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

James M. Nason† and **Ellis W. Tallman**‡

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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 different crisis and non-crisis regimes. This MS-BVAR model shows the responses of the macro and financial variables to the credit supply and demand shocks differ by SV regime.

JEL Classification Numbers: $E37$, $E44$, $E47$, $E51$, $N11$, $N12$.

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

† *e-mail*: jim.nason@phil.frb.org, *voice*: (215) 574–3463, *address*: Research Department, Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA 19106 and the Centre for Applied Macroeconomic Analysis.

‡ *e-mail*: ellis.tallman@oberlin.edu, *voice*: (440) 775–8592, *address*: Department of Economics, 223 Rice Hall, Oberlin, OH, 44074 and the Federal Reserve Bank of Cleveland.

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1 Introduction

Not since the Great Depression has the U.S. been confronted by a major financial crisis and at the same time a deep and persistent economic slowdown. However, just over a decade into the new millennium this is the state in which the U.S. finds itself. Economists have responded by revisiting the Great Depression as well as the financial panics that afflicted the U.S. from the end of the Civil War to 1914. Their aim is to gain insights useful for anticipating and preventing similar events in the future.

There is a literature that seeks to uncover predictors of financial crises. Recent examples are Bussiere and Fratzscher (2006), Mendoza and Terrones (2008), Reinhart and Rogoff (2009, 2011), Bordo and Haubrich (2010), Claessens, Kose, and Terrones (2011), Jordà, Schularick, and Taylor (2011a,b), Jalil (2012), Gourinchas and Obstfeld (2012), and Schularick and Taylor (2012). These papers single out observed macro aggregates and financial variables that predict crises at business cycle and longer horizons for emerging and developed economies.[1]

This paper is motivated by an issue that needs to be addressed before asking if it is possible to predict economic and financial crises. We pursue the hypothesis that crises and non-crises regimes are produced using the same economic primitives. The hypothesis is examined on a long annual data that begins in 1890 and ends with 2010. These 121 observations are used to estimate Markov-switching Bayesian vector autoregressions (MS-BVARs). A MS-BVAR is an effective tool to explore this hypothesis because it draws from the same density function (*i.e.*, the likelihood) of the model to generate estimates of the probabilities of crisis and non-crisis regimes. It is the interactions of economic primitives that differ by regime. Hence, the MS-BVARs yield evidence about whether economic and financial crises are recurring that is necessary to conduct a credible search for predictors of these events.

There is a long tradition in analyzing financial crises using macro and financial data. Useful studies 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 use the financial 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) to identify the shocks and latent factors that contribute to financial and economic crises.

[1] Ahmadi (2009), Helbling, Huidrom, Kose, and Otrok (2011) and Eickmeier and Ng (2011) have similar objectives. A factor-VAR is estimated by Ahmadi that allows for time-varying parameters and SV. His goal is to recover a business cycle factor conditioned on macro and interest rate spreads. The second paper also uses 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 credit shocks are estimated to have large and persistent effects on real international economic activity.

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.[2] 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.

The MS-BVAR models are estimated on a sample of 121 annual observations. The long annual sample consists of output, the price level, the unemployment rate, the credit aggregate of inside money, short- and long-term interest rates, and a measure of the riskiness of the composition of the aggregate balance sheet of U.S. financial firms.[3] The risk variable is the ratio of long-term private assets held by financial firms to their holdings of public assets. These data provide identifying information on which we judge whether financial shocks are a source of crisis regimes for the U.S. economy.

By beginning the sample in 1890, we have data from the pre-Fed National Banking Era, the early Fed of World War I and the 1920s, the 1935 to 1981 "quiet period" as defined by Gorton (2010), and the past thirty years of increasing deregulation of U.S. financial markets. During the sample, the beginnings of financial crises are associated with 1893, 1907, 1914, 1929, and 2007. The sample also covers 12 NBER dated recessions with a duration of 14 months or more, which are listed in table 1. These include 4 recessions between 1893 and 1904 that lasted 17 to 23 months, 2 recessions running 23 to 24 between 1910 and 1913, 2 recessions in the 1920s lasting at least 14 months, the Great Depression which the NBER dates to 1929, the first oil price shock recession of 1973, the recession of the early 1980s, and the 2003–2008 "housing boom-bust" cycle. Thus, a casual glance suggests that deep and long recessions and financial crises do not always coincide conditional on NBER recessions dates and the history of U.S. financial crises.

We study whether our sample can recover these episodes as crisis and non-crisis regimes using methods developed by Sims and Zha (2006) and Sims, Waggoner, and Zha (2008) to estimate MS-BVAR models.[4] The MS-BVARs are identified under a Cholesky identification. This recursive structure places a macro ($\mathcal{M}$) block consisting of output, the price level, and the unemployment rate, before a financial ($\mathcal{F}$) block of inside money, the short-term and long-term interest rate, and the risk ratio. This ordering is inspired by the reduced-form regressions and evidence of King and Plosser (1984). The $\mathcal{M}$ block

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

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

responds to credit supply and demand shocks identified using inside money and the short-term interest rate. This identification relies on inside money to recover credit supply shocks because these short-term liabilities support the acquisition of long-dated and riskier assets, while shocks to the short-term interest rate capture shifts in the demand for these liabilities.

The choice of a Cholesky identification is driven, in part, by the annual data. Annual data makes problematic identifications that, say, assume participants in the financial markets cannot contemporaneously observe $\mathcal{M}$ block variables. This issue is germane for placing the $\mathcal{M}$ block ahead of the $\mathcal{F}$ block in the MS-BVARs. However, we interpret the recursive identifying scheme as representing a combination of new classical, Keynesian, and monetarist restrictions. For example, embedded in the MS-BVARs is a Lucas-Sargent Phillips curve-like restriction that the unemployment rate responds to price level shocks at impact. Next, the unemployment rate reacting to output shocks at impact gives an Okun's Law-like relation. 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-term interest rate precedes the long-term rate, the identification contains 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 financial balance sheets play in the long annual U.S. sample.

The identification relies on the 7 variables found in the $\mathcal{M}$ and $\mathcal{F}$ blocks. In part, we engage 7 variable MS-BVARs to keep the models tractable and interpretable. More importantly, deleting any of the 7 variables would preclude the MS-BVARs from identifying credit supply and demand shocks as well as the new classical, Keynesian, and monetarist restrictions discussed above.

The MS-BVARs make it possible to explain responses to identified credit supply and demand shocks across crisis and non-crisis regimes. This paper examines these effects with BVAR models in which MS is imposed only on the stochastic volatility (SV) of the regression errors. Hence, we take as a maintained assumption the "good luck-bad luck" results of Sims and Zha (2006). Conditional on SV being the source of systematic differences across crisis and non-crisis regimes, estimated MS-BVARs yield the probabilities of being in these regimes along with the regime dependent responses of output, prices, the unemployment rate, inside money, the short- and long-term interest rates, and the risk ratio to identified credit supply and demand shocks. We limit the BVARs to MS in SV as a first step in a research effort that studies the role of credit supply and demand shocks in crises and non-crisis business cycles as well as to hold the model space to a manageable size. Nonetheless, we include in the model space 15 MS-BVARs to cover a wide variety of parameterizations of the data generating processes (DGPs) of crisis and non-crisis regimes.

This paper reports estimates of a fixed coefficient-homoskedastic BVAR and 15 MS-BVARs. The latter BVAR is dominated in fit by the 15 MS-BVAR models in which SV is the only source of shifts in regime. The best fitting MS-BVAR model contains 3 SV regimes in the $\mathcal{M}$ block and 3 distinct SV regimes in the $\mathcal{F}$ block with inside money affected by all the SV regimes. Estimates of this MS-BVAR model yield a $\mathcal{M}$ block with regimes that cover world wars and the Great Depression, another containing the National Banking Era, economic recoveries and post-World War II inflations, and a third that captures the era of the modern Fed and moderations in macro aggregates since the end of World War II. The $\mathcal{F}$ block reveal similar regimes, but adds a regime representing the last 40 years of financial innovations and deregulation, but this regime excludes the financial boom and crisis of the 2003–2008 period. This favorite MS-BVAR of the data also produces regime dependent impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). These IRFs and FEVDs show that the economic interpretation of the identified credit supply and demand shocks is regime dependent.

The next section reviews a selection of the extant 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.

2 A Brief Literature Review

The financial crisis of 2007–2009 has reinvigorating research into the sources of economic and financial crises. One tradition uses structural VARs to uncover the sources and causes of financial crises. Another strand of research seeks to find observables that are useful for predicting financial crises that lead to deep and persistent recessions. Our interest is not in prediction. Instead, we are motivated to examine whether financial and economic crises are generated by different economic primitives than are non-crisis business cycle fluctuations within structural MS-BVARs. This section discusses the gap in the literature about whether the economic primitives driving crisis and non-crisis regimes differ.

2.1 Recent Research on Financial Crises

Schularick and Taylor (2012) exploit a panel of 14 countries on a long annual sample to evaluate the impact of financial crises on real economic activity. Their cross-country panel data shows that during the last 60 years there was an expansion of loans funded with liabilities other than bank deposits. Prior to World War II, the sample yields a large positive correlation between credit and monetary aggregates. These observation motivate Schularick and Taylor to hypothesize that when financial market leverage rises above a threshold defined on output a financial crisis ensues. Hence, financial crises follow a period of excess growth in the real value of bank loans relative to output growth. Schularick and Taylor provide empirical results that indicate a rapid growth in the real value of bank loans relative to output growth 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 rates of interest far below its steady state by Jordà, Schularick, and Taylor (2011a), while they see substantial increases in current accounts in the subsequent years. This paper also finds that the comovement of credit growth and current account deficits has become stronger in the last 30 years. 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 identify the underlying sources of the credit shock they estimate to have a large predictive role in financial crises and large 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 in the last 50 years, according to Claessens, Kose, and Terrones. Mendoza and Terrones add to this list of financial crisis predictors real currency appreciations and large current account deficits. Similar evidence is found in Bussiere and Fratzscher and Gourinchas and Obstfeld. They report panel data panel data regressions that control for differences in crisis and non-crisis states. The regression estimates confirm that excessive credit growth and real currency appreciations have power to predict financial crises. Rather than developing a predictive model, Bordo and Haubrich compare the 2007–2009 episode to financial crises in the U.S. during the previous 140 years. They argue that deposit insurance and other regulatory standards limited the impact on outside money during the 2007–2009 crisis, unlike the Great Depression, and instead put the onus on the short-term credit markets.

Reinhart and Rogoff (2009) gauge the extent measures of financial risk anticipate substantial economic downturns in several centuries of cross country data. They argue that the memory of crises is fleeting in history across countries and through the centuries. The argument is that when a crisis is in the making, there appear advocates to claim “this time is different.”[5] 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 in the view of Reinhart and Rogoff.[6] They argue, as a result, that movements in observed financial aggregates yield warning signals for current and future real activity that can alert policymakers to a potential crisis.

Krishnamurthy and Vissing-Jorgensen (2010) have a different view 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, according to Krishnamurthy and Vissing-Jorgensen (KVJ) . For example, investors may prize public securities as safe havens along with the liquidity these assets possess.[7] 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 Macro Literature Identifying Financial Shocks

In a related literature, Donaldson (1992) and Canova (1994) examine U.S. data from the Civil War to the Great Depression to discern the impact of financial crises on the U.S. economy. Regression and nonparametric estimators of business cycle comovement are used by Donaldson to generate evidence about whether banking panics in the U.S. are “systematic events” produced by the same probability

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

[6]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 will accept as collateral, they withdraw funding from interbank markets.

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

distribution from which typical business cycle fluctuations are drawn or "special events" drawn from an entirely different distribution.[8] He concludes that the start date of banking panics are unforecastable, but that there are states of the world in which banking panics are more likely.[9] 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.[10] 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

[8] These events are detailed in full by Gorton (1988), Calomiris and Gorton (1991), and Wicker (2000, 2005).
[9] 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.
[10] Silber (2007) discusses the impact the World War I episode had on the evolution of U.S. financial markets.

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

3 Data

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

3.1 Macro Aggregates

The macro block contains aggregate output, the aggregate price level, and the unemployment rate. We employ real per capita GDP to measure aggregate output. The corresponding aggregate price level 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).

3.2 Monetary Aggregates

We equate the stock of short-term liabilities issued by financial firms to inside money. These liabilities are constructed as M2 net of the monetary base. The former monetary aggregate is found for the early part of the sample in Balke and Gordon (1986) and the Board of Governors of the Federal Reserve System for 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. Hence, this measure of inside money equates an increase in M2 net of the monetary base with financial firms issuing more 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. The short-term rate is a synthetic series because the financial contract that plays the role of a short-term riskless asset has evolved in U.S. financial markets since 1890. This asset is identified with stock exchange loans, prime bankers acceptances, short-term Treasury securities, and 3-month Treasury bills from 1890 to 2010. We obtain return data on these assets from *Banking and Monetary Statistics, 1914–1941*, Board of Governors of the Federal Reserve System (1976a), and the FRED online data base.[11]

The long-term interest rate is taken from Shiller (2005).[12] 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 refer to

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

the aggregate assets that remain as "private debt" or assets that are "claims on private entities" held by financial firms in the U.S., while their ownership of cash, Treasury securities, agency, state, local, and other municipal debt holdings is labeled "public debt" or "claims on public entities." The ratio of private debt to public debt is one means for measuring the risk composition of the asset side of the aggregate 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 assets, movements in this ratio reflect changes in the composition of assets on the aggregate balance sheet of financial firms. We avoid identification issues caused by confounding financial and real shocks because the risk ratio does not mix credit aggregates, say, with real GDP. There are other ways to measure financial risk, but the ratio of private to public assets held by U.S. financial firms contains useful information about changes in the riskiness of the composition of their aggregate balance sheet.

3.5 The Data in Historical Context

The data is plotted in figures 1 and 2. The top panel of figure 1 presents the log levels of y_t, P_t, and $M_{I,t}$ multiplied by 100. The growth rate of y_t and level of ur_t are shown in the middle panel of figure 1 from 1891 to 2010. These macro aggregates are less volatility since the late 1948. From 1891 to 1947, the standard deviations of output growth and the unemployment rate 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 ur_t is dominated by the 1931–1935 episode. During this period, ur_t equals 15.6, 22.9, 20.9, 16.2, and 14.4 percent, respectively.

The bottom panel of figure 1 contains the growth rates of P_t and $M_{I,t}$ from 1891 to 2010. The volatility of U.S. inflation and inside money growth 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 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 inside money growth rates 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 inflation and inside money growth 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 and especially for 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 states or regimes of the world than do typical business cycle fluctuations. Nonetheless, these regimes are drawn from the same probability density function. The MS-BVAR models are engaged to estimate the responses of output, aggregate price level, unemployment rate, and long-term interest rate to credit supply and credit demand shocks.[13] Besides IRFs and FEVDs, the estimates include the regime transition probabilities, the (first-order) Markov transition matrix of the regimes, and the impact coefficient matrix of the preferred MS-BVAR(2) model. This is the evidence we use to assess the impact of identified credit supply and demand shocks on the U.S. economy conditional on regime switching. We lean heavily on Sims and Zha (2006) and Sims, Waggoner, and Zha (2008) to generate this evidence.

4.1 Model Specification

Sims, Waggoner, and Zha (2008) provide tools to estimate and conduct inference on MS-BVARs models of lag length k. They study the MS-BVAR(k) model

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

where A_0 is a $n \times n$ non-singular matrix, s_t is the h dimensional vector of regimes which are independent first-order Markov chains, h is in the finite set of integers H, each A_j is a $n \times n$ matrix, C is the vector

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

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.[14] Key assumptions made by Sims, Waggoner, and Zha (SWZ) include those on the densities of the MS-BVAR disturbances

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

and on the information set

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

where $\mathcal{Z}_t = \Big[Z_1' \;\; Z_2' \ldots,\, Z_t'\Big]'$, $\mathcal{S}_t = \Big[S_0' \;\; S_1' \;\; S_2' \ldots,\, Z_t'\Big]'$, ω denotes the vector of Markov chains, $\Theta = \Big[A_0(1) \;\; A_0(2) \ldots A_0(h) \;\; \mathcal{A}(1) \;\; \mathcal{A}(2) \ldots \mathcal{A}(h) \;\; C(1) \;\; C(2) \ldots C(h) \;\; \Gamma(1) \;\; \Gamma(2) \ldots \Gamma(h)\Big]'$, $\mathcal{A}(\cdot) = \Big[A_1(\cdot) \;\; A_2(\cdot) \ldots,\, A_k(\cdot)\Big]$, $\mu_Z(\cdot) = \Big[\mathcal{A}(\cdot) \;\; C(\cdot)\Big]A_0^{-1}(\cdot)\,\Big[\mathcal{Z}_t \;\; 1\Big]'$, and $\Sigma_Z(\cdot) = \Big[A_0(\cdot)\,\Gamma(\cdot)^2 A_0'(\cdot)\Big]^{-1}$.

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

$$\ln \mathcal{P}\Big(Z_T \Big| \mathcal{Z}_T,\, \omega,\, \Theta\Big) \;=\; \sum_{t=1}^{T} \ln\Bigg[\sum_{s_t \in H} \mathcal{P}\Big(Z_t \Big| \mathcal{Z}_{t-1},\, \mathcal{S}_t,\, \omega,\, \Theta\Big)\mathcal{P}\Big(\mathcal{S}_t \Big| \mathcal{Z}_{t-1},\, \omega,\, \Theta\Big)\Bigg], \tag{4}$$

where $\mathcal{P}\Big(\mathcal{S}_t \Big| \mathcal{Z}_{t-1},\, \omega,\, \Theta\Big)$ 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, $\mathcal{P}\Big(\Theta \Big| \mathcal{Z}_{t-1},\, \mathcal{S}_t,\, \omega\Big)$, and ω, ω, $\mathcal{P}\Big(\Theta \Big| \mathcal{Z}_{t-1},\, \mathcal{S}_t,\, \Theta\Big)$.[15] Note also that the vector of regimes $\mathcal{S}_T$ is integrated out of the likelihood (4) of Z_T.

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

$$\mathcal{P}\Big(\omega,\, \Theta \Big| Z_T,\, \mathcal{Z}_T,\, \omega,\, \Theta\Big) \propto \mathcal{P}\Big(Z_T \Big| \mathcal{Z}_T,\, \omega,\, \Theta\Big)\mathcal{P}\Big(\omega,\, \Theta\Big), \tag{5}$$

where $\mathcal{P}\Big(\omega,\, \Theta\Big)$ denotes the priors of ω and Θ. Posterior odds of competing MS-BVAR models are computed using (5).

[14] 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).

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

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

Sims and Zha (2006) and SWZ impose prior restrictions to limit the dimensionality of the time-variation of the parameter space of MS-BVAR models. The restrictions are placed on the slope coefficients and intercepts of the MS-BVAR(k), $\mathbb{A}(s_t) \equiv \left[A_1(s_t)\ A_2(s_t)\ \ldots\ A_k(s_t)\ C(s_t)\right]'$, 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 $\overline{\mathcal{D}}\,\mathcal{A}(s_t)$.[16] 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.

4.2 Priors and Identification

We follow Sims and Zha (2006) and SWZ by endowing $\mathcal{D}(s_t)$ with a mean zero prior distribution in the spirit of Sims and Zha (1998). The prior is implemented by moving the MS-BVAR(k) in the direction of random walk behavior. Otherwise, our priors match those of Sims and Zha (1998). They place a normal prior on the elements of $\mathcal{A}(\cdot)$ whether or not these parameters are regime dependent, while the squared diagonal elements of $\Gamma(\cdot)$ 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 at date $t-1$. Another part of our prior is that we set $k = 2$, given $T = 121$ for the annual sample.

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

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

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

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

Our study of the impact of credit supply and demand shock limits regime switching to the SV scaling matrix $\Gamma(s_t)$. 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, distinct from usual business cycle fluctuations, 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 only consider MS-BVAR models in which there is SV regimes on the errors ε_t. The 15 MS-BVAR models have either one or two chains associated with 2, 3, or 4 SV regimes. When there is one chain it is shared or is common to the macro block $\mathcal{M}$ and the financial block $\mathcal{F}$. Since there are 2, 3, or 4 SV regimes, this gives 3 MS-BVAR models. Next, we separate the chains for the $\mathcal{M}$ and $\mathcal{F}$ blocks, but assume that the $\mathcal{F}$ block always has 3 SV chains. This produces 3 more MS-BVAR models with the $\mathcal{M}$ block taking on 2, 3, or 4 regimes. The remaining 9 models are created by adding $M_{I,t}$ and $R_{S,t}$ one at a time and together to the 2 and 3 SV regimes MS-BVARs.

We condition 12 of the 15 MS-BVAR models on 3 SV regimes in the $\mathcal{F}$ block. This gives the MS-BVAR models and the data the flexibility to estimate 3 financial SV regimes that differ systematically in economic and calendar time. That is the MS-BVAR models can find different crisis and non-crisis regimes at different moments in time. This enriches the model space enough to cover a large array of data generating processes, but not make it impossible 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 the steps

1. Set the random walk and durations priors on the MS-BVAR(2).[17]
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.[18]
3. Given estimates of A_0, A_1, A_2, C, and $\Gamma(1)$, $\ldots$ $\Gamma(h)$ of the MS-BVAR(2), run 10 millions steps of the MCMC simulator.
4. Construct the posterior of a MS-BVAR(2) by drawing 10 million times from the proposals created by running the Markov chain-Monte Carlo (MCMC) simulator.
5. Choose among the competing MS-BVAR(2) models by calculating posterior odds ratios using log marginal data densities computed on the posterior distributions of the previous step.

[17] 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.

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

6. Rerun the MS-BVAR(2) model(s) most favored by the data to produce transition probabilities and regime-dependent IRFs and FEVDs.[19]

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

5 Results

5.1 A Fixed Coefficient-Homoskedastic BVAR(2)

This section reports estimates of a fixed coefficient-homoskedastic BVAR(2) on Z_t to establish a baseline against which to judge the MS-BVAR models.[20] The estimates are grounded in the restriction $\Gamma(s_t) = \Gamma$ across all regimes.[21] Figure 3 contains IRFs generated from these estimates. Median IRFs are plotted in black and error bands are shaded grey in figure 3. The FEVDs are found in table 3.

The IRFs display a priori expected shapes as well as shapes that are not intuitively appealing in figure 3. The shock to y produces an own hump-shaped response decaying fully around 4 years, raises P permanently, creates a negative hump-shaped response in ur that also dies out in about 4 years suggesting a dynamic Okun's law-like relation, permanently increases M_I that holds its real balances to a proportionate change, yields a hump-shaped response in R_S peaking at 2 years and returning to steady state within 4 years, has little effect on R_L, and raises r_R for about 4 years. Higher M_I in response to a y shock also suggests that the supply of inside money accommodates (income) demand shifts as Leeper, Sims, Zha (1996) find for outside money. Figure 3 also depicts a Lucas-Sargent Phillips curve-like relation because ur falls at impact given a shock P. This shock raises P for at least 16 years. The responses of M_I and r_R are also of interest. Inside money is higher at short horizons before returning to steady state, while the risk ratio rises at longer horizons. Hence, financial markets react to y shocks by producing more short-term liabilities and long-terms assets.

There are two IRFs at odds with with conventional economic theory. One is the response of y with respect to an ur shock. This IRF rises from impact to the longer horizons. The fixed coefficient-

[19] 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.

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

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

homoskedastic BVAR also produces the price puzzle in which a shock to R_S generates a permanent increase in P.

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

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

5.2 The Fit of MS-BVAR(2) Models

The fit of the MS-BVAR models is evaluated using log marginal data densities. The log marginal data densities are listed in table 4.[22] Table 4 shows the asterisk symbol, $*$, for the log marginal data densities of models 6, 9, 12, 14, and 15 instead of numerical values. The asterisk indicates that the MCMC simulators of these models yield badly approximated log marginal data densities. Except for 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. This information is odds ratios, which signal that the MS-BVAR models are all preferred by the data to the fixed coefficient-homoskedastic BVAR. Hence, the MS-BVAR models provide evidence that there is regime switching in the long annual 1890–2010 sample.

Among the MS-BVARs, model 8 achieves the best fit to the data according to the log marginal data densities of table 4. This model imposes distinct MS chains of 3 SV regimes on the $\mathcal{M}$ block and 3 SV regimes on the $\mathcal{F}$ block, but these blocks hold the SV regimes of the errors of the M_I regression in common. The evidence for this is very strong when model 8 is compared to the other MS-BVARs

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

predicated on 3 SV regimes (models 3, 5 and 11), to the models that rely on 2 SV regimes (models 1, 4, 7, 10, and 13), and to the single chain 4 SV regime model 4. Model 4 produces the second largest log marginal data density. However, the gap between it and the log marginal data density of model 8 indicate a odds ratio strongly in its favor.[23].

5.3 Regime Probabilities

Part of the output of the estimated MS-BVAR models are the probabilities of being in regime j at date t. We plot these probabilities for Model 2, a single chain of 3 SV regimes, in figure 4, for Model 3, a single chain of 4 SV regimes, in figure 5, and in figures 6 and 7 for Model 8's two MS chains of 3 SV regimes. The regime probabilities of Models 2 and 3 are reported as a contrast to 2 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 beging drawn from the 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.[24] 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 recession in regime 1 to match the severity of these recessions, with the exception of the 1957–1958 recession, is the 1981–1982 recession. Regimes 1 and 3 also contain several armed conflicts that engaged the U.S., but none match the economic and financial impact of the world wars of the 20th century. Regime 2 also lacks periods of robust economic growth, which are found in regimes 1 and 3 during the 1920s, the 1960s, and 1990s.

Figure 5 contains the 4 SV regime probabilities of Model 3. The top (bottom) window of figure

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

[24] 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.

5 (6) presents the probabilities 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 with exception of the 2007–2009 Great Recession. This recession and recessions of World War I, 1913–1921, the Great Depression, 1930–1933, and the 1957–1958 recession make up regime 3. 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 1935–1954, which include the Great Depression financial market reforms, the Eccles chairmanship of the Fed, and the transition to an independent Fed. Figure 5 shows that the value added of Model 3 stems from its grouping together similar Fed chairmanships into separate regimes, while separating these regimes from earlier episodes in U.S. financial history.

Model 8 refines the narrative provided by its regime probability plots. These regime probabilities 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. For the former block, the refinements are that the world wars and the Great Depression are contained in regime 1 of the $\mathcal{M}$ block. Regime 2 of the $\mathcal{F}$ block also contain World War I, World II, the Vietman War, and the Iraqi War. Hence, splitting the 3 SV regimes across the $\mathcal{M}$ and $\mathcal{F}$ blocks with M_I held in common gives Model 8 the ability to identify the Great Depression as an economic crisis and several conflicts that engaged the U.S. as financial crises.

Regime 3 of the $\mathcal{M}$ block and regime 1 of the $\mathcal{F}$ block also have much in common as shown in figures 6 and 7. These regimes dominate the last 50 years of the sample within their respective MS chains. The modern Fed and the Great Moderations are notable events that occur in regime 3 of the $\mathcal{M}$ block. Regime 1 of the $\mathcal{F}$ block starts up in the late 1960s running to the end of the sample, except for the financial boom and bust of the 2003–2008 period, which gives to this regime an era of rapid financial innovations and deregulation.

There are two more useful refinements of the regime probabilities produced by Model 8 that are gleaned from figures 6 and 7. The $\mathcal{M}$ block together with M_I create regime 2 that adds the first half of Chairman Martin's stewardship of the Fed, the Great Inflation and stop-go monetary policy of the 1970s, the Volcker disinflation, and subsequent recovery of the early 1980s to the National Banking Era, the economic boom of the 1920s, the recovery from the Great Depression, and the inflation episode of the late 1940s. The National Banking Era, the interwar period, and the Martin Fed are grouped together by the $\mathcal{F}$ block and M_I into regime 3 by Model 8. Thus, Model 8 states that the same $\mathcal{F}$

block SV regime generates the transition to an independent Fed, the Martin chairmanship of the Fed, the National Banking Era and the interwar period. The $\mathcal{F}$ block SV regime 2 is similar, but eliminates the Great Depression and second half of the Martin chairmanship of the Fed, while adding the Great Inflation of the 1970s.

The regime probabilities of figures 4–7 help explain the preference of the data for Model 8. The data appreciates the extra SV regime of Model 3 compared to Model 2. The date use the extra SV regime of the MS-BVAR of Model 3 to separate economic crises from financial and other crises. Nonetheless, the MS-BVAR of Model 8 is better yet because it parameterizes distinct $\mathcal{M}$ and $\mathcal{F}$ SV regimes, while holding SV of the errors of the M_I regression in common, which is what the data most prefers given the model space of table 2.

5.4 Regime Dependent IRFs

The MS-BVARs generate IRFs that are regime dependent. We report IRFs with respect to the identified shocks of M_I and R_S in figures 7 and 8, respectively.[25] These IRFs receive our attention because they provide evidence about whether the MS-BVAR-model 8 is effective at identifying economically informative credit supply and demand shocks.

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

The M_I shocks drives y and P higher, lowers ur, produces a smaller term spread, and leads financial firms to hold relatively more long-dated risky assets on their balance sheets as shown in figure 8. These IRFs are qualitatively similar to the IRFs found in row 4 of figure 3 which are estimated using the fixed coefficient-homoskedastic BVAR(2).

Figure 8 provides additional information in the form of IRFs whose height is regime dependent. Regimes 1 and 2 are associated with IRFs that have about the same height, but are relatively small compared to the IRFs generated within regime 3. Regime 3 yields IRFs with respect to the M_I shock in its bottom row that are higher by a factor of 3 when laid against the IRFs of the first two rows of figure 8. However, we cannot tie the regime dependent IRFs of figure 8 to specific economic and financial episodes because the SV of the M_I is common to the MS chains of the $\mathcal{M}$ and the $\mathcal{F}$.

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

Figure 9 contains regime dependent IRFs with respect to the R_S shock. These IRFs are qualitatively similar to the IRFs found in row 5 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.

The regime dependent IRFs of figure 9 can be matched to specific economic and financial episodes. Since R_S resides only in the $\mathcal{F}$ block of model 8, the height of the IRFs of figure 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.

5.5 Regime Dependent FEVDs

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

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

Tables 6 and 7 show regime dependent FEVDs that are strikingly different from those of table 5. Regime 2 FEVDs depart from those of regime 1 because shocks to r_R drive variation in y, P, R_S, and R_L, especially at longer horizons. Inside money dominates the regime dependent FEVDS of the 7 variables of the MS-BVAR in table 7. It is not possible to give economic interpretations to the regime dependent FEVDs. Nonetheless, 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 provides evidence that crisis and non-crisis regimes differ systematically in a long annual sample of the last 120 years of U.S. economic and financial history. We estimate Markov switching-BVAR models predicated on identified credit supply and demand shocks. The data favors a MS-BVAR model that separates 3 stochastic volatility regimes on macro aggregate variables from 3 stochastic volatility regimes on financial variables. This parameterization of the Markov switching-BVAR model produces estimates of the probabilities of the macro and financial volatility regimes that cover important eras, events, and episodes in U.S. economic and financial history. Conditional on the volatility regimes, the height of the impulse response functions differ. The regimes also alter the composition of the shocks that explains variation in the macro and financial variables. For example, inside money or credit supply shocks take on a larger role in explaining the variation of output, the price level, the unemployment rate, a short-term interest rate, a long-term interest rate, and a financial risk variable in one regime. Another regime gives an important role in driving aggregate fluctuations to a financial risk variable, which reflects riskiness in the composition of the balance sheets of U.S. financial firms.

Our results rely on stochastic volatility being the lone source of Markov switching in the BVARs. Although this class of models is a useful starting point, estimating BVARs with regime switching on intercept and slope coefficients is potentially useful. Given estimates of these BVARs, it is possible to ask whether it is "good luck-bad luck" or private and public policy decisions driving shifts in crises and non-crises regimes. We also report estimates that 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 supporting an expansion of their liabilities with private assets.

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

Long-term Interest Rate: The long-term interest rate is constructed by Shiller (2005). Homer and Sylla (2005) is cited by Shiller as his source for the long-term interest rate from 1871 to 1952. These rates are yields on New England municipal bonds from 1890 to 1900 (p. 284, table 38), the average of high grade municipal bonds from 1901 to 1920 (p. 342, table 46), and the yield average of long-term government bond from 1921 to 1952 (p. 351 and p. 375, tables 48 and 51). After 1952, he sets this interest rate equal to the yield on the 10-year U.S. Treasury bond. Our long-term interest rate consists of the 1890–2010 observations that Shiller provides; see http://www.econ.yale.edu/~shiller/data/chapt26.xls. We also need a long-term interest rate on private assets. The need is satisfied by the long-term consistent interest rate of Officer (2011).

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

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

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

Table 1: NBER Business Cycle Dates, 1890–2010

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

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

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

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

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

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

Regime j common to the macro block $\mathcal{M}$ and financial block $\mathcal{F}$ is denoted $\Gamma(j)$. The restriction $\Gamma\left(\mathcal{M},x,j\right)$ 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)

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

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

ln Marginal Data Densities			
Fixed Coefficient-Homoskedastic BVAR(2): -1713.6			
	Number of Stochastic Volatility Regimes		
	2	3	4
Model Number	1	2	3
A Single Markov Switching Chain	-1589.9	-1549.5	-1492.4
Two Markov Switching Chains			
3 Regimes on $\mathcal{F}$: M_I, R_S, R_L, $r_{R,t}$			
Model Number	4	5	6
Regimes on $\mathcal{M}$: y, P, ur	-1520.6	-1502.3	$*$
Model Number	7	8	9
Regimes on M_I and $\mathcal{M}$	-1505.8	$\mathbf{-1489.0}$	$*$
Model Number	10	11	12
Regimes on $R_{S,t}$ and $\mathcal{M}$	-1518.7	-1499.2	$*$
Model Number	13	14	15
Regimes on $M_{I,t}$, $R_{S,t}$, and $\mathcal{M}$	-1506.6	$*$	$*$

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

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

	Year	Shock						
		y	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_R}$
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 6: Regime 2 FEVDs of MS-BVAR(2) Model 8

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

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

	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	0.51	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

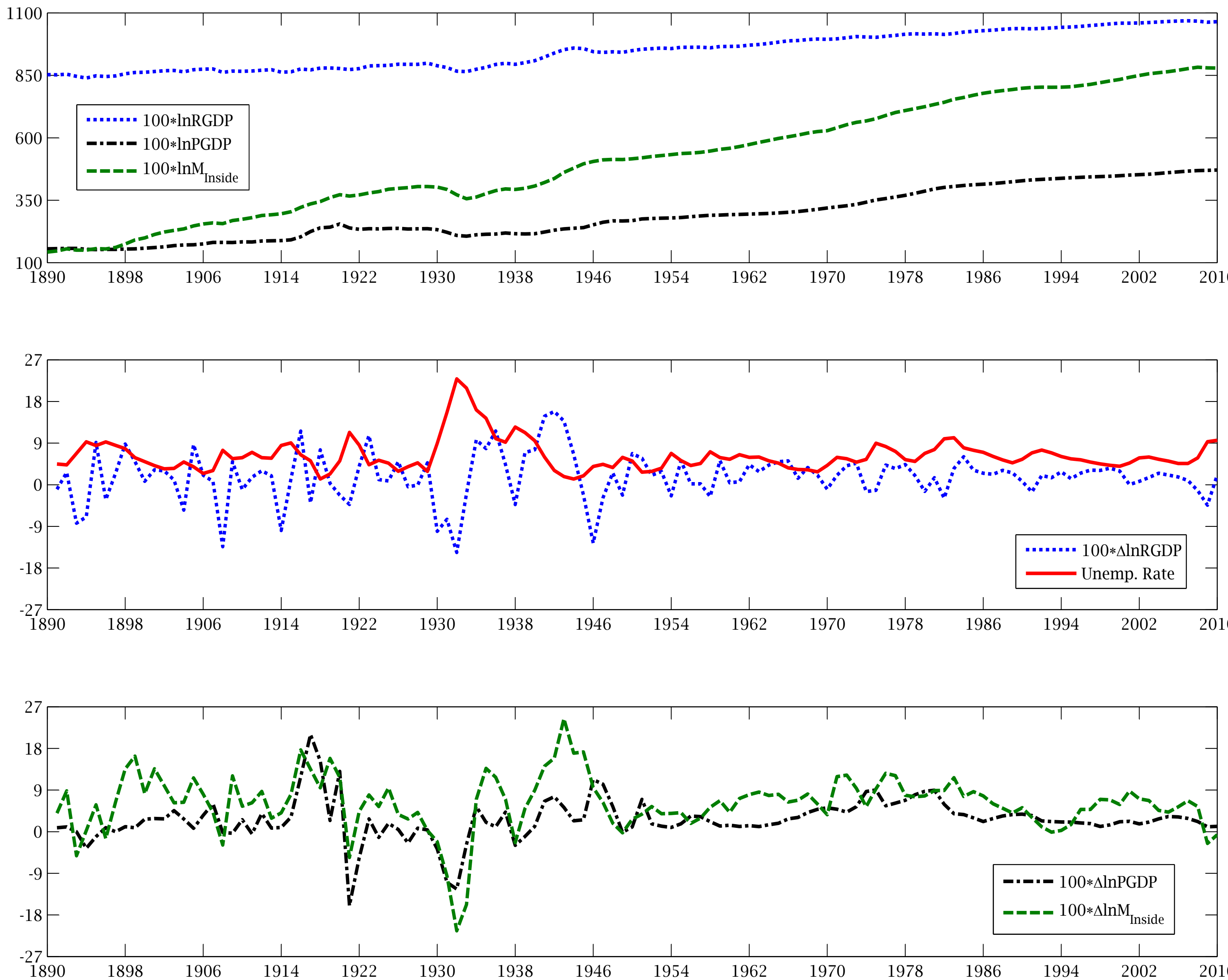

Figure 2: U.S. Short Rate, Long Rate, and Risk Ratio, 1890–2010

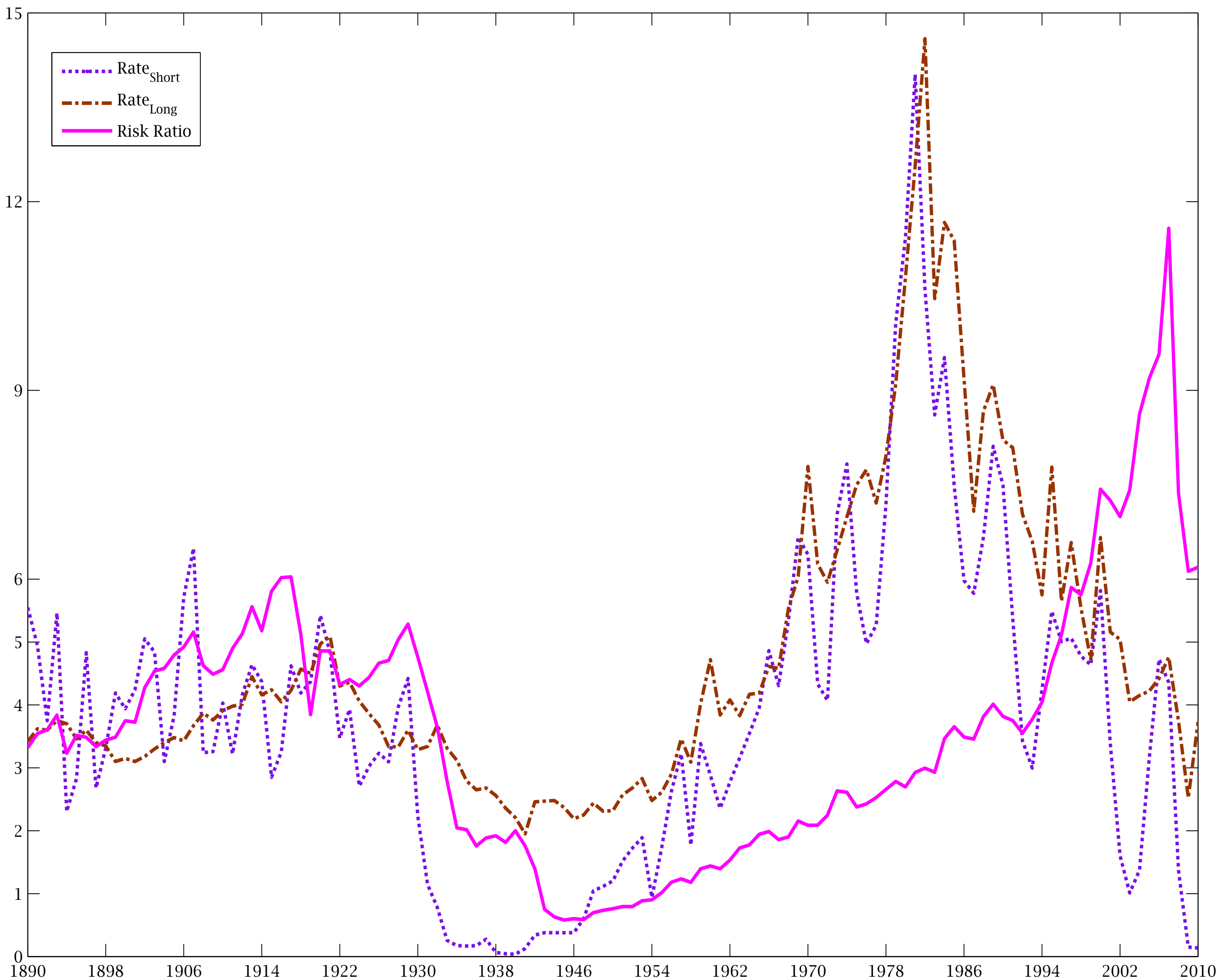

Figure 3: IRFs of Fixed Coefficient-Homoskedastic BVAR(2)

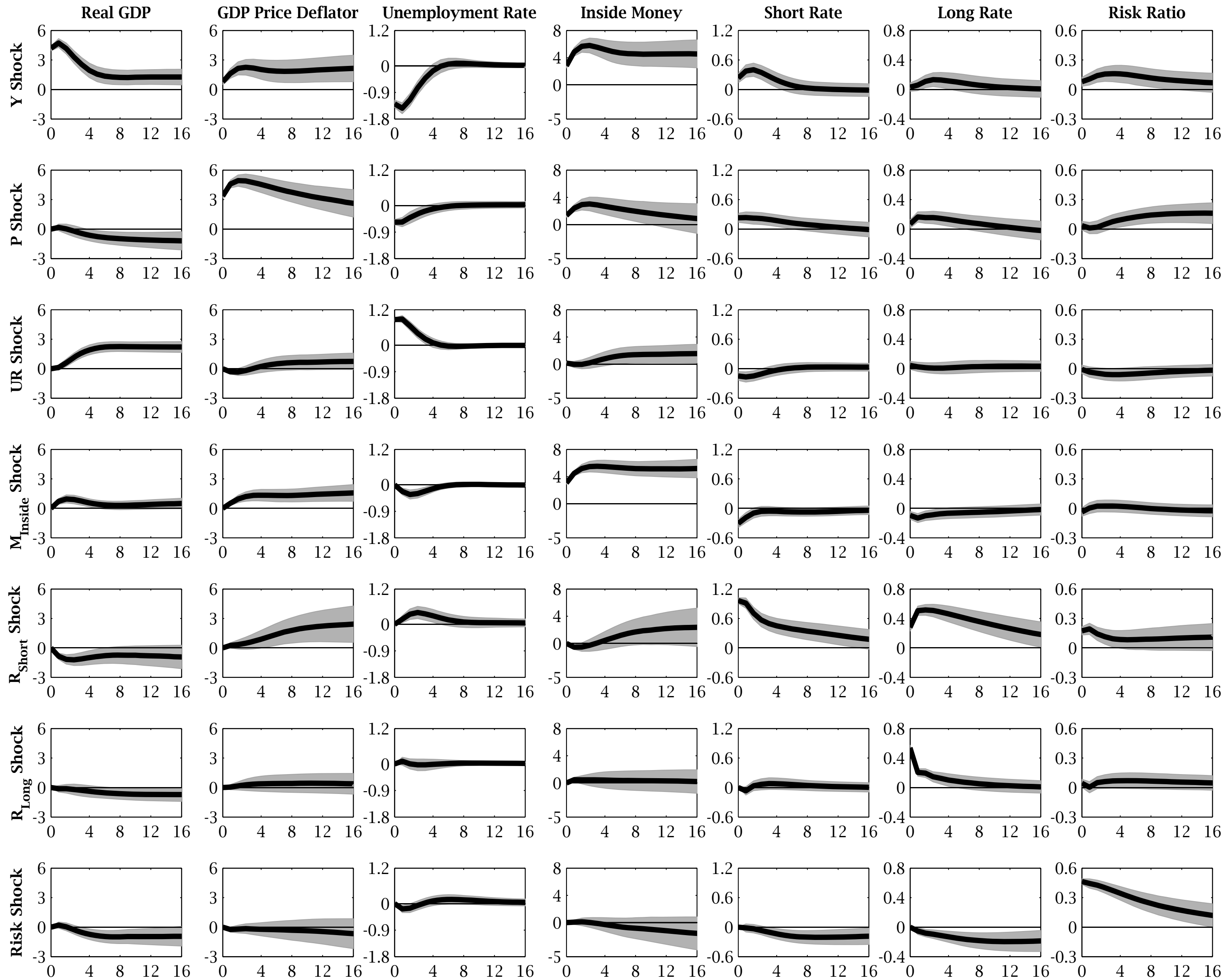

Figure 4: 3 SV Regime Probabilities: Estimates of MS-BVAR(2) Model 2, 1891-2010

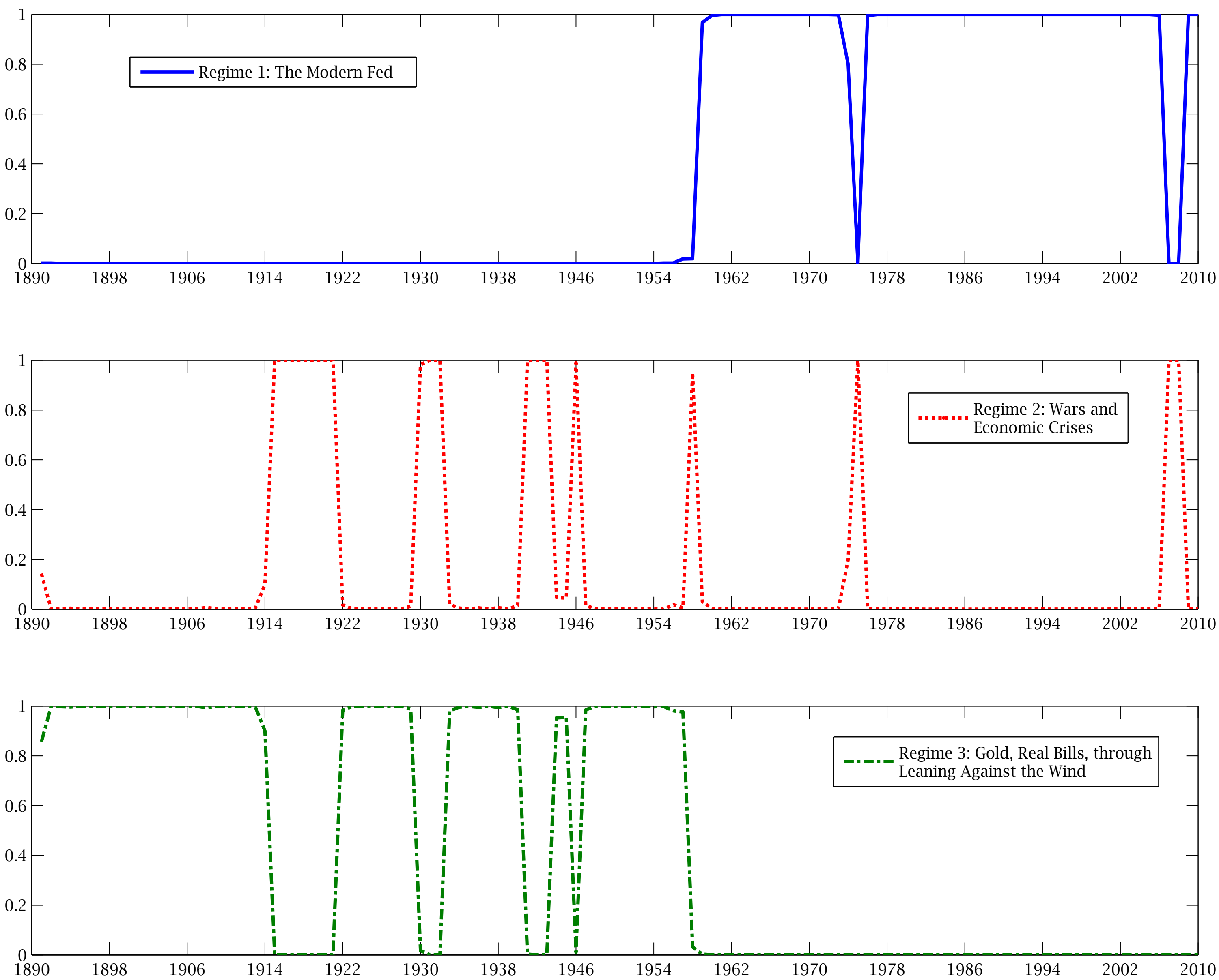

Figure 5: 4 SV Regime Probabilities: Estimates of MS-BVAR(2) Model 3, 1891-2010

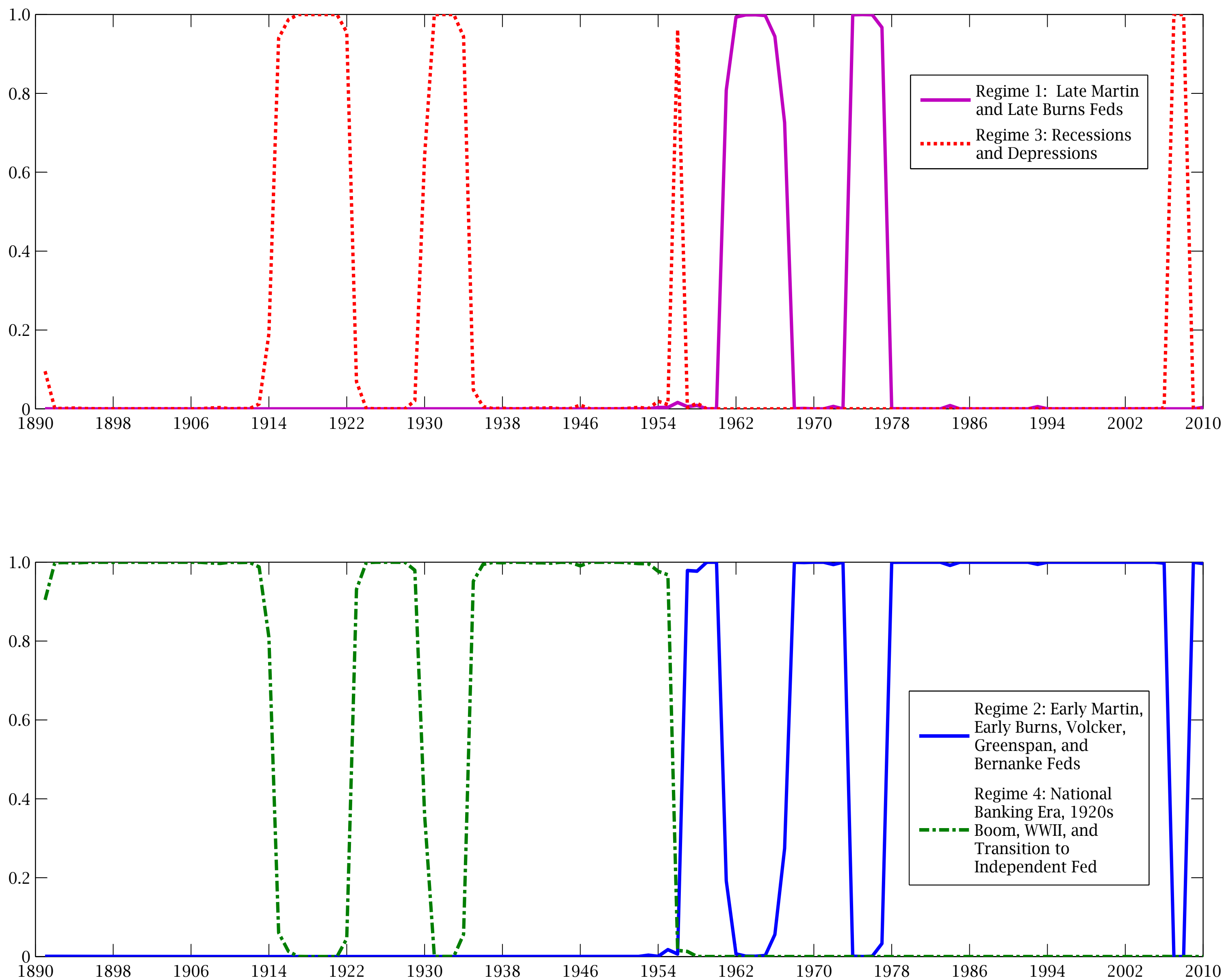

Figure 6: 3 SV Regime Probabilities of the $\mathcal{M}$ Block: Estimates of MS-BVAR(2) Model 8, 1891-2010

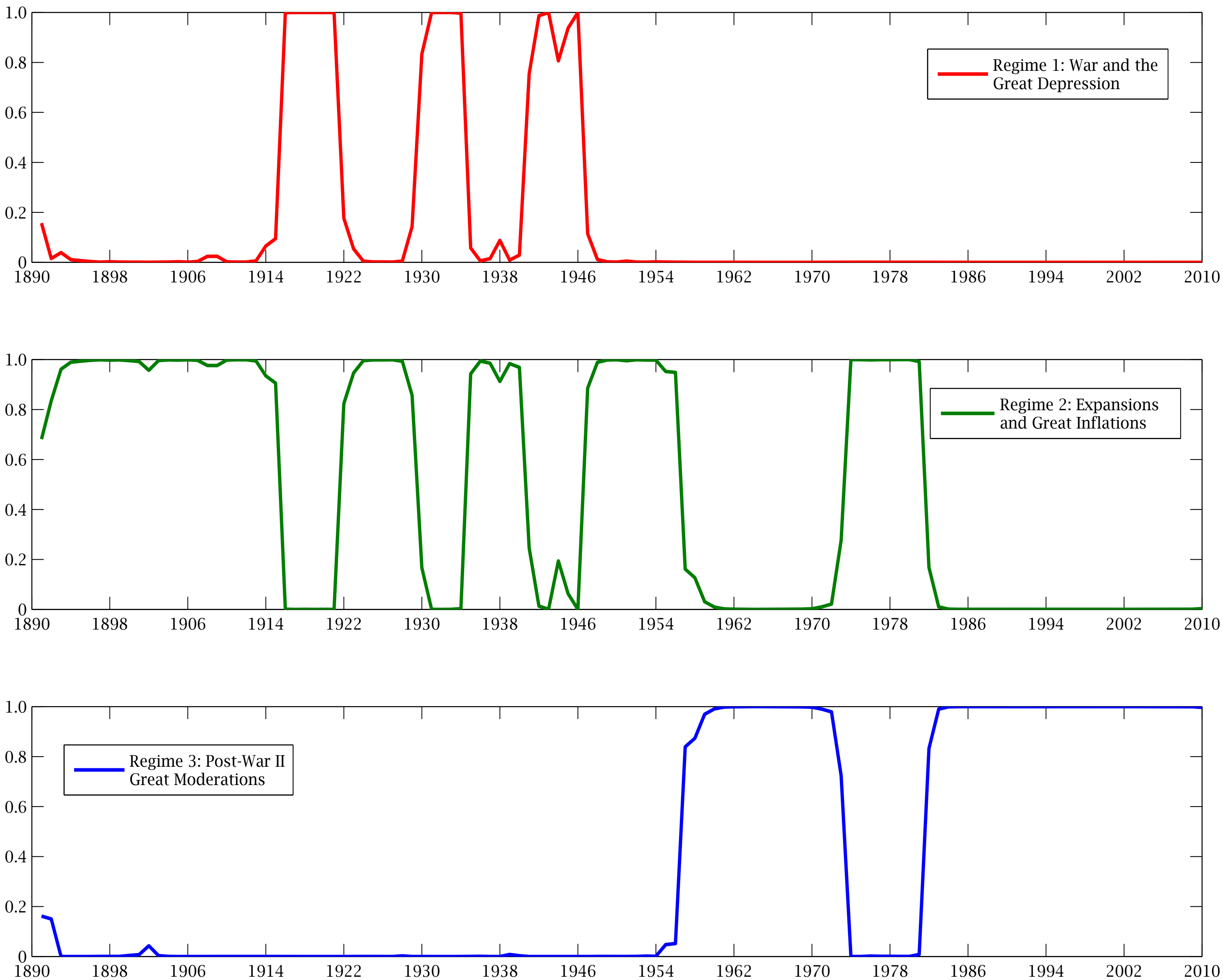

Figure 7: 3 SV Regime Probabilities of the $\mathcal{F}$ Block: Estimates of MS-BVAR(2) Model 8, 1891-2010

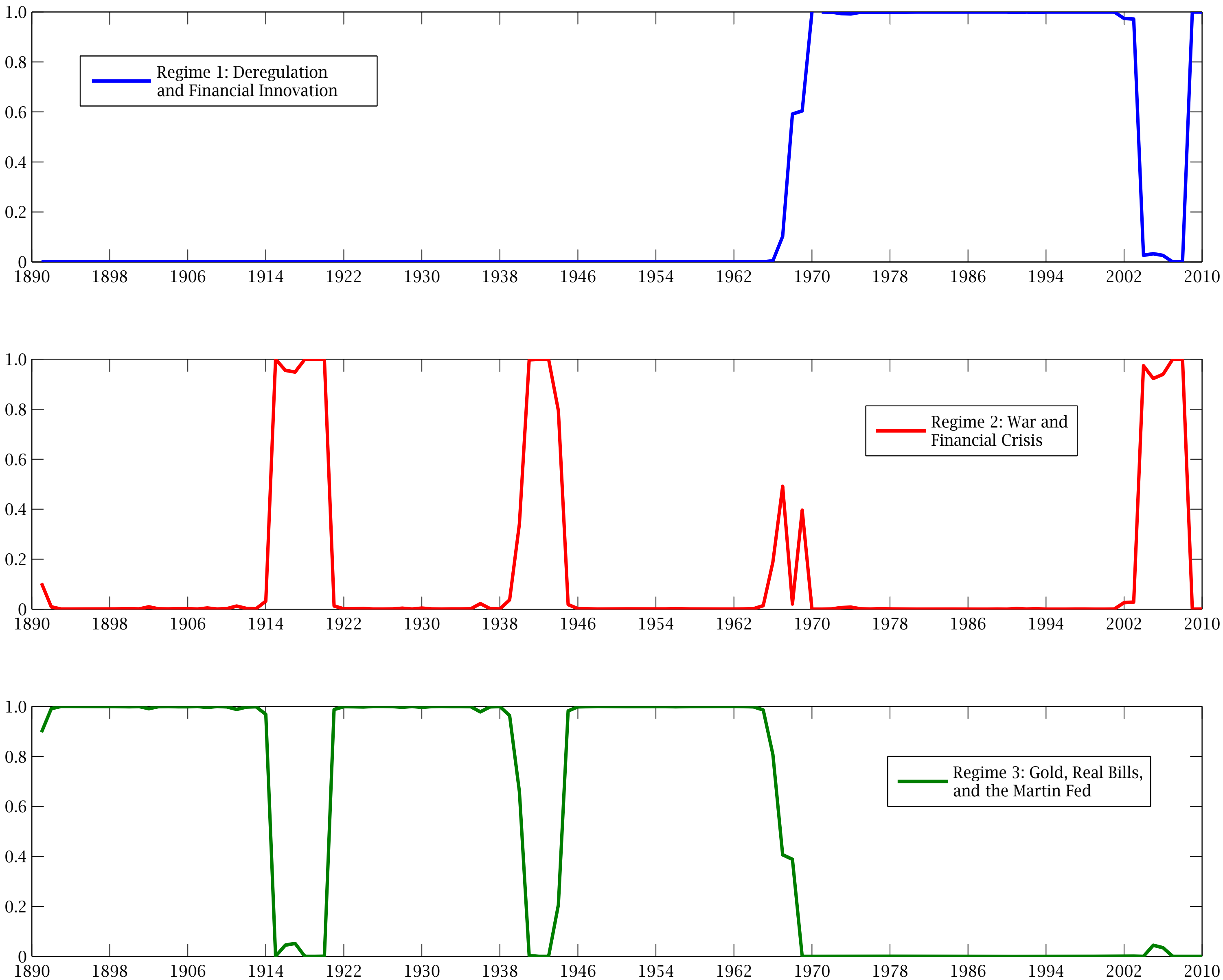

Figure 8: Regime Dependent IRFs w/r/t Inside Money Shock of MS-BVAR(2) Model 8

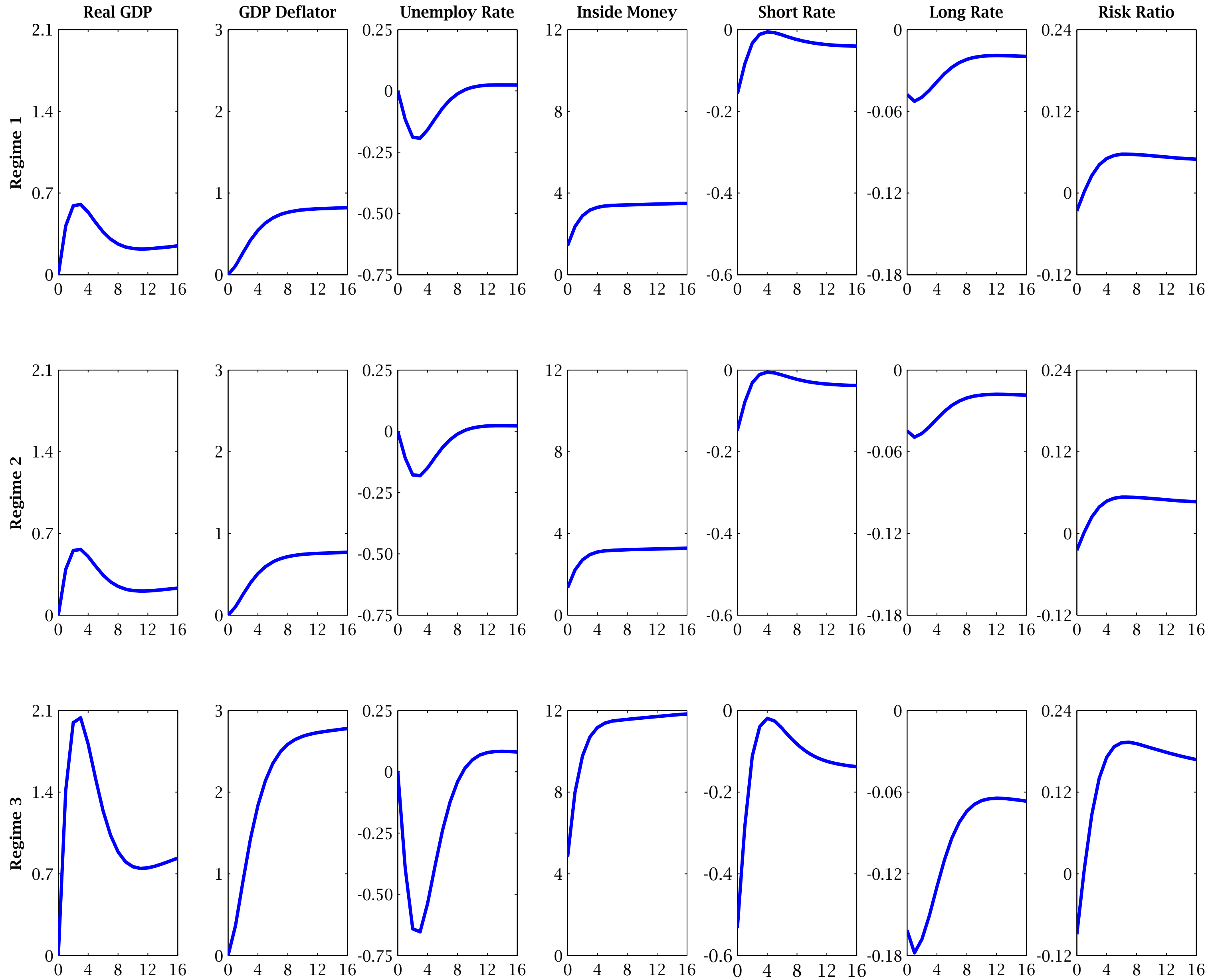

Figure 9: Regime Dependent IRFs w/r/t Short Rate Shock of MS-BVAR(2) Model 8