This Draft: 1/20/2011

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BUSINESS CYCLES AND FINANCIAL CRISES: THE ROLES OF CREDIT SUPPLY AND DEMAND SHOCKS

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The authors thank Joseph Haubrich, Hugh Rockoff, Richard Sylla, and James Thompson for useful suggestions and the participants of Cliometrics II session at the Southern Economics Association meetings to be held in Washington, D.C. November 19, 2011. We also thank Joy Zhu for expert research assistance.

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The paper was previously entitled, “Financial Crisis on Financial Crisis: How Likely Was Output to Go Its Own Way?”

I INTRODUCTION

Seldom has the U.S. been confronted by a major financial crisis and at the same time a deep and persistent economic slowdown since the Great Depression. However, just over a decade into the new millennium this is the position in which the U.S. finds itself. The response of economists has been to revisit the Great Depression as well as the financial panics that afflicted the U.S. between the end of the Civil War and 1929.

Much recent research focuses on predicting financial crises using observed macro and financial aggregate data. Leading examples are Eichengreen and Mitchener. (2003), Reinhart and Rogoff (2009), Bordo and Haubrich (2010), Schularick and Taylor (2010), and Jordà, Schularick, and Taylor (2011). These papers present evidence on the co-movement of macro aggregates and indicators of financial risk over the business cycle and at longer horizons for the U.S. and internationally. Bordo and Haubrich (2010) and Jordà, Schularick, and Taylor (2011) engage non-parametric methods to measure co-movement of real activity and financial risk, while Reinhart and Rogoff (2009) include unconditional moments to gauge the extent measures of financial risk anticipate substantial economic downturns. Eichengreen and Mitchener (2003) regress output growth on credit growth on a cross-country sample from the late 1920s and ealry 1930s. The regressions reveal that a pre-1929 credit boom contributed to the Great Depression. The notion that credit growth drives financial crises associated with large and persistent recessions is developed further by Schularick and Taylor (2010). Their aim is to determine the predictors of financial crises using a long annual sample cross country sample. Predictability is associated with the regression covariates that help most to explain the probability of financial crisis in a country. They interpret their empirical results as showing that the shocks financial markets propagate into real activity can originate within this sector of the economy.

This paper picks up from Schularick and Taylor (2010) by estimating structural VARs that identify supply and demand shocks to aggregate credit. We estimate these SVARs on a long annual sample running from 1897 to 2010. By beginning the sample in 1896, we have observations that measure part of the pre-Federal Reserve Era, the pre-Federal Deposit Insurance Corporation (FDIC) Era, the "quiet period" 1935-1981 (Gorton 2010), and the past thirty years of increasing deregulation. The sample data consists of real GNP, the GNP implicit price deflator, a 1-year interest rate, inside money, and three variables that proxy for financial market risk. The financial variables are the ratio of private assets held by banks to public assets held by banks, the ratio of private bank assets to bank capital, and a AAA corporate-long Treasury bond yield spread data. The ratio reflect different aspects of the risk in the composition of bank assets, while the corporate-Treasury bond spread captures changes in the relative demand of risky private assets to public assets. The yield spread is a commonly used proxy of financial market risk, which we include as a conservative metric for whether our banking aggregates are useful indicators of financial risk. Inside money in the SVARs enables identifications in movements of the short-term liabilities the banking system employs to support its acquisition of longer-dated assets. This identification scheme gives the SVARs a map to estimate the impact of credit supply and demand shocks on real GDP, inflation, and short-term interest rates.

A small set of macroeconomic and financial market aggregate measures are used to keelp the SVARs tractable and interpretable. The SVARs are estimated on the log of real GNP (in levels or growth rates), the log of implicit GNP price deflator (or inflation), the log of inside model (in levels or growth rates), the 1-year interest rate, and one of the three financial risk variables. We ground the SVARs on short-run identifications to uncover credit supply and demand shocks that help explain subsequent contractions in real output. Our preliminary results suggest that there is credit supply-demand system that is recoverable from our financial market risk proxies. When the SVAR is estimated using the bank asset ratio, we recover a reasonable credit supply and demand system. A bank asset-credit demand shock drives inside money higher and the 1-year rate lower 2 to 3 years later. On the supply side, the bank asset rate rises at impact in response to an inside money-liability supply shock, while the 1-year rate falls at the same time. Thus, this paper aims to explain responses to identified credit supply and demand shocks in all periods as opposed only estimating the impact on real activity in and around the time of financial crises. Our ultimate goal is to gain a deeper understanding of the way the financial sector propagates own, real, and nominal shocks. Estimates of this propagation mechanism should help us to measure the relative contributions of real, nominal, and credit supply and demand shocks to fluctuations in output, inflation, and other macro variable.

We outline briefly a selection of the existing literature on financial risk measures and macroeconomic performance. We highlight that the literature rarely addresses the question of identifying underlying supply and demand shocks to credit. Recognizing the difficulty of measuring these latent shocks, we suggest alternative paths to address the question and motivate our construction of two banking measures of financial risk, which are not commonly exploited in macroeconomic models. Section III describes our bank asset ratio, bank asset-bank capital ratio, and the corporate-Treasury bond spread. We discuss the SVAR identification in section IV. Preliminary results are reported in section V. We conclude in section VI.

II BACKGROUND

The recent financial crisis (2007-2009) has motivated a number of investigations into the sources of financial distress. Recent research by Schularick and Taylor (2010) emphasizes that banks worldwide had expanded loans and funded those loans with liabilities other than deposits. In the paper, the authors illustrate that there had been a closer connection between aggregate credit (assets) and aggregate money (liabilities) prior to World War 2; the authors argue that the subsequent separation of the two quantities generated an excess of credit that was effectively unchecked because the liability measures were what was being monitored. The research shows that a rapid growth in the real value of bank loans is a significant predictor of future financial crisis. Underlying their analysis was the inference that financial market leverage was rising above normal thresholds.

Schularick and Taylor (2009) also generate empirical results indicating that financial crises have a predictable relationship with the growth rate of the real value of bank loans. A financial crisis arises following a period of excessive growth in the real value of bank loans. The paper displays strong empirical results because it effectively exploits a large set of time series observations and a large number of countries. In such a circumstance, the number of financial crisis observations accumulates to allow an empirical investigation to proceed. In an investigation of an individual country, the number of financial crisis periods would be too small to make statistical inferences.1 This paper extends the idea that bank liabilities, assets and capital are a potential source for identifying shocks to credit supply and demand. These shocks are latent financial market risk factors that are sources of aggregate fluctuations at business cycle and longer frequencies.

Gorton (2010) argues that the 2007-2009 financial crisis was effectively a run on overnight repurchase agreement funding arising from asymmetric information about the value of assets that underlay the collateral for the repo arrangements. In related work, Brunnermeier

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1 Jalil (2010) is an exception, and it provides analysis of the real output costs of financial crisis for the United States.

(2009) emphasizes that there are two important forms of liquidity -- market liquidity and funding liquidity. In the recent crisis, firms found that both forms were compromised after the failure of Lehman Brothers. These works investigate the factors that led to the crisis, but eschew normative analysis in these papers.

Krishnamurthy and Vissing-Jorgensen (2010) have a different view on the factors that drive the demand for financial securities. This view places great weight on the impact changes in the supply of Treasury securities have for returns on other assets. Besides being a source of liquidity, Treasury securities are an asset investors prize for their safety. Krishnamurthy and Vissing-Jorgensen (KVJ) build an asset pricing model in which a demand for safety and liquidity generate risk premia on Treasury securities. This asset pricing model motivates yield spread regressions that include the Treasury debt-GDP ratio. KVJ run these regression on annual samples from 1926 to 2008 to construct estimates of Treasury safety and liquidity risk premia. The estimates indicate that investors received a 46 basis point liquidity premium in return for holding AAA-corporate bonds rather than 10-year Treasury bonds. Treasury bills earn a safety premium of about 26 basis points over short-term private assets according to the estimates of KVJ. We take from KVJ's asset pricing model and estimates that the composition of private and public assets on bank balance sheets contains information about the demand for risky assets.

Reinhart and Rogoff (2009) demonstrate that there is a long history of financial crises across countries and through the centuries but the memory of crises is fleeting. Each time a crisis is in the making, there are scores of advocates claiming that "this time is different" and that there is a fundamental support to asset prices. Other researchers have emphasized how the investment banks in the U.S. relied heavily upon overnight funding sources and placed, by extension, the entire financial market at risk as a result of the internal linkages across intermediaries -- highlighting both funding risk and counter-party risk (Brunnermeier 2009). In most cases, the leading research effectively follows the path of destruction and uses the wreckage to guide them toward the usual suspects in the financial crisis. For example, the role of mortgage and housing related assets, residential mortgage backed securities (RMBS) comprised of subprime mortgage loans and ineffective risk management at banks led to large losses on real estate investments at commercial and investment banks. It is clear that if we look at bank assets related to real estate, we will find a problem for the banking sector. Finding the source of the last crisis is valid and explaining the developments as they ensued is fine economic historical scholarship. There are other observable warning signals in observed financial aggregates for current and future real activity that should alert policymakers to a potential financial crisis, according to Reinhart and Rogoff. Prompted by Reinhart and Rogoff, we explore whether the underlying credit supply and demand shocks can be identified from observed macro and financial aggregates.

The next section presents the over 100 years of U.S. data that we engage to try to answer this question.

III DATA

This section describes the data on which Bayesian VARs are estimated to uncover the responses of U.S. real GNP, inflation, and nominal interest rates to identified credit demand and supply shocks. The data is grounded on a long annual sample ranging from 1986 to 2010. The estimation sample begins with 1897 and ends in 2010 because the VAR information sets include real GNP growth, as well as first differences of several of our proxies for financial market risk.

III.a Data Construction

We employ real GNP to measure aggregate real activity on a long annual U.S. sample from 1896 to 2010. The corresponding aggregate price level is the implicit GNP deflator (i.e., the ratio of nominal to real GNP). The log of real GNP and log of the implicit GNP deflator are differenced to compute output growth and the inflation rate. Details on the construction of the nominal and real GNP series are found in Balke and Gordon (1986) and the data appendix to this paper.

A 1-year interest rate series plays the role of the short-term rate in the VARs. This series is an update of the short-term interest rate series reported in Shiller (2005).2 He constructs a synthetic asset with a 1-year holding period return using the 4-6 month commercial paper rate from 1896 to 1938, the 6-month commercial rate from 1939 to 1997, and secondary market rate on 6-month certificates of deposit from 1998 to 2010.

We construct our bank variables from various sources. The data appendix provides more detail about the sources of the banking data. The banking aggregates -- total assets, total liabilities, and the relevant sub-categories -- are from All Bank Statistics, 1896-1955, a publication of the Board of Governors of the Federal Reserve System. These data measure quantities for all deposit-taking institutions including savings and loans and trust companies. We get comparable data from the Federal Deposit Insurance Corporation (FDIC) for the period 1934-2010. However, these data include only commercial banks from 1934-1983; the statistics have an obvious jump in 1984 when savings and loan data were reported to the FDIC and these series were added to the aggregates for commercial banks. At the time of this draft, we are

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2 The short-term interest rate data is available online at www.econ.yale.edu/~shiller/data/ie_data.xls, which is a web page maintained by Robert Shiller.

searching for a source for the savings and loan data from 1956-1983. In the interim, we have made a short-hand adjustment to the series to modify the jump in 1984. The pre- and post-1984 data are spliced together using the average differences between the All Bank Statistics and the FDIC data for 1934-1955 because this is the period over which we have data from both sources. From these observations, we draw a trend line adjustment to create a level shift with an upward drift in the series. The underlying fluctuations in the underlying FDIC series are still apparent but there is no longer a level jump from 1983 to 1984.

We take the total assets of banks and subtract "cash and due froms" -- a broad measure of cash items – as well as subtracting "Treasury Debt holdings, agency debt, and state and other political entities" from the total. We refer to this aggregate as "private debt" or "claims on private entities" held by banks, while the sum of broad cash holdings and the Treasury, agency and state debt holdings is labeled "public debt" or "claims on public entities" held by banks. The ratio of private debt to public debt is one means for measuring the risk composition of the asset side of the aggregate bank balance sheet. We display this ratio in Figure 1.

Our "inside money" variable yields information about the composition of aggregate bank liabilities. This measure of bank liabilities is constructed from M1 and M2 aggregates. These monetary aggregates are obtained on a quarterly frequency from Balke and Gordon (1986) and extended from 1959 to 2010 using the monthly monetary aggregate series from the Board of Governors of the Federal Reserve System. The M1 series, however, begins in 1915.[3] Here, we attempt to estimate an M1 aggregate by first arguing that commercial bank deposits were less consistently measured prior to the Fed, and make a strong claim that the state bank and trust

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3 Friedman and Schwartz (1970) argue that the distinction between demand deposits and time deposits was not functionally relevant in distinguishing between M1 and M2 in the pre-Fed era. As a result, the M2 aggregate series goes back further and is continuous prior to 1915.

deposits that are included in the M2 aggregate are less "transactions" related than deposits in national banks. This is a strong claim. However, one justification surrounds the case of New York City trust companies, in which deposit turnover was only 7 percent of the turnover experienced by New York City national banks.[4] State bank deposit turnover was higher than that of trusts, but still national banks were the predominant transactions balances in New York City. Hence, with the caveats noted, the assumption gives a clear path to a measurable M1 aggregate. Deposits of state and trust banks are removed from the M2 aggregate to produce our pre-1915 M1 series.

The corporate-Treasury bond yield spread is the result of joining together several bond yield series. Bond yields prior to the Great Depression are taken from Homer and Sylla (2005) and Macaulay (1936); also see Shiller (2005). Otherwise the data is available online from the data resources provided by the Federal Reserve Bank of St. Louis.

III.b Unconditional Evidence

Figure 1 displays the ratio of private assets to public assets held by banks in the U.S. from 1896 to 2010.[5] The shading highlights four instances of financial crisis: 1907, 1929, 1984, and 2007. These were the instances of financial distress emphasized in Taylor and Schularick (2009). The figure indicates, for instance, that in 1929 banks in the U.S. held private assets in approximately four times the quantity of its public asset holdings. Notably, the ratio falls to a

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4 See Barnett (1910), pages 133-134. Further, Barnett notes that trust companies were less inclined to hold deposits of other institutions, also indicating how their deposit holdings played a lower profile role in payments.

5 We note that the ratio is smoothed to incorporate the introduction of savings and loans data into the aggregate FDIC numbers as of 1984.

nadir of 0.3 in 1945 indicating both the quantity of U.S. Treasury debt issued and the amount held by the banks.

The graph displays two notable periods in which the ratio of private to public assets on bank balance sheets rose and then subsequently fell sharply.[6] The ratio rose until 1929 and then fell sharply, most precipitously later on in 1932. In the later example, the ratio rose in a similar manner from mid 2003 through 2007, and the ratio rose beyond previous levels. The sharp plummet of the series in 2007-2009 displays another similarity with the behavior observed in the series during the Great Depression. The other two crises do not display this pattern; the decline in the ratio comes after the Panic of 1907, and there appears to be no decline in the ratio in 1984.[7]

Table 1 presents summary statistics for our sample data. The first half of table includes unconditional statistics for the variables that are stationary in levels. Statistics for growth rate and differenced data appear in the bottom half of table 1.

The figures and table 1 offer casual observation, not causal evidence. The ratio of private assets to public assets on bank balance sheets displays the composition of bank assets. It is not surprising that following the banking crises of the Great Depression that banks held an increasing proportion of bank assets in the form of government debt. Similarly, in the aftermath of the 2007-2009 financial crisis, banks shifted their asset holdings toward lower risk assets. The

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6 The sharp decline in the ratio in 1917-1919 likely reflects the increase in bank purchases of Liberty war bonds during World War I.

7 The lack of a decline in the ratio may reflect the introduction of the savings and loan data in the series. We do not draw a strong inference from this observation. We seek to solve this data issue in a revision of the paper.

declines in the ratio are therefore understandable and not surprising. The question is whether the "run up" in the ratio provides a signal for policymakers that a financial crisis is in the making.

V SVAR IDENTIFICATION AND ESTIMATION

We employ vector autoregressions (VARs) to study the effect of credit supply and demand shocks on real output, the price level, and the short-term interest rate. The estimation process starts with the unrestricted *p*th-order VAR

$$X(t) = \mathbf{A}(\mathbf{L})X(t\text{-}1) + u(t),$$

where $X(t) = [y(t)\;\; P(t)\;\; R(t)\;\; D(t)\;\; Z(t)]'$, which includes the log of real GNP, the log of implicit GNP price deflator, the log of inside money, and a financial market risk proxy, the matrix lag polynominal $\mathbf{A}(\mathbf{L})$ is invertible, and u(t) is a vector of Gaussian forecast innovations with covariance matrix $\mathbf{\Omega} = \mathbf{E}\{u(t)\, u(t)'\}$. Corresponding to the unrestricted VAR is an unrestricted vector moving average

$$X(t) = \mathbf{B}(\mathbf{L})\varepsilon(t),$$

where $\mathbf{B}(\mathbf{L})$ is square summable and ε(t) are the structural or Wold innovations with unit variance $\mathbf{E}\{\boldsymbol{\varepsilon}(t)\, \varepsilon(t)'\} = \mathbf{I}$. The structural innovations are computed as $\varepsilon(t) = \boldsymbol{C}^{-1}\hat{u}(t)$, where $\boldsymbol{C}$ is the Choleski decomposition of $\mathbf{\Omega}$ and $\hat{u}(t)$ are estimates of unrestricted forecast innovations u(t). The Choleski decompostion contains recursive restrictions that are our short-run identification scheme. It follows that the impulse response functions are constructed using $\mathbf{B}(j) = \mathbf{A}(j)\varepsilon(t)$, where it is clear that the $\mathbf{A}(j)$ are estimates of the true VAR coefficients.8

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8 See Hamilton (1994) for details about the estimation of SVAR using short run identifying restrictions and for computing confidence bands of impulse response functions.

The unrestricted VAR is estimated with either the bank asset ratio, the private asset-bank capital ratio, or the corporate-Treasury bond yield spread. This gives us three VAR models that differ only in the selected measure of financial risk. The first financial risk variable measures the asset composition of the banking sector, which we define as the ratio of private assets to public assets on bank balance sheets. An increase in this ratio indicates greater "riskiness" in financial markets. The second financial risk variable gives us observations on bank leverage. Our notion of bank leverage is the ratio of private bank assets to bank capital. This is a measure of riskiness in financial markets that rises with bank leverage. Last, we employ a "risk spread" variable that is the difference between Moody's AAA bond yield and the long-term Treasury composite yield. The corporate-Treasury bond yield spread is a forward-looking signal about financial risk in the U.S. economy. This signals heightened financial risk tied to expectations of greater corporate defaults and/or demand for long-term Treasury securities.

V ECONOMETRIC RESULTS

We estimate our VAR in first differences as a first pass. Tests for stationarity of the time-series data indicated that each data series except for the short-term interest rate had a unit root. As a result, we first difference the data prior to estimation. The data are discussed in more detail below.

Figure 2 presents a graphical display of all the series (except for the yield spread, which is in Figure 3). Visual inspection suggests that these series display non-stationarity in levels. We examine the time-series properties of the data series and found that only the one year interest rate and the risk spread were stationary in levels. All other series were differenced to induce stationarity; in the case of real GNP, the deflator, and inside money, we took logs and differenced them so that the series were in percentage changes. Tests of lag length indicated that one lag of the data series were sufficient for the VAR.

We identify the VAR by use of a Choleski causal ordering, which follows the ordering as described above. By leaving the financial variables last in the system, the impulse response results indicate the effect of shocks associated with the financial variables that are orthogonal to shocks associated with real GNP, the implicit price deflator, the one year interest rate, and inside money. Figure 3 displays the graphs of the data series in the difference transformation (and also displays the risk yield spread. It is notable that the change in the ratio of private to public assets displays the largest decline following 2007. In contrast, the risk spread measure rises by more than twice the increase posted in 2007; the increase in the spread during the 1981-82 recession was also larger than the one in 2007.

Figure 5 presents impulse response graphics for the VAR model of the growth rate in real GNP, the inflation rate (measured by the implicit GNP deflator), the one year interest rate, the growth rate of inside money, and the difference in the ratio of private assets to public assets held by banks. The impulse response functions have error bounds that represent the 16th and 84 percentiles of Monte Carlo simulations of the VAR estimations. These bounds are indicators of statistical significance. The findings do not support any significant effect on real output growth arising from innovations associated with the financial risk proxy as measured by the ratio, although an increase in the asset ratio is associated with a decrease in the growth rate of real GDP. However, an innovation associated with the asset ratio has a significant negative effect on the inflation rate, a significant negative effect on the growth rate of (nominal) inside money, and a positive effect on the nominal one year interest rate. The effects on the inflation rate and the nominal interest rate are notable, and may suggest that an increase in the ratio of private to public assets on bank balance sheets increases short-term interest rates although the effect appears to diminish rapidly. In contrast, an increase in the ratio is associated with lower inflation. The negative response of inside money growth to the increase in private relative to public assets on bank balance sheets may indicate that banks can fund these private assets with liabilities like narrowly defined transactions balances (like M1). The asset ratio responds notably to innovations associated with the short term interest rate and with the growth rate of inside money. A higher growth rate of inside money leads to higher ratio of private to public assets, consistent with the converse relationship. The innovation in the one year interest rate, however, leads to a higher ratio of private to public asset ratio.

Figure 6 displays the impulse response graphs for the five variable VAR that includes the difference in the leverage ratio as the financial variable. The graphics indicate that there is no statistically significant effect of the innovation associated with leverage on any of the other series in the VAR.

Figure 7 presents the impulse responses for the VAR that uses the risk yield spread as the financial risk indicator variable. There is a slight positive effect on real output growth arising from an innovation associated with the risk spread. In constrast, there is a slight negative effect on the implicit deflator from an innovation associated with the risk spread. The risk spread falls in response to an innovation associated with real output growth, and it rises in response to an innovation associated with the short term interest rate.

VI PRELIMINARY CONCLUSIONS

This paper estimates structural VARs to obtain estimates of the responses to identified supply and demand credit shocks on a long annual U.S. samples that begins in 1896 and ends with 2010. We construct three proxy measures of financial risk to explore the robustness of the SVAR identification. Our estimates suggest that the SVAR are able to uncover reasonable estimates of the credit supply and demand shocks, but the initial results do not indicate that these shocks offer significant explanatory power to explain the subsequent path of real output growth.

However, the ratio of private assets to public assets on bank balance sheets is a source of future movements of the short-term nominal interest rate, the inflation rate and the growth rate of inside money. In future work, we intend to aim effort toward clarifying the implications of this finding, and toward finding more comprehensive aggregate measures for the expansion of private credit.

APPENDIX 1A – DATA SOURCES

Nominal GNP – Quarterly observations are taken from Balke and Gordon (1986) from 1896 to 1929 and are averaged. From 1929 to the 2010, we use the Annual Nominal GNP figures from the National Income and Product Accounts from the Bureau of Economic Analysis.

Real GNP, Implicit GNP deflator – as above, splicing Balke and Gordon (1986) with NIPA data.

1-year interest rate – the annual interest rate on short-term assets. From 1896 to 1938 the asset is 4-6 month commercial paper. The asset is 6-month commercial paper between 1939 and 1997. compounded for the calendar year. Data limitations forces a switch to 6-month certificates of deposit from 1998 to the end of the sample.

M2 Money Stock – We use the quarterly M2 aggregate figures from Balke and Gordon (1986) from 1896 to 1958 and calculate annual average numbers. The Board of Governors of the Federal Reserve System produces monthly M2 numbers from 1959 to 2010, from which we calculate annual averages. From these two sources, we get a full sample of M2 data.

M1 Money Stock – We use the quarterly M1 aggregate figures from Balke and Gordon (1986) from 1915 to 1958 and calculate annual average numbers. The Board of Governors of the Federal Reserve System produces monthly M2 numbers from 1959 to 2010, from which we calculate annual averages. From these two sources, we get a full sample of M2 data. The period 1896 to 1914 is more problematic. We generate an aggregate using deposits at national banks (as distinct from state banks and trusts) for the period 1896 to 1914 using data from A.P. Andrew (1910) and from Friedman and Schwartz (1970).

Inside Money – We estimate this quantity by taking the difference between M2 and M1. In essence, we consider an increase in M2 that is distinct from M1 as indicating a bank expansion of liabilities supported by private assets.

Bank Assets and Bank Capital – taken from All Bank Statistics (195?) for data for all commercial banks and thrifts for 1896 to 1955. We also accumulated the Federal Deposit Insurance Corporation (FDIC) figures for 1934 -2010 for all member banks, which did not include savings banks and thrifts. We are looking to supplement the data with savings bank data. For the meantime, we merged the two series in 1943 when they were closest.

Leverage: We accumulate the private sector assets of banks (from All Bank Statistics and FDIC sources) and take the ratio of private assets to bank total capital.

Risk spread: We take the difference between the Moody's AAA yield and the Long Term Treasury composite yield as the risk spread. Subsequent to 1930, these yields are obtained from the FRED2 data bank at the Federal Reserve Bank of St. Louis. The observations for the Treasury yield series prior to 1930 are taken from Shiller (2005). The data for Moody's AAA series begins in 1919. For the earlier dates, we merge observations from the Standard and Poors High Grade corporate yield that starts in 1900. For 1896 to 1900, we estimate the yield as bearing a slight premium over high grade Railroad bond yields taken from Macaulay (1937).

DATA APPENDIX II: Time Series Properties of Data Series

Annual Data From 1896 until 2010

SERIES IN LEVELS

Correlations of the *log of real GNP*

Auto	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	0.99	0.99	0.99	0.98	0.98
Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	-0.48	-0.08	0.03	-0.10	-0.10

Correlations of the *log of GNP deflator*

Auto	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	0.99	0.99	0.98	0.98	0.97
Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	-0.61	0.00	-0.26	0.15	-0.31

Correlations of the *log of Inside Money*

Auto	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	0.99	0.99	0.99	0.98	0.98
Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	-0.80	-0.07	-0.16	-0.12	-0.06

Annual Data From 1896 until 2010

Correlations of *Leverage*

Auto	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	0.97	0.95	0.92	0.90	0.86
Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.99	-0.13	-0.04	-0.23	0.07	-0.13

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Table 1: SUMMARY STATISTICS FOR DATA

SAMPLE PERIOD: 1896 THROUGH 2010

Levels

	Num	Mean	Std Error	Min	Max
AAA less Treasury yield	115	1.20	0.63	0.37	4.20
One year Interest rate	115	4.61	2.99	0.46	17.63
Velocity of money	115	3.31	1.25	2.07	7.74

Time Series Properties of Data Series Annual Data From 1896 until 2010

SERIES IN LEVELS

Correlations of *AAA Treasury Yield Spread*

Autocorrelations at lag --

	1	**2**	**3**	**4**	**5**	**6**
	0.83	0.61	0.44	0.33	0.29	0.28

Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.83	-0.28	0.11	0.01	0.11	0.05

Correlations of the *Short term (one year) interest rate*

Auto	**1**	**2**	**3**	**4**	**5**	**6**
	0.86	0.71	0.63	0.58	0.57	0.56

Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.86	-0.13	0.20	0.01	0.23	-0.02

Correlations of *Velocity of Inside Money (Nominal GNP/Inside Money)*

Auto	**1**	**2**	**3**	**4**	**5**	**6**
	0.98	0.95	0.91	0.89	0.87	0.85

Partial	**1**	**2**	**3**	**4**	**5**	**6**
	0.98	-0.32	0.13	0.14	-0.10	0.05

Table 1: SUMMARY STATISTICS FOR DATA(continued)

SAMPLE PERIOD: 1897 THROUGH 2010

	Num	Mean	Std Error	Min	Max
Real GNP growth rate	114	3.31	5.25	-14.05	16.86
Inflation rate	114	2.80	4.81	-20.44	20.93
Inside money growth rate	114	7.20	6.73	-21.89	35.13
Change in bank asset ratio	114	0.00	0.30	-1.65	0.91
Change in bank leverage	114	0.04	0.53	-1.57	3.28

Growth rate of real GNP
Autocorrelations at lag --

1	2	3	4	5	6
0.27	0.03	-0.19	-.16	-0.13	0.06

Partial 1	2	3	4	5	6
0.27	0.03	-0.20	-0.06	-0.08	0.09

Implicit GNP deflator inflation
Autocorrelations at lag --

1	2	3	4	5	6
0.48	0.15	0.17	-0.01	0.06	0.07

Partial 1	2	3	4	5	6
0.48	-0.09	0.18	-0.22	0.24	-0.14

Inside Money Growth Rate
Autocorrelations at lag --

1	2	3	4	5	6
0.56	0.26	0.14	0.09	0.03	-0.01

Partial 1	2	3	4	5	6
0.56	-0.08	0.05	0.00	-0.03	-0.02

Change in the ratio of private assets to public assets on bank balance sheets
Autocorrelations at lag --

1	2	3	4	5	6
0.20	-0.04	0.01	-0.13	-0.01	-0.02

Partial 1	2	3	4	5	6
0.20	-0.08	0.04	-0.15	0.05	-0.05

Table 2: FORECAST ERROR VARIANCE DECOMPOSITION OF DIFFERENCE VAR

Decomposition of Variance for real GNP

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	97.0	0.4	0.1	0.5	1.0
	94.2,98.7	0.0, 1.8	0.0, 0.5	0.1, 1.9	0.1, 2.9
8	91.3	1.3	2.7	1.0	1.7
	86.1,95.1	0.4, 3.3	1.1, 5.7	0.3, 3.1	0.4, 4.7
40	85.9	2.5	6.0	1.4	1.6
	74.2,92.9	0.9, 5.8	2.0,15.0	0.4, 4.0	0.4, 4.4

Decomposition of Variance for Implicit Price Deflator

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	8.9	87.2	0.2	0.6	1.9
	4.1,15.2	80.8,92.3	0.0, 0.7	0.1, 2.0	0.5, 4.2
8	17.2	70.9	3.8	1.2	4.4
	9.9,26.0	61.6,79.5	1.8, 7.1	0.4, 3.4	1.6, 8.7
40	19.6	61.9	9.3	1.8	3.8
	11.6,29.5	47.2,73.6	3.8,20.3	0.6, 4.7	1.4, 7.6

Decomposition of Variance for Inside Money

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	5.2	5.7	86.1	0.3	0.9
	1.9,10.4	2.1,11.0	79.5,91.5	0.0, 1.2	0.2, 2.2
8	20.8	11.6	59.2	3.3	1.2
	10.8,32.7	4.7,21.1	46.4,71.9	0.6, 8.7	0.5, 2.8
40	26.8	12.0	52.0	3.7	1.1
	14.7,40.6	4.5,22.4	37.4,66.6	0.6,10.1	0.3, 3.0

Decomposition of Variance for 1-year interest rate

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	24.6	8.8	3.4	57.9	3.4
	16.8,32.9	4.5,14.3	1.3, 6.6	50.0,65.9	1.5, 6.0
8	33.1	8.4	10.9	38.6	5.9
	24.3,42.7	4.4,14.4	6.4,16.4	30.9,47.1	2.6,10.7
40	32.8	9.7	20.1	28.9	4.3
	23.4,43.2	5.0,16.8	11.1,32.7	18.9,38.8	1.8, 8.4

Decomposition of Variance for Bank Asset Ratio

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	2.1	3.0	13.6	5.6	73.3
	0.6, 5.2	0.8, 6.9	8.6,19.7	2.9, 9.4	66.3,79.8
8	3.4	4.6	13.7	9.8	65.9
	1.5, 6.6	1.6, 9.5	9.1,19.4	5.3,15.5	58.3,73.3
40	3.8	4.7	14.3	9.7	64.9
	1.7, 7.4	1.7, 9.7	9.6,20.0	5.2,15.3	56.8,72.6

NOTE: Below percentage of error explained at the given time horizon is a range that indicates the 16th and 84th percentiles.

Table 3: FORECAST ERROR VARIANCE DECOMPOSITION OF VAR IN LEVELS

Decomposition of Variance for real GNP

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	96.8	0.2	1.9	0.2	0.2
	94.5,98.4	0.0, 0.9	0.6, 3.9	0.0, 0.7	0.0, 0.9
8	83.2	1.5	6.7	1.5	3.0
	71.5,91.6	0.3, 4.7	1.7,16.1	0.3, 5.3	0.8, 8.1
40	51.5	5.3	9.9	4.9	14.6
	28.0,73.8	1.3,17.3	2.4,28.8	1.3,14.3	3.4,31.5

Decomposition of Variance for Implicit Price Deflator

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	12.1	85.0	0.2	0.2	1.7
	6.2,19.4	77.8,91.1	0.0, 0.7	0.0, 0.9	0.6, 3.5
8	39.1	53.3	1.5	1.2	1.9
	26.0,51.7	40.7,66.2	0.3, 5.2	0.2, 4.4	0.7, 4.5
40	53.0	21.6	6.2	3.6	5.8
	34.4,68.2	12.4,35.4	1.5,18.5	1.0,11.1	1.6,16.2

Decomposition of Variance for Inside Money

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	3.0	5.9	87.7	0.3	1.1
	0.9, 7.3	2.1,11.6	80.9,93.0	0.0, 1.2	0.2, 3.0
8	11.5	10.3	69.5	2.0	2.0
	4.2,21.9	3.8,20.3	57.0,80.7	0.4, 6.2	0.6, 5.1
40	13.1	12.5	59.8	4.3	4.2
	5.3,24.4	5.6,22.9	44.9,73.0	1.4,10.6	1.5, 9.8

Decomposition of Variance for One year interest rate

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	28.2	8.0	4.9	55.8	1.1
	20.0,36.7	3.8,13.6	1.9, 9.4	47.7,64.3	0.3, 2.4
8	62.0	7.2	2.6	22.7	1.6
	49.5,72.4	2.5,15.2	1.0, 6.2	14.7,33.3	0.4, 4.9
40	57.5	6.8	6.5	7.4	9.7
	35.7,75.6	2.4,17.2	1.5,21.1	3.5,17.7	2.0,25.0

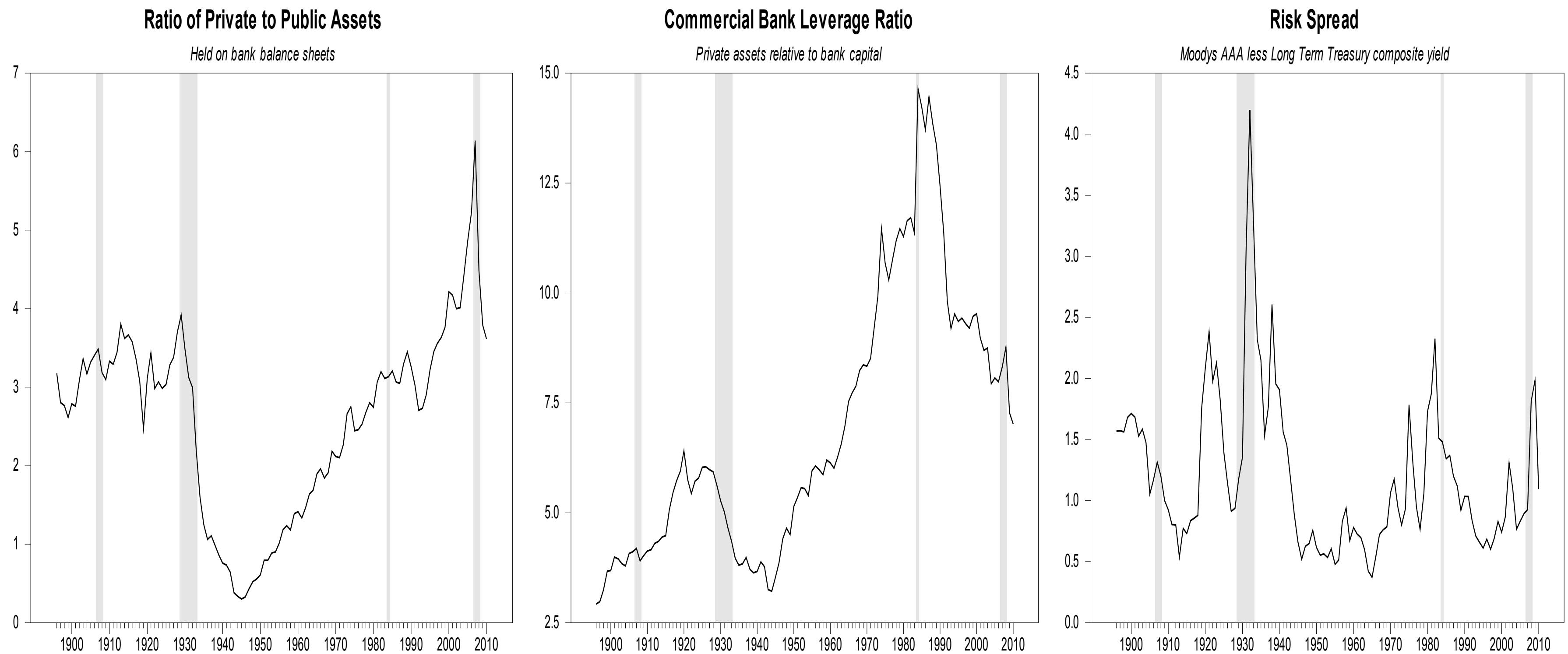
Decomposition of Variance for Bank Asset Ratio

Horizon	Y shock	Inflation shock	IM shock	Interest Shock	Asset Ratio shock
2	1.0	0.9	23.4	2.4	69.7
	0.2, 3.6	0.2, 2.9	15.8,31.8	0.5, 5.9	61.3,77.8
8	9.5	11.4	18.0	3.5	51.9
	3.3,19.1	3.8,22.4	9.9,28.7	1.5, 7.3	38.8,65.5
40	18.3	22.2	13.6	7.4	27.4
	7.9,32.0	8.6,40.8	6.2,27.2	2.4,17.8	15.1,42.8

NOTE: Below percentage of error explained at the given time horizon is a range that indicates the 16th and 84th percentiles.

Figure 1: Financial Risk Proxy Data Series

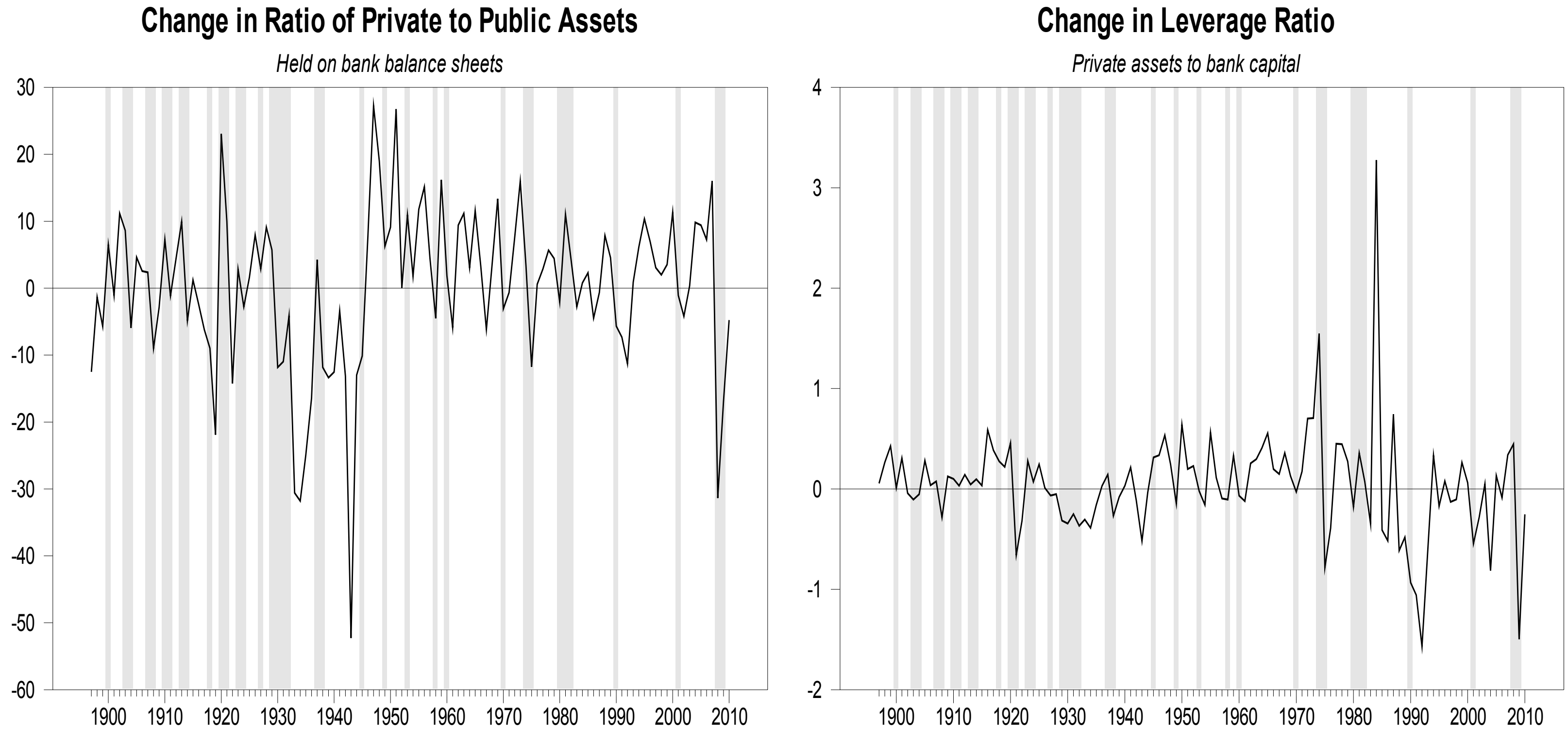
Shading for Financial Crises



Full sample, 1896-2010

Figure 2: Financial Risk Proxy Series: First Differences

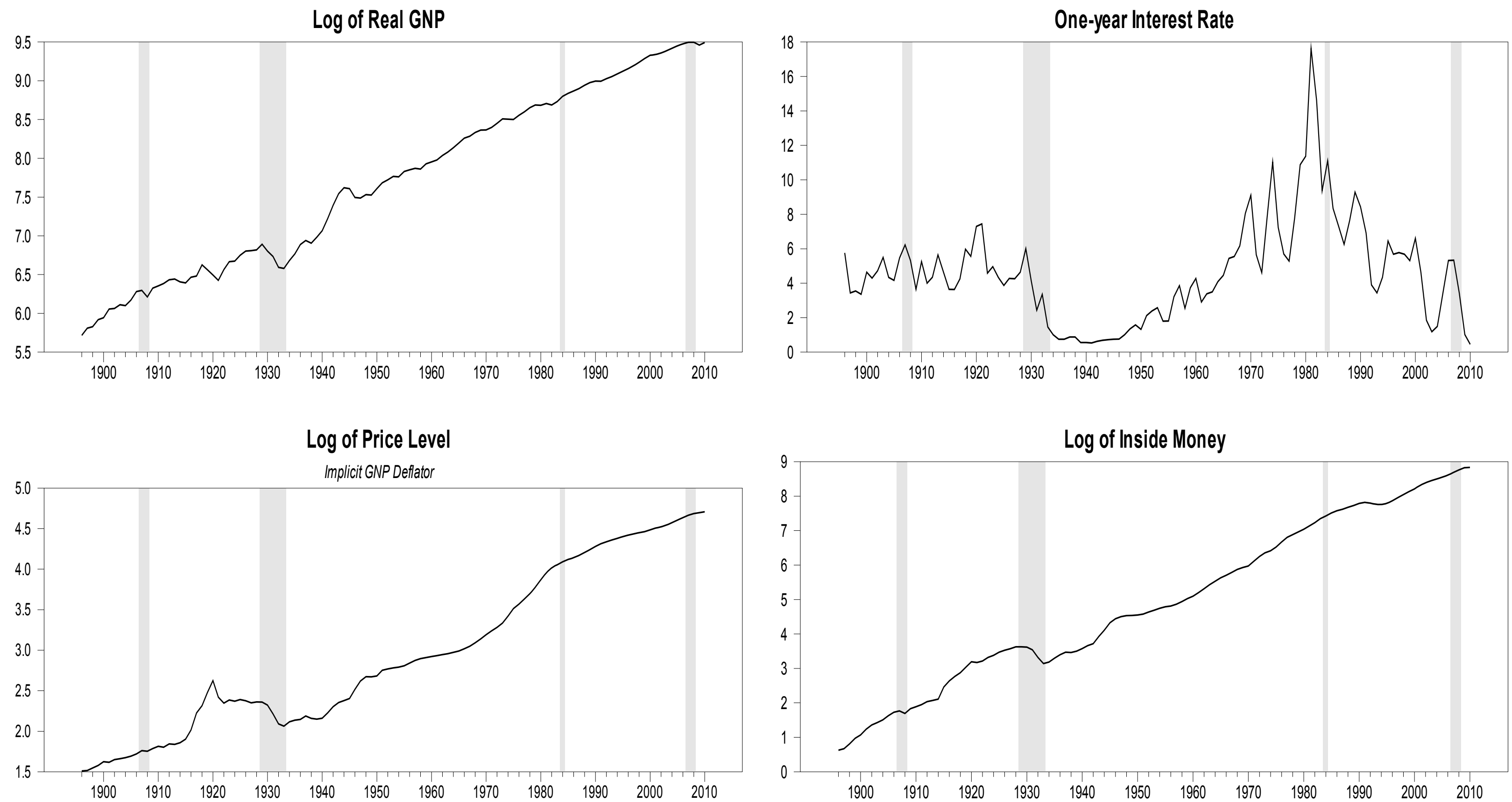
Shading for Recessions



Full sample, 1897-2010

Figure 3: Data Series in Levels

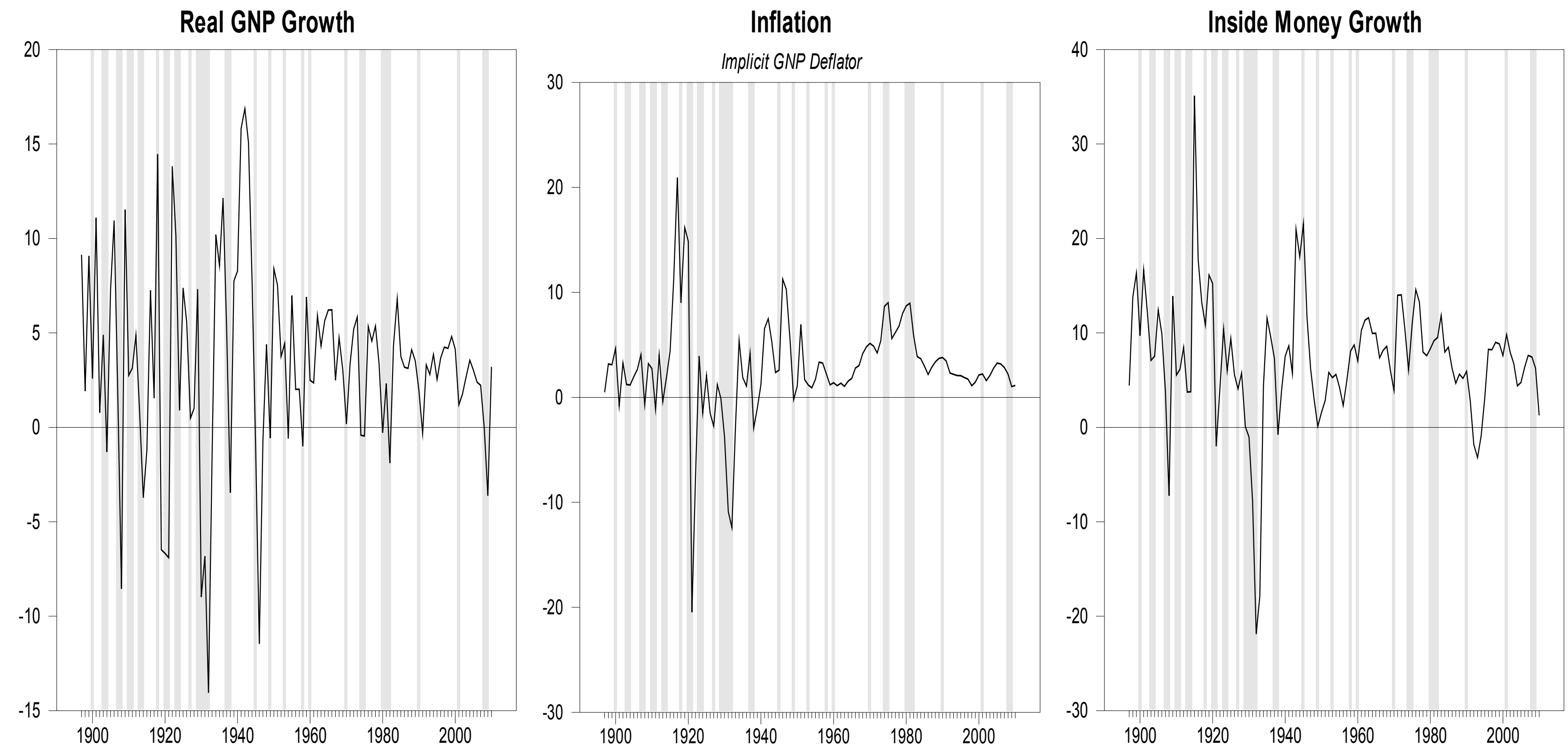
Shading for Financial Crises



Full sample, 1896-2010

Figure 4: Data Series in First Differences

Shading for Recessions



Full sample, 1897-2010

Figure 5: Impulse Responses for First Differences

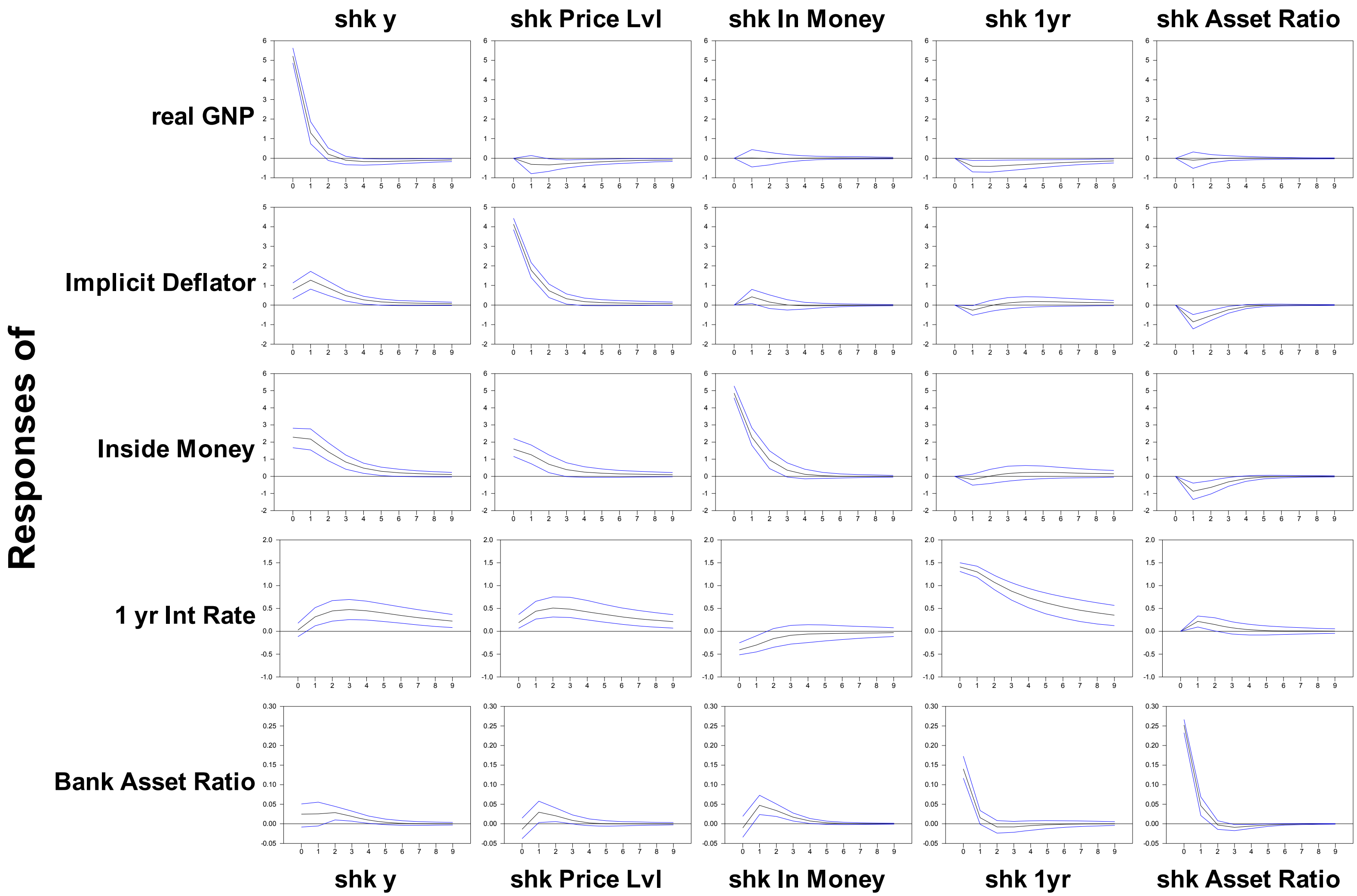


Figure 6: Impulse Responses for First Differences

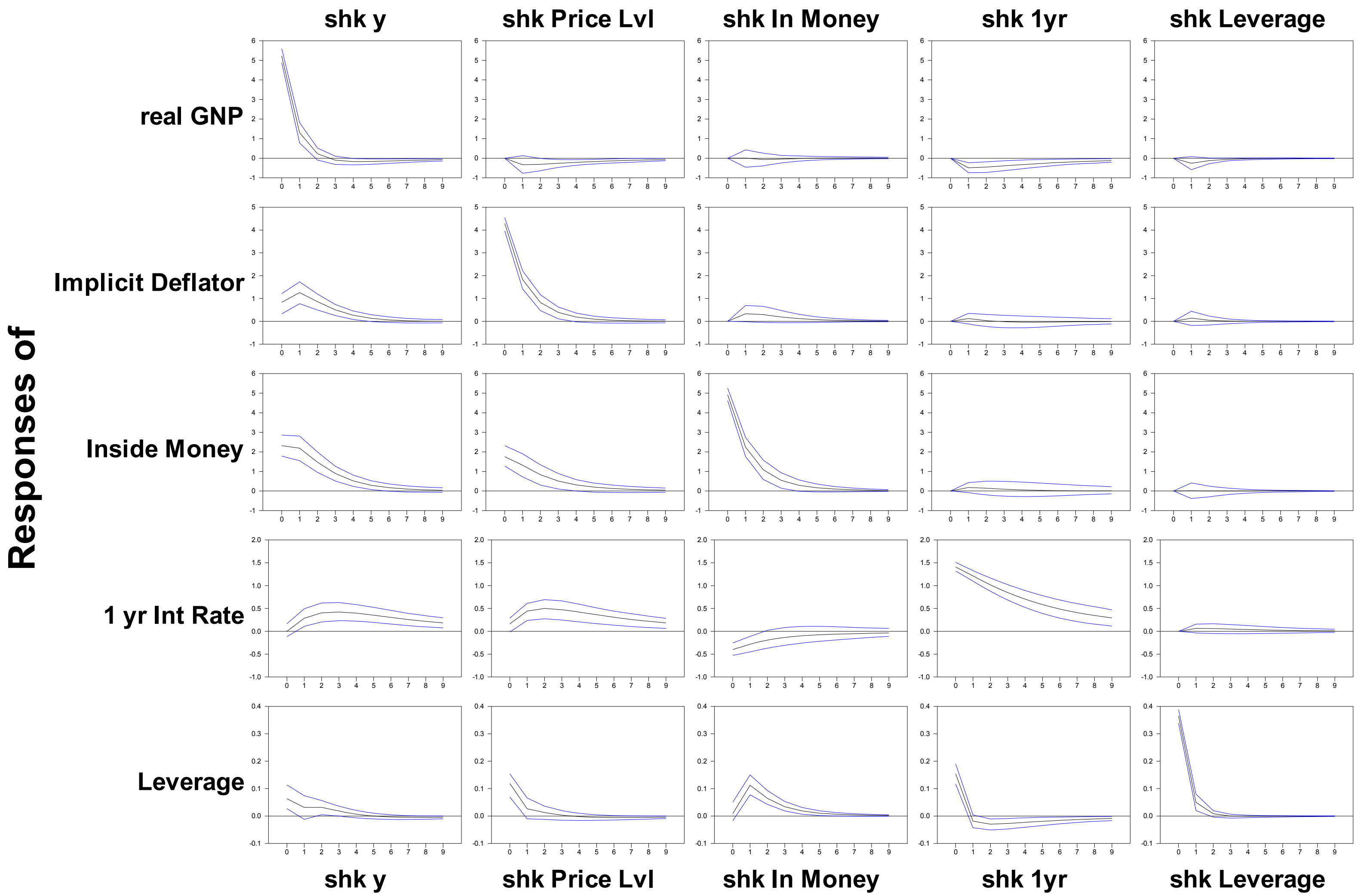


Figure 7: Impulse Responses for First Differences

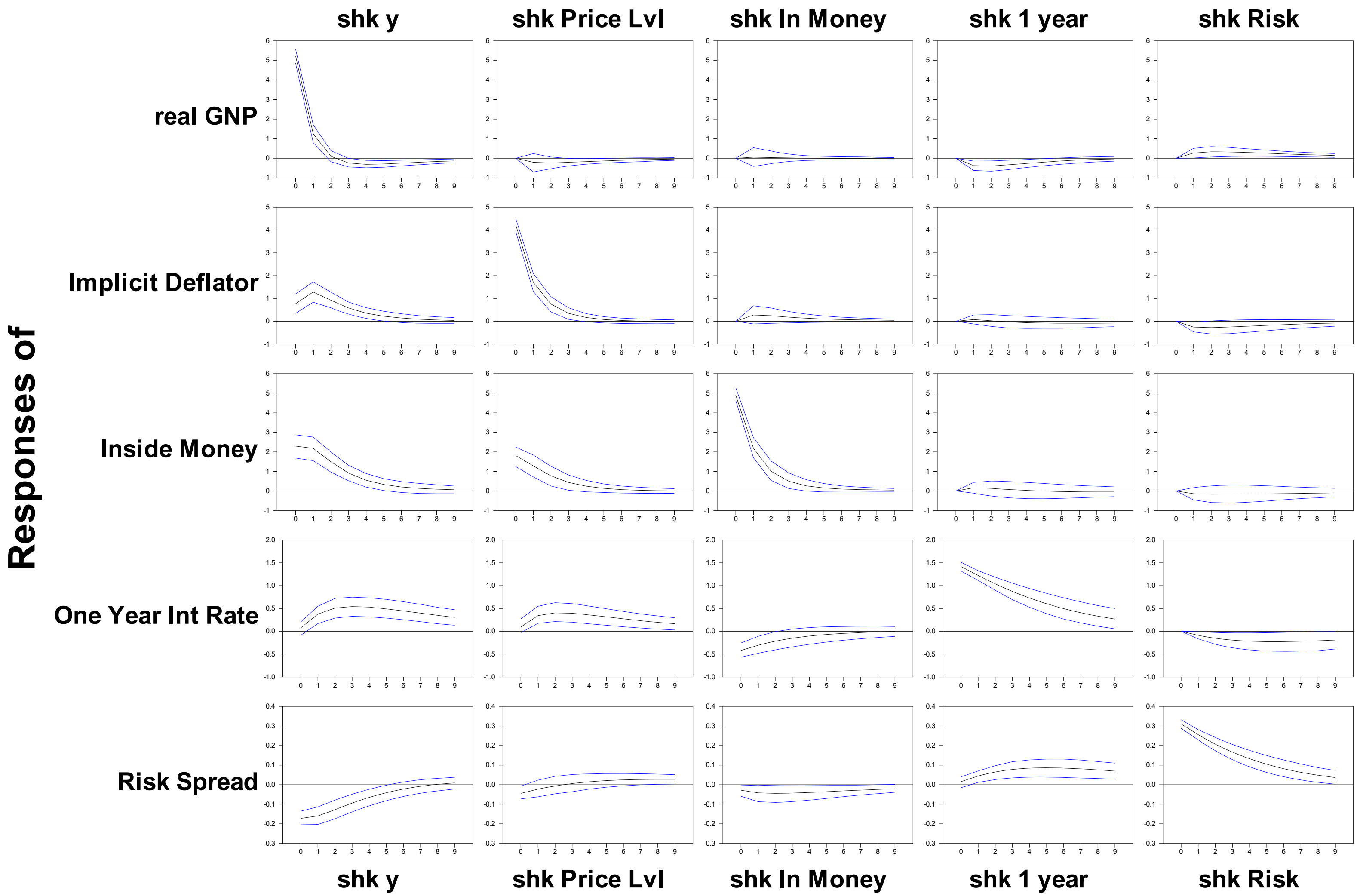


Figure 8: Impulse Responses for Level Specification (w/Trend)