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

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Abstract

This paper explores the hypothesis that the sources of financial and economic crises differ from non-crisis business cycle fluctuations. We employ Markov-switching Bayesian vector autoregressions (MS-BVARs) to gather evidence about the hypothesis on a long annual U.S. sample running from 1890 to 2010. The sample covers several episodes useful for understanding U.S. economic and financial history, which generate variation in the data that aids in identifying credit supply and demand shocks. We identify these shocks within MS-BVARs by tying credit supply and demand movements to shifts in inside money and its intertemporal price. The space of models is limited to stochastic volatility (SV) in the errors of the MS-BVARs. This focuses our study on a "good luck-bad luck" story that the U.S. economy shifts between crisis and non-crisis regimes. Of the 15 MS-BVARs estimated, the data favor a model in which the SV of macro variables and financial variables are generated by crisis and non-crisis regimes that repeat through the long annual sample. This MS-BVAR model also shows the responses of the macro and financial variables to the credit supply and demand shocks differ by SV regime.

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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 and the financial panics that afflicted the U.S. from the end of the Civil War to 1914.

The U.S. has a history of deep and long recessions that are not always proceeded by financial crises. Table 1 shows that the duration of the median NBER recession is 13 months, while an average recession lasts about 15 months on the 1890–2010 sample. There are 12 NBER dated recessions with a length of 14 months or more listed in table 1. Of those recessions, the four most associated with financial crises start in January 1893, December 1895, August 1929, and December 2007 and last 17, 18, 43, and 18 months, respectively.[1] The remaining eight recessions that run for at least 14 months begin in June 1899, September 1902, January 1910, January 1913, January 1920, May 1923, November 1973, and July 1981.

Questions persist about the sources of the Panics of 1893, 1896, and 1907, the financial crisis at start of World War I (1914), the beginning of the Great Depression (1929), and the financial crisis of 2007–2009.[2] Concerns about the U.S. commitment to the gold standard is given prominence as the source of the Panics of 1893 and 1896; see table 1 of Bordo and Haubrich (2010). There is little consensus about the source(s) of the Panic of 1907, but a subset of financial intermediaries (*i.e.* trust companies) were run in the fall of 1907. This is an example of a (negative) credit supply shock because the ability of the financial markets to produce inside money was greatly diminished by the increase in the demand for cash by the depositors of these institutions. The Great Depression and Great Recession are tied to credit shocks with links to real estate markets being especially important. Although casual observation suggests that the U.S. has experienced deep and long recessions without also suffering financial crises, credit shocks, which seem to precipitate U.S. financial crises, are often accompanied by recessions with durations longer than average or the median.

This paper assesses the role credit shocks have in U.S. financial crises and business cycles on an annual sample running from 1890 to 2010. We contribute to the literature that studies the role credit flows have in financial crises and business cycles by identifying credit supply shocks separately from credit demand shocks in Markov-switching Bayesian vector autoregressions (MS-BVARs). This

[1] The Panic of 1907 is associated with a NBER dated recession that lasted 13 months.

[2] Table 1 of Bordo and Haubrich (2010) is a source of greater detail about U.S. financial crises and business cycles since 1873. Jalil (2012) provides similar information about U.S. financial crises back to 1825.

identification is employed to explore the hypothesis that U.S. financial crisis regimes are recurring events drawn from the same underlying probability density from which non-crisis regimes are drawn. An implication is that in the U.S. crisis and non-crisis regimes are grounded in the same economic primitives, but preferences, technologies, and market structure interact differently across crisis and non-crisis regimes creating disparate data generating processes (DGPs). The alternative hypothesis is that financial crises are described by once and for all structural breaks.

We explore questions raised by our hypothesis with methods developed by Sims and Zha (2006) and Sims, Waggoner, and Zha (2008) to estimate MS-BVAR models.[3] A MS-BVAR draws from only one density function (*i.e.*, the likelihood) to estimate probabilities of crisis and non-crisis regimes. These probabilities provide evidence to judge the hypothesis that the same economic primitives are responsible for U.S. crisis and non-crisis business cycle fluctuations. However, the alternative that U.S. financial crises are isolated events can also be evaluated. The first-order transition matrices of the MS-BVARs are flexible enough to let the data decide whether crisis regimes that occur, say, early in the sample reoccur later or are different from those that arise later in the long annual U.S. sample.

Identification of credit supply and demand shocks in the MS-BVARs rests on two elements. First, the MS-BVARs are estimated on an information set, Z_t, consisting of 7 variables. We compile time series on output, the price level, the unemployment rate, inside money, short- and long-term interest rates, and the ratio of long-term private assets held by financial firms to their holdings of public assets from 1890 to 2010 .[4] A motivation to equate credit supply with inside money, rather than broader credit aggregates, in the MS-BVARs is the reduced-form evidence of King and Plosser (1984). They report that the correlations of inside money growth with output growth dominates its correlation with outside money. Inside money is also included in Z_t because these short-term liabilities support the acquisition of private long-dated risky assets. Similarly, the structural MS-BVAR identifies shocks to the intertemporal opportunity cost of this liability, the short-term interest rate, with shifts in credit demand. Hence, changes in inside money demand are tied to identified short-term interest rate shocks. Limiting Z_t to these 7 variables also maintains tractability of the MS-BVAR estimation process.

The MS-BVARs are also identified using a Cholesky decomposition to order the elements of Z_t. Within this recursive structure, a macro ($\mathcal{M}$) block consisting of output, the price level, and the unemployment rate is placed before a financial ($\mathcal{F}$) block that includes inside money, short-term and

[3]The econometric foundations of this class of models are found in Hamilton (1994), Kim (1994), and Kim and Nelson (1999).

[4]The data is described in section 3 and in the appendix.

long-term interest rates, and the risk ratio.[5] We interpret the recursive identification as a combination of Keynesian, new classical, and rational expectations restrictions. For example, ordering output first is consistent with Keynesian and new classical macro models that have supply shocks driving price fluctuations and movements in labor and financial markets from impact onward. Whether responses to the identified supply shock match predictions of Keynesian or new classical models is a question to be settled by the data. Also, embedded in the MS-BVARs is a Lucas-Sargent Phillips curve-like restriction that the unemployment rate responds to price shocks at impact. In the $\mathcal{F}$ block, we have monetarist-like assumptions that inside money (the short-term interest rate) responds to shifts in the supply (demand) for credit. Since the short rate precedes the long rate, the identification relies on the rational expectations term structure prediction that the long rate is a function of shocks to the short rate. Finally, we place the risk ratio last in the ordering to be conservative about the role the composition of the aggregate balance sheet of U.S. financial firms plays generating financial crisis regimes.

This paper reports estimated structural MS-BVARs in which the only source of regime switching is stochastic volatility (SV) of the regression errors. The MS-BVARs yield estimated regime probabilities along with regime dependent responses of the elements of Z_t to identified credit supply and demand shocks given SV is the lone source of systematic differences across crisis and non-crisis regimes. This paper restricts the MS-BVARs to SV because, at the very least, financial and economic crises are associated with shocks whose size are larger than those generating non-crisis business cycle fluctuations. Although allowing only SV to define crisis and non-crisis regimes limits the model space, we include 15 MS-BVARs in the model space to cover a wide variety of SV parameterizations of the DGPs of crisis and non-crisis regimes.

Estimates of the 15 MS-BVARs support our hypothesis on our long annual 1890–2010 sample. We report unconditional regime probabilities from several MS-BVARs that show U.S. financial and economic crises from earlier and later parts of the sample are generated by the same regime. This is evidence that U.S. financial and economic crisis and non-crisis regimes are recurring events drawn from a single underlying probability density from 1890 to 2010.

The next section reviews a selection of the literature that searches for financial risk measures that matters for aggregate fluctuations. 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.

[5]The choice of a Cholesky identification is motivated by arguments borrowed from Keynesian, new classical, and rational expectations models, rather than on information flows among the variables of the long annual data set.

2 A Brief Literature Review

The financial crisis of 2007–2009 has reinvigorating research into the sources of economic and financial crises. Representative of these efforts is research that seeks to uncover predictors of financial and economic crises for emerging and advanced economies. Recent examples are, among others, Bussiere and Fratzscher (2006), Mendoza and Terrones (2008), Reinhart and Rogoff (2009, 2011), Claessens, Kose, and Terrones (2011), Jordà, Schularick, and Taylor (2011a,b), Gourinchas and Obstfeld (2012), and Schularick and Taylor (2012). These papers rely on structural breaks in an economy's underlying data generating process (DGP) to identify predictors of financial and economic crises at business cycle and longer horizons using cross-country data.[6] Credit growth is found by these studies to be a reliable predictor of financial crises, especially those associated with deep and long recessions.

An alternative tradition analyzes financial crises using VARs and other empirical tools familiar to macroeconomists. Examples include, among others, Canova (1991, 1994), Donaldson (1992), Coe (2002), Eichengreen and Mitchener (2003), Anari, Kolari, and Mason (2005), and Chin and Warusawitharana (2010). These papers identify the shocks and latent factors that contribute to financial and economic crises using information in the panics of the U.S. National Banking Era (1867–1914) as well as the 1920–1921 recession and the Great Depression (1929–1933) of the interwar sample (1920–1940).

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 observations motivate Schularick and Taylor to hypothesize that when financial market leverage rises above an arbitrary threshold defined ex post on output a financial crisis ensues. Hence, financial crises follow a period of growth in excess of the real value of bank loans relative to the output growth threshold. Schularick and Taylor provide empirical results that indicate a rapid growth in the real

[6] Ahmadi (2009), Helbling, Huidrom, Kose, and Otrok (2011) and Eickmeier and Ng (2011) identify latent variables that predict financial crises. A factor-VAR is estimated by Ahmadi that allows for time-varying parameters and stochastic volatility. His goal is to recover a business cycle factor conditioned on macro variables and interest rate spreads. Helbling et al 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. These papers report that estimated latent credit factors have large and persistent effects on real international economic activity.

value of bank loans relative to their output growth threshold has significant predictive power for future financial crisis. A related idea is excessive growth in this and other credit aggregates signal a deep and long recession is in the offing.

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 rate of interest far below its steady state according to Jordà, Schularick, and Taylor (2011a). This paper also finds that the comovement of credit growth and current account deficits has become stronger in the last 30 years. Similarly, 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. Nonetheless, Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2011a,b) do not present an explicit identification of the underlying shocks to credit flows that they argue predict financial crises and deep persistent 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. Stock market booms and lending into housing markets are leading indicators of financial crises across developed economies during the last 50 years in the analysis of 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. These papers report 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 compare the 2007–2009 crisis to U.S. financial crises during the previous 140 years. They argue that deposit insurance and other regulatory standards limited the impact of the 2007–2009 crisis on outside money, unlike the Great Depression, and instead put stress on short-term interbank 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."[7] Implicit in this claim is that the new state of the world produces fundamentals to support asset prices not available in early states. Ex post, these episodes are not systematically different from previous states of the world according to Reinhart and Rogoff.[8] 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 model of the risk factors that alter the demand for financial securities. These risk factor are tied to the impact shifts in the supplies of securities with different characteristics have on asset returns in the view of Krishnamurthy and Vissing-Jorgensen (KVJ). For example, investors may prize public securities as safe havens along with the liquidity these assets possess.[9] 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.

2.2 Identifying Financial Shocks Using Financial Crises

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.[10] He concludes that the start date of banking panics are unforecastable, but that there are states

[7]Parent (2012) is a useful critique of the "this time is different" thesis.

[8]An example highlighting the role expectations play in financial booms and busts is given by Brunnermeier (2009). He discusses the part beliefs that houses would always appreciate in value had in the 2007–2009 financial crisis. These beliefs increased counter-party risk because of the reliance of the shadow banking system on short-term interbank funds to support investment bank holdings of residential mortgage backed securities (RMBS), 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 not fall. After these beliefs were revised, investment banks found it difficult to fund their RMBS holdings. Gorton and Ordoñez (2012) construct a theory to explain these observations. The theory predicts that when lenders find it is costly to evaluate long-term assets they are considering to accept as collateral, they will withdraw funding from interbank markets.

[9]KVJ build an asset pricing model in which a demand for safety and liquidity to hold Treasury securities instead of private securities generates risk premia. 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. These estimates are interpreted by KVJ as a 46 basis point liquidity premium that investors received 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.

[10]These events are detailed in full by Gorton (1988), Calomiris and Gorton (1991), and Wicker (2000, 2005).

of the world in which banking panics are more likely.[11] 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.

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.[12] Prior to World War I, the U.S. has no institution responsible for supplying liquidity in the face of a financial crisis. Hence, the supply of currency was not especially elastic in response to external shocks in the U.S. prior to World War I. The Fed is created, in part, to supply an elastic currency when the U.S. is buffeted by external shocks. 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, the lack of an elastic currency and seasonal shifts in currency demand magnify the impact of international currency shocks on real economic activity in the U.S.. The creation of the Fed lessens the impact of these shocks in the estimates Canova reports. He argues his empirical results 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. These results also suggest that changes in the design of financial and economic institutions creates variation in the data useful for identifying the sources and causes of financial shocks, which is needed to estimate shifts between crisis and non-crisis regimes.

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 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

[11] 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.

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

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 are financial.

This paper is closest in spirit to Canova (1991, 1994) and Donaldson (1992). Our identification of credit supply and demand shocks is similar in approach to the way Canova (1991) identifies currency supply and demand shocks.[13] However, we estimate BVARs in which the volatility of the identified shocks is stochastic and conditional on the MS regime. Donaldson (1992) and Canova (1994) are interested in whether the same factors that drive non-crisis business cycle fluctuations also drive economic and financial crises. We estimate MS-BVAR models to evaluate a similar hypothesis.

3 Data

This section describes the sample data on which the MS-BVARs are estimated. By beginning in 1890, the sample covers the pre-Fed National Banking Era, the early Fed, the Great Depression, the 1935 to 1981 "quiet period" defined by Gorton (2010), as well the past forty years of U.S. financial market deregulation. The macroeconomic events include the NBER dated peaks and troughs listed in table 1, along with the world wars and other conflicts with engaged the U.S. during the 1890–2010 sample.

The information set Z_t consists of U.S. per capita real GDP (y_t), the implicit GDP deflator (P_t), the unemployment rate (ur_t), per capita inside money ($M_{I,t}$), a short-term nominal interest rate ($R_{S,t}$), a long-term nominal interest rate ($R_{L,t}$), and the ratio of long-term private assets to public debt held by financial firms, $r_{R,t}$. Since $Z_t = \begin{bmatrix} y_t & P_t & ur_t & M_{I,t} & R_{S,t} & R_{L,t} & r_{R,t} \end{bmatrix}'$ is grounded on a long annual 1890–2010 sample, $T = 121$. The appendix contains more details about the construction of the data.

3.1 Macro Aggregates

The $\mathcal{M}$ block contains y_t, P_t, and ur_t. We employ real per capita GDP to measure y_t. The corresponding P_t is the implicit GDP deflator (i.e., the ratio of nominal to real GDP). The log of real per capita GDP and log of the implicit GDP 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).

[13]Canova (1991) analyzes the power external factors have to magnify currency supply and demand shock in pre-World War I and interwar samples. We put aside open economy issues for later work.

3.2 Monetary Aggregates

We equate the stock of short-term liabilities issued by financial firms to inside money, $M_{I,t}$. 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 the later part of 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 observations through 2010. The quarterly and monthly M2 and monetary base data are temporally aggregated into the annual frequency and hen divide by population to obtain per capita inside money, $M_{I,t}$. Hence, this measure of $M_{I,t}$ equates an increase in M2 net of the monetary base with financial firms issuing more loans and short-term liabilities, for example, to purchase long-term assets for their balance sheets.

3.3 Interest Rates

A 1-year interest rate series plays the role of the intertemporal price of short-term funds in financial markets, $R_{S,t}$. This rate is a synthetic series because the contract that fills the role of a short-term riskless asset has evolved in U.S. financial markets since 1890. The 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.

Shiller (2005) is the source of the long-term interest rate, $R_{L,t}$. 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, which runs from 1953 to 2010 for our sample, is used by Shiller to complete his long term interest rate series.

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 Federal Deposit Insurance Corporation (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.

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 equate the private assets owned by U.S. financial firms to their holdings of securities that are "claims on private entities." These same firms 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 assets to public debt is our measure of the risk composition of the asset side of the aggregate balance sheet of U.S. financial firms.

The financial risk variable is novel. Since financial risk is measured as the ratio of private assets held by U.S. financial firms to their ownership of public debt, movements in this ratio reflect changes in the composition of assets on the aggregate U.S. financial balance sheet. This ratio avoids identification issues caused by confounding financial and real shocks because the risk ratio does not, say, net output growth from credit growth.

In summary, $M_{I,t}$, $R_{S,t}$, $R_{L,t}$, and $r_{R,t}$ define the financial block $\mathcal{F}$.

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 for the complete 1890–2010 sample. The growth rate of y_t, $\Delta \ln y_t$, and ur_t are shown in the middle panel of figure 1 from 1891 to 2010. These macro aggregates are less volatility since the late 1948. From 1891 to 1947, the standard deviations of $\Delta \ln y_t$ and ur_t are 6.81 and 4.50, while these statistics fall to 3.02 and 1.76 in the second half of the sample. Output growth shows large negative annual growth rates around the Panic of 1907 (−13.4 percent), the depth of the Great Depression in 1931 (−14.6 percent), and the end of World War II in 1945 (−12.6 percent). The unemployment rate 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 1 contains the growth rates of P_t, $\Delta \ln P_t$, and $M_{I,t}$, $\Delta \ln M_{I,t}$, from 1891 to 2010. The volatility of $\Delta \ln P_t$ and $\Delta \ln M_{I,t}$ also are greater in the first part of the sample, 5.81 and 8.21, compared to 2.55 and 3.23 in the 1948-2010 subsample. Inflation shows peaks during World War I of 12 to 20 percent, at the end of World War II of more than 10 percent (1945 and 1946), at the time of the first oil price shock in 1973–1974 of 8.5 to 9.0 percent, and in the 1978–1980 period of 8.0 to 9.0 percent. The smallest $\Delta \ln M_{I,t}$ are -9.6 to -21.4 percent at the depth of the Great Depression, while the peaks occur during the world wars at 16 to 24 percent. Note also that $\Delta \ln P_t$ and $\Delta \ln M_{I,t}$ exhibit substantial comovement from the Panic of 1907 to 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. First, $R_{S,t}$ is only a bit more volatile than $R_{L,t}$ over the entire sample, 2.59 to 2.40. Next, there are periods, 1899 to 1907, 1912 to 1914, 1928 and 1929, 1973 and 1974, and 1978 to 1980, during which $R_{S,t}$ is greater than $R_{L,t}$. Since 1981, the opposite is true for every year except 2006, 2009, and 2010. At the end of the sample, $R_{S,t}$ falls 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 in the middle of the sample, from 1933 to 1997, $r_{R,t}$ is less than $R_{L,t}$. The inequality is flipped (mostly) at the beginning and the end of the sample.

4 A MS-BVAR Model

Our motivation for estimating MS-BVAR models rests on the idea that economic and financial crises represent different DGPs or regimes of the world than do non-crisis business cycle fluctuations. Nonetheless, crisis and non-crisis regimes are built on the same economic primitives and drawn from the same probability density function, the likelihood, of a MS-BVAR. The estimated MS-BVARs yield the responses of output, aggregate price level, unemployment rate, and long-term interest rate to credit supply and credit demand shocks.[14] Besides IRFs and FEVDs, the estimates include the regime transition probabilities, the (first-order) Markov transition matrix of the regimes, the impact coefficient matrix, and the SV factor loadings of the best fitting MS-BVAR. 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 MS-BVARs models of lag length k. They study the MS-BVAR(k) model

[14] Primiceri (2005) and Cogley and Sargent (2005) develop a different regime change model estimator.

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

where Z_t is $n(=7)\times 1$, 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 SVs of the elements of ε_t.[15] Key distributional assumptions made by Sims, Waggoner, and Zha (SWZ) include those on the densities of the MS-BVAR disturbances

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

and on the information set

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

where $\mathcal{Z}_t = \left[Z_1' \;\; Z_2' \ldots, Z_t'\right]'$, $\mathcal{S}_t = \left[S_0' \;\; S_1' \ldots, S_t'\right]'$, ω is the vector of probabilities attached to the Markov chains,

$$\Theta = \left[A_0(1) \;\; A_0(2) \ldots A_0(h) \;\; \mathcal{A}(1) \;\; \mathcal{A}(2) \ldots \mathcal{A}(h) \;\; C(1) \;\; C(2) \ldots C(h) \;\; \Gamma(1) \;\; \Gamma(2) \ldots \Gamma(h)\right]',$$

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

SWZ also restrict the (first-order) Markov transition matrices. These matrices are the laws of motions of the Markov chains in which the regime probabilities reside. The restrictions placed on the transition matrix Q only permit switching between adjacent regimes and that this switching is symmetric. The result is

[15] 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).

$$
(4) \qquad Q = \begin{bmatrix} \varrho_1 & 0.5(1-\varrho_2) & 0 & 0 & \dots & 0 & 0 \\ 1-\varrho_1 & \varrho_2 & 0.5(1-\varrho_3) & 0 & \dots & 0 & 0 \\ 0 & 0.5(1-\varrho_2) & \varrho_3 & 1-\varrho_4 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \varrho_{h-1} & 1-\varrho_h \\ 0 & 0 & 0 & 0 & \dots & 0.5(1-\varrho_{h-1}) & \varrho_h \end{bmatrix}.
$$

Estimation of the MS-BVAR generates values for the transition probabilities $\varrho_1, \varrho_2, \dots, \varrho_h$. The map that relates the vector of Markov chain probabilities ω to the transition matrix Q is

$$
(5) \qquad q_{\cdot,j} = M_{\cdot,j}\omega_{\cdot,j},
$$

where $q_{\cdot,j}$ is the jth column of Q and M is a matrix of zeros and ones whose dimension is a function of the number of Markov chains and regimes within each chain. The matrix M transforms the vector of probabilities ω into the probability of remaining within a regime. Priors are placed on the duration (in years) of remaining within a regime which maps into the probabilities ω.

The matrix Q given in (4) allows for a rich set of transition probability dynamics. Suppose $h = 3$. In this case, the regimes could spend the early part of the sample, say, in regime 1 before transiting to regime 2 during the middle part of the sample, and moving to regime 3 toward the end of the sample. Or the MS-BVAR, priors, and data could generate estimates that repeatedly move between regimes during the sample. The latter set of transition probabilities would support the hypothesis that crises are events that occur in the early, middle, and later parts of the sample

The MS-BVAR(k) model (1) relies on assumptions (2)–(5) to construct the log likelihood function of Z_T

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

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 this density along with conditional densities of

Θ, $\mathcal{P}\left(\Theta \middle| \mathcal{Z}_{t-1}, \mathcal{S}_t, \omega\right)$, and ω, ω, $\mathcal{P}\left(\Theta \middle| \mathcal{Z}_{t-1}, \mathcal{S}_t, \Theta\right)$.[16] Note that the vector of regimes S_T is integrated out of the likelihood (6) of Z_T.

Evaluation of MS-BVARs rely on the joint posterior distribution of Θ and ω. This posterior is calculated using Bayes rule, which gives

$$\mathcal{P}\left(\omega, \Theta \middle| Z_T, \mathcal{Z}_T, \omega, \Theta\right) \propto \mathcal{P}\left(Z_T \middle| \mathcal{Z}_T, \omega, \Theta\right)\mathcal{P}\left(\omega, \Theta\right), \tag{7}$$

where $\mathcal{P}\left(\omega, \Theta\right)$ denotes the priors of ω and Θ. Posterior odds of competing MS-BVAR models are computed using (7).

4.2 Priors and Identification

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), $\mathbb{A}(s_t) \equiv \left[A_1(s_t)\ \ A_2(s_t)\ \ldots\ A_k(s_t)\ \ C(s_t)\right]'$, with

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

where $\overline{\mathcal{D}} = \left[\mathbf{I}_n \quad \mathbf{0}_{n\times 1}\right]'$ and $\mathcal{D}(s_t)$ are conformable with $\mathbb{A}(s_t)$ and $\overline{\mathcal{D}}\,\mathcal{A}(s_t)$.[17] A mean zero prior distribution is bestowed on $\mathcal{D}(s_t)$ by Sims and Zha (2006) and SWZ. Their prior matches the 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 the random walk prior is, in the view of SWZ, independent of beliefs about the unconditional variance of Z_t.

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 $\Gamma(\cdot)$ 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

[16]These methods rest on analysis SWZ provide in their appendix A.
[17]Waggoner and Zha (2003b) supply a rule to normalize the signs of $\mathbb{A}(s_t)$.

at date $t-1$. Another part of our prior is that we set $k = 2$, given $T = 121$ for the annual sample.[18]

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 $\mathcal{M}$ block, y_t, P_t, and ur_t, prior to the $\mathcal{F}$ block, $M_{I,t}$, $R_{S,t}$, $R_{L,t}$, and $r_{R,t}$. The $\mathcal{M}$ block captures dynamic aggregate 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 $\mathcal{F}$ block contains 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 $\mathcal{F}$ 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 model 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 MS to the SV scaling matrix $\Gamma(s_t)$. 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 are generated by "good or bad luck" credit supply and demand shocks. 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

[18] 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. Given $n = 7$, 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 $T = 121$.

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 Markov chains generating 2, 3, and 4 SV regimes on the $\mathcal{M}$ block. For example, models 7, 8, and 9 hold that shocks to $M_{I,t}$ respond to changes in the SV regime of the $\mathcal{M}$ and $\mathcal{M}$ blocks. This assumption imposes nine SV regimes on $M_{I,t}$ in models 7, 8, and 9.

We condition 12 of the 15 MS-BVAR models on separate Markov chains for the $\mathcal{M}$ and $\mathcal{F}$ blocks. This gives the MS-BVAR models conditional on the priors and data the flexibility to estimate SV regimes for the $\mathcal{M}$ and $\mathcal{F}$ blocks that differ systematically in economic and calendar time. That is the MS-BVAR models can find crisis and non-crisis regimes that either repeat throughout the 1890–2010 sample or occur only in the early or later parts of the sample. This enriches the model space enough to cover a large array of DGPs, but makes it possible to estimate the 15 MS-BVARs in real 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

1. set the random walk, smoothness, cointegration, and duration priors on the MS-BVAR(2),[19]
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,[20]

[19]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. The duration priors set the average time of remaining in regime j given the current regime is j. We set this prior to be no more than 6 years and no less than 2 years.

[20]Dynare's MS-BVAR code employs an optimizer adapted from the csminwel software developed by Chris Sims.

3. given estimates of A_0, A_1, A_2, C, and $\Gamma(1)$, $\dots$ $\Gamma(h)$ of the MS-BVAR(2), run 10 millions steps of the Markov chain-Monte Carlo (MCMC) simulator,

4. construct the posterior of a MS-BVAR(2) by drawing 10 million times from the proposals created by the 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, and

6. rerun the MS-BVAR(2) model(s) most favored by the data to produce the transition probabilities $\varrho_1, \dots, \varrho_h$, regime-dependent IRFs, and FEVDs.

The next sections engages these procedures to generate estimates of 15 MS-BVAR(2)s 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.[21] The estimates are grounded in the restriction $\Gamma(s_t) = \Gamma$ across all potential regimes.[22] Figure 3 plots IRFs generated from the estimated fixed coefficient-homoskedastic BVAR(2). Median IRFs are plotted in black and error bands are shaded grey. Table 3 presents FEVDs.

The median IRFs of figure 3 display a priori expected shapes as well as shapes that are not intuitively appealing. For example, the first row of figure 3 shows that a 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, permanently increases M_I, while holding its real balances to a proportionate change, yields a hump-shaped response in R_S peaking at 2 years before returning to steady state within 4 years, has little effect on R_L, but raises r_R for about 4 years.

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.

[21] We estimate 5 additional 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.

[22] Fixed coefficient-homoskedastic BVARs are analyzed by Sima and Zha (1998) and Roberston and Tallman (2001).

The responses of P and ur to the supply shock are consistent with Keynesian models in which frictions drive prices up and inhibit the labor market from returning quickly to steady state. An increase in M_I in response to a y shock suggests that the supply of inside money accommodates (income) demand shifts as Leeper, Sims, and Zha (1996) find for outside money. Financial markets react to y shocks by producing more short-term liabilities and long-term private assets relative to public debt, according to the estimated fixed coefficient-homoskedastic BVAR(2).

A Lucas-Sargent Phillips curve-like relation is depicted in the second row of figure 3. Given a shock to P, ur falls at impact. This shock raises P for at least 16 years. The reactions of M_I and r_R to a P shock are of interest because the former is higher at short horizons before returning to steady state, while the latter rises at longer horizons. Hence, the fixed coefficient-homoskedastic BVAR(2) estimates that a P shock generates more M_I in the medium run which is transformed into long-term private assets compared to public debt.

The identified credit supply shock is consistent a priori with new classical theory as articulated by King and Plosser (1984). With respect to a M_I shock, y (ur) exhibits a small (negative) hump-shaped response peaking at 2 years, R_S and R_L are modestly lower in the short-run, and P is permanently higher in the fourth row of figure 3. These reactions to a M_I shock suggests a long-run inside money neutrality result in which P rises proportionally.

The fifth row of figure 3 shows that a shock to R_S generates money demand-like response in y and ur. These variables indicate there is a contraction in real activity in reaction to a positive R_S shock. The responses of R_L and R_S to this shock show the term spread shrinks at short horizons before return to its steady state in the long-run. In the short-run, r_R also rises given a R_S shock. Hence, the tighter term spread is consistent with smaller risk premia that suggest U.S. financial firms take more risk by holding a larger share of their balance sheets in long-term private assets.

The remaining shocks either generate few economically interesting responses with one exception. These are the dynamic responses R_L and R_S to a r_R shock in the bottom row of figure 3. The latter IRF is permanently lower, which given the short-run response of R_S to a r_R shock, indicates a larger term spread is required for U.S. financial firms to hold a larger share of the balance sheets in long-term private assets relative to public debt.

Nonetheless, the fixed coefficient-homoskedastic BVAR(2) produces two IRFs at odds with with conventional economic theory. One is the response of y to an ur shock in the third row of figure 3. This IRF rises from impact to the longer horizons, which is inconsistent with a dynamic Okun's law-like relation. The other is the fixed coefficient-homoskedastic BVAR(2) produces the price puzzle in which a shock to R_S generates a permanent increase in P as depicted in the fifth row of figure 3.

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 its own shock dominate.

5.2 The Fit of the 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.[23] 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.[24] Except for 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.

The log marginal data densities of table 4 possess information to judge the fit of the fixed coefficient-homoskedastic BVAR and MS-BVARs to the data. The information comes in the form of odds ratios, which signal the MS-BVAR(2)s are all preferred by the data to the fixed coefficient-homoskedastic BVAR(2). Hence, the MS-BVAR models provide evidence that there is regime switching in the SV of Z_t on the long annual 1890–2010 sample.

Among the MS-BVAR(2)s, model 8 achieves the best fit to the data, according to the log marginal data densities of table 4. This model imposes 3 distinct MS chains on the SV of the $\mathcal{M}$ block and 3 more on the SV $\mathcal{F}$ block, but these blocks hold the SV regimes of the errors of the M_I regression in common. The implication is that each of the nine transition probabilities defined by the MS chains on the $\mathcal{M}$ and $\mathcal{F}$ blocks is associated with a different estimate of the volatility scaling the error of the M_I regression. The evidence that this restriction on the M_I regression errors is preferred by the data is strong when model 8 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 this log

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

[24]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.

marginal data density and the log marginal data density of model 8 indicate a odds ratio strongly in favor of the latter model.[25]

5.3 Estimates of the MS-BVAR(2) Model 8

Table 5 presents estimates of the transition matrix Q for the $\mathcal{M}$ block, which includes M_I and the $\mathcal{F}$ block, impact matrix $\widehat{A}_0$, and regime dependent diagonals of the SV scaling matrices $\widehat{\Gamma}(s_t)$ of model 8. The estimated transition matrix for the $\mathcal{M}$ block shows that its regimes 1 and 2 are persistent and that the probability of moving between these regimes is less than 5 percent. Regime 3 is less persistent, which implies a probability of nearly 20 percent moving from regime 3 to regime 2 in the $\mathcal{M}$ block. Similar transition dynamics arise for the $\mathcal{F}$ block. However, this estimated transition matrix gives low probabilities of leaving either regimes 1 or 3 given the $\mathcal{F}$ block is already in either regime. There is also a 10 percent probability of being in regime 2 and transiting to either regime 1 or regime 3.

The estimated fixed coefficient impact matrix $\widehat{A}_0$ is found in the middle of table 5. The estimated own shock responses for P, ur, M_I, R_S, R_L, and r_R are larger than the estimates of responses to other shocks. The only possible exception is that M_I exhibits nearly as large a reaction at impact to y and ur shocks as its own shock.

The bottom panel of table 5 lists the estimated regime dependent diagonals of the SV scaling matrices $\widehat{\Gamma}(s_t)$. The SWZ code standardizes the elements of $\widehat{\Gamma}(\cdot)$ to regime 1 of the $\mathcal{M}$ block with M_I conditional on regime 1 of the $\mathcal{F}$ block, $s_{\mathcal{M},M_I} = 1|s_{\mathcal{F}} = 1$. These estimates indicate that the largest shock volatilities of y, P, ur, R_S, and r_R arise in regime 1, whether in the $\mathcal{M}$ or $\mathcal{F}$ block. The largest estimated shock volatilities of M_I and R_L reside in regime 2. Note that the shock volatilities of M_I differ in across the 9 conditional regimes of the MS-BVAR of model 8. This suggests the 1890–2010 sample favors model 8 (conditional on the priors) because it allows there to be greater variability in the regime dependent shock volatilities of M_I.

5.4 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 MS chain of 3 SV regimes, in figure 4, for model 3, a single MS chain of 4 SV regimes, in figure 5, and in figures 6 and 7 for model 8's two MS chains of 3

[25] A Bayes factor of 31.19 (= exp(3.44)) translates, at least, into strong evidence for model 8; see Jeffreys (1998).

SV regimes. The regime probabilities of models 2 and 3 are reported to contrast with the 2 MS chains of 3 SV regimes of model 8.

Figure 4 shows that model 2 is consistent with the hypothesis that crisis and non-crisis regimes represent different economic outcomes, while being drawn from the same probability density. 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.[26] 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 regime 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, 1973–1975, and 2007–2009 recessions. The only recessions in regime 1 to match the severity of these recessions are the 1957–1958 and 1981–1982 recessions. 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. However, the key difference between these regimes and regime 2 is that it reoccurs in the early, middle, and late parts of the 1890–2010 sample. This is support for the hypothesis that U.S. financial crisis regimes are events that are repeatedly drawn from the same underlying probability density from which non-crisis regimes are drawn.

Figure 5 displays the 4 SV regime probabilities of model 3. The top (bottom) window of figure 5 presents the date t probability of the odd (even) numbered regimes. Regime 1 covers the late Martin and Burns chairmanships of the Fed, which are 1959–1968 and 1973–1978, respectively. The early chairmanships of Martin and Burns, along with those of Volcker, Greenspan, and Bernanke are found in regime 2 except for the 2007–2009 Great Recession. Regime 4 contains three seemingly different regulatory regimes. These are the National Banking Era from 1890 to 1913, the early Fed of the 1920s, and the 1935–1954 period, which includes the Great Depression financial market reforms and the transition to an independent Fed. However, figure 5 shows that the value added of model 3 stems from its regime 3 grouping together the recessions of 1913 to 1921, the Great Depression of 1930–1933,

[26]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.

the 1957–1958 recession, and the 2007–2009 Great Recession. Since regime 3 repeats throughout the 1890–2010 sample, model 3 is consistent with the hypothesis that U.S. financial and economic crisis are generated by the same underlying economic primitives during the last 120 years.

Model 8 produces regime probability estimates that refines the narrative of U.S. crisis and non-crisis business cycle fluctuations. These probability estimates are displayed in figures 6 and 7. Figure 6 depicts the regime probabilities associated with the $\mathcal{M}$ block and M_I, while figure 7 does the same for the regime probabilities of the $\mathcal{F}$ block and M_I.

The U.S. crisis and non-crisis narrative is altered by model 8 in two key ways. First, the middle panel of figure 6 shows that model 8 generates regime 2 of the $\mathcal{M}$ block together with M_I in which resides the National Banking Era, the economic boom of the 1920s, the recovery from the Great Depression, the inflation episode of the late 1940s, the first half of Chairman Martin's stewardship of the Fed, the Great Inflation of the 1970s, the stop-go monetary policy of the 1970s, the Volcker disinflation, and subsequent recovery of the early 1980s. This regime is covers the early, middle, and later parts of the 1890–2010 sample, which represents more than 50 percent of this sample. Second, the $\mathcal{F}$ block regime that includes four brief episodes from the early, middle, and later parts of the 1890–2010 sample that appear in the middle panel of figure 7. This is regime 2 of the $\mathcal{F}$ block and contains World War I, World War II, and the Vietnam and Iraqi wars. Hence, model 8 generates support for the hypothesis that the events defining U.S. crisis and non-crisis regimes arise in the sample at different occasions in the 1890–2010 sample.

There are several other notable refinements of the regime probabilities produced by model 8. Among these are that the world wars and the Great Depression are placed in regime 1 of the $\mathcal{M}$ block, which includes M_I, by model 8. The Great Depression is found in regime 3 of the $\mathcal{F}$ block. This regime also includes the National Banking Era, the interwar period, the transition to an independent Fed, and the Martin chairmanship of the Fed. Note that model 8 gives most of the latter part of the 1890–2010 sample to regime 3 of the $\mathcal{M}$ block together with M_I and regime 1 of the $\mathcal{F}$ block. However, the latter regime excludes the 2003-2009 period, which contains the Iraqi war and a financial boom-bust cycle, while the Great Inflation of the 1970s and Volcker disinflation is absent from the former regime.

The regime probabilities of figures 4–7 help explain the preference of the data for model 8. Although the data appreciates the extra SV regime of model 3 compared to model 2, which is used to separate economic crises from financial and other crises, the MS-BVAR of model 8 is a better fit for the data (given the priors). The reason is that model 8 parameterizes distinct $\mathcal{M}$ and $\mathcal{F}$ block SV regimes. This gives each of the 3 $\mathcal{M}$ and $\mathcal{F}$ block regimes its own SV scaling on the errors of the M_I regression.

We interpret the preference of the data for model 8 as evidence that the nine SV credit supply shocks produced by placing $M_{I,t}$ in the macro and financial block MS chains is useful for estimating separate crisis from non-crisis regimes.

5.5 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 8 and 9, respectively.[27] These IRFs receive our attention because they provide evidence about impact of regime switching on responses to identified credit supply and demand shocks that is produced by the MS-BVAR of model 8. We display the IRFs dependent on the $\mathcal{M}$ with M_I and $\mathcal{F}$ blocks residing in regimes 1, 2, and 3 in the top, middle, and bottom rows of figures 8 and 9. The regime dependent IRFs have the same shape because the only MS is on the SV of the regression errors. Hence, model 8 produces IRFs whose height is regime dependent.

The IRFs of figure 8 are qualitatively similar to the IRFs found in row 4 of figure 3. These IRFs are estimated using the fixed coefficient-homoskedastic BVAR(2). Figure 8 shows shocks to M_I drive y and P higher, lowers ur, produces a smaller term spread, and leads financial firms to hold relatively more private assets on their balance sheets across the three regimes. However, regime dependence in the IRFs appears in first two rows of figure 8 compared to its bottom row. The height of the IRFs in regimes 1 and 2 are small compared to the IRFs generated by regime 3. Regime 3 yields IRFs with respect to the M_I shock in the bottom row of figure 8 that are higher by a factor of 3 compared to the IRFs of the first two rows of this figure.

Regime dependent IRFs with respect to the R_S shock appear in figure 9. These IRFs are qualitatively similar to those of the fixed coefficient-homoskedastic BVAR that are found in the fifth row of figure 3. Across the rows of regime dependent IRFs of figure 9, 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. However, the price puzzle remains. Of equal interest, is that the IRFs of R_L and R_S reveal the term spread shrinks at the same time financial firms take on more risk by shifting the composition of their balance sheets to hold relatively more long-term private assets. Since R_S resides only in the $\mathcal{F}$ block of model 8, the height of the IRFs of figure 9 suggest that the greatest impact of this shock arises during the wars and financial crises of the first two-thirds of the sample of regimes 2 and 3. In this case, the height of the IRFs of regime 1, the top row of figure 9, is about half the size of those in the lower two rows.

[27] The IRF plots lack error bands. These will be added in a later draft of the paper.

5.6 Regime Dependent FEVDs

We employ model 8 to generate regime dependent FEVDs. These FEVDs appear in tables 6, 7, and 8. These tables present FEVDs of regime 1, regime 2, and regime 3 that are conditional on the $\mathcal{M}$ with M_I and $\mathcal{F}$ blocks being in the same regime.

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 explains variation in R_L that is tied to its own shock at short horizons, but shocks to R_S become more important at longer horizons.

Tables 7 and 8 show regime dependent FEVDs that are strikingly different from those of table 5. The regime 2 FEVDs of figure 7 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 8. It is not possible to give economic interpretations to the regime dependent FEVDs. Nonetheless, the regime dependent FEVDs show that in 2 of the 3 regimes shocks to financial variables, such as M_I and r_R, become more important for explaining aggregate fluctuations than is found for regime 1 or the fixed-coefficient-homoskesdatic BVAR.

6 Conclusion

This paper studies the impact of credit supply and demand shocks on U.S. financial crisis and non-crisis business cycle fluctuations on a long annual 1890–2010 sample. We estimate MS-BVAR models predicated on identified credit supply and demand shocks and stochastic volatility in the regression errors. The MS-BVARs are employed to evaluate the hypothesis that the same U.S. financial crisis regimes repeat through the sample. The hypothesis is consistent with crisis and non-crisis regimes being generated by the same preferences, technologies, and market structure. However, different data generating processes are implied by these economic primitives across the crisis and non-crisis regimes.

The estimated MS-BVARs yield evidence that backs the hypothesis that the same financial crisis regimes recur throughout the 1890–2010 sample. We report regime probabilities of estimated MS-BVARs in which the same regimes recur throughout the long annual 1890-2010 sample. For example, the best fitting MS-BVAR produces a regime for macro aggregates that includes episodes as disparate as the boom of the 1920s, the Great Inflation of the 1970s, and the Volcker disinflation. The world wars of the 20th century and the Vietnam and Iraqi wars are placed within a financial variable regime by this MS-BVAR.

We present regime dependent IRFs and FEVDs that reveal the identified credit supply and demand shocks are economically meaningful. The stochastic volatility of the best fitting MS-BVAR generate IRFs with respect to credit supply and demand (*i.e.*, inside money and short-term interest rate) shocks whose height differs by regime. The height of the responses to the latter shock are smallest in the financial innovation and deregulation regime from 1967 to 2010 excluding the 2003–2009 period. The best fitting MS-BVAR generates FEVDs that are similar to ones produced by a fixed coefficient-homoskedastic BVAR in one regime, but in other regimes the FEVDs reveal the importance of credit supply shocks and shocks to the composition of the aggregate balance sheet of U.S. financial firms for explaining output and price level 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 important. 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 business cycle fluctuations. We also report estimates that 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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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 expanding their short-term liabilities to support the acquisition of 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

Model Number	Dimension of MS Chains and Regimes per Chain on the Stochastic Volatility Scaling Matrix Γ 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): −1713.60

	Number of Stochastic Volatility Regimes		
	2	3	4
Model Number	1	2	3
A Single Markov Switching Chain	−1589.94	−1549.55	−1492.41
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	−1520.64	−1502.34	$*$
Model Number	7	8	9
Regimes on M_I and $\mathcal{M}$	−1505.78	**−1488.97**	$*$
Model Number	10	11	12
Regimes on $R_{S,t}$ and $\mathcal{M}$	−1518.65	−1499.24	$*$
Model Number	13	14	15
Regimes on $M_{I,t}$, $R_{S,t}$, and $\mathcal{M}$	−1506.56	$*$	$*$

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: Estimates of MS-BVAR(2) Model 8

First-Order Markov Transition Matrices

$\hat{Q}$: $\mathcal{M}$ Block and M_I			$\hat{Q}$: $\mathcal{F}$ Block		
0.975	0.045	0.000	0.957	0.102	0.000
0.025	0.909	0.193	0.043	0.797	0.027
0.000	0.045	0.807	0.000	0.102	0.973

Impact Matrix $\hat{A}_0$

y	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_R}$
0.634	0.208	0.683	−0.583	0.112	0.090	−0.221
0.000	−1.575	0.333	−0.194	0.124	0.039	−0.101
0.000	0.000	2.357	−0.688	−0.144	0.170	−0.247
0.000	0.000	0.000	0.701	−0.156	−0.064	0.064
0.000	0.000	0.000	0.000	−1.411	0.676	−0.431
0.000	0.000	0.000	0.000	0.000	−4.136	−0.437
0.000	0.000	0.000	0.000	0.000	0.000	6.834

Diagonals of SV Matrices $\hat{\Gamma}(s_t)$

	y	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_R}$
$s_{\mathcal{M},M_I} = 1 \mid s_{\mathcal{F}} = 1$	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$s_{\mathcal{M},M_I} = 1 \mid s_{\mathcal{F}} = 2$	1.000	1.000	1.000	0.950	0.321	2.241	0.011
$s_{\mathcal{M},M_I} = 1 \mid s_{\mathcal{F}} = 3$	1.000	1.000	1.000	0.815	0.262	0.048	0.334
$s_{\mathcal{M},M_I} = 2 \mid s_{\mathcal{F}} = 1$	0.162	0.077	0.257	0.181	1.000	1.000	1.000
$s_{\mathcal{M},M_I} = 2 \mid s_{\mathcal{F}} = 2$	0.162	0.077	0.257	1.139	0.321	2.241	0.011
$s_{\mathcal{M},M_I} = 2 \mid s_{\mathcal{F}} = 3$	0.162	0.077	0.257	0.769	0.262	0.048	0.334
$s_{\mathcal{M},M_I} = 3 \mid s_{\mathcal{F}} = 1$	0.028	0.005	0.069	0.030	1.000	1.000	1.000
$s_{\mathcal{M},M_I} = 3 \mid s_{\mathcal{F}} = 2$	0.028	0.005	0.069	0.087	0.321	2.241	0.011
$s_{\mathcal{M},M_I} = 3 \mid s_{\mathcal{F}} = 3$	0.028	0.005	0.069	0.001	0.262	0.048	0.334

Table 6: Regime 1 FEVDs of MS-BVAR(2) Model 8

	Year	Shock **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	0.01	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 7: 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 8: 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

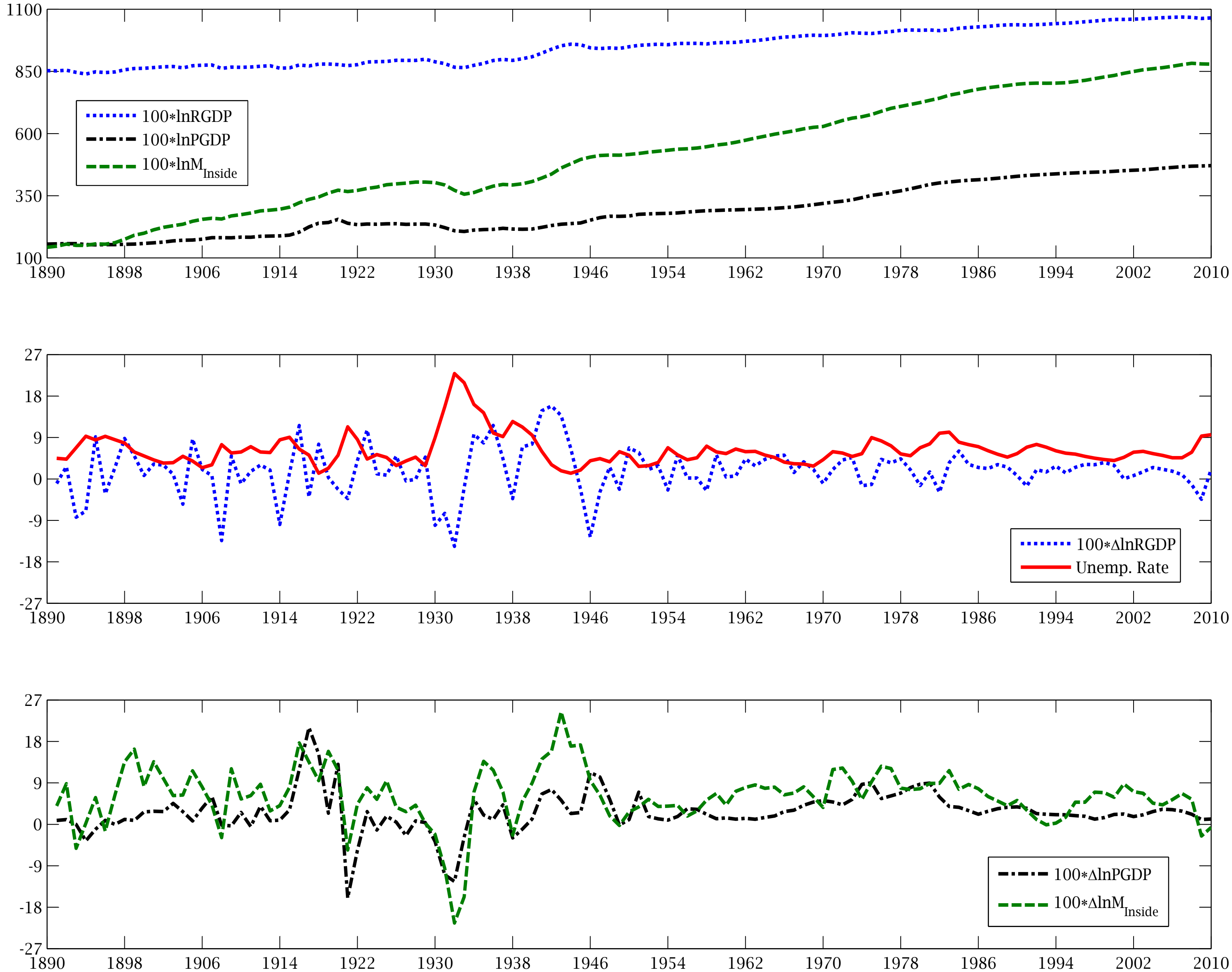

Figure 2: U.S. Short Rate, Long Rate, and Risk Ratio, 1890–2010

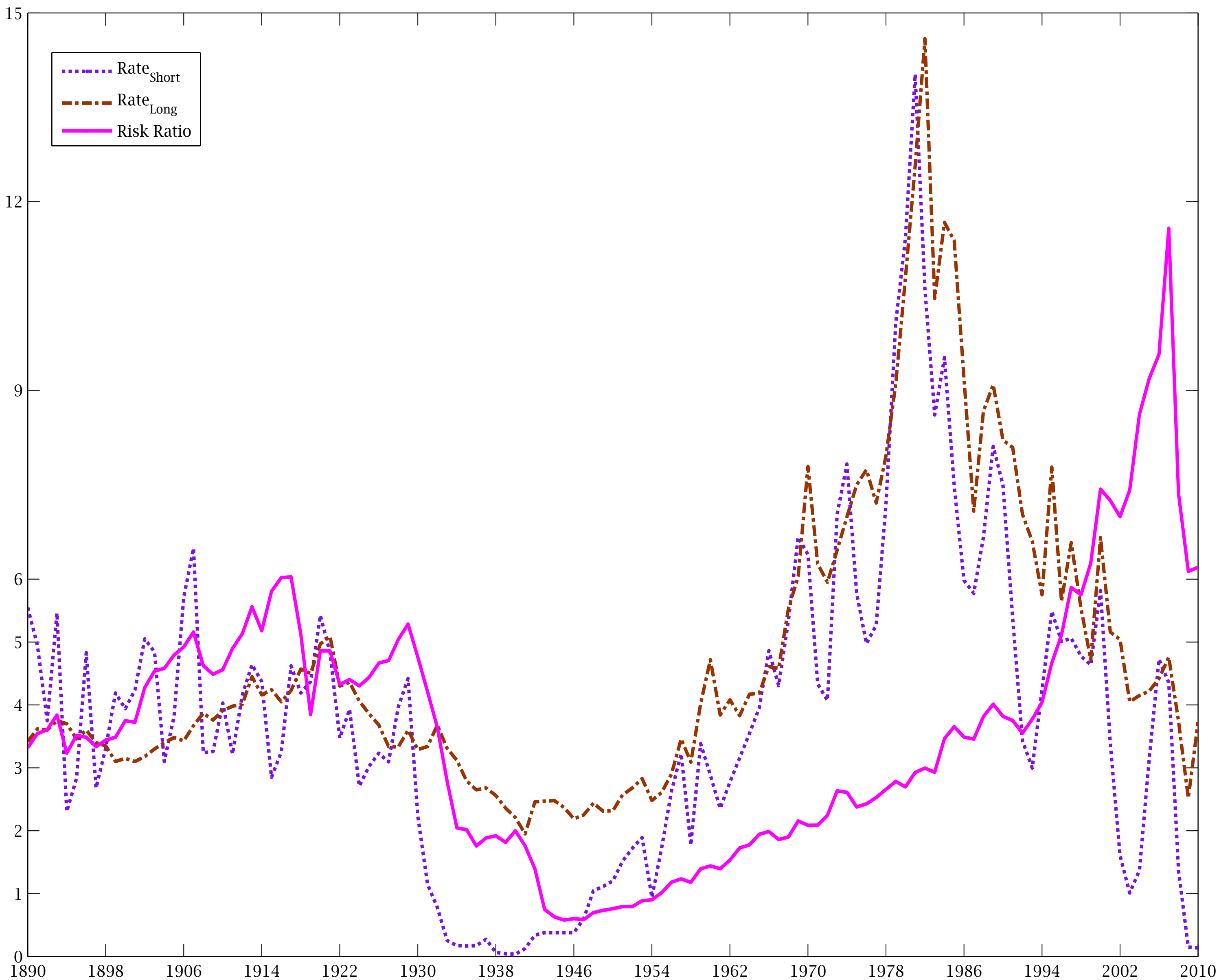

Figure 3: IRFs of Fixed Coefficient-Homoskedastic BVAR(2)

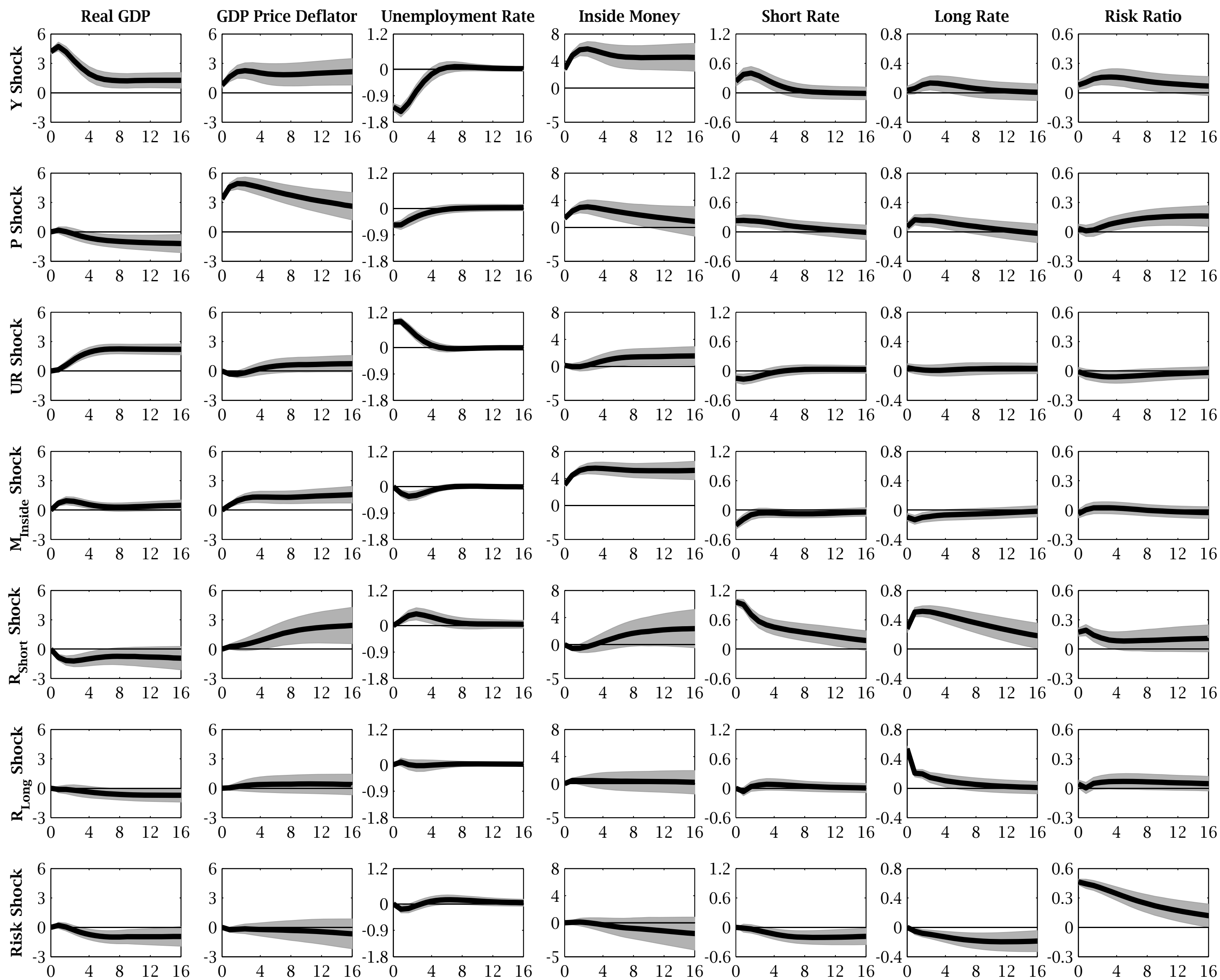

FIGURE 4: 3 SV REGIME PROBABILITIES: ESTIMATES OF MS-BVAR(2) MODEL 2, 1891-2010

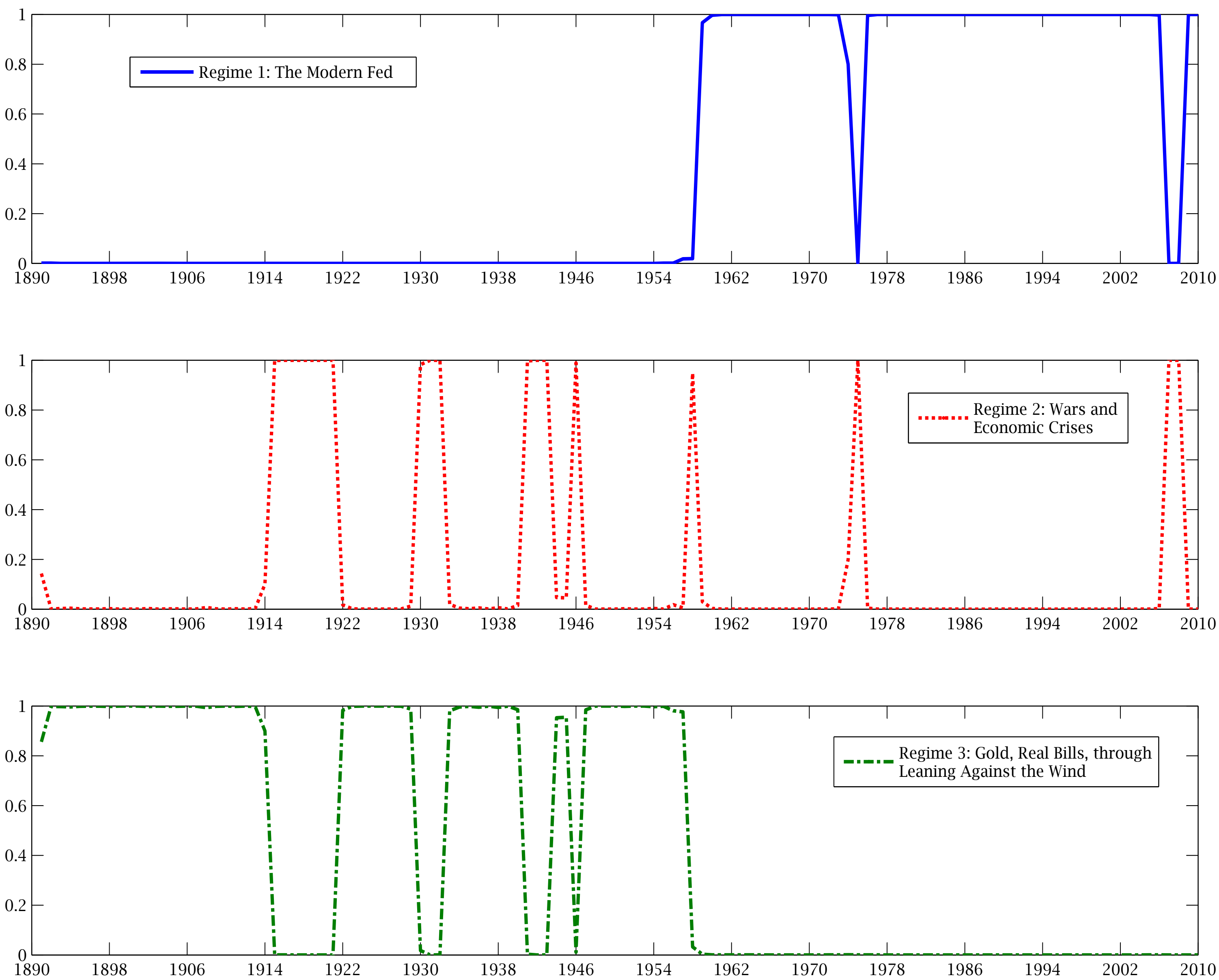

Figure 5: 4 SV Regime Probabilities: Estimates of MS-BVAR(2) Model 3, 1891-2010

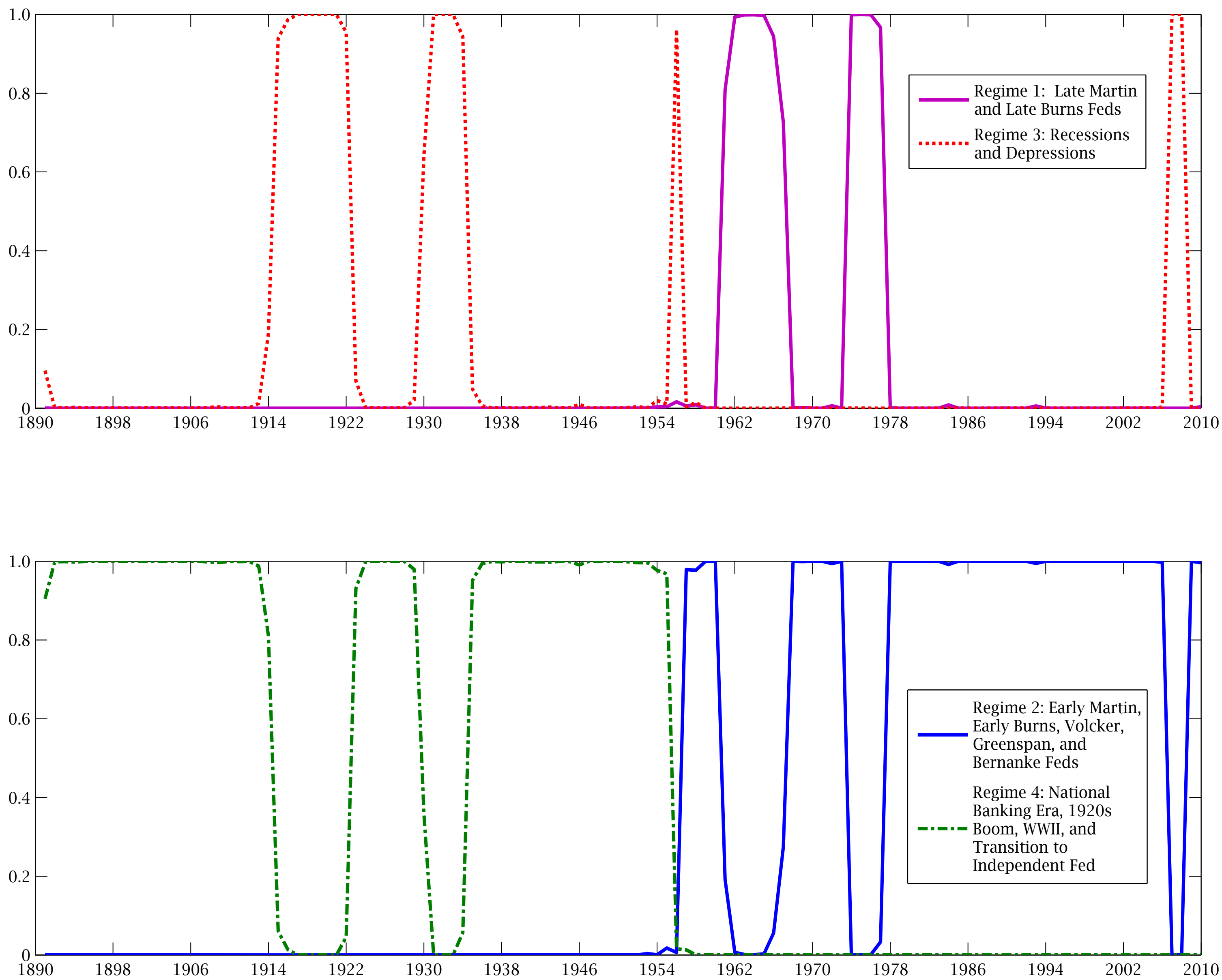

Figure 6: 3 SV Regime Probabilities of the $\mathcal{M}$ Block: Estimates of MS-BVAR(2) Model 8, 1891-2010

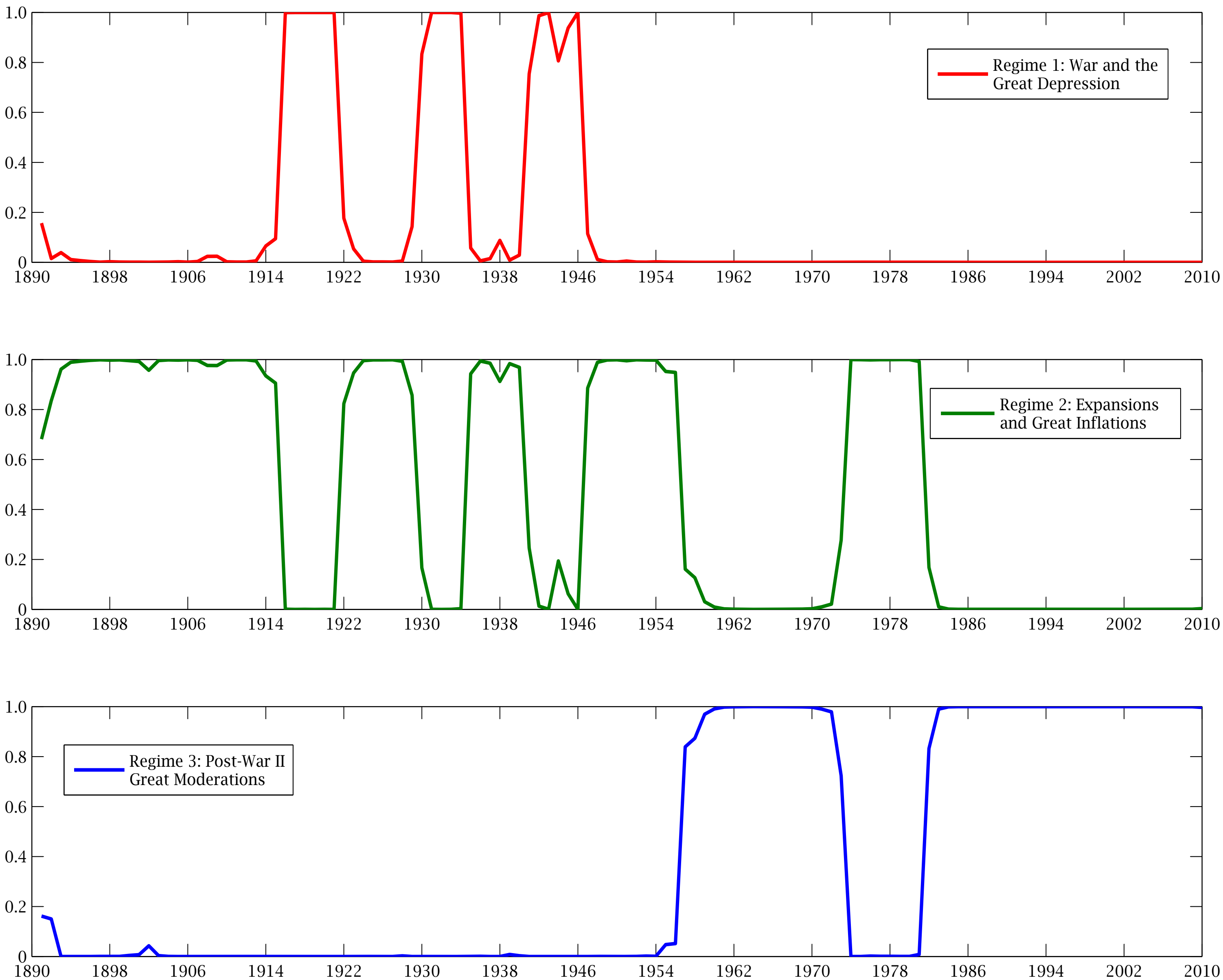

Figure 7: 3 SV Regime Probabilities of the $\mathcal{F}$ Block: Estimates of MS-BVAR(2) Model 8, 1891-2010

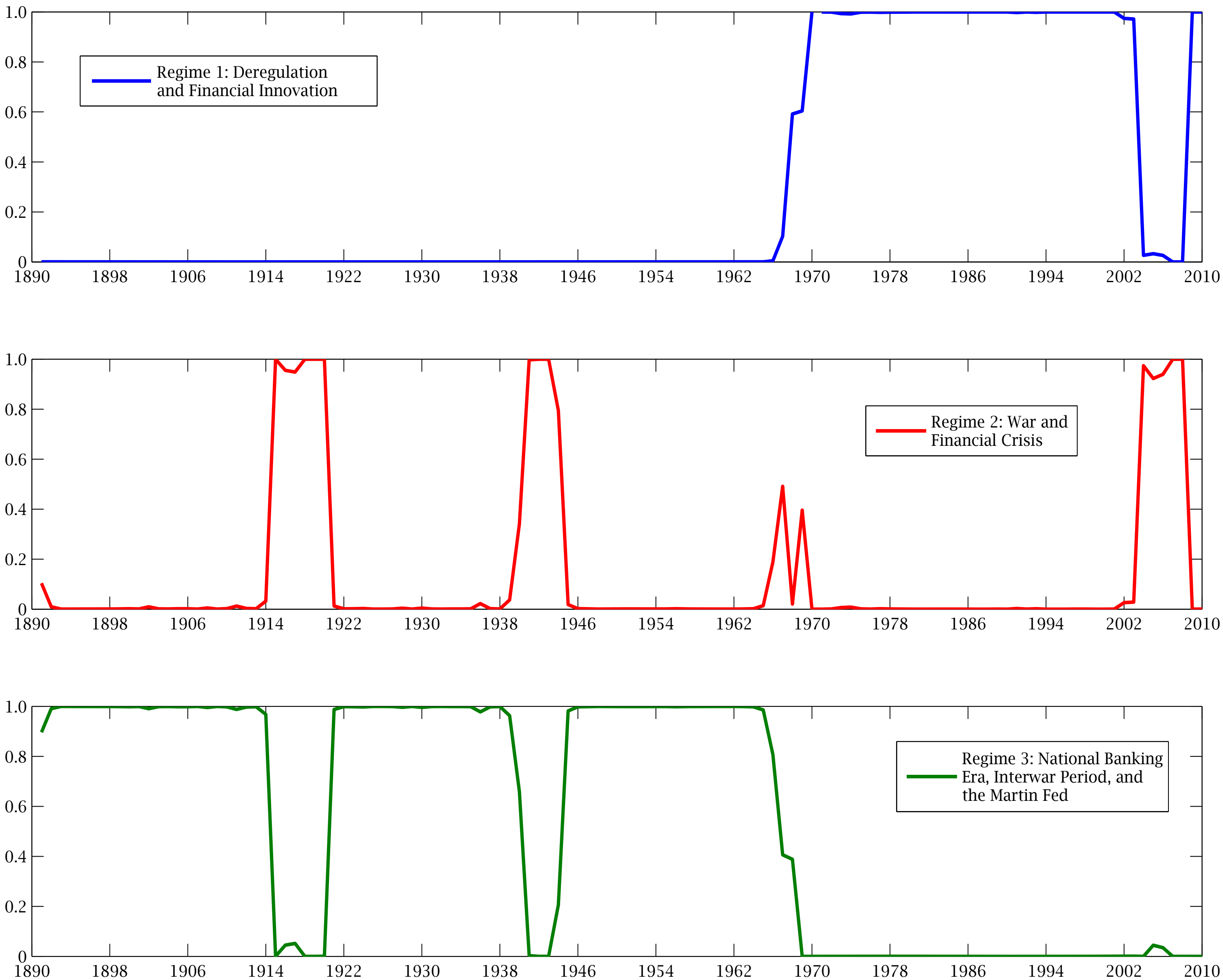

Figure 8: Regime Dependent IRFs w/r/t Inside Money Shock of MS-BVAR(2) Model 8

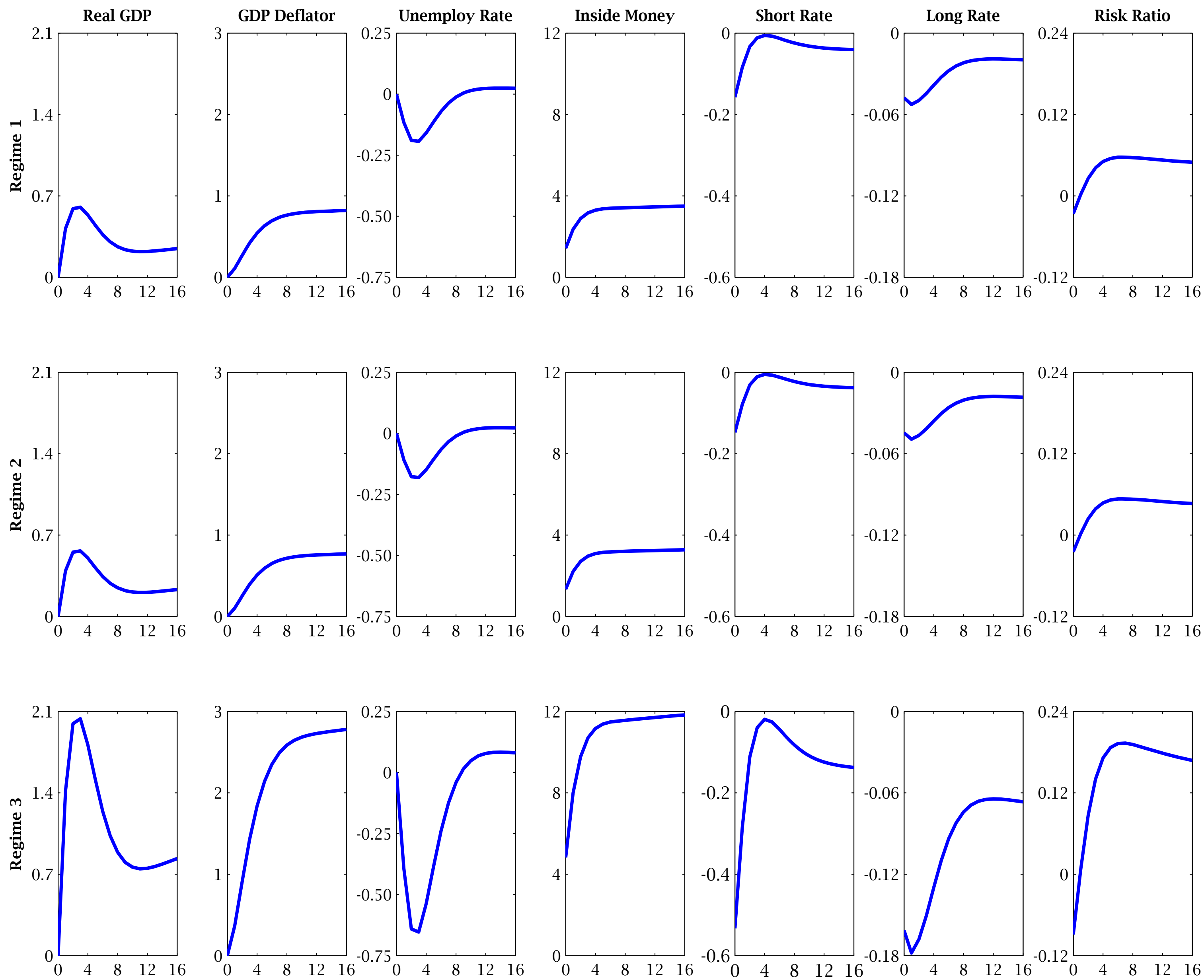

FIGURE 9: REGIME DEPENDENT IRFS W/R/T SHORT RATE SHOCK OF MS-BVAR(2) MODEL 8