Business Cycles and Financial Crises: The Roles of Credit Supply and Demand Shocks*

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Abstract

This paper explores the hypothesis that financial and economic crises are systematically different from non-crisis business cycle fluctuations. Markov-switching Bayesian vector autoregressions (MS-BVARs) are recruited to generate evidence about the hypothesis given this data. We employ an identification scheme that identifies credit supply and demand shocks. These shocks are recovered by estimating MS-BVAR models on a long annual U.S. sample that runs from 1890 to 2010. The sample contains a bevy of episodes in U.S economic and financial history. The space of MS-BVAR models are limited to MS in the stochastic volatility (SV) of the errors in the BVARs. This focuses our study on the "good luck-bad luck" story of shifting between crisis and non-crisis regimes. Of the 15 MS-BVARs we estimate, the data favors a model that recovers 3 SV regimes for output, the aggregate price level, the unemployment rate, and inside money and 3 distinct SV regimes for inside money, a short-term interest rate, a long-term interest rate, and a measure of financial risk. The estimates of this MS-BVAR model show that SV of crisis and non-crisis regimes differ systematically in the last 120 years of U.S. data.

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Key Words: inside money; credit shock; Markov-switching; Bayesian vector autoregression; stochastic volatility.

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1 Introduction

Not since the Great Depression has the U.S. been confronted by a major financial crisis and at the same time a deep and persistent economic slowdown. However, just over a decade into the new millennium this is the state in which the U.S. finds itself. Economists have responded by revisiting the Great Depression as well as the financial panics that afflicted the U.S. from the end of the Civil War to 1941. The motivation is to gain insights useful for anticipating and preventing similar events in the future.

This paper is similarly motivated. We employ structural Markov-switching Bayesian vector autoregressions (MS-BVARs) to identify credit supply and credit demand shocks. The objective is to assess the role these shocks play, if any, in subsequent contractions in output, changes in the aggregate price level, and increases in the unemployment rate on a long annual sample starting in 1890 and ending in 2010. The MS-BVARs make it possible to explain responses to identified credit supply and demand shocks at all dates across crisis and non-crisis states of the world as opposed only to estimating the impact on real activity in and around the time of financial crises. Thus, we aim to recover estimates of the probabilities of being in crisis and non-crisis regimes along with the regime dependent responses of output, prices, and the unemployment rate to identified credit supply and demand shocks. This identification is imposed on BVAR models in which MS is only imposed on the stochastic volatility (SV) of the regression errors. Hence, our results are conditional on volatility being the lone source of systematic differences across crisis and non-crisis regimes.

There is a research tradition that seeks instead to predict financial crises using observed macro and financial aggregate data. Useful earlier studies includes, among others, Canova (1991, 1994), Donaldson (1992), Coe (2002), and Eichengreen and Mitchener (2003). More recent examples are, among others, Anari, Kolari, and Mason (2005), Bussiere and Fratzscher (2006), Mendoza and Terrones (2008), Reinhart and Rogoff (2009, 2011), Bordo and Haubrich (2010), Chin and Warusawitharana (2010), Claessens, Kose, and Terrones (2011), Jordà, Schularick, and Taylor (2011a,b), Jalil (2012), Gourinchas and Obstfeld (2012), and Schularick and Taylor (2012). These papers present evidence on the co-movement of macro aggregates and indicators of financial risk over the business cycle and at longer horizons for the U.S. and internationally.

The idea of associating financial crises with large and long recessions is developed by Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2011a,b). Their aim is to uncover predictors of financial crises using a long annual-cross country sample. This work relies on defining leverage as growth in credit aggregates (in constant currency units) net of output growth. Predictability arises when regressors are found that explain the probability of financial crisis in an economy whether or not this event is followed by a severe and long recession. These papers interpret their results as supporting the hypothesis that shocks to financial markets cause deep and persistent losses in real activity.

Canova (1991) takes another tact to examining the impact of U.S. financial crises in monthly data from 1891 to 1937. Currency supply and demand shocks are identified using BVARs on pre- and post-World War I samples. The samples are split on the World War I episode because it coincides with the founding of the Fed. Prior to World War I, the U.S. has no institution responsible for supplying liquidity in the face of a financial crisis. The Fed is created, in part, to play this role. The BVAR estimates reveal that the U.S. economy responded differently to international currency shocks in the pre- and post-World War I samples. In the early sample, stickiness in domestic currency supply and seasonal shifts in currency demand magnify the impact of international currency shocks on real economic activity. The creation of the Fed lessens the impact of these shocks on the U.S. according to Canova's results. Hence, Canova shows that changes in the design of financial and economic institutions creates variation in the data useful for identifying and estimating regimes shifts.

This paper is closest in spirit to Canova (1991), Donaldson (1992) and Canova (1994), and Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2011b). We identify credit supply and demand shock similar to Canova (1994) because we identify credit supply and demand shocks, but estimates of these shocks are conditional on MS regimes.[1] By conditioning the identification on MS regimes, the BVAR estimates can be used to evaluate whether economic and financial crises differ systematically, in the spirit of Donaldson (1992) and Canova (1994), from typical business cycle fluctuations. The MS regimes are estimated using Bayesian methods of Sims and Zha (2006) and Sims, Waggoner, and Zha (2008).[2] We engage aggregate data, a credit aggregate, short- and long-term interest rates, and a measure of the risk on aggregate balance sheet of the U.S. financial firms to gauge the impact of financial market shocks on the macroeconomy as do Schularick and Taylor and Jordà, Schularick, and Taylor. However, this paper puts aside open economy issues leaving these questions for later.

The MS-BVAR models are estimated on a long annual 1890–2010 sample. By beginning the sample in 1890, we have observations that measure part of the pre-Federal Reserve National Banking

[1] Related work is Ahmadi (2009), Helbling, Huidrom, Kose, and Otrok (2011) and Eickmeier and Ng (2011). A factor-VAR is estimated by Ahmadi that allows for time-varying parameters and SV. His goal is to recover a business cycle factor conditioned on macro and interest rate spreads. The second paper also use a factor augmented-VARs, but the interest is in estimating a common credit factor in 20 years of quarterly G–7 data. Eickmeier and Ng apply a generalized VAR to recover a common world credit shock in a large panel of developed and emerging economies during the last 30 years. Credit shocks are estimated to have large and persistent effects on international real activity by these papers.

[2] For economists, foundations of this class of MS models are found in Hamilton (1994) and Kim and Nelson (1999).

Era, the early Fed of the 1920s, the pre-Federal Deposit Insurance Corporation (FDIC) Era, the 1935 to 1981 "quiet period" as defined by Gorton (2010), and the past thirty years of increasing deregulation of U.S. financial markets. During the sample, the beginnings of financial crises are associated with 1893, 1907, 1914, 1929, and 2007. The sample also covers 12 NBER dated recessions with a duration of 14 months or more, which are listed in table 1. These include 4 recessions between 1893 and 1904 that lasted 17 to 23 months, 2 recessions running 23 to 24 between 1910 and 1913, 2 recessions in the 1920s lasting at least 14 months, the Great Depression which the NBER dates to 1929, the first oil price shock recession of 1973, the recession of the early 1980s, and the 2007–2009 "housing bust" recession. Thus, a casual glance suggests that persistent recessions and financial crises do not often coincide conditional on NBER recessions dates and the history of U.S. financial crises.

The sample data consists of 7 variables with sample size $T = 121$. The variables are real GDP, the implicit GDP price deflator, the unemployment rate, inside money measured as the difference between M2 and the monetary base, an intertemporal price of credit that represents the cost of short-term funds in U.S. financial markets, the long-term interest rate of Shiller (2005), and a financial risk variable. The data is described below and in the data appendix.

The financial risk variable is novel. We measure financial risk as the ratio of private assets held by U.S. financial firms to their ownership of public assets. Movements in this ratio reflect changes in the composition of assets on the aggregate balance sheet of financial firms. Since our risk variable does not mix credit aggregates, say, with real GDP, we avoid identification issues caused by confounding financial and real shocks. There are other ways to measure financial risk, but the ratio of private to public assets held by U.S. financial firms contains useful information about changes in the riskiness of their aggregate balance sheets.

The MS-BVARs employ these 7 variables to keep the models tractable and interpretable. We ground the MS-BVAR models on a recursive Cholesky identification to uncover credit supply and demand shocks. The recursive structure places the macro block $\mathcal{M}$ consisting of output, the price level, and the unemployment rate, before the financial block $\mathcal{F}$ of inside money, the short-term interest rate, the long-term interest rate, and the risk ratio. This ordering is done to identify the response of the former block in response to the credit supply and demand shocks of the latter block, which is inspired by the reduced-form regressions and evidence of King and Plosser (1984). The credit supply and demand shocks are identified using the inside money and short-term interest rate variables. The identification relies on inside money to recover credit supply shocks because these short-term liabilities support the acquisition of long-dated and riskier assets, while shocks to the short-term interest rate capture shifts in the demand for these liabilities.

We estimate a fixed coefficient-homoskedastic BVAR and 15 MS-BVARs. The latter BVAR is dominated in fit by the 15 MS-BVAR models in which SV is the only source of shifts in regime. Hence, the estimated MS-BVAR models indicate that the SV of crisis and non-crisis regimes are systematically different. Moreover, the best fitting MS-BVAR model is one in which there are distinct regimes across the SV regimes in the $\mathcal{M}$ block and 3 distinct SV regimes in the $\mathcal{F}$ block with inside money held in common in these blocks. Estimates of this MS-BVAR model yield a $\mathcal{M}$ block with regimes that cover world wars and the Great Depression, another containing the National Banking Era, economic recoveries and post-World War II inflations, and a third that captures the era of the modern Fed and moderations in macro aggregates since the end of World War II. The $\mathcal{F}$ block reveal similar regimes, but adds a regime representing the last 40 years of financial innovations and deregulation. This regime excludes the financial boom and crisis of 2003 to 2008, which is included in a regime with World War I and World War II. This favorite MS-BVAR model of the data also produces regime dependent impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). These IRFs and FEVDs reveal that the economic interpretation of the identified credit supply and demand shocks changes across regimes.

The next section briefly reviews a selection of the extant literature that searches for financial risk measures that matters for aggregate fluctuations. The review highlights that the literature rarely addresses questions of whether and how to identify latent credit supply and demand shocks. Section 3 describes our long annual sample. We outline the methods and procedures employed to estimate and conduct inference on MS-BVARs in section 4. Results are reported in section 5. Section 6 concludes.

2 A Brief Literature Review

The financial crisis of 2007–2009 has reinvigorating research into the sources of economic and financial crises. One tradition uses structural VARs to uncover the sources and causes of financial crises. Canova (1991) is an early and useful example. Another strand of research seeks to find observables that are useful for predicting financial crises that lead to deep and persistent recessions. Our interest is not in prediction. Instead, we are motivated by this literature to obtain observable financial market data that contain information useful for evaluating whether financial and economic crises are generated by a different regime than typical business cycle fluctuations. The next section offers a brief survey of this research.

2.1 Recent Research on Financial Crises

Schularick and Taylor (2012) exploit a panel of 14 countries on a long annual sample to evaluate the impact of financial crises on real economic activity. Their cross-country panel data shows that during the last 60 years there was an expansion of loans funded with liabilities other than bank deposits. Prior to World War II, the sample yields a large positive correlation between credit and monetary aggregates. These observation motivate Schularick and Taylor to hypothesize that when financial market leverage rises above a threshold defined on output a financial crisis ensues. Hence, financial crises follow a period of excess growth in the real value of bank loans relative to output growth. Schularick and Taylor provide empirical results that indicate a rapid growth in the real value of bank loans relative to output growth is a significant predictor of future financial crisis. Nonetheless, Schularick and Taylor do not identify the underlying sources of the credit shock they estimate to have a large predictive role in financial crises and large persistent recessions.

Jordà, Schularick, and Taylor (2011a) investigate the impact on the natural rate of interest and current accounts of excessive credit growth net of output growth using a panel similar to that of Schularick and Taylor (2012). The years before a financial crisis are associated with a natural rates of interest far below its steady state by Jordà, Schularick, and Taylor (2011a), while they see substantial increases in current accounts in the subsequent years. This paper also finds that the comovement of credit growth and current account deficits has become stronger in the last 30 years. Likewise, Jordà, Schularick, and Taylor (2011b) view domestic credit markets as driving business cycle fluctuations. They argue that their empirical works supports the hypothesis of credit growth net of output growth being a key predictor of severe and long lasting recessions.

Bussiere and Fratzscher (2006), Mendoza and Terrones (2008), Bordo and Haubrich (2010), Claessens, Kose, and Terrones (2011), and Gourinchas and Obstfeld (2012) use nonparametric and parametric methods to describe the comovement between financial and macro variables. A common thread of this research is that financial crises are associated with deep and long lasting recessions. These papers argue, with the exception of Bordo and Haubrich, that their empirical work reveals excessive credit growth to be a good predictor of financial crises. Stock market booms and lending into housing markets are leading indicators of financial crises across developed economies in the last 50 years, according to Claessens, Kose, and Terrones. Mendoza and Terrones add to this list of financial crisis predictors real currency appreciations and large current account deficits. Similar evidence is found in Bussiere and Fratzscher and Gourinchas and Obstfeld. They report panel data panel data regressions that control for differences in crisis and non-crisis states. The regression estimates confirm that excessive credit growth and real currency appreciations have power to predict financial crises. Rather than developing a predictive model, Bordo and Haubrich are interesting in comparing the 2007–2009 episode to financial crises in the U.S. during the previous 140 years. They argue that deposit insurance and other regulatory standards limited the impact on outside money, unlike the Great Depression, during the 2007–2009 crisis and instead put the onus on the short-term credit markets.

Reinhart and Rogoff (2009) gauge the extent measures of financial risk anticipate substantial economic downturns in several centuries of cross country data.They argue that the memory of crises is fleeting in history across countries and through the centuries. The argument is that when a crisis is in the making, there appear advocates to claim “this time is different.”[3] Implicit in this claim is that in the new state of the world there arise fundamentals to support asset prices not available in early states. Ex post these episodes are not systematically different from previous states of the world in the view of Reinhart and Rogoff.[4] They argue, as a result, that movements in observed financial aggregates yield warning signals for current and future real activity that can alert policymakers to a potential crisis.

Krishnamurthy and Vissing-Jorgensen (2010) have a different view on the factors that drive the demand for financial securities. Financial risk arises from the impact on returns of changes in the relative supplies of securities with different characteristics according to Krishnamurthy and Vissing-Jorgensen (KVJ) . For example, investors may prize public securities for their relative safety besides being a source of liquidity.[5] We take from KVJ that there is information about the demand for risky assets in the composition of private and public assets on the balance sheets of financial firms.

[3]Parent (2012) is a useful critique of the “this time is different” thesis.

[4]An example highlighting the role expectations of always rising house prices had in the 2007–2009 financial crisis is given by Brunnermeier (2009). He argues that counter-party risk generated by the reliance of the shadow banking system on short-term interbank funding prior which supported investment bank holdings of residential mortgage backed securities, which were comprised heavily of subprime mortgage loans. When house prices ceased rising in 2006, lenders into the interbank market reassessed their beliefs that these prices could never reprise the busts of the 1970s and 1980s. Gorton and Ordoñez (2012) construct a theory to explain these observations. The theory predicts that when these lenders find it is costly to evaluate long-term assets to be collateralized, they will withdraw funding from the interbank markets.

[5]KVJ build an asset pricing model in which a demand for safety and liquidity generate risk premia to hold private securities instead of Treasury securities. The asset pricing model motivates yield spread regressions that include the U.S. Treasury debt-GDP ratio. Regressions are run on annual samples from 1926 to 2008 to construct estimates of Treasury safety and liquidity risk premia. The estimates indicate that investors received a 46 basis point liquidity premium for holding AAA-corporate bonds rather than 10-year Treasury bonds. KVJ also report that Treasury bills earn a discount of 26 basis points because of the safety these securities offer compared to private short-term private assets.

2.2 Macro Literature Identifying Financial Shocks

In a related literature, Donaldson (1992) and Canova (1994) examine U.S. data from the Civil War to the Great Depression to discern the impact of financial crises on the U.S. economy. Regression and nonparametric estimators of business cycle comovement are used by Donaldson to generate evidence about whether banking panics in the U.S. are "systematic events" produced by the same probability distribution from which typical business cycle fluctuations are drawn or "special events" drawn from an entirely different distribution.[6] He concludes that the start date of banking panics are unforecastable, but that there are states of the world in which banking panics are more likely.[7] Canova reaches a similar conclusion when he reports that seasonality and financial variables have power to predict financial crisis in-sample, but real activity variables do not. Only measures of financial volatility have out-of-sample forecasting power in this paper.

A different approach to studying U.S. financial crises in the 40 years before WWII is Canova (1991). He estimates structural BVARs that identify currency supply and demand shocks on monthly samples from 1891 to 1913 and from 1924 to 1937, which drop the World War I period as well as the founding of the Fed.[8] A unique feature of this model is that it accounts for external shocks to gold flows. Canova presents results from which he argues that changes in the institutional design of U.S. financial markets altered the sources and causes of financial crises as well as the impact on the macroeconomy. For example, the supply of currency was not especially elastic in response to external shocks in the sample prior to World War I, according to Canova. The lack of an elastic currency, seasonal currency demand, and these shocks contributed to the plethora of U.S. financial crises during this period. Canova argues his empirical result show that the founding of the Fed altered the sources of financial shocks in the post-World War I sample, but for the U.S. this did not put an end to financial crises.

A similar approach is also applied by Coe (2002), Eichengreen and Mitchener (2003), Anari, Kolari, and Mason (2005), Chin and Warusawitharana (2010), and Diebolt, Parent, and Trabelsi (2010), among others, to study the Great Depression. They provide a mixed picture of the role financial shocks had in the Great Depression. Coe (2002) engages MS methods to recover the probability that the U.S. financial system was in a crisis state during the 1920s and 1930s. These probabilities have predictive power for output in regressions that he reports. Eichengreen and Mitchener (2003) regress output growth on credit growth on a cross-country sample from the late 1920s and early 1930s. Their regressions reveal

[6] These events are given content by Gorton (1988), Calomiris and Gorton (1991), and Wicker (2000, 2005).

[7] An alternative view is Jalil (2012). He provides evidence for the U.S. that banking panics had significant negative effects on output and these effects were persistent in more than 100 years of data before the Great Depression.

[8] Silber (2007) discusses the impact the World War I episode had on the evolution of U.S. financial markets.

that a pre-1929 credit boom contributed to the Great Depression. The remaining papers use structural VARs to identify and gauge the impact of financial shocks on real economic activity and inflation. The link between financial shocks and the Great Depression is weak according to Anari, Kolari, and Mason and Chin and Warusawitharana, but Diebolt, Parent, and Trabelsi present results supporting the view that the origins of the Great Depression were financial.

We are animated by this literature to identify credit supply and demand shocks in MS-BVAR models. The next section discusses the data on which these MS-BVAR models are estimated.

3 Data

This section describes the data on which MS-BVARs are estimated to uncover the responses of U.S. per capita real GDP (y_t), the implicit GDP inflation (P_t), the unemployment rate (ur_t), inside money ($M_{I,t}$), a short-term nominal interest rate ($R_{S,t}$), and long-term nominal interest rate ($R_{L,t}$), and the ratio of long-term public to public assets held by financial firms ($r_{R,t}$) to identified credit demand and supply shocks. The data is grounded on a long annual sample starting in 1890 and ending with 2010, T = 121. The appendix contains more details about the construction of the data.

3.1 Macro Aggregates

The macro block contains aggregate output, the aggregate price level, and the unemployment rate. We employ real per capita GDP to measure aggregate output on a long annual U.S. sample from 1890 to 2010. The corresponding aggregate price level is the implicit GDP deflator (i.e., the ratio of nominal to real GNP). The log of real per capita GDP and log of the implicit GNP deflator are multiplied by 100. The source of real GDP, its price deflator, and U.S. population is Johnston and Williamson (2011). The unemployment rate brings labor market information into the MS-BVAR models. Carter, Gartner, Haines, Olmsted, Sutch, and Wright (2006) collect a long annual sample of unemployment rate observations from Weir (1992).

3.2 Monetary Aggregates

We equate the stock of short-term liabilities issued by financial firms to inside money. These liabilities are constructed as M2 net of the monetary base. The former monetary aggregate is found for the early part of the sample in Balke and Gordon (1986) and the Board of Governors of the Federal Reserve

System for later in the sample. Balke and Gordon also contain monetary base data that is spliced to the adjusted monetary base of the Federal Reserve Bank of St. Louis to obtain monetary base observations through 2010. The quarterly and monthly M2 and monetary base data are temporally aggregated into the annual frequency. Hence, this measure of inside money equates an increase in M2 net of the monetary base with financial firms issuing more short-term liabilities. A financial firm can supply more of these liabilities to purchase long-term assets for its balance sheet.

3.3 Interest Rates

A 1-year interest rate series plays the role of the intertemporal price of short-term funds in financial markets for estimating the MS-BVAR models. The short-term rate is a synthetic series because the financial contract that plays the role of a short-term riskless asset has evolved in U.S. financial markets since 1890. This asset is identified with stock exchange loans, prime bankers acceptances, short-term Treasury securities, and 3-month Treasury bills from 1890 to 2010. We obtain return data on these assets from *Banking and Monetary Statistics, 1914–1941*, Board of Governors of the Federal Reserve System (1976a), and the FRED online data base.[9]

The long-term interest rate is taken from Shiller (2005).[10] He ties municipal bond yields from 1890 to 1920 to yields on long-term government securities from 1921 to 1952 that are found in Homer and Sylla (2005). The yield on 10-year U.S. Treasury bonds is used by Shiller to complete his long term interest rate series, which runs from 1953 to 2010 for our sample.

3.4 Risk Ratio

The risk ratio divides total long-term private assets held by U.S. financial firms by their ownership of public short- and long-term debt. The universe of these firms includes commercial banks, savings banks and thrifts, and investment banks. Data on the asset holdings of these firms are constructed using various sources. The sources are the Board of Governors, the FDIC, the United States League of Savings Associations, United States Savings and Loan League and Compustat. The Board of Governors and the FDIC are the sources for data on commercial banks. Information in the balance sheets of savings and loans are published by the FDIC, the United States League of Savings Associations, United States Savings and Loan League. Compustat contains data on U.S. investment banks.

[9]The 3-month Treasury bill rate data is available at http://research.stlouisfed.org/fred2/series/TB3MS?cid=116.
[10]The long-term interest rate data is available online at the web page maintained by Robert Shiller http://www.econ.yale.edu/~shiller/data/ie_data.xls.

The long-term private assets of financial firms excludes cash broadly construed, Treasury securities and agency debt, as well as state, local and other municipal debt obligations. We refer to the aggregate assets that remain as "private debt" or assets that are "claims on private entities" held by financial firms in the U.S., while their ownership of cash, Treasury securities, agency, state, local, and other municipal debt holdings is labeled "public debt" or "claims on public entities." The ratio of private debt to public debt is one means for measuring the risk composition of the asset side of the aggregate bank balance sheet.

3.5 The Data in Historical Context

The data is plotted in figures 1 and 2. The top panel of figure 1 presents the log levels of y_t, P_t, and $M_{I,t}$ multiplied by 100. The growth rate of y_t and level of ur_t are shown in the middle panel of figure 1 from 1891 to 2010. These macro aggregates are less volatility since the late 1940s on the ocular metric. Output growth shows large negative annual growth rates around the Panic of 1907, the Great Depression, and after World War II, while ur_t is dominated by the 1931–1935 episode. During this period, ur_t equals 15.6, 22.9, 20.9, 16.2, and 14.4 percent, respectively. The bottom panel of figure contains the growth rates of P_t and $M_{I,t}$ from 1891 to 2010. The volatility of U.S. inflation also appear to have fallen beginning the late 1940s compared to the period from 1890 to 1945. The same is true of $100\Delta \ln M_{I,t}$. Note that inflation and inside money growth show substantial comovement from about the Panic of 1907 to about 1938.

Figure 2 depicts $R_{S,t}$, $R_{L,t}$, and $r_{risk,t}$ from 1890 to 2010. Several phenomena stand out in this chart. Prior to the 1922, $R_{S,t}$ is often greater and more volatility than $R_{L,t}$. This changes in the 1920s when $R_{L,t}$ consistently exhibits rate of return dominance over $R_{S,t}$. Since 1981, this is true for every year except 2006 and especially for 2009 and 2010 when $R_{S,t}$ fell to 15 basis point or less. The only other episode during which $R_{S,t}$ is near the zero lower bound occurs from 1933 to 1941 when it is less than 30 basis points. Another observation of interest is that $r_{risk,t}$ is less than $R_{L,t}$ from 1933 to 1997.

4 A MS-BVAR Model

Our motivation for estimating MS-BVAR models rests on the idea that economic and financial crises represent different states or regimes of the world than do typical business cycle fluctuations. The MS-BVAR models are engaged to estimate the responses of output, aggregate price level, unemployment rate, and long-term interest rate to credit supply and credit demand shocks.[11] Besides IRFs and FEVDs, the estimates include the regime transition probabilities, the (first-order) Markov transition matrix of the regimes, and the impact coefficient matrix of the preferred MS-BVAR(2) model. This is the evidence we use to assess the impact of identified credit supply and demand shocks on the U.S. economy conditional on regime switching. We lean heavily on Sims and Zha (2006) and Sims, Waggoner, and Zha (2008) to generate this evidence.

4.1 Model Specification

Sims, Waggoner, and Zha (2008) provide tools to estimate and conduct inference on a structural MS-BVAR model of lag length k. The MS-BVAR(k) model is

$$Z_t' A_0\left(s_t\right) = \sum_{j=1}^{k} Z_{t-j}' A_j\left(s_t\right) + C\left(s_t\right) + \varepsilon_t' \Gamma^{-1}\left(s_t\right), \quad t = 1, \ldots, T, \tag{1}$$

where A_0 is a $n \times n$ non-singular matrix, s_t is the h dimensional vector of regimes which are independent first-order Markov chains, h is in the finite set of integers H, each A_j is a $n \times n$ matrix, C is the vector of n intercept terms, ε_t is vector of n unobserved shocks, and Γ is a $n \times n$ diagonal matrix of factor loadings scaling the stochastic volatilities (SVs) of the elements of ε_t.[12] Key assumptions made by Sims, Waggoner, and Zha (SWZ) include those on the densities of the MS-BVAR disturbances

$$\mathcal{P}\left(\varepsilon_t \,\middle|\, \mathcal{Z}_{t-1}, \mathcal{S}_t, \omega, \Theta\right) = \mathcal{N}\left(\varepsilon_t \,\middle|\, \mathbf{0}_{n\times 1}, \mathbf{I}_n\right), \tag{2}$$

and on the information set

$$\mathcal{P}\left(Z_t \,\middle|\, \mathcal{Z}_{t-1}, \mathcal{S}_t, \omega, \Theta\right) = \mathcal{N}\left(Z_t \,\middle|\, \mu_Z(s_t), \Sigma_Z(s_t)\right), \tag{3}$$

where $\mathcal{Z}_t = \left[Z_1' \;\; Z_2' \ldots, Z_t'\right]'$, $\mathcal{S}_t = \left[S_0' \;\; S_1' \;\; S_2' \ldots, Z_t'\right]'$, ω denotes the vector of Markov chains, Θ

[11] Primiceri (2005) and Cogley and Sargent (2005) develop different estimators of regime change models.

[12] Sims, Waggoner, and Zha require the number of regimes h within s_t to be finite and not a function of time t. This assumption is required for only regimes of date t, s_t, to matter for Z_t given its own history, which in turn is necessary to construct the likelihood of a MS-BVAR(k).

$= \Big[A_0(1) \;\; A_0(2) \ldots A_0(h) \;\; \mathcal{A}(1) \;\; \mathcal{A}(2) \ldots \mathcal{A}(h) \;\; C(1) \;\; C(2) \ldots C(h) \;\; \Gamma(1) \;\; \Gamma(2) \ldots \Gamma(h) \Big]'$, $\mathcal{A}(\cdot) = \Big[A_1(\cdot) \;\; A_2(\cdot) \;\ldots,\; A_k(\cdot) \Big]$, $\mu_Z(\cdot) = \Big[\mathcal{A}(\cdot) \;\; C(\cdot) \Big] A_0^{-1}(\cdot) \Big[\mathcal{X}_t \;\; 1 \Big]'$, and $\Sigma_Z(\cdot) = \Big[A_0 \Gamma^2 A_0' \Big]^{-1}$.

The MS-BVAR(k) model (1) relies on assumptions (2) and (3) to construct the log likelihood function of $\mathcal{Z}_T$

$$\text{(4)} \qquad \ln \mathcal{P}\Big(Z_T \Big| \mathcal{Z}_T, \omega, \Theta \Big) \;=\; \sum_{t=1}^{T} \ln \left[\sum_{s_t \in H} \mathcal{P}\Big(Z_t \Big| \mathcal{Z}_{t-1}, S_t, \omega, \Theta \Big) \mathcal{P}\Big(S_t \Big| \mathcal{Z}_{t-1}, \omega, \Theta \Big) \right],$$

where $\mathcal{P}\Big(S_t \Big| \mathcal{Z}_{t-1}, \omega, \Theta \Big)$ is the density used to sample the probability that s_t is in regime ℓ given $s_{t-1} = j$. SWZ develop Gibbs sampling methods to construct the density of the recursion.[13] Note also that the vector of regimes S_T is integrated out of the likelihood (4) of Z_T.

The MS-BVAR(k) model can become too highly parameterized to be estimated without restrictions on the dimension of Z_t, n, and the lag length k. The data described in section 3 sets the dimension of Z_t, n, to 7. Given this, suppose $k = 3$ and that all parameters are permitted to shift in all the regimes of the MS-BVAR. In this case, the number of parameters per regime equals 171, which would be a strain on the information content of a sample whose length is $T = 121$.

Sims and Zha (2006) and SWZ impose prior restrictions to limit the dimensionality of the time-variation of the parameter space of MS-BVAR models. The restrictions are placed on the slope coefficients and intercepts of the MS-BVAR(k), $\mathbb{A}(s_t) \equiv \Big[A_1(s_t) \;\; A_2(s_t) \;\ldots\; A_k(s_t) \;\; C(s_t) \Big]'$, with

$$\mathbb{A}(s_t) \;=\; \mathcal{D}(s_t) \;+\; \overline{\mathcal{D}} A_0(s_t),$$

where $\overline{\mathcal{D}} = \Big[\mathbf{I}_n \;\; \mathbf{0}_{n\times 1} \Big]'$, and $\mathcal{D}(s_t)$ is conformable with $\mathbb{A}(s_t)$ and $\overline{\mathcal{D}}\,\mathcal{A}(s_t)$.[14] A mean zero prior distribution is bestowed on $\mathcal{D}(s_t)$ by Sims and Zha (2006) and SWZ. Their prior matches the reduced-form random walk prior of Sims and Zha (1998). Tightening in the direction of the random walk prior reduces the variances of ε_t, which pushes up persistence in $\mathcal{A}(\cdot)$. The underlying notion is that random walk prior is, in the view of SWZ, independent of beliefs about the unconditional variance of Z_t.

[13] These methods rest on analysis SWZ provide in their appendix A.

[14] Waggoner and Zha (2003b) supply the rule to normalize the signs of $\mathbb{A}(s_t)$.

4.2 Priors and Identification

We follow Sims and Zha (2006) and SWZ by endowing $\mathcal{D}(s_t)$ with a mean zero prior distribution in the spirit of Sims and Zha (1998). The prior is implemented by moving the MS-BVAR(k) in the direction of random walk behavior. Otherwise, our priors match those of Sims and Zha (1998). They place a normal prior on the elements of $\mathcal{A}(\cdot)$ whether or not these parameters are regime dependent, while the squared diagonal elements of Γ are drawn from the gamma distribution; also see Robertson and Tallman (2001). A Dirichlet prior is imposed on the transition probabilities of ω by SWZ. This prior controls the (average) duration of remaining in regime ℓ at date t conditional on being in that regime at date $t-1$. Another part of our prior is that we set $k = 2$, given $T = 121$ for the annual sample.

Identification of credit supply and demand shocks relies on a recursive Cholesky ordering and sample information. Recursive Cholesky orderings are consistent with the restrictions SWZ place on time-variation of $\mathbb{A}(s_t)$ and $A_0(s_t)$; also see Waggoner and Zha (2003a). We order

$$Z_t = \begin{bmatrix} y_t & P_t & ur_t & M_{I,t} & R_{S,t} & R_{L,t} & r_{R,t} \end{bmatrix}'.$$

Credit supply and demand shocks are identified, in part, by placing the block of aggregate macro variables, y_t, P_t, and ur_t, prior to the block of financial variables, $M_{I,t}$, $R_{S,t}$, $R_{L,t}$, and $r_{R,t}$. The macro block captures dynamic macro relationships. For example, a dynamic Okun's law results from placing y_t before ur_t and a Lucas-Sargent Phillips curve by having ur_t respond to the P_t shock at impact.

The financial block contains the information useful for recovering the credit supply and demand shocks. A dynamic demand function for short-term liabilities in the financial markets is implied by $M_{I,t}$ and $R_{S,t}$ given y_t and P_t. The financial block also recovers information about the term structure from $R_{L,t}$ and $R_{S,t}$. Shocks to the latter rate impinge on the former rate at impact, but the converse is ruled out by our identification. This is consistent with a rational expectations story of the term structure. The long-term rate also provides information about the opportunity cost of holding riskier long-term assets. The riskiness of these assets is captured by $r_{R,t}$. The risk variable injects information about the composition of the aggregate balance sheet of U.S. financial firms into the financial block. This information aids in driving the relative demand for risky long-term private assets conditional on $M_{I,t}$, which is the source of fund supporting an increase in $r_{R,t}$. Since the recursive ordering places the risk proxy last, the identification ties shocks to M_I, and $R_{S,t}$ to funding long-term securities.

Our study of the impact of credit supply and demand shock limits regime switching to the SV scaling matrix Γ. In this case, the dynamics of the MS-BVAR(2) models are the same across all regimes. The impact matrix A_0, the coefficient matrices A_1 and A_2 on Z_{t-1} and Z_{t-2}, and the intercept vector C are unchanged across regimes, which forces the BVAR dynamics to be constant across regimes. Hence, our maintain assumption is that economic and financial crises, distinct from usual business cycle fluctuations, are generated by "good or bad luck" credit supply and demand shocks. The the efficacy of this hypothesis is not explored in this paper.

Table 2 presents the parameterizations of 15 MS-BVAR(2) models. As mentioned previously, we only consider MS-BVAR models in which there is SV regimes on the errors ε_t. The 15 MS-BVAR models have either one or two chains associated with 2, 3, or 4 SV regimes. When there is one chain it is shared or is common to the macro block $\mathcal{M}$ and the financial block $\mathcal{F}$. Since there are 2, 3, or 4 SV regimes, this gives 3 MS-BVAR models. Next, we separate the chains for the $\mathcal{M}$ and $\mathcal{F}$ blocks, but assume that the $\mathcal{F}$ block always has 3 SV chains. This produces 3 more MS-BVAR models with the $\mathcal{M}$ block taking on 2, 3, or 4 regimes. The remaining 9 models are created by adding $M_{I,t}$ and $R_{S,t}$ one at a time and together to the 2 and 3 SV regimes MS-BVARs.

We condition 12 of the 15 MS-BVAR models on 3 SV regimes in the $\mathcal{F}$ block. This gives the MS-BVAR models and the data the flexibility to estimate 3 financial SV regimes that differ systematically in economic and calendar time. That is the MS-BVAR models can find different crisis and non-crisis regimes at different moments in time.

4.3 Estimation and Inference Methods

The MS-BVAR(2) are estimated using a multi-step procedure. Estimation and inference relies on code described in SWZ that has been integrated into the unstable version of Dynare; see Adjemian, Bastani, Juillard, Maih, Mihoubi, Prerndia, Ratto, and Villemot (2012). The procedure to estimate a collection of models and infer which is or are most favored by the data involve the steps

1. Set the random walk and durations priors on the MS-BVAR(2).[15]

[15] Sims and Zha (1998) decompose their prior into 6 scalar parameters. The decomposition is $\lambda = \begin{bmatrix}\lambda_0 & \lambda_1 & \lambda_2 & \lambda_3 & \lambda_4 & \lambda_5\end{bmatrix}$. These parameters control the tightness of the random walk prior on the own first lag in a regression, the tightness of the random walk on the other lags in a regression, the tightness on the intercept of the random walk prior, tightness of the prior that smooths the distributed lags of a regression, the random walk prior applied to the sum of own coefficients in a regression, and cointegration prior implying stationary relationships among the elements of X_t. Our prior is $\lambda = \begin{bmatrix}2.5 & 1 & 1 & 0.5 & 0.75 & 1.25\end{bmatrix}$, which is weighted to greater persistence and is relatively agnostic about cointegration.

2. Construct the posterior mode of the MS-BVAR(2) model using optimization methods robustifed for the possibility of multiple peaks in the likelihood and a potentially flat posterior.[16]

3. Given estimates of A_0, A_1, A_2, C, and $\Gamma(1)$, $\ldots$ Γ_h of the MS-BVAR(2), run 10 millions steps of the MCMC simulator.

4. Construct the posterior of a MS-BVAR(2) by drawing 10 million times from the proposals created by running a Markov chain-Monte Carlo (MCMC) simulator.

5. Choose among the competing MS-BVAR(2) models by calculating posterior odds ratios using log marginal data densities computed on the posterior distributions of the previous step.

6. Rerun the MS-BVAR(2) model(s) most favored by the data to produce transition probabilities and regime-dependent IRFs and FEVDs.[17]

The next sections engages this procedure to generate estimates of 15 MS-BVAR(2) models and conduct inference on these models.

5 Results

5.1 A Fixed Coefficient-Homoskedastic BVAR(2)

This section reports estimates of a fixed coefficient-homoskedastic BVAR(2) on Z_t to establish a baseline against which to judge the MS-BVAR models.[18] The estimates are generated by restricting $\Gamma(s_t) = \Gamma$ across all regimes.[19] Figure 3 contains IRFs and FEVDs are found in table 3 generated from these estimates. Median IRFs are plotted in black and error bands are shaded grey in figure 3.

The IRFs display a priori expected shapes as well as shapes that are not intuitively appealing in figure 3. The shock to y produces an own hump-shaped response decaying fully around 4 years, raises P permanently, creates a negative hump-shaped response in ur that also dies out in about 4 years

[16] Dynare's MS-BVAR code employs an optimizer adapted from the csminwel software developed by Chris Sims. The optimizer breaks the problem into blocks that iterates back an forth between solving for Θ conditional on ω and for ω given Θ until a convergence criteria is met.

[17] There are MS-BVAR specification and data combinations that can yield a regime with a transition probability equal to zero for all dates t. In private communication, Dan Waggoner and Tao Zha taught us that in this degenerate case not to trust the reported marginal data density.

[18] We estimate 5 more fixed coefficient-homoskedastic BVAR(2) models. These models include the first 5 elements of Z_t, adding R_L, adding R_L and a long-term private interest rate, and replacing r_R in Z_t with a measure of aggregate financial leverage, the first principal component of r_R, the long-term private interest rate, and the measure of aggregate financial leverage. These results are available on request.

[19] This BVAR is analyzed by Sima and Zha (1998) and Roberston and Tallman (2001).

suggesting a dynamic Okun's law-like relation, permanently increases M_{Inside} holds its real balances to a proportionate change, yield a hump-shaped response in R_S peaking at 2 years and returning to steady state within 4 years, has little effect on R_L, and raises r_R for about 4 years. Higher M_I in response to a y shock also suggests that the supply of inside money accommodates (income) demand shifts as Leeper, Sims, Zha (1996) find for outside money. Figure 3 also depicts a Lucas-Sargent Phillips curve-like relation because ur falls at impact given a shock P. This shock raises P for at least 16 years. The responses of M_I and r_R are also of interest. Inside money is higher at short horizons before returning to steady state, while the risk ratio rises at longer horizons. Hence, financial markets react to y shocks by producing more short-term liabilities and long-terms assets.

There are two IRFs at odds with with conventional economic theory. One is the response of y with respect to an ur shock. This IRF rises from impact to the longer horizons. The other oddity is the fixed coefficient-homoskedastic BVAR produces the price puzzle in which a shock to R_S generates a permanent increase in P.

The remaining shock either generate few economically interesting responses with two exceptions. These are the dynamic responses of r_R and $R_L$to a r_S shock and R_L to a r_R. The former two IRFs show a hump-shaped response that peaks at 2 to 3 years. These responses indicate the term spread shrinks at short horizons and that financial firms are taking more long-term private assets onto their balance sheets. The other IRF is permanently lower, which given the response of R_S to the r_R, suggests a larger term spread is required to hold long-term private assets.

The FEVDs are consistent with prior views of the shocks that are major contributors to aggregate fluctuations. Shocks to y and ur explain most of the variation in y and ur. Variation in P is tied to its own shock. The shock to M_I is responsible for not more than half of its movements with the bulk of the rest explained by income shocks. Fluctuations in R_S and r_R are driven by own shocks, while the FEVDs of R_L exhibit term structure behavior as R_S and the own shock dominate.

5.2 The Fit of MS-BVAR(2) Models

The fit of the MS-BVAR models is evaluated using log marginal data densities. The log marginal data densities are listed in table 4.[20] Table 4 shows the asterisk symbol, $*$, for the log marginal data densities of models 6, 9, 12, 14, and 15 instead of numerical values. The asterisk indicates that the MCMC simulators of these models yield badly approximated log marginal data densities. Except for

[20]We generate log marginal data densities using the step function option for the density proposal.

model 14, these models place 4 SV regimes in the $\mathcal{M}$ block. Model 14 makes the SV regimes of the errors of the M_I and R_S regressions common across the $\mathcal{M}$ and $\mathcal{F}$ blocks.

Model 8 is supported by the data according to the log marginal data densities of table 4. This model imposes distinct MS chains of 3 SV regimes on the $\mathcal{M}$ block and the $\mathcal{F}$ block, but these blocks hold the SV regimes of the error in the M_I regression in common. The odds ratio signal that the MS-BVAR models are all preferred by the data to the fixed coefficient-homoskedastic BVAR. Hence, the MS-BVAR models provide evidence that crisis and non-crisis regimes differ systematically.

Among the MS-BVARs, Model 8 is greatly favored by the data. The evidence for this is very strong, when this model is compared to the other MS-BVARs predicated on 3 SV regimes (models 3, 5 and 11), to the models that rely on 2 SV regimes (models 1, 4, 7, 10, and 13), and to the single chain 4 SV regime model 4. Model 4 produces the second largest log marginal data density. However, the gap between it and the log marginal data density of model 8 indicate a odds ratio strongly in its favor.[21].

5.3 Regime Probabilities

Part of the output of the estimated MS-BVAR models are the probabilities of being in regime j at date t. We plot these probabilities for Model 2, a single chain of 3 SV regimes, in figure 4 and in figures 5 and 6 for Model 8's two MS chains of 3 SV regimes in figures 5 and 6. The regime probabilities of Model 2 are reported to give more evidence of the superiority of model 8.

Figure 4 shows that model 2 is consistent with the hypothesis that crisis and non-crisis regimes represent different economic outcomes. Regime 1 of model 2 is plotted in the top panel of figure 4. We interpret this regime, which runs from 1957 to 1974, 1977 to 2006, and 2009–2010, as the era of the modern Fed and Great Moderations episodes.[22] Much of the first 60 percent of the sample is subsumed into regime 3, which is displayed in the bottom panel of figure 4. This regimes includes the panics of the National Banking Era from 1890 to 1914, the economic boom of the 1920s, the recovery from the Great Depression, and the inflation episode of the late 1940s that lead to an independent Fed in 1951. Hence, regimes 1 and 3 differ by being based in the early and later parts of the sample and by covering periods in which the design of the U.S. financial system are in stark contrast.

The middle panel of figure 4 contains regime 2, which is a distinct from regimes 1 and 3 in several ways. Regime 2 consists of World War I, the Great Depression, World War II, as well as the 1957–1958,

[21]An odds ratio of 3.4 in natural log units difference translates into strong evidence; see Jeffreys (1998).

[22]Nason and Smith (2008) date a moderation in output growth, consumption growth, and inflation to 1946 by comparing the 1946–1983 period to the 1915–1945 period.

1973–1975, and 2007–2009 recessions. The only recession in regime 1 to match the severity of these recessions, with the exception of the 1957–1958 recession, is the 1981–1982 recession. Regimes 1 and 3 also contain several armed conflicts that engaged the U.S., but none match the economic and financial impact of the world wars of the 20th century. Regime 2 also lacks periods of robust economic growth, which are found in regimes 1 and 3 during the 1920s, the 1960s, and 1990s.

Model 8 refines the narrative provided by its regime probability plots. These regime probabilities are displayed in figures 5 and 6. Figure 5 depicts the regime probabilities associated with the $\mathcal{M}$ block and M_I, while figure 6 does the same for the regime probabilities of the $\mathcal{F}$ block and M_I. For the former block, the refinements are that the world wars and the Great Depression are contained in regime 1 of the $\mathcal{M}$ block. Regime 2 of the $\mathcal{F}$ block also contain World War I, World II and the financial boom from 2003 to 2008. Hence, splitting the 3 SV regimes across the $\mathcal{M}$ and $\mathcal{F}$ blocks with M_I held in common gives Model 8 the ability to identify the Great Depression as an economic crisis and the events leading up to the Great Recession as a financial crisis.

Regime 3 of the $\mathcal{M}$ block and regime 1 of the $\mathcal{F}$ block also have much in common. These regimes dominate the last 50 years of the sample within their respective MS chains. The modern Fed and the Great Moderations are notable events that occur in regime 3 of the $\mathcal{M}$ block. Regime 1 of the $\mathcal{F}$ block starts up in the late 1960s covering an era of rapid financial innovations and deregulation, except for the financial boom and bust of the 2003–2008 period.

There are two more useful refinements produce by model 8. The $\mathcal{M}$ block of model 8 creates regime 2 that adds the first half of Chairman Martin's stewardship of the Fed, the Great Inflation and stop-go monetary policy of the 1970s, and the Volcker disinflation and subsequent recover of the early 1980s to the National Banking Era, the economic boom of the 1920s, the recovery from the Great Depression, and the inflation episode of the late 1940s. The National Banking Era, the interwar period, and the Martin Fed are grouped together with the $\mathcal{F}$ block of model 8. Thus, model 8 uncovers economically meaningful regimes across the $\mathcal{M}$ and $\mathcal{B}$ blocks by allowing the 2 MS chains to hold M_I in common.

5.4 Regime Dependent IRFs

The MS-BVARs generate IRFs that are regime dependent. We report IRFs with respect to the identified shocks of M_I and R_S in figures 7 and 8, respectively.[23] These IRFs receive our attention because

[23]The IRF plots lack error bands. These will be added in the next draft of the paper.

they provide evidence about whether the MS-BVAR-model 8 is effective at identifying economically informative credit supply and demand shocks.

The regime dependent IRFs have the same shape because only MS is allowed on the SV of the regression errors. Nonetheless, scaling the SV generates regime dependent IRFs that are economically informative. This information is displayed by presenting IRFs dependent on regimes 1, 2, and 3 in the top, middle, and bottom rows of figures 7 and 8.

The M_{Inside} shocks drives y and P higher, lowers ur, produces a smaller term spread, and leads financial firms to hold relatively more long-dated risky assets on their balance sheets as shown in figure 7. These IRFs are qualitatively similar to the IRFs found in row 4 of figure 3 which are estimated using the fixed coefficient-homoskedastic BVAR(2). Figure 7 provides additional information in the form of IRFs whose height is regime dependent. Regimes 1 and 2 are associated with IRFs that have about the same height, but are relatively small compared to the IRFs generated within regime 3. Regime 3 yields IRFs with respect to the M_I shock in its bottom row that are higher by a factor of 3 when laid against the IRFs of the first two rows of figure 7. However, we cannot tie the regime dependent IRFs of figure 7 to specific economic and financial episodes because the SV of the M_I is common to the MS chains of the $\mathcal{M}$ and the $\mathcal{F}$.

Figure 8 contains regime dependent IRFs with respect to the R_S shock. These IRFs are also qualitatively similar to the IRFs found in row 5 of figure 3. Hence, y fall, ur rises, there is a proportionate change in the real stock of M_I, and R_L and r_R are higher in response to a R_S shock across the 3 rows of regime dependent IRFs in figure 8. However, the price puzzle remains. Of equal interest, is that the IRFs of R_L and R_S indicate there is shrinking of the term spread that coincides with financial firms taking on more risk by shifting the composition of their balance sheets to hold relatively more long-term private assets.

The regime dependent IRFs of figure 8 can be matched to specific economic and financial episodes. Since R_S resides only in the $\mathcal{F}$ block of model 8, the height of the IRFs of figure 8 suggest that the greatest impact of this shock arises during wars, financial crises, and the first two-thirds of the sample. In this case, the height of the IRFs of regime 1, the top row of figure 8, is about half the size of those in the lower two rows.

5.5 Regime Dependent FEVDs

We employ model 8 to generate regime dependent FEVDs. These FEVDs appear in tables 5, 6, and 7. These tables present regime 1, regime 2, and regime 3 FEVDs, respectively.

Regime 1 FEVDs resemble the FEVDs produced by the fixed coefficient-homoskedastic BVAR that are listed in table 3. Shocks to y and ur dominate variation in these variables. Price shocks explain fluctuations in P, but shocks to y and M_I contribute to variation in P at longer horizons. The same is true for M_I except that at longer horizons its movements are increasingly driven by ur shocks. Table 3 also depicts own shocks as being most responsible for fluctuations in R_S and r_R. A term structure relationship helps to motivate why variation in R_{Long} is tied to its own shock at short horizons, but shocks to R_{Short} take over at the longer horizons.

Tables 6 and 7 show regime dependent FEVDs that are strikingly different from those of table 5. Regime 2 FEVDs depart from those of regime 1 because shocks to r_R drive variation in y, P, R_S, and R_L, especially at longer horizons. Inside money dominates the regime dependent FEVDS of the 7 variables of the MS-BVAR in table 7. It is not possible to give economic interpretations to the regime dependent FEVDs. Nonetheless, we show that in 2 of the 3 regimes shocks to financial variables, such as M_I and r_R, are important for explaining aggregate fluctuations.

6 Conclusion

This paper provides evidence that crisis and non-crisis regimes differ systematically in a long annual sample of the last 120 years of U.S. economic and financial history. We estimate Markov switching-BVAR models predicated on identified credit supply and demand shocks. The data favors a MS-BVAR model that separates 3 stochastic volatility regimes on macro aggregate variables from 3 stochastic volatility regimes on financial variables. This parameterization of the Markov switching-BVAR model produces estimates of the probabilities of the macro and financial volatility regimes that cover important eras, events, and episodes in U.S. economic and financial history. Conditional on the volatility regimes, the height of the impulse response functions differ. The regimes also alter the composition of the shocks that explains variation in the macro and financial variables. For example, inside money or credit supply shocks take on a large role in explaining the variation of output, the price level, the unemployment rate, a short-term interest rate, a long-term interest rate, and a financial risk variable in one regime. Another regime gives this role to the financial risk variable, which reflects risk in the composition of the balance sheets of U.S. financial firms that drives aggregate fluctuations.

Our results rely on stochastic volatility being the lone source of Markov switching in the BVARs. Although this class of models is a useful starting point, estimating BVARs with regime switching on intercept and slope coefficients is potentially useful. Given estimates of these BVARs, it is possible to ask whether it is “good luck-bad luck” or private and public policy decisions driving shifts in crises and non-crises regimes. We also report estimates that in some regimes attribute to inside money a central role in explaining aggregate fluctuations. This raises questions about using interest rate rules to gauge monetary and macroprudential policies when there are regimes in which inside money matters. We leave these questions for future research, but note that for researchers and policymakers these issues are likely to become more important rather than less.

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7 Data Appendix

Real GDP, Implicit GDP Deflator, and Population: Johnston and Williamson (2011) provide annual observations on U.S. per capita real GDP, the implicit GDP price deflator, and population from 1790 to 2010 at http://www.measuringworth.org/usgdp/. We extract these time series, but only for our sample of 1890 to 2010.

Unemployment Rate: We obtain annual unemployment rate data from Carter, Gartner, Haines, Olmsted, Sutch, and Wright (2006) and from the FRED data based maintained by the Federal Reserve Bank of St Louis. The former source is the *Historical Statistics of the United States: Millennial Edition*, which is available online at http://www.cambridge.org/us/americanhistory/hsus/default.htm and the later at http://research.stlouisfed.org/fred2/. Its tables Ba475–476 contain annual unemployment rate series from 1890 to 1990; also see Weir (1992, pp., 341–343). We select the unemployment rate that equals the unemployed as a percentage of the civilian labor force. The post-1990 data is the series FRED series UNRATE, which we temporally aggregate from monthly to annual observations. These two series are spliced together to produce an unemployment rate series from 1890 to 2010.

M2: Balke and Gordon (1986) list quarterly aggregate M2 data that begins in 1890 and ends with 1958. We temporally aggregate this data to calculate an annual average monetary aggregate. The Board of Governors of the Federal Reserve System produces monthly M2 numbers from 1959 to 2010, from which we calculate annual averages. From these two sources, we generate a 1896-2010 sample of M2.

Monetary Base: A monetary base series is found in Balke and Gordon (1986) from $1875Q1$ to $1922Q4$. The Federal Reserve Bank of St. Louis provides an adjusted monetary base series that start in $1918M01$; see http://research.stlouisfed.org/fred2/series/BASE?cid=124. We extract observations from $1923M01$ to $2010M12$. These data are temporally aggregate and spliced together at 1923 to produce an annual monetary base series for the 1890–2010 sample.

Inside Money: Subtract the monetary base from M2 and divide by the population to obtain our measure of per capita inside money. We consider an increase in M2 that is distinct from the monetary base as indicating that financial firms are supporting an expansion of their liabilities with private assets.

Short-term Interest Rate: This is a 1-year annualized interest rate on short-term assets. Since the notion of a (near) riskless short-term asset has changed as U.S. financial markets have evolved, a continuous 1-year interest rate series representing the cost to financial market participants of obtaining another dollar of funds does not exist from 1890 to 2010. We splice together several existing times series to create one. From 1890 to 1917, the time series is the rate on stock exchange time loans with a maturity of 90 days. This short-term loan market was often the source of funds for banks to support their balance sheets at the margin. We use two observations of the prime bankers' acceptance rate for 1918 and 1919. These data are obtained from Board of Governors of the Federal Reserve System (1976a, Section 12, pp. 448–449); see http://fraser.stlouisfed.org/publication/?pid=38. The interest rate on Treasury debt with a maturity of 3- to 6-months augments these data from 1920 through 1933; Board of Governors of the Federal Reserve System (1976a, p. 460). Subsequently, we convert the 3-month Treasury bill rate (TB3MS in the FRED data base) from monthly to an annual data series by temporal averaging. Listing these observations sequentially gives a 1-year annualized interest rate on short-term assets from 1890 to 2010.

Long-term Interest Rate: The long-term interest rate is constructed by Shiller (2005). Homer and Sylla (2005) is cited by Shiller as his source for the long-term interest rate from 1871 to 1952. These rates are yields on New England municipal bonds from 1890 to 1900 (p. 284, table 38), the average of high grade municipal bonds from 1901 to 1920 (p. 342, table 46), and the yield average of long-term government bond from 1921 to 1952 (p. 351 and p. 375, tables 48 and 51). After 1952, he sets this interest rate equal to the yield on the 10-year U.S. Treasury bond. Our long-term interest rate consists of the 1890–

2010 observations that Shiller provides; see http://www.econ.yale.edu/~shiller/data/chapt26.xls. We also need a long-term interest rate on private assets. The need is satisfied by the long-term consistent interest rate of Officer (2011).

Private and Public Asset Holdings of Financial Firms: The 1890–1895 observations are from Carter, Gartner, Haines, Olmsted, Sutch, and Wright (2006), *Historical Statistics of the United States, Millenium Edition*. For state bank data, we use series Cj150 for total assets, series Cj151 for loans and discounts, series Cj152 for investments in government (and other securities), Cj152 for cash and cash items, and series Cj157 for state bank capital. Data on national banks is obtained from series Cj204–Cj207, and Cj211 for total assets, loans and discounts, investments in government (and other securities), cash and cash items, and national bank capital, respectively. We take from *All Bank Statistics*, Board of Governors of the Federal Reserve System (1976b), data on the private and public asset holdings of all commercial banks and thrifts from 1896 to 1955. This data separate out government securities from the aggregate securities holdings of banks. We use observations from 1896 to 1917 to estimate a model that predicts the proportion of "other" securities that were mixed with government securities and backcast to generate synthetic observations from 1890 to 1895 using the model. The predicted proportion of securities other than government are 0.1624, 0.1977, 0.2322, 0.2649, 0.2967, and 0.327 for these years. We also accumulated the Federal Deposit Insurance Corporation (FDIC) figures on the ownership of these assets for 1934–2010 for all member banks, which did not include savings banks and thrifts in the aggregate statistics until 1984. The *Savings and Loan Sourcebook*, United States League of Savings Associations (1957–1978), and *Savings and Loan Fact Book*, United States Savings and Loan League (1979–1984), are the sources of balance sheet data for savings and loan institutions from 1956 through 1983. Compustat provides investment bank asset holdings starting in 1959. This data is aggregated across the universe of investment banks in the Compustat files and added to the private and public debt holdings of commercial banks, savings banks, thrifts, and investment banks.

Risk Ratio of Private to Public Asset Holdings of Financial Firms: Subtract the estimated government securities and cash holdings of U.S. financial firms from estimates of the private assets on their aggregate balance sheet to arrive the risk ratio.

Leverage Ratio of the Assets of Financial Firms to Their Capital: The estimate of total private asset holdings of U.S. financial firms is divided by the estimated capital of those firms.

Table 1: NBER Business Cycle Dates, 1890–2010

Length of a NBER Recession in Months
Median = 13, Mean = 14.8, STD = 7.7

Reference Dates		Duration in Months	
Peak	Trough	Contraction	Expansion
1890M07	1891M05	10	27
1893M01	**1894M06**	**17**	20
1895M12	**1897M06**	**18**	18
1899M06	**1900M12**	**18**	24
1902M09	**1904M08**	**23**	21
1907M05	1908M06	13	33
1910M01	**1912M01**	**24**	19
1913M01	**1914M12**	**23**	12
1918M08	1919M03	7	44
1920M01	**1921M07**	**18**	10
1923M05	**1924M07**	**14**	22
1926M10	1927M11	13	27
1929M08	**1933M03**	**43**	21
1937M05	1938M06	13	50
1945M02	1945M10	8	80
1948M11	1949M10	11	37
1953M07	1954M05	10	45
1957M08	1958M04	8	39
1960M04	1961M02	10	24
1969M12	1970M11	11	106
1973M11	**1975M03**	**16**	36
1980M01	1980M07	6	58
1981M07	**1982M11**	**16**	12
1990M07	1991M03	8	92
2001M03	2001M11	8	120
2007M12	**2009M06**	**18**	73

The NBER business cycle dates are found at http://www.nber.org/cycles/cyclesmain.html.

Table 2: Space of MS-BVAR(2) Models

Dimension of MS Chains and Regimes per Chain
on the Stochastic Volatility Scaling Matrix Γ

Model Number	Parameterizations of Γ
1	$\{\Gamma(1)\ \ \Gamma(2)\}$
2	$\{\Gamma(1)\ \ \Gamma(2)\ \ \Gamma(3)\}$
3	$\{\Gamma(1)\ \ \Gamma(2)\ \ \Gamma(3)\ \ \Gamma(4)\}$
4	$\{\Gamma(\mathcal{M},1)\ \ \Gamma(\mathcal{M},2)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
5	$\{\Gamma(\mathcal{M},1)\ \ \Gamma(\mathcal{M},2)\ \ \Gamma(\mathcal{M},3)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
6	$\{\Gamma(\mathcal{M},1)\ \ \ldots\ \ \Gamma(\mathcal{M},4)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
7	$\{\Gamma(\mathcal{M},M_I,1)\ \ \Gamma(\mathcal{M},M_I,2)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
8	$\{\Gamma(\mathcal{M},M_I,1)\ \ldots\ \Gamma(\mathcal{M},M_I,3)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
9	$\{\Gamma(\mathcal{M},M_I,1)\ \ldots\ \Gamma(\mathcal{M},M_I,4)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
10	$\{\Gamma(\mathcal{M},R_S,1)\ \ \Gamma(\mathcal{M},R_S,2)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
11	$\{\Gamma(\mathcal{M},R_S,1)\ \ldots\ \Gamma(\mathcal{M},R_S,3)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
12	$\{\Gamma(\mathcal{M},R_S,1)\ \ldots\ \Gamma(\mathcal{M},R_S,4)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
13	$\{\Gamma(\mathcal{M},M_I,R_S,1)\ \ \Gamma(\mathcal{M},M_I,R_S,2)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
14	$\{\Gamma(\mathcal{M},M_I,R_S,1)\ \ldots\ \Gamma(\mathcal{M},M_I,R_S,3)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$
15	$\{\Gamma(\mathcal{M},M_I,R_S,1)\ \ldots\ \Gamma(\mathcal{M},M_I,R_S,4)\ \ \Gamma(\mathcal{F},1)\ \ \Gamma(\mathcal{F},2)\ \ \Gamma(\mathcal{F},3)\}$

Regime j common to the macro block $\mathcal{M}$ and financial block $\mathcal{F}$ is denoted $\Gamma(j)$. The restriction $\Gamma(\mathcal{M},x,j)$ refers to placing the financial block variables $x = M_I,\ R_S$, or both also in the macro block $\mathcal{M}$ SV regimes.

Table 3: FEVDs of Fixed Coefficient-Homoskedastic BVAR(2)

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_R}$
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.97	0.00	0.00	0.01	0.02	0.00	0.00
	4	0.89	0.00	0.02	0.03	0.05	0.00	0.00
	8	0.70	0.02	0.15	0.03	0.06	0.01	0.03
	20	0.41	0.08	0.33	0.02	0.06	0.03	0.07
P	1	0.05	0.94	0.00	0.00	0.00	0.00	0.00
	2	0.09	0.90	0.00	0.01	0.00	0.00	0.00
	4	0.13	0.83	0.00	0.03	0.00	0.00	0.00
	8	0.14	0.78	0.00	0.05	0.03	0.00	0.00
	20	0.16	0.59	0.01	0.08	0.14	0.01	0.01
ur	1	0.61	0.12	0.28	0.00	0.00	0.00	0.00
	2	0.62	0.11	0.26	0.01	0.00	0.00	0.01
	4	0.60	0.10	0.23	0.03	0.03	0.00	0.01
	8	0.58	0.09	0.22	0.03	0.06	0.00	0.01
	20	0.57	0.09	0.21	0.03	0.06	0.00	0.02
M_I	1	0.41	0.09	0.00	0.49	0.00	0.00	0.00
	2	0.45	0.11	0.00	0.43	0.00	0.00	0.00
	4	0.45	0.12	0.00	0.42	0.00	0.00	0.00
	8	0.42	0.11	0.01	0.45	0.01	0.00	0.00
	20	0.37	0.06	0.03	0.46	0.05	0.00	0.02
R_S	1	0.05	0.04	0.02	0.08	0.81	0.00	0.00
	2	0.09	0.05	0.02	0.06	0.79	0.00	0.00
	4	0.13	0.06	0.02	0.04	0.74	0.00	0.00
	8	0.13	0.07	0.02	0.03	0.73	0.01	0.02
	20	0.10	0.06	0.02	0.03	0.69	0.01	0.10
R_L	1	0.00	0.01	0.01	0.02	0.20	0.76	0.00
	2	0.01	0.04	0.00	0.04	0.45	0.46	0.00
	4	0.02	0.06	0.00	0.03	0.60	0.28	0.02
	8	0.03	0.06	0.00	0.02	0.67	0.17	0.04
	20	0.02	0.04	0.00	0.02	0.65	0.11	0.14
r_R	1	0.02	0.00	0.00	0.00	0.11	0.01	0.84
	2	0.03	0.00	0.00	0.00	0.13	0.00	0.82
	4	0.06	0.00	0.01	0.00	0.10	0.01	0.81
	8	0.09	0.03	0.01	0.00	0.08	0.02	0.77
	20	0.09	0.13	0.01	0.00	0.10	0.02	0.63

Table 4: Measures of Fit of Competing MS-BVAR(2) Models

ln Marginal Data Densities
Fixed Coefficient-Homoskedastic BVAR(2): −1713.6

	Number of Stochastic Volatility Regimes		
	2	3	4
Model Number	1	2	3
A Single Markov Switching Chain	−1589.9	−1549.5	−1492.4
Two Markov Switching Chains			
3 Regimes on $\mathcal{F}$: M_I, R_S, R_L, $r_{R,t}$			
Model Number	4	5	6
Regimes on $\mathcal{M}$: y, P, ur	−1520.6	−1502.3	$*$
Model Number	7	8	9
Regimes on M_I and $\mathcal{M}$	−1505.8	**−1489.0**	$*$
Model Number	10	11	12
Regimes on $R_{S,t}$ and $\mathcal{M}$	−1518.7	−1499.2	$*$
Model Number	13	14	15
Regimes on $M_{I,t}$, $R_{S,t}$, and $\mathcal{M}$	−1506.6	$*$	$*$

Markov-switching occurs only on forecast innovation shock volatilities (SVs). The sample period is 1890 to 2010, $T = 121$. The ln Marginal Data Densities are computed using procedures described in Sims, Waggoner, and Zha (2008) and grounded in 10 million MCMC steps and 10 million draws from the posterior of the relevant MS-BVAR(2) model. The asterisk symbol, $*$, indicates convergence problems for the MCMC simulator of a MS-BVAR(2) model that shows up as a poorly approximated log marginal data density.

Table 5: Regime 1 FEVDs of MS-BVAR(2) Model 8

	Year	Shock y	P	ur	M_I	R_S	R_L	r_R
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.92	0.01	0.01	0.03	0.02	0.00	0.01
	4	0.74	0.03	0.08	0.09	0.09	0.00	0.01
	8	0.50	0.04	0.30	0.09	0.09	0.01	0.02
	20	0.21	0.04	0.51	0.05	0.05	0.08	0.08
P	1	0.10	0.90	0.00	0.00	0.00	0.00	0.00
	2	0.12	0.85	0.00	0.01	0.02	0.00	0.00
	4	0.17	0.76	0.00	0.05	0.02	0.00	0.00
	8	0.21	0.64	0.00	0.13	0.02	0.01	0.00
	20	0.20	0.49	0.02	0.19	0.07	0.01	0.03
ur	1	0.56	0.02	0.42	0.00	0.00	0.00	0.00
	2	0.57	0.01	0.39	0.02	0.00	0.00	0.01
	4	0.52	0.01	0.32	0.07	0.06	0.00	0.02
	8	0.47	0.02	0.29	0.09	0.12	0.00	0.02
	20	0.44	0.02	0.26	0.08	0.13	0.01	0.05
M_I	1	0.26	0.00	0.06	0.68	0.00	0.00	0.00
	2	0.20	0.00	0.08	0.71	0.00	0.00	0.00
	4	0.14	0.00	0.13	0.72	0.00	0.00	0.00
	8	0.09	0.00	0.18	0.67	0.05	0.00	0.00
	20	0.06	0.00	0.21	0.55	0.17	0.01	0.00
R_S	1	0.02	0.01	0.01	0.05	0.92	0.00	0.00
	2	0.04	0.01	0.01	0.04	0.91	0.00	0.00
	4	0.06	0.00	0.01	0.03	0.89	0.00	0.00
	8	0.06	0.00	0.01	0.02	0.88	0.01	0.00
	20	0.05	0.00	0.01	0.02	0.83	0.03	0.05
R_L	1	0.00	0.00	0.00	0.03	0.18	0.78	0.00
	2	0.01	0.00	0.00	0.04	0.34	0.60	0.01
	4	0.01	0.01	0.00	0.03	0.46	0.47	0.01
	8	0.03	0.01	0.00	0.03	0.56	0.36	0.02
	20	0.03	0.00	0.00	0.02	0.65	0.24	0.07
r_R	1	0.05	0.00	0.00	0.03	0.10	0.01	0.81
	2	0.07	0.00	0.00	0.01	0.05	0.00	0.85
	4	0.10	0.00	0.00	0.02	0.02	0.01	0.85
	8	0.11	0.00	0.00	0.04	0.02	0.01	0.82
	20	0.12	0.01	0.00	0.05	0.02	0.01	0.79

Table 6: Regime 2 FEVDs of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_R}$
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.92	0.02	0.01	0.00	0.01	0.00	0.04
	4	0.79	0.06	0.06	0.01	0.03	0.00	0.04
	8	0.48	0.08	0.18	0.01	0.02	0.00	0.22
	20	0.11	0.04	0.18	0.00	0.01	0.00	0.64
P	1	0.05	0.95	0.00	0.00	0.00	0.00	0.00
	2	0.06	0.93	0.00	0.00	0.01	0.00	0.00
	4	0.10	0.89	0.00	0.00	0.01	0.00	0.00
	8	0.13	0.84	0.00	0.01	0.01	0.00	0.01
	20	0.11	0.59	0.01	0.02	0.02	0.00	0.25
ur	1	0.56	0.02	0.42	0.00	0.00	0.00	0.00
	2	0.57	0.01	0.39	0.02	0.00	0.00	0.01
	4	0.52	0.01	0.32	0.07	0.06	0.00	0.02
	8	0.47	0.02	0.29	0.09	0.12	0.00	0.02
	20	0.44	0.02	0.26	0.08	0.13	0.01	0.05
M_I	1	0.66	0.01	0.09	0.24	0.00	0.00	0.00
	2	0.50	0.01	0.13	0.25	0.00	0.00	0.10
	4	0.36	0.01	0.21	0.26	0.00	0.00	0.17
	8	0.25	0.01	0.30	0.25	0.06	0.00	0.13
	20	0.15	0.01	0.35	0.21	0.22	0.00	0.05
R_S	1	0.03	0.02	0.02	0.01	0.91	0.00	0.00
	2	0.07	0.02	0.02	0.01	0.88	0.00	0.00
	4	0.11	0.02	0.01	0.01	0.84	0.00	0.01
	8	0.11	0.01	0.01	0.01	0.77	0.00	0.08
	20	0.04	0.01	0.00	0.00	0.34	0.00	0.61
R_L	1	0.03	0.02	0.00	0.03	0.57	0.36	0.00
	2	0.02	0.03	0.00	0.01	0.50	0.13	0.32
	4	0.03	0.03	0.00	0.01	0.48	0.07	0.38
	8	0.04	0.02	0.00	0.01	0.45	0.04	0.43
	20	0.02	0.01	0.00	0.00	0.24	0.01	0.72
r_R	1	0.00	0.00	0.00	0.00	0.00	0.00	0.99
	2	0.01	0.00	0.00	0.00	0.00	0.00	0.99
	4	0.01	0.00	0.00	0.00	0.00	0.00	0.99
	8	0.01	0.00	0.00	0.00	0.00	0.00	0.99
	20	0.01	0.00	0.00	0.00	0.00	0.00	0.99

Table 7: Regime 3 FEVDs of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_R}$
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.51	0.02	0.00	0.47	0.00	0.00	0.00
	4	0.23	0.05	0.01	0.71	0.00	0.00	0.00
	8	0.16	0.06	0.04	0.74	0.00	0.00	0.00
	20	0.11	0.10	0.11	0.66	0.00	0.02	0.00
P	1	0.02	0.98	0.00	0.00	0.00	0.00	0.00
	2	0.02	0.93	0.00	0.04	0.00	0.00	0.00
	4	0.03	0.74	0.00	0.23	0.00	0.00	0.00
	8	0.03	0.50	0.00	0.47	0.00	0.00	0.00
	20	0.03	0.34	0.00	0.63	0.00	0.00	0.00
ur	1	0.67	0.12	0.21	0.00	0.00	0.00	0.00
	2	0.48	0.04	0.13	0.35	0.00	0.00	0.00
	4	0.22	0.03	0.05	0.70	0.06	0.00	0.00
	8	0.16	0.03	0.04	0.76	0.12	0.00	0.00
	20	0.16	0.03	0.04	0.76	0.13	0.01	0.00
M_I	1	0.02	0.00	0.00	0.98	0.00	0.00	0.00
	2	0.01	0.00	0.00	0.99	0.00	0.00	0.00
	4	0.01	0.00	0.00	0.99	0.00	0.00	0.00
	8	0.01	0.00	0.00	0.99	0.00	0.00	0.00
	20	0.00	0.00	0.01	0.99	0.00	0.00	0.00
R_S	1	0.01	0.02	0.00	0.88	0.08	0.00	0.00
	2	0.04	0.02	0.00	0.85	0.09	0.00	0.00
	4	0.07	0.03	0.01	0.79	0.11	0.00	0.00
	8	0.09	0.03	0.01	0.74	0.13	0.01	0.00
	20	0.07	0.02	0.00	0.77	0.11	0.02	0.01
R_L	1	0.00	0.01	0.00	0.62	0.02	0.36	0.00
	2	0.00	0.02	0.00	0.69	0.03	0.26	0.00
	4	0.01	0.03	0.00	0.70	0.04	0.22	0.00
	8	0.03	0.04	0.00	0.66	0.06	0.21	0.00
	20	0.04	0.03	0.00	0.61	0.10	0.20	0.01
r_R	1	0.06	0.02	0.00	0.82	0.01	0.01	0.08
	2	0.17	0.04	0.00	0.62	0.01	0.01	0.16
	4	0.15	0.02	0.00	0.72	0.00	0.00	0.10
	8	0.09	0.01	0.00	0.84	0.00	0.00	0.05
	20	0.08	0.03	0.00	0.85	0.00	0.00	0.04

Figure 1: Levels and Growth Rates of U.S. Macro Aggregates, 1890–2010

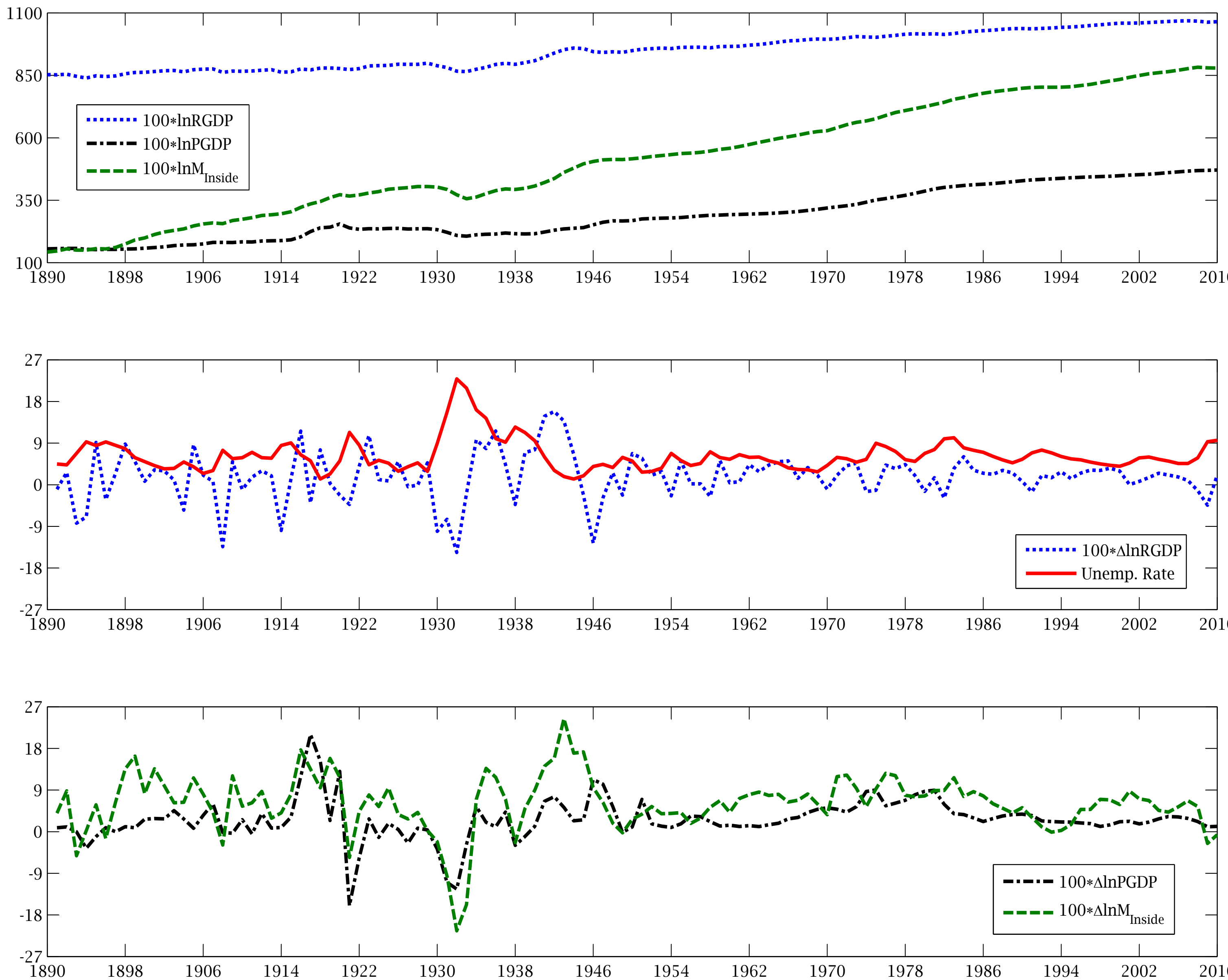

FIGURE 2: U.S. SHORT RATE, LONG RATE, AND RISK RATIO, 1890–2010

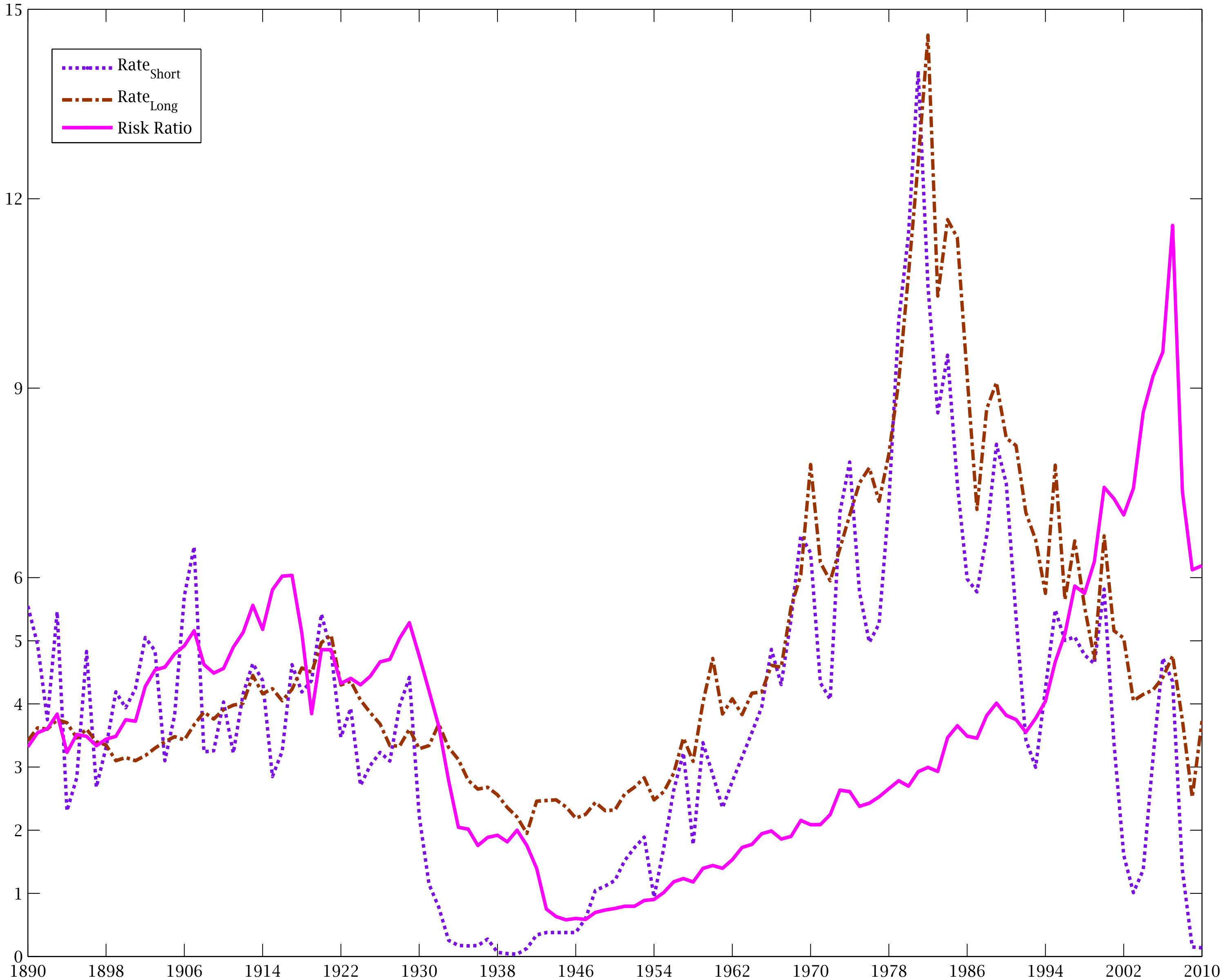

Figure 3: IRFs of Fixed Coefficient-Homoskedastic BVAR(2)

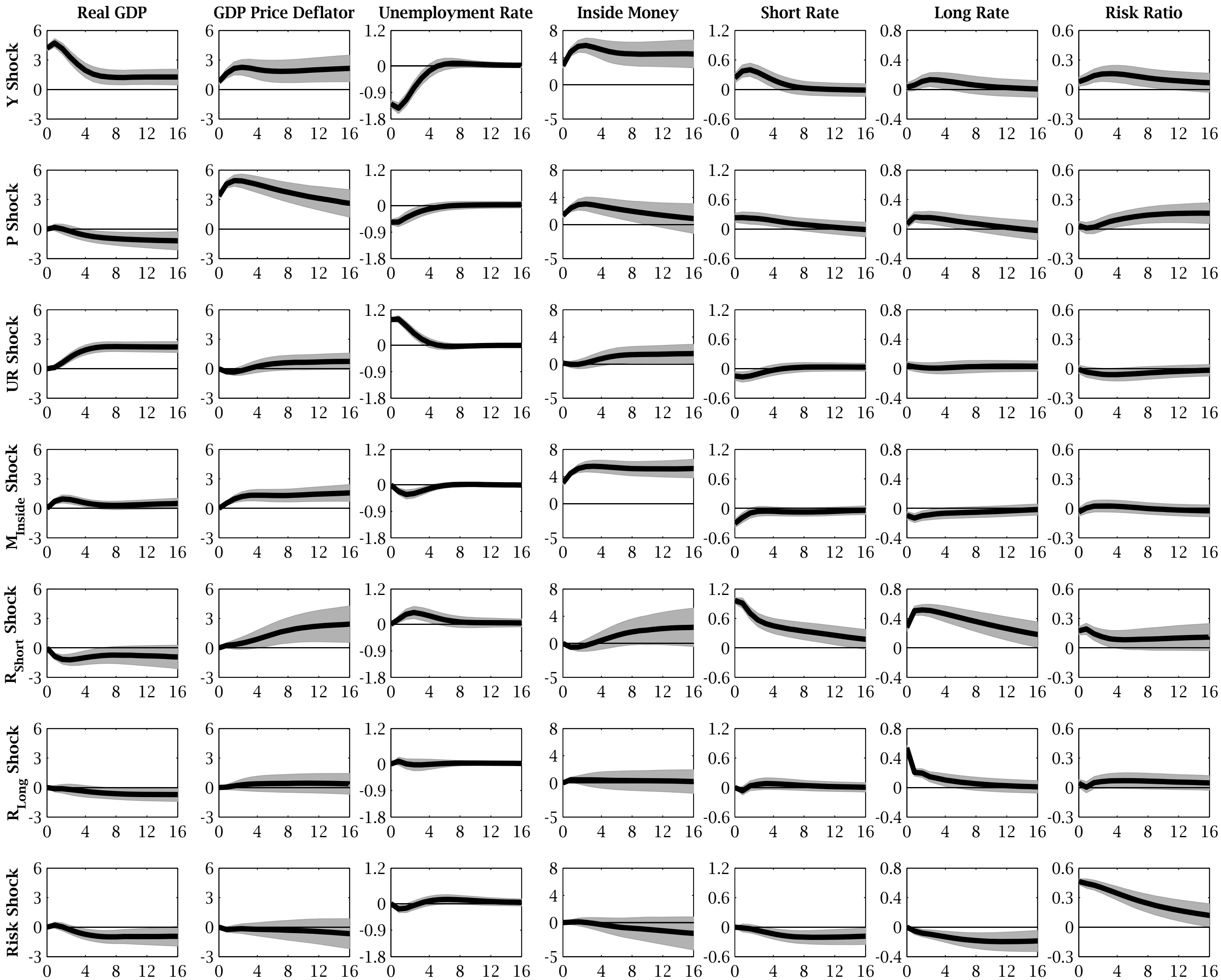

Figure 4: SV Regime Probabilities: Estimates of MS-BVAR(2) Model 2, 1891-2010

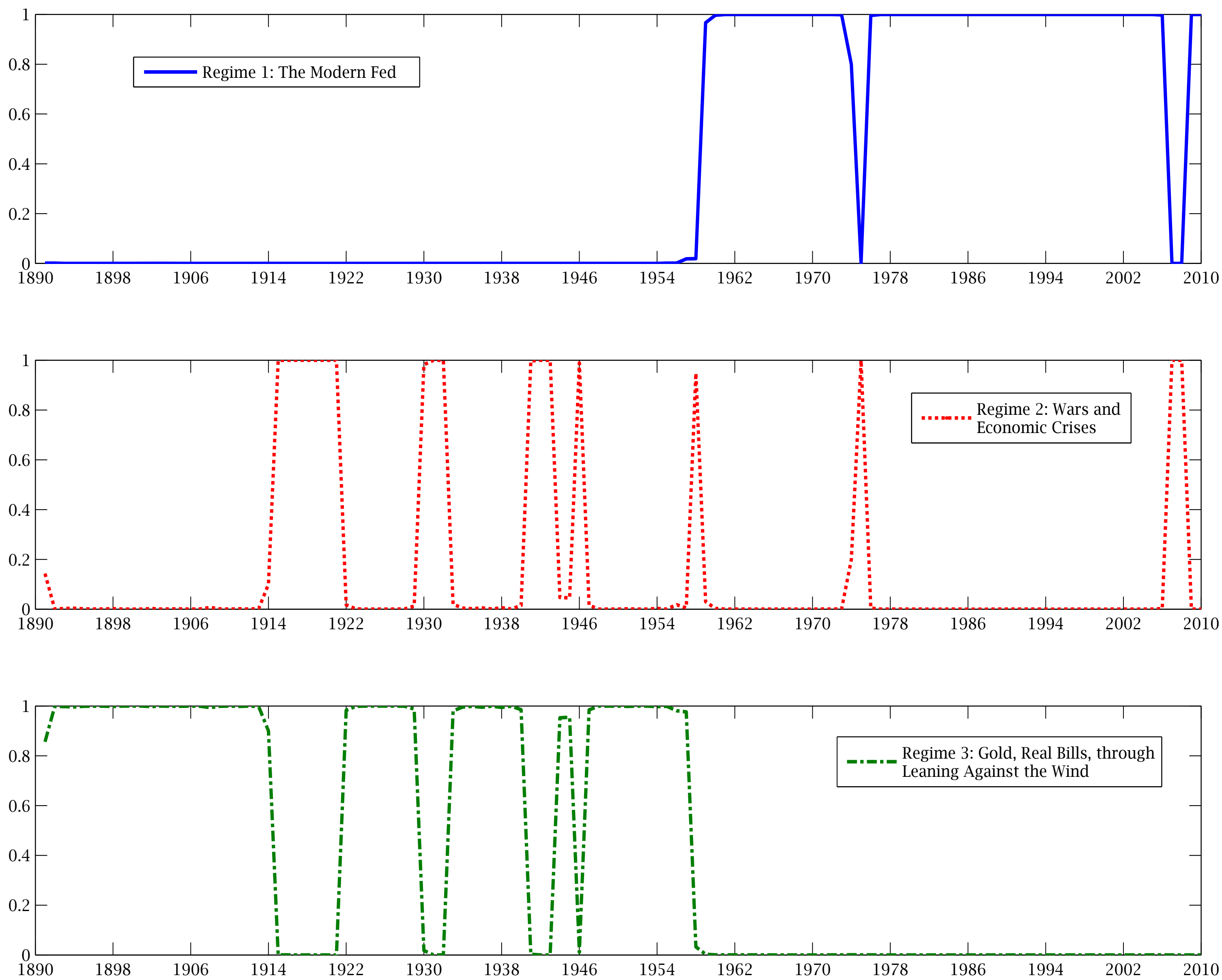

Figure 5: SV Regime Probabilities of the $\mathcal{M}$ Block: Estimates of MS-BVAR(2) Model 8, 1891-2010

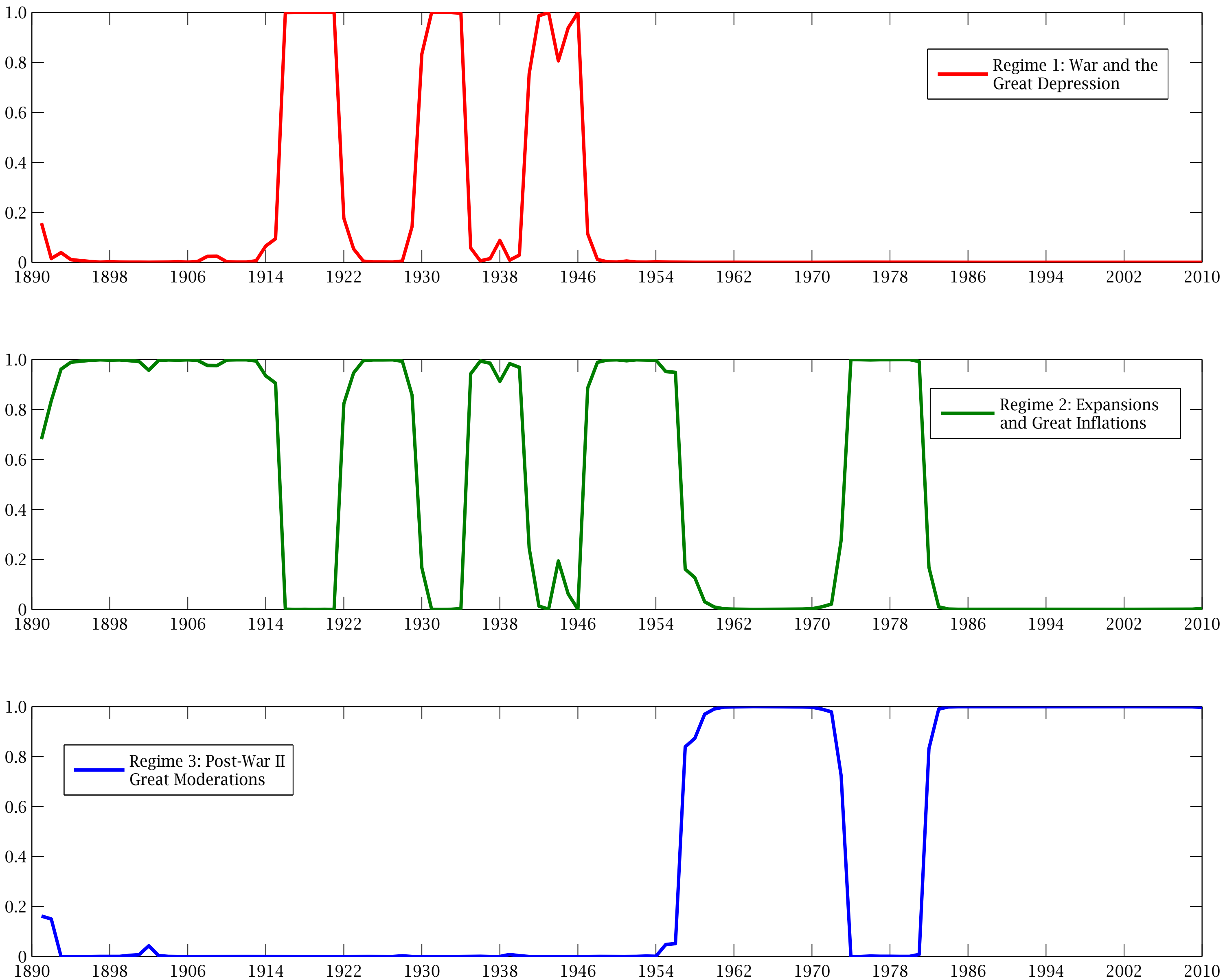

FIGURE 6: SV REGIME PROBABILITIES OF THE $\mathcal{F}$ BLOCK: ESTIMATES OF MS-BVAR(2) MODEL 8, 1891-2010

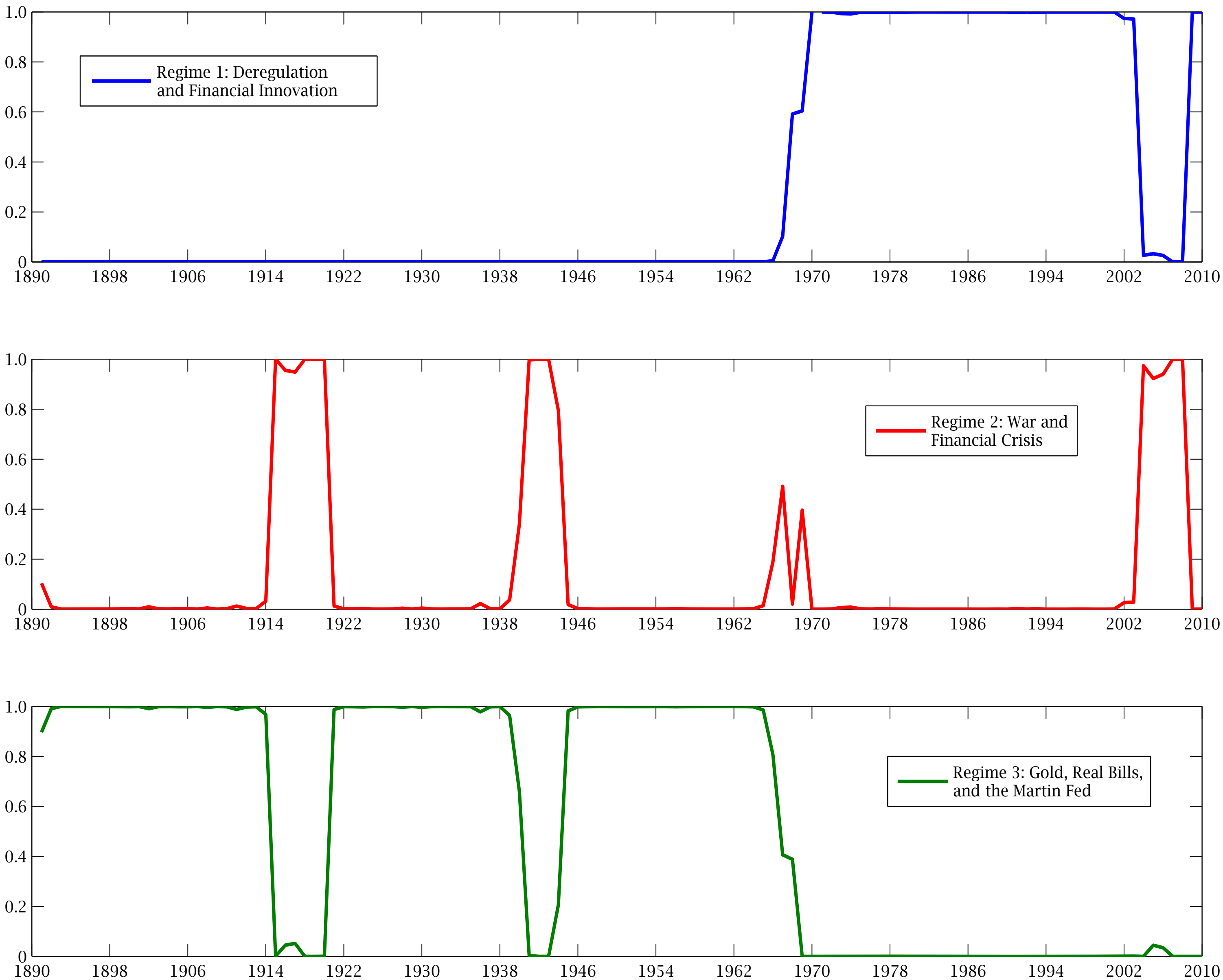

Figure 7: Regime Dependent IRFs w/r/t Inside Money Shock of MS-BVAR(2) Model 8

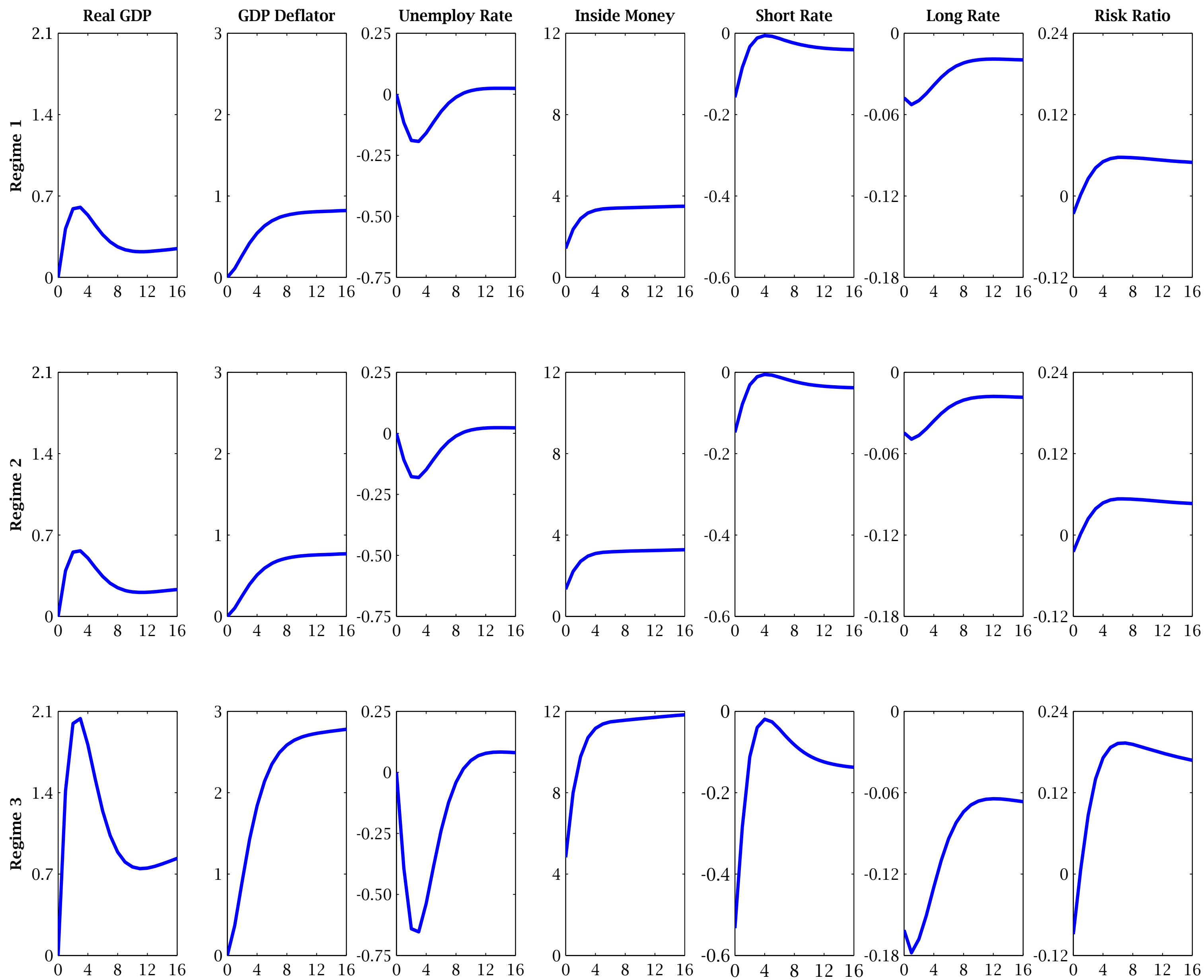

Figure 8: Regime Dependent IRFs w/r/t Short Rate Shock of MS-BVAR(2) Model 8