The Link between Federal Funds Rate and Banking System Distress: An Empirical Investigation

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Abstract

We use the Taylor rule rate (TRR) as an “implied monetary policy rate” to investigate the impact of monetary policy rate changes on the banking system distress between 2001 and 2013 within an unrestricted vector auto-regression model. Our base model of distress includes a systemic risk indicator (Expected capital shortfall), and three macroeconomic indicators—real GDP growth, inflation, and TRR. We consider two model extensions; (i) we include a measure of bank lending standards to account for the changes in the systemic risk due to credit tightening, (ii) we replace inflation with house price growth rate to check robustness. Three results are drawn. First, the impulse response functions (IRF) show that raising the monetary policy rate contributed to insolvency problems for the US banks, with a one percentage point increase in the rate raising the banking systemic stress by 1.6 and 0.8 percentage points, respectively, in the base and extended models. Second, variance decomposition analysis (VD) shows that up to ten percent of error variation in the systemic risk can be attributed to innovations in the policy rate in the extended model. Third, our results support the view that policy rate hikes led to the housing bubble burst and contributed to the crisis of 2007-2009. This demonstrates that monetary policy making gets more complex during bubbles and it must be conducted with utmost caution.
1. INTRODUCTION

Since the financial crisis of 2007-2009, academics and practitioners alike have sought to define and measure “systemic risk”, and to identify the factors that contribute to it, in order to better assess the vulnerabilities of the financial system at the domestic and international levels\(^1\). In this context, recent research has suggested a significant link between a monetary policy of low interest rates over an extended period and higher risk-taking by banks (Borio and Zhu, 2008, Delis et al. 2017). In response to the dotcom bubble burst in 2000, the Fed adopted a strong accommodative monetary policy by lowering its target fed funds rate (FFR) from 6.5% in Dec. 2000 to 1% in June 2003, where it stayed for a year. This historically low FFR pattern resulted in negative real FFR values from November 2002 to August 2005, as inflation hovered around 2.5% during this period (Dokko, Doyle, et al., 2009). The actions of the Fed in the early years of 2000s was in pursuit of its dual mandate of maintaining price stability and promoting maximum sustainable employment.

The Fed also aims to help financial markets function in an orderly manner, but “it does not seek to protect financial market participants from the consequences of their financial choices” (Plosser, 2007), out of concern for moral hazard. In particular, the easy monetary policy (low interest rates) which began during the financial crisis in 2008 was designed to support financial markets, rather than individual banks (Delis and Kouretas, 2011)\(^2\). However, monetary policy decisions do affect the overall banking sector by encouraging or discouraging risk-taking by individual banks. For example, the excessive liquidity produced by an easy monetary policy can encourage unsound lending practices on the part of the banks, as detailed in the next sections.

In this article, we investigate the impact of the changes in the effective federal funds rate (FFR), a primary monetary policy interest rate, on banking system distress in an unrestricted vector autoregression (VAR) model from 2001 through 2013. The base model of distress includes a systemic

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\(^2\) Protecting banks against the consequences of their financial choices became part of the Fed mandate with the Dodd-Frank Act (2010). Since then, the Fed has pursued financial stability by requiring banks to run stress tests and to prepare capital plans accordingly. If Dodd-Frank is repealed under the current administration, new measures will have to be introduced.
risk indicator and three macroeconomic indicators as its determinants: the real GDP growth rate, inflation, and the monetary policy interest rate (the FFR). These four variables represent a potentially complete macro-economy with demand (the FFR), supply (systemic risk indicator), output, and prices. Different versions of this model have been widely used in the macro and monetary literature (Christiano et al., 1996; Bernanke and Mihov, 1998; Lown and Morgan, 2004).

Our extended model includes a lending criteria indicator (senior loan officer survey; discussed in section 3.1) to account for the impact of these criteria on bank distress. As another extension, we replace inflation with a house price index in both the base and extended models to investigate the robustness of the results. Changes in lending policies over the business cycle may potentially affect borrowers’ ability to stay current on their debt obligations. As such, tightening credit standards (making it difficult to obtain loans) may add to borrowers’ burdens by making it harder to refinance (pay back) existing loans, contributing to bank distress, and vice versa. Regarding house prices, the period we investigate overlaps with the US housing boom years of 2001-2006 and housing bust years and 2007-2010. Because housing-related loans make up the largest share of household balance sheets, as a robustness test, we replace inflation with house prices in our base and extended models to see if this alters the effect of a rate increase on systemic risk.

Our systemic risk indicator for the banking system follows an Expected Shortfall (ES) concept, similar in spirit to the one proposed by Acharya et al. (2010). The ES concept uses conditional expectations of losses due to bank default under extreme conditions, where the shortfall refers to a hypothetical insurance premium needed to offset the losses. Normalizing the losses with total liabilities outstanding in the banking system (households’ and firms’ assets are banks’ liabilities), the systemic risk indicator shows the ratio of losses to total liabilities (the proportion of assets lost in case of a bank failure) in the banking system. Next, we estimate a Taylor Rule Rate (TRR) for 2001-2013 and use it as a proxy for the main policy interest rate in the model. The Fed used the FFR as a primary policy tool before and during the 2007-2009
After the FFR rate hit the zero bound in the last quarter of 2008, the Fed introduced asset purchase programs, the so-called quantitative easing (QE). It is claimed in the literature that these asset purchase programs actually imply further cuts in the FFR (Bernanke 2011). Because historically FFR follows the Taylor Rule Rate (TRR) very closely (Bernanke 2011) and TRR does not have a zero bound, we use the latter as a proxy for the monetary policy rate in our model.

Our main goal is to examine the effect of changes in the main monetary policy interest rate on systemic risk. For this purpose, we look at Impulse Response Functions (IRFs) and Variance Decompositions (VDs) in the VAR models including systemic risk and macroeconomic variables. We find that raising the monetary policy rate (TRR) leads to insolvency problems in BHCs operating in the US. In terms of the magnitude, in the base model, a one percentage point increase in the TRR raises the systemic risk indicator by 1.6 percentage points while in the model extended to include credit tightening criteria the impact is reduced to 0.8 percentage points. The rationale for the lower impact of TRR changes in the extended model is that tighter lending policies, represented by the lending criteria indicator, lead to a surge in credit losses of banks, curtailing the contribution of TRR to systemic risk. During the crisis, the link between banking system distress and the monetary policy rate was blurred, as many borrowers defaulted due to being unable to borrow even though interest rates were lower. Including a lending criteria indicator in the model addresses the impact of credit tightening on bank distress.

Our sample span of 2001 through 2013 covers both the housing boom (2001-2006) and the housing bust (2007-2010) periods that need to be accounted for. This is important because the housing market's contribution to US GDP is significant and, more importantly, the bursting of housing bubble in 2007 is believed to have triggered the credit crisis, leading to the Great Recession of 2007-2009 (Holt, 2009). Thus, as another modification of the model, we replace inflation with the growth rate of home prices in both the base and extended models in order to investigate robustness of our findings. In this alternative model, we observe similar but larger

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3 According to NBER definition, the recession started in December 2007 and ended in June 2009.
impacts from monetary policy on systemic risk. Specifically, a one percentage point increase in the TRR raises the systemic risk indicator by 2.1 and 1.4 percentage points, respectively, in the base and extended models.

Variance decomposition (VD) analysis based on our models also reveals strong evidence for the impact of the monetary policy interest rate on bank distress. In the base model, innovations in the TRR account for 25% of error variance in the systemic risk indicator at six quarters and nearly 40% at twelve quarters. In the extended model including the lending criteria, the error variation in systemic risk due to variations in the TRR remains significant in magnitude, though it declines to 20% at six quarters and 10% at twelve quarters (Figure 6b). Error variance due to innovations in output and inflation in total, initially rises to 15%, but declines to 8% over time. The effect of TRR is quite considerable and its presence is an indication that the policy rate contributes to the variation in systemic risk to a slightly greater extent than real GDP and inflation combined. These results suggest that the Fed can exert a direct impact on bank distress by changing the monetary policy rate. According to the IRFs from extended model, the policy rate’s effect on bank distress is durable, but not persistent. Thus, policy makers must consider the short-term effects of the policy rate changes on bank distress while implementing monetary policy. In the models that replace inflation with a house price index, the error variation figures are similar to those in the original base and extended models. Overall, our findings strengthen the view that accommodative monetary policy during the pre-crisis period helped create a credit frenzy in the run-up to the crisis (Taylor, 2009), and that tightening the monetary policy between 2004 and 2006 accelerated the bursting of the housing bubble in 2007, with severe consequences for banks.

Our contribution to the literature is twofold. First, the systemic risk indicator time series used here encompasses all BHCs in the US, as compared to other indicators that include only a group of banks (Tarashev et al., 2010; Huang et al., 2012, and Cummins, 2014). To construct this measure, we introduce a bank-level insolvency indicator, distress indicator, as a probability of default. Probability of default is used in a model of stochastic losses to define a fail/survive condition of a bank in Monte Carlo simulations (See section 3.2.2.2). Our paper is the first to use
such an indicator as a default probability in developing a systemic risk indicator. An important benefit of this distress indicator is that it can be determined for all banks at any point in time whereas other measures such as Expected Default Frequency (EDF) used in Tarashev (2010) are available only for a number of banks. Second, using our systemic risk indicator, we explore the effect of changes in the FFR on bank distress over a period that includes the pre-crisis, crisis, and post-crisis period. We use an implied policy rate, the TRR, to expand the sample beyond the 2007-2009 period due to the FFR’s zero boundary. The framework built here is simple, but it can serve as a basis for more sophisticated models. The rest of the article is organized as follows. Section 2 is the literature review. Section 3 discusses the methods, data, and models. Section 4 analyzes the estimation results and Section 5 concludes.

2. Literature Review

This section reviews the literature on macro-finance and the measurement of systemic risk as related to the current study. Systemic risk is difficult to measure due to the complexity of causal events and/or mechanisms. A survey of systemic risk literature prepared for the US Treasury’s Office of Financial Research (2012) defines systemic risk as “any set of circumstances that threatens the stability of or public confidence in the financial system.” The European Central Bank (ECB) (2010) defines systemic risk as a risk of financial instability “so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially.” Yet another definition of systemic risk is a risk in which many market participants simultaneously suffer severe losses, which then spreads through the system (Benoit et al, 2015).

2.1 Measures of Systemic Risk

Systemic risk has become a prolific research field over the last decade at the crossroads of banking, macroeconomics, econometrics, and network theory. A survey by Benoit et al. (2010) gives an excellent review of the theoretical and empirical literature on systemic risk. According to this survey, the literature has developed along two distinct approaches. The first approach focuses on the sources of systemic risk, such as contagion, bank runs, and liquidity crises. This “source-
specific approach” explains why many financial firms take bets that are both large and correlated. In other words, it explains why financial firms expose themselves to default and their counterparts to contagion. Some forces leading to co-movement among banks are common sources of risk, such as engagement of large banks in loan commitment and off-balance sheet activities\(^4\). Papers that take this approach also look at how losses can spill over from one part of the financial system to another, or why small shocks can have large impacts. Studies in this strand are generally grounded in theory. Therefore, they permit identification of the sources of risk.

A second strand of research aims to derive global measures of systemic risk and is more statistical in nature. This “global approach” does not take a particular stand on the causes of systemic risk and does not examine channels of transmission, but rather takes a multi-channel approach that potentially encompasses all the mechanisms studied in the first group of papers. These studies treat the financial system as a portfolio of firms and aim to quantify systemic risk. Examples of these studies include Kuritzkes et al. (2005), Goodhart and Sergoviano (2008), Geluk et al. (2009), Acharya et al. (2010), Tarashev et al. (2010), Huang et al. (2012) and Cummins (2014). Measures of systemic risk in these papers have two common features: (i) they all provide a single risk metric that can potentially encompass all firms in the system\(^5\) and (ii) they can be applied to any subset of firms in the system such as money center banks (MCBs), systemically important financial institutions (SIFIs), or large banks, in whatever way defined. Given these two features, the systemic risk implied by the measure can be allocated across institutions using attribution methodology\(^6\). Some papers in this strand propose replacing a host of complex macro-prudential tools with a simple “systemic risk tax,” a type of insurance premium, to be paid by large banks that would restore an optimal level of risk-taking (Huang et al., 2012 and Cummins, 2014). The basic idea is that if markets are efficient, much may be learned from current market prices of

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\(^4\) The aggregate level of funds in the system is limited. Hence, during a credit crunch, banks may find it difficult to honor all of their loan commitments. This is similar to the externality faced in markets when all participants act simultaneously affecting the cost of each participant adversely, e.g., in Fed funds borrowing the cost of funds to each bank rises as they all scramble for funds.

\(^5\) The structure of the metric allows it to be used for all institutions. However, data limitations restrict the use the metric for a small number of institutions. We try to overcome this limitation by using an indicator that can be used for all banks.

\(^6\) See Tarashev et al. (2010).
the securities issued by financial firms or the derivatives written on them. As such, prices for credit default swaps or loan spreads may reveal sudden shifts in systemic risk regimes.

A large stream of research has focused on building an index or indicator for systemic risk using market data-based measures. The most important of these measures are Systemic Expected Shortfall (SES) introduced by Acharya et al. (2010a), and Delta Conditional Value-at-Risk (CoVaR) put forward by Adrian and Brunnermeier (2014)\(^7\). SES and CoVaR are conceptually different measures: SES measures the sum of losses due to each bank failure, or the marginal expected shortfall (MES) conditional on the system being in distress. “Shortfall” refers to the capital needed to offset the loss during a systemic event. CoVaR measures the system losses conditional on each and every bank being in distress. By contrast, it cannot be consistently aggregated across subgroups, due to the lack of the additive property. Over the past ten years, hundreds of research articles have discussed, implemented, and sometimes generalized these systemic risk measures. Hence, these measures have become the most central metrics in the systemic risk literature. The framework we develop belongs to the SES approach\(^8\).

2.2 Relation to the Macro-Finance Literature

The literature on bank risk and monetary policy has developed mainly in the areas of finance and micro-econometrics. The macro literature studying the relation between bank distress and monetary policy is fairly small. Our work shares some of the findings in the financial accelerator literature in the macro-finance side. One strand explains the financial accelerator mechanism on the banks’ funding channel (Gertler and Kiyotaki, 2010; Gertler and Karadi, 2011): A reduction in the FFR raises the value of banks’ balance sheets and capital, reduces spreads on banks’ external funding and reduces bank risk. In these models, bank capital moves and bank risk move in opposite directions; as capital increases, bank risk declines. Another strand of papers focuses on firms’

\(^7\) A survey cited in footnote 1 discusses 31 quantitative measures of systemic risk in the literature.

\(^8\) Acharya et al. (2010) use the term Systemic Expected Shortfall. Essentially, they use the method to measure the potential loss incurred by a firm as a whole in an extreme event known as “Expected Shortfall,” but add the term “Systemic” referring to systemic risk. We use ES instead because we follow an algorithm developed by Tsatsaronis et al. (2010) who also use the term ES. Both terms refer to the same concept.
lending frictions through the balance sheet channel of monetary transmission (Bernanke et al., 1999). The effect of monetary policy is similar to the funding channel: a fall in the FFR raises balance sheet values by boosting asset prices more than liability values because assets have a longer term to maturity. Therefore, monetary policy expansion raises firm values and reduces overall bank risk. The main findings of the studies in both strands are related to our results. However, because their primary focus is the transmission mechanism, they use an indirect definition of risk such as bank capital.

We do not focus on monetary policy transmission channels. We are interested in the end result, that is, how changes in the monetary policy rate are linked to systemic risk, regardless of the channel through which these changes are transmitted. We build a systemic risk indicator for the entire banking system. Therefore, we can quantitatively assess the impact of rate changes on systemic risk. Based on this discussion of transmission channels and how they affect the bank distress, we propose the following hypothesis:

H1: Systemic risk is positively associated with effective FFR: increases (reductions) in FFR are associated with greater (lesser) distress on banks.

3. METHODOLOGY, DATA, AND MODELS

3.1 The Sample

This section describes data sources and variable construction. The sample runs from 2001Q1 to 2013Q4. We derive a systemic risk indicator based on US BHC balance sheet data. In the rest of the text, we use the term banking system distress indicator interchangeably with systemic risk indicator. We do not go below the BHC level to consider subsidiaries separately because: (i) this maintains homogeneity in the data, (ii) most management decisions are made at the BHC level, rather than by subsidiaries, (iii) BHCs switch (transfer) assets across subsidiaries for window dressing and tax purposes, making the subsidiary level data unreliable. The primary source for balance sheet data is the Call Report from the Chicago Fed’s Consolidated Financial Statements.
for Bank Holding Companies (FR Y-9C database), available via Wharton Research Data Services. Table 1 presents summary statistics for the bank distress indicator and its components.

For macroeconomic drivers, we use several sources. Gross Domestic Product (GDP) data are obtained from the US Bureau of Economic Analysis’ National Income and Product Accounts. These data are 2009 constant prices and seasonally adjusted annualized values. The US Bureau of Labor Statistics is the source for Consumer Price Index (CPI) data. CPI is a seasonally adjusted index tied to 100 at 1982-84. We obtain Core Personal Consumption Expenditures (PCE) data from the Bureau of Economic Analysis, Department of Commerce. This is a seasonally adjusted chain price index tied to 100 at 2009. The source for the FRR is the US Board of Governors of the Fed System’s H.15 interest rate release. We use effective FFR data. Unemployment data come from the Bureau of Labor Statistics’ household survey. The natural rate of unemployment data come from the economic research division of the Federal Reserve Bank of St. Louis. House price data are from S&P’s Case-Shiller US National Home Price Index, seasonally adjusted (Q1-2000=100). Figure 4 shows the macroeconomic data used in the models (Taylor Rule Rate, Real GDP growth rate, Inflation, House Price growth rate and Senior Loan Officers Survey, all in %).

Our lending criteria indicator is from the Federal Reserve’s Senior Loan Officer Opinion Survey on Bank Lending Practices. Specifically, we use the net percentage of domestic respondents tightening standards for commercial and industrial loans (C&I) to large and middle-market firms as our lending criteria indicator. The survey is conducted quarterly and it goes back to 1990. A one-unit increase (decrease) in this survey shows that the percentage of lenders restricting credit from a quarter ago is up (down) by one percentage point.

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9 FFR is the overnight, interbank lending rate among depository institutions. The weighted average of this rate across all transactions is the effective FFR. The Federal Open Market Committee (FOMC) aims to keep the rate near its target, called the federal funds target rate. Daily and weekly effective rates are very volatile while quarterly rates are stable.

10 The sample covers the housing boom and bust periods. Because surveys on real estate related loans are not available for the entire sample period, we use lending standards for commercial and industrial loans (C&I). The correlations between C&I loans and commercial mortgage loans, prime mortgage loans and non-traditional mortgage loans are 0.89, 0.93 and 0.88, respectively.
3.2 Model Specification and Variable Construction

3.2.1 The Model

Our base model is a standard unrestricted VAR model which includes three macroeconomic aggregates and the systemic risk indicator (four equations). The macro aggregates are the real GDP year-to-year growth rate, inflation (year-to-year change in CPI), and the implied policy interest rate (TRR). The sample period runs from 2001Q1 to 2013Q4. In a VAR model, each time series is regressed against lagged values of its own and multiple other time series. In the simplest form, when coefficients are assumed to be stable and error terms are assumed to have constant variances, each equation in a VAR becomes an example of a multiple linear regression. We design the VAR model to create mutual feedback effects among macroeconomic indicators and the systemic risk indicator because we are interested in investigating the impact of the implied policy rate on systemic risk. We favor the reduced form VAR because the relation between the real economy and the banking system is very difficult, if not impossible, to delineate with a theory-based approach (Goodhart et al., 2006; De Grave, 2008). The base VAR model has the following form:

\[ Z_t = \alpha + B_1 Z_{t-1} + \ldots + B_k Z_{t-k} + u_t \]  

where \( Z_t = \begin{pmatrix} R \\ Y \\ P \\ S \end{pmatrix}_t \)

\( B_t \) is a 4x4 matrix of feedback coefficients, \( R \) is the TRR, \( Y \) is real GDP growth rate, \( P \) is inflation, and \( S \) is the systemic risk indicator. These four variables represent a potentially complete macro-economy with demand (the monetary policy rate), supply (systemic risk indicator), output, and prices. The systemic risk indicator accounts for the supply side because the solvency level of the banking system determines how much credit can be supplied to an economy. Different versions of this model have been widely used in the macro and monetary literature (Christiano et al., 1996; Bernanke and Mihov, 1998; Lown and Morgan, 2004). Then we expand the base model, adding lending standards as a regressor. Controlling for lending criteria strengthens the supply block in the model. Hence, the model may better capture the impact of changes in policy rate on the
systemic risk indicator. Subsequently, we replace inflation with the house price growth rate in the base and extended models. We do all the necessary stability and residual tests for lag selections (Appendix A) and look at impulse responses (IRFs) and variance decompositions (VDs) in the model. IRFs and VDs are discussed in Section 4.

3.2.2 The Systemic Risk Indicator

3.2.2.1 The Bank Distress Indicator

Following Cole and White (2012), we use a book-value insolvency measure for each bank in our sample to build our systemic risk indicator. This measure is defined as non-performing assets divided by the sum of equity capital and loan loss reserves. Cole and White (2012) classify banks that do not have enough equity capital and loan loss reserves to cover non-performing assets as "in technical failure" (or insolvent). Holding poorly performing assets makes banks more vulnerable to financial distress. Thus, banks are required to hold a loan-loss allowance account to absorb losses both from loans currently identified as bad loans and from other loans that will later prove to be uncollectable. This account acts as a cushion: If a bank’s loan-loss allowance account exceeds its expected credit losses, the bank can absorb more unexpected losses without failing and imposing losses on the Federal Deposit Insurance Corporation (FDIC). Conversely, loan-loss allowances less than expected losses ultimately reduce the bank’s equity capital. If equity capital falls below a certain level, the bank can be closed by regulators. Non-performing assets are those more than 90 days past due. Cole and White assume a haircut of 20% to loans that are 30-89 days past due and still accruing interest, 50% to loans that are 90+ days past due and still accruing, 11 This measure is very similar to the so-called “Texas Ratio” (non-performing assets divided by the sum of equity capital and loan loss reserves) developed by Gerrard Cassidy and his colleagues at RBC Capital for analyzing troubled banks during the 1980s with only one difference: in the original form, non-performing assets include those that are delinquent more than 90-days. Cole and White (2012) include early delinquencies into the ratio with some haircuts.

12 We use “technical failure” because it may take some time for regulators to close the bank even after the minimum capital ratio is bridged. Cole and White (2012) show that most banks in this status failed eventually (See footnote 13)
and 100% to loans in nonaccrual status (write-offs) and other real estate owned (REO). Using these haircuts, Cole and White define the following ratio for bank distress:

$$\text{Distress Indicator} = \left( 0.2 \times 30 - 89d\ DEL + 0.5 \times 90d\ plus\ DEL + \ WOF + \ REO \right) / \left( Equity + LLA \right)$$  \hspace{1cm} (2)

If the distress indicator is equal to one, the bank is considered to be in “technical default.” As such, a rising distress indicator indicates that stress is building up. We refer to Cole and White (2012) for a robustness check and adopt an off-the-shelf definition. To the best of our knowledge, Cole and White’s (2012) definition of technical failure is the only criterion proposed in the literature to define insolvency by using balance sheet measures.

More recently, Chernykh and Cole (2015) developed a capital ratio, quite similar to the “technical failure” condition, as an alternative to several other capital ratio measures used in the literature. Their approach differs in how they treat this ratio in an equation. They put the capital ratio on the right-hand side as a balance sheet indicator and look at its predictive power, showing that it outperforms others in predicting bank failure. Cole and White use this measure in probit and logit models as a bank status of “fail” or “survive.” We build a time series of distress as an indicator using two of its features: (i) it defines distress as a proportion in the [0,1] interval, except in very rare extreme stress cases, and (ii) it enables us to create a continuous distress indicator time series.

This distress indicator has several advantages, the main one being that it accounts for the two primary banking risks – capital adequacy and asset quality – in a simple measure. Severe regulatory forbearance and delays in closing banks have been issues for the banking system for years (Chernykh and Cole, 2015). Banks with extreme levels of non-performing assets and grossly insufficient loan-loss reserves, but with “adequate” equity capital can survive several years before action is taken. Similarly, a bank with a liquidity shortage may see its equity base and loan loss reserves melt while assets on its balance sheet still appear prudent. By accounting for the two

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13 Cole and White assign different haircuts to different components of non-performing assets. They pick the one that has the highest predictive power for bank failures. They find that at the end of 2009 there were 347 banks that satisfied this definition of technical failure. Of the 74 banks that failed in the first half of 2010, 68 (92%) were in this group of 347.

14 The distress indicator may go below zero in extreme cases. In such cases, we set the indicator to 1 as it potentially shows that the bank is insolvent and in “technical failure” status.
primary bank risks, one can observe sections of the balance sheet that have deteriorated and increased bankruptcy risk, or improved, reducing bankruptcy risk\textsuperscript{15}. Next, we develop a systemic risk indicator time series by employing the distress indicator as the probability of default for a particular bank.

\textbf{3.2.2.2 Constructing a Systemic Risk Indicator: A Model of Stochastic Losses}

In developing a systemic risk measure, treating the financial system explicitly as a portfolio of institutions (or banks) has become common (Tarashev et al. 2009, Acharya et al. 2010, Huang et al. 2012). One method widely used in the literature utilizes the concept of Expected Shortfall (ES). This is essentially a standard measure of firm-level risk which refers to portfolio credit losses during extreme conditions (or events) and the capital needed to offset the losses. Extreme events are defined by a percentile distribution in which the total loss exceeds a certain level.

More recently a stream of research has used the ES concept to create a metric of systemic risk by treating the financial system as a portfolio of firms (Tarashev et al. 2009, Acharya et al. 2010). A formal method of attributing systemic risk to institutions was proposed by Acharya, et al. (2010). Using the ES concept for an aggregate loss associated with failures in the banking system is straightforward. Company-wide losses or revenues for any firm can be decomposed into contributions from individual departments in the company. A similar way of thinking can be applied to derive a systemic risk indicator. A financial system comprises a number of banks just as a firm comprises a number of sub-divisions (Acharya et al, 2010). In this approach, we treat the banking system as a portfolio of banks. Tarashev et al. (2010) define and use ES in a similar way, and provide a method of developing a systemic risk measure based on the loss associated with the failure of individual banks, and a numerical algorithm to determine the sum of losses due to a set of bank failures. Our approach is quite similar to Acharya et al. (2010), but we use a numerical algorithm similar to the one used by Tarashev et al. (2010).

\textsuperscript{15} A common measure of bank risk used in literature is the Z-index. We use a distress indicator because it can be used as a probability of default as it is bounded with 0 and 1 (except in very extreme cases). The Z-index can take positive values in a large range. However, there are several risks that are left out in this systemic risk indicator, such as operating risk, interest rate risk and off-balance sheet assets (OBSA) risk.
In the ES approach, following Tarashev et al. (2010), we employ the Value-at-Risk (VaR) concept to determine the potential loss (losses incurred by households and businesses: assets for households and businesses are liabilities for banks) associated with bank failures in an extreme event. VaR conveys the maximum level of losses exceeded with a given probability alpha and ES provides the mean over the range from VaR to the greatest possible loss. More specifically, $VaR_\alpha$ is the maximum level of the losses (system wide loss) associated with the default of banks with confidence level $(1 - \alpha)$, e.g. $\alpha = 5\%$, such that probability of the total loss going over the $VaR_\alpha$ level is alpha, $Pr(Loss > VaR_\alpha) = \alpha$, with Loss being the loss level$^{16}$. The ES is then defined as expected system-wide loss, conditional on the loss being greater than the $VaR_\alpha$ level. A systemic event is an extreme event that is assumed to occur when the system-wide loss exceeds the value specified by $VaR_\alpha$. Specifically,

$$ES_\alpha = E[Loss|Loss \geq VaR_\alpha]$$ (3)

In other words, ES is the expectation of system-wide loss when the loss exceeds its $VaR_\alpha$ limit. $VaR_\alpha$ conveys the maximum level of losses exceeded with a given probability alpha, and ES provides the mean over the range from $VaR_\alpha$ to the greatest possible loss$^{17}$. As in the firm level concept, ES is the capital (or a hypothetical insurance premium) needed to offset the systemic loss$^{18}$. Aggregate losses in the system can be obtained by summing the losses across the banks:

$$ES_\alpha = \sum \ E[|l_i - Loss \geq VaR_\alpha]$$ (4)

where $Loss = \sum l_i$, and $l_i$ is the size of the loss associated by a bank $i$'s default.

$$l_i = s_i \cdot LGD_i \cdot l_i$$ (5)

In this expression, $s_i$ is the size of the bank $i$'s debt (the book value of its non-equity liabilities). We normalize the overall size of the system to 1, $\sum s_i = 1$. $LGD_i$ is loss-given-default which shows

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$^{16}$ Typically, $\alpha$ is selected as 1% or 5% and the VaR gives the most a bank can lose with 99% and 95% confidence, respectively.

$^{17}$ Acharya et al. (2010) use equity return data to define capital loss. That is, expected capital shortfall is the amount that equity falls below target level.

$^{18}$ This is the capital to offset the losses incurred by public (households and businesses). Banks’ liabilities are the public’s assets. The support from FDIC is assumed to be zero for the bank losses. Look for a similar treatment in Tarashev et al. (2010), Huang et al. (2012) and Cummins (2014).
how much of the losses are recovered if bank $i$ defaults. The default indicator, $l_i$, is either 0 (bank survives) or 1 (bank fails) and determined for each bank and time period as a function of its probability of default. As a probability of default, we use the bank distress indicator, $PD_{i,t}$ developed in section 3.2.2.1. For deriving the default indicator, we employ a model of stochastic losses similar to Tarashev (2009)\textsuperscript{19}. The distribution of defaults $\{l_i\}_{i=1}^n$ is determined via Monte Carlo simulations\textsuperscript{20}. Applying $\{s_i\}_{i=1}^n$ and loss-given-default to the distribution of defaults, as in equation (5), we determine the probability distribution of individual banks’ losses, $\{l_i\}_{i=1}^n$. Aggregate loss is the sum of all simulated losses across the banks, $\sum l_i$. It is then straightforward to obtain the ES of the system as in equation (4). Repeating these steps for each quarter, a time series of the systemic risk indicator is created for the 2001-2013 period.

In the ES concept, aggregate $L$ is defined in the interval of $[0, 1]$. If LGD is assumed to be 1 (no recovery of losses) and all banks fail, $Loss$ becomes 1. On the other extreme case, where either LGD is assumed to be 0 (all the losses are recovered) or no bank failure, $Loss$ becomes 0. Thus, in each quarter ES is determined in the interval of $[0, 1]$, and conveys the information for how much capital is needed to restore losses in the system as a ratio of total liabilities\textsuperscript{21}.

The bank distress indicator that we use as a probability of default is a physical (actual or real world) default concept. A probability of default measure that is developed based on balance sheet information is a physical default concept because it is based on a structural definition of default, e.g. a firm defaults when its market value falls below its debt obligations (Hull et al., 2005; Tarashev and Zhu, 2008)\textsuperscript{22}. On the other hand, default probabilities constructed using market asset

\textsuperscript{19} Tarashev (2009) uses a model of stochastic losses to determine banks fail/survive conditions. We employ the same procedure. Similar procedures are used by Huang et al. (2012) and Cummins (2014).

\textsuperscript{20} Tarashev (2009) and Cummins (2014) generate distribution of bank status (fail/survive condition) with Monte Carlo simulations. We repeat the same procedure to determine the distribution of bank status.

\textsuperscript{21} Reading it for a banking system just as an individual bank would translate into a systemic default risk; a distress indicator that is equal to 0.2 means a 20% default probability for that bank. Similarly, an ES of 0.2 means that the banking system’s probability of default is 20%.

\textsuperscript{22} Tarashev (2010) uses another physical default concept, expected default frequency (EDF), as a probability of default to develop a systemic risk indicator. EDF is Moody’s KMV’s market product that estimates expected one-year (physical) default rates for individual firms based on their balance sheet information. The method is based on the Merton (1974) framework and explained in detail in Crosbie and Bohn (2002) Modeling Default Risk, KMV White Paper.
prices are known as *risk-neutral default* probabilities because they are composed of default risk and risk premia. A physical default concept is superior to the risk-neutral default concept because the risk premia in market prices of assets (bonds, loans, etc.) are an extra return to compensate for the risks that investors are bearing on the top of the actuarial probability of default (Hull et al., 2005). In other words, market prices of these instruments reflect not only the odds of future events (and the corresponding cash flows), but they also involve opportunity costs. Therefore, real-world default probabilities are usually less than risk-neutral default probabilities. The bank distress indicator developed in our paper is a physical default concept, defined by two main features. First, we use a structural definition of default under which a bank defaults when the sum of its non-performing assets exceeds its equity capital and loss reserves. Second, historical data show that this indicator is quite useful in predicting bank failures in the great recession of 2007-2009 (Cole and White, 2012). Moreover, the capital ratio based on this concept outperforms all other capital ratios used in the literature in predicting distress (Cole and Cheneskyh, 2015).

To the best of our knowledge, our paper is the first to use such a default probability in developing a systemic risk indicator. This is one of our main contributions. An important benefit of this distress indicator is that it can be determined for all banks at any point in time, whereas Credit Default Swaps (CDS) or bond yields are available for only a number of banks. Similarly, Expected Default Frequency (EDF), another physical default concept used by Tarashev (2010), is available only for a number of banks. Employing a bank distress indicator (explained in section 3.2.2.1) enables us to create a systemic risk indicator that encompasses the entire banking system.

**3.2.3 The Taylor Rule Rate (TRR)**

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23 Several other measures of default probability are used in the literature. One common measure is constructed by using CDS spreads (Duffie (1999), Tarashev and Zhu (2008), and Huang (2012)). A CDS contract offers protection against default losses in return for periodic premium payments. Other measures use bond and loan spreads (Blanco et al. (2005), Forte and Pena (2009), and Norden and Wagner (2008)). The CDS spread of a bank will rise if the investors on CDS contracts see risks increase for the bank. The rising spread could be based on liquidity or solvency concerns, but the risk factor created by CDS spreads reflect the perception of investors of a particular bank based on the available information.

24 Risk-neutral default probabilities are used when credit-dependent instruments are valued. Real-world default probabilities are used in scenario analysis and in the calculation of bank capital under Basel II.
The recession of 2007-2009 marked the sharpest downturn in the US economy since the Great Depression, according to several indicators. Policy responses were accordingly unprecedented. The Federal Reserve typically does not set its FFR below zero. After the FFR hit the zero bound in December 2008, and the Fed could not set a negative target (Blinder, 2010), it used unconventional policy tools, such as the so-called quantitative easing (QE), to add liquidity to the market and to reduce long-term rates to spur demand for domestic loans. Switching from FFR to QE complicates our analysis, because a time series of the policy rate is needed for the entire sample period (2001-2013). The primary question then becomes, if the FFR were not constrained by a zero lower bound, could a negative FFR have replaced QE? As an alternative to FFR, we consider the “implicit policy rate” or the Taylor Rule rate (TRR), which is not bounded by zero.

The Taylor rule is a simple monetary policy rule introduced by John Taylor (1993) that relates the central bank's interest rate target to the current state of the economy. It prescribes in a systematic way how a central bank should adjust its interest-rate policy instrument in response to inflation and macroeconomic activity. While no central bank strictly follows a simple Taylor rule at all times, a variant of the original Taylor rule provides guidance for policymakers. Therefore, estimated Taylor rules are often used to analyze actions of the Fed and other central banks (Kahn et al. 2010; Lubik and Schorfheide, 2007; Schmidt-Hebbel and Werner, 2002; Clarida et al.; 1998). What the Taylor rule suggests and what central banks follow have been debated since the original rule was proposed in 1993, and this has continued after the Fed hit the zero lower bound and began its QE policy in December 2008 (Nikolasko-Rzhevskyy and Papell, 2012). The rule points to a negative nominal interest rate when the unemployment rate is much higher than the natural rate and the inflation rate is much lower than the target rate. As such, variants of the Taylor rule have pointed to negative nominal rates since 2008 (Nikolasko-Rzhevskyy and Papell, 2012;}

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25 The supply side was a bigger problem because markets were frozen and banks did not lend. The Fed wanted to boost the loan supply and it is unclear to what extent it succeeded.

26 Specifically, the rule states that the real short-term interest rate is determined according to three factors: (i) where actual inflation stands relative to the Fed's target level, (ii) to what extent economic activity has deviated from its full-employment level, and (iii) what the real short-term interest rate should be consistent with full employment. The Taylor rule has become the dominant metric for analyzing monetary policy since it was introduced in 1993.
(Meyer 2009; Gagnon, 2010; Dudley, 2010; Neely, 2012; Bernanke, 2015) (further discussion of this issue is provided in Appendix B, for reviewers interest).

Several versions of the rule have been suggested over the years. We use the version that includes the unemployment gap, defined as the difference between the natural rate of unemployment (NAIRU), and the actual unemployment rate. This version of the Taylor rule has the form:

\[ i_t = \text{constant} + \beta(\pi_t - \bar{\pi}) + \gamma(ue_t - \bar{ue}) \]  

(6)

where \( i_t \) is the effective FFR, \( \pi_t \) is the inflation rate, \( \bar{\pi} \) is the inflation target, \( ue_t \) is the actual unemployment rate, and \( \bar{ue} \) is the natural rate of unemployment. Equation (6) tells us that there is a “neutral” FFR, \( \text{constant} \), which prevails when inflation and unemployment are at respective target levels. The neutral rate setting for the FFR, \( i_t \), consists of two components: (i) a real interest rate generally assumed to be around 2% (Rosenberg, 2010), and (ii) the Fed's implicit target for inflation, \( \bar{\pi} \), which we assume to be around 1.5%. Hence, the neutral nominal FFR setting, \( \text{constant} \), would be on the order of 3.5% (Rosenberg, 2010).

The Taylor rule prescribes the specific amount by which the nominal FFR should rise (fall) relative to the neutral rate setting if actual inflation exceeds (falls short of) the Fed's implicit target. Or, similarly, assuming the inflation gap is zero, if the unemployment rate exceeds (falls short of) the natural rate of unemployment, how much the nominal FFR should decline to lower the “real” FFR in order to increase domestic demand and gradually reduce unemployment to its natural rate.

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27 See Nikolsko-Rzjevskyy, Papell (2012) for a detailed discussion of Taylor rules developed over time. The original rule has the form: \( i_t = \bar{r} + \pi_t + \beta(\pi_t - \bar{\pi}) + \lambda(y_t - \bar{y}) \), where \( i_t \) is the FFR, \( \pi_t \) is the inflation rate, \( \bar{\pi} \) is the inflation target, \( y_t \) is output growth, \( \bar{y} \) is the potential output growth, and \( \bar{r} \) is the real interest rate. One variant of the Taylor Rule was developed by substituting the output gap, \( (y_t - \bar{y}) \), with the unemployment gap (Rosenberg 2010). The unemployment gap is defined as the difference between the natural rate of unemployment, or NAIRU, and the actual unemployment rate. There has been a well-established inverse relationship between the level of the output gap and the unemployment gap; when output falls below potential, the unemployment rate tends to rise above its natural rate and vice versa (Prachowny, 1993). This inverse relation is known as Okun’s Law and is formulated as \( (y_t - \bar{y}) = \mu(ue_t - \bar{ue}) \).

28 The unemployment rate gap is preferred because of its availability at a monthly frequency. High frequency estimations use the unemployment rate instead of the output gap. We prefer the unemployment rate gap to the output gap because the notion of full employment (or the non-accelerating inflation rate of unemployment) is better defined than is the output gap in a limited time span.

29 If \( (\pi_t - \bar{\pi}) > 0 \), the nominal fed funds rate should rise by \( \beta \) times the inflation gap. For example, assuming \( \beta \) is 1.5 and the unemployment gap is zero, if the actual inflation rate exceeds the Fed's implicit inflation target by 1%, then the fed funds rate should rise by 1.5 percentage points. This will insure that if inflation rises above target, the "real" FFR will rise to slow domestic demand enough to gradually bring the inflation rate back to its target level. Similarly, assuming \( \gamma \) is -2 and the inflation gap is zero,
We estimate the coefficients of inflation and the unemployment rate gaps in equation (6) using the Ordinary Least Square (OLS) for the period 1994 through 2008, and then compare the estimated rate with a generic calculation of the Taylor rule by using already established coefficients (Table 2). For a generic calculation, we use the coefficients proposed by Rosenberg (2010). The estimation is based on the effective FFR, and, thus, assumes the Fed strictly followed the Taylor rule in setting its policy rate. We report the estimation results in Table 2 and demonstrate the “implied policy rate” in Figure 2. Our results show that despite some differences between the estimated TRR and FFR, in general, the FFR followed the TRR closely during the 1994-2008 period and creates a basis for using the estimated rate as an “implied policy rate” in our model (see Appendix B).

4. EMPIRICAL RESULTS

The models are estimated using quarterly data covering 2001 - 2013. We cannot expand the data back beyond 2001 because the BHC delinquency and default data were not reported quarterly before this date. Estimation results for the base and extended models are discussed in sections 4.1.2 and 4.1.3. Results from the models with house price index are reviewed in section 4.1.4. Since 13 years of quarterly data may be insufficient for a VAR model, in section 4.1.5, we provide a robustness check by estimating the same model using a longer dataset (1993-2013) for large banks designated as Systemically Important Banks (SIBs) for which more data are available. In Section 4.2, we discuss the findings on the SIB results and draw policy implications.

One potential limitation for a short-span data for VAR models is over-parametrization\textsuperscript{30}. A traditional approach to addressing over-parametrization is selecting a low and universal lag order for all of the regressors to restrict the number of parameters (Nicholson, et al., 2016). However, this approach requires a strong assumption of short-term dependence among the variables in the model and restricts the dynamic relationship (Nicholson, et al., 2016). Therefore, we take the

\textsuperscript{30} Sims (1980) describes the over-parametrization problem and calls it as “profligate parametrization”. 
traditional approach of picking short lags, two lags and three lags for the basic models, and the extended model, respectively, for all components, and assume a short-term dynamic relation among the variables in the models. The lag order is selected according to information criteria (IC) (Appendix A). We look at two ICs, Akaike information criterion (AIC) and Schwarz information criterion (SIC), instead of one, to improve the lag selection accuracy.

4.1 A VAR Model of Macroeconomic and Systemic Risk Indicators

We estimate the reduced-form VAR model (Eq. 1) using quarterly series of macro indicators (GDP growth rate, inflation, and the implied policy rate) and the systemic risk indicator over the sample period (2001-2013) as a base model. Then, we extend the model to include a lending-standards indicator (the senior loan officer survey). Raising short-term rates may create distress for lenders due to rate resets, resulting in higher default rates, and lower demand for loans, particularly mortgage loans. The distress on banks during rising interest rate periods may also result from tightening credit standards such as collateral requirements, compensating balances, more frequent application denials etc. Many borrowers default because they are unable to refinance their loans. In a credit crunch, bank distress rises as delinquencies and defaults increase while credit growth remains restricted due to extremely tight lending standards. In such a case, cutting interest rates may not offset the burdens on lenders and borrowers because market liquidity dries up due to bank risk aversion. To distinguish the impact of policy rate changes on bank distress from the impact of tighter lending criteria, we extend the base VAR model by including a lending criteria indicator based on the senior loan officer survey. Extending the base model does not change the structure of the model fundamentally. The model still represents the complete macro-economy: demand (monetary policy rate), supply (senior loan officer survey, systemic risk indicator), output (the real GDP growth) and price (inflation).

31 This approach may constrain the relation between the components: e.g. the impact of a policy rate cut may continue to affect systemic risk after four quarters, which is ignored when a three-quarter lag is used. However, Hafer and Sheehan (1989) find that relatively short-lagged models are more accurate, on average, than longer-lagged specifications.
Much of the burden on banks during the housing boom and bust years (2001-2006 and 2007-2010) was created by real-estate-related loans that soured as home equity evaporated with declining house prices. Thus, we also investigate the link between the policy rate and banking system distress in a model that replaces inflation with a house price index (the Case-Schiller House Price Index) in both base and extended VAR models. In the next subsections, we will examine the results based on the impulse response functions (IRFs) and variance decompositions (VDs) for each model to determine how the findings change when inflation is replaced by house prices.

### 4.1.1 Impulse Responses and Variance Decompositions

We examine the impulse responses (IRFs) of the systemic risk indicator to the implied policy rate and systemic risk indicator’s variance decompositions (VDs) to determine the power of implied policy rate changes relative to the macro variables in determining systemic risk. The model presented in Eq.1 is a reduced form VAR model, and it has to be transformed into a structural VAR model in order to generate IRF and VD. Transformation of a reduced form model to structural form requires identifying assumptions that establish causal links among variables. We employ the Cholesky decomposition as an identification technique. In Cholesky decomposition, responses of variables to a particular shock depend on the ordering of the variables in the VAR model (Sims, 1980). Therefore, it is necessary to place the model variables in a precise order.

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32 Replacing inflation with house price index does not change the structure of the model fundamentally because we are replacing one price index with another. The model continues to capture a complete macro-economy as before. We do not include both inflation and house price in the model because of the short data span.

33 IRF traces out the response of current and future values of an endogenous variable to a one-time shock of a one-unit, or a one-standard deviation, increase in the current value of another endogenous variable. VD decomposes the variation in an endogenous variable into the component shocks. Both computations are useful in assessing how shocks to economic variables reverberate through a system. In general, VAR models are presented through IRFs and VDs because the VAR coefficients are biased due to endogeneity. In most cases, the coefficients for a given variable turn out to have opposite signs in different lags and mask the real impact of that driver on the dependent variable. Therefore, in the unrestricted VAR model estimated on a reduced form, the innovations generated by the model are uninterpretable. Innovations are the error terms in reduced form VAR.

34 A reduced form VAR model expresses each variable as a linear function of its own past values and the past values of all other variables being considered. This type model needs to be transformed into a structural VAR model in order to generate IRF and VD because, a structural VAR uses economic theory to sort out contemporaneous links among the variables.

35 There are several identification techniques used to this end in the literature. We use Cholesky decomposition for parsimony, but do robustness tests with Generalized Impulse Responses which do not depend on the ordering of the variables (section 4.1.5).
ordering justified by the adjustment speed of each variable to contemporaneous shocks\textsuperscript{36}. We order the macro variables as the TRR, GDP growth rate, and inflation, and then put systemic risk measures after macro variables in the base model\textsuperscript{37}. As a diagnostics check, in all model outputs, we first look at the responses of GDP growth and inflation to a given impulse on the TRR for the direction of causality. If the responses have the right directions, it suggests that the Cholesky ordering is also correct. More specifically, with a theoretical prior, we check if GDP growth and inflation responses are negative in some periods after a unit shock is introduced to TRR. Because the time span of the data is short, we want to make sure that the link between the policy rate and output and inflation are accounted for well in the models before we look at the responses of TRR. We examine the results for each model next.

\textbf{4.1.2 The Base Model}

The results of the IRFs and VDs are presented in Figures 5 and 6, respectively. In the base model, we find that a one unit (100bp) increase in the TRR reduces GDP growth and inflation until the end of six quarters after the shock is introduced. More specifically, the impact of a rate increase on GDP growth peaks at -1.2 percentage points in the sixth quarter, subsiding thereafter and disappearing after twelve quarters (Figure 5a, upper-right panel). The results also show that inflation is very sensitive to changes in the policy rate. The impact of a one-unit increase in the TRR on inflation peaks at -0.5 percentage points in the seventh quarter, declines thereafter and nearly disappears after twelve quarters (Figure 5a, bottom-left panel). The response of GDP growth and inflation responses to a unit shock in TRR verify that the directions of the effects among the macro variables are captured well in the model. According to VDs, innovations in TRR account for 8\% of error variance in output growth after one quarter and 45\% after eight quarters (Figure

\textsuperscript{36} Sims (1980) introduces the Cholesky decomposition and discusses the impacts of the variable ordering. A common application of Cholesky ordering is that the first variable should be selected such that it is the only one with potential immediate impact on all other variables. The second variable may have an immediate impact on the other variables except the first one: that is, the first variable has a quicker impact on the second one than the second has on the first.

\textsuperscript{37} See a similar ordering in Lown and Morgan (2006). We experiment with the Generalized Impulse Responses method proposed by Pesaran and Shin (1998) for comparison. These authors construct an orthogonal set of innovations. Therefore, unlike the Cholesky impulse response analysis, this approach is invariant to the ordering of the variables in the VAR. The results from Generalized Impulse Responses are found not to be materially different from those of the Cholesky decomposition. We provide some of the results in the robustness check section. Others are available upon request.
6a, upper-right panel). Innovations in TRR account for nearly half of the total error variance in inflation after six quarters and remain flat thereafter (Figure 6a, bottom-left panel). Inflation shows persistence. Nearly one quarter of the error variance of inflation remains for twenty-four quarters.

Both VDs demonstrate that a significant portion of error variations in output growth and inflation are due to variations in TRR, as expected.

In the base model, we find that one-unit increase in the TRR raises the systemic risk at varying degrees over ten quarters after the shock with the impact peaking at 1.6 percentage points in the tenth quarter (Figure 5a, bottom-right panel). More specifically, if the policy rate rises 25 bps, e.g., from 3% to 3.25%, the banking system distress rises by 40 bps after ten quarters, e.g. from 10% to 10.4%. The impact of the rate hike on systemic risk disappears gradually after the peak: the effect is not permanent, but it is durable; it takes time to vanish. In the base model, comparing the error variance of the systemic risk indicator due to innovations across macroeconomic variables suggests that the implied policy rate has a larger impact on systemic risk measures than do the macroeconomic factors considered (GDP growth and inflation). Innovations in the TRR account for nearly 40% of error variation in the system distress after the twelfth quarter and remains flat thereafter; Inflation and GDP growth account only for the remaining 10% (Figure 6a, bottom-right panel)\(^{38}\). The high share of TRR (40%) in banking system distress encourages us to introduce the lending criteria into the model in order to verify robustness of the results. In section 4.1.3, we discuss the model extended to include the lending standards.

We modify the VAR model with a different ordering of macro variables and lag lengths (three and four quarters), and look at the IRF and VD. None of these modifications change the results substantially\(^{39}\). All the evidence from VAR models with various specifications shows that changes in the implied policy rate had a considerable effect on systemic risk over the 2001-2013 period. A policy rate hike during this time period clearly increased distress in the banking system.

\(^{38}\) TRR and inflation have a correlation of 0.62, which corresponds to VIF of 4.56. The critical value for VIF may be chosen as 10 (Wooldridge, 2002); above this threshold, multicolinearity becomes a problem.

\(^{39}\) Changing the rank order of the variables gives an IRF for SRI due to implied policy rate ranging from 1.6% to 1.2%. VDs of SRI due to implied policy rate range from 24% to 40%.
4.1.3 Expanding the Base Model to Account for Lending Standards

The results of IRFs and VDs based on the extended model are presented in Figures 5 and 6, respectively. The direction of the effects among the macro variables are captured well in this model as well\textsuperscript{40}. Once we introduce the lending-criteria indicator into the model, we find that it takes away some of the strength of TRR to constitute about 20% of the error variation in GDP. This suggests that the variations in economic activity do not come from the interest rate hike alone as the lending criteria are also associated with changes in GDP to a considerable degree (Figure 6b, upper-right panel). However, in contrast to GDP, the error variance in inflation due to TRR is found to remain essentially unchanged, compared to the base model, suggesting that TRR is the dominant factor affecting inflation (Figure 6b, bottom-left panel). This makes TRR the policy instrument of choice for inflation targeting. The results also show that including lending criteria in the model reduces the impact of the TRR on systemic risk indicator substantially through the link remains strong. In this extended model too, a one-unit shock to the TRR raises the systemic risk indicator for about two years after the shock is introduced; the effect peaks at 0.8 percentage points in the eight quarter, compared to 1.6 percentage points after ten quarters in the base model. More specifically, if the TRR rises by 25 bps, e.g., from 3% to 3.25%, bank distress rises, e.g., from 10% to 10.2% after eight quarters.

Adding the senior loan officer survey to the model changes the results for the impact from TRR on systemic risk in the base model in two ways; the impact from a unit shock to TRR lasts for a shorter period (it is less durable) and the magnitude of the impact declines to half until the ninth quarter, and then falls rapidly. In the extended model, innovations in the senior loan officer survey are associated with the largest error variance in bank distress among other variables (Figure 6b, bottom-right panel). Movements in the senior loan officer survey account for less than 10% of

\textsuperscript{40} A unit shock to TRR reduces output growth until the twelfth quarter and inflation until the ninth quarter after the shock is introduced. The responses disappear thereafter. The magnitude and the timing of the impact on output and inflation are similar to the ones we observe in the base model. More specifically, the impact on output growth peaks at -1.2 percentage points in the sixth quarter. The response of inflation from a unit increase to TRR peaks at -0.6 percentage points in the sixth quarter and then declines thereafter. The responses of GDP growth and inflation to a unit shock in the TRR verify that the directions of the link among the macro variables are captured reasonably well in the model. According to VDs (Fig. 5), the error variation of GDP growth due to TRR peaks at 40% in the eighth quarter, and then gradually declines below 20% (compared to 45% in the base model) over time.
the error variance until the end of first year, then rise to 25% after three years. The share of TRR among total variation rises initially to 20% over four quarters, then declines gradually to below 10% thereafter. Error variance due to innovations in output and inflation in total initially rises to 15%, but declines to 8% over time. In brief, putting lending standard into the model: (i) reduces the error variance share of TRR in systemic risk from 40% to 10%, and (ii) causes TRR’s variations to decline over time, whereas the base model shows a flat share of error variance. The TRR does not have a long-term effect on bank distress as the base model signified41, suggesting that policy makers should focus on the short-term effects of the policy rate changes on bank distress.

**4.1.4 Replacing Inflation with House Price Index**

The results for IRFs and VDs are presented in Figures 5, and 7, respectively. The period we investigate overlaps with the US housing boom and bust years of 2001-2006 and 2007-2010. Housing-related loans make up the largest share of household balance sheets and the housing downturn created significant distress on households and, thereby banks, during the Great Recession. Thus, as a robustness test, we explore the effect of the policy rate changes on banking system distress in a model with a house price index. Replacing inflation with house price index does not fundamentally change the model structure. The model continues to include the main indicators representing a potentially complete macro-economy: an output, a price index that reflects the change of value of the largest asset in household balance sheets, demand (the monetary policy rate) and supply (systemic risk indicator).

After replacing inflation with housing price index, the main results continue to hold directionally though they alter considerably in terms of magnitude. Similar to the base model with inflation, the model with a house price index captures the direction of the effect well: House price growth declines after a positive shock to TRR, but much more so than does inflation, which shows house prices are more elastic with respect to the changes in policy rates than is inflation. Housing is dramatically sensitive to interest rates because payments of (adjustable rate) mortgages reflect

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41 See Lown and Morgan, 2004 for the impact of lending standards on loan originations.
the interest rate changes and creates a burden on homeowners. Moreover, an increase in rates reduces the demand for mortgage loans, and thereby home sales, and puts pressure on house prices\footnote{Another reason for higher sensitivity of house prices compared to inflation is that Consumer Price Index is a basket of several household expenditures and house prices are one of the expenditure classes (indices) that constitute Consumer Price Index. Fluctuations in house prices are reflected in CPI if they are large enough, but the magnitude of fluctuation is reduced according to the scale of the weight assigned to house price index in CPI. See Bureau of Labor Statistics’ (BLS) monthly CPI report \url{https://www.bls.gov/opub/hom/pdf/homch17.pdf}.}. In the modified base model, a positive shock to TRR reduces house price growth until nearly six quarters following the shock (Figure 5b, bottom-left panel), two quarters sooner than its impact peaks on inflation. However, the magnitude of the effect is much larger: a 25 bps increase in the TRR starts reducing house price growth right away, the effect peaks at 1.7 percentage points (0.13 percentage points for inflation) in the sixth quarter (eighth quarter for inflation), and then subsides gradually thereafter. It takes more than 12 quarters to disappear.

Adding lending criteria to the model reduces the impact of interest rate shock on the house price index: as seen in Figure 5b, bottom-left panel, a 25 bps increase in TRR reduces house price growth by 1.3 percentage points (0.14 percentage points for inflation) at its peak in the fifth quarter (sixth quarter for inflation), compared to 1.7 percentage points (0.13 percentage points for inflation) decline in the base model, and then subsides thereafter to disappear in the tenth quarter. According to VD values, shown in Figure 7a, the bottom-left panel, in the base model changes in the policy rate explain nearly 60% of the variation in house prices (nearly 50% for inflation) but house price growth does not show strong persistence: similar to inflation, only 25% of the effect of TRR increase sustains itself beyond six quarters. Adding lending criteria to the model reduces the variation due to the policy rate substantially, from 60% to 20% (from 50% to 10% for inflation) (Figure 7b, the bottom-left panel). Rising rates curb demand for housing as loans become costly, and house prices decline accordingly. However, the weakness in the housing market is not just a result of increasing interest rates, tighter lending criteria also curb demand as fewer potential borrowers come to the market and fewer of those who do are able to obtain mortgages. Changes in the lending criteria account for 40% of the variation in house prices (Figure 7b, bottom-left panel). The house price response to a unit shock in TRR verifies that the directions of the effect
among the macro variables are captured well in the modified extended model, since rising interest rates theoretically reduce demand for housing and house prices to decline accordingly.

Next, we turn to the systemic risk indicator. According to the modified base model, the impact of an increase in TRR on banking system risk is positive and peaks in the tenth quarter (Figure 5b, bottom-right panel). A unit shock to the policy rate raises the systemic risk indicator by 2 percentage points until the tenth quarter, and then the effect subsides gradually. Specifically, if the policy rate rises from, e.g., 3% to 3.25%, bank distress goes up from 10% to 10.5% after ten quarters. In the extended model that accounts for lending criteria, the impact of one-unit shock to TRR on bank distress declines nearly by half, compared to the base model, until the ninth quarter (Figure 5b, bottom-right panel). Analytically, if the policy rate rises by 25 bps in this quarter, banking system risk rises by 35 bps, e.g., from 10% to 10.35%, after nine quarters.

According to VDs, in the base model, changes in the policy rate account for a whopping 60% of the variation in the systemic risk indicator, which persists over time (Figure 7a, bottom-right panel). However, adding the lending criteria indicator reduces the share of policy rate changes to 15%; the share rises to 25% in the tenth quarter before declining to 15% thereafter (Figure 7a, bottom-right panel). It is clear that credit tightening is also positively and strongly associated with rising banking system distress, in addition to the policy rate.

Including lending criteria in the model reduces the effects of TRR on all variables, but the decline in TRR’s impact is most noticeable on the systemic risk indicator. A higher policy rate is one factor for rising banking system distress, but our results show that tight credit policy leads to higher distress, too. Including lending criteria also reduces the effect of the interest rate on house prices materially. Adding lending criteria to the model strengthens the supply side, thus the model is able to capture the factors affecting the housing market better: tight credit issuance accompanied with rising interest rates reduce the demand in the housing market and raises home prices.

4.1.5 Robustness Checks

We carry out two robustness checks; (i) the data span and (ii) the decomposition method used. VAR models are more reliable if the data span is long. Thus, we investigate whether the
relationship we found between the TRR and bank distress level based on the 2001-2013 sample period holds in a longer sample period. Since performance data with a longer history are available mostly for larger banks, we focus on Systemically Important Banks (SIBs)\(^{43}\) consisting of thirty-four banks that participated in the Dodd-Frank Act Stress Tests (Appendix C). This also helps sample homogeneity. Our SIB sample includes 21 banks with historic data going back as far as 1993Q1. The Bank Compustat dataset reports total non-performing assets (NPA), but does not disaggregate it into past-due cohorts: NPAs include assets that are more than 90 days past due and accruing interest, and assets in non-accrual status. Therefore, instead of applying a haircut to past-due cohorts, we use total NPAs. Thus, for robustness check, we use \((\text{Non-performing Assets + Real Estate Owned (REO)})/(\text{Equity Capital + Total Allowance})\) as a distress indicator, and create a systemic risk indicator accordingly\(^{44}\). IRFs for the extended model with inflation and house prices are presented in Figures 8. As can be seen from these figures, the basic results continue to hold: A unit positive shock to the implied policy rate creates distress on banks (Figure 8a, the model with inflation; Figure 8b, the model with house price).

Since in Cholesky decomposition, used in our analysis, IRFs are dependent on the ordering of the variables, we experiment also with the Generalized Impulse Response method (GIRF) proposed by Pesaran and Shin (1998) for comparison. These authors construct an orthogonal set of innovations to address the ordering problem. Unlike the Cholesky IRF analysis, this approach is invariant to variable ordering chosen in the VAR. The GIRF results, presented in Figures 9, are nearly identical to those from the Cholesky decomposition.

\(^{43}\) There are 34 BHCs that are designated as SIBs. Some are designated as Global Systemically Important Banks (G-SIBs) and the rest as Domestic Systemically Important Banks (D-SIBs). G-SIB is an official designation of the Financial Stability Board (FSB) and the Basel Committee on Banking Supervision (BCBS), based on a framework that accounts for the contribution of the banks to systemic risk. The method equally weights each of the five categories of systemic importance: size, cross-jurisdictional activity, interconnectedness, substitutability/financial institution infrastructure, and complexity. D-SIB is not an official designation of the FSB or BCBS, yet these large U.S.-based BHCs participate in the Dodd–Frank Act Stress Test (DFAST).

\(^{44}\) Cole and White (2012) tested total NPA as well as applying several haircuts to the delinquency cohorts. They found that their results do not differ by a larger margin.
5. CONCLUDING REMARKS

In this paper, we investigate the relationship between the main US monetary policy rate (the fed funds rate, FFR) and systemic risk between 2001 and 2013, using an unrestricted reduced form VAR model. We build a systemic risk indicator based on an insolvency criterion for BHCs to gauge the level of distress in the banking system. Then, we estimate a Taylor Rule rate and use it as an implied policy rate, to account for the period when the policy rate, FFR, was restricted by a zero bound. We find that the monetary policy rate is positively associated with banking system distress during our sample period; easing monetary policy reduces the stress on bank balance sheets while tightening it adds stress. The sample period includes early 2000s when the unusually low interest rates caused a credit boom and helped to create the housing bubble, followed by a credit crisis, the housing market downturn and a severe recession. In the run-up to the financial crisis, keeping the policy rate too low for too long incentivized lenders to ease the lending standards and reach out to borrowers that were previously denied credit to shore up revenues. Abundant credit inflated house prices as many borrowers who were denied loans earlier obtained loans and purchased houses. Rising rates, on the other hand, reduced the incentive to borrow and put pressure on borrowers resulting in defaults and foreclosures. The monetary policy tightening period of June 2004 to September 2007 was associated with rising housing related losses (mortgage loan defaults), creating a positive correlation between short-term rates and the banking system's stress level: The positive relation between short-term rates and banking system stress before the crisis reflects consumer credit dynamics, particularly in housing-related loans, during the credit boom era followed by the housing downturn. While housing related loans played a central role, as they were by far the largest liabilities on household balance sheets, similar trends occurred in other loan segments, such as credit card loans, auto loans, and commercial credit. The relation between the monetary policy rate and systemic risk became more complicated during the 2007-2009 crisis and in the post-crisis period because of the multifaceted nature of the policy implementation and the strong spillover potential of macroeconomic and policy shocks. Although
raising short-term rates creates distress on lenders due to rate resets and lower demand\textsuperscript{45}, tightening credit standards strengthen this effect as many borrowers cannot refinance or roll over their outstanding debt.

Recessions accompanied by a financial crisis are very costly in terms of lost output because in these periods business investment plunges amid a credit crunch (Jorda, Schularick and Taylor, 2012)\textsuperscript{46}. A credit crunch refers to a sudden decline in the supply of funds available for lending. It is essentially a market failure due to widespread lack of liquidity across markets and firms (Acharya et al. 2011; Grochulski and Morrosin, 2014). The crisis of 2007-2009 was accompanied by a historic credit crunch triggered by a sharply rising bank risk aversion in consumer and commercial credit. Defaults and bankruptcies surged quickly after credit dried up and caused money and credit markets to freeze in the last quarter of 2008. The recession deepened, in several dimensions, to a level that had not been seen since the Great Depression. The Fed responded to the downturn by slashing short-term rates (the target FFR was cut from 5.25\% in September 2007 to 0.25\% in December 2008) and engaging in quantitative easing (QE). The Fed’s bold response (represented as an implied policy rate below zero in our model) might have reduced some of the burden on bank balance sheets, but it was clearly insufficient to counterbalance the effect of heightened risk aversion: The credit crunch (sharply tightening lending standards in our model) caused borrowers, households, and businesses in need of fresh credit to default on their loan obligations, leading to a surge in banking system distress. Lending standards embedded in the extended models are found to underpin the effect of policy rate changes on banking distress better than the base models.

Credit is critical for an economy and especially for the funds-intensive housing industry, and banks sit in the core of the financial system. Even though monetary policy decisions may affect

\textsuperscript{45} Loan resets increase bank revenue (and limit bank interest rate risk), but if lower demand offsets the revenue increase, a rate increase creates a burden on households and causes loan defaults to increase.

\textsuperscript{46} The links between lending standards, economic activity, and loan repayments have been widely investigated in the literature (Lown and Morgan, 2004).
the banking sector's health by encouraging or discouraging risk-taking, moral hazard concerns led
the Fed to avoid moving to alleviate the distress on banks before the 2007-2009 crisis. Our results
show that if there is a bubble in the economy, monetary policy-making becomes more complicated
and requires the utmost caution. It may be easier to prevent a bubble by avoiding an overly
accommodative monetary policy, than to work through a bubble once it exists. The results here
show that monetary policymaking in the last decade carries many lessons for policymakers.
Appendix A: VAR Lag Selection and Diagnostics Tests

The number of lags in a VAR model should be selected such that the model is stable—that is, it is stationary and passes the residual tests.

*Stability.* We check the stability of the model for specification of lags from one quarter to four quarters. We do not go beyond four quarters to have enough degrees of freedom in the data. For each lag specification, we look at the Akaike information criterion (AIC) and Schwarz information criterion (SIC), then run the Walt-test for that specification to see whether the coefficients for the corresponding lags are equal to zero (VAR lag exclusion test). The optimal lag structure should be selected such that it gives the lowest information criteria (AIC) that show the goodness of fit, but at the same time passes the Walt-test for the joint significance of the coefficients. Next, we look at the unit roots of the AR polynomial of the model for each lag specification. A VAR model is stationary if all roots have an absolute value less than one and lie inside the unit circle. After the tests, it turns out that the base model with *two lags* has a good fit, the coefficients are jointly significant and the model is stable. For the extended models, we use *three lags*.

*Residual-Tests.* There is trade-off in the determination of lag length between reduced autocorrelation in the error terms and decrease in degrees of freedom. Having selected the lag length of two and three quarters, we look at autocorrelation Lagrange Multiplier (LM) tests. We also check whether normality and homoskedasticity hold in error terms. We first look at VAR model specification that satisfies the stability condition—with two and three lags—and then test the models with four lags. None of the models show serious autocorrelation in error terms. It shows some autocorrelation in error terms in all lag lengths, but the model with two lags turns out to have the least autocorrelation. For normality, we test the lags for the null that residuals are multivariate normal. The models pass the test. Finally, we use White's heteroskedasticity test to check heteroskedasticity in residuals, and detect no heterogeneity at 5% significance.
Appendix B: Taylor Rule Discussion

Appendix B.1: Negative Taylor Rule Rate

A strand of papers in the literature claims that the Fed’s Quantitative Easing (QE) program actually implies further short-term rate cuts, if the FFR was not constrained by the zero lower bound. Gagnon (2010) estimates that the Fed’s announcements of future security purchases in early 2009 caused the 10-year yields to fall by about 0.5 to 0.75 percentage points. Dudley (2010) suggests that the $500 billion asset purchases provide about as much stimulus as a reduction in the FFR of between half a point and three quarters of a point. Separately, Rodenbusch (2010) argues that the output growth sensitivity to movements in the 10-year yields is four times as large as the output growth sensitivity to short-term interest rates. He estimates the impact of unconventional monetary policy to be equivalent to a short-term rate cut of 4%. Neely (2012) estimates 5% equivalent decrease in the FFR for the first round of QE. Yet, another argument for a link between asset purchases and federal funds rate comes from Bernanke (2011). He argued that QE2 had an impact on the economy equivalent to 40-120 basis point reduction in the FFR. Because the Fed’s asset purchase programs started after the FFR hit the zero band, and the credible research suggests that asset purchases caused short-term interest rates to decline further (Gagnon, 2010; Dudley, 2010; Bernanke, 2011; Neely, 2012), we use the Taylor Rule rate (TRR) for the period that FFR remained at zero bound: if TRR points to normative policy rates below zero after the Fed began quantitative easing, then it can be used as a substitute for the FFR to imply the stimulatory effects of QE in our model. As Bernanke (2015) states “If the Taylor rule predicts a sharply negative funds rate, which of course is not feasible, then it seems sensible for the FOMC to have done what it did: keep the funds rate close to zero (about as low as it can go) while looking for other tools (like purchases of securities) to achieve further monetary ease”. Even though TRR remains as an implied policy rate, FFR has historically followed TRR closely (see Figure 2).
Appendix B.2: Discussing Estimation Results

According to the results, reported in Table 2, all the coefficients are significant at 1% and quite similar to the ones assumed in Rosenberg (2010)’s generic rule. The model has an adjusted R² of 0.5947. The constant term, sum of the real interest rate and the inflation target, is 3.74. This is in line with the common assumption that the real interest rate in the economy is close to 2%, and the Fed sets the inflation target range to 1.5% - 2% (Rosenberg, 2010). An estimate of the constant term located between 3.5 and 4 is broadly acceptable. The model estimates the coefficient for the inflation gap as 1.1 and for the unemployment gap as -2.2. Units for the inflation and unemployment rate are percentage points. This result suggests that the unemployment rate has a bigger effect on TRR than inflation. Despite some differences between the estimated TRR and FFR, our result verifies that, in general, the FFR followed the TRR closely during the 1994-2008 period and creates a basis for using the estimated rate as an “implied policy rate” in our model. Beyond 2008, we rely on the coefficients estimated in the 1994-2008 period in developing an “implied policy rate.” We estimate the TRR declining as low as 6.8% below zero in 2009Q4, which is close to the lower boundary suggested in the literature (Meyer 2009). Our findings suggest that the implied policy rate returned to positive territory in the last quarter of 2013. Figure 2 compares our estimate with the actual FFR and the generic TRR. The model estimate closely follows the generic rule rate constructed according to Rosenberg (2010). Therefore, we use the estimated TRR in our model.

47 This is not a poor in-sample fit, but shows that, at the very least, there were times that monetary policymakers deviated from the Taylor rule. For example, according to our estimation, while the Fed’s policy was more restrictive than the Taylor rule suggested in the 1994-1998 period, it was not as tight as the Taylor rule suggested following the recession in 2001. Both of these have been common criticisms of the Fed’s policy in the past. Particularly, for the period of 2003 and 2005, the Fed was blamed for keeping rates too low for too long and contributing to the housing bubble.
### Appendix C: List of 34 Systemically Important Banks (SIB)

<table>
<thead>
<tr>
<th>SIB Name</th>
<th>Designation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ally Financial Inc.</td>
<td>D-SIB (D for Domestic)</td>
</tr>
<tr>
<td>American Express Company</td>
<td>D-SIB</td>
</tr>
<tr>
<td>BancWest Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Bank of America Corporation</td>
<td>G-SIB (G for Global)</td>
</tr>
<tr>
<td>The Bank of New York Mellon Corporation</td>
<td>G-SIB</td>
</tr>
<tr>
<td>BB&amp;T Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>BBVA Compass Bancshares, Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>BMO Financial Corp.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Capital One Financial Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>CIT Group Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Citigroup Inc.</td>
<td>G-SIB</td>
</tr>
<tr>
<td>Citizens Financial Group, Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Comerica Incorporated</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Deutsche Bank Trust Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Discover Financial Services</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Fifth Third Bancorp</td>
<td>D-SIB</td>
</tr>
<tr>
<td>The Goldman Sachs Group, Inc.</td>
<td>G-SIB</td>
</tr>
<tr>
<td>HSBC North America Holdings Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Huntington Bancshares Incorporated</td>
<td>D-SIB</td>
</tr>
<tr>
<td>JPMorgan Chase &amp; Co.</td>
<td>G-SIB</td>
</tr>
<tr>
<td>KeyCorp</td>
<td>D-SIB</td>
</tr>
<tr>
<td>M&amp;T Bank Corporation</td>
<td>G-SIB</td>
</tr>
<tr>
<td>Morgan Stanley</td>
<td>G-SIB</td>
</tr>
<tr>
<td>MUFG Americas Holdings Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Northern Trust Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>The PNC Financial Services Group, Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Regions Financial Corporation</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Santander Holdings USA, Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>State Street Corporation</td>
<td>G-SIB</td>
</tr>
<tr>
<td>SunTrust Banks, Inc.</td>
<td>D-SIB</td>
</tr>
<tr>
<td>TD Group US Holdings LLC</td>
<td>D-SIB</td>
</tr>
<tr>
<td>US Bancorp</td>
<td>D-SIB</td>
</tr>
<tr>
<td>Wells Fargo &amp; Company</td>
<td>G-SIB</td>
</tr>
<tr>
<td>Zions Bancorporation</td>
<td>D-SIB</td>
</tr>
</tbody>
</table>
Table 1: Summary Table for Bank Distress Indicator and Its Components

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Min</th>
<th>10th</th>
<th>25th</th>
<th>Mean</th>
<th>Median</th>
<th>75th</th>
<th>90th</th>
<th>Max</th>
<th>Std. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bank Distress Indicator</td>
<td>0.000</td>
<td>0.014</td>
<td>0.032</td>
<td>0.073</td>
<td>0.115</td>
<td>0.129</td>
<td>0.247</td>
<td>1.000</td>
<td>0.176</td>
</tr>
<tr>
<td>Capital/Asset</td>
<td>0.006</td>
<td>0.064</td>
<td>0.077</td>
<td>0.094</td>
<td>0.091</td>
<td>0.107</td>
<td>0.128</td>
<td>0.275</td>
<td>0.028</td>
</tr>
<tr>
<td>Loan Loss Reserves/Assets</td>
<td>0.000</td>
<td>0.006</td>
<td>0.007</td>
<td>0.012</td>
<td>0.009</td>
<td>0.011</td>
<td>0.015</td>
<td>0.155</td>
<td>0.005</td>
</tr>
<tr>
<td>Non-Perf. Assets/Assets</td>
<td>0.000</td>
<td>0.001</td>
<td>0.003</td>
<td>0.011</td>
<td>0.007</td>
<td>0.013</td>
<td>0.025</td>
<td>0.134</td>
<td>0.013</td>
</tr>
</tbody>
</table>

This table presents the summary statistics for the components of bank distress indicator. The data is winsorized at 1% and 99%. There are 72,760 observations in the panel, from 2001Q1 to 2013Q4. The non-performing assets is the same as the one used in bank distress indicator: NPA = 20% of assets delinquent 30-89 days + 50% of assets delinquent 90 plus days + assets in nonaccrual status + real estate owned by banks.

Table 2: Taylor Rule Rate (TRR) Estimation

\[ i_t = constant + \beta(\pi_t - \bar{\pi}) + \gamma(u_{e_t} - \bar{u_e}) \]

\( i_t \) is Taylor rule rate, \( \pi_t \) is inflation, \( \bar{\pi} \) is inflation target, \( u_{e_t} \) is unemployment rate, \( \bar{u_e} \) is non-accelerating inflation rate of unemployment (NAIRU)

| Dependent variable | Coefficient | T-stat | P > |t| |
|--------------------|-------------|-------|-----|---|
| Federal Funds Rate, percentage points (ppt) | 3.740 | 17.50 | 0.000 |
| Inflation gap, \( \gamma \) | 1.106 | 2.52 | 0.015 |
| Unemployment gap, \( \beta \) | -2.186 | -9.21 | 0.000 |

R-sq: 0.60
Adjusted R-sq: 0.59
Least squares, # of obs (94Q1 – 08Q4): 56

This table presents the results of the Taylor Rule estimation based on the equation provided above. The control variables are as follows: Inflation gap is year to year change in core personal consumption expenditures (PCE) index minus Fed’s inflation target of 1.5 ppt. Unemployment gap is unemployment rate minus non-accelerating inflation rate of unemployment (NAIRU). For generic Taylor rule, we use the coefficients from Rosenberg (2010). In his specifications, the intercept or constant term which is sum of equilibrium real interest rate (2 ppt) and inflation target (1.5 ppt) is 3.5. Inflation gap is 1.5 and unemployment gap is 2. The Interest rate shocks (residuals) have a normal distribution. This distribution passes Shapiro-Wilk Test of Normality at 5% significance with \( p = 0.062 \) (\( H_0 \): population is normally distributed). The average of the residuals is zero. According to Breuach-Pagan-Godfey Test, the residuals do not show heteroscedasticity (\( p = 0.725 \)). There is no multicollinearity among the independent variables: VIFs of inflation and unemployment gaps are less than 5.
Figure 1: Macroeconomic data used in Taylor Rule Estimation

![Figure 1](image)

Figure 2: Monetary Policy Rates: Federal Funds rate versus Taylor Rule rate, %

![Figure 2](image)

Effective Federal Funds Rate is the interest rate that depository institutions use to lend each other overnight. It is negotiated between two banks, and the weighted average of this rate across all transactions is the federal funds effective rate.
Figure 3: Systemic Risk Indicator, %

![Systemic Risk Indicator Graph](image)

Figure 4: Macroeconomic Indicators used in the VAR model

![Macroeconomic Indicators Graph](image)

Senior Loan Officers Survey: Banks Tightening Commercial and Industrial Loans to Larger Firms, %
Taylor Rule Rate: Implied policy rate (estimated), %.
GDP Growth: Real GDP, year-over-year growth rate, %
Inflation: CPI-Urban, year-over-year change, %
House Price Growth: Case-Schiller HP index, year-over-year growth, %
Systemic Risk Index: The risk indicator derived following the procedure explained in section 1.2.2.2b
Figure 5: Impulse Responses (IRF) - Base and Extended Models

a) Model with Inflation (Base and Extended)

b) Model with House Price Growth (Base and Extended)

\[ Z_t = \alpha + B_1 Z_{t-1} + \cdots + B_k Z_{t-k} + u_t, \text{where } Z_t = (R_t, Y_t, P_t, S_L, S_S)^T, \text{ } R_t \text{ is Taylor Rule Rate (TRR), } Y_t \text{ is GDP growth, } P_t \text{ is Inflation (INF) and House Price (HP) Growth, } S_L \text{ is Senior Loan Officer Survey (SLOS) and } S_S \text{ is Systemic Risk Indicator (SRI); all in percentage points. Each lag is a quarter. Base models exclude SLOS. Charts present the response of each variable to Cholesky one-unit innovation.} \]
Figure 6: Variance Decomposition - Models with Inflation

a) The Base Model

Variance Decomposition of TRR

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SRI

Variance Decomposition of GDP Growth

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SRI

Variance Decomposition of INF

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SRI

Variance Decomposition of SRI

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SRI

b) The Extended Model

Variance Decomposition of TRR

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SLOS SRI

Variance Decomposition of GDP Growth

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SLOS SRI

Variance Decomposition of INF

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SLOS SRI

Variance Decomposition of SRI

0 20 40 60 80 100
2 4 6 8 10 12 14 16 18 20 22 24
TRR GDP Growth INF SLOS SRI

\[ Z_t = \alpha + B_1 Z_{t-1} + \cdots + B_k Z_{t-k} + \epsilon_t, \text{where } Z_t = (R_t, Y_t, P_t, SL_t, S_t)'. \]

\( R_t \) is Taylor Rule Rate (TRR), \( Y_t \) is GDP growth, \( P_t \) is Inflation (INF), \( SL_t \) is Senior Loan Officer Survey (SLOS) and \( S_t \) is Systemic Risk Indicator (SRI); all in percentage points. Each lag is a quarter. The Base model excludes SLOS. The Base model has 2-lags; extended model has 3-lags.

Each chart reports the decomposition of the variance of the forecast error of the series in the panel heading. Charts show the share (%) of the variance at each horizon attributable to the variable in each chart title.
Figure 7: Variance Decomposition - Models with House Prices

a) The Base Model

Variance Decomposition of TRR

Variance Decomposition of GDP Growth

Variance Decomposition of HP

Variance Decomposition of SRI

b) The Extended Model

Variance Decomposition of TRR

Variance Decomposition of GDP Growth

Variance Decomposition of HP Growth

Variance Decomposition of SRI

\[
Z_t = \alpha + B_1 Z_{t-1} + \cdots + B_k Z_{t-k} + u_t, \text{ where } Z_t = (R_t, Y_t, P_t, S_{LOS}, S_{RI})', R_t \text{ is Taylor Rule Rate (TRR), } Y_t \text{ is GDP growth, } P_t \text{ is House Price (HP) growth, } S_{LOS} \text{ is Senior Loan Officer Survey (SLOS) and } S_{RI} \text{ is Systemic Risk Indicator (SRI); all in percentage points. Each lag is a quarter. Base model exclude SLOS. The Base model has 2-lags; extended model has 3-lags.}
\]

Each chart reports the decomposition of the variance of the forecast error of the series in the panel heading. Charts show the share (%) of the variance at each horizon attributable to the variable in each chart title.
Figure 8: Robustness Check I - Impulse Responses (IRFs)

a) The Extended model with Inflation

Response of TRR to one unit TRR shock

Response of INF to one unit TRR shock

Response of GDP to one unit TRR shock

Response of SRI to one unit TRR shock

b) The Extended model with House Price Growth

Response of TRR to one unit TRR shock

Response of GDP Growth to one unit TRR shock

Response of HP Growth to one unit TRR shock

Response of SRI to one unit TRR shock

This figure presents the response of each variable to Cholesky one-unit innovation. RT stands for Robustness-Tests. In each chart, IRFs from the original models are compared to IRFs from the models estimated for robustness tests.
Figure 9: Robustness Check II - Generalized Impulse Responses (GIRFs)

a) The Extended model with Inflation

This figure presents the response of each variable to Generalized one-unit innovation. Charts present GIRFs from the models estimated for robustness tests.

b) The Extended model with House Price Growth

This figure presents the response of each variable to Generalized one-unit innovation. Charts present GIRFs from the models estimated for robustness tests.
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