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

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Abstract

Fiscal foresight—the phenomenon by which households, workers, firms, and investors preemptively react to anticipated future policy changes—limits conventional structural VARs' ability to reliably assess the impact of fiscal policy on the real economy. This paper addresses this issue by measuring the effects of government spending and tax shocks on U.S. output in a Markov-switching Bayesian VAR (MS-BVAR). The MS-BVAR accounts for foresight by explicitly capturing agents' expectations about future fiscal regime changes. Three key findings emerge. First, the size of the spending multiplier varies across different states of the U.S. business and financial cycle. During expansions, spending multipliers are approximately one but increase to 1.4 to 1.8 during recessions. Second, this paper finds no compelling evidence for an unambiguously large tax multiplier. Contrary to previous empirical estimates ranging from -2 to -3, the tax multiplier estimates fall between -0.1 to -0.4 and are swamped with uncertainty. This finding aligns more closely with results obtained by fiscal DSGE models. Third, given the estimated spending multipliers are larger in magnitude than the tax multipliers, this paper lends empirical support to the traditional Keynesian notion that U.S. output responds more to spending shocks than to tax shocks.

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Keywords: Fiscal policy, fiscal foresight, state-dependent multipliers, Markov switching, Bayesian VAR.

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1. Introduction

In response to the 2007-2009 financial crisis and COVID-19 pandemic, U.S. fiscal authorities implemented various policy measures aimed at stimulating the economy and stabilizing the business cycle. These events have reignited interest among policymakers and researchers in evaluating how changes in U.S. government spending and tax policy affect the real economy. Much of the empirical research in this area follows the tradition set by Blanchard and Perotti (2002), relying on structural VARs (SVARs) to examine these effects. These studies often summarize their findings in terms of multipliers, which measure the dollar amount change in output resulting from a one-dollar change in government spending or tax revenue.[1] Despite the extensive body of work, there is still no consensus on the size of these fiscal multipliers.

One possible explanation for the disparate multiplier estimates lies in Leeper, Walker, and Yang (2013) (LWY). They argue that standard SVARs struggle to provide reliable estimates due to the anticipation effects of fiscal policy. For instance, households, workers, firms, and investors often anticipate and react to future changes in spending and tax policy well before their implementation. This phenomenon, known as "fiscal foresight," stems from the inherent time delays within the policymaking process.[2] LWY show that such foresight poses a formidable identification challenge for SVARs. When foresight is present, the econometrician cannot recover the true fundamental policy shocks of interest from current and past observable data. This limitation arises because the information set of the agents is strictly larger than that available to the econometrician. This misalignment of information sets leads to the recovery of non-fundamental shocks that lack information of the anticipation effects. According to LWY, SVARs that fail to account for fiscal foresight may yield biased multiplier estimates and produce misleading conclusions about the dynamic impacts of fiscal policy.

The primary contribution of this paper is to address the issue of fiscal foresight by estimat-

[1] Ramey (2019) offers a comprehensive overview of the government spending and tax multiplier literature.

[2] For instance, changes in U.S. fiscal policy involve two distinct lags: a legislative lag—between the announcement of a new fiscal measure and its passage through Congress and approval by the President—and an implementation lag—from the moment the President signs the legislation into law to when it takes effect.

ing Markov-switching Bayesian VARs (MS-BVARs). An MS-BVAR resolves the identification issue posed by foresight by explicitly capturing agents' expectations of future fiscal regime changes. In this context, rational agents are assumed to form expectations based on all available information. If agents observe fiscal regime switches in the past, they will incorporate the possibility of switching regimes in the future when forming expectations.[3] This paper employs an MS-BVAR to recover the same underlying probability distribution of possible future policies that agents draw from. As a result, the MS-BVAR realigns the agents' and the econometrician's information sets, thereby resolving the aforementioned identification issue.

The motivation behind this MS approach comes from Davig and Leeper (2007b). Using a rational expectations (RE) MS model, they demonstrate that the determinacy of RE equilibrium depends not only on the current policy stance but also on all possible future policies and the transition probabilities among policy regimes. Davig and Leeper illustrate this by partitioning the parameter space of their model into two disjoint regions: one where a unique, determinate RE equilibrium exists, and another with multiple, indeterminate equilibria influenced by non-fundamental shocks. Interestingly, the MS model expands the region of determinacy compared to its fixed-regime equivalent. This finding is significant as it suggests that a MS model, unlike a fixed-regime one, has the capability to identify and recover fundamental shocks in situations where fiscal foresight complicates matters.

Another advantage of the MS technology is its ability to compute state-dependent fiscal multipliers, an area that has received increasing attention in recent years. One interesting question is whether fiscal multipliers are higher than normal during recessions. Current findings on this matter are inconclusive. Auerbach and Gorodnichenko (2012), Fazzari, Morley, and Panovska (2015, 2021), and Jo and Zubairy (2022) find that fiscal multipliers tend to be larger during recessions due to reduced crowding-out effects on private consumption and investment. In contrast, Owyang, Ramey, and Zubairy (2013), Ramey and Zubairy (2018), Rossi, Inoue, and Wang (2022), and Laumer and Phillips (2023) do not observe substantial

[3] This point has been emphasized by Cooley, LeRoy, and Raymon (1984) and Sims (1987), among others.

variations in multipliers. Thus, a second contribution of this paper is to shed light on whether spending and tax multipliers depend on the state of the business cycle.

The MS-BVARs are estimated on quarterly U.S. per capita real government spending, real tax revenue, real GDP, inflation, and short- and long-term government interest rates spanning from 1960 to 2019. By incorporating inflation and interest rates, this paper extends the information set used by Blanchard and Perotti (2002).[4] This extension serves two purposes. First, as noted by Caldara and Kamps (2017) and Yong and Dingming (2019), prices and interest rates react to signals about future policy changes. Incorporating these variables can address the information deficiency issue detailed by Forni and Gambetti (2014) and Forni, Gambetti, and Sala (2019). Second, the inclusion of these variables offers a better picture of how fiscal policy transmits to the nominal, financial, and real sides of the economy.

Identification of the MS-BVARs builds on the framework proposed by Blanchard and Perotti (2002). Fiscal policy shocks are identified using a non-recursive strategy grounded in three key assumptions. First, government spending only responds to its own shock within the same period. This identifying assumption reflects the fact that changing spending decisions often takes time due to the legislative and implementation lags inherent in the political process. Second, tax revenue responds only 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 of variables is placed before the macro/financial block of variables, implying spending and tax shocks have an immediate effect on the production and financial sectors.

The recursive ordering within the macro/financial block identifies four additional shocks. Ordering output before inflation assumes that aggregate supply shocks drive price fluctuations at impact, while output has a delayed response to aggregate demand shocks. Both interest rates react instantly to aggregate supply and demand shocks. Following Favero and Giavazzi (2007), unanticipated movements in the short-term interest rate signify changes in the government debt financing cost. Lastly, by having the long-term rate immediately adjust

[4] Perotti (2005) and Caldara and Kamps (2017) also integrated inflation and the long-term government interest rate into the Blanchard and Perotti (2002) information set.

to short-term rate shocks, a RE term structure is embedded into the MS-BVAR.

Estimation of the MS-BVARs is carried out using a Metropolis-within-Gibbs Markov chain Monte Carlo (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 these posteriors to determine the MS-BVAR that best fits the data.

The best-fit MS-BVAR imposes two distinct Markov chains on the structural coefficients of the fiscal policy block regressions, two more on the structural coefficients 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 and coincides with NBER dated recessions. However, there is a large degree of uncertainty regarding the scale of fiscal policy and term premium shocks in the other SV regime.

Furthermore, the best-fit MS-BVAR produces evidence indicating frequent regime switching in the structural coefficients of the fiscal policy and macro/financial block regressions. One fiscal policy regime is associated with historical episodes of tax cuts and expansions in government spending. This finding resembles the fiscal policy regimes mentioned by Steuerle (2006) and Davig and Leeper (2007a). During these episodes, taxes are only responsive to aggregate supply shocks, while tax and aggregate supply shocks produce a larger response in the other fiscal policy regime. The macro/financial regimes mirror the U.S. business and financial cycle, as output responds more significantly to fiscal policy shocks at impact during recessions compared to expansions.

Three key findings emerge. First, the size of the spending multiplier is influenced by the U.S. business and financial cycle. During periods of economic expansion, the spending multiplier remains close to one, but it increases to a range of 1.4 to 1.8 during recessions. Such observations give backing to the claim of state-dependent multipliers as suggested by Auerbach and Gorodnichenko (2012), Fazzari, Morley, and Panovska (2015, 2021), and Jo and Zubairy (2022).

Second, the best-fit MS-BVAR does not present compelling evidence supporting a significantly large tax multiplier. Previous studies, such as Romer and Romer (2010) and Mertens and Ravn (2013), identified tax multipliers between -2 to -3, while Mountford and Uhlig (2009) pinpointed an even greater tax multiplier at -5. The tax multiplier estimates in this paper are considerably lower, ranging from -0.1 to -0.4, and they are accompanied by a considerable degree of uncertainty. While at odds with previous estimates, this finding resonate with findings from fiscal DSGE models, as seen in Coenen et al. (2012) and Ramey (2019).

Third, given the spending multipliers are larger in magnitude than the tax multipliers, this paper lends empirical support to the traditional Keynesian notion that U.S. output responds more to spending shocks than to tax shocks.

The rest of this paper is organized as follows. Section 2 describes the identification strategy. Section 3 introduces the MS-BVARs and outlines the estimation and model evaluation procedure. Model fit and estimation results appear in section 4. Section 5 employs the best-fit MS-BVAR to assess the dynamic impacts of fiscal policy on U.S. output. Section 6 concludes.

2. Identifying Fiscal Policy Shocks

This section identifies fiscal policy shocks within a constant coefficient framework. I begin by mapping Blanchard and Perotti's (2002) fiscal policy SVAR to the SVAR proposed by Sims and Zha (1998). As will be seen, the Sims-Zha SVAR is the constant coefficient version of the MS-BVARs employed later in the paper. Identification is achieved by imposing Blanchard and Perotti's short-run (zero) restrictions on the contemporaneous relationships among the fiscal and macroeconomic variables. After mapping the Blanchard-Perotti SVAR, I expand their identification strategy to incorporate financial variables.

2.1. A Constant Coefficient SVAR

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

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

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

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

$$y_t' A_0 = x_t' A_+ + \varepsilon_t', \quad \varepsilon_t \sim \mathcal{N}(0_{n\times 1}, I_n), \tag{2.2}$$

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-form regressions

$$y_t' = x_t' \Phi + u_t', \quad u_t \sim \mathcal{N}(0_{n\times 1}, \Sigma_u), \tag{2.3}$$

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

2.2. Mapping the Fiscal Policy SVAR of Blanchard and Perotti (2002)

Blanchard and Perotti (2002) (BP) assess the effects of fiscal policy on U.S. output using the SVAR

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

where $y_t \equiv [\mathrm{GOV}_t \ \mathrm{TAX}_t \ \mathrm{RGDP}_t]'$, GOV_t is the log of per capita real government spending, TAX_t is the log of per capita real tax revenue, and 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, while the SZ-SVAR (2.1) leaves these coefficients unrestricted. Second, the BP-SVAR (2.4) allows for restrictions on the response matrix of the structural shocks B, while the SZ-SVAR (2.1) assumes $B = I_n$.

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 ε_t. BP posit this mapping can be expressed as $A' u_t = B' \varepsilon_t$ such that

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

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

and

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

Equation (2.5) states GOV shocks (ε_t^{GOV}) are driven by forecast innovations in GOV and RGDP (u_t^{GOV} and u_t^{RGDP}) and TAX shocks (ε_t^{TAX}). A similar interpretation applies to TAX shocks in equation (2.6). Moving on to equation (2.7), it specifies that aggregate supply shocks (ε_t^{RGDP}) are driven by the three forecast innovations u_t^{GOV}, u_t^{TAX}, and u_t^{RGDP}. Notably, aggregate supply shocks do not directly affect GOV and TAX shocks. Writing equations (2.5)-(2.7) in matrix form yields

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

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

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

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

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

To identify fiscal policy shocks within the SVAR framework, I impose certain restrictions based on Blanchard and Perotti (2002). These restrictions are as follows. First, the impact of forecast innovations in RGDP and TAX on GOV within a quarter is set to zero ($b_1 = b_2 = 0$). This reflects the belief that government spending decisions are often made in advance and require time to change due to legislative and implementation lags. Additionally, government decisions on spending are assumed to be taken before decisions on revenue, meaning that structural TAX shocks do not affect GOV at impact. Second, the impact of forecast innovations in GOV and RGDP on TAX within a quarter are left unrestricted (a_1 and a_2 are free parameters). This means that structural TAX shocks can be influenced by forecast errors in GOV and RGDP within the same quarter. Third, the asymptotic 95% confidence interval of a_2 contains zero, which justifies setting $\frac{B_{21}}{A_{0,22}} = 0$. This restriction is based on empirical evidence suggesting that the impact of government spending on real GDP may not be entirely transmitted to tax revenues in the short term.

By applying these restrictions, the BP-SVAR (2.4) is mapped to the SZ-SVAR (2.1) as follows

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

where

$$A_0^* = \frac{A_{0,11}A_{0,22}}{A_{0,11}A_{0,22} - B_{12}B_{21}} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & \frac{A_{0,23}}{A_{0,22}} \\ \frac{A_{0,31}}{A_{0,33}} & \frac{A_{0,32}}{A_{0,33}} & 1 \end{bmatrix} = \begin{bmatrix} A_{0,11}^* & 0 & 0 \\ 0 & A_{0,22}^* & A_{0,23}^* \\ A_{0,31}^* & A_{0,32}^* & A_{0,33}^* \end{bmatrix}.$$ [5]

2.3. Expanding the Blanchard-Perotti Fiscal Policy SVAR

This section expands upon the Blanchard-Perotti fiscal policy SVAR by incorporating fiscal, macroeconomic, and financial variables. The information set y_t consists of two blocks: a fiscal policy ($\mathcal{FP}$) block, consisting of GOV_t and TAX_t, followed by a macro/financial ($\mathcal{MF}$) block, comprising RGDP_t, the GDP deflator inflation rate (π_t), the three-month U.S. Treasury bill

[5] 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.

rate ($R_{3m,t}$), and the constant maturity yield on ten-year U.S. Treasury bonds ($R_{10yr,t}$).[6] This redefines y_t as the $6(= n) \times 1$ vector

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

The sample period runs from 1960Q1 to 2019Q4, totaling $T = 240$ observations. Data for the fiscal and macro variables come from the National Income and Product Accounts (NIPA) tables, published by the Bureau of Economic Analysis (BEA). Short- and long-term government interest rates are gathered from the Federal Reserve Bank of St. Louis's FRED database. Quantity variables are expressed in natural logs and scaled by 100, while inflation and interest rates are in percentage terms. Further details on data construction and sources are available in the Data Appendix.

Expanding the information set y_t enables an examination of how fiscal policy shocks are transmitted to the nominal, financial, and real sides of the economy. Additionally, inflation and interest rates offer insights into agents' expectations related to future fiscal policy and term premiums, as suggested by Caldara and Kamps (2017) and Yong and Dingming (2019).

2.4. Identifying the Fiscal Policy Transmission Mechanism

In this section, I present three different approaches to identify the fiscal policy transmission mechanism. These identification schemes rely on imposing short-run (zero) restrictions on the impact matrix A_0'. The first identification scheme follows Blanchard and Perotti's (2002) identifying assumptions regarding the timing of tax, transfer, and spending programs. The other two identifications are recursive and serve as straightforward robustness checks.

[6] An alternative approach was considered, which involved partitioning the $\mathcal{MF}$ block into separate macro ($\mathcal{M}$) and financial ($\mathcal{F}$) blocks. However, attempts to estimate MS-BVARs with distinct Markov chains on the $\mathcal{FP}$, $\mathcal{M}$, and $\mathcal{F}$ block regressions prove unsuccessful. This issue will be revisited in future research.

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

The first identification is non-recursive.[7] The mapping between the reduced-form regression errors of the system (2.3) to the errors of the SEM (2.2) can be represented as

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

The identifying restrictions on the $\mathcal{FP}$ block mirror those imposed by Blanchard and Perotti (2002). Specifically, the fiscal policy variables, GOV and TAX, do not respond to the other fiscal policy shock at impact. Additionally, I assume that TAX immediately responds to RGDP shocks. This identifying assumption implies that the fiscal authority follows a policy rule that adjusts TAX to accommodate aggregate supply shocks.

The $\mathcal{MF}$ block comes after the $\mathcal{FP}$ block, implying that the macro and financial variables respond to fiscal policy shocks at impact. Placing RGDP before π assumes that aggregate supply shocks immediately affect prices, while aggregate demand shocks have a lagged effect on output.

Interest rates are ordered last and respond to fiscal policy and macro shocks in the same quarter. As suggested by Favero and Giavazzi (2007), an unanticipated increase in $\mathrm{R_{3m}}$ raises the cost of financing government debt, thereby leading me to identify shocks to $\mathrm{R_{3m}}$ are identified as debt financing shocks. Additionally, I embed a rational expectations term structure in the SVAR by ordering $\mathrm{R_{3m}}$ before $\mathrm{R_{10yr}}$. This ordering thus identifies an unanticipated change in $\mathrm{R_{10yr}}$ as a term premium shock.

[7] 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 can be found in Appendix B.

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 in section 2.3. In this identification approach, I impose restrictions on A_0' to be lower-triangular, resulting in the following structure

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

This recursive ordering place GOV first, assuming that GOV does not respond to TAX and $\mathcal{MF}$ block shocks at impact. This assumption is justified by BP, who argue that spending decisions are predetermined. TAX is ordered second, indicating 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. The identification of shocks in the $\mathcal{MF}$ block remains the same as before.

2.4.3. *Recursive Impact Matrix: Government Spending Rule*

Switching the order of GOV and TAX in y_t leads to the second recursive identification

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

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

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 propose the following structural MS-BVAR

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

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 ε_t. The values of s_t are belong to a finite set $\{1, \ldots, H\}$, where H represents the number of regimes. SWZ collect all the parameters across each state to form $A_0 \equiv \{A_0(h)\}$, $A_+ \equiv \{A_+(h)\}$, and $\Xi \equiv \{\Xi(h)\}$ for $h = 1, \ldots, H$. Let $\theta \equiv \{A_0, A_+, \Xi\}$ and $Y_T \equiv \{y_1, \ldots, y_T\}$.

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

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

The likelihood function for the MS-BVAR (3.1) is given by:

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

where $p(s_t|Y_{t-1}, \theta, Q)$ represents 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 $S_T \equiv \{s_1, \ldots, s_T\}$ from the likelihood (3.2).

The joint posterior distribution of θ and Q is calculated using Bayes' rule

$$p(\theta, Q|Y_T) \propto p(Y_T|\theta, Q)\, p(\theta, Q), \tag{3.3}$$

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

3.2. Accounting for Fiscal Foresight in MS-BVARs

Standard identification strategies assume that the fundamental shocks can be recovered from current and past observable data in y_t. However, Ramey (2011) and Leeper, Walker, and Yang (2013) argue that this assumption may not hold when identifying a conventional fiscal policy SVAR. They contend that the GOV and TAX shocks recovered by the econometrician are predictable and likely to have been anticipated by households, workers, firms, and investors. This anticipation of future changes in spending and tax policy is commonly referred to as "fiscal foresight," which arises due to legislative and implementation lags associated with fiscal policymaking. As a result, there is a misalignment between the information sets of the econometrician and the agents in the SVAR.

Lippi and Reichlin (1994) offer one empirical approach that can address fiscal foresight. Their approach starts from the observation that anticipated shocks are the source of forward-looking non-fundamental MA components in VARs. The existence of non-fundamental MA components leads to the non-existence of a direct mapping from the reduced-form regression errors of the system (2.3) to the errors of the SEM (2.2). This violation of the Wold Decomposition theorem makes it challenging for the econometrician to recover the fundamental shocks of interest from current and past information in y_t. Lippi and Reichlin (1994) use Blaschke matrices to discount the forward-looking MA components subject to anticipated shocks, effectively addressing the problem of non-fundamentalness in a VAR. Building on this strategy, Mertens and Ravn (2010) apply the Lippi and Reichlin (1994) estimation method to recover anticipated fiscal policy shocks in a SVAR.

Another empirical approach to tackle fiscal foresight is through an MS-BVAR. The inspiration for considering MS-BVARs is derived from the insights of Davig and Leeper (2007b). Using a conventional new Keynesian model, Davig and Leeper explore the consequences of a violation of the Taylor principle in an environment where agents ember the possibility of policy regime switches into their expectations formation. They find that as long as agents assign a positive probability to switching to a stable regime, temporarily violating the Taylor rule does not lead to price level indeterminacy. Consequently, an MS model expands the region of equilibrium determinacy in the parameter space compared to its constant coefficient counterpart.

Expanding on Davig and Leeper's (2007b) reasoning, the concept of fiscal foresight can be incorporated. For instance, if agents are currently in one fiscal policy regime but anticipate a switch to another regime in the future, they implicitly construct probability distributions over these regimes. According to Davig and Leeper, these probability distributions are an important component of the agents' information set and play a crucial role in how they base their current expectations and decisions. An MS-BVAR provides the econometrician these probability distributions. As a result, the information sets of the agents and econometrician should realign.

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 the SV factor loadings in θ. Following Sims, Waggoner, and Zha (2008), I apply Sims and Zha's (1998) random walk prior to θ.

This prior assumes that y_t consists of n independent random walk processes. The behavior of these random walk processors is controlled via six hyperparameters, which are gather in the vector $\Lambda = [\lambda_0\ \lambda_1\ \lambda_3\ \lambda_4\ \mu_5\ \mu_6]$.[8] 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 probabilities in Q, which reflects beliefs about regime switching in the model. As will be discussed in section 3.4, various estimated MS-BVARs impose restrictions on the Markov chain for the structural coefficients of the $\mathcal{FP}$ block regressions compared to those of the $\mathcal{MF}$ block regressions. To achieve this, I employ a Dirichlet prior with a four-year setting for the $\mathcal{FP}$ block Markov chain. This choice is informed by the observation that fiscal policy changes are often initiated within the first term of a U.S. presidential administration. For the $\mathcal{MF}$ block Markov chain, I set the Dirichlet prior to three years, aligning with the belief that U.S. business and financial cycles typically last for a duration similar to a U.S. presidential administration. This prior setting is motivated by Drazen's (2001) evidence of a U.S. political business cycle.

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 that constitute the model space. The labels "#c" and "#v" for MS-BVAR-1 to -9 indicate the number of structural coefficient regimes and the number of SV regimes, respectively. For example, models MS-BVAR-1 to -3 are labeled as "1c2v," indicating models with constant structural coefficients and MS in the SVs. Models MS-BVAR-4 to -6 are MS-BVARs with MS structural coefficients and constant volatilities.

[8] Sims and Zha (1998) describe these hyperparameters as controlling the overall tightness of the prior on own first lags, λ_0, the relative tightness of the prior on lags of the other $n-1$ variables in y_t, λ_1, the relative tightness of the prior on the rate of lag decay, λ_3, the relative tightness of the prior on the intercept term, λ_4, and the prior beliefs about unit roots, μ_5, and cointegration relationships, μ_6, among the variables in y_t.

Models MS-BVAR-7 to -9 assume MS in both the structural coefficients and SVs.

Models MS-BVAR-10 to 15 introduce the possibility of distinct MS regimes for the structural coefficients in the $\mathcal{FP}$ and $\mathcal{MF}$ block regressions, as well as for the SVs. These specifications account for the possibility that fiscal policy and macroeconomic/financial conditions may evolve differently from one another. The labels "$\#\mathcal{FP}$c" and "$\#\mathcal{MF}$c" indicate the number of structural coefficient regimes in the $\mathcal{FP}$ and $\mathcal{MF}$ block regressions, respectively. Models MS-BVAR-10 to -12 are labeled as "2$\mathcal{FP}$c, 2v" to represent MS-BVARs with MS restricted to the $\mathcal{FP}$ block's structural coefficients and SVs while keeping the $\mathcal{MF}$ block's structural coefficients constant. Models MS-BVAR-13 to -15 allow for distinct MS structural coefficients in both the $\mathcal{FP}$ and $\mathcal{MF}$ blocks, as well as SVs.

Post-1960 U.S. fiscal policy can be classified into two regimes. One regime, as argued by Steuerle (2006) and Davig and Leeper (2007a), is characterized by increases in government spending or tax cuts. Examples of this regime include President LBJ's "Great Society" social programs and the response of the Bush and Obama administrations to the 2007-2009 financial crisis and recession. Additionally, President Kennedy's 1963 tax cuts and President Reagan's series of tax cuts and reforms in 1981, 1982, 1983, and 1986 fall under this category. The second fiscal policy regime aims at balancing the budget or stabilizing the debt-to-GDP ratio, describing the Clinton era fiscal and the later portion of the Obama administration.

3.5. Estimation and Model Evaluation Procedure

The MS-BVARs are estimated with a Metropolis-within-Gibbs MCMC algorithm. This section briefly describes the algorithm and the procedure used to select the best-fit model, leaving the technical details to Sims, Waggoner, and Zha (2008).

Given the sample data, priors, and $p = 2$,[9] 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.

[9]The Hannan-Quinn Criterion (HQC) selects $p = 2$ as the optimal lag length for the MS-BVAR.

Step 1. Estimate the posterior mode of θ 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 θ 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

$$p\left(S_T^{(k)}|Y_T, \theta^{(k-1)}, Q^{(k-1)}\right),$$
$$p\left(Q^{(k)}|Y_T, S_T^{(k)}, \theta^{(k-1)}\right),$$

and
$$p\left(\theta^{(k)}|Y_T, Q^{(k)}, S_T^{(k)}\right),$$

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

Step 4. Discard the first $K_1 = 5$ million draws as the burn-in sample. Construct the posterior distribution of the MS-BVAR with the remaining $K_2 = 10$ million draws.

Step 5. Calculate the MDD with SWZ's truncated modified harmonic mean (HMH) estimator.[10]

The MS-BVARs are estimated and evaluated using Dynare's SWZ MS-BVAR code within Matlab; see Adjemian et al. (2011) for details.[11]

4. Estimation Results

This section presents the estimation results for the best-fit MS-BVAR.

[10]Due to the substantial computational costs associated with generating a full set of estimation results for an MS-BVAR, only the MDD is computed during the first estimation run. A complete set of results is generated during a second round of estimation for the best-fit MS-BVAR(s). The preference of the data for this (or these) MS-BVAR(s) is once again verified by checking the posterior(s) constructed in the second round.

[11]The computations were performed on high-performance computing (HPC) clusters to handle the computational demands of the estimation process. I thank the HPC centers at North Carolina State University and the University of Mississippi for allowing me access to their Linux clusters. Codes are available upon request.

4.1. Model Fit of the MS-BVARs

Table 2 summarizes the model fit of the MS-BVARs, along with three constant coefficient BVARs corresponding to different identification schemes (see section 2.4). The constant coefficient BVARs are used as a baseline for comparing the preference of the data for either constant or MS coefficient specifications. The results show that the MS-BVARs (MS-BVAR-1 to -15) outperform the constant coefficient BVARs (BVAR-1 to -3) in terms of model fit. Introducing MS in the structural coefficients and/or SVs improves the model fit. However, the data strongly prefer the MS-BVARs (MS-BVAR-7 to -15) with MS in both the structural coefficients and SVs, over the ones with MS only in SVs (MS-BVAR-1 to -3) or structural coefficients (MS-BVAR-4 to -6).

The most significant finding in table 2 is that the MS-BVAR-13 achieves the best fit to the data. This MS-BVAR employs two distinct Markov chains for the structural coefficients in the $\mathcal{FP}$ block, two more for the structural coefficients in the $\mathcal{MF}$ block, and assumes two regimes for the SVs. Moveover, the MS-BVAR-13 is identified using the non-recursive impact matrix in section 2.4.1. The log MDD estimates in table 2 demonstrate a strong preference of the data for MS-BVAR-13 compared to other MS-BVARs with either the same identification (MS-BVAR-1, -4, -7, and -10) or the same MS specification (MS-BVAR-14 and -15). The difference in log MDD between MS-BVAR-13 and MS-BVAR-14, which has 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 subsequent analysis focuses on estimates produced by MS-BVAR-13.

4.2. Transition Matrices of MS-BVAR-13

The estimated posterior medians of the regime transition matrices for the structural coefficients of the $\mathcal{FP}$ block and the $\mathcal{MF}$ block, denoted as $\widehat{Q}^{\mathcal{FP}c}$ and $\widehat{Q}^{\mathcal{MF}c}$ respectively, are presented below

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

where the brackets below each estimate contain 90% Bayesian credible sets.[12]

The $\widehat{Q}^{\mathcal{FP}c}$ matrix shows that the first $\mathcal{FP}$ block regime exhibits less persistence compared to the second regime. The expected duration of the first regime is approximately six quarters, while the second regime is more persistent, with an expected duration of around sixteen quarters. In contrast, the $\widehat{Q}^{\mathcal{MF}c}$ matrix indicates both $\mathcal{MF}$ block regimes last on average for twelve quarters. These results suggest that fiscal policy behavior is more likely to change than macroeconomic and financial conditions.

Additionally, the SV regimes are found to be quite persistent, as shown in the following estimated posterior medians for $\widehat{Q}^{sv}$

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

The first SV regime has an expected duration of over twelve quarters, while the second SV regime is expected to last for approximately thirty quarters. These findings suggest that the sizes of structural shocks hitting the economy do not change frequently.

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

Figure 1 presents the smoothed conditional probabilities of the SV regimes and the structural coefficient regimes for the $\mathcal{FP}$ and $\mathcal{MF}$ block regressions from 1960Q1 to 2019Q4. The probabilities are smoothed following the method of Kim (1994). The shaded bars in each panel indicate NBER recession dates.

[12]The 90% Bayesian credible sets are the 5th and 95th quantiles of the posterior distributions.

The top panel of figure 1 shows the SV regime probabilities of MS-BVAR-13. The first SV regime aligns with most of the NBER-dated recessions in the sample, but it is dormant during periods of economic expansions. However, it fails to capture the 1991 and 2001 recessions. Notably, the SV regime probabilities provide insights into the dynamics of the business/financial cycle.

The middle panel of figure 1 displays the conditional probabilities of the $\mathcal{FP}$ block regimes. The first $\mathcal{FP}$ block regime covers historical episodes of tax cuts and expansions in government spending, such as the tax cut of 1975 after the 1973 oil crisis, the Tax Reform Act of 1986, and the fiscal responses to the 2001 and 2007-2009 recessions. Additionally, the regime corresponds to the passage of the American Recovery and Reinvestment Act of 2009, aimed at mitigating the effects of the 2007-2009 recession and financial crisis. After 2010Q1, the first $\mathcal{FP}$ block regime becomes more frequent, consistent with the increase in government spending and tax cuts implemented during the aftermath of the 2007-2009 recession and financial crisis under the Obama and Trump administrations.

The bottom panel of figure 1 presents the probabilities for the second $\mathcal{MF}$ block regime, which captures the U.S. business cycle. It covers the run-up and duration of each NBER-dated recession in the sample. Notably, the regime does not precisely match the exact quarters of every peak and trough of the business cycle. This discrepancy can be attributed to the fact that the structural coefficients of the macro variable regressions in the $\mathcal{MF}$ block switch regimes at the same time as the financial variable regressions. As a result, the second $\mathcal{MF}$ block regime also captures the financial cycle, explaining its ability to detect events like the Savings and Loan (S&L) Crisis in the mid-1980s, as well as the Mexican and Asian financial crises in the 1990s.

4.4. Impact and SV Matrices of MS-BVAR-13

Table 3 provides the median estimates of the regime-dependent scale volatilities $\Xi^{-1}(s_t)$ for the MS-BVAR-13, along with the corresponding 90% Bayesian credible sets. As in Sims, Waggoner, and Zha (2008), the scale volatilities of the first SV regime ($s_t^{sv} = 1$) are reported after being normalized to one. The results show that the second SV regime ($s_t^{sv} = 2$) exhibits less volatility compared to the first regime. For instance, the loading scales on GOV, TAX, RGDP, π, $\mathrm{R}_{3\mathrm{m}}$, and $\mathrm{R}_{10\mathrm{yr}}$ shocks are smaller by factors of 1.5, 1.9, 3.6, 2.9, 8.2, and 1.4, respectively, when the economy is in the second SV regime. This suggests that episodes of greater SV in aggregate supply, aggregate demand, and debt financing shocks coincide with NBER-dated recessions. It is worth noting that there is relatively wide uncertainty (indicated by wide credible sets) regarding the scale of GOV, TAX, and term premium shocks across regimes, implying considerable uncertainty about the size of these shocks.

Tables 4 and 5 present the median estimates of the impact matrices $\widehat{A_0}(s_t^{FPBc} = i | s_t^{MFBc} = i)$ for $i = 1, 2$ for MS-BVAR-13.[13] A comparison between the two impact matrices reveals interesting differences between the first and second $\mathcal{FP}$ block regimes. For example, the estimated median own shock response for GOV is higher when the economy is in the first $\mathcal{FP}$ block regime. Moreover, TAX is only responsive to aggregate supply shocks in the first $\mathcal{FP}$ block regime, but when the economy switches to the second $\mathcal{FP}$ block regime, the TAX response to its own shock increases more than fourfold. Similarly, the response of TAX to aggregate supply shocks also increases significantly.

Regarding the $\mathcal{MF}$ block regimes, the second regime captures the U.S. business cycle, covering the run-up and duration of each NBER-dated recession in the sample. Interestingly, the $\mathcal{MF}$ block regime's response to GOV shocks is larger during recessions than in expansions, as evidenced by the response of RGDP to GOV shocks increasing almost threefold when switching to the second regime. Furthermore, there is little evidence of TAX shocks having an immediate effect on RGDP in either regime. The $\mathrm{R}_{3\mathrm{m}}$ response to aggregate supply shocks is stronger in the first $\mathcal{FP}$ block regime, but its own shock response is significantly higher in the second regime. Finally, the impact of aggregate demand shocks on $\mathrm{R}_{10\mathrm{yr}}$ is over

[13] To conserve space, appendix C reports the median estimates of impact matrices $\widehat{A_0}(s_t^{FPBc} = 1 | s_t^{MFBc} = 2)$ and $\widehat{A_0}(s_t^{FPBc} = 2 | s_t^{MFBc} = 1)$. However, these impacts matrices can be produced by combining the separate $\mathcal{FP}$ and $\mathcal{MF}$ block estimates together.

eleven times higher in the second $\mathcal{MF}$ block regime, indicating that inflation shocks have a strong effect on the term premium during recessions.

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

This section examines the effects of GOV and TAX shocks on RGDP through two different approaches. First, I construct GIRFs using an algorithm adapted from Karamé (2015) and Bianchi (2016). The GIRFs capture the responses of RGDP to GOV and TAX shocks, while taking into account the possibility of regime changes. Second, I employ the constructed GIRFs to compute present-value GOV and TAX multipliers.

5.1. GIRFs of U.S. Output to Government Spending Shocks

Figure 2 presents the conditional GIRFs of RGDP to a unit GOV shock. The dashed blue line represent the median responses while the shaded yellow areas are the corresponding 68% uncertainty bands. Each subplot in the figure shows the response of RGDP under the assumption that the specified $\mathcal{FP}$ and $\mathcal{MF}$ block regimes remain in place over the relevant horizon, while agents anticipate the possibility of regime changes.

Across all possible regime combinations, the median GIRFs demonstrate that RGDP responds positively to a GOV shock at all horizons. However, the shape of the response varies depending on the current state of the $\mathcal{MF}$ block regime, rather than the $\mathcal{FP}$ block regimes. When the first $\mathcal{MF}$ block regime prevails, RGDP exhibits an inverted hump-shaped response, reaching its lowest point at the 2-quarter horizon. It then takes about ten quarters for RGDP to reach its peak and remain at a permanently higher level. On the other hand, under the second $\mathcal{MF}$ block regime, the median GIRFs show an upward-trend shaped response of RGDP, with strictly positive 68% uncertainty bands throughout the relevant horizon. The shape of the GIRFs does not significantly differ across the $\mathcal{FP}$ block regimes. These findings indicate that the response of RGDP to a GOV shock depends more on the current state of the business/financial cycle rather than the prevailing fiscal policy regime.

5.2. GIRFs of U.S. Output to Tax Shocks

Figure 3 displays the conditional GIRFs of RGDP in response to a unit TAX shock, based on the median of the posterior of MS-BVAR-13. The magnitude of the responses is relatively small across all regimes. The largest impact response of RGDP to a TAX shock is around 0.02 in absolute terms. The median response when conditioning on the first $\mathcal{MF}$ block regime exhibits a hump-shaped pattern, peaking at the 3-quarter horizon and taking between five to eight quarters to revert back to zero. The 68% uncertainty bands around this median response are wide at all horizons, indicating considerable uncertainty in estimating the RGDP response to a TAX shock. When conditioning on the second $\mathcal{MF}$ block regime, the response of RGDP follows an L-shaped pattern, with the impact falling and remaining at a permanently lower level after two quarters. The 68% uncertainty bands are relatively narrow in this case. However, the uncertainty bands still contain zero at all horizons. As with the response to GOV shocks, the shape of the response to TAX shocks is more influenced by the current state of the business/financial cycle than the fiscal policy regime.

5.3. Present-Value Fiscal Multipliers

This section calculates present-value government spending and tax multipliers using the constructed GIRFs. As Leeper, Traum, and Walker (2017) explain, present-value multipliers account for the discounting of future changes in RGDP resulting from a fiscal policy shock. The k-period ahead present-value fiscal multipliers are computed as follows

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

and

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

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

Figures 4 and 5 display the median present-value GOV and TAX multiplier estimates, along with their 68% uncertainty bands. The results show that RGDP increases by more than a dollar in response to a GOV shock at impact, except when both the first $\mathcal{FP}$ and $\mathcal{MF}$ block regimes are present, resulting in an increase of about 84 cents. The largest GOV multiplier at impact is estimated to be 1.60, observed under the second $\mathcal{FP}$ and $\mathcal{MF}$ block regimes. The estimates are characterized by wide uncertainty bands, suggesting that the posterior of MS-BVAR-13 is unable to provide a precise estimate of the GOV multiplier. Additionally, the GOV multiplier is larger when conditioning on the second $\mathcal{MF}$ block regime compared to the first $\mathcal{MF}$ block regime, indicating the business/financial cycle regime plays a more significant role in shaping the GOV multiplier than fiscal policy regime changes.

In contrast, the median TAX multiplier remains negative for all 40 quarters after the initial TAX shock, with wide 68% uncertainty bands. This indicates considerable uncertainty surrounding the estimates of the TAX multiplier. At its widest range, the 68% uncertainty bands fluctuate from -1.5 to 0.5. This finding contrasts with previous studies that report TAX multipliers ranging from -2 to -3, as summarized by Ramey (2019).

5.4. Summary of Findings

To summarize, the posterior of MS-BVAR-13 suggests that RGDP responds positively to a GOV shock, with the GOV multiplier larger during recessions than expansions. However, there is no strong evidence of a large negative TAX multiplier, which is at odds with some previous studies. Nonetheless, the results shown here indicate that the GOV multiplier is larger than the TAX multiplier in all cases, aligning with the consensus in traditional Keynesian macroeconomics.

6. Conclusion

Fiscal foresight complicates the task of measuring the effect government spending and tax shocks have on output. The anticipation effects caused by agents reacting to future policy changes must be taken into account to fully understand how fiscal policy influences real economic activity. In this paper, I employ MS-BVARs as a means to address these anticipation effects. The MS-BVARs are estimated using quarterly U.S. fiscal, macroeconomic, and financial data spanning from 1960 to 2019.

Using the best-fit MS-BVAR, I compute generalized impulse response functions (GIRFs) and fiscal multipliers to assess how output responds to government spending and tax shocks. Several notable findings emerge. First, following a government spending shock, output experiences a permanent increase. However, the response of output to a spending shock varies depending on the prevailing state of the business cycle. Spending shocks have a more substantial positive effect on real GDP during recessions compared to expansions. Second, while tax shocks negatively impact output, the response of output to tax shocks is relatively small, regardless of the business cycle regime. Third, the estimated tax multipliers in this paper are also relatively small, contradicting previous research that reported significant negative effects of tax shocks on output. Finally, the finding that the spending multiplier is larger than the tax multiplier aligns with traditional Keynesian macroeconomics views.

One promising avenue for future research is exploring how the interaction between monetary and fiscal policies influences 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 behavior in accordance to fiscal authority actions. Integrating both monetary and fiscal policy variables into an MS-BVAR would enable a comprehensive examination of how fiscal policy impacts the transmission mechanism of monetary policy, and vice versa. Such investigation would provide valuable insights into the interplay between these policies and their combined effect on the economy.

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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

	Specification					
Identification	Constant Coefficient	1c2v	2c1v	2c2v	2$\mathcal{FP}$c,2v	2$\mathcal{FP}$c,2$\mathcal{MF}$c,2v
Non-Recursive Impact Matrix:	BVAR-1	MS-BVAR-1	MS-BVAR-4	MS-BVAR-7	MS-BVAR-10	**MS-BVAR-13**
Extended Blanchard-Perotti	-1772.60	-1629.91	-1648.83	-1578.62	-1583.31	**-1566.07**
Recursive Impact Matrix:	BVAR-2	MS-BVAR-2	MS-BVAR-5	MS-BVAR-8	MS-BVAR-11	MS-BVAR-14
Tax Rule	-1773.70	-1630.80	-1653.73	-1585.95	-1604.04	-1577.07
Recursive Impact Matrix:	BVAR-3	MS-BVAR-3	MS-BVAR-6	MS-BVAR-9	MS-BVAR-12	MS-BVAR-15
Government Spending Rule	-1773.70	-1629.93	-1653.34	-1610.76	-1596.42	-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	π	R_{3m}	R_{10yr}
$s_t^{sv} = 1$	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 $\widehat{A}_0'(s_t^{\mathcal{FP}c} = 1|s_t^{\mathcal{MF}c} = 1)$, MS-BVAR-13, 1960Q1 to 2019Q4

Shock \ Variable	GOV	TAX	RGDP	π	R_{3m}	R_{10yr}
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]

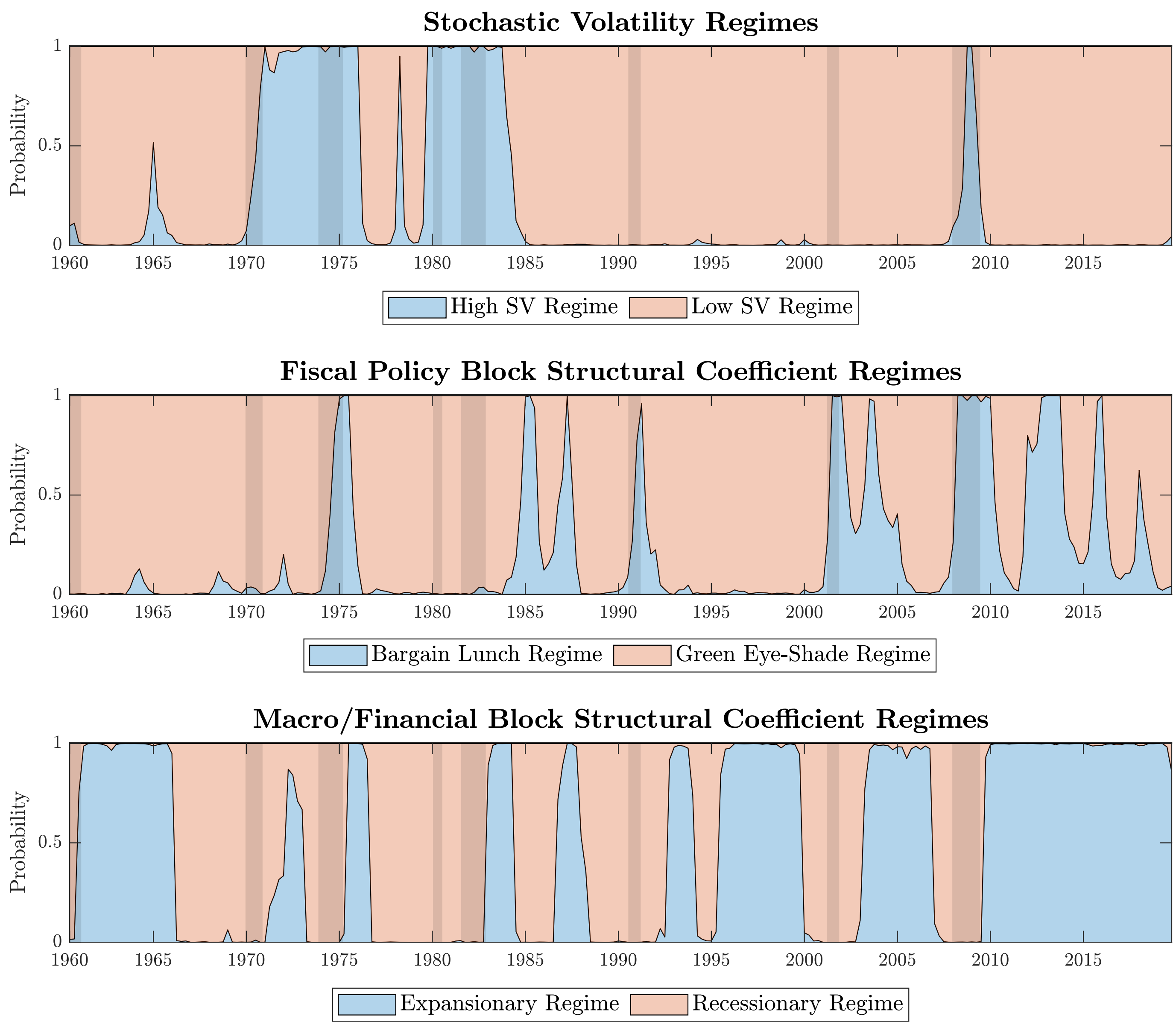
Notes: The elements of $\widehat{A}_0'(s_t^{\mathcal{FP}c} = 1|s_t^{\mathcal{MF}c} = 1)$ are at the median of the posterior of MS-BVAR-13. Each row represents a behavioral equation. The behavioral equations are labeled by their respective structural shock. The column labels indicate which variables enter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

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

Shock \ Variable	GOV	TAX	RGDP	π	R_{3m}	R_{10yr}
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]

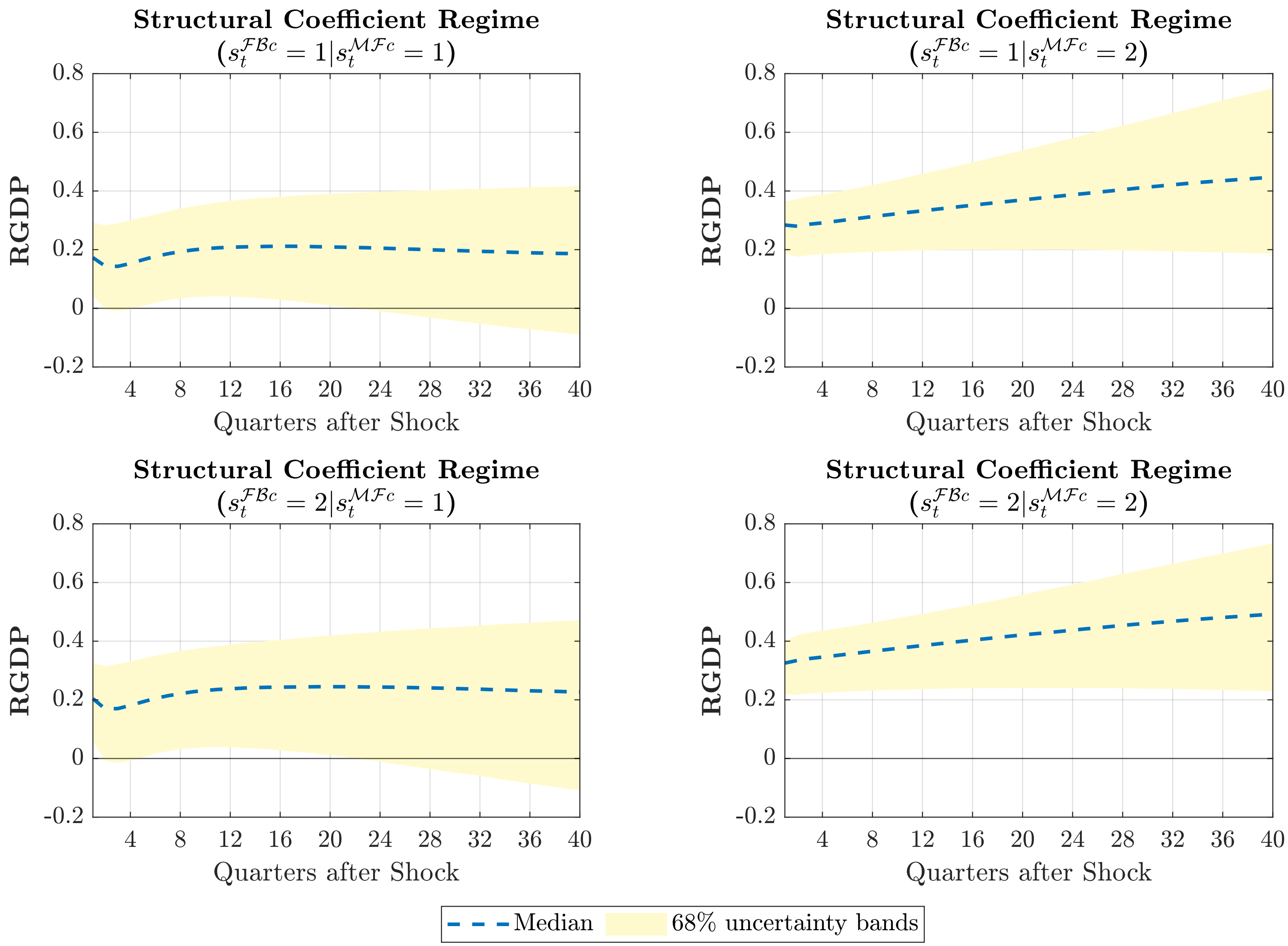
Notes: See the notes to table 4.

Figure 1: Smoothed Conditional Regime Probabilities of MS-BVAR-13, 1960Q1 to 2019Q4



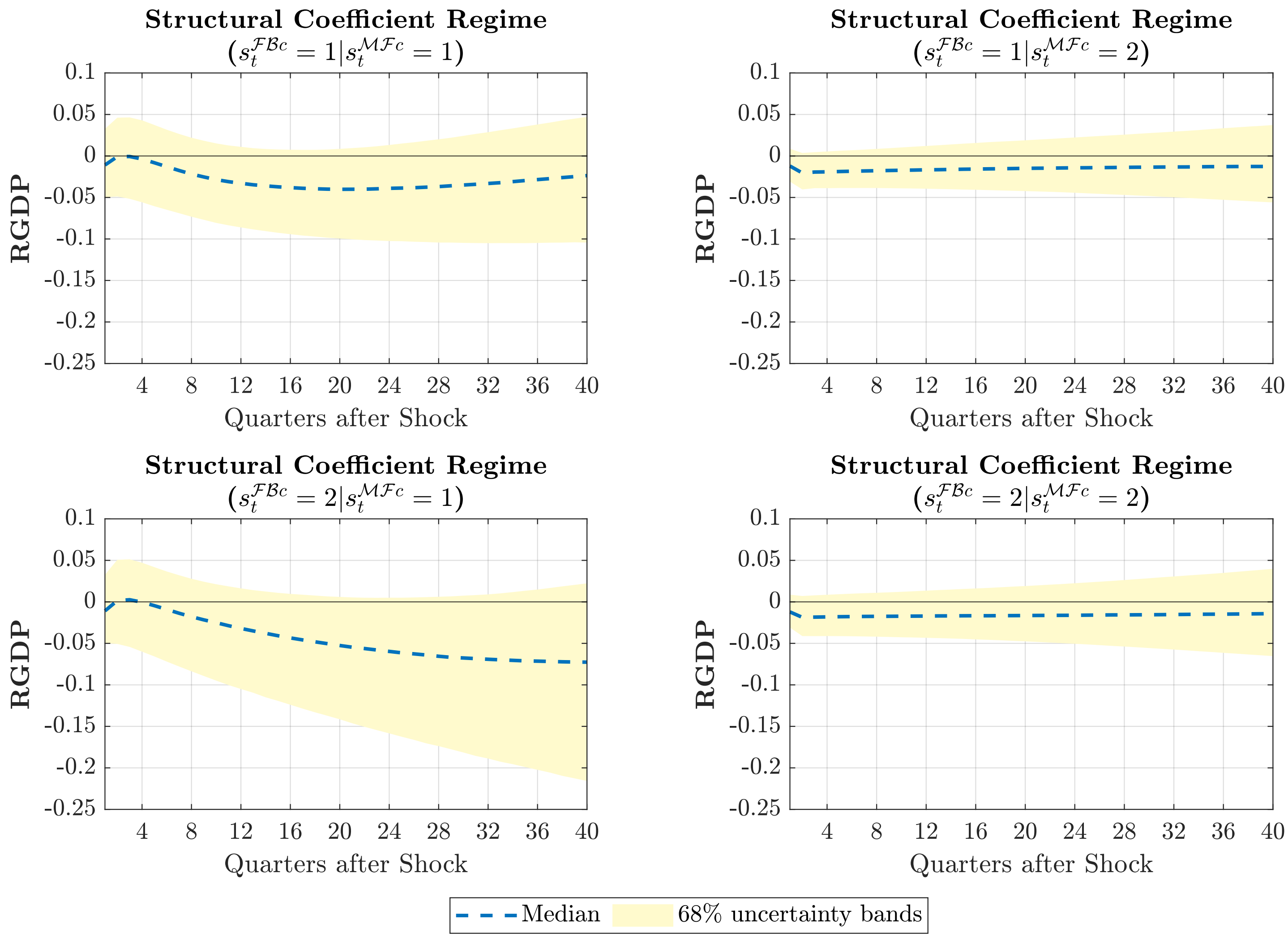
Notes: Shaded bars indicate NBER recession dates.

Figure 2: Conditional GIRFs of RGDP with Respect to a Government Spending Shock of MS-BVAR-13



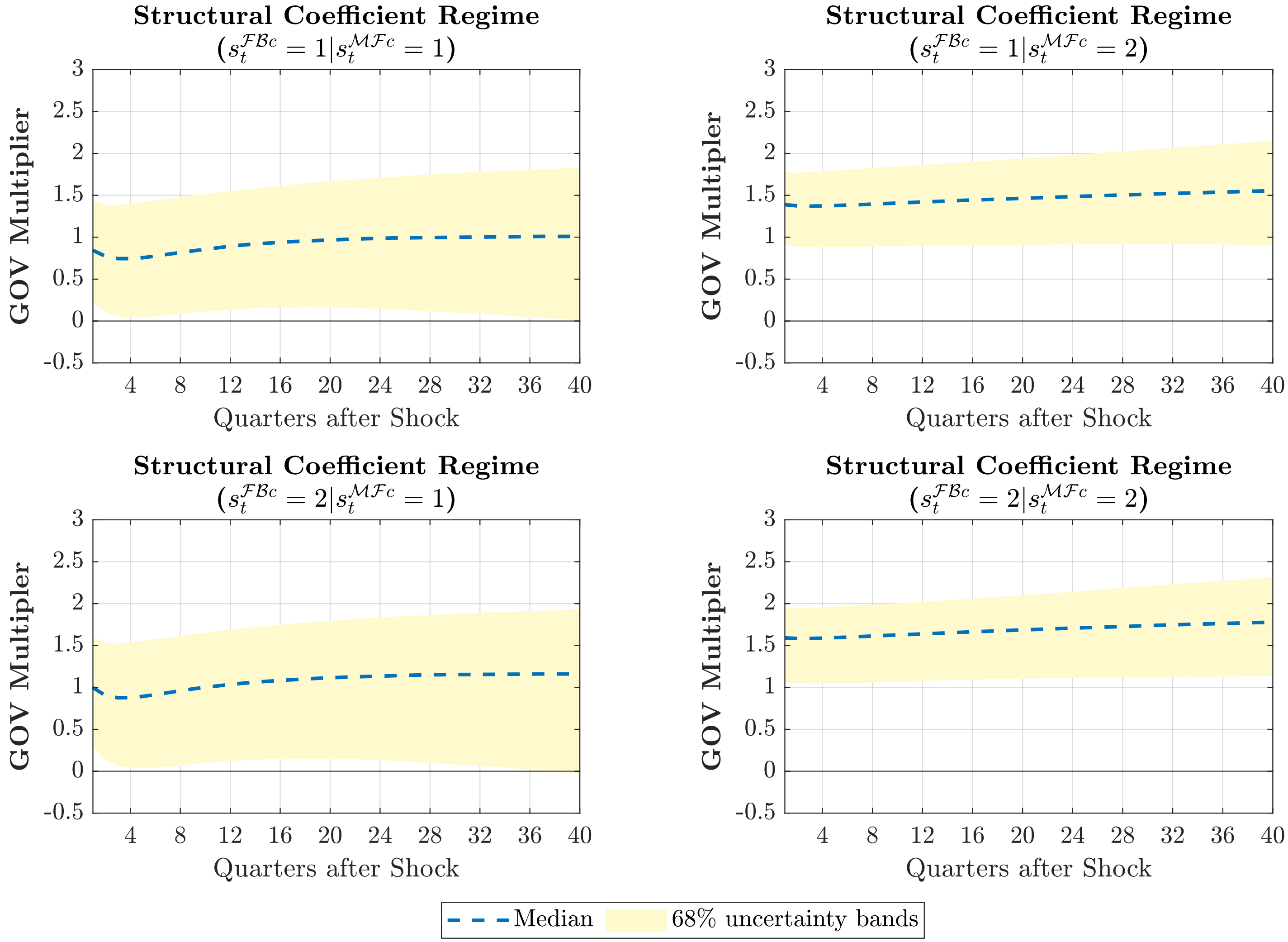
Notes: The GIRFs are conditional on the first (second) $\mathcal{FP}$ and $\mathcal{MF}$ block structural coefficient regimes being in place at the time of the shock. The median responses (blue dashed line) are presented with 68% uncertainty bands (yellow shaded area).

Figure 3: Conditional GIRFs of RGDP with Respect to a Tax Shock of MS-BVAR-13



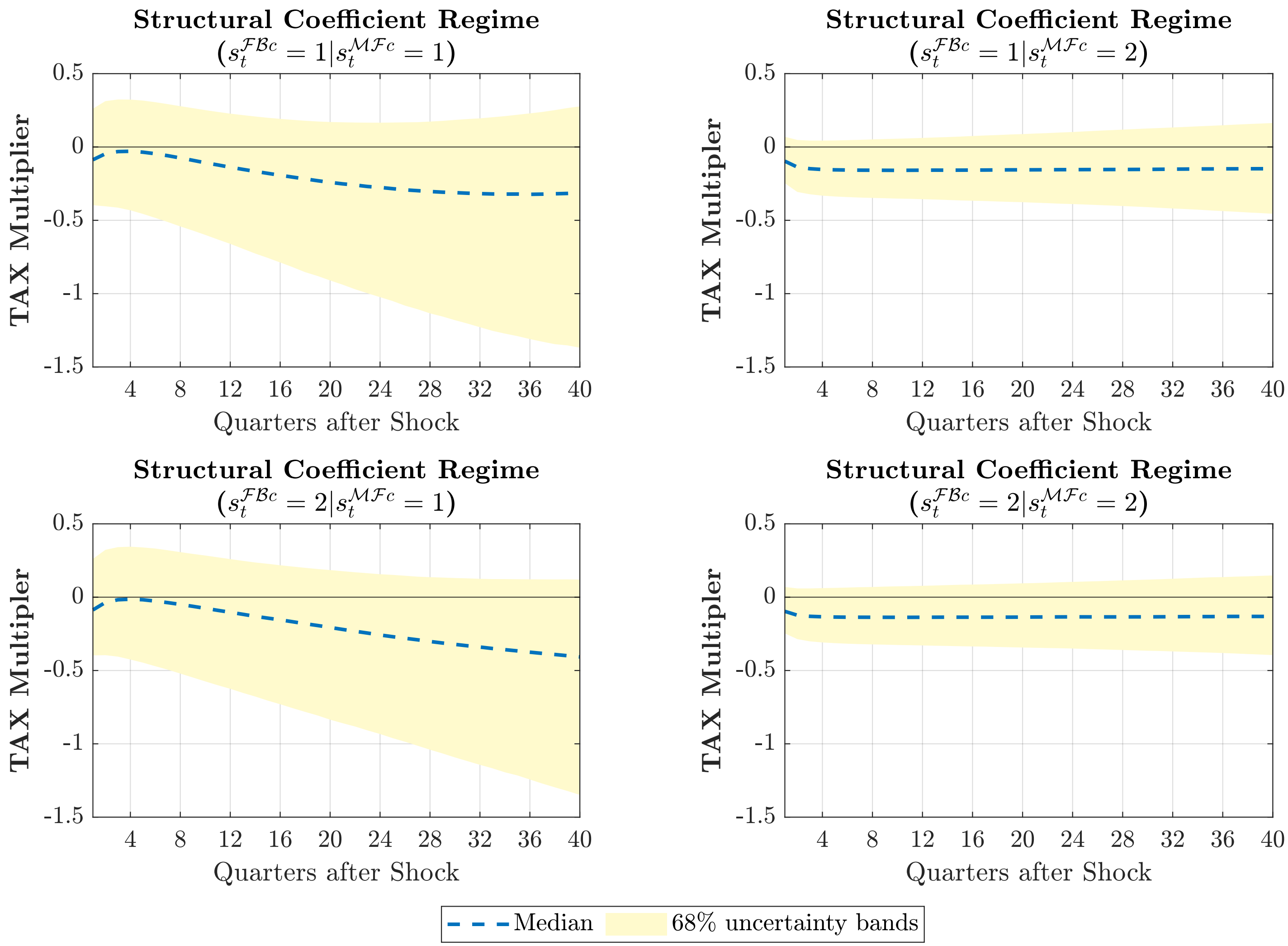
Notes: See the notes to figure 2.

Figure 4: 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. The median multiplier estimates (blue dashed line) are presented with 68% uncertainty bands (yellow shaded area).

Figure 5: Present-Value Tax Multipliers of MS-BVAR-13



Notes: See the notes to figure 4.