keynesian DSGE model, Davig and Leeper study whether a violation of the Taylor principle leads to an explosive or indeterminate equilibrium in a world where agents' expectations incorporate the possibility of policy regime switches. As long as agents place a positive probability of switching to a stable regime, temporarily violating the Taylor rule does not cause price level indeterminacy. The authors conclude a MS model expands the equilibrium determinacy region of the parameter space relative to its constant coefficient counterpart.

[Davig and Leeper's \(2007b\)](#) reasoning can be extended to confront fiscal foresight. For instance, if agents are currently in one fiscal policy regime and anticipate being in another policy regime in the future, agents form probability distributions over these regimes. Fiscal foresight is accounted for if agents attach positive probabilities attached to these distributions. Therefore, if a MS-BVAR estimates probability distributions with positive probabilities, a MS-BVAR accounts for fiscal foresight.

### 3.3. Priors

The MS-BVAR prior  $p(\theta, Q)$  contains two distinct elements. The first part of the prior applies to the structural (impact and lag) coefficients and SV factor loadings in  $\theta$ . Following [Sims, Waggoner, and Zha \(2008\)](#), I endow  $\theta$  with [Sims and Zha's \(1998\)](#) random walk prior distribution. Their prior is built on the belief that  $y_t$  consists of  $n$  independent random walk processes. The behavior of these random walk processes is controlled via six hyperparameters, which are gathered in the vector  $\Lambda = [\lambda_0 \lambda_1 \lambda_3 \lambda_4 \mu_5 \mu_6]$ .<sup>6</sup> I set  $\Lambda = [1.0 \ 0.2 \ 1.0 \ 1.0 \ 1.0 \ 1.0]$ , which matches [Sims and Zha's \(1998\)](#) prior setting for quarterly BVARs.

The second part of the prior imposes a Dirichlet distribution on the transition probabili-

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<sup>6</sup>[Sims and Zha \(1998\)](#) describe these hyperparameters as controlling the overall tightness of the prior on own first lags,  $\lambda_0$ , the relative tightness of the prior on lags of the other  $n - 1$  variables in  $y_t$ ,  $\lambda_1$ , the relative tightness of the prior on the rate of lag decay,  $\lambda_3$ , the relative tightness of the prior on the intercept term,  $\lambda_4$ , and the prior beliefs about unit roots,  $\mu_5$ , and cointegration relationships,  $\mu_6$ , among the variables in  $y_t$ .

ties in  $Q$ . As will be discussed in section 3.4, several of the estimated MS-BVARs restrict the Markov chain on the structural coefficients of the  $\mathcal{FP}$  block regressions to be distinct from the Markov chain on the  $\mathcal{MF}$  block regressions. In this case, I set the Dirichlet prior on the  $\mathcal{FP}$  block Markov chain to four years. This prior setting rests on observing fiscal policy changes are often enacted early in a U.S. presidential administration. The Dirichlet prior on the  $\mathcal{MF}$  block Markov chain is set to three years, reflecting a belief that U.S. business and financial cycles have a duration similar to the U.S. presidential administration. Drazen’s (2001) evidence of a U.S. political business cycle motivates this prior setting.

### 3.4. Model Space

The model space is populated with MS-BVARs with different assumptions regarding whether the structural coefficients and/or the SVs of the structural shocks are constant or MS. Each MS specification is considered for each identification scheme discussed in section 2.4.

Table 1 lists the 15 MS-BVARs occupying the model space. For MS-BVAR-1 to -9, the label #c indicates the number of structural coefficient regimes, while the label #v represents the number of SV regimes. For instance, MS-BVAR-1 to -3 are labeled as “1c2v” to represent MS-BVARs with constant structural coefficients and MS in the SVs. The MS-BVAR-4 to -6 are MS-BVARs with MS structural coefficients and constant volatilities. The MS-BVAR-7 to -9 assume MS in the structural coefficients and SVs.

The MS-BVAR-10 to 15 restrict the Markov chain on the structural coefficients of the  $\mathcal{FP}$  block regressions to be distinct from the Markov chain on the  $\mathcal{MF}$  block regressions. Therefore, the label # $\mathcal{FP}$ c (# $\mathcal{MF}$ c) indicates the number of structural coefficient regimes in the  $\mathcal{FP}$  ( $\mathcal{MF}$ ) block regressions. The MS-BVAR-10 to -12 are labeled as “2 $\mathcal{FP}$ c, 2v” to indicate MS-BVARs with MS restricted to the  $\mathcal{FP}$  block structural coefficients and SVs, while leaving the  $\mathcal{MF}$  block structural coefficients constant. The MS-BVAR-13 to -15 allow for distinct MS structural coefficients in the  $\mathcal{FP}$  and  $\mathcal{MF}$  blocks as well as SVs.

Post-1960 U.S. fiscal policy can be classified as having switched between two regimes.

Steuerle (2006) and Davig and Leeper (2007a) argue one fiscal policy regime is defined by increases in government spending or tax cuts. Examples of this regime include President LBJ’s “Great Society” social programs and the Bush and Obama administrations’ response to the 2007-2009 financial crisis and recession. President Kennedy’s 1963 tax cuts and President Reagan’s series of tax cuts and reforms in 1981, 1982, 1983, and 1986 also fall under this regime. The second fiscal policy regime aimed at balancing the budget or stabilizing the debt-to-GDP ratio. This regime describes Clinton-era fiscal policy along with the practice during the later portion of the Obama administration.

### 3.5. Bayesian Estimation and Model Evaluation

This section summarizes the estimation and evaluation procedure, while leaving the technical details to Sims, Waggoner, and Zha (2008). Given the sample data, priors, and  $p = 2$ ,<sup>7</sup> the procedure for estimating a sequence of MS-BVARs and evaluating which of the competing model(s) is (are) favored by the data is sketched below.

- Step 1.** Estimate the posterior mode of  $\theta$  and  $Q$  in (3.3) with SWZ’s blockwise optimization algorithm.
- Step 2.** Initialize the Metropolis-within-Gibbs MCMC sampler at the posterior mode estimates of  $\theta$  and  $Q$ . Initializing the sampler at the peak of the posterior distribution (3.3) should increase the sampler’s ability to explore the entire parameter space while avoiding getting stuck in a local mode.
- Step 3.** Simulate  $K_1 + K_2 = 15$  million draws from the proposal distribution  $p(\theta, Q, S_T|Y_T)$ . The Metropolis-within-Gibbs MCMC algorithm simulates draws from  $p(\theta, Q, S_T|Y_T)$  by sequentially sampling from the conditional posterior distributions

$$\begin{aligned}
 & p\left(S_T^{(k)}|Y_T, \theta^{(k-1)}, Q^{(k-1)}\right), \\
 & p\left(Q^{(k)}|Y_T, S_T^{(k)}, \theta^{(k-1)}\right), \\
 \text{and} & p\left(\theta^{(k)}|Y_T, Q^{(k)}, S_T^{(k)}\right),
 \end{aligned}$$

where  $k = 1, \dots, K_1 + K_2$ .

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<sup>7</sup>The Hannan-Quinn Criterion (HQC) selects  $p = 2$  as the optimal lag length of the SVAR (2.1).

- Step 4.** Discard the first  $K_1 = 5$  million draws as the burn-in sample. Construct the posterior distribution of a MS-BVAR with the remaining  $K_2 = 10$  million draws.
- Step 5.** Calculate the MDD with SWZ’s truncated modified harmonic mean (HMH) estimator.<sup>8</sup>

The MS-BVARs are estimated and evaluated using Dynare’s SWZ MS-BVAR code within MATLAB; see [Adjemian et al. \(2011\)](#).<sup>9</sup>

## 4. Results

This section describes the estimation results of the best-fit MS-BVAR.

### 4.1. Fit of the MS-BVARs

Table 2 summarizes the fit of the MS-BVARs. The table also reports the fit of three constant coefficient BVARs, one for each identification scheme discussed in section 2.4. The constant coefficient BVARs serve as a baseline against which to evaluate whether the data prefer constant or MS coefficient specifications. Table 2 shows the MS-BVARs (MS-BVAR-1 to -15) are overwhelmingly favored by the data in comparison to the constant coefficient BVARs (BVAR-1 to -3). Adding MS in the structural coefficients or SVs improves model fit. However, the data prefer the addition of MS structural coefficients and SVs (MS-BVAR-7 to -15) over restricting MS to only the SVs (MS-BVAR-1 to -3) or the structural coefficients (MS-BVAR-4 to -6).

The key finding in table 2 is the MS-BVAR-13 achieves the best fit to the data. This MS-BVAR imposes two distinct Markov chains on the structural coefficients of the  $\mathcal{FP}$  block, two more on the structural coefficients of the  $\mathcal{MF}$  block, and assumes two regimes in the SVs. The MS-BVAR-13 also is identified using the non-recursive impact matrix in section 2.4.1.

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<sup>8</sup>Given the high computational costs of producing a complete set of estimation results for a MS-BVAR, only a MDD is computed during the first estimation run. A complete set of estimation results for the best-fit MS-BVAR(s) are generated during a second round of estimation. Whether the data continue to prefer this (these) MS-BVAR(s) is checked subsequent to constructing the posterior(s) a second time.

<sup>9</sup>The MATLAB and Dynare code is run on the Henry2 Linux cluster of the High Performance Computing Center at North Carolina State University. Codes are available upon request.

The log MDD estimates in table 2 show the data have a strong preference for MS-BVAR-13 when compared to the other MS-BVARs sharing either the same identification (MS-BVAR-1, -4, -7, and -10) or the same MS specification (MS-BVAR-14 and -15). The log MDD difference between MS-BVAR-13 and MS-BVAR-14, the MS-BVAR with the second highest log MDD, is 11.00. This difference yields a Bayes factor estimate of 59,874.14 ( $= \exp(11.00)$ ), which, according to Kass and Raftery (1995), indicates *very strong* evidence in favor of MS-BVAR-13. Hence, the remainder of the paper focuses on estimates produced by MS-BVAR-13.

#### 4.2. Transition Matrices of the MS-BVAR-13

There are important differences in the estimates of the posteriors of the  $\mathcal{FP}$  and  $\mathcal{MF}$  block structural coefficient regime transition matrices,  $\hat{Q}^{\mathcal{FP}c}$  and  $\hat{Q}^{\mathcal{MF}c}$ . These transition matrices are

$$\hat{Q}^{\mathcal{FP}c} = \begin{bmatrix} 0.823 & 0.061 \\ [0.701, 0.928] & [0.030, 0.106] \\ 0.177 & 0.939 \\ [0.073, 0.300] & [0.894, 0.970] \end{bmatrix} \quad \text{and} \quad \hat{Q}^{\mathcal{MF}c} = \begin{bmatrix} 0.917 & 0.082 \\ [0.853, 0.960] & [0.039, 0.147] \\ 0.083 & 0.918 \\ [0.040, 0.147] & [0.853, 0.961] \end{bmatrix},$$

at the medians of the posterior of MS-BVAR-13. The brackets below each estimate contain 90% Bayesian credible sets.<sup>10</sup>

The estimated conditional transition probabilities in  $\hat{Q}^{\mathcal{FP}c}$  and  $\hat{Q}^{\mathcal{MF}c}$  provide a way to understand how fiscal policy regime changes compare with U.S. business cycle regimes. Starting with the  $\mathcal{FP}$  block, the estimated transition probability  $\hat{p}_{11}^{\mathcal{FP}c} = 0.823$  indicates the first  $\mathcal{FP}$  block regime exhibits less persistence compared with the second regime. The expected duration of the first regime is  $(1 - 0.823)^{-1}$  or nearly 6 quarters. The second  $\mathcal{FP}$  block regime is more persistent,  $\hat{p}_{22}^{\mathcal{FP}c} = 0.939$ , with an expected duration of around 16 quarters. The duration of the two  $\mathcal{FP}$  block regimes are quite different from each other. This is not the case for the  $\mathcal{MF}$  block regimes. The conditional transition probabilities  $\hat{p}_{11}^{\mathcal{MF}c} = 0.917$  and  $\hat{p}_{22}^{\mathcal{MF}c} = 0.918$  are almost identical. Each  $\mathcal{MF}$  block regime lasts on

<sup>10</sup>The 90% Bayesian credible sets are the 5th and 95th quantiles of the posterior distributions.

average for 12 quarters. Thus, the first (second)  $\mathcal{FP}$  block regime moves faster (slower) than the business cycle. Note the probability of leaving the first  $\mathcal{FP}$  block regime,  $\hat{p}_{21}^{\mathcal{FP}c} = 0.177$ , is more than double the probability of moving out of the first  $\mathcal{MF}$  block regime,  $\hat{p}_{21}^{\mathcal{MF}c} = 0.083$ . Assuming the economy starts in the first  $\mathcal{FP}$  and  $\mathcal{MF}$  block regimes, this implies fiscal policy behavior is more likely to change than macroeconomic and financial conditions.

The SV regimes are quite persistent, according to

$$\hat{Q}^{sv} = \begin{bmatrix} 0.918 & 0.033 \\ [0.822, 0.981] & [0.009, 0.073] \\ 0.082 & 0.967 \\ [0.019, 0.178] & [0.927, 0.991] \end{bmatrix}.$$

The expected duration of the first SV regime is over 12 quarters, as indicated by  $\hat{p}_{11}^{sv} = 0.918$ . Conditional on the economy being in the first SV regime at time  $t - 1$ , there is less than a one in ten chance the economy switches to the second SV regime at date  $t$ . Given the economy is in the second SV regime, it is expected to remain there for 30 quarters because  $\hat{p}_{22}^{sv} \approx 1 - 1/30$ . The probability the economy leaves the second SV regime and moves to the first SV regime is less than 5% ( $> \hat{p}_{12}^{sv} = 0.033$ ). Overall, these findings suggest that the size of structural shocks hitting the economy does not change often.

#### 4.3. Smoothed Conditional Regime Probabilities of the MS-BVAR-13

The MS-BVAR-13 produces probabilities of the SV regimes as well as the structural coefficient regimes for the  $\mathcal{FP}$  and  $\mathcal{MF}$  block regressions at time  $t$ . Figures 1 to 3 plot the smoothed conditional probabilities for these regimes from 1960Q1 to 2019Q4. These probabilities are smoothed in the sense of Kim (1994). The shaded bars in each figure represent the NBER recession dates.

Figure 1 presents the first SV regime probabilities of MS-BVAR-13. The first SV regime coincides with most of the NBER dated recessions in the sample. However, the two recessions in 1991 and 2001 are not captured by the first SV regime. The first SV regime is also dormant during periods of economic expansions.

The conditional probabilities of the first  $\mathcal{FP}$  and second  $\mathcal{MF}$  block regimes appear in figures 2 and 3. The first  $\mathcal{FP}$  block regime covers several historical episodes of tax cuts and expansions in government spending. For instance, President Ford’s tax cut in 1975 following the 1973 oil crisis is detected. This regime also observes the passage of the Tax Reform Act of 1986, which lowered federal income tax rates, while eliminating many tax incentives, which increased the efficiency of the federal income tax system. President George W. Bush’s 2001 and 2003 tax cuts and increase in federal spending following 9/11 are also captured. The first  $\mathcal{FP}$  block regime also coincides with the passage of the American Recovery and Reinvestment Act of 2009. It was aimed at mitigating the effects of the 2007-2009 recession and financial crisis. After 2010Q1, the first  $\mathcal{FP}$  block regime becomes more frequent. This is consistent with the Obama and Trump administrations’ increase in government spending and tax cuts during the aftermath of the 2007-2009 recession and financial crisis.

Figure 3 shows the second  $\mathcal{MF}$  block regime captures the U.S. business cycle. For instance, the second  $\mathcal{MF}$  block regime covers the run-up and duration of each NBER dated recession in the sample. One interesting observation is the second  $\mathcal{MF}$  block regime does not match the exact quarter of every peak and trough of the business cycle. One explanation for this follows. Recall the structural coefficients of the macro variable regressions in the  $\mathcal{MF}$  block switch regime at the same time as the financial variable regressions. Thus, the second  $\mathcal{MF}$  block regime is also capturing the financial cycle. This explains why the second  $\mathcal{MF}$  block regime is able to detect the Savings and Loan (S&L) Crisis starting in the mid-1980s as well as the Mexican and Asian financial crises in the 1990s.

#### 4.4. *Impact and SV Matrices of the MS-BVAR-13*

Table 3 reports the median of the posterior of the regime-dependent scale volatilities  $\Xi^{-1}(s_t)$ . The 90% Bayesian credible sets are also shown. The scale volatilities of the first SV regime ( $s_t^{sv} = 1$ ) are normalized to one. The second SV regime ( $s_t^{sv} = 2$ ) exhibits less volatility compared to the first SV regime. When the economy is in the second SV regime, the loading

scales on GOV, TAX, RGDP,  $\pi$ ,  $R_{3m}$ , and  $R_{10yr}$  shocks are smaller by factors of 1.5, 1.9, 3.6, 2.9, 8.2, and 1.4, respectively. Hence, episodes of greater SV in aggregate supply, aggregate demand, and debt financing shocks coincide with NBER dated recessions. The scale volatilities on GOV, TAX, and term premium shocks possess relatively wide 90% credible sets. This indicates a large degree of uncertainty over the scale of these shocks across regimes.

The posterior median estimates and 90% Bayesian credible sets of the impact matrices  $\widehat{A}_0(s_t^{FPBc} = i | s_t^{MFBc} = i)$  for  $i = 1, 2$  are presented in tables 4 and 5.<sup>11</sup> A comparison of the two impact matrices yields interesting differences between the two  $\mathcal{FP}$  block regimes. First, the estimated median own shock response for GOV is largest when the economy is in the first  $\mathcal{FP}$  block regime. Second, TAX is only responsive to aggregate supply shocks in the first  $\mathcal{FP}$  block regime. When the economy moves to the second  $\mathcal{FP}$  block regime, the TAX response to its own shock increases by over a factor of 4 from 0.082 to 0.340. The response of TAX to aggregate supply shocks also increases from 0.486 to 0.675 in absolute terms.

There are also interesting differences between the two  $\mathcal{MF}$  block regimes. For instance, GOV shocks have a larger effect on RGDP at impact in the second  $\mathcal{MF}$  block regime. The RGDP response to GOV shocks increases almost threefold from 0.174 to 0.468 when switching to the second  $\mathcal{MF}$  block regime. This suggest the response of RGDP to GOV shocks is larger during recession than in expansions. There is little evidence that TAX shocks have an immediate effect on RGDP in either regime. The  $R_{3m}$  response to aggregate supply shocks is stronger in the first  $\mathcal{FP}$  block regime. This response falls from 0.250 to 0.022 under the second  $\mathcal{FP}$  block regime. However, its own shock response almost triples from 0.890 to 2.494. Finally, the impact of aggregate demand shocks on  $R_{10yr}$  is over eleven times higher in the second  $\mathcal{MF}$  block regime. The  $R_{10yr}$  response to aggregate demand shocks rises from -0.083 to 0.960. This suggest that during recessions inflation shocks have very strong effects on the term premium.

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<sup>11</sup>To conserve space, I omit presenting  $\widehat{A}_0(s_t^{FPc} = 1 | s_t^{MFc} = 2)$  and  $\widehat{A}_0(s_t^{FPc} = 2 | s_t^{MFc} = 1)$ . These impact matrices are in appendix C.

## 5. The Effects of Fiscal Policy Shocks on U.S. Output

This section measures the effects of GOV and TAX shocks on RGDP in two ways. First, I construct GIRFs using an algorithm adapted from [Karamé \(2015\)](#) and [Bianchi \(2016\)](#). The GIRFs measure the responses of RGDP to GOV and TAX shocks conditioning on the probability of changes in regime. Second, I employ the constructed GIRFs to compute present-value GOV and TAX multipliers.

### 5.1. GIRFs of U.S. Output to Fiscal Policy Shocks

Figure 4 plots the conditional GIRFs of RGDP to a unit GOV shock. The median GIRFs are computed from the median of the posterior of MS-BVAR-13. 68% uncertainty bands are also reported. Each subplot in figure 4 shows the response assuming the specified  $\mathcal{FP}$  and  $\mathcal{MF}$  block regimes remain in place over the relevant horizon. However, these conditional GIRFs assume agents anticipate the possibility of regime changes.<sup>12</sup>

Across all possible regime combinations, the median GIRFs show the response of RGDP to a GOV shock is positive for all horizons. When conditioning on the first  $\mathcal{MF}$  block regime, the GIRF of RGDP features an inverted hump-shaped response, which reaches its lowest point at the 2-quarter horizon. The median response then takes about ten quarters before reaching its peak. Afterwards, the GIRF of RGDP remains at a permanently higher level. Note the shape of the GIRFs do not differ across the  $\mathcal{FP}$  block regimes. This is not the case when the  $\mathcal{MF}$  regime changes. Under the second  $\mathcal{MF}$  block regime, the median GIRFs exhibit a upward-trend shaped response. Also note the 68% uncertainty bands are strictly positive throughout the relevant horizon. Overall, RGDP is permanently higher following a GOV shock. The shape of the response depends more on whether the economy is in an expansion or recession rather than the prevailing fiscal policy regime.

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<sup>12</sup>Another approach to measure these responses is to compute unconditional GIRFs. Unconditional GIRFs assume the initial regime can change probabilistically over the relevant horizon. Reporting unconditional GIRFs is left to future work.

The GIRFs of RGDP with respect to a unit TAX shock appear in figure 5. The magnitudes of the responses are relatively small across the regimes. The largest response of RGDP at impact is barely 0.02 in absolute terms. When conditioning on the first  $\mathcal{MF}$  block regime, the response of RGDP to a TAX shock is hump-shaped, peaking at the 3-quarter horizon. RGDP starts to revert back to zero between five and eight years after the shock. The 68% uncertainty bands around this median response are wide at all horizons. A L-shaped response appears when conditioning on the second  $\mathcal{MF}$  block regime. The response falls and remains at a permanently lower level two quarters after the initial shocks. The 68% uncertainty bands are narrow. Similar to before, the response of RGDP to a TAX shock relies more heavily on the current state of the business cycle rather than the fiscal policy regime.

## 5.2. Present-Value Fiscal Multipliers

This section presents present-value government spending and tax multipliers using the GIRFs. As [Leeper, Traum, and Walker \(2017\)](#) explain, present-value multipliers properly discount the effects of future changes in RGDP with respect to a fiscal policy shock. The  $k$ -period ahead present-value fiscal multipliers are

$$\text{Present-Value GOV Multiplier}(k) = \frac{E_t \sum_{j=0}^k \left( \prod_{i=0}^k \beta^i \right) \Delta RGDP_{t+j}}{E_t \sum_{j=0}^k \left( \prod_{i=0}^k \beta^i \right) \Delta GOV_{t+j}}$$

and

$$\text{Present-Value TAX Multiplier}(k) = \frac{E_t \sum_{j=0}^k \left( \prod_{i=0}^k \beta^i \right) \Delta RGDP_{t+j}}{E_t \sum_{j=0}^k \left( \prod_{i=0}^k \beta^i \right) \Delta TAX_{t+j}},$$

where  $\beta$  denotes the quarterly discount factor. I calibrate  $\beta = 0.997$ , which is  $1/(1 - \bar{R}_{3m})$ , where  $\bar{R}_{3m}$  is the sample average of the return on 3-month Treasury Bills, 1.36%, from 1960Q1 to 2019Q4.

Figures 6 and 7 report the median present-value GOV and TAX multiplier estimates with 68% uncertainty bands. There are several interesting results in figure 6. First, RGDP

increases by greater than a dollar in response to a GOV shock at impact. The exception is when the economy is in the first  $\mathcal{FP}$  and  $\mathcal{MF}$  block regimes. When these regime prevails, RGDP instead rises by about 84 cents. Second, the largest GOV multiplier at impact is 1.60, which occurs under the second  $\mathcal{FP}$  and  $\mathcal{MF}$  block regimes. Third, the median estimates are surrounded by wide 68% uncertainty bands. The wide uncertainty bands imply the posterior of the MS-BVAR is unable to provide a precise estimate of the GOV multiplier. Finally, the GOV multiplier is largest when conditioning on the second  $\mathcal{MF}$  block regime compared to conditioning on the first  $\mathcal{MF}$  block regime. The GOV multipliers do not appear to be quantitatively across the  $\mathcal{FP}$  block regimes (holding the  $\mathcal{MF}$  block regime fixed). This suggest that business cycle regime changes play a more important role in shaping the GOV multiplier than regime changes in fiscal policy.

Figure 7 plots the median TAX multiplier across each regime. The median TAX multiplier remains negative for all 40 quarters after the initial TAX shock. The surrounding 68% uncertainty bands are wide. This suggests uncertainty swamps the estimates of the TAX multiplier. However, at its widest point, the 68% uncertainty bands range from -1.5 to 0.5. This finding is at odds with previous studies that report TAX multipliers ranging from -2 to -3; see [Ramey \(2019\)](#) for a summary of these studies.

In summary, the posterior of the MS-BVAR-13 argues RGDP responds positively to a GOV shock. Similar to [Auerbach and Gorodnichenko \(2012\)](#) and [Ramey and Zubairy \(2018\)](#), the GOV multiplier is larger when the economy is in a recession than in an expansion. However, there is no strong evidence of a large negative TAX multiplier. This stands in contrast to [Mountford and Uhlig \(2009\)](#) and [Mertens and Ravn \(2012\)](#). Regardless, the GOV multiplier is larger than the TAX multiplier in all cases, which matches the consensus held by traditional Keynesian macroeconomics.

## 6. Conclusion

Fiscal foresight complicates the task of measuring the effects of government spending and tax shocks on output. If agents anticipate changes in future policy prior to implementation, these anticipation effects must be accounted for to understand how fiscal policy affects real economic activity. In this paper, I employ MS-BVARs as a way to account for these anticipation effects. The MS-BVARs are estimated on quarterly U.S. fiscal, macroeconomic, and financial data from 1960 to 2019.

Using the MS-BVAR favored by the data, GIRFs and fiscal multipliers are reported to assess the effects government spending and tax shocks have on real GDP. Several interesting results emerge. First, output is permanently higher following a GOV shock. However, the response of RGDP to a GOV shock is state-dependent. GOV shocks have a stronger positive effect on RGDP during recessions compared with expansions. Second, while TAX shocks have a negative effect on output, the output response is small regardless of which business cycle regime is in place. Third, the TAX multipliers estimated in this paper are also relatively small. This is at odds with previous findings that TAX shocks have a large negative effect on RGDP. Finally, finding the GOV multiplier is larger than the TAX multiplier is consistent with the views of traditional Keynesian macroeconomics.

One potential avenue for future research is to consider how the interaction of monetary and fiscal policies influence the effects of fiscal policy shocks on output. This paper is silent on the role of monetary policy. This implicitly assumes the monetary authority adjusts its policy behavior in accordance to the fiscal authority. A MS-BVAR with monetary and fiscal policy variables would also be able to study how fiscal policy influences the monetary policy transmission mechanism.

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# Tables and Figures

Table 1: List of MS-BVAR Model Space

MS-BVAR	Specification	Identification
1	1c2v	Non-Recursive Impact Matrix: Extended Blanchard-Perotti
2	1c2v	Recursive Impact Matrix: Tax Rule
3	1c2v	Recursive Impact Matrix: Government Spending Rule
4	2c1v	Non-Recursive Impact Matrix: Extended Blanchard-Perotti
5	2c1v	Recursive Impact Matrix: Tax Rule
6	2c1v	Recursive Impact Matrix: Government Spending Rule
7	2c2v	Non-Recursive Impact Matrix: Extended Blanchard-Perotti
8	2c2v	Recursive Impact Matrix: Tax Rule
9	2c2v	Recursive Impact Matrix: Government Spending Rule
10	$2\mathcal{FP}_c, 2v$	Non-Recursive Impact Matrix: Extended Blanchard-Perotti
11	$2\mathcal{FP}_c, 2v$	Recursive Impact Matrix: Tax Rule
12	$2\mathcal{FP}_c, 2v$	Recursive Impact Matrix: Government Spending Rule
13	$2\mathcal{FP}_c, 2\mathcal{MF}_c, 2v$	Non-Recursive Impact Matrix: Extended Blanchard-Perotti
14	$2\mathcal{FP}_c, 2\mathcal{MF}_c, 2v$	Recursive Impact Matrix: Tax Rule
15	$2\mathcal{FP}_c, 2\mathcal{MF}_c, 2v$	Recursive Impact Matrix: Government Spending Rule

Notes: The MS-BVARs. The MS-BVAR-1 to -9 have one Markov chain on the structural (impact and lag) coefficients and another Markov chain on the SVs. The number of structural coefficient regimes is indicated by the label  $\#c$ , while the number of SV regimes is specified by the label  $\#v$ . This differs from MS-BVAR-10 to -12, which have one Markov chain on the structural coefficients of the  $\mathcal{FP}$  block regressions and one Markov chain on the SVs. The MS-BVAR-13 to -15 assume one Markov chain on the  $\mathcal{FP}$  block structural coefficients, another chain on the  $\mathcal{MF}$  block structural coefficients, and a final chain on the SVs. The label  $\#\mathcal{FP}_c$  ( $\#\mathcal{MF}_c$ ) indicates the number of  $\mathcal{FP}$  ( $\mathcal{MF}$ ) block structural coefficient regimes.

Table 2: Log Marginal Data Densities, ln MDDs, of the MS-BVARs

Identification	Specification					
	Constant Coefficient	1c2v	2c1v	2c2v	$2\mathcal{FP}_{c,2v}$	$2\mathcal{FP}_{c,2\mathcal{MF}_{c,2v}}$
Non-Recursive Impact Matrix: Extended Blanchard-Perotti	BVAR-1 -1772.60	MS-BVAR-1 -1629.91	MS-BVAR-4 -1648.83	MS-BVAR-7 -1578.62	MS-BVAR-10 -1583.31	<b>MS-BVAR-13</b> <b>-1566.07</b>
Recursive Impact Matrix: Tax Rule	BVAR-2 -1773.70	MS-BVAR-2 -1630.80	MS-BVAR-5 -1653.73	MS-BVAR-8 -1585.95	MS-BVAR-11 -1604.04	MS-BVAR-14 -1577.07
Recursive Impact Matrix: Government Spending Rule	BVAR-3 -1773.70	MS-BVAR-3 -1629.93	MS-BVAR-6 -1653.34	MS-BVAR-9 -1610.76	MS-BVAR-12 -1596.42	MS-BVAR-15 -1573.95

Notes: The log marginal data densities (MDDs) of the constant coefficient BVARs (BVAR-1 to -3) are calculated with the modified harmonic mean (MHM) estimator of [Gelfand and Dey \(1994\)](#) and [Geweke \(2005\)](#). [Sims, Waggoner, and Zha \(2008\)](#) develop a truncated MHM estimator suitable for MS-BVARs with multimodal posteriors. This estimator is employed to calculate the MDDs of the MS-BVARs (MS-BVAR-1 to -15). The results shown are based on 10 million MCMC draws and the 1960Q1 to 2019Q4 sample. The best-fit MS-BVAR and its estimated ln MDD are in bold.

Table 3: Regime Dependent Scale Volatilities of  $\hat{\Xi}^{-1}(s_t^{sv})$ , MS-BVAR-13, 1960Q1 to 2019Q4

	GOV	TAX	RGDP	$\pi$	R <sub>3m</sub>	R <sub>10yr</sub>
$s_t^{sv} = 1$	1.000	1.000	1.000	1.000	1.000	1.000
$s_t^{sv} = 2$	0.655	0.516	0.280	0.342	0.122	0.731
	[0.391, 1.038]	[0.269, 0.919]	[0.181, 0.469]	[0.212, 0.553]	[0.084, 0.198]	[0.401, 2.697]

Notes: The regime dependent scale volatilities are the medians of the posterior of MS-BVAR-13. Ninety percent Bayesian credible sets (i.e., 5th and 95th quantiles) are in brackets. The results depend on 10 million MCMC draws.

Table 4: The Regime Conditional Impact Matrix  $\widehat{A}'_0(s_t^{\mathcal{F}Pc} = 1 | s_t^{\mathcal{M}F_c} = 1)$ , MS-BVAR-13, 1960Q1 to 2019Q4

Shock \ Variable	GOV	TAX	RGDP	$\pi$	R <sub>3m</sub>	R <sub>10yr</sub>
Government Spending	1.219 [0.921, 1.563]					
Tax		0.082 [0.061, 0.103]	-0.486 [-1.157, 0.450]			
Aggregate Supply	-0.174 [-0.345, 0.019]	0.008 [-0.064, 0.057]	0.897 [0.709, 1.106]			
Aggregate Demand	0.044 [-0.080, 0.181]	-0.046 [-0.075, -0.018]	0.024 [-0.155, 0.214]	2.435 [2.068, 2.830]		
Debt Financing	0.130 [0.038, 0.233]	0.001 [-0.019, 0.019]	-0.250 [-0.428, -0.114]	-0.554 [-0.911, -0.267]	0.890 [0.754, 1.035]	
Term Premium	0.055 [-0.120, 0.235]	0.006 [-0.028, 0.039]	-0.102 [-0.348, 0.109]	0.083 [-0.425, 0.643]	-1.077 [-1.399, -0.781]	2.820 [2.241, 3.509]

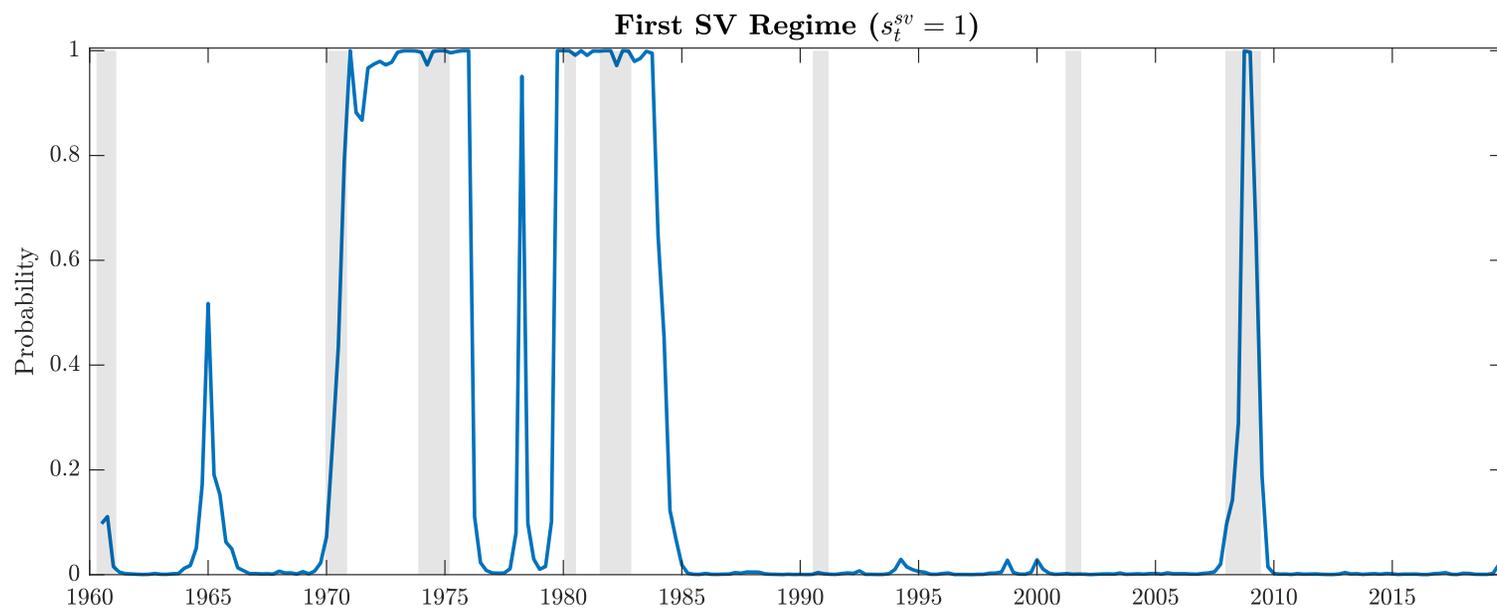
Notes: The elements of  $\widehat{A}'_0(s_t^{\mathcal{F}Pc} = 1 | s_t^{\mathcal{M}F_c} = 1)$  are at the median of the posterior of MS-BVAR-13. Each row represents a behavioral equation. The behavioral equations are labeled by their respective structural shock. The column labels indicate which variables enter each behavioral equation at impact. Otherwise, see the notes to table 3.

Table 5: The Regime Conditional Impact Matrix  $\hat{A}'_0(s_t^{FPc} = 2 | s_t^{MFc} = 2)$ , MS-BVAR-13, 1960Q1 to 2019Q4

Shock \ Variable	GOV	TAX	RGDP	$\pi$	R <sub>3m</sub>	R <sub>10yr</sub>
Government Spending	0.908 [0.765, 1.070]					
Tax		0.340 [0.272, 0.406]	-0.675 [-0.935, -0.360]			
Aggregate Supply	-0.468 [-0.675, -0.239]	0.017 [-0.040, 0.054]	1.376 [1.072, 1.777]			
Aggregate Demand	-0.017 [-0.182, 0.143]	0.001 [-0.023, 0.025]	0.176 [-0.089, 0.454]	2.914 [2.195, 3.791]		
Debt Financing	-0.106 [-0.262, 0.082]	-0.001 [-0.019, 0.018]	-0.022 [-0.237, 0.198]	-0.445 [-0.847, -0.083]	2.494 [1.819, 3.443]	
Term Premium	-0.061 [-0.314, 0.160]	-0.008 [-0.053, 0.033]	-0.161 [-0.705, 0.286]	-0.960 [-1.793, -0.159]	-1.468 [-2.296, -0.667]	2.974 [2.106, 5.609]

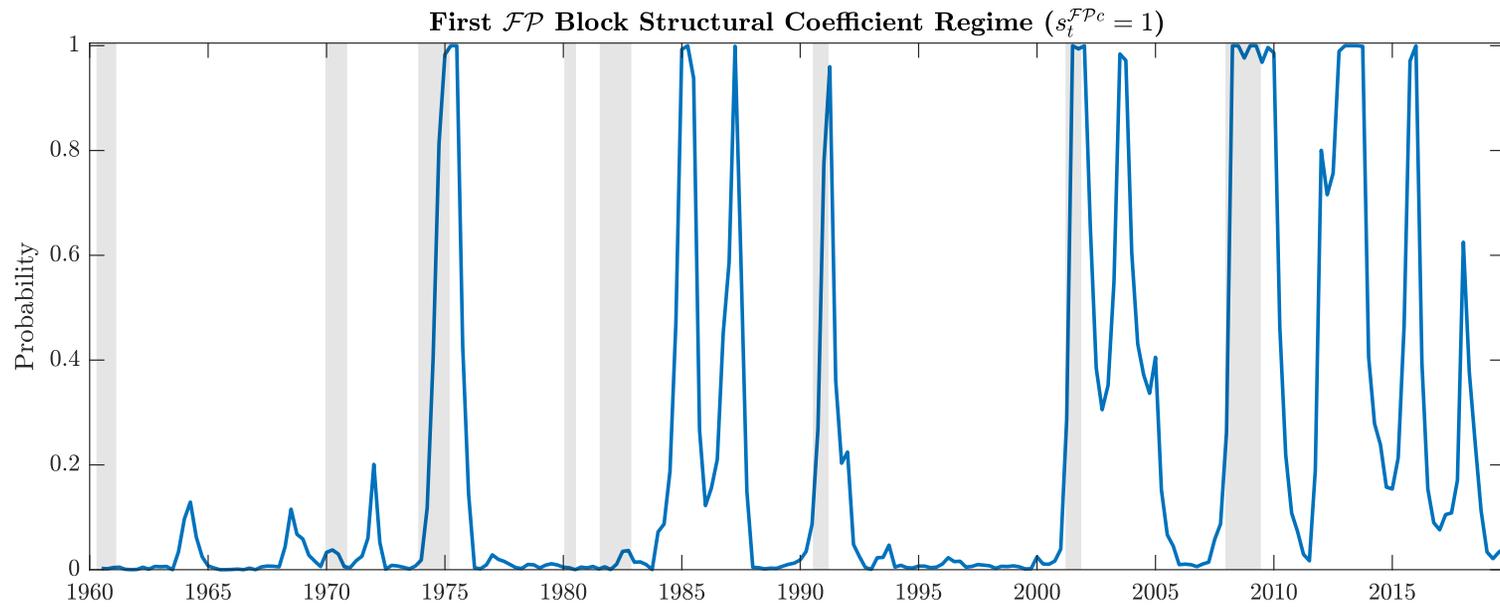
Notes: See the notes to table 4.

Figure 1: Smoothed Probabilities of the First Stochastic Volatility Regime of MS-BVAR-13, 1960Q1 to 2019Q4



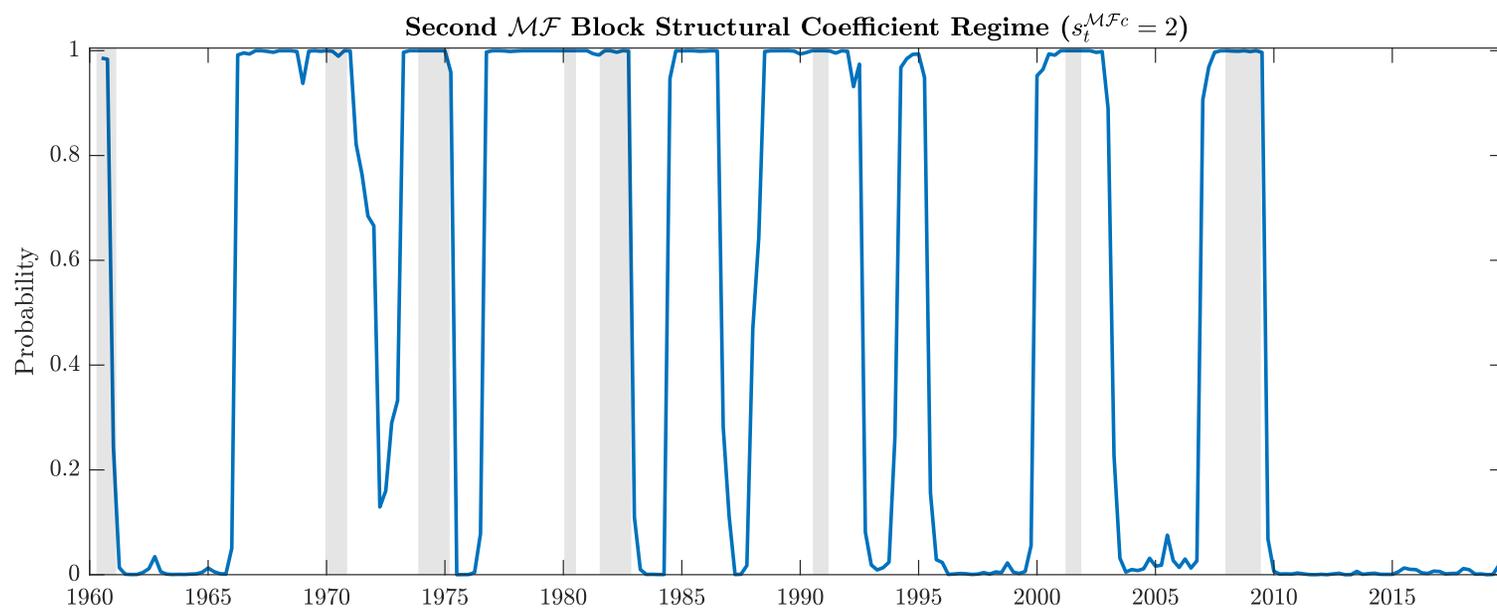
Notes: The shaded bars represent NBER recession dates.

Figure 2: Smoothed Probabilities of the First  $\mathcal{FP}$  Block Structural Coefficient Regime of MS-BVAR-13, 1960Q1 to 2019Q4



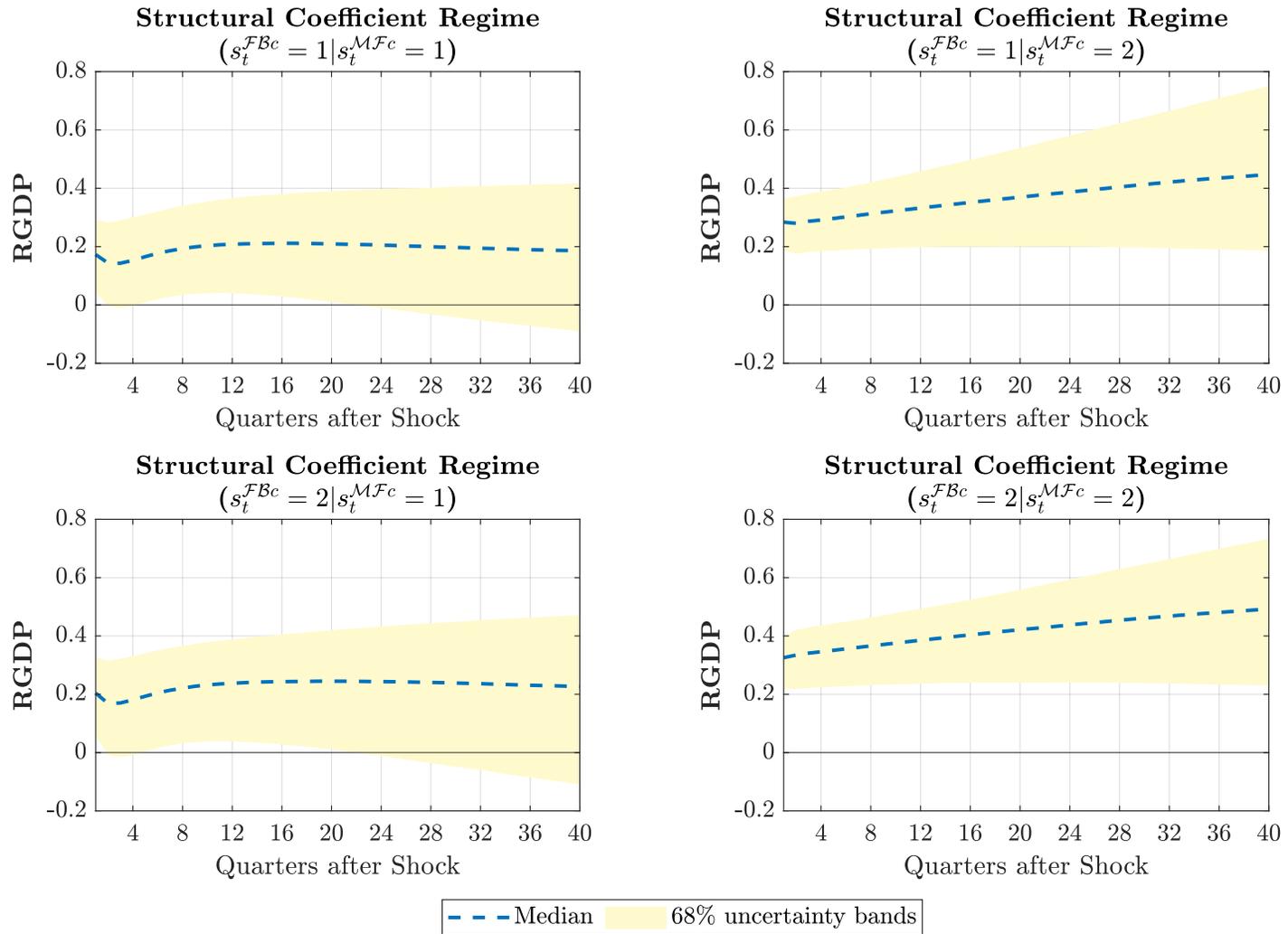
Notes: See the notes to figure 1.

Figure 3: Smoothed Probabilities of the Second  $\mathcal{MF}$  Block Structural Coefficient Regime of MS-BVAR-13, 1960Q1 to 2019Q4



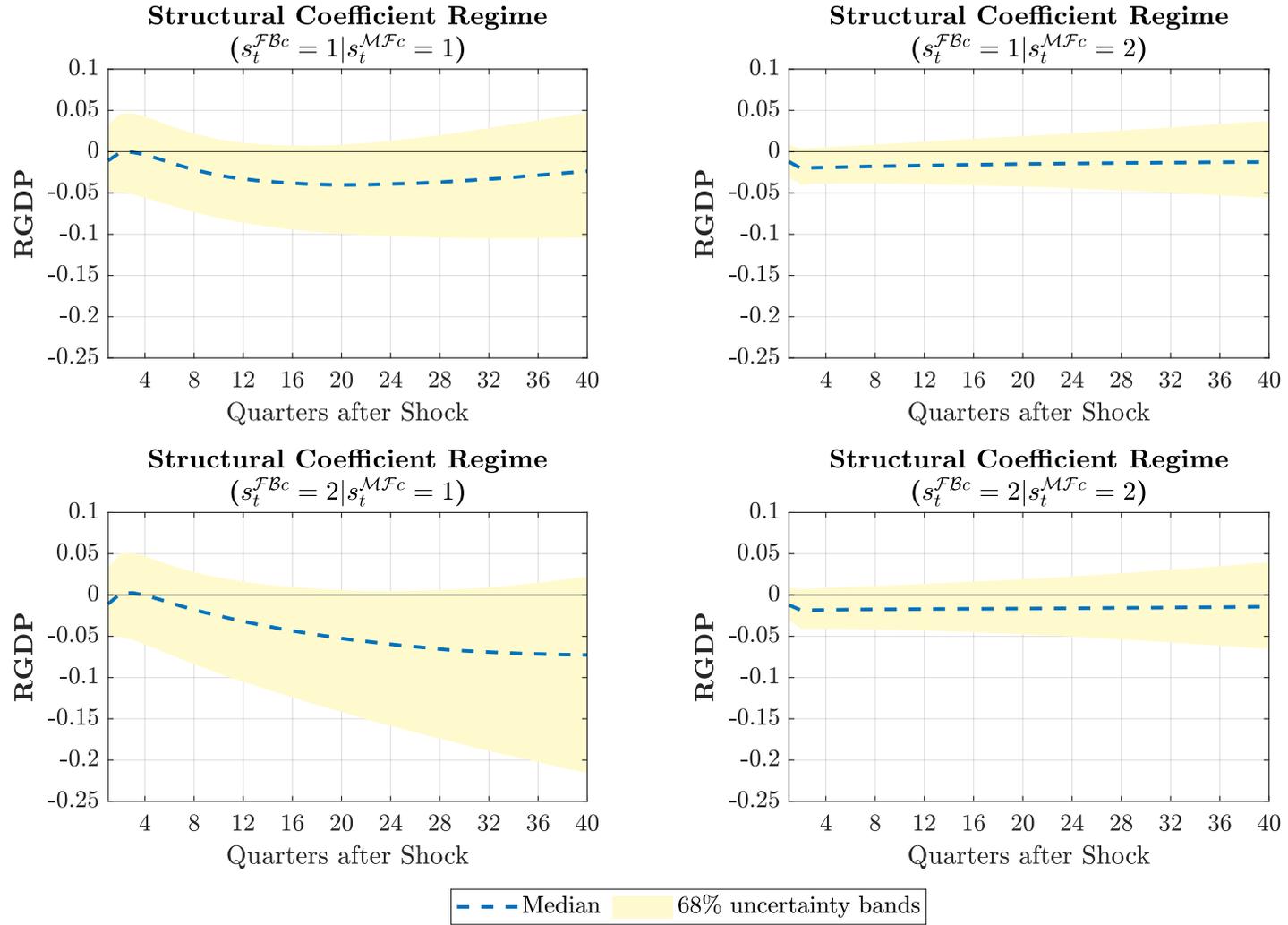
Notes: See the notes to figure 1.

Figure 4: Conditional GIRFs of RGDP with Respect to a Government Spending Shock of MS-BVAR-13



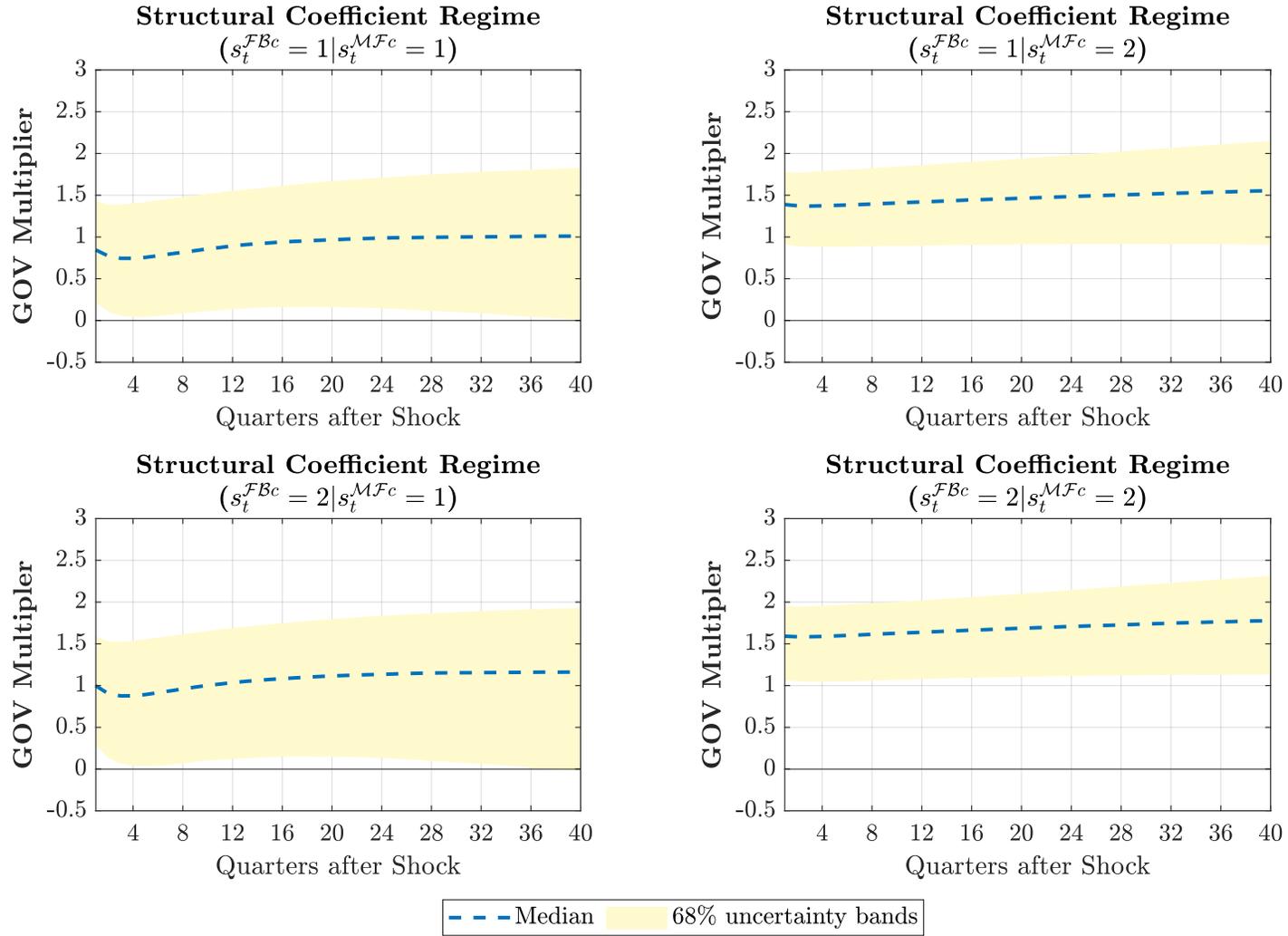
Notes: The GIRFs are conditional on the first (second)  $\mathcal{FP}$  and  $\mathcal{MF}$  block structural coefficient regimes being in place at the time of the shock.

Figure 5: Conditional GIRFs of RGDP with Respect to a Tax Shock of MS-BVAR-13



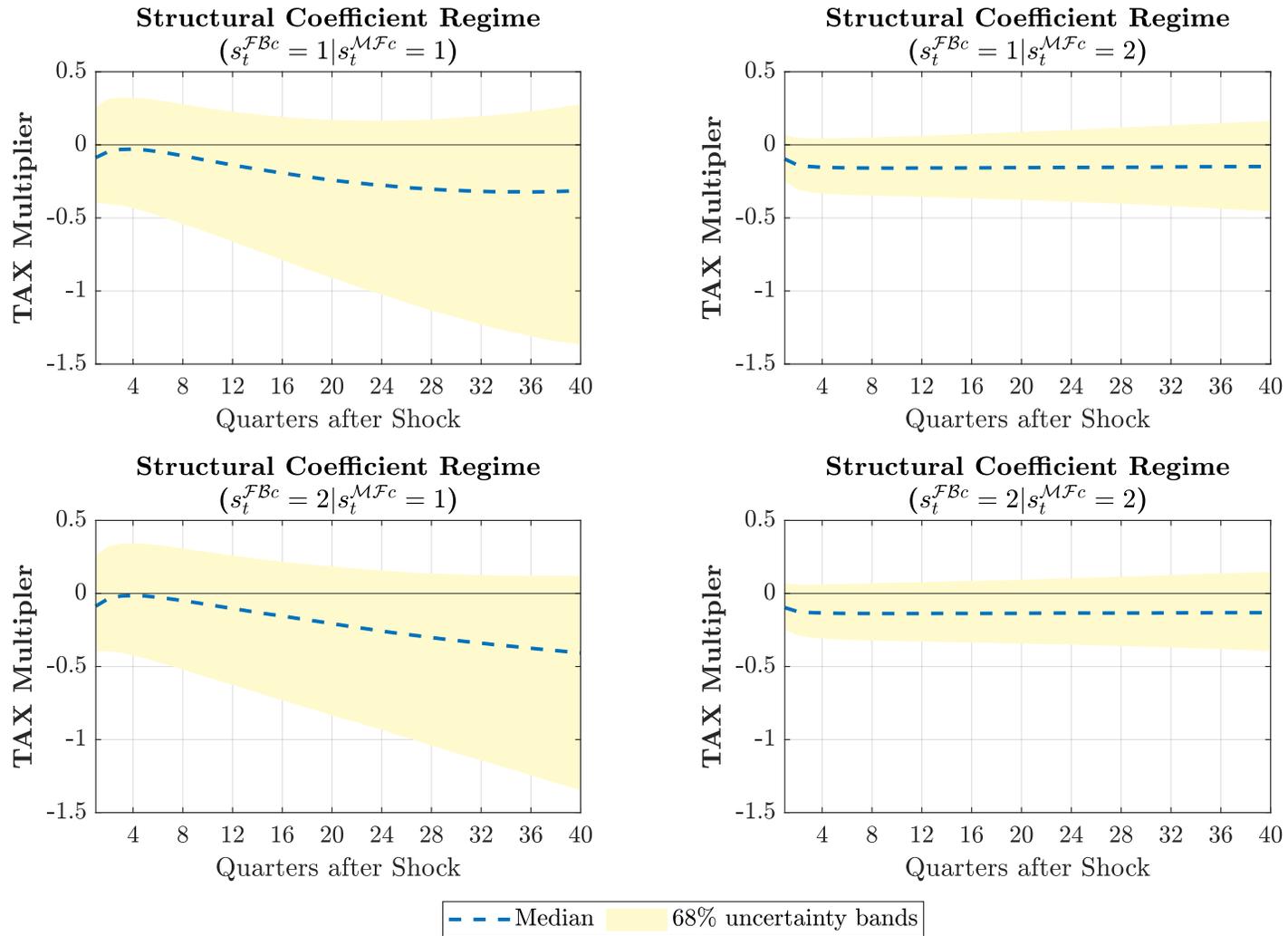
Notes: See the notes to figure 4.

Figure 6: Present-Value Government Spending Multipliers of MS-BVAR-13



Notes: The fiscal multipliers are conditional on the first (second)  $\mathcal{FP}$  and  $\mathcal{MF}$  block structural coefficient regimes being in place at the time of the shock.

Figure 7: Present-Value Tax Multipliers of MS-BVAR-13



Notes: See the notes to figure 6.