Interest Rates, Money, and Fed Monetary Policy in a Markov-Switching Bayesian VAR*

Kenneth M. Rich†
Department of Economics
University of Mississippi

November 17, 2022

Abstract

This paper evaluates the roles of short- and long-term private and government interest rates and inside and outside money in the monetary transmission mechanism. With money and credit markets present, changes in monetary policy set off a chain of relative price and portfolio adjustments affecting output and prices. I study interest rate and money supply rules within this monetary transmission mechanism by estimating several Markov-switching Bayesian vector autoregressions (MS-BVARs) on a quarterly U.S. sample from 1960 to 2018. The best-fit MS-BVAR restricts MS to the impact and lag coefficients of the monetary policy and money demand regressions and the stochastic volatilities (SVs) of the structural shocks. Estimates of this MS-BVAR yield evidence of a SV regime that coincides with NBER dated recessions. This MS-BVAR also identifies a regime switch in the Feds interest rate rule and banks demand for outside money around the dot-com bust of 2000 and again from the 2007-2009 recession and financial crisis to the end of the sample. Counterfactual simulations show the 2007-2009 recession and financial crisis would have not been as deep and long-lasting if the fed funds rate had been as low as -8% in 2009 and remained negative from 2010 through 2016.

JEL Classification: E52, E44, E58, E43, E51, G1.

Keywords: Monetary policy transmission mechanism, Markov switching, Bayesian VAR.

*Acknowledgments: This paper is based on the first chapter of my Ph.D. dissertation. I am thankful for my graduate advisor, Jim Nason, for his support. I am also grateful to my dissertation committee members, Ayse Kabukcuoglu-Dur, Doug Pearce, Mark Walker, and Xiaoyong Zheng for their comments and suggestions. I have also benefited from conversations with Saroj Bhattarai, John Conlon, Lee Craig, Andrew Glover, Josh Hendrickson, Ron Mau, Elmar Mertens, Chris Sims, Tao Zha, and the macroeconomics workshop and seminar participants at North Carolina State University, University of Mississippi, and West Chester University. My thanks also goes to an anonymous referee, whose comments and suggestions substantially improved the paper. Finally, I extend my thanks to the staff at the High Performance Computing (HPC) centers at the University of Mississippi and North Carolina State University as well as the development team of Dynare for computing support. All remaining errors are my own. Supplement and Additional Results appendices are available at https://kennethmrich.com/research.

†Department of Economics, University of Mississippi, 319 Odom Hall, University, MS 38677-1848. e-mail: kmrich2@olemiss.edu

1. Introduction

Standard new Keynesian models often discuss monetary policy without any explicit reference to monetary aggregates. A leading example is Smets and Wouters (2007). They examine the monetary transmission mechanism in a new Keynesian model with an interest rate rule that excludes monetary aggregates. Implicit is the notion that money is unnecessary for explaining business cycle fluctuations and studying the monetary transmission mechanism. This notion rests on two assumptions. First, an interest rate rule sufficiently describes monetary policy. The second assumption is the central bank elastically supplies currency and reserves (i.e., the monetary base or "outside money") to the private economy to insulate it from the effects of changes in the money supply.

Sims and Zha (2006) challenge the validity of the first assumption. They identify and estimate several Markov-switching Bayesian vector autoregressions (MS-BVARs). Their MS-BVARs produce evidence that the Fed operated under a fed funds targeting regime from 1960 to 2003 except between 1979 and 1982. During the latter period, a money supply targeting regime was in place. This is evidence, according to Sims and Zha, that monetary aggregates at times play a role in the Fed's policy decisions and actions. Thus, they argue economists must confront evidence that the Fed changes its policy rule and operating procedures.

Sims and Zha's concerns about policy evaluation remain relevant today given recent developments in Fed monetary policy implementation. In the wake of the 2007-2009 recession and financial crisis, the fed funds rate dropped to effectively zero, where it remained for seven years. With the fed funds rate at its zero lower bound, the Fed turned to new policy measures as a way to provide needed stimulus to the economy. Among these were programs aimed at providing liquidity to money and credit markets, such as quantitative easing (QE) and large scale asset purchases (LSAPs). As a result, the Fed's balance sheet and the amount of reserves in banking system rapidly increased. A model without money nor regime-switching not only would be unable to properly characterize post-crisis Fed monetary policy behavior but also

would assume the observed rapid expansion of the monetary base has no real effects on the economy.

This paper extends Sims and Zha (2006) in three ways to address their concerns. First, I include inside and outside money to the MS-BVAR information set. Second, short- and long-term private and government interest rates are also added in the MS-BVAR. Third, I update Sims and Zha's (2006) sample to 2018Q4. These 15 years of data bring information about the 2007-2009 recession and financial crisis along with the subsequent recovery into my estimation sample.

I enlarge the information set on which the MS-BVARs are estimated for three reasons. First, as noted by Goodfriend (2005), operating monetary policy with a fed funds target only accommodates outside money demand shocks. Whether the Fed insulates the economy from these shocks depends on how asset and output markets respond to changes in the monetary base. Second, Tobin (1961) and Brunner and Meltzer (1972, 1988) show changes in the monetary base have real effects when private and government assets are imperfect substitutes. When assets are imperfect substitutes, multiple independent interest rates exist. Thus, changes in monetary policy lead to relative price movements across asset markets. These relative price changes set off a chain of portfolio adjustments affecting aggregate output and prices. Third, not including inside money in a model ignores the role of financial intermediation. This omission implicitly assumes the Fed can impose its will on the creation of inside money in the credit market. Tobin and Brunner and Meltzer contend inside money creation depends on financial intermediaries' capacity to supply credit and the private sector's demand for loans. This is my motivation to assess the credibility of the assumption that the central bank outside money supply function is perfectly elastic.

The idea behind considering multiple interest rates and financial intermediation is labeled the Tobin-Brunner-Meltzer (TBM) monetary transmission mechanism in this paper. The TBM transmission process begins when the Fed changes the amount of outside money in the banking system. The Fed's goal is to achieve an interest rate or money supply target in

the money market. Changes in the amount of outside money alter the relative price of inside money to outside money. These factors influence the supply and demand for inside money in the credit market and initiates a series of portfolio adjustments by financial intermediaries. Portfolio rebalancing continues until premiums on long-term government and private assets adjust to clear the markets in these assets. Changes in the amount of liquidity in the credit market as well as changes in long-term interest rates influence investment decisions in the private sector through the bank lending and balance sheet channels.

Identification of the TBM monetary transmission mechanism imposes short-run zero restrictions on the impact matrices of the MS-BVARs. Similar to Gordon and Leeper (1994) and Leeper and Roush (2003), I consider recursive and non-recursive identification strategies. A shortcoming of recursive identification is that it does not allow for the simultaneous determination of prices and quantities in the money and credit markets. Sims (1992) argues that failure to account for the simultaneous supply and demand interactions inside and between these markets leads to misleading results about the impact of monetary policy. Non-recursive identification accounts for these interactions.

The TBM monetary transmission mechanism provides a framework to evaluate interest rate and money supply rules. An interest rate rule identifies unanticipated movements in the fed funds rate as the monetary policy shock. This leaves shocks to the monetary base to reflect shifts in the demand for outside money by banks. Under a money supply rule, orthogonalized innovations in the monetary base identify the non-systematic component of monetary policy. Outside money demand shocks are tied to similar innovations in the fed funds rate. I also identify Fed monetary policy behavior with an interest rate/money supply rule similar to the one in Sims and Zha (2006). Under this rule, the Fed is allowed to switch between using the fed funds rate and monetary base as its policy instrument. The regime-dependent impact coefficients reveal the relative importance of each instrument over time.

I study the TBM monetary transmission mechanism by estimating several MS-BVARs on a quarterly U.S. sample that runs from 1960 through 2018. Estimation of the MS-BVARs

relies on Bayesian techniques described in Sims, Waggoner, and Zha (2008). Posterior distributions of the MS-BVARs are constructed using a Metropolis-within-Gibbs Markov chain Monte Carlo (MCMC) sampler.

Of the 35 MS-BVARs estimated, the best-fit MS-BVAR restricts MS to the impact and lag coefficients of the monetary policy and outside money demand regressions and the stochastic volatilities (SVs) of the structural shocks. This best-fit MS-BVAR is estimated under a non-recursive identification scheme which describes Fed monetary policy as an interest rate rule.

The best-fit MS-BVAR yields evidence of a SV regime which coincides with periods of high volatility and NBER dated recessions. The three largest SVs affect monetary policy, credit supply, and credit demand shocks. The best-fit MS-BVAR also detects two regime switches in the impact and lag coefficients. The first regime occurs for the majority of the sample, up until 2007. Under this regime, monetary policy and banks' demand for outside money hardly respond to monetary policy and credit supply shocks. This regime prevails during periods when the Fed's balance sheet and banks' willingness to hold outside money is relatively small. The second regime takes place around the dot-com bust of 2000 and again from 2007 to 2008. During these episodes, the Fed's balance sheet and banks' willingness to hold outside money is relatively large. Under this regime, monetary policy and credit supply shocks produce larger responses in the demand for outside money by the banking system at impact.

Generalized impulse response functions (GIRFs) of the best-fit MS-BVAR reaffirm the responses of outside money to monetary policy and credit supply shocks differ across the two regimes of the impact and lag coefficients. While monetary policy and credit supply shocks lower the amount of outside money in the short run, the size of the response is smaller under the first regime. Moreover, outside money does not respond to monetary policy and credit supply shocks at impact when conditioning on the first regime. The GIRFs also show credit supply shocks do not affect the real economy in either regime. This result stands in contrast to Gorton and Metrick (2012), who argue the 2007-2009 recession and financial crisis was

the result of a credit supply shock.

I report two counterfactual experiments. The first asks whether credit supply or credit demand shocks were responsible for explaining the recession of 2007-2009. The counterfactual experiments, which rely on the posterior of the best-fit MS-BVAR, lack evidence credit supply or credit demand shocks contributed to the 2007-2009 recession and financial crisis. The second counterfactual experiment fixes the monetary policy and money demand regressions to the regime that did not occur during the dot-com bust of 2000 and the 2007-2009 recession and financial crisis. The result is a counterfactual path for real GDP that would have returned to its pre-crisis path in 2010. However, returning real GDP back to its pre-crisis path would have required the fed funds rate to be as low as -8% in 2009. Moveover, to maintain the recovery, the fed funds rate would have had to remain negative from 2010 to 2016.

This paper contributes to a growing literature that studies the interaction between monetary policy, financial markets, and the real economy using regime-switching models. Hubrich and Tetlow (2015) employ MS-BVARs to assess the impact of monetary policy during periods of high and low financial stress. They find that monetary policy has a weaken effect during periods in which financial markets tighten their lending terms and standards. Lhuissier and Tripier (2021) also yield evidence from their best-fit MS-BVAR that future uncertainty shocks have larger effects during high financial stress periods. Both papers use recursive identification schemes and a financial stress index to summarize financial market behavior. This paper instead uses recursive and non-recursive short-run restrictions and information from short- and long-term interest rates to identify supply and demand shocks in the money and credit markets as well as term and risk premium shocks. Check (2021) also finds evidence of regime switches in the Fed's interest rate rule.

Another recent related paper is Geromichalos and Herrenbrueck (2022). Geromichalos and Herrenbrueck also study how monetary policy affects the real economy through its effects on multiple interest rates and money. Their New Monetarist DSGE model relies on similar arguments as the one told by the Tobin-Brunner-Meltzer monetary transmission mechanism.

The rest of the paper proceeds as follows. Section 2 identifies the TBM monetary transmission mechanism in a MS-BVAR. Section 3 describes the data and the best-fit MS-BVAR. GIRF and counterfactual results produced by the best-fit MS-BVAR appear in sections 4 and 5. Section 6 concludes.

2. Identifying the Monetary Transmission Mechanism

This section gives motivation for including multiple interest rates and inside and outside money in an MS-BVAR. Identification of the MS-BVAR rests on Tobin's (1961) and Brunner and Meltzer's (1972, 1988) theories of the monetary transmission mechanism.

2.1. The Tobin-Brunner-Meltzer Monetary Transmission Mechanism

The TBM monetary transmission mechanism adds elements often missing from new Keynesian models. Among these are the roles of financial intermediation, portfolio choice, and liquidity, term, and risk premia.[1] The TBM monetary transmission mechanism incorporates these elements by assuming inside and outside money, bonds, and other financial assets are imperfect substitutes, both in the short and long run. Tobin (1961) and Brunner and Meltzer (1972, 1988) argue imperfect substitution across assets is a reason the monetary transmission mechanism generates non-neutralities.

2.1.1. The Initial Monetary Policy Shock

The TBM transmission process begins when the Fed either supplies or withdraws outside money from the money market. Prior to 2008, the Fed primarily changed the amount of outside money in the money market via open market operations (OMOs). After 2008, the

[1] This paper omits the role of exchange rates in the TBM monetary transmission mechanism. Two reasons motivate this decision. First, my focus is on Fed monetary policy. Exchange rate policy is determined by the U.S. Treasury. Second, this paper follows the Sims-Zha tradition of evaluating Fed monetary policy in a closed economy. It is beyond the slope of this paper to study the TBM monetary transmission mechanism in an open economy setting.

Fed relied on quantitative easing (QE) and large scale asset purchases (LSAPs) to implement monetary policy. In either case, when the Fed wants to increase the amount of outside money, it does so by purchasing assets off the balance sheets of financial intermediaries. Outside money pays a nominal interest rate below the market rates of other financial assets.[2] Therefore, financial intermediaries use the additional outside money to rebalance their portfolios towards holding a larger share of these higher-interest-bearing assets.

2.1.2. Financial Intermediaries

Financial intermediaries rebalance their portfolios in two ways. First, financial intermediaries can use the additional outside money to extend lending in the credit market. This issuance of credit is how inside money is created. Bernanke and Gertler (1989) argue financial intermediaries specialize in overcoming informational and other agency frictions associated with the intermediation process. Thus, an information friction in credit markets induces a premium on rates in credit markets compared with money market returns.

Second, financial intermediaries can instead purchase long-term financial assets. A reason for this is to obtain the higher yields these financial securities offer. Yields on U.S. Treasury bonds often include a term premium over the short-term government rate to compensate bondholders for the expected real value loss due to inflation. In addition, long-term corporate bonds often include a risk premium over U.S. Treasury bonds. For example, Krishnamurthy and Vissing-Jorgensen (2012) document U.S. Treasuries possess liquidity and safety attributes not present in corporate bonds.

2.1.3. Liquidity and the Money, Credit, and Financial Markets

By increasing the amount of liquidity in the credit market and lowering long-term yields, monetary policy is transmitted to the real economy through the credit channel of the TBM

[2]The nominal interest rate paid on outside money is traditionally, but not necessarily, zero. For instance, the Board of Governors has paid interest on reserves since 2008. The interest rate paid on reserves, although greater than zero, is below market rates (e.g., the commercial paper rate and return on 3-month Treasury bills). This suggests interest on reserves is a non-binding constraint on the demand for outside money.

monetary transmission mechanism. The credit channel can be broken into two parts. First, Bernanke and Blinder (1988) argue more liquidity in the credit market provides more loanable funds to firms for their investment projects. This is sometimes called the bank lending channel. Second, the balance sheet channel of Bernanke and Gertler (1995) ties the market value of assets to the quality of the asset side of borrowers' balance sheets, which raises borrowers' ability to obtain credit. As a result, real economic activity and inflation increase.

2.1.4. Monetary Propagation for Tobin-Brunner-Meltzer

To sum up, as the Fed alters the amount of outside money in banking system, relative prices across money, credit, financial, and output markets change. These relative price changes occur because of imperfect asset substitutability across these markets. Banks respond to these relative price changes by rebalancing their portfolios towards holding assets with higher rates of return. These portfolio adjustments affect aggregate output and prices by influencing the amount of liquidity in the credit market and the private sector's ability to borrow.

2.2. An MS-BVAR to Evaluate U.S. Monetary Policy

This section uses an MS-BVAR to discuss alternative identifications of the TBM monetary transmission mechanism. The MS-BVAR is

$$y_t' A_0(s_t) = x_t' A_+(s_t) + \varepsilon_t' \Xi^{-1}(s_t), \quad \varepsilon_t \sim \mathcal{N}(0_{n\times 1}, I_n), \quad t = 1, \ldots, T, \tag{2.1}$$

where y_t is an $n \times 1$ vector of endogenous variables, x_t is an $m \times 1$ vector of all lagged variables plus the intercept term, ε_t is an $n \times 1$ vector of serially and mutually uncorrelated structural shocks, A_0 is an invertible $n \times n$ matrix of structural impact coefficients, A_+ is an $m \times n$ matrix of structural lag coefficients, p is the lag length, T is the sample size, and $m = np + 1$.[3]

[3] Appendix A provides details on the priors, estimation, and inference procedure of the MS-BVAR.

The unobservable state (regime) variable s_t evolves according to a Markov process with the transition matrix $Q = [q_{i,j}]$, where $q_{ij} = \text{Prob}\,[s_t = i | s_{t-1} = j]$ for $i, j = 1, \ldots, H$ and H denotes the number of regimes. The $n \times n$ diagonal matrix $\Xi(s_t)$ contains factor loadings which scale the degree of SV of the structural shocks in ε_t.

The information set y_t consists of quarterly observations on U.S. per capita real GDP (RGDP_t), the implicit GDP price deflator (P_t), unemployment rate (UR_t), effective fed funds rate (FFR_t), per capita monetary base (MB_t), commercial paper rate ($\text{R}_{\text{CP},t}$), per capita inside money (MI_t), constant maturity yield on ten-year U.S. Treasury bonds ($\text{R}_{\text{10yr},t}$), and Moody's Baa corporate bond yield ($\text{R}_{\text{Baa},t}$).[4] These $9(= n)$ variables define y_t as

$$y_t \equiv \left[\underbrace{[\text{RGDP}_t \;\; \text{P}_t \;\; \text{UR}_t]}_{\text{Production}} \; \underbrace{[\text{FFR}_t \;\; \text{MB}_t]}_{\text{Monetary Policy}} \; \underbrace{[\text{R}_{\text{CP},t} \;\; \text{MI}_t \;\; \text{R}_{\text{10yr},t} \;\; \text{R}_{\text{Baa},t}]}_{\text{Financial}} \right]'.$$

2.3. *Five Alternative Identification Schemes*

Identification of the TBM monetary transmission mechanism is achieved by imposing short-run zero restrictions on the impact matrix $A_0(s_t)$. Five alternative identification schemes are considered.[5] Two identifications rely on recursive orderings of the variables in y_t. The other three identifications are non-recursive.[6] Monetary policy is conducted either with an interest rate rule, a money supply rule, or an interest rate/money supply rule.

2.3.1. *Recursive Identification: Interest Rate Rule*

The first identification scheme relies on a recursive ordering of the variables in y_t as shown in section 2.2. These variables are separated into three blocks to represent the production, monetary, and financial sectors of the U.S. economy. The production block consisting of RGDP, P, and UR is placed before a monetary policy block and a financial block. Ordering the

[4] The information set y_t does not include a measure of commodity prices. This contrasts Sims and Zha (2006), who include a commodity price index as a way to incorporate information about inflation expectations into their MS-BVARs. However, as noted in section 2.1.2, the implicit term spread between R_{10yr} and FFR also contains information about inflation expectations. Thus, I omit commodity prices from entering y_t.

[5] Results for the constant coefficient SVARs are available in the online Additional Results Appendix.

[6] Necessary and sufficient conditions for global identification of the non-recursive SVARs are verified using the tools provided by Rubio-Ramírez, Waggoner, and Zha (2010). Results appear in appendix B.

production block first assumes output, pricing, and employment decisions do not respond to shocks from outside the production sector at impact. Leeper, Sims, and Zha (1996) and Sims and Zha (2006) impose a similar identifying assumption in their monetary policy SVARs.

The recursive ordering of RGDP, P, and UR within the production block identifies three shocks. Ordering RGDP before P assumes aggregate supply shocks cause price level fluctuations at impact, while aggregate demand shocks have only a lagged effect on RGDP. Since shocks to the UR also affect RGDP with a lag, ordering RGDP before the UR embeds a dynamic Okun's law relation into the MS-BVAR. A Samuelson-Solow Phillips curve results from also having P respond to labor supply shocks with a lag.

Next, the monetary policy block uses the FFR and the MB to identify supply and demand shocks in the money market. Placing the monetary policy block after the production block assumes the Fed and the money market responds to production sector shocks at impact. Under this recursive ordering, the Fed is assumed to follow an interest rate rule. The monetary policy shock is the part of the interest rate rule that is non-systematic. This leaves innovations in the MB to reflect shifts in the demand for outside money in the money market. Since the FFR precedes MB, money demand shocks are assumed to not affect the FFR at impact. The implication is the Fed supplies sufficient outside money to clear the money market at the target FFR.

The financial block is ordered last and includes R_{CP}, MI, R_{10yr}, and R_{Baa}. Within this block, R_{CP} and MI span the information necessary to identify credit supply and credit demand shocks. Credit supply shocks are identified as unanticipated movements in R_{CP}. Motivation for this identifying assumption comes from Gorton and Metrick (2012). They argue financial intermediaries are the price setters in the credit market. As such, any unanticipated change in R_{CP} signals a rise or fall in the amount of liquidity in the credit market. This leaves shocks to MI to reflect shifts in the demand for inside money.

The long-term interest rates R_{10yr} and R_{Baa} provide information about the opportunity costs of holding long-term government and private assets instead of inside or outside money.

These long-term rates are ordered last under the assumption long-term asset markets react to output, labor, money, and credit market shocks at impact. Since R_{10yr} responds to shocks to the FFR at impact, this regression of the MS-BVAR has a rational expectations term structure restriction embedded in it. A term structure shock is the unexpected component of the R_{10yr} regression. Krishnamurthy and Vissing-Jorgensen (2012) present evidence that the spread between R_{Baa} and R_{10yr} measures a risk premium on corporate bonds because liquidity and safety premiums are priced into U.S. Treasuries securities. This identifies the shock to R_{Baa} as an unanticipated change in the risk premium.

2.3.2. Recursive Identification: Money Supply Rule

The second recursive identification scheme switches the order of the FFR and the MB in the monetary policy block. McCallum (1987) proposes a money supply rule under which the Fed responds to deviations of nominal GDP from its target by adjusting the MB. An implication of a money supply rule is the Fed sets the MB and the money market determines the FFR. As a result, the TBM monetary transmission mechanism depends on financial markets to change the relative price of inside money to outside money.

2.3.3. Non-Recursive Identifications

Recursive identifications do not allow for simultaneous supply and demand interactions between money and credit markets. Sims (1992), Gordon and Leeper (1994), and Leeper and Roush (2003) argue this omission leads to misleading results about the impact of monetary policy. Table 1 presents impact matrices of the MS-BVARs restricted with non-recursive identification schemes. The non-recursive identifications differ by tying monetary policy to either an interest rate rule, a money supply rule, or an interest rate/money supply rule.

An "X" entry in table 1 represents an unrestricted impact coefficient in A_0. A blank space denotes a zero restriction. Each column represents a behavioral equation. The behavioral equations are labeled at the top by their respective structural shock. The row labels indicate

which variables enter each behavioral equation at impact.

The monetary policy column in table 1 considers three non-recursive monetary policy rules. One monetary policy is defined by the interest rate rule studied by Taylor (1993),

$$a_{76}(s_t)\mathrm{RGDP}_t + a_{86}(s_t)\mathrm{P}_t + a_{66}(s_t)\mathrm{FFR}_t = \xi_{66}(s_t)\varepsilon_t^{mp}, \tag{2.2}$$

where a_{ij} denotes the ij-th element of A_0, ε_t^{mp} denotes the monetary policy shock, $\xi_{66}(s_t)$ scales the degree of SV of the monetary policy shock, and the intercept and lag terms are suppressed for notational convenience. Replacing the FFR with the MB gives the outside money supply rule,

$$a_{76}(s_t)\mathrm{RGDP}_t + a_{86}(s_t)\mathrm{P}_t + a_{56}(s_t)\mathrm{MB}_t = \xi_{66}(s_t)\varepsilon_t^{mp}, \tag{2.3}$$

proposed by McCallum (1987). Both policy rules assume the Fed adjusts its policy instrument in response to changes in RGDP and P. The third policy rule comes from Sims and Zha (2006). They include the FFR and the MB into the monetary policy equation

$$a_{66}(s_t)\mathrm{FFR}_t + a_{56}(s_t)\mathrm{MB}_t = \xi_{66}(s_t)\varepsilon_t^{mp}. \tag{2.4}$$

This interest rate/money supply rule assumes the Fed switches between using the FFR and the MB as its policy instrument over time. The relative importance of the FFR and the MB as the instrument is captured by the regime-dependent coefficients $a_{56}(s_t)$ and $a_{66}(s_t)$.

The interaction between the money and credit markets can be seen in the outside money demand function,

$$a_{75}(s_t)\mathrm{RGDP}_t + a_{85}(s_t)\mathrm{P}_t + a_{65}(s_t)\mathrm{FFR}_t + a_{55}(s_t)\mathrm{MB}_t + a_{35}(s_t)\mathrm{R}_{\mathrm{CP},t} = \xi_{55}(s_t)\varepsilon_t^{md}, \tag{2.5}$$

in the money demand column of table 1. Allowing the demand for outside money to depend on both short-term rates establishes a link between money and credit markets along with disentangling money demand shocks (ε_t^{md}) from credit supply and credit demand shocks.

2.4. Model Space

Seven model specifications of the MS-BVAR (2.1) are considered for each identification scheme. The first four model specifications differ in whether the impact and lag coefficients

or the SVs of the structural shocks are constant or MS.[7] When constant impact and lag coefficients and volatilities are assumed, the MS-BVAR (2.1) reduces to a standard constant coefficient BVAR. The constant coefficient BVARs are evaluated against the MS-BVARs to assess whether the data prefer constant or MS coefficient specifications.

The fifth model specification restricts MS to the impact and lag coefficients of the monetary policy rule regression and the SVs. This model specification resembles one of Sims and Zha's (2006) best-fit MS-BVAR. Although their overall best-fit MS-BVAR assumes MS only in the SVs, their best-fitting MS-BVAR among those with MS impact and lag coefficients limits these MS coefficients to the monetary policy rule regression.

The final two model specifications impose MS in the monetary policy block (money supply and money demand) regressions and the SVs. These two model specifications differ by either allowing for synchronized money supply and money demand regime switches or not. Allowing money demand to vary over time attempts to capture shifts in banks' demand over the assets they want to hold. For instance, Gorton and Metrick (2012) document an increase in banks' demand for outside money relative to their demand for inside money (credit) and long-term securities during the 2007-2009 financial crisis. Testing whether the data prefer MS-BVARs with synchronized or independent money supply and money demand switches also serves as an useful Lucas critique evaluation exercise.

Table 2 lists the 35 considered constant coefficient and MS-BVARs. The label #c indicates the number of impact and lag coefficient regimes, while the label #v specifies the number of SV regimes. For example, models 1 to 5 are labeled as "1c1v" to denote constant coefficient BVARs. From here, it follows models 6 to 10 represent MS-BVARs with constant impact and lag coefficients and SVs, models 11 to 15 assume MS impact and lag coefficients and constant volatilities, and models 16 to 20 permit MS impact and lag coefficients and SVs.[8] Models

[7]The regime-dependent intercept terms are not estimated. This is because the Sims and Zha (1998) prior drives the intercept terms to zero to satisfy the random walk prior.

[8]Motivation for limiting the number of impact and lag coefficient and SV regimes to two comes from preliminary estimation results. After several attempts, I found that the chains of the Metropolis-within-Gibbs MCMC sampler fail to converge when the MS-BVARs have three or more impact and lag coefficient regimes. MS-BVARs with two impact and lag coefficient regimes and three SV regimes also encountered

21 to 25 (labeled "2MPc2v") restrict MS to the impact and lag coefficients of the monetary policy (money supply) regression and the SVs. Models 26 to 30 (labeled "2MPBc2v") assume synchronized regime changes in the money supply and money demand regressions as well as SVs. Finally, models 31 to 35 (labeled "2MPc2MDc2v") separate the MS chains on the money supply and money demand regressions and SVs.[9]

3. Empirical Results

This section reports the estimation results of the MS-BVARs. The sample data on which the MS-BVARs are estimated are described in section 3.1. Section 3.2 evaluates how well each of the estimated MS-BVARs fit the data and selects the best-fit MS-BVAR. Posterior estimates and plots of the conditional transition probabilities produced by the best-fit MS-BVAR appear in sections 3.3 and 3.4. The economic implications of the estimated impact and SV matrices are discussed in section 3.5.

3.1. Data

The MS-BVARs are estimated on a quarterly U.S. sample that runs from 1960Q1 to 2018Q4, yielding a total of $T = 236$ observations. The data are gathered from the Federal Reserve Bank of St. Louis's FRED database and the FRASER digital archive.

As mentioned in section 2.2, the information set y_t consists of U.S. per capita real GDP, the implicit GDP price deflator, unemployment rate, effective fed funds rate, per capita monetary base, commercial paper rate, per capita inside money, constant maturity yield on ten-year U.S. Treasury bonds, and Moody's Baa corporate bond yield. The per capita stock of inside money, MI, equals M2 minus currency and traveler's checks divided by U.S. population.

convergence issues.

[9]Following a referee's suggestion, I also estimated MS-BVARs with three regimes in the monetary policy equation as well as MS-BVARs with three regimes in the monetary policy block regressions. The model fit results show the data do not strongly prefer any of these MS-BVARs over the best-fit MS-BVAR presented in this paper. These model fit results are available in the online Additional Results Appendix.

This equates inside money to bank deposits plus other short-term liabilities issued by the banking system. The total stock of outside money is measured using the adjusted monetary base as calculated by the Federal Reserve Bank of St. Louis. All variables in y_t are expressed in natural logarithms and scaled by 400 except for the interest rates and the unemployment rate, which are expressed in percents. Details of the data construction and sources are given in appendix C. Appendix D plots the sample data.

3.2. Model Fit

Table 3 reports the log marginal data densities (MDDs) for each estimated model. The MDDs of the MS-BVARs are computed using Sims, Waggoner, and Zha's (2008) truncated modified harmonic mean (MHM) estimator, whereas Gelfand and Dey's (1994) and Geweke's (2005) MHM estimator is used to calculate the MDDs of the constant coefficient BVARs. An asterisk ($*$) in table 3 indicates the chains of the Metropolis-within-Gibbs MCMC sampler did not converge for the relevant model. In this case, the model being estimated lacks a well-approximated MDD.

According to these log MDD results, model 28 achieves the best fit to the data. Model 28 is estimated using the interest rate rule of equation (2.2) and the non-recursive identification described in section 2.3.3. This best-fitting MS-BVAR also assumes two regimes in the impact and lag coefficients of the monetary policy and money demand regressions and two regimes in the SVs as discussed in section 2.4. Table 3 also shows the difference between the log MDDs associated with model 28 and its closest competitor, model 30, is 3.53. Converting this difference into a Bayes factor yields an estimate of 34.12 ($= \exp(3.53)$), which, according to Kass and Raftery's (1995) model selection criterion, constitutes *strong* evidence the data favor model 28 over model 30. The Bayes factors between model 28 and the remaining models are well above 150.

Before proceeding to the estimation results of model 28, there are several other interesting results worth noting in table 3. First, with the exception of models 3, 18, and 19, the non-

recursive models under each model specification fit the data better than their recursive counterparts. Sims (1992), Gordon and Leeper (1994), and Leeper and Roush (2003) report similar results. Second, the data overwhelmingly favor MS-BVARs (models 5 to 35) over constant coefficient BVARs (models 1 to 4) across all five identification schemes. Third, a closer inspection of the second and third columns reveals the data prefer the addition of SVs (models 6 to 10) over MS impact and lag coefficients (models 11 to 15). This finding initially supports Sims and Zha's (2006) critique that omitting SVs from a model biases results towards favoring MS impact and lag coefficients. However, the last four columns provide *very strong* evidence against their claim that the data no longer favor MS impact and lag coefficients once SVs are properly accounted for. Finally, the data strongly prefer the inclusion of MS in the money supply and money demand regressions over restricting MS to only the monetary policy equation. There is also *very strong* evidence in support of allowing for synchronized regime switching in the money supply and money demand equations over separating the MS chains. These findings taken together suggest the Lucas critique is important when studying money market participant behavior.

3.3. Transition Matrices of the MS-BVAR Model 28

The posterior median estimates of the conditional transition probabilities of the impact and lag coefficient and SV regimes, $\hat{Q}^c$ and $\hat{Q}^{sv}$, are

$$\hat{Q}^c = \begin{bmatrix} 0.986 & 0.037 \\ [0.967, 0.996] & [0.008, 0.101] \\ 0.014 & 0.963 \\ [0.004, 0.033] & [0.889, 0.992] \end{bmatrix} \quad \text{and} \quad \hat{Q}^{sv} = \begin{bmatrix} 0.738 & 0.075 \\ [0.601, 0.849] & [0.042, 0.119] \\ 0.262 & 0.926 \\ [0.151, 0.399] & [0.881, 0.958] \end{bmatrix},$$

where the brackets contain 90% Bayesian credible sets.[10] Estimates of the conditional transition probabilities $\hat{p}^c_{11} = 0.986$ and $\hat{p}^c_{22} = 0.963$ indicate the impact and lag coefficient regimes are highly persistent. The expected durations of the impact and lag coefficient regimes are about 71 and 27 quarters, respectively.

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

The SV regimes are less persistent. The estimated conditional transition probability $\hat{p}_{11}^{sv} = 0.738$ implies the first SV regime is expected to last less than 4 quarters. There is also a 26% probability of moving from the first SV regime to the second SV regime. Once the economy moves to the second SV regime, it is expected to remain there for more than three years, according to $\hat{p}_{22}^{sv} = 0.926$. The probability of the economy moving back to the first SV regime from the second SV regime is 7.5%.

3.4. Smoothed Conditional Regime Probabilities of the MS-BVAR Model 28

Figure 1 reports the smoothed conditional regime probabilities of model 28 from 1960Q1 to 2018Q4. The top panel presents the SV regime probabilities, while the bottom panel summarizes the probabilities of the impact and lag coefficient regimes. These probabilities are estimated using Kim's (1994) smoothing algorithm. The shaded bars correspond to the NBER recession dates.

Of the eight recorded NBER recession dates in figure 1, all but two occur when the first SV regime prevails. Hence, the first SV regime coincides with NBER dated recessions, while the second SV regime dominates during economic expansions.

Figure 1 also yields evidence of less frequent regime switching in the impact and lag coefficients. For example, with the exception of the dot-com bust of 2000, the first impact and lag coefficient regime runs from the beginning of the sample to around 2007. After 2007, the second impact and lag coefficient regime dominates. One interpretation of these findings is that the Fed's interest rate rule and banks' demand for currency and reserves entered a new regime around the dot-com bust of 2000 and again from the 2007-2009 recession and financial crisis to the end of the sample. This second regime appears to occur when the Fed's balance sheet is large and banks' demand for currency and reserves is high. For instance, in the later portion of 1999 and early 2000, the FOMC documents a spike in currency in circulation due to "strong currency demands" from banks during this time.[11] After 2007, the Fed's balance

[11] See FOMC (1999b,a, 2000).

sheet rapidly expanded again as QE and LSAP measures increased the amount of reserves in the banking system. Banks also appear to be more willing to hold excess reserves than they did prior to the crisis. Thus, I label the first regime as a "scarce outside money" regime. The second regime is labeled as an "abundant outside money" regime.

The results in figure 1 contrast with those in Sims and Zha (2006). Their best-fit MS-BVAR does not report evidence of monetary policy regime switches. Figure 2 attributes the disparate results to two factors. First, Sims and Zha estimate their MS-BVARs on a sample ending in 2003, which does not cover the 2007-2009 recession, financial crisis, and aftermath of these events. Extending the sample period to 2018Q4 gives model 28 sufficient information to identify and estimate the two impact and lag coefficient regimes. Second, Sims and Zha's estimation sample neither includes outside money nor multiple interest rates. The plots in figure 2 show regime shifts mostly occur with observed spikes in the MB, the liquidity spread ($\mathrm{R_{CP}} - \mathrm{FFR}$), the term spread ($\mathrm{R_{10yr}} - \mathrm{FFR}$), and the risk spread ($\mathrm{R_{Baa}} - \mathrm{R_{10yr}}$). This suggests including these additional variables to the MS-BVAR information set aids model 28 in capturing these regime shifts.

3.5. Impact and SV Matrices of the MS-BVAR Model 28

Table 4 reports the diagonals of the estimated SV matrices $\hat{\Xi}^{-1}(s_t^{sv})$. Following Sims and Zha (2006) and Sims, Waggoner, and Zha (2008), the factor loadings of the SVs for the first SV regime ($s_t^{sv} = 1$) are normalized to one. By comparison, the factor loadings for the second SV regime ($s_t^{sv} = 2$) are all estimated to be less than one. This implies the first SV regime is more volatile than the second SV regime. When the economy is in the first SV regime, the factor loadings on $\mathrm{R_{Baa}}$, $\mathrm{R_{10yr}}$, $\mathrm{R_{CP}}$, MI, MB, FFR, RGDP, P, and UR shocks are larger by factors of 4.8, 2.7, 5.6, 5.3, 2.3, 14.8, 4.1, 5.2, and 4.1, respectively.

A key takeaway from table 4 is variation in the shocks of the production, monetary policy, and financial blocks of model 28 are greater in the first regime than the second. Combining this finding with those presented in figure 1 shows NBER recessions coincide with episodes

of greater SV in monetary policy, credit supply, and credit demand shocks.

Tables 5 and 6 report the posterior median estimates and the 90% Bayesian credible sets of the impact matrices for the first and second impact and lag coefficient regimes. Since model 28 restricts MS to the impact and lag coefficients of the monetary policy block regressions, only the monetary policy and money demand columns differ across the two tables.

One interesting difference between the two impact and lag coefficient regimes is the estimated own shock response for the FFR. This response is 0.78 in the first impact and lag coefficient regime, but in the second impact and lag coefficient regime increases to 2.88. These results indicate the FFR response to an exogenous monetary policy shock is larger in the second impact and lag coefficient regime by more than a factor of three.

Another interesting difference are the estimated shock responses in the money demand columns. The estimated responses for the MB to R_{CP} and FFR shocks are 0.01 and -0.02, respectively, and their 90% Bayesian credible sets contain zero. This suggests that during the first impact and lag coefficient regime, banks' demand for outside money is not interest rate sensitive. This changes in the second impact and lag coefficient regime. The estimated responses to R_{CP} and FFR shocks increase to 2.72 and 1.73, respectively. In addition, the 90% Bayesian credible sets no longer contain zero. These findings are consistent with Gorton and Metrick (2012). Their estimates also show changes in the interest rate elasticities of money demand during the financial crisis of 2007-2009.

4. Generalized Impulse Response Functions

This section examines how each variable in y_t responds to a monetary policy, credit supply, and credit demand shock. These responses are computed as GIRFs using model 28 and an algorithm described in Karamé (2015) and Bianchi (2016); see appendix E for details. For non-linear models, GIRFs provide evidence about the dynamic response of a variable with respect to an identified shock. Figures 3, 4, and 5 contain GIRFs constructed under the

assumption that the regime is known with certainty at impact. Nonetheless, the algorithm takes into the account the probability the regime can change in the future. Hence, these are conditional GIRFs. Median GIRFs are the dashed blue lines in the figures, while the surrounding yellow areas are 68% uncertainty bands.

4.1. Respect to a Monetary Policy Shock

Figure 3 reports the GIRFs with respect to an identified monetary policy shock. The left column of figure 3 displays GIRFs conditional on the first impact and lag coefficient regime being in place at the time of the shock. The GIRFs conditioning on the second impact and lag coefficient regime are presented in the right column.

The heights of all the GIRFs conditioning on the first impact and lag coefficient regime are smaller than those conditioning on the second impact and lag coefficient regime. Across both impact and lag coefficient regimes, a monetary policy shock lowers RGDP and raises UR 12 quarters after impact. The estimated 68% uncertainty bands for the GIRFs of UR lie above zero in the near short run. However, the price puzzle appears in the production block results. The median GIRF of the FFR has a hump shape in response to its own shock when conditioning on the first regime, peaking at 2 quarters before falling back to zero at the 12-quarter horizon. When conditioning on the second regime, the FFR does not display a hump-shaped response to its own shock. This response peaks at the 12-quarter horizon and falls back to zero 34 quarters after the initial shock. The GIRFs of MB and MI lie below zero in the short run. This is consistent with the TBM monetary transmission mechanism prediction that an increase in the FFR lowers the amount of inside and outside money in the economy. Conditioning on the second regime at impact, a monetary policy shock has a larger negative impact on MB than conditioning on the first regime. This is in line with the earlier finding that outside money demand appears to be more interest rate sensitive in the second regime. Finally, the GIRFs of R_{CP}, R_{10yr}, and R_{Baa} reveal the liquidity, term, and risk spreads shrink at impact across both regimes. However, the spreads shrink to a larger

degree and rise in the short run when conditioning on the second regime.

4.2. Respect to a Credit Supply Shock

The GIRFs with respect to an identified credit supply shock appear in figure 4. Credit supply shocks appear not to have a significant impact on any of the production block variables across impact and lag coefficient regimes, according to the GIRFs of RGDP, P, and UR. However, a credit supply shock increases the FFR in the short run. Across both regimes, the responses of the FFR have 68% uncertainty bands that are strictly positive only at the 1- to 8-quarter horizon. This suggests a credit supply shock alters the relative price of inside money to outside money, as the TBM monetary transmission mechanism predicts. Credit supply shocks also reduce MB. Under the first regime, the GIRFs of MB have 68% uncertainty bands that are strictly negative only at the 4- to 12-quarter horizon. When conditioning on the second regime, the 68% uncertainty bands are negative and do not contain zero from impact to the 12-quarter horizon. This shows credit supply shocks only have a significant impact on MB within the first year when the second regime is in place.

4.3. Respect to a Credit Demand Shock

Figure 5 presents the median and 68% uncertainty bands of the GIRFs with respect to an identified credit demand shock. Conditioning on the first regime, a credit demand shock leads a hump-shaped increase (decrease) in RGDP (UR) and increase in P in the short run. Across both regimes, the 68% uncertainty bands for the GIRFs of the FFR and MB contain zero at all forecast horizons.

5. Historical Counterfactuals

This section conducts two counterfactual experiments. The goal of the first is to quantify the importance of credit supply and credit demand shocks to explain the 2007-2009 recession

and financial crisis. The second counterfactual experiment alters the impact and dynamic responses of monetary policy and money demand to study the same episodes. Both counterfactual experiments are computed using model 28.

5.1. Suppressing Credit Market Shocks

The first counterfactual experiment addresses whether shocks in the credit market are independent impulses into the real economy or part of the TBM monetary transmission mechanism. The first counterfactual exercise suppresses credit supply shocks from 2000Q1 to 2018Q4 by setting the shocks in the credit supply function to zero.

Figure 6 presents the results of the first counterfactual exercise. These results show the historical contribution of credit supply shocks to each variable in y_t. The solid black line in each subplot of figure 6 represents the actual path observed during the sample period. The median counterfactual paths (the dashed blue lines) are plotted with 68% uncertainty bands (the surrounding yellow areas).

The results in figure 6 show the actual paths of RGDP and UR lie entirely within their 68% uncertainty bands. This suggests credit supply shocks were not the driving force behind the recession of 2007-2009. This evidence stands in contrast to the results of Gorton and Metrick (2012), who argue the recession of 2007-2009 was caused by a credit supply shock hitting the economy.

Figure 7 plots the second counterfactual results. In this experiment, I suppress the credit demand shocks from 2000Q1 to 2018Q4. Once again, the median counterfactual paths (the dashed blue lines) are plotted with 68% uncertainty bands (the surrounding yellow areas). According to these counterfactual results, credit demand shocks are also not able to explain the 2007-2009 recession. Taken together with the results in figure 6, there is no substantial evidence credit supply or credit demand shocks independently feed into the real economy.

5.2. Fixing the Monetary Policy and Money Demand Regressions

The next counterfactual experiment evaluates whether regime switches in the impact and lag coefficients contributed to the 2007-2009 recession and financial crisis. To produce this evidence, the exercise eliminates the second regime of the impact and lag coefficients. As a result, only the first regime coefficients are used to generate the counterfactual paths of y_t.[12]

Figure 8 displays the historical and counterfactual paths of y_t assuming the first impact and lag coefficient regime prevails throughout the entire sample. Perhaps the most interesting observations in figure 8 are the historical and counterfactual paths of the FFR, RGDP, and UR. The median counterfactual path of the FFR turns significantly negative during the 2007-2009 financial crisis. However, the actual historical path of FFR remains close to zero. The counterfactual paths of RGDP and UR indicate the 2007-2009 recession would have not been as prolonged and severe if the FFR dropped below zero. The median counterfactual path of RGDP increases substantially and at a faster pace compared to the actual path. Moreover, the median counterfactual path of RGDP shows it returns to its previous growth path almost immediately after the 2007-2009 recession. The actual path does not return to its previous growth path until near the end of the sample. I interpret this counterfactual experiment to show that holding the FFR at zero or above contributed to a slow and low-growth recovery.

The counterfactual path of the FFR in figure 8 resembles the shadow FFR of Krippner (2013), Wu and Xia (2016), and Johannsen and Mertens (2021). Figure 9 plots these various shadow rate estimates in the monetary policy SVAR literature alongside the counterfactual path of the FFR in figure 8.[13] Two observations can be made. First, the shadow rate estimate produced by model 28 is substantially lower than the other shadow rate estimates between 2008 and 2010. Second, the other shadow rates mostly reside within the 68% uncertainty bands and are below zero between 2010 to 2012. Krippner (2013), Wu and Xia (2016), and Johannsen and Mertens (2021) also produce counterfactuals showing RGDP recovers faster

[12] Counterfactual results that keep the first regime of the impact and lag coefficients throughout the sample and suppress credit supply or credit demand shocks are not qualitatively different from the results here.

[13] I thank Elmar Mertens for providing me with the shadow rate data from Johannsen and Mertens (2021).

after their shadow rates dropped below zero.

There are several other results worth noting in figure 8. First, model 28 attributes the sudden and abrupt increase in the MB to a regime switch in the impact and lag coefficients. If this regime switch had not occurred, the counterfactual path reveals the MB would have followed a trajectory similar to its pre-crisis path. Second, counterfactual results also show the counterfactual path of the MB prevented disinflation, giving support to the new Keynesian and Fed's claim that QE and LSAPs prevented disinflation during and after the 2007-2009 recession. Third, MI does not follow a similar counterfactual path. This evidence supports Tobin (1961) and Brunner and Meltzer (1972, 1988). They argue the Fed's control of outside money is not sufficient for control over the stock of inside money in the economy. Inside money creation depends on whether financial intermediaries use the additional outside money to issue more credit. However, financial intermediaries appeared to supply more credit because counterfactual exercise produces a spread of R_{CP} over the FFR that is insufficiently different from the predicted median paths of these rates. This can be seen in figure 10, which plots the historical and counterfactual paths of the liquidity, term, and risk spreads.

Interestingly enough, figure 10 shows the counterfactual term and risk spreads are briefly sufficiently different from their historical counterparts. One interpretation of this finding is similar to the predictions of the TBM monetary transmission mechanism. Figure 8 predicts while the counterfactual median paths of the FFR, R_{CP}, and R_{10yr} drop below zero, the counterfactual median path of R_{Baa} remains positive. Investors, seeking higher yields, rebalance their portfolios from the negative interest bearing assets to the alternative long-term private assets. This portfolio rebalancing has two effects. First, the increased selling of U.S. Treasuries caused by investors' portfolio rebalancing lowers the price of the long-term government assets, leading to an increase in R_{10yr}. As R_{10yr} increases and the FFR continues to fall well below zero, the term spread widens, as seen in the middle panel of figure 10. An opposite effect occurs with the yield on long-term private assets. As the demand for long-term private assets increase, R_{Baa} falls. This is shown in figure 8. As a result, the risk spread between

the R_{Baa} and R_{10yr} would also drop. Hence, the counterfactual experiment displays another channel by which an extraordinary level of expansionary monetary policy by the Fed would have achieve its policy goals to stabilize financial markets by lowering risk premiums.

6. Conclusion

This paper extends Sims and Zha (2006) to evaluate the roles of short- and long-term private and government interest rates and inside and outside money in the monetary transmission mechanism. I estimate several MS-BVARs on a quarterly U.S. sample from 1960Q1 to 2018Q4. Identification of the MS-BVARs rests on a theory of the monetary transmission mechanism consistent with Tobin (1961) and Brunner and Meltzer (1972, 1988). Their theory assumes money, credit, and financial markets play important roles in transmitting monetary policy to the real economy.

Of the 35 MS-BVARs estimated, the data favor an MS-BVAR which restricts MS to the impact and lag coefficients of the monetary policy and money demand regressions and the SVs of the structural shocks. This is in contrast to Sims and Zha's (2006) best-fit MS-BVAR. Their MS-BVAR does not find evidence of monetary policy regime switches. I show that extending the estimation sample to 2018Q4 and including additional variables to the model gives the best-fit MS-BVAR sufficient information to detect these regime switches. The best-fit MS-BVAR also is estimated under a non-recursive identification scheme that describes Fed monetary policy as an interest rate rule. The non-recursive identification scheme underscores the interaction of money and credit markets is key to understanding the monetary transmission mechanism as argued by Tobin (1961), Brunner and Meltzer (1972, 1988), Sims (1992), Gordon and Leeper (1994), and Leeper and Roush (2003).

Counterfactual simulations produced by the best-fit MS-BVAR comment on Fed monetary policy since 2007. If the Fed monetary policy and money demand regime switch had not occurred, real activity in the U.S. would have returned to its growth path within three

years after the end of the 2007-2009 recession. However, this would have required the FFR to be as low as -8% in 2009 and remain negative from 2010 through 2016. This shadow rate estimate of the FFR is lower than those reported by Krippner (2013), Wu and Xia (2016), and Johannsen and Mertens (2021).

There are several directions for future research to pursue. One is to apply the TBM monetary transmission mechanism to the open economy. For example, the Fed's response to the end of the Bretton Woods system can be evaluated by marrying the TBM monetary transmission mechanism to an open economy MS-BVAR. Another is suggested by my counterfactual experiment examining Fed monetary policy in the 2000s and 2010s. In this case, the goal is to evaluate the balance sheet policies necessary for the FFR to reach -8% in 2009 and remain below zero through 2016. Finally, one can study the TBM monetary transmission mechanism in a MS-DSGE. A starting place for this experiment would be to incorporate MS into the New Monetarist DSGE model of Geromichalos and Herrenbrueck (2022). I hope this paper stimulates future monetary policy research on these questions.

References

Bernanke, Ben and Mark Gertler (1989). "Agency Costs, Net Worth, and Business Fluctuations". *American Economic Review* 79.1, pp. 14–31.

Bernanke, Ben S. and Alan S. Blinder (1988). "Credit, Money, and Aggregate Demand". *American Economic Review* 78.2, pp. 435–439.

Bernanke, Ben S. and Mark Gertler (1995). "Inside the Black Box: The Credit Channel of Monetary Policy Transmission". *The Journal of Economic Perspectives* 9.4, pp. 27–48.

Bianchi, Francesco (2016). "Methods for Measuring Expectations and Uncertainty in Markov-Switching Models". *Journal of Econometrics* 190.1, pp. 79–99.

Brunner, Karl and Allan H. Meltzer (1972). "Money, Debt, and Economic Activity". *Journal of Political Economy* 80.5, pp. 951–977.

— (1988). "Money and Credit in the Monetary Transmission Process". *American Economic Review* 78.2, pp. 446–51.

Check, Adam (2021). *Estimating the FOMC's Interest Rate Rule with Variable Selection and Partial Regime Switching*. Working Paper.

FOMC (1999a). *Minutes of the Federal Open Market Committee — November 16, 1999*. FOMC Minutes. FOMC.

— (1999b). *Minutes of the Federal Open Market Committee — October 5, 1999*. FOMC Minutes. FOMC.

— (2000). *Minutes of the Federal Open Market Committee — February 1-2, 1999*. FOMC Minutes. FOMC.

Gelfand, A. E. and D. K. Dey (1994). "Bayesian Model Choice: Asymptotics and Exact Calculations". *Journal of the Royal Statistical Society. Series B* 56.3, pp. 501–514.

Geromichalos, Athanasios and Lucas Herrenbrueck (2022). "The Liquidity-Augmented Model of Macroeconomic Aggregates: A New Monetarist DSGE approach". *Review of Economic Dynamics* 45, pp. 134–167.

Geweke, John (2005). *Contemporary Bayesian Econometrics and Statistics*. Hobeken, New Jersey: John Wiley.

Goodfriend, Marvin (2005). "Narrow Money, Broad Money, and the Transmission of Monetary Policy". *Models of Monetary Policy: Research in the Tradition of Dale Henderson, Richard Porter, and Peter Tinsley*. Federal Reserve Bank of Richmond.

Gordon, David B. and Eric M. Leeper (1994). "The Dynamic Impacts of Monetary Policy: An Exercise in Tentative Identification". *Journal of Political Economy* 102.6, pp. 1228–1247.

Gorton, Gary and Andrew Metrick (2012). "Securitized Banking and the Run on Repo". *Journal of Financial Economics* 104.3, pp. 425–451.

Hubrich, Kirstin and Robert J. Tetlow (2015). "Financial Stress and Economic Dynamics: The Transmission of Crises". *Journal of Monetary Economics* 70, pp. 100–115.

Johannsen, Benjamin K. and Elmar Mertens (2021). "A Time Series Model of Interest Rates With the Effective Lower Bound". *Journal of Money, Credit and Banking* 0.0, pp. 1–46.

Karamé, Frédéric (2015). "Asymmetries and Markov-Switching Structural VAR". *Journal of Economic Dynamics and Control* 53, pp. 85–102.

Kass, Robert E. and Adrian E. Raftery (1995). "Bayes Factors". *Journal of the American Statistical Association* 90.430, pp. 773–795.

Kim, Chang-Jin (1994). "Dynamic Linear Models with Markov-Switching". *Journal of Econometrics* 60.1, pp. 1–22.

Krippner, Leo (2013). "Measuring the Stance of Monetary Policy in Zero Lower Bound Environments". *Economics Letters* 118.1, pp. 135–138.

Krishnamurthy, Arvind and Annette Vissing-Jorgensen (2012). "The Aggregate Demand for Treasury Debt". *Journal of Political Economy* 120.2, pp. 233–267.

Leeper, Eric M. and Jennifer E. Roush (2003). "Putting "M" Back in Monetary Policy". *Journal of Money, Credit and Banking* 35.6, pp. 1217–1256.

Leeper, Eric M., Christopher A. Sims, and Tao Zha (1996). "What Does Monetary Policy Do?" *Brookings Papers on Economic Activity* 2, pp. 1–63.

Lhuissier, Stéphane and Fabien Tripier (2021). "Regime-Dependent Effects of Uncertainty Shocks: A Structural Interpretation". *Quantitative Economics* 12.4, pp. 1139–1170.

McCallum, Bennett T. (1987). *The Case for Rules in the Conduct of Monetary Policy: A Concrete Example*. Working Paper. Federal Reserve Bank of Richmond, pp. 10–18.

Rubio-Ramírez, Juan F., Daniel F. Waggoner, and Tao Zha (2010). "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference". *Review of Economic Studies* 77.2, pp. 665–696.

Sims, Christopher A. (1992). "Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy". *European Economic Review* 36.5, pp. 975–1000.

Sims, Christopher A., Daniel F. Waggoner, and Tao Zha (2008). "Methods for Inference in Large Multiple-Equation Markov-Switching Models". *Journal of Econometrics* 146.2, pp. 255–274.

Sims, Christopher A. and Tao Zha (1998). "Bayesian Methods for Dynamic Multivariate Models". *International Economic Review* 39.4, pp. 949–968.

— (2006). "Were There Regime Switches in U.S. Monetary Policy?" *American Economic Review* 96.1, pp. 54–81.

Smets, Frank and Rafael Wouters (2007). "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach". *American Economic Review* 97.3, pp. 586–606.

Taylor, John B. (1993). "Discretion Versus Policy Rules in Practice". *Carnegie-Rochester Conference Series on Public Policy* 39.1, pp. 195–214.

Tobin, James (1961). "Money, Capital, and Other Stores of Value". *American Economic Review* 51.2, pp. 26–37.

Wu, Jing Cynthia and Fan Dora Xia (2016). "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound". *Journal of Money, Credit and Banking* 48.2-3, pp. 253–291.

Tables and Figures

Table 1: Non-Recursive Identifying Restrictions on the Impact Matrix $A_0(s_t)$

	Behavioral Equation								
Variable \ Shock	Risk Premium	Term Premium	Credit Supply	Credit Demand	Money Demand	Monetary Policy	Aggregate Supply	Aggregate Demand	Labor Supply
R_{Baa}	X								
R_{10yr}	X	X							
R_{CP}	X	X	X	X	X				
MI	X	X	X	X					
MB	X	X	X		X	X_1			
FFR	X	X	X	X	X	X_2			
RGDP	X	X	X	X	X	X_3	X	X	X
P	X	X	X	X	X	X_4		X	X
UR	X	X	X						X

Notes: Each column in this table represents a behavioral equation. The behavioral equations are labeled at the top by their respective structural shock. The row labels indicate which variables enter each behavioral equation at impact. An "X" entry represents an unrestricted impact coefficient, while a blank space denotes a zero restriction. Restrictions on X_i $(i = 1, 2)$ in the Monetary Policy column specify whether the policy rule is an interest rate rule, $X_1 = 0$, a money supply rule, $X_2 = 0$, or an Interest Rate/Money Supply rule, $X_3 = X_4 = 0$.

Table 2: List of the Constant Coefficient and MS-BVARs

Model	**Model Specification**	**Identifying Restrictions on $A_0(s_t)$**
Model 1	1c1v	Recursive Identification: Interest Rate Rule
Model 2	1c1v	Recursive Identification: Money Supply Rule
Model 3	1c1v	Non-Recursive Identification: Interest Rate Rule
Model 4	1c1v	Non-Recursive Identification: Money Supply Rule
Model 5	1c1v	Non-Recursive Identification: Interest Rate/Money Supply Rule
Model 6	1c2v	Recursive Identification: Interest Rate Rule
Model 7	1c2v	Recursive Identification: Money Supply Rule
Model 8	1c2v	Non-Recursive Identification: Interest Rate Rule
Model 9	1c2v	Non-Recursive Identification: Money Supply Rule
Model 10	1c2v	Non-Recursive Identification: Interest Rate/Money Supply Rule
Model 11	2c1v	Recursive Identification: Interest Rate Rule
Model 12	2c1v	Recursive Identification: Money Supply Rule
Model 13	2c1v	Non-Recursive Identification: Interest Rate Rule
Model 14	2c1v	Non-Recursive Identification: Money Supply Rule
Model 15	2c1v	Non-Recursive Identification: Interest Rate/Money Supply Rule
Model 16	2c2v	Recursive Identification: Interest Rate Rule
Model 17	2c2v	Recursive Identification: Money Supply Rule
Model 18	2c2v	Non-Recursive Identification: Interest Rate Rule
Model 19	2c2v	Non-Recursive Identification: Money Supply Rule
Model 20	2c2v	Non-Recursive Identification: Interest Rate/Money Supply Rule
Model 21	2MPc2v	Recursive Identification: Interest Rate Rule
Model 22	2MPc2v	Recursive Identification: Money Supply Rule
Model 23	2MPc2v	Non-Recursive Identification: Interest Rate Rule
Model 24	2MPc2v	Non-Recursive Identification: Money Supply Rule
Model 25	2MPc2v	Non-Recursive Identification: Interest Rate/Money Supply Rule
Model 26	2MPBc2v	Recursive Identification: Interest Rate Rule
Model 27	2MPBc2v	Recursive Identification: Money Supply Rule
Model 28	2MPBc2v	Non-Recursive Identification: Interest Rate Rule
Model 29	2MPBc2v	Non-Recursive Identification: Money Supply Rule
Model 30	2MPBc2v	Non-Recursive Identification: Interest Rate/Money Supply Rule
Model 31	2MPc2MDc2v	Recursive Identification: Interest Rate Rule
Model 32	2MPc2MDc2v	Recursive Identification: Money Supply Rule
Model 33	2MPc2MDc2v	Non-Recursive Identification: Interest Rate Rule
Model 34	2MPc2MDc2v	Non-Recursive Identification: Money Supply Rule
Model 35	2MPc2MDc2v	Non-Recursive Identification: Interest Rate/Money Supply Rule

Notes: The label #c indicates the number of states in the impact and lag coefficients, while #v specifies the number of SV regimes. In addition, the label #MPc indicates only the monetary policy rule regression has MS impact and lag coefficients. The label #MPBc indicates only the monetary policy block regressions (FFR and MB) have MS impact and lag coefficients. The label #MPc#MDc indicates the impact and lag coefficients of the money supply and money demand regressions follow independent MS chains.

Table 3: Log Marginal Data Densities of the Constant Coefficient and MS-BVARs

	Model Specification						
Identifying Restrictions on $A_0(s_t)$	1c1v	1c2v	2c1v	2c2v	2MPc2v	2MPBc2v	2MPc2MDc2v
Recursive Identification: Interest Rate Rule	Model 1	Model 6	Model 11	Model 16	Model 21	Model 26	Model 31
	-2872.47	-2571.60	-2602.28	-2419.46	-2560.34	-2384.34	-2409.80
Recursive Identification: Money Supply Rule	Model 2	Model 7	Model 12	Model 17	Model 22	Model 27	Model 32
	-2872.62	-2571.33	-2603.06	-2424.40	-2563.16	-2389.06	-2417.10
Non-Recursive Identification: Interest Rate Rule	Model 3	Model 8	Model 13	Model 18	Model 23	**Model 28**	Model 33
	-2877.28	-2566.76	-2593.23	$*$	-2413.09	**-2370.43**	-2395.69
Non-Recursive Identification: Money Supply Rule	Model 4	Model 9	Model 14	Model 19	Model 24	Model 29	Model 34
	-2867.46	-2562.93	-2588.01	$*$	-2491.21	-2375.36	-2397.04
Non-Recursive Identification: Interest Rate/Money Supply Rule	Model 5	Model 10	Model 15	Model 20	Model 25	Model 30	Model 35
	-2863.80	-2556.81	-2581.10	-2432.50	-2454.35	-2373.96	-2376.45

Notes: Marginal data densities (MDDs) of the MS-BVARs are computed using the truncated modified harmonic mean (MHM) estimator of Sims, Waggoner, and Zha (2008). MDDs of the constant coefficient BVARs (models 1 to 4) are computed using the MHM estimator of Gelfand and Dey (1994) and Geweke (2005). The results shown are expressed in logarithms and are based on 10 million MCMC draws and the full data sample from 1960Q1 to 2018Q4. An asterisk ($*$) indicates the chains of the Metropolis-within-Gibbs MCMC sampler did not converge for the relevant model. In this case, the model being estimated lacks a well-approximated MDD. The model number and log MDD corresponding to the best-fit MS-BVAR are highlighted in bold.

Table 4: Diagonals of the SV Matrices $\hat{\Xi}^{-1}(s_t^{sv})$, Model 28

	R_{Baa}	R_{10yr}	R_{CP}	MI	MB	FFR	RGDP	P	UR
$s_t^{sv} = 1$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]
$s_t^{sv} = 2$	0.210	0.367	0.177	0.190	0.444	0.068	0.243	0.193	0.243
	[0.146, 0.306]	[0.247, 0.539]	[0.127, 0.246]	[0.133, 0.272]	[0.287, 0.663]	[0.052, 0.089]	[0.174, 0.338]	[0.138, 0.274]	[0.174, 0.341]

Notes: This table reports the posterior median estimates of the diagonal elements of the SV matrices for the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. The 90% Bayesian credible sets (i.e., the 5th and 95th quantiles) are reported in brackets. The results shown are based on 10 million MCMC draws and the full data sample from 1960Q1 to 2018Q4.

Table 5: Posterior Estimates of the Impact Matrix $\hat{A}_0(s_t^c = 1)$, Model 28

	Behavioral Equation								
Variable \ Shock	Risk Premium	Term Premium	Credit Supply	Credit Demand	Money Demand	Monetary Policy	Aggregate Supply	Aggregate Demand	Labor Supply
R_{Baa}	3.033								
	[2.616, 3.506]								
R_{10yr}	-1.907	2.228							
	[-2.240, -1.600]	[1.891, 2.579]							
R_{CP}	-0.443	-1.404	2.506	-0.362	0.009				
	[-0.793, -0.109]	[-1.842, -0.999]	[2.122, 2.874]	[-1.324, 0.616]	[-0.417, 0.419]				
MI	-0.023	0.041	0.065	0.216					
	[-0.049, 0.002]	[0.010, 0.073]	[-0.016, 0.143]	[0.171, 0.253]					
MB	-0.009	-0.003	-0.015		0.314				
	[-0.017, -0.002]	[-0.010, 0.004]	[-0.023, -0.007]		[0.262, 0.370]				
FFR	0.373	0.761	-2.184	0.544	-0.023	0.777			
	[0.061, 0.687]	[0.413, 1.133]	[-2.533, -1.797]	[-0.332, 1.375]	[-0.420, 0.385]	[0.687, 0.872]			
RGDP	0.025	-0.029	-0.033	-0.019	-0.010	-0.042	0.236	0.020	0.136
	[-0.004, 0.057]	[-0.064, 0.007]	[-0.062, -0.005]	[-0.048, 0.010]	[-0.047, 0.026]	[-0.061, -0.024]	[0.203, 0.270]	[-0.004, 0.044]	[0.104, 0.173]
P	0.031	-0.128	-0.082	-0.037	-0.078	-0.071		0.526	0.011
	[-0.028, 0.091]	[-0.199, -0.055]	[-0.143, -0.024]	[-0.103, 0.034]	[-0.175, 0.010]	[-0.124, -0.021]		[0.457, 0.597]	[-0.052, 0.074]
UR	-0.319	0.586	0.279						3.301
	[-0.701, 0.040]	[0.149, 1.022]	[-0.063, 0.464]						[2.861, 3.786]

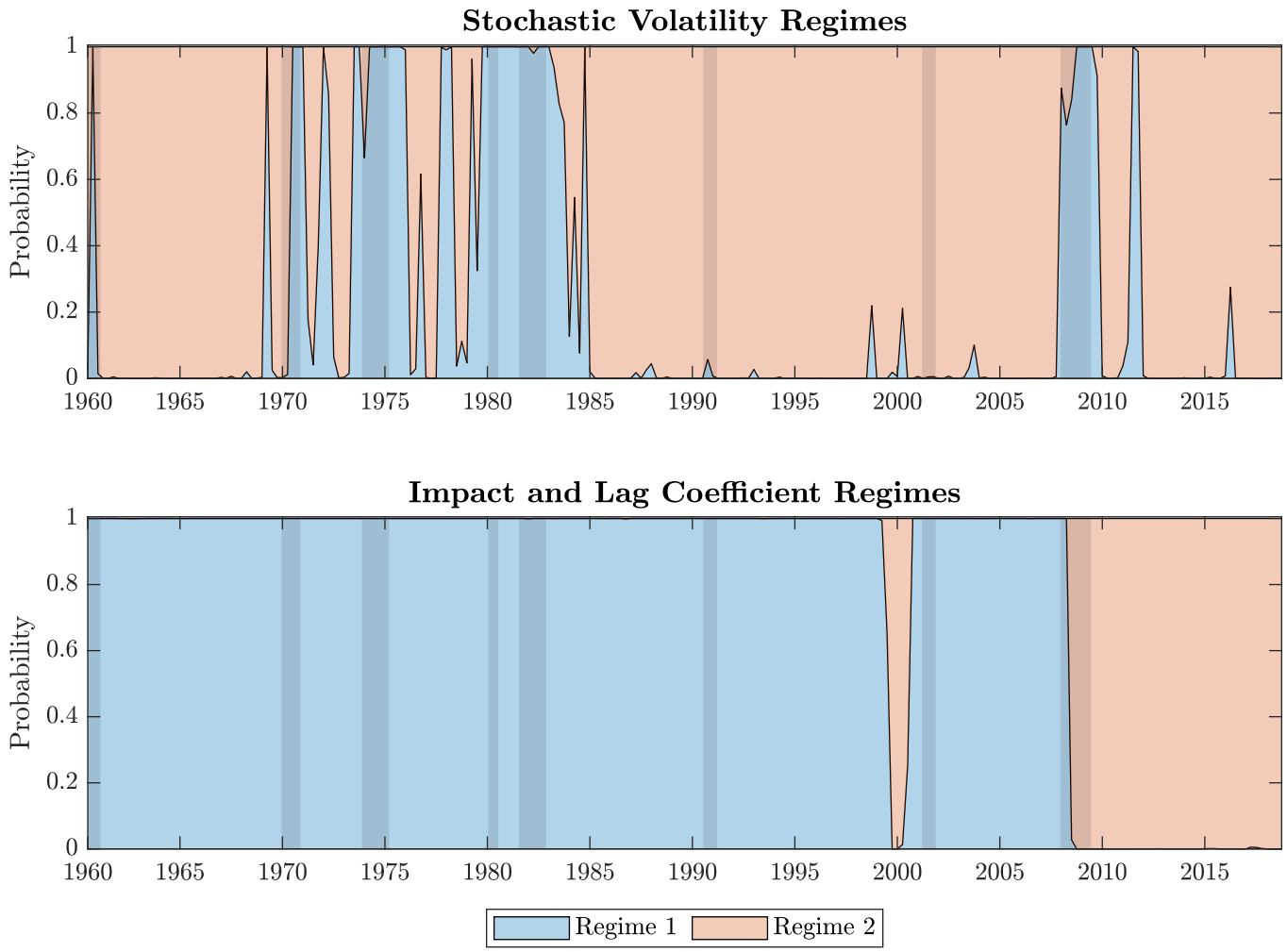
Notes: This table reports the posterior median estimates of the impact matrix for the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR under the first impact and lag coefficient regime. The 90% Bayesian credible sets (i.e., the 5th and 95th quantiles) are reported in brackets. The results shown are based on 10 million MCMC draws and the full data sample from 1960Q1 to 2018Q4. Each column in this table represents a behavioral equation. The behavioral equations are labeled at the top by their respective structural shock. The row labels indicate which variables enter each behavioral equation at impact.

Table 6: Posterior Estimates of the Impact Matrix $\hat{A}_0(s_t^c = 2)$, Model 28

	Behavioral Equation								
Variable \ Shock	Risk Premium	Term Premium	Credit Supply	Credit Demand	Money Demand	Monetary Policy	Aggregate Supply	Aggregate Demand	Labor Supply
R_{Baa}	3.033								
	[2.616, 3.506]								
R_{10yr}	-1.907	2.228							
	[-2.240, -1.600]	[1.891, 2.579]							
R_{CP}	-0.443	-1.404	2.506	-0.362	2.716				
	[-0.793, -0.109]	[-1.842, -0.999]	[2.122, 2.874]	[-1.324, 0.616]	[1.287, 3.996]				
MI	-0.023	0.041	0.065	0.216					
	[-0.049, 0.002]	[0.010, 0.073]	[-0.016, 0.143]	[0.171, 0.253]					
MB	-0.009	-0.003	-0.015		0.036				
	[-0.017, -0.002]	[-0.010, 0.004]	[-0.023, -0.007]		[0.026, 0.046]				
FFR	0.373	0.761	-2.184	0.544	1.731	2.878			
	[0.061, 0.687]	[0.413, 1.133]	[-2.533, -1.797]	[-0.332, 1.375]	[0.285, 3.171]	[2.364, 3.436]			
RGDP	0.025	-0.029	-0.033	-0.019	-0.052	-0.050	0.236	0.020	0.136
	[-0.004, 0.057]	[-0.064, 0.007]	[-0.062, -0.005]	[-0.048, 0.010]	[-0.165, 0.066]	[-0.102, 0.003]	[0.203, 0.270]	[-0.004, 0.044]	[0.104, 0.173]
P	0.031	-0.128	-0.082	-0.037	-0.165	0.024		0.526	0.011
	[-0.028, 0.091]	[-0.199, -0.055]	[-0.143, -0.024]	[-0.103, 0.034]	[-0.404, 0.060]	[-0.080, 0.126]		[0.457, 0.597]	[-0.052, 0.074]
UR	-0.319	0.586	0.279						3.301
	[-0.701, 0.040]	[0.149, 1.022]	[-0.063, 0.464]						[2.861, 3.786]

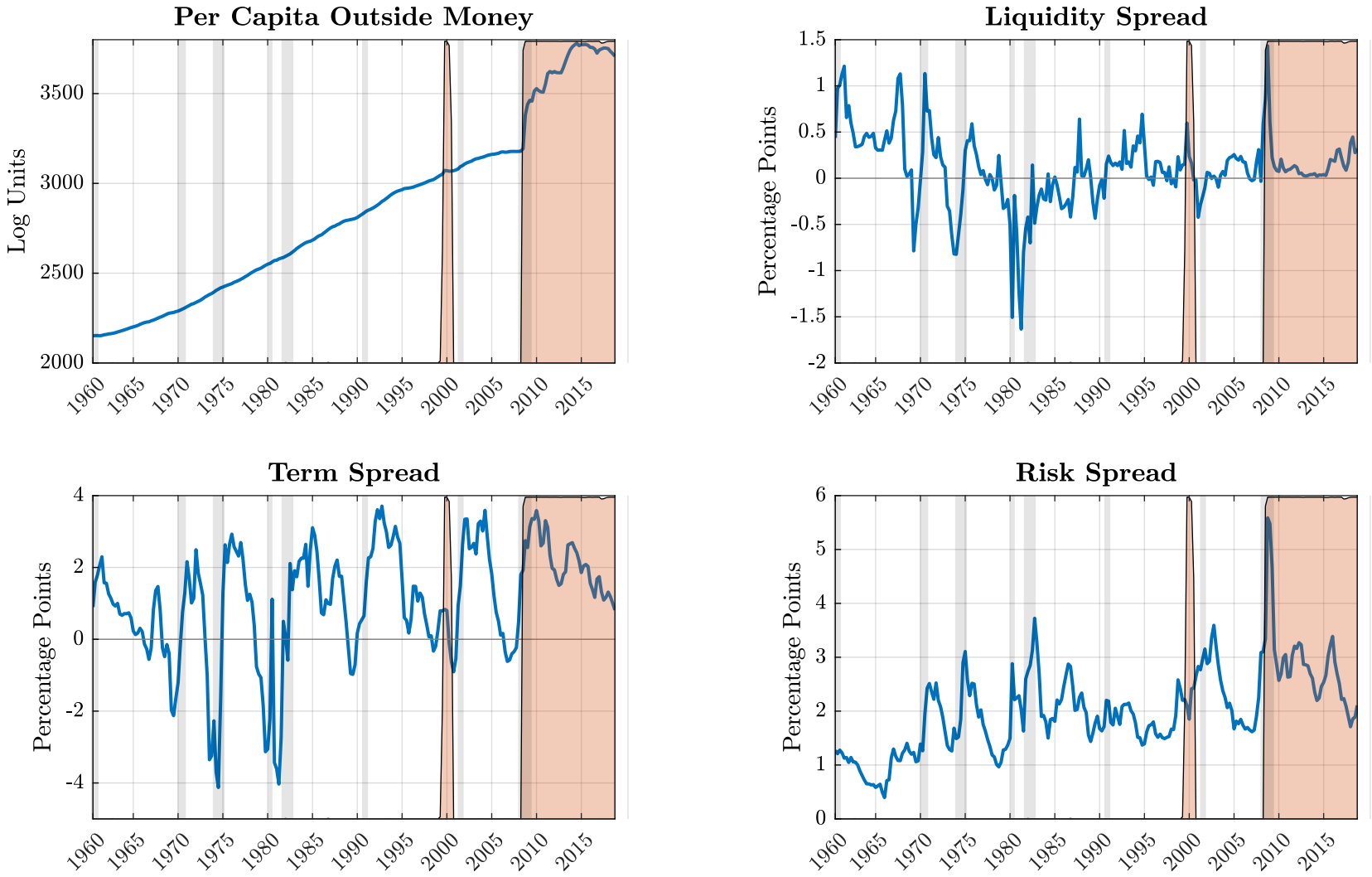
Notes: This table reports the posterior median estimates of the impact matrix for the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR under the second impact and lag coefficient regime. Otherwise, see the notes to table 5.

Figure 1: Smoothed Conditional Regime Probabilities of Model 28, 1960Q1 to 2018Q4



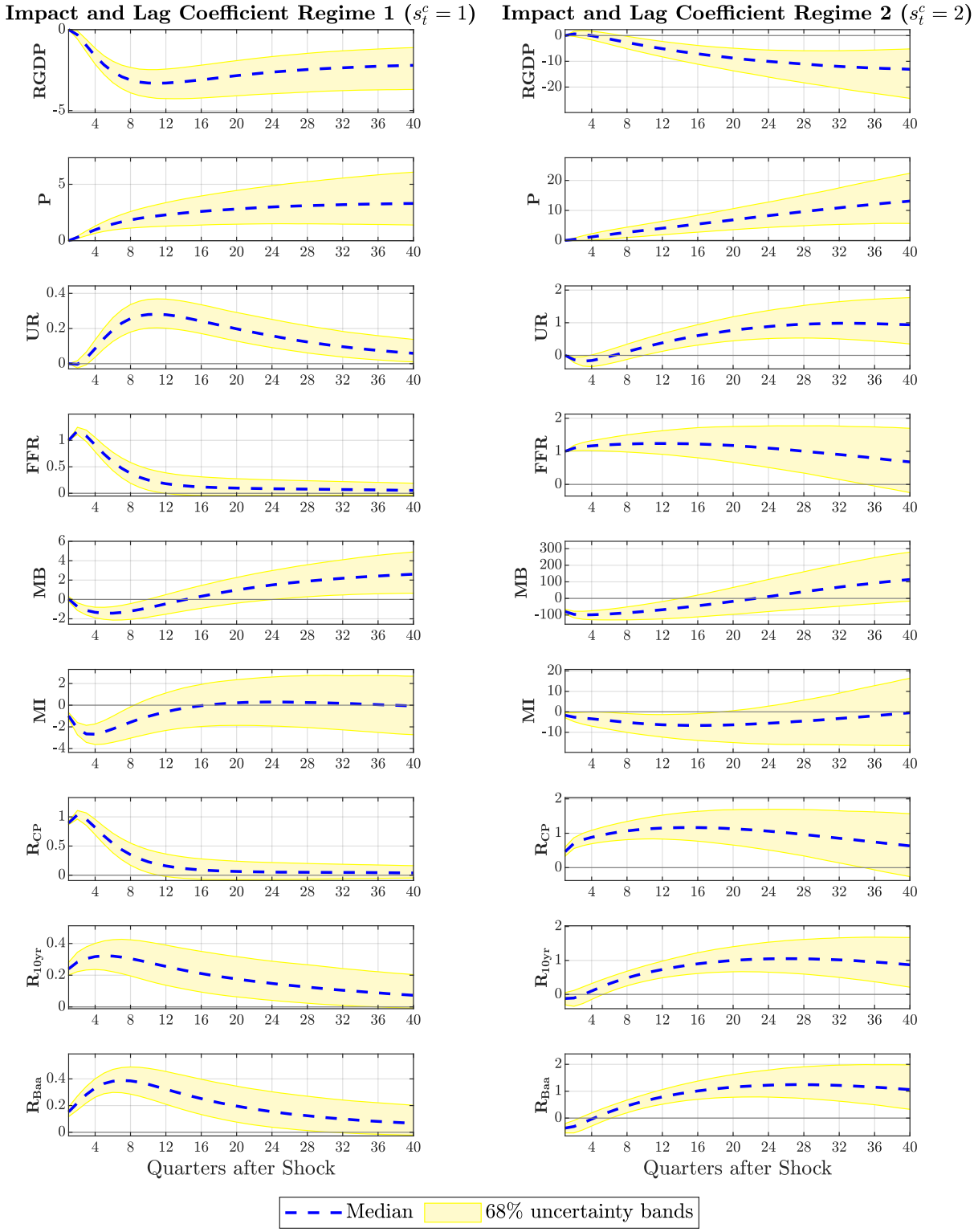
Notes: This figure plots the smoothed conditional SV and impact and lag coefficient regime probabilities of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. The results shown are based on 10 million MCMC draws and the full data sample from 1960Q1 to 2018Q4. The shaded bars correspond to the NBER recession dates.

Figure 2: Per Capita Outside Money and Interest Rate Spreads, 1960Q1 to 2018Q4



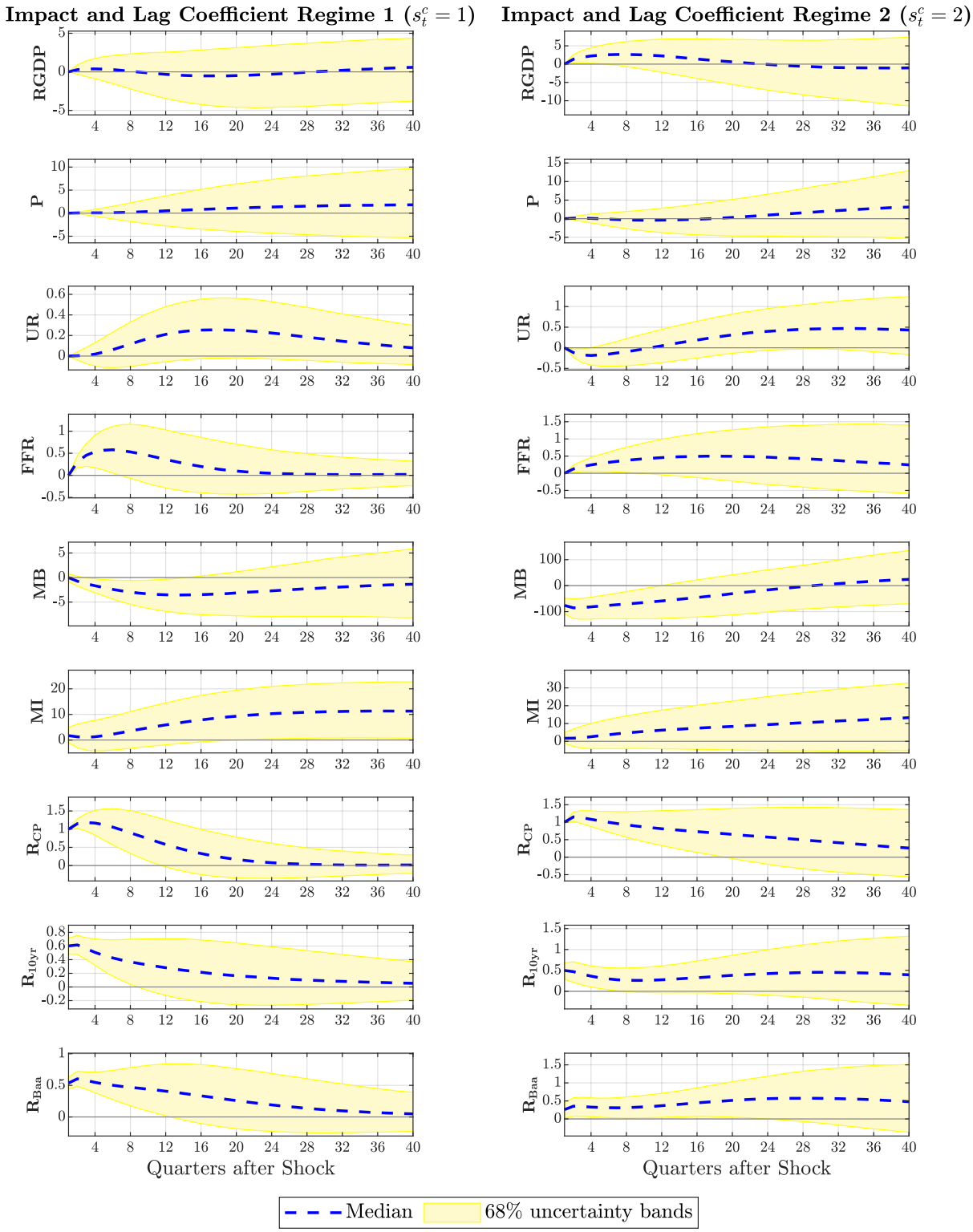
Notes: This figure plots the MB and the liquidity, term, and risk spreads. The red areas denote periods during which the second impact and lag coefficient regime of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR prevails. In each subplot, the observed time series is traced with blue lines. The results shown are based on 10 million MCMC draws and the full data sample from 1960Q1 to 2018Q4. The shaded bars correspond to the NBER recession dates.

Figure 3: Conditional GIRFs with Respect to a Monetary Policy Shock of Model 28



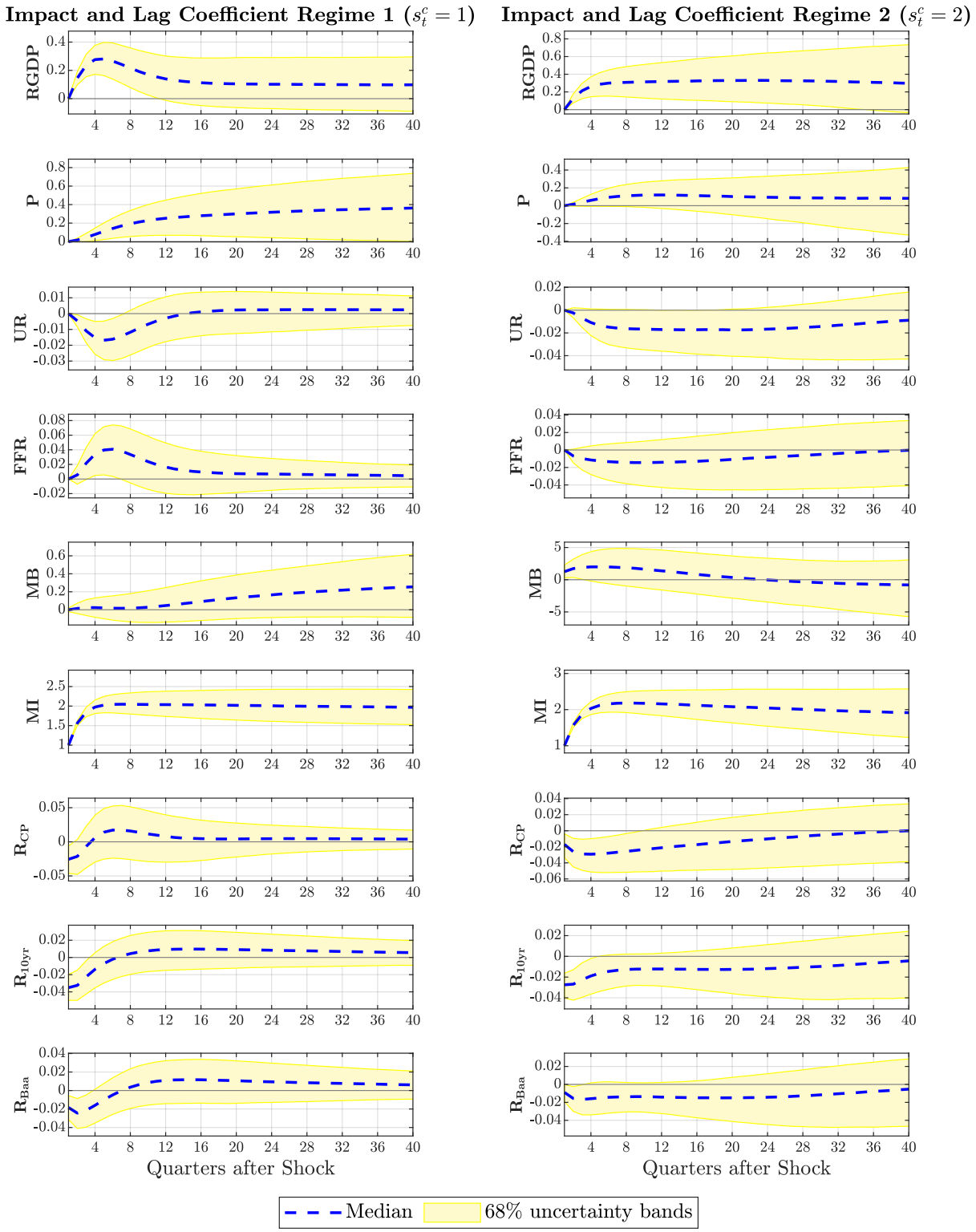
Notes: This figure plots the conditional GIRFs with respect to a monetary policy shock of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. The GIRFs in the left (right) column are conditional on the first (second) impact and lag coefficient regime being in place at the time of the shock. The dashed blue lines represent the median GIRFs, while the surrounding yellow areas represent 68% uncertainty bands.

Figure 4: Conditional GIRFs with Respect to a Credit Supply Shock of Model 28



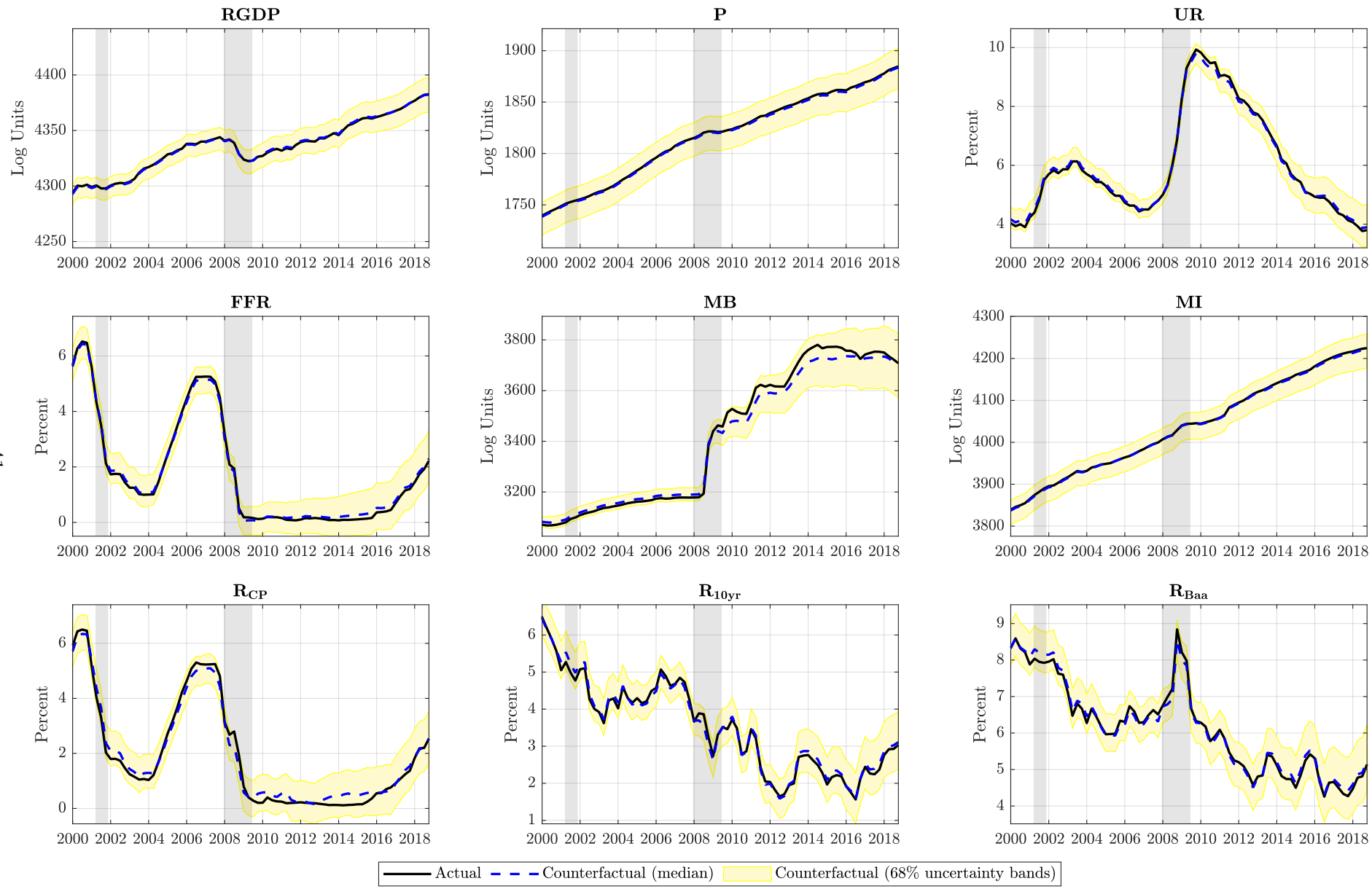
Notes: This figure plots the conditional GIRFs with respect to a credit supply shock of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. Otherwise, see the notes to figure 3.

Figure 5: Conditional GIRFs with Respect to a Credit Demand Shock of Model 28



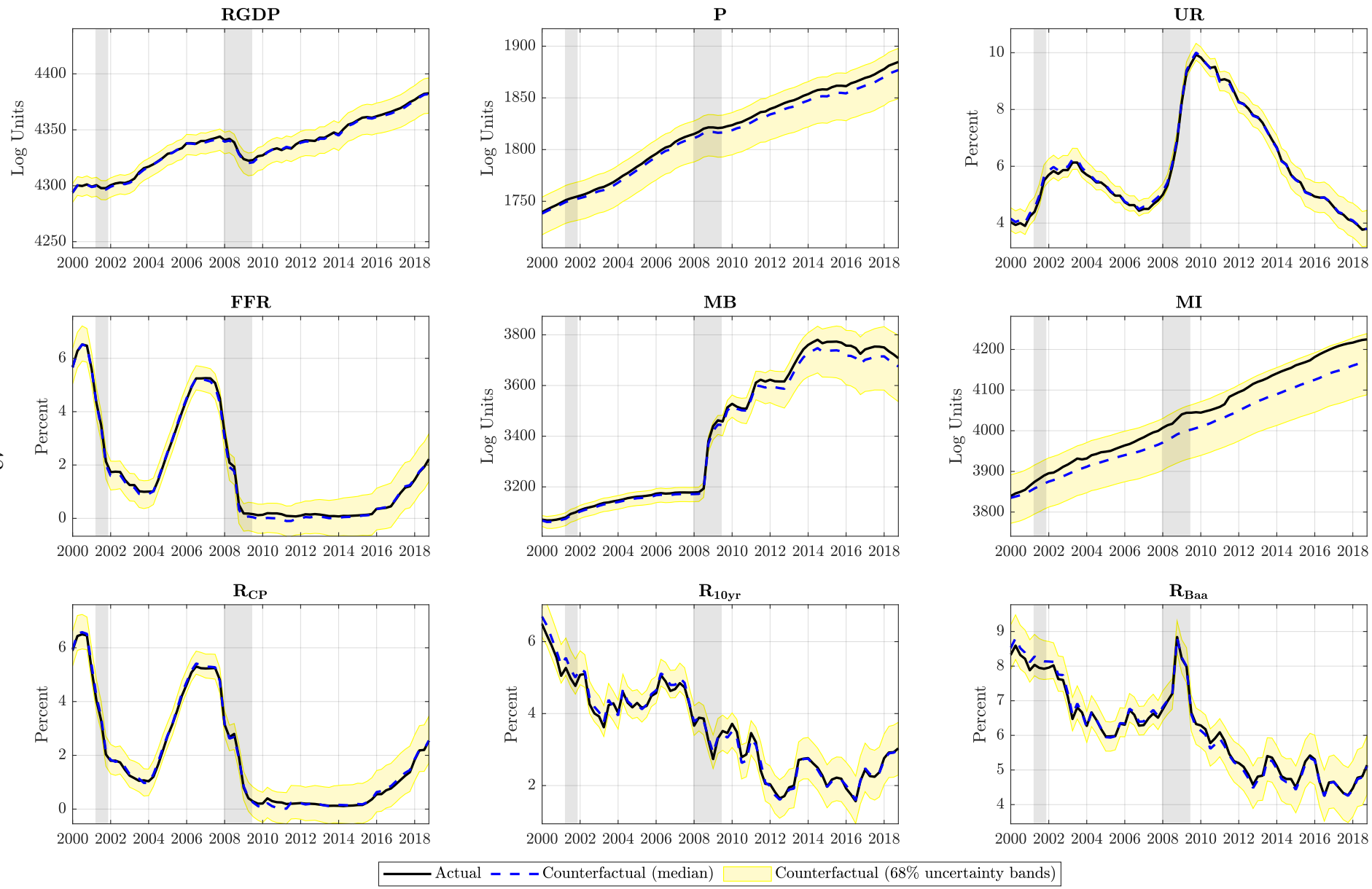
Notes: This figure plots the conditional GIRFs with respect to a credit demand shock of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. Otherwise, see the notes to figure 3.

Figure 6: Counterfactual Results of Model 28: Suppressing Credit Supply Shocks, 2000Q1 to 2018Q1



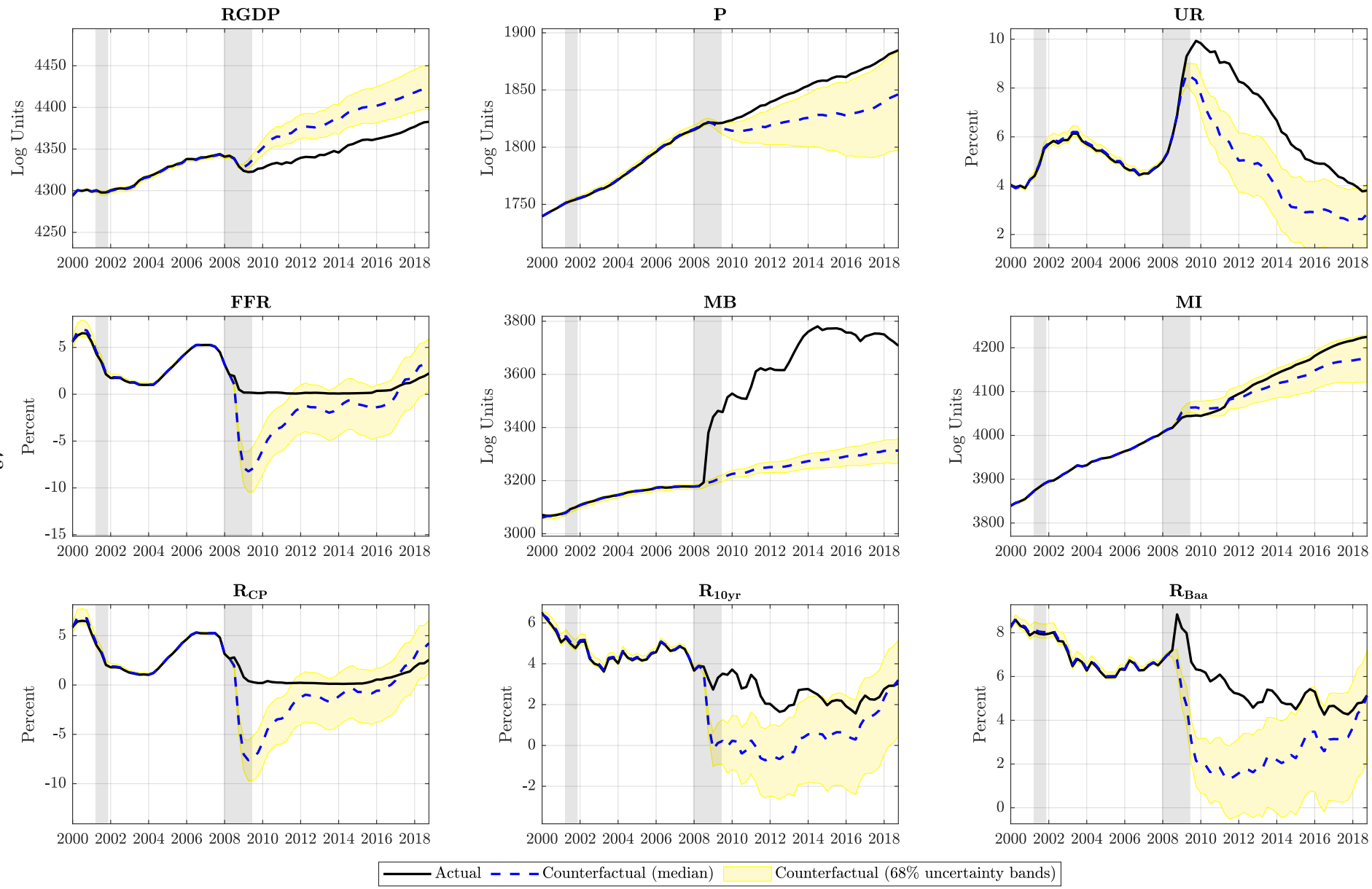
Notes: This figure plots the "Suppressing Credit Supply Shocks" counterfactual results of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. In each subplot, the solid black line represents the observed time series while the dashed blue line corresponds to the median counterfactual path. The surrounding yellow shaded areas represent 68% uncertainty bands. The gray shaded bars correspond to NBER recession dates.

Figure 7: Counterfactual Results of Model 28: Suppressing Credit Demand Shocks, 2000Q1 to 2018Q1



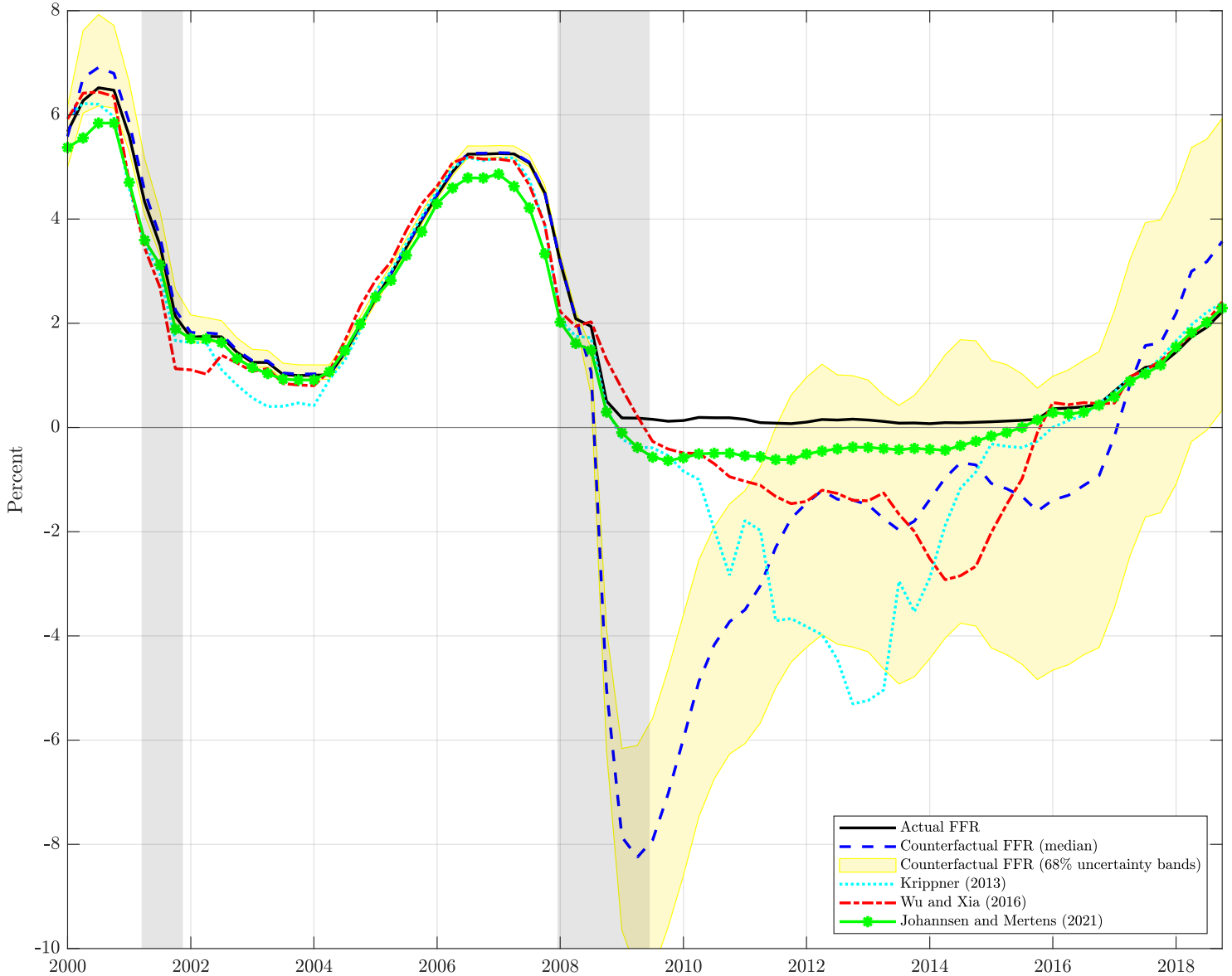
Notes: This figure plots the "Suppressing Credit Demand Shocks" counterfactual results of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. Otherwise, see the notes to figure 6.

Figure 8: Counterfactual Results of Model 28: Fixing the Monetary Policy and Money Demand Regressions, 2000Q1 to 2018Q4



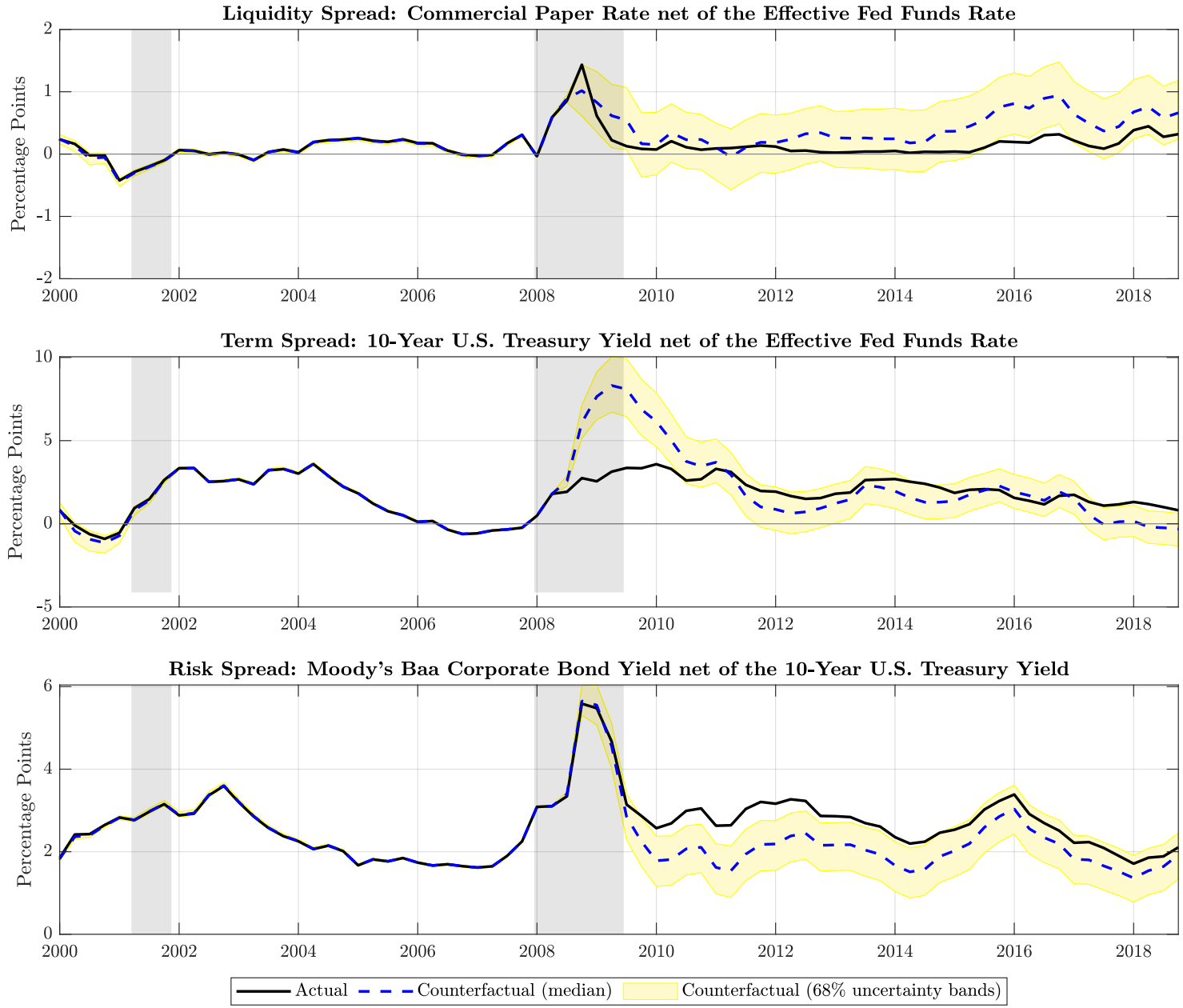
Notes: This figure plots the "Fixing the Monetary Policy and Money Demand Regressions" counterfactual results of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. Otherwise, see the notes to figure 6.

Figure 9: Shadow Rate Estimates and the Effective Fed Funds Rate, 2000Q1 to 2018Q4



Notes: This figure plots the observed (solid black line) and counterfactual (dashed blue line) paths of the FFR alongside various shadow rate estimates in the monetary policy SVAR literature. The surrounding yellow shaded areas represent 68% uncertainty bands for the counterfactual FFR. The gray shaded bars correspond to NBER recession dates.
Sources: Authors calculations, Krippner (2013), Wu and Xia (2016), and Johannsen and Mertens (2021).

Figure 10: Counterfactual Results of Model 28: Interest Rate Spreads, 2000Q1 to 2018Q4



Notes: This figure plots the liquidity, term, and risk spreads associated with the "Fixing the Monetary Policy and Money Demand Regressions" counterfactual results of the "Non-Recursive Identification: Interest Rate Rule" 2MPBc2v MS-BVAR. Otherwise, see the notes to figure 6.