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

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This paper explores the hypothesis that the sources of economic and financial crises differ from those of 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 inside money and its intertemporal price. The model space is limited to stochastic volatility (SV) in the errors of the MS-BVARs. Of the 15 MS-BVARs estimated, the data favor a MS-BVAR in which economic and financial crises and non-crisis business cycle regimes recur throughout the long annual sample. The best-fitting MS-BVAR also isolates SV regimes in which shocks to inside money dominate aggregate fluctuations.

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

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1 Introduction

Not since the Great Depression has the U.S. been confronted with 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 accompanied 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 in a sample running from 1890 to 2010. 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 started in January 1893, December 1895, August 1929, and December 2007 and lasted 17, 18, 43, and 18 months, respectively.[1] The remaining eight recessions that ran for at least 14 months began 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 the 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) experienced runs 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 those 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 the average or the median.

This paper assesses the role of credit shocks 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 of credit flows 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 an 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 dating 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 a financial crisis is well described as a once-and-for-all structural break.

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] An 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. crises and non-crises 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 seven 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 dominate the correlations 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 seven variables also maintains the 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 are described in section 3 and in the appendix.

long-term interest rates, and the financial balance sheet composition ratio. We interpret the recursive identification as an assembly of restrictions gathered from Keynesian, new classical, and rational expectations models. 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 financial balance sheet composition ratio last in the ordering to be conservative about the role shock to the composition of the aggregate balance sheet of U.S. financial firms plays in generating financial crisis regimes.

This paper reports estimated structural MS-BVARs in which the only source of regime switching is the stochastic volatility (SV) of the regression errors. This paper restricts the MS-BVARs to SV because, at the very least, financial and economic crises are associated with shocks whose sizes 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. The estimated MS-BVARs yield 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. The unconditional regime probabilities show that 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 matter 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 reinvigorated 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 DGP to identify predictors of financial and economic crises at business cycle and longer horizons using cross-country data.[5] A reliable predictor of financial crises, especially those associated with deep and long recessions, is credit growth, according to these papers.

An alternative tradition studies 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 (1863–1914), as well as the 1920–1921 recession and the Great Depression (1929–1933) that are part of the interwar sample (1920–1940).[6]

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 show that, during the last 60 years, there was an expansion of loans funded with liabilities other than bank deposits. Prior

[5] Ahmadi (2009), Helbling, Huidrom, Kose, and Otrok (2011), and Eickmeier and Ng (2011) identify latent variables that predict financial crises. Ahmadi estimates a factor-VAR 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 VAR, 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.

[6] Ciccarelli, Maddaloni, and Peydró (2010), and Gambetti and Musso (2012) estimate structural VARs to recover bank loan supply and demand shocks on more recent Euro Area, U.K., and U.S. samples. The former structural VARs identify the impact of the credit channel (*i.e.*, the balance sheet capacity of banks, firms, and households) on the monetary transmission mechanism. The credit channel operates on bank, firm, and household balance sheets and amplifies monetary policy shocks, especially during the 2007–2009 financial crisis, according to Ciccarelli, Maddaloni, and Peydró. Time-varying parameter VARs with SV and sign restrictions are estimated by Gambetti and Musso. They report that loan supply shocks have asymmetric effects on output that become more important during recessions than expansions.

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

Jordà, Schularick, and Taylor (2011a) study the impact of excessive credit growth net of output on the natural rate of interest and current accounts, 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 their estimates support the hypothesis of credit growth net of output growth being a key predictor of severe, 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 in housing markets have been leading indicators of financial crises across developed economies during the last 50 years according to 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 in 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 the 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 to which measures of financial risk anticipate substantial economic downturns using 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, advocates appear who claim "this time is different."[7] Implicit in this claim is that the new state of the world produces fundamentals to support asset prices that were not available earlier. 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 financial aggregates yield warning signals for current and future real activity that can alert policymakers to a potential crisis.

Krishnamurthy and Vissing-Jorgensen (2012) have a different model of the risk factors that alter the demand for financial securities. These risk factors are tied to the impact that shifts in the supplies of securities with different characteristics have on asset returns as viewed by 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. Donaldson uses regression and nonparametric estimators of business cycle comovement to generate evidence about whether banking panics in the U.S. are "systematic events" produced by the same probability distribution from which typical busi-

[7] Parent (2012) offers 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 that 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 heavily comprised of subprime mortgage loans. When house prices ceased rising in 2006, lenders in the interbank market reassessed their beliefs that these prices could not fall. After these beliefs were revised, investment banks faced difficulties funding their RMBS holdings. Gorton and Ordoñez (2012) construct a theory to explain these observations. The theory predicts that when lenders find it costly to evaluate long-term assets they are considering 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-to-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 short-term private assets.

ness cycle fluctuations are drawn, or "special events" drawn from an entirely different distribution.[10] He concludes that the start dates of banking panics are unforecastable, but that there are states 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 the 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 approach 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. had 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 was created, in part, to supply an elastic currency in times 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 that his empirical results show that the founding of the Fed altered the sources of financial shocks in the post-World War I sample, but this did not put an end to U.S. financial crises. These results also suggest that changes in the design of financial and economic institutions create variation in the data useful for identifying the sources and causes of financial shocks. This variation in the data is also useful for estimating 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 the regressions that he reports. Eichengreen and Mitchener (2003) regress output growth on credit growth using a cross-country sample from the late 1920s and early 1930s. Their regressions

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

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

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

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 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 The 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 1935–1981 "quiet period" defined by Gorton (2010), and the past 40 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 in which the U.S. engaged 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 nominal long-term private assets to nominal public debt held on financial firms' balance sheets ($r_{FBS,t}$). These seven variables define Z_t, which 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 the log of the implicit GDP deflator are multiplied by 100. The source of real GDP, its price deflator,

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

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 per capita 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). The Board of Governors of the Federal Reserve System is the source for the later part of the sample. Balke and Gordon also provide monetary base data that are 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 then divided 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. We also take the log of $M_{I,t}$ and multiply it by 100.

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 database.

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). Shiller uses the yield on 10-year U.S. Treasury bonds, which runs from 1953 to 2010 for our sample, to complete his long-term interest rate series.

3.4 Financial Balance Sheet Composition Ratio

The financial balance sheet composition 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, saving banks and thrifts, and investment banks. Data on the asset holdings of these firms are constructed using various sources: the Board of Governors, the Federal Deposit Insurance Corporation (FDIC), the United States League of Savings Associations, the United States Savings and Loan League, and Compustat. The Board of Governors and the FDIC provide data on commercial banks. Information on the contents of savings and loan balance sheets is published by the FDIC, the United States League of Savings Associations, and the United States Savings and Loan League. Compustat has data on U.S. investment banks.

The long-term private assets of financial firms exclude 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 debt, state and 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 balance sheet composition 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 conflating financial and real shocks because the financial balance sheet composition ratio does not, say, net output growth from credit growth.

3.5 Summarizing the Information Set Z_t

In summary, the $\mathcal{M}$ block consists of y_t, P_t, and ur_t, while $M_{I,t}$, $R_{S,t}$, $R_{L,t}$, and $r_{FBS,t}$ define the $\mathcal{F}$ block. Given three of the seven variables are logged and multiplied by 100, the information set becomes

$$Z_t = \left[100 \ln y_t \quad 100 \ln P_t \quad ur_t \quad 100 \ln M_{I,t} \quad R_{S,t} \quad R_{L,t} \quad r_{FBS,t} \right]'.$$

We discuss below the reasons for placing the $\mathcal{M}$ block prior to the $\mathcal{F}$ block.

3.6 The Data in Historical Context

The data are 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 rates of y_t, $\Delta \ln y_t$, and ur_t are shown in the middle panel of figure 1 for the period from 1891 to 2010. These macro aggregates have been less volatile since 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 $\Delta \ln M_{I,t}$ is also 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 values of $\Delta \ln M_{I,t}$ range from -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, 1899–1907, 1912–1914, 1928–1929, 1973–1974, and 1978–1980, 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 points 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, $r_{FBS,t}$ is less than $R_{L,t}$. The inequality is flipped (mostly) at the beginning and at the end of the sample.

4 An MS-BVAR Model

Our motivation for estimating MS-BVAR models rests on the idea that economic and financial crises represent DGPs or regimes of the world that differ from those of non-crisis business cycle fluctuations.[14] The crisis and non-crisis regimes, although different, are built on the same economic primitives and drawn from the same probability density function, the likelihood, of an MS-BVAR. The estimated MS-BVARs yield the responses of Z_t to credit supply and credit demand shocks, among others. Besides

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

FEVDs, the estimates include the marginal data densities, the regime transition probabilities, the (first-order) Markov transition matrix of the regimes, the impact coefficient matrix, and the SV factor loadings of the MS-BVAR models. 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-BVAR models of lag length k. They study the MS-BVAR(k) model

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

where Z_t is $n(=7)\times 1$, A_0 is an $n\times n$ non-singular matrix, S_t is the h dimensional vector of regimes that are independent first-order Markov chains, h is in the finite set of integers H, each A_j is an $n\times n$ matrix, C is the vector of n intercept terms, ε_t is the vector of n unobserved shocks, and Γ is an $n\times n$ 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

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

and on the information set

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

where $\mathcal{Z}_t = \left[Z_1' \;\; Z_2' \ldots, Z_t'\right]'$, $\mathcal{S}_t = \left[S_0' \;\; S_1' \ldots, S_t'\right]'$, 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 $\Sigma_Z(\cdot) = \left[A_0(\cdot)\,\Gamma(\cdot)^2 A_0'(\cdot)\right]^{-1}$.

[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 only for 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 an MS-BVAR(k).

We limit MS to the diagonal matrix $\Gamma(S_t)$ that scales the volatility of the BVAR shock innovations, ε_t. The impact matrix A_0, the coefficient matrices A_1, A_2, $\ldots$, $A(k)$, and the intercept vector C are unchanged across regimes, which restricts the MS-BVAR dynamics to be constant across regimes.[16] These restrictions yield the MS-BVAR(k)

$$Z_t' A_0 = \sum_{j=1}^{k} Z_{t-j}' A_j + C + \varepsilon_t' \Gamma^{-1}\Big(S_t\Big), \tag{4}$$

estimated for this paper, where Θ is modified to $\Big[A_0 \ A_1 \ldots \ A_k \ C \ \Gamma(1) \ \Gamma(2) \ldots \Gamma(h)\Big]'$.[17]

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

$$Q = \begin{bmatrix} \varrho_1 & 0.5(1-\varrho_2) & 0 & 0 & \ldots & 0 & 0 \\ 1-\varrho_1 & \varrho_2 & 0.5(1-\varrho_3) & 0 & \ldots & 0 & 0 \\ 0 & 0.5(1-\varrho_2) & \varrho_3 & 1-\varrho_4 & \ldots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & \varrho_{h-1} & 1-\varrho_h \\ 0 & 0 & 0 & 0 & \ldots & 0.5(1-\varrho_{h-1}) & \varrho_h \end{bmatrix}. \tag{5}$$

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

$$q_{\cdot,j} = M_{\cdot,j}\omega_{\cdot,j}, \tag{6}$$

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 the 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 that maps to the probabilities ω.

[16]A motivation is that the MS-BVAR(k) model can become too heavily parameterized to be estimated without restrictions given the dimension of Z_t, n, and the lag length k. Given $n = 7$, let $k = 2$ and suppose that all the slope coefficients are permitted to shift in all the regimes of a MS-BVAR. In this case, the number of coefficients per regime equals 98, which would strain the information content of a sample whose length T is 121.

[17]The signs of the As are normalized using a rule of Waggoner and Zha (2003b).

The matrix Q given in (5) 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 transitioning 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 likelihood of the MS-BVAR model (4) is built on Z_T and assumptions (2), (3), (5), and (6). These data and assumptions are raw materials for the tools that SWZ develop to estimate the log likelihood

$$\ln \mathcal{P}\Big(\mathcal{Z}_T \,\Big|\, \omega, \Theta\Big) \;=\; \sum_{t=1}^{T} \ln \left[\sum_{S_t \in H} \mathcal{P}\Big(Z_t \,\Big|\, \mathcal{Z}_{t-1}, S_t, \omega, \Theta\Big) \mathcal{P}\Big(S_t \,\Big|\, \mathcal{Z}_{t-1}, \omega, \Theta\Big) \right], \tag{7}$$

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 $S_{t-1} = j$. This sampling procedure employs a backward recursion that SWZ discuss in detail. SWZ propose Gibbs sampling methods to construct the log likelihood (7) along with the conditional densities of Θ, $\mathcal{P}\Big(\Theta \,\Big|\, \mathcal{Z}_{t-1}, S_t, \omega\Big)$, and ω, $\mathcal{P}\Big(\omega \,\Big|\, \mathcal{Z}_{t-1}, S_t, \Theta\Big)$.[18] Note that the vector of regimes S_T is integrated out of the log likelihood (7).

Evaluation of the MS-BVAR model (4) relies on the joint posterior distribution of Θ and ω. This posterior is calculated in the MS-BVAR model (4) using Bayes' rule, which gives

$$\mathcal{P}\Big(\omega, \Theta \,\Big|\, \mathcal{Z}_T\Big) \propto \mathcal{P}\Big(\mathcal{Z}_T \,\Big|\, \omega, \Theta\Big) \mathcal{P}\Big(\omega, \Theta\Big), \tag{8}$$

where $\mathcal{P}\Big(\omega, \Theta\Big)$ denotes the priors of ω and Θ. The data decide which version(s) of the MS-BVAR(k) model (4) fit best using ratios of the posterior (8). These ratios, or posterior odds, are computed for versions of the MS-BVAR(k) model (4) that differ by the number of regimes h embedded in $\Gamma(S_t)$.

4.2 Priors

We follow Sims and Zha (2006) and SWZ by endowing $\mathcal{A}$ (= $\Big[A_1 \; \ldots, \; A_k\Big]$) with a mean zero prior distribution in the spirit of Sims and Zha (1998). Sims and Zha (1998) decompose their prior into six scalar parameters. The decomposition is $\lambda = \Big[\lambda_0 \;\; \lambda_1 \;\; \lambda_2 \;\; \lambda_3 \;\; \lambda_4 \;\; \lambda_5\Big]$. These parameters control the tightness of the random walk prior on the own first lag in a regression, the tightness of the random

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

walk on other lags in a regression, the tightness on the intercept of the random walk prior, tightness of the prior that smooths distributed lags of a regression, the random walk prior applied to the sum of own coefficients in a regression, and the cointegration prior implying stationary relationships among the elements of Z_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. Thus, the intent of our prior is to move the MS-BVAR(k) in the direction of random walk behavior given annual U.S. data from 1890 to 2010. Otherwise, our prior rests on advice found in Sims, Waggoner, and Zha (2008).[19] For example, our duration prior, which sets the average time of remaining in regime j given the current regime is j, is restricted to no more than six years and no less than two years.

Tightening in the direction of the random walk prior reduces $\Gamma^{-1}(\cdot)$, which contains the factor loadings that scale the SV of ε_t. This increases persistence in $\mathcal{A}$. 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. Thus, a normal prior is placed on $\mathcal{A}$ (whether or not there is MS), while the squared diagonal elements of $\Gamma(\cdot)$ are drawn from the gamma distribution; see also Robertson and Tallman (2001).[20] 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.

4.3 Identification

Identification of credit supply and demand shocks relies on a recursive Cholesky ordering and sample information.[21] We order $Z_t = \begin{bmatrix} 100\ln y_t & 100\ln P_t & ur_t & 100\ln M_{I,t} & R_{S,t} & R_{L,t} & r_{FBS,t} \end{bmatrix}'$. Credit supply and demand shocks are identified, in part, by placing the $\mathcal{M}$ block, which consists of y_t, P_t, and ur_t, prior to the elements of the $\mathcal{F}$ block, $M_{I,t}$, $R_{S,t}$, $R_{L,t}$, and $r_{FBS,t}$. The $\mathcal{M}$ block captures dynamic aggregate relationships. For example, a Lucas-Sargent Phillips curve results by placing P_t before ur_t and a dynamic Okun's law by having y_t respond to a ur_t shock with a lag.

[19] The same prior is applied when estimating the MS-BVAR model (1). In this case, Sims and Zha (2006) and SWZ impose prior restrictions to limit the dimension of the time variation of the slope coefficients, the As, and the intercepts, C. The restrictions are $\mathbb{A}(s_t) = \mathcal{D}(s_t) + \overline{\mathcal{D}}A_0(s_t)$, where $\mathbb{A}(s_t) \equiv \begin{bmatrix} A_1(s_t) & A_2(s_t) & \ldots & A_k(s_t) & C(s_t) \end{bmatrix}'$, $\overline{\mathcal{D}} = \begin{bmatrix} \mathbf{I}_n & \mathbf{0}_{n\times 1} \end{bmatrix}'$, and $\mathcal{D}(s_t)$ is conformable with $\mathbb{A}(s_t)$ and $\overline{\mathcal{D}}\,\mathcal{A}(s_t)$. A mean zero prior distribution is bestowed on $\mathcal{D}(s_t)$ by Sims and Zha (2006) and SWZ, which matches the random walk prior of Sims and Zha (1998).

[20] An implication is that the elements of Γ have independent priors. Thus, Γ is not a direct function of $\mathcal{A}$. Rather, the coefficients of a MS-BVAR model are computed simultaneously when estimating the log likelihood (7).

[21] Recursive Cholesky orderings are consistent with the restrictions SWZ place on time variation in MS-BVARs; see also Waggoner and Zha (2003a).

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 $r_{FBS,t}$. The risk variable injects information about the composition of the aggregate balance sheet of U.S. financial firms into the $\mathcal{F}$ 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 funds that support an increase in $r_{FBS,t}$. 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.

4.4 Model Space

Our study of the impact of credit supply and demand shocks limits MS to the SV scaling matrix $\Gamma(S_t)$ of regression error vector ε_t. Table 2 presents the parameterizations of 15 MS-BVAR(2) models given this restriction on MS in the BVAR models. The 15 MS-BVAR models have either one or two Markov chains associated with h = 2, 3, or 4 SV regimes. When there is one Markov chain in these three MS-BVAR models, it is common to the $\mathcal{M}$ block and the $\mathcal{F}$ block. Thus, there are $h \times 7$ elements in $\Gamma(S_t)$ with its dimensionality rising with the number of SV regimes. We label the MS-BVARs with 2, 3, or 4 SV regimes models 1, 2, and 3, respectively. Next, separate the chains for the $\mathcal{M}$ and $\mathcal{F}$ blocks, but assume that the $\mathcal{F}$ block always has $h_{\mathcal{F}} = 3$ SV regimes.[22] This produces three more MS-BVAR models, with the $\mathcal{M}$ block taking on $h_{\mathcal{M}}$ = 2, 3, or 4 regimes. The remaining nine models are created by adding $M_{I,t}$ and $R_{S,t}$ one at a time and then adding $M_{I,t}$ and $R_{S,t}$ at the same time to the $\mathcal{M}$ block. This yields Markov chains generating 2, 3, and 4 SV regimes on the $\mathcal{M}$ block that includes either $M_{I,t}$, $R_{S,t}$, or $M_{I,t}$ and $R_{S,t}$.

Adding $M_{I,t}$, $R_{S,t}$, or $M_{I,t}$ and $R_{S,t}$ to the $\mathcal{M}$ block also increases the dimension of $\Gamma(S_t)$. Consider MS-BVAR models 7, 8, and 9. In these models, the value of the SV scaling parameter Γ_{M_I} is driven by the regime of the $\mathcal{M}$ block conditional on the $\mathcal{F}$ block regime. The implication is that $\Gamma_{M_I}(i|\ell)$ is in $\mathcal{M}$ block regime i, $i = 1, \ldots, h_{\mathcal{M}}$, given the $\mathcal{F}$ block is in regime ℓ, $\ell = 1, 2, 3$. Thus, including M_I in the $\mathcal{M}$ and $\mathcal{F}$ blocks imposes $h_{\mathcal{M}} \times 3$ SV regimes on $\Gamma_{M_I}(S_t)$ in models 7, 8, and 9. However, the remaining SV scaling parameters, $\Gamma_j(S_t)$, $j = y,\ P$, and ur, of the $\mathcal{M}$ block have $h_{\mathcal{M}}$ different values only across

[22] When we tried to estimate MS-BVARs with $h_{\mathcal{M}}$ = 2, 3, or 4 regimes conditional on $h_{\mathcal{F}} = 4$ SV regimes, the results were always poorly approximated MDDs.

the $h_{\mathcal{M}} \times 3$ SV regimes.

We condition 12 of the 15 MS-BVAR models on separate Markov chains for the $\mathcal{M}$ and $\mathcal{F}$ blocks. Conditional on the priors and data, this gives the MS-BVAR models 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 SV 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 the 15 MS-BVARs can still be estimated in a reasonable amount of time.

4.5 Estimation and Inference Methods

The MS-BVAR(2) models are estimated using a multi-step procedure. The procedure to estimate a model space and infer which of its members is or are most favored by the data involves

1. setting the random walk, smoothness, cointegration, and duration priors on the MS-BVAR(2),
2. constructing 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,[23]
3. equating the posterior mode of the MS-BVAR(2) model with initial conditions of A_0, A_1, A_2, C, and $\Gamma(1), \ldots, \Gamma(h)$ of the MS-BVAR(2) to start up a Markov chain-Monte Carlo (MCMC) simulator that is run to produce 10 millions steps,
4. constructing the posterior of an MS-BVAR(2) by generating 10 million draws from the proposals created by the MCMC simulator,
5. choosing 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. rerunning the MS-BVAR(2) model(s) most favored by the data to obtain the regime probabilities, $\varrho_1, \ldots, \varrho_h$, regime-dependent residuals, and regime-dependent FEVDs.[24]

Estimation and inference rely on the code described in SWZ that was integrated into the unstable version of Dynare; see Adjemian, Bastani, Juillard, Maih, Mihoubi, Prerndia, Ratto, and Villemot (2012). The next section engages this code and these procedures to generate estimates of 15 MS-BVAR(2)s and conduct inference on these models.

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

[24] When the MS-BVARs were estimated, the Dynare code did not provide a means to restart a model at the posterior mode. Given the computational costs of generating a complete set of results for each model, we generated MDDs in a first estimation round only. The most favored model was reestimated, verifying that this model retains its most favored status, to produce a complete set of results.

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.[25] The estimates are grounded in the restriction $\Gamma(S_t) = \Gamma$ across all potential regimes. Figure 3 plots IRFs generated from the estimated fixed coefficient-homoskedastic BVAR(2). Median IRFs are plotted in black and error bands are shaded gray. 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 four years; raises P permanently; creates a negative hump-shaped response in ur that also dies out in about four years; permanently increases M_I, while holding its real balances to a proportionate change; yields a hump-shaped response in R_S peaking at two years before returning to steady state within four years; and has little effect on R_L but raises r_{FBS} for about four years. 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_{FBS} 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 an M_I shock, y (ur) exhibits a small (negative) hump-shaped

[25]We estimate five additional fixed coefficient-homoskedastic BVAR(2) models. These models include the first five elements of Z_t, adding R_L, adding R_L and a long-term private interest rate, and replacing r_{FBS} in Z_t with a measure of aggregate financial leverage, the first principal component of r_{FBS}, the long-term private interest rate, and the measure of aggregate financial leverage. These BVARs yield results that are qualitatively similar to ones generated by the BVAR estimated on Z_t. These results are available on request.

response peaking at two 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 an M_I shock suggest long-run inside monetary neutrality because P rises proportionally.

The fifth row of figure 3 shows that a shock to R_S generates a money demand-like response in y and ur. These variables indicate that 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 that the term spread shrinks at short horizons before returning to its steady state in the long run. In the short run, r_{FBS} also rises given an R_S shock. Hence, the tighter term spread is consistent with smaller risk premia, which suggests that U.S. financial firms take more risk by holding a larger share of their balance sheets in long-term private assets.

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

Nonetheless, the fixed coefficient-homoskedastic BVAR(2) produces two IRFs at odds with conventional economic theory. One is the response of y to a 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 that 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, and the bulk of the rest is explained by income shocks. Fluctuations in R_S and r_{FBS} are driven by own shocks, while the FEVDs of R_L exhibit term structure behavior as its own shock and the shock to R_S 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, which are listed in table 4.[26] Table 4 displays the 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

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

badly approximated log marginal data densities.[27] Except for model 14, these models place four 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 that 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 three distinct MS chains on the SV of the $\mathcal{M}$ block and three 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 conditional 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 on the error of the M_I regression, $\widehat{\Gamma}_{M_I}(\cdot)$. The evidence is that the data have a strong preference for model 8 when compared to the other MS-BVARs predicated on three SV regimes (models 3, 5 and 11), to the MS-BVARs that rely on two SV regimes (models 1, 4, 7, 10, and 13), or to the single-chain four SV regime MS-BVAR of model 4. Although model 4 produces the second largest log marginal data density, the distance from this log marginal data density to the log marginal data density of model 8 gives an odds ratio strongly in favor of the latter model.[28]

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 $\widehat{\Gamma}(\cdot)$ 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 nearly 20 percent probability of moving from regime 3 to regime 2 in the $\mathcal{M}$ block with M_I. 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

[27] 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 not to trust the reported marginal data density in this degenerate case. This is true for any model we attempted to estimate with separate MS chains for the $\mathcal{M}$ and $\mathcal{F}$ blocks and four SV regimes on either block.

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

is also a 10 percent probability of being in regime 2 and transitioning 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_{FBS} 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 $\widehat{\Gamma}(\cdot)$. Note that 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, $S_{\mathcal{M},M_I} = 1|S_{\mathcal{F}} = 1$. Otherwise, these estimates indicate that $\widehat{\Gamma}(\cdot)$ on the shock innovations, ε_t, of the y, P, ur, M_I, R_S, and R_L regressions arise in regime 3, whether in the $\mathcal{M}$ or $\mathcal{F}$ blocks. Since the volatility scaling on the shock innovations is $\Gamma^{-1}(\cdot)$, relative to the regime combination $S_{\mathcal{M},M_I} = 1|S_{\mathcal{F}} = 1$, the loadings on $\varepsilon_{y,t}$, $\varepsilon_{P,t}$, $\varepsilon_{ur,t}$, $\varepsilon_{M_I,t}$, $\varepsilon_{R_S,t}$, and $\varepsilon_{R_L,t}$ when $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 3$ are larger by factors of 36, 200, 14, 1000, 4, and 21, respectively. The largest estimated $\widehat{\Gamma}_{FBS}(\cdot)$s reside in regime 2 of the $\mathcal{F}$ block regardless of the regime of the $\mathcal{M}$ block. This $\widehat{\Gamma}_{FBS}$ is about 91 times larger compared to its value of unity when $s_{\mathcal{M},M_I} = 1|s_{\mathcal{F}} = 1$. Applying these scalings to the IRFs of the fixed coefficient-homoskedastic BVAR(2) gives a good approximation to IRFs produced by the MS-BVAR model 8. That is, the shape of the IRFs of figure 3 is unchanged, but the height of the IRFs varies roughly with the inverse of the estimates of $\Gamma(S_t)$.[29]

The shock volatilities of M_I, $\widehat{\Gamma}_{M_I}(\cdot)$s differ across the nine conditional regimes of the MS-BVAR of model 8. The estimates of the shock volatilities of M_I range from 0.172 (in $S_{\mathcal{M},M_I} = 2|S_{\mathcal{F}} = 1$) to 1.466 (for $S_{\mathcal{M},M_I} = 2|S_{\mathcal{F}} = 3$) in regimes 1 and 2 of the $\mathcal{M}$ block. Regime 3 of the $\mathcal{M}$ block holds the smallest estimates of the shock volatilities of M_I. Thus, in this regime, shocks to M_I generate the greatest volatility across the regimes of the $\mathcal{F}$ block. This suggests that the long annual 1890–2010 sample favors model 8 (conditional on the priors) because it allows greater variability in the responses of Z_t to the nine conditional shock innovation volatilities $\varepsilon_{M_I,t}\widehat{\Gamma}_{M_I}(\cdot)^{-1}$.

5.4 Regime Probabilities

The estimated MS-BVAR models produce probabilities of regime j, $j = 1, \ldots, h$, at date t. We plot probabilities for MS-BVAR model 2, a single MS chain of three SV regimes, in figure 4. Figure 5 presents probabilities for MS-BVAR model 3, which is a single MS chain of four SV regimes. The MS-BVAR model 8 generates probabilities that are found in figures 6 and 7 for MS chains of $\mathcal{M}$ and $\mathcal{F}$ blocks, both of

[29]The ergodic IRFs of the MS-BVAR model 8 are qualitatively and quantitatively similar to those of table 2. These results are available on request.

which contain M_I.

Figure 4 shows that model 2 is consistent with the hypothesis that crisis and non-crisis regimes represent different economic outcomes but are drawn from the same probability density. Regime 1 of model 2 is plotted in the top panel of figure 4. We interpret this regime that runs from 1957 to 1974, 1977 to 2006, and 2009 to 2010, as the era of the modern Fed and the Great Moderation episodes.[30] The bottom panel of figure 4 displays regime 3, which contains most of the first half of the sample. 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 led to an independent Fed in 1951. A distinguishing feature of the earlier regime 1 and later regime 3 is the stark differences in the design of the U.S. financial system.

The middle panel of figure 4 contains regime 2, which is distinct from regimes 1 and 3 in several ways. Regime 2 consists of World War I, the Great Depression, World War II, and the 1957–1958, 1973–1975, and 2007–2009 recessions. The only recessions in regime 1 to match the severity of these are the 1957–1958 and 1981–1982 recessions. Regimes 1 and 3 also contain several armed conflicts in which the U.S. engaged, 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 this regime reoccurs in the early, middle, and late parts of the 1890–2010 sample. This supports 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 four 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, but it excludes the 2007–2009 Great Recession. Regime 4 contains three seemingly different regulatory regimes: 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, 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 crises

[30]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.

have been generated by the same underlying economic primitives during the last 120 years.

Model 8 produces regime probability estimates that refine 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 with M_I, while figure 7 does the same for the regime probabilities of the $\mathcal{F}$ block.

The U.S. crisis and non-crisis narrative is altered by model 8 in several ways. First, model 8, our priors, and the data place the world wars and the Great Depression in regime 1 of the $\mathcal{M}$ block when it includes M_I. The top panel of figure 6 plots the regime 1 probabilities. Given these regime probabilities approach 100 percent from 1915 to 1921, 1930 to 1934, and 1941 to 1946, model 8 estimates that economic crises in the $\mathcal{M}$ block, when it includes M_I, coincide with realizations of Δy_t, $\Delta \ln P_t$, and $\Delta \ln M_{I,t}$ (ur_t) that are more than 2 standard deviations below (above) the associated sample means.[31] Thus, model 8 ties economic crises to regime 1 because it yields estimates of $\Gamma_y(\cdot)$, $\Gamma_P(\cdot)$, $\Gamma_{ur}(\cdot)$, and $\Gamma_{M_I}(\cdot)$ that are large relative to the estimates associated with regimes 2 and 3. Next, the middle panel of figure 7 displays the crises regime probabilities generated by model 8, the priors, and the data for the $\mathcal{F}$ block. This is regime 2 of the $\mathcal{F}$ block and contains World War I, World War II, and the Vietnam and Iraq wars. Hence, model 8 generates support for the hypothesis that the events defining U.S. crisis and non-crisis regimes recur throughout the 1890–2010 sample.

The recurring regime probabilities of the $\mathcal{M}$ block that also includes M_I appear in the middle panel of figure 6. This is regime 2 of the $\mathcal{M}$ block containing M_I. These probabilities show that regime 2 of the $\mathcal{M}$ block with M_I covers 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, which cover more than 50 percent of the sample. Thus, model 8 produces evidence that regime 2 of the $\mathcal{M}$ block including M_I, which contains neither the Great Depression nor the Great Recession, is recurring.

There are several other notable refinements of the regime probabilities produced by model 8. Among these are that the Great Depression is found in regime 3 of the $\mathcal{F}$ block. This regime also

[31] The means (standard deviations) of $\Delta \ln y_t$, $\Delta \ln P_t$, ur_t, and $\Delta \ln M_{I,t}$ are 1.77 (5.08), 2.63 (4.43), 6.29 (3.35), and 6.14 percent (6.00). For 1930, 1931, 1932, 1933, 1934, 2008, 2009, and 2010, the realizations of $\Delta \ln y_t$ are, in percent, $\left[-10.08,\ -7.48,\ -14.65,\ -1.89,\ 9.70,\ -1.26,\ -4.41,\ 2.14\right]$. The same observations of $\Delta \ln P_t$, ur_t, and $\Delta \ln M_{I,t}$ are $\left[-3.75,\ -10.95,\ -12.42,\ -2.76,\ 5.44,\ 2.18,\ 1.06,\ 1.15\right]$, $\left[8.94,\ 15.65,\ 22.89,\ 20.90,\ 16.20,\ 5.80,\ 9.30,\ 9.60\right]$, and $\left[-2.16,\ -9.55,\ -21.44,\ -15.75,\ 6.96,\ 5.43,\ -2.53,\ -0.66\right]$, also in percent. These statistics and observations suggest that real and nominal macroeconomic volatility was several orders of magnitude greater during the Great Depression compared to the Great Recession.

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 Iraq war and a financial boom-bust cycle, while the Great Inflation of the 1970s and the Volcker disinflation are absent from the former regime.

The regime probabilities of figures 4 to 7 help explain the preference of the data for model 8. Although the data appreciate 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 but includes M_I in both regimes. This makes the 3 $\mathcal{M}$ block with M_I regimes and the 3 $\mathcal{F}$ block regimes inputs into the $\widehat{\Gamma}_{M_I}(\cdot)$ that scale the SV of $\varepsilon_{M_I,t}$. We interpret the preference of the data for model 8 as evidence that identifying nine credit supply shock SV regimes is useful for estimating separate and recurring crisis from non-crisis regimes.

5.5 Regime-Dependent Residual Estimates

Figure 8 contains estimates of the scaled residuals, $\widehat{\varepsilon}_t'\widehat{\Gamma}^{-1}(\cdot)$, generated by the MS-BVAR model 8. Scaled residuals of the $\mathcal{M}$ block, $\widehat{\varepsilon}_{y,t}\widehat{\Gamma}_y^{-1}(\cdot)$, $\widehat{\varepsilon}_{P,t}\widehat{\Gamma}_P^{-1}(\cdot)$, and $\widehat{\varepsilon}_{ur,t}\widehat{\Gamma}_{ur}^{-1}(\cdot)$, appear in the top window of figure 8. Spread across the middle and bottom windows of figure 8 are residuals of the $\mathcal{F}$ block, $\widehat{\varepsilon}_{M_I,t}\widehat{\Gamma}_{M_I}^{-1}(\cdot)$, $\widehat{\varepsilon}_{R_S,t}\widehat{\Gamma}_{R_S}^{-1}(\cdot)$, $\widehat{\varepsilon}_{R_L,t}\widehat{\Gamma}_{R_L}^{-1}(\cdot)$, and $\widehat{\varepsilon}_{r_{FBS},t}\widehat{\Gamma}_{r_{FBS}}^{-1}(\cdot)$.

The top window of figure 8 shows scaled residuals of the $\mathcal{M}$ block that display two bursts of volatility. The first volatility episode in the $\mathcal{M}$ block-scaled residuals begins in 1915 and ends by 1923. The onset of the Great Depression in 1930 sees the second volatility burst in $\widehat{\varepsilon}_{y,t}\widehat{\Gamma}_y^{-1}(\cdot)$, $\widehat{\varepsilon}_{P,t}\widehat{\Gamma}_P^{-1}(\cdot)$, and $\widehat{\varepsilon}_{ur,t}\widehat{\Gamma}_{ur}^{-1}(\cdot)$ that ends only in 1951 at about the same time the Treasury-Fed accord was signed. These volatility episodes coincide with the SV probabilities of regime 1 and (part of) regime 2 of the $\mathcal{M}$ block that appear in the top two windows of figure 6.

The volatility of $\widehat{\varepsilon}_{M_I,t}\widehat{\Gamma}_{R_S}^{-1}(\cdot)$, $\widehat{\varepsilon}_{R_S,t}\widehat{\Gamma}_{R_L}^{-1}(\cdot)$, and $\widehat{\varepsilon}_{R_L,t}\widehat{\Gamma}_{M_I}^{-1}(\cdot)$, as appears in the middle window of figure 8, lines up with the estimated SV regime probabilities of figure 7. For example, the scaled residual of M_I is more volatile in the first half of the sample, from 1891 to 1947, than in the second. This volatility history occurs during the SV regime probabilities in the bottom windows of figure 7 that include the National Banking Era, World War I, the interwar period including the Great Depression, and World War II. The scaled residuals of R_S and R_L have greater volatility starting in the 1970s. These volatility episodes are consistent with the $\mathcal{F}$ block SV regime probabilities of the top window of figure 7. That is, $\hat{\varepsilon}_{R_S,t}\hat{\Gamma}^{-1}_{R_S}(\cdot)$ and $\hat{\varepsilon}_{R_L,t}\hat{\Gamma}^{-1}_{R_L}(\cdot)$ exhibit heightened volatility during the era of financial deregulation and innovation from the 1970s to the end of the sample.

The residuals of the scaled shock innovation of $r_{FBS,t}$, $\hat{\varepsilon}_{r_{FBS},t}\hat{\Gamma}^{-1}_{r_{FBS}}(\cdot)$, is presented in the bottom panel of figure 8 because of its large volatility burst between 2007 and 2009. However, figure 8 also displays bouts of volatility in $\hat{\varepsilon}_{r_{FBS},t}\hat{\Gamma}^{-1}_{r_{FBS}}(\cdot)$ during World War I, World War II, and from 1998 to 2005. Although these are episodes with much less volatility than is observed for the scaled shock innovation of $r_{FBS,t}$ during the financial crisis of 2007–2009, these events line up with the war and financial crisis $\mathcal{F}$ block SV regime probabilities in the middle window of figure 7.

5.6 Regime-Dependent FEVDs

We employ model 8 to generate regime-dependent FEVDs. The FEVDs appear in tables 6 to 10 at horizons of 1, 2, 4, 8, and 20 years. Tables 6, 7, 8, 9, and 10 present FEVDs of the joint regime $S_{\mathcal{M},M_I} = 1|S_{\mathcal{F}} = 2$, $S_{\mathcal{M},M_I} = 2|S_{\mathcal{F}} = 3$, $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 1$, $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 2$, and $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 3$, respectively. The joint regime $S_{\mathcal{M},M_I} = 1|S_{\mathcal{F}} = 2$ consists of the World War I and World War II years, which run from 1915 to 1920 and from 1941 to 1944. Most of the first half of the sample is found in the joint regime $S_{\mathcal{M},M_I} = 2|S_{\mathcal{F}} = 3$, which covers the years 1891–1914, 1922–1929, 1935–1940, and 1947–1956. The joint regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 1$ contains the years 1969–1973, 1982–2003, 2009, and 2010, which is most of the last third of the sample. The 2004–2008 period, which is the joint regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 2$, covers the recent financial crisis as well as the years before it. The latter part of the Martin Fed is represented by the joint regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 3$ because it runs from 1959 to 1966.

Table 6 contains the FEVDs of the joint regime $S_{\mathcal{M},M_I} = 1|S_{\mathcal{F}} = 2$. These FEVDs, which differ from the FEVDs found in table 3 for the fixed coefficient-homoskedastic BVAR, show that own shocks explain movements in y, P, M_I, and R_S from 1- to 4-year horizons. At the same horizons, fluctuations in ur are split between own and y shocks. About 30 percent of the movements in M_I are explained by the r_{FBS} shock at these horizons, while at longer horizons its own shock and the R_S shock contribute between 35 to 40 percent of this variation. This contrasts with the FEVDs of y, P, and ur that are dominated by the r_{FBS} shock at longer horizons. Own shocks are responsible for most of the movements in R_S and r_{FBS} with one exception. More than 60 percent of the variation in R_S is attributed to the r_{FBS} shock at the 20-year horizon, while at the 1-year horizon the R_S shock drives almost 60 percent of the movements in R_L. Its FEVD is a mix of its own shock and the R_S shock from 2- to 8-year horizons, but the r_{FBS} shock explains 60 percent of the variation at the longest horizon. Thus, table 6 gives evidence that the r_{FBS} shock explains a third or more of fluctuations in Z_t during the regime that covers the major conflicts of the 20th century.

The FEVDs of the joint regime $S_{\mathcal{M},M_I} = 2$ and $S_{\mathcal{F}} = 3$ are shown in table 7. This table contains FEVDs that are similar to the FEVDs found in table 3, which is not surprising given this regime covers much of the first half of the sample. The only qualitative differences are that for the joint regime that covers most of the first half of the sample (i) about 30 percent of the variation in M_I is attributed to the ur shock at the longer horizons and another 25 percent to the R_S shock at the 20-year horizon, and (ii) most of the fluctuations in R_L are contributed by its own shock.

The joint regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 1$ yields FEVDs that drive fluctuations in R_S and r_{FBS} with shocks to y and M_I. These FEVDs appear in table 8 and reveal that the y shock explains from 30 to 50 percent of the variation in R_S and r_{FBS}, while the M_I shock is responsible for about 20 percent of these movements on average. For movements in R_L, its own shock and the M_I shock explain 20 to 40 percent of the variation at the 1- to 2-year horizons, which is more than the 10 to 30 percent seen at the 3- to 8-year horizons. At longer horizons, shocks to y, P, and M_I contribute more than half of the fluctuations in R_L. Thus, table 8 indicates that, during the Great Moderation and a period of financial innovation and deregulation, $\mathcal{M}$ block and M_I shocks contributed to fluctuations in R_S, R_L, and r_{FBS}.

The impact of $\mathcal{M}$ block variables on $\mathcal{F}$ block variables is weaker according to the FEVDs of table 9. This table, which contains FEVDs for the joint regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 2$ of the financial boom-bust of 2004–2008, drives movements in R_S with y and P shocks at lower horizons. At longer horizons, own shock matters more, but the r_{FBS} shock contributes almost half of the variation in R_S at the 20-year horizon. Fluctuations in R_L are tied to P, R_S, and r_{FBS} shocks from 2- to 8- year horizons, while at the longest horizon the latter shock is responsible for 60 percent of this variation. Along with the FEVDs of table 8, these results support the view that $\mathcal{M}$ block variables can explain movements in $\mathcal{F}$ block variables but not in all regimes.[32]

Inside money dominates the FEVDs of Z_t created by the MS-BVAR model 8 for the joint regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 3$, according to table 10. This table shows that fluctuations in y, P, u, R_S, R_L, and r_{FBS} are dominated by shocks to M_I in the regime $S_{\mathcal{M},M_I} = 3|S_{\mathcal{F}} = 3$. These FEVDs are tied to an estimate of 0.001 of the factor loading scaling the SV of the M_I regression innovation, $\varepsilon_{M_I,t}$. We interpret this as evidence that a monetary variable dominates U.S. aggregate fluctuations from 1959 to 1966, which coincides with the latter part of William McChesney Martin's chairmanship of the Fed.

[32] Otherwise, the FEVDs of tables 8 and 9 resemble the FEVDs of table 3.

6 Conclusion

This paper studies the role of credit supply and demand shocks in U.S. financial crises and non-crisis business cycle fluctuations on an annual sample that begins in 1890 and ends in 2010. We identify credit supply and demand shocks in MS-BVAR models with inside money and its intertemporal price. Changes in financial and business cycle regimes are limited to stochastic volatility in the regression errors of the MS-BVARs. The MS-BVARs are employed to evaluate the hypothesis that financial and business cycle regimes recur throughout the long annual U.S. 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 because the scaling of shock innovations differs across crisis and non-crisis regimes.

We estimate MS-BVARs that yield evidence backing the hypothesis that U.S. financial crisis regimes recur throughout the 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 Iraq wars are placed within a financial crisis regime by this MS-BVAR.

The same MS-BVAR model contributes regime-dependent residuals and FEVDs revealing that the identified credit supply and demand shocks are economically meaningful. The identified shock innovations exhibit bursts of volatility that coincide with important episodes in U.S. financial and economic history. The best-fitting MS-BVAR is also responsible for 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 inside money shocks and shocks to the composition of the aggregate balance sheet of U.S. financial firms for explaining aggregate fluctuations. Thus, the FEVDs show that the SV regimes of MS-BVAR model 8 reveal economically meaningful aggregate fluctuations in regimes that are not possible in the fixed-coefficient-homoskesdatic BVAR.

This paper reports that the estimated MS-BVARs attribute central roles to inside money and stochastic volatility in explaining aggregate fluctuations. When inside money matters, interest rate rules may not serve as useful guides to monetary and macroprudential policies. However, our results depend 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 intercept and slope coefficient regime switching 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 that drive an economy out of a non-crisis regime and into a crisis. We leave these questions for future research, but 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 database 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 latter at http://research.stlouisfed.org/fred2/. Its tables Ba475–476 contain annual unemployment rate series from 1890 to 1990; see also 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 are the 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 begin in 1890 and end in 1958. We temporally aggregate these 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. Splicing the subsamples at 1958–1959 generates an 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 starts in $1918M01$; see http://research.stlouisfed.org/fred2/series/BASE?cid=124. We extract observations from $1923M01$ to $2010M12$. These data are temporally aggregated and spliced together at 1923 to produce an annual monetary base series for the 1890–2010 sample.

Inside Money: We 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 seeking 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 the 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 database) 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). Shiller cites Homer and Sylla (2005) 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 bonds from 1921 to 1952 (p. 351 and p. 375, tables 48 and 51). After 1952, Shiller 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 are 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. From *All Bank Statistics*, Board of Governors of the Federal Reserve System (1976b), we take the data on the private and public asset holdings of all commercial banks and thrifts from 1896 to 1955. These 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. These data are 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.

Financial Balance Sheet Composition Ratio of Private to Public Asset Holdings of Financial Firms: We 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 at the financial balance sheet composition 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 an 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	Parameterizations of Γ
	Dimension of MS Chains and Regimes per Chain on the Stochastic Volatility Scaling Matrix $\Gamma(\cdot)$
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	$\left\{\Gamma_{\mathcal{M}}\left(1\right)\ \Gamma_{\mathcal{M}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
5	$\left\{\Gamma_{\mathcal{M}}\left(1\right)\ \Gamma_{\mathcal{M}}\left(2\right)\ \Gamma_{\mathcal{M}}\left(3\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
6	$\left\{\Gamma_{\mathcal{M}}\left(1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(4\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
7	$\left\{\Gamma_{\mathcal{M}}\left(M_I, 1\right)\ \Gamma_{\mathcal{M}}\left(M_I, 2\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
8	$\left\{\Gamma_{\mathcal{M}}\left(M_I, 1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(M_I, 3\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
9	$\left\{\Gamma_{\mathcal{M}}\left(M_I, 1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(M_I, 4\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
10	$\left\{\Gamma_{\mathcal{M}}\left(R_S, 1\right)\ \Gamma_{\mathcal{M}}\left(R_S, 2\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
11	$\left\{\Gamma_{\mathcal{M}}\left(R_S, 1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(R_S, 3\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
12	$\left\{\Gamma_{\mathcal{M}}\left(R_S, 1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(R_S, 4\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
13	$\left\{\Gamma_{\mathcal{M}}\left(M_I, R_S, 1\right)\ \Gamma_{\mathcal{M}}\left(M_I, R_S, 2\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
14	$\left\{\Gamma_{\mathcal{M}}\left(M_I, R_S, 1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(M_I, R_S, 3\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$
15	$\left\{\Gamma_{\mathcal{M}}\left(M_I, R_S, 1\right)\ \ldots\ \Gamma_{\mathcal{M}}\left(M_I, R_S, 4\right)\ \Gamma_{\mathcal{F}}\left(1\right)\ \Gamma_{\mathcal{F}}\left(2\right)\ \Gamma_{\mathcal{F}}\left(3\right)\right\}$

When regime j is common to the $\mathcal{M}$ and $\mathcal{F}$ blocks, the SV scaling matrix is denoted $\Gamma(j)$. Otherwise, the number of regimes in the $\mathcal{M}$ and $\mathcal{F}$ blocks of the SV scaling matrices are $j_{\mathcal{M}}$ and $j_{\mathcal{F}}$, as in $\Gamma_{\mathcal{M}}(j_{\mathcal{M}})$ and $\Gamma_{\mathcal{F}}(j_{\mathcal{F}})$. The notation $\Gamma_{\mathcal{M}}(x, j)$ places $x = M_I,\ R_S$, or both into the $\mathcal{M}$ block of the SV scaling matrix.

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

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
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_{FBS}	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, $r_{FBS,t}$			
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 symbol $*$ indicates convergence problems for the MCMC simulator of a MS-BVAR(2) model that shows up as a poorly approximated ln marginal data density.

Table 5: Estimates of MS-BVAR(2) Model 8

First-Order Markov Transition Matrices

$\widehat{Q}$: $\mathcal{M}$ Block and M_I			$\widehat{Q}$: $\mathcal{F}$ Block		
0.975	0.046	0.000	0.956	0.102	0.000
0.025	0.908	0.192	0.044	0.797	0.027
0.000	0.046	0.808	0.000	0.102	0.973

Impact Matrix $\widehat{A}_0$

y	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
0.625	0.203	0.675	−0.590	0.110	0.087	−0.218
0.000	−1.579	0.327	−0.196	0.120	0.039	−0.088
0.000	0.000	2.320	−0.752	−0.147	0.178	−0.225
0.000	0.000	0.000	0.711	−0.152	−0.059	0.062
0.000	0.000	0.000	0.000	−1.406	0.683	−0.426
0.000	0.000	0.000	0.000	0.000	−4.201	−0.552
0.000	0.000	0.000	0.000	0.000	0.000	6.932

Diagonals of SV Matrices $\widehat{\Gamma}(S_t)$

	y	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
$s_{\mathcal{M},M_I} = 1 \mid s_{\mathcal{F}} = 1$	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	0.536	0.335	1.872	0.011
$s_{\mathcal{M},M_I} = 1 \mid s_{\mathcal{F}} = 3$	1.000	1.000	1.000	0.780	0.266	0.048	0.323
$s_{\mathcal{M},M_I} = 2 \mid s_{\mathcal{F}} = 1$	0.167	0.074	0.266	0.172	1.000	1.000	1.000
$s_{\mathcal{M},M_I} = 2 \mid s_{\mathcal{F}} = 2$	0.167	0.074	0.266	0.685	0.335	1.872	0.011
$s_{\mathcal{M},M_I} = 2 \mid s_{\mathcal{F}} = 3$	0.167	0.074	0.266	1.466	0.266	0.048	0.323
$s_{\mathcal{M},M_I} = 3 \mid s_{\mathcal{F}} = 1$	0.028	0.005	0.071	0.027	1.000	1.000	1.000
$s_{\mathcal{M},M_I} = 3 \mid s_{\mathcal{F}} = 2$	0.028	0.005	0.071	0.010	0.335	1.872	0.011
$s_{\mathcal{M},M_I} = 3 \mid s_{\mathcal{F}} = 3$	0.028	0.005	0.071	0.001	0.266	0.048	0.323

Table 6: FEVDs of Regime $S_{\mathcal{M},M_I} = 1 \mid S_{\mathcal{F}} = 2$ of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	**$\mathbf{M_I}$**	**$\mathbf{R_S}$**	**$\mathbf{R_L}$**	**$\mathbf{r_{FBS}}$**
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.70	0.01	0.01	0.03	0.06	0.00	0.20
	4	0.54	0.02	0.06	0.07	0.12	0.00	0.19
	8	0.20	0.02	0.12	0.04	0.05	0.00	0.58
	20	0.03	0.00	0.06	0.01	0.01	0.00	0.88
P	1	0.10	0.90	0.00	0.00	0.00	0.00	0.00
	2	0.11	0.82	0.00	0.01	0.06	0.00	0.00
	4	0.16	0.72	0.00	0.05	0.06	0.00	0.00
	8	0.20	0.58	0.00	0.12	0.05	0.00	0.05
	20	0.05	0.13	0.00	0.05	0.05	0.00	0.71
ur	1	0.56	0.02	0.42	0.00	0.00	0.00	0.00
	2	0.34	0.01	0.23	0.01	0.00	0.00	0.41
	4	0.21	0.00	0.13	0.03	0.07	0.00	0.56
	8	0.17	0.01	0.10	0.03	0.14	0.00	0.55
	20	0.07	0.00	0.04	0.01	0.07	0.00	0.80
M_I	1	0.25	0.00	0.06	0.69	0.00	0.00	0.00
	2	0.16	0.00	0.07	0.57	0.00	0.00	0.20
	4	0.10	0.00	0.09	0.52	0.00	0.00	0.28
	8	0.07	0.00	0.13	0.49	0.10	0.00	0.21
	20	0.04	0.00	0.14	0.39	0.36	0.00	0.08
R_S	1	0.01	0.00	0.01	0.02	0.97	0.00	0.00
	2	0.01	0.00	0.00	0.01	0.96	0.00	0.00
	4	0.02	0.00	0.00	0.01	0.95	0.00	0.01
	8	0.02	0.00	0.00	0.01	0.87	0.00	0.09
	20	0.01	0.00	0.00	0.00	0.35	0.00	0.63
R_L	1	0.00	0.00	0.00	0.03	0.59	0.37	0.00
	2	0.00	0.00	0.00	0.02	0.51	0.13	0.33
	4	0.01	0.00	0.00	0.01	0.50	0.07	0.40
	8	0.01	0.00	0.00	0.01	0.48	0.04	0.46
	20	0.00	0.00	0.00	0.00	0.24	0.01	0.74
r_{FBS}	1	0.00	0.00	0.00	0.00	0.00	0.00	0.99
	2	0.00	0.00	0.00	0.00	0.00	0.00	1.00
	4	0.00	0.00	0.00	0.00	0.00	0.00	1.00
	8	0.00	0.00	0.00	0.00	0.00	0.00	1.00
	20	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Table 7: FEVDs of Regime $S_{\mathcal{M},M_I} = 2 \mid S_{\mathcal{F}} = 3$ of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.95	0.02	0.01	0.01	0.02	0.00	0.00
	4	0.82	0.07	0.06	0.02	0.03	0.00	0.00
	8	0.58	0.09	0.22	0.02	0.03	0.06	0.01
	20	0.22	0.08	0.34	0.01	0.02	0.29	0.04
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	0.01	0.01	0.00	0.00
	8	0.13	0.83	0.00	0.02	0.01	0.01	0.00
	20	0.14	0.76	0.01	0.03	0.03	0.02	0.01
ur	1	0.64	0.05	0.31	0.00	0.00	0.00	0.00
	2	0.67	0.02	0.29	0.00	0.00	0.01	0.00
	4	0.64	0.03	0.25	0.01	0.04	0.01	0.01
	8	0.59	0.04	0.23	0.02	0.09	0.01	0.01
	20	0.56	0.04	0.21	0.02	0.10	0.03	0.03
M_I	1	0.59	0.01	0.08	0.32	0.00	0.00	0.00
	2	0.48	0.01	0.13	0.35	0.00	0.03	0.00
	4	0.36	0.01	0.21	0.39	0.01	0.03	0.01
	8	0.24	0.01	0.29	0.36	0.08	0.01	0.00
	20	0.13	0.01	0.31	0.27	0.24	0.04	0.00
R_S	1	0.03	0.02	0.02	0.02	0.92	0.00	0.00
	2	0.06	0.02	0.01	0.01	0.89	0.00	0.00
	4	0.09	0.01	0.01	0.01	0.86	0.03	0.00
	8	0.10	0.01	0.01	0.01	0.81	0.06	0.00
	20	0.07	0.01	0.01	0.01	0.74	0.13	0.04
R_L	1	0.00	0.00	0.00	0.00	0.04	0.95	0.00
	2	0.00	0.00	0.00	0.00	0.09	0.89	0.00
	4	0.01	0.01	0.00	0.00	0.15	0.83	0.00
	8	0.02	0.01	0.00	0.00	0.22	0.75	0.01
	20	0.02	0.01	0.00	0.00	0.32	0.63	0.03
r_{FBS}	1	0.09	0.01	0.00	0.01	0.12	0.06	0.72
	2	0.14	0.01	0.00	0.00	0.06	0.03	0.76
	4	0.18	0.01	0.00	0.01	0.02	0.03	0.74
	8	0.20	0.01	0.00	0.02	0.02	0.05	0.70
	20	0.21	0.03	0.00	0.02	0.02	0.06	0.66

Table 8: FEVDs of Regime $S_{\mathcal{M},M_I} = 3 \mid S_{\mathcal{F}} = 1$ of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.92	0.04	0.00	0.03	0.00	0.00	0.00
	4	0.74	0.15	0.03	0.08	0.00	0.00	0.00
	8	0.55	0.22	0.13	0.10	0.00	0.00	0.00
	20	0.31	0.29	0.32	0.07	0.00	0.00	0.00
P	1	0.02	0.98	0.00	0.00	0.00	0.00	0.00
	2	0.03	0.97	0.00	0.00	0.00	0.00	0.00
	4	0.04	0.95	0.00	0.01	0.00	0.00	0.00
	8	0.06	0.91	0.00	0.03	0.00	0.00	0.00
	20	0.07	0.87	0.00	0.06	0.00	0.00	0.00
ur	1	0.67	0.12	0.21	0.00	0.00	0.00	0.00
	2	0.72	0.07	0.20	0.02	0.00	0.00	0.00
	4	0.67	0.08	0.16	0.08	0.00	0.00	0.00
	8	0.62	0.11	0.15	0.11	0.00	0.00	0.00
	20	0.62	0.11	0.15	0.11	0.01	0.00	0.00
M_I	1	0.28	0.01	0.02	0.68	0.00	0.00	0.00
	2	0.22	0.01	0.04	0.73	0.00	0.00	0.00
	4	0.16	0.01	0.06	0.77	0.00	0.00	0.00
	8	0.12	0.01	0.09	0.78	0.00	0.00	0.00
	20	0.09	0.01	0.13	0.77	0.01	0.00	0.00
R_S	1	0.14	0.24	0.05	0.35	0.21	0.00	0.00
	2	0.30	0.21	0.04	0.26	0.20	0.00	0.00
	4	0.44	0.16	0.04	0.18	0.18	0.00	0.00
	8	0.48	0.15	0.03	0.15	0.18	0.00	0.00
	20	0.43	0.15	0.03	0.18	0.19	0.01	0.01
R_L	1	0.06	0.10	0.00	0.43	0.08	0.33	0.00
	2	0.06	0.26	0.00	0.38	0.11	0.19	0.00
	4	0.13	0.34	0.00	0.29	0.11	0.12	0.00
	8	0.24	0.33	0.00	0.20	0.13	0.09	0.00
	20	0.28	0.24	0.00	0.17	0.20	0.07	0.02
r_{FBS}	1	0.41	0.15	0.00	0.21	0.02	0.00	0.20
	2	0.58	0.13	0.00	0.08	0.01	0.00	0.19
	4	0.65	0.07	0.00	0.12	0.00	0.00	0.15
	8	0.61	0.06	0.00	0.21	0.00	0.00	0.12
	20	0.51	0.19	0.00	0.21	0.00	0.00	0.09

Table 9: FEVDs of Regime $S_{\mathcal{M},M_I} = 3 \mid S_{\mathcal{F}} = 2$ of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
y	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.93	0.04	0.00	0.01	0.00	0.00	0.01
	4	0.77	0.15	0.03	0.03	0.00	0.00	0.01
	8	0.56	0.23	0.13	0.03	0.00	0.00	0.04
	20	0.25	0.23	0.25	0.02	0.00	0.00	0.24
P	1	0.02	0.98	0.00	0.00	0.00	0.00	0.00
	2	0.03	0.97	0.00	0.00	0.00	0.00	0.00
	4	0.04	0.95	0.00	0.00	0.00	0.00	0.00
	8	0.06	0.93	0.00	0.01	0.00	0.00	0.00
	20	0.07	0.88	0.00	0.02	0.00	0.00	0.03
ur	1	0.67	0.12	0.21	0.00	0.00	0.00	0.00
	2	0.71	0.06	0.19	0.01	0.00	0.00	0.02
	4	0.67	0.08	0.16	0.03	0.01	0.00	0.05
	8	0.63	0.12	0.15	0.04	0.01	0.00	0.06
	20	0.55	0.10	0.13	0.03	0.01	0.00	0.17
M_I	1	0.51	0.03	0.04	0.42	0.00	0.00	0.00
	2	0.42	0.02	0.07	0.47	0.00	0.00	0.02
	4	0.32	0.02	0.12	0.52	0.00	0.00	0.03
	8	0.23	0.03	0.18	0.53	0.01	0.00	0.02
	20	0.17	0.02	0.25	0.51	0.04	0.00	0.01
R_S	1	0.11	0.20	0.04	0.10	0.55	0.00	0.00
	2	0.24	0.17	0.03	0.07	0.49	0.00	0.00
	4	0.34	0.13	0.03	0.05	0.45	0.00	0.00
	8	0.35	0.11	0.02	0.04	0.42	0.00	0.05
	20	0.18	0.06	0.01	0.03	0.26	0.00	0.46
R_L	1	0.09	0.15	0.00	0.21	0.34	0.21	0.00
	2	0.06	0.24	0.00	0.12	0.31	0.08	0.20
	4	0.10	0.27	0.00	0.08	0.28	0.04	0.22
	8	0.16	0.22	0.00	0.05	0.28	0.03	0.27
	20	0.09	0.08	0.00	0.02	0.20	0.01	0.60
r_{FBS}	1	0.02	0.01	0.00	0.00	0.00	0.00	0.96
	2	0.03	0.01	0.00	0.00	0.00	0.00	0.96
	4	0.05	0.01	0.00	0.00	0.00	0.00	0.95
	8	0.05	0.01	0.00	0.01	0.00	0.00	0.94
	20	0.06	0.02	0.00	0.01	0.00	0.00	0.91

Table 10: FEVDs of Regime $S_{\mathcal{M},M_I} = 3 \mid S_{\mathcal{F}} = 3$ of MS-BVAR(2) Model 8

		Shock						
	Year	**y**	**P**	**ur**	$\mathbf{M_I}$	$\mathbf{R_S}$	$\mathbf{R_L}$	$\mathbf{r_{FBS}}$
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_{FBS}	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

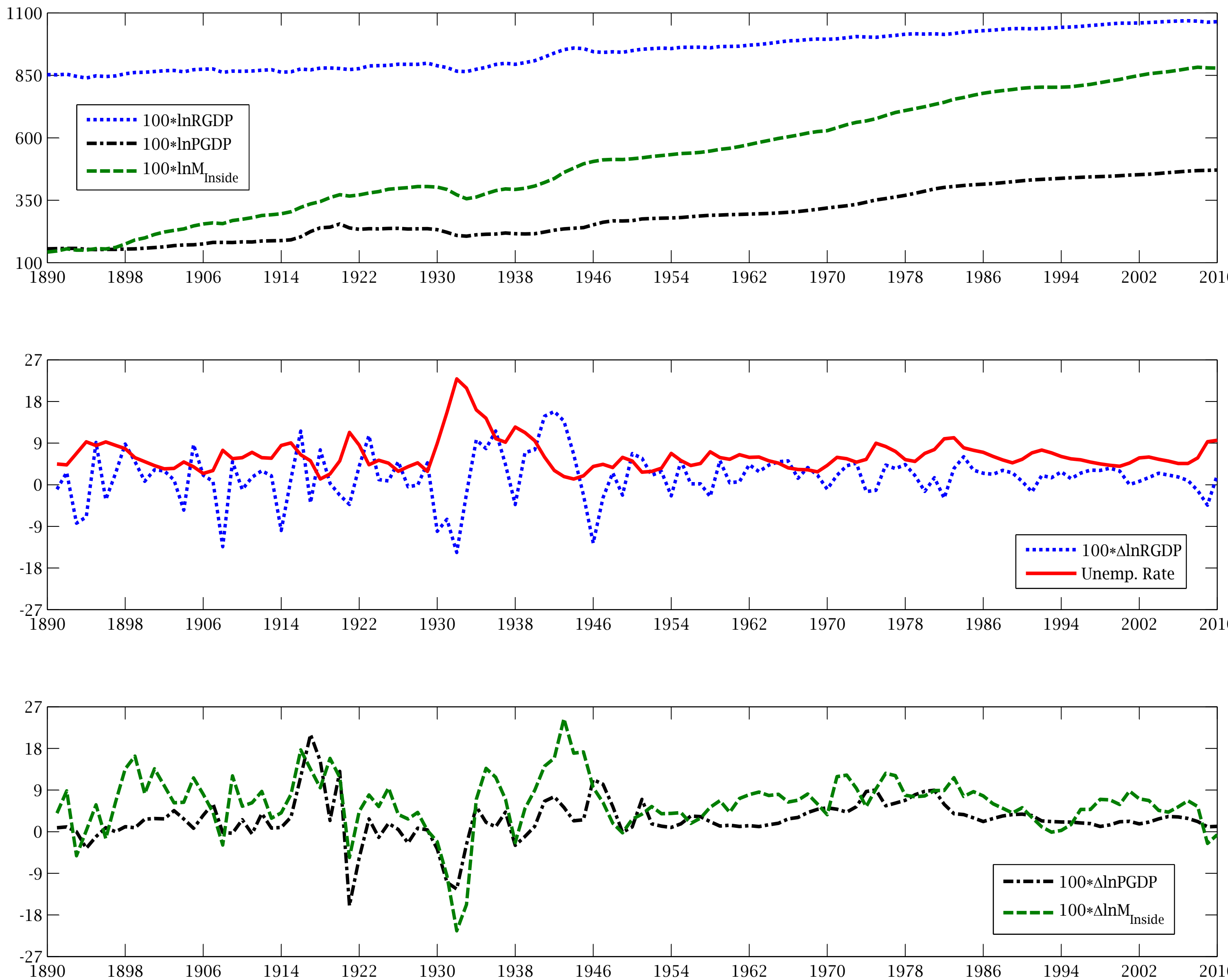

Figure 2: U.S. Short Rate, Long Rate, and Risk Ratio, 1890–2010

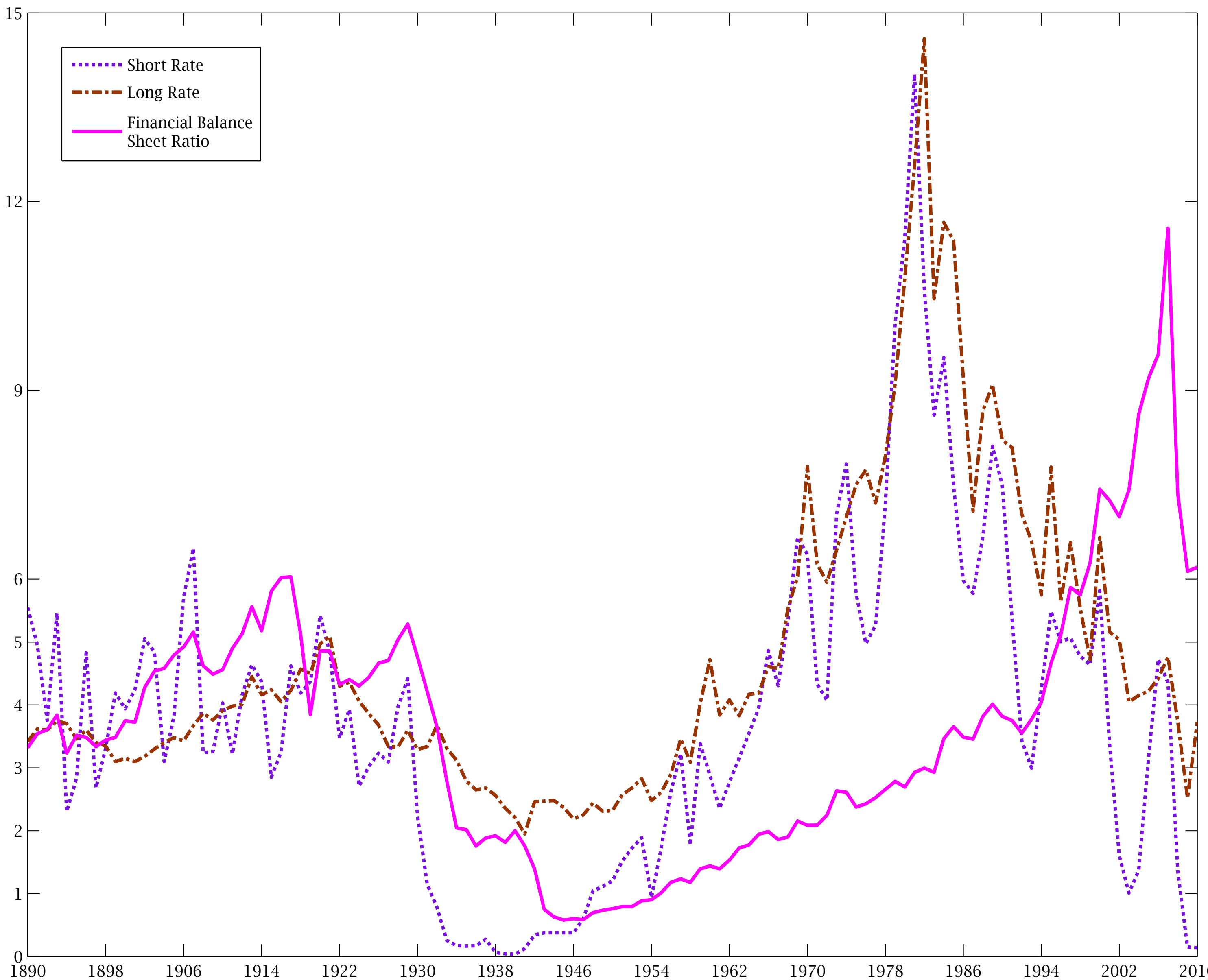

Figure 3: IRFs of Fixed Coefficient-Homoskedastic BVAR(2)

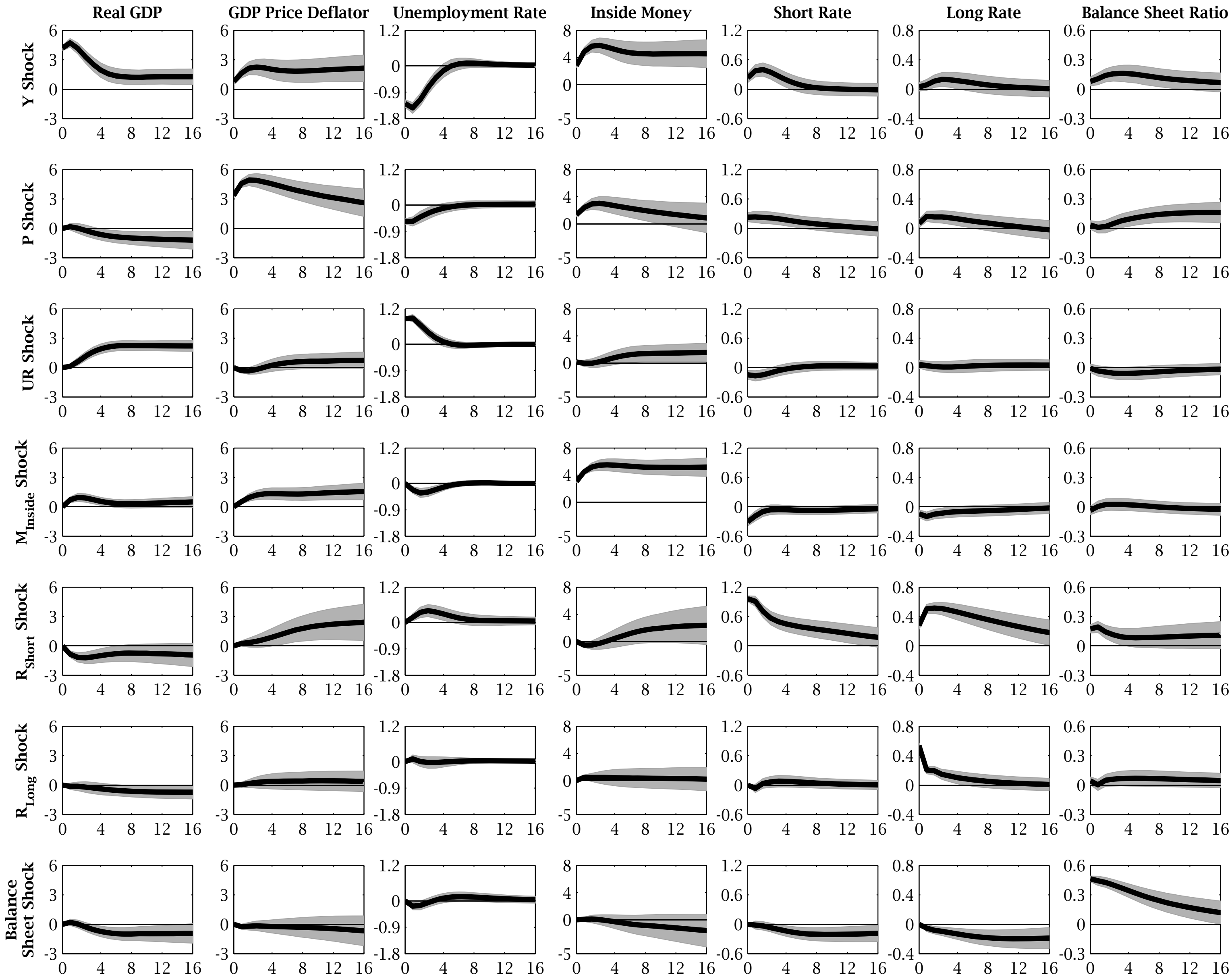

Figure 4: 3 SV Regime Probabilities: Estimates of MS-BVAR(2) Model 2, 1891-2010

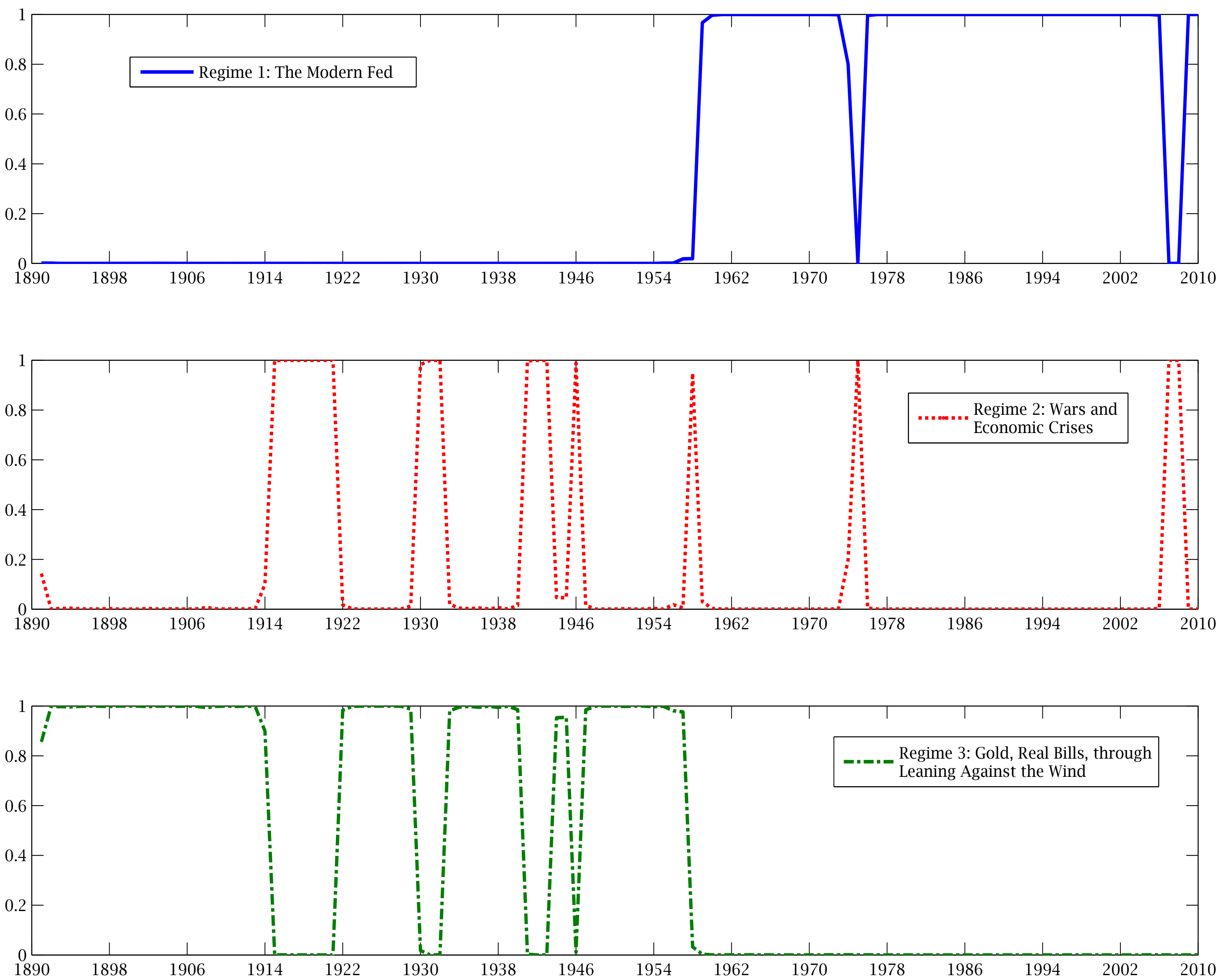

Figure 5: 4 SV Regime Probabilities: Estimates of MS-BVAR(2) Model 3, 1891-2010

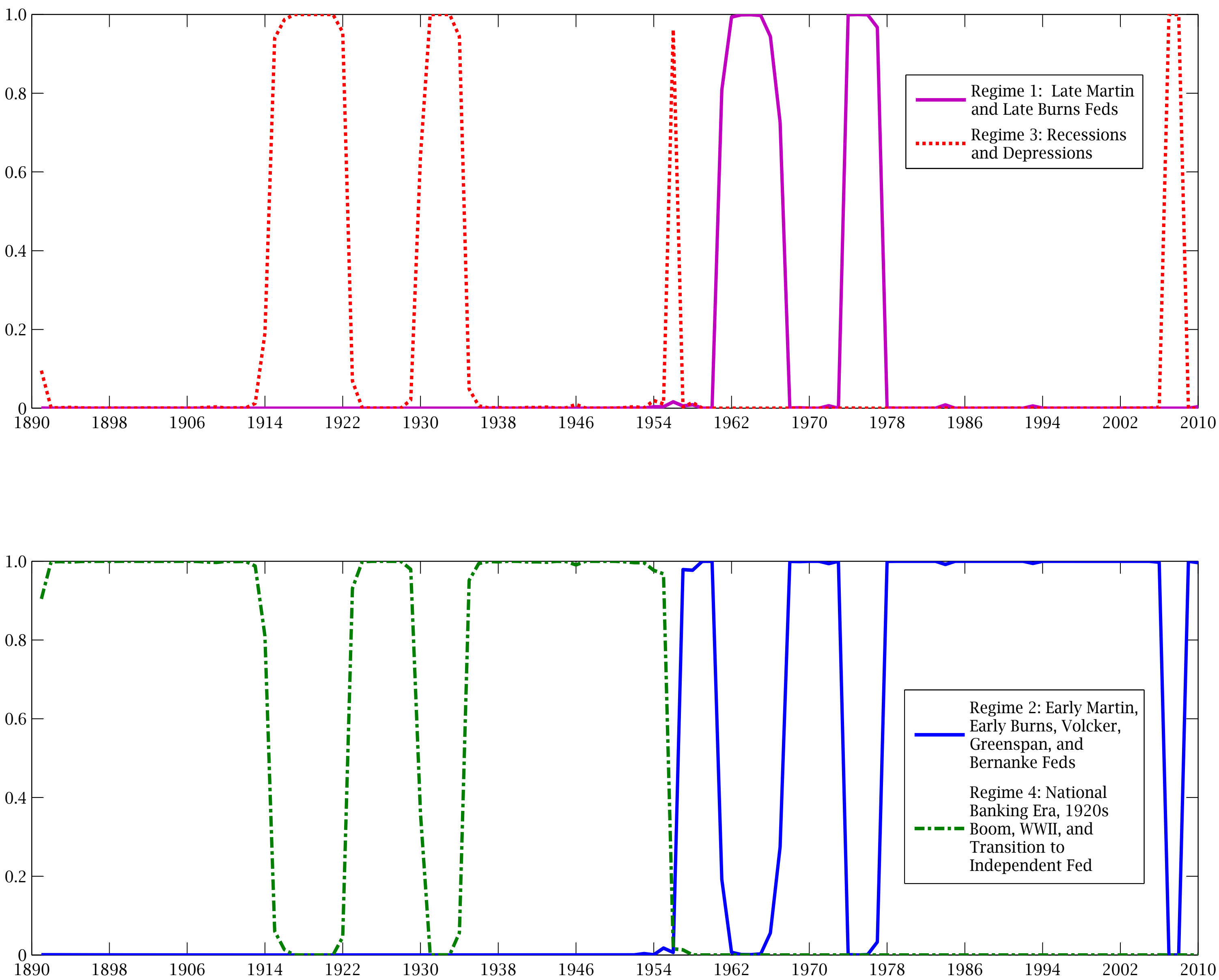

FIGURE 6: 3 SV REGIME PROBABILITIES OF THE $\mathcal{M}$ BLOCK: ESTIMATES OF MS-BVAR(2) MODEL 8, 1891-2010

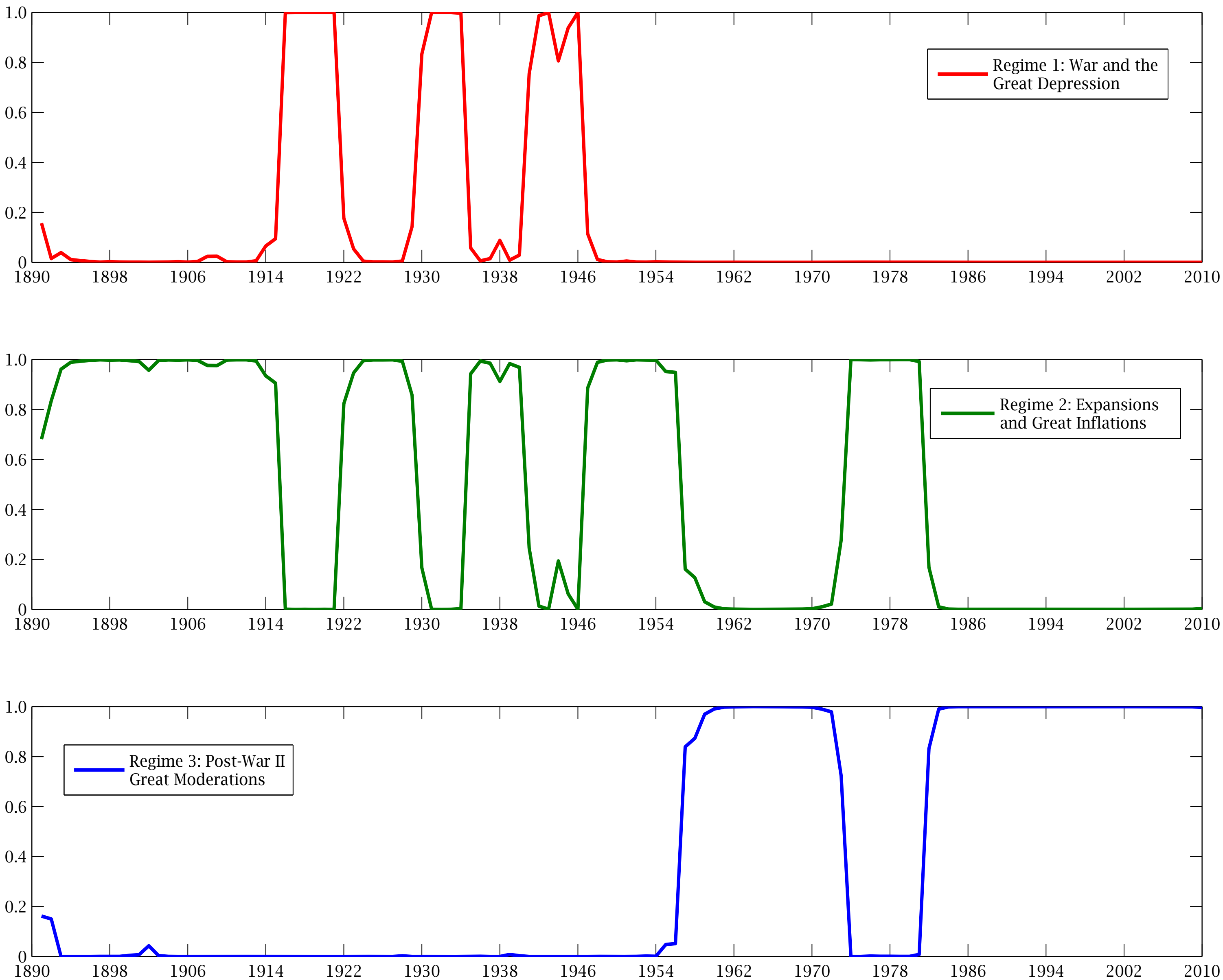

Figure 7: 3 SV Regime Probabilities of the $\mathcal{F}$ Block: Estimates of MS-BVAR(2) Model 8, 1891-2010

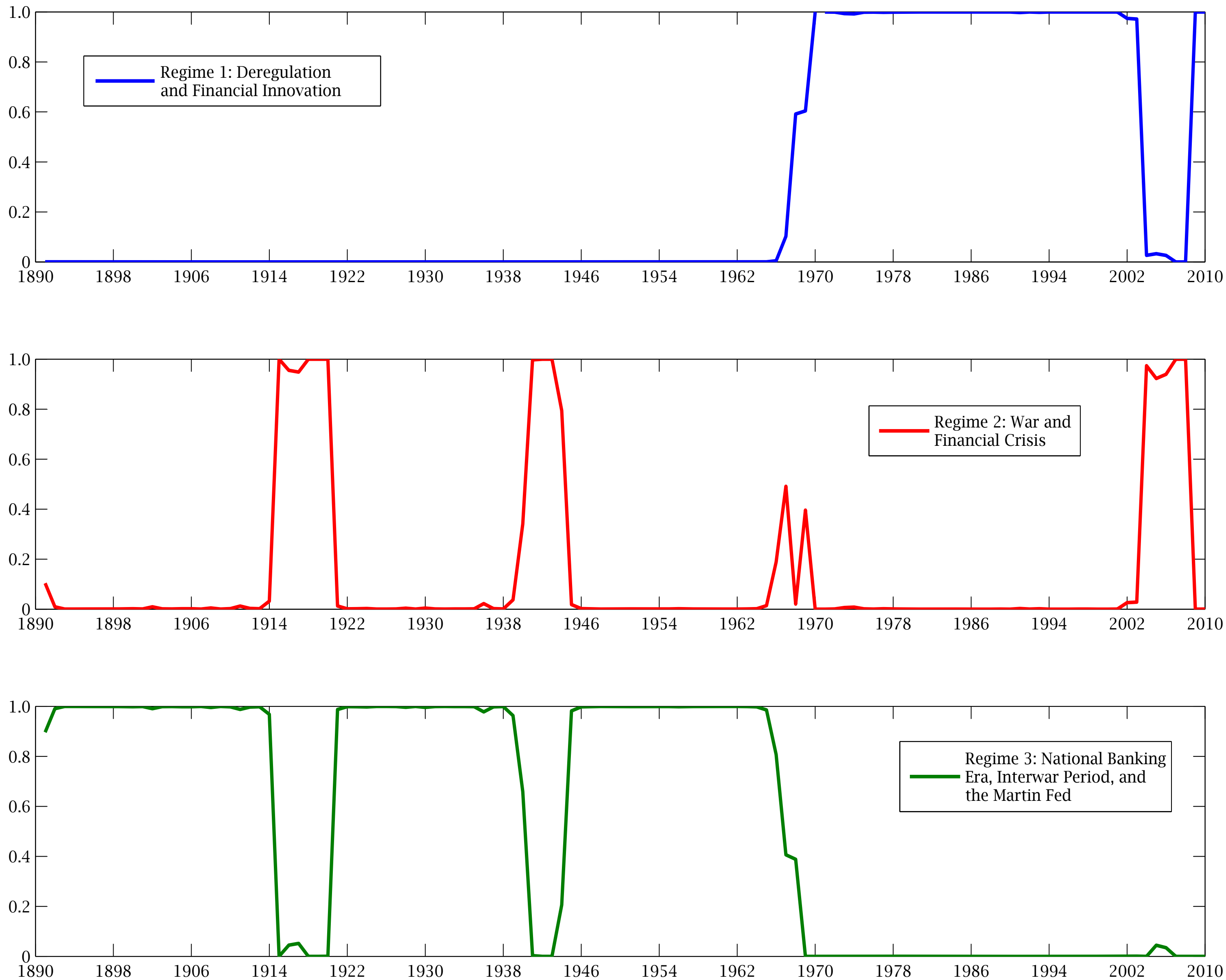

Figure 8: Regime-Dependent Residual Estimates of MS-BVAR Model 8