THREE ESSAYS ON THE IMPACT OF MONETARY POLICY TARGET INTEREST RATES ON BANK DISTRESS AND SYSTEMIC RISK

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ABSTRACT

My dissertation topic is on the impact of changes in the monetary policy interest rate target on bank distress and systemic risk in the U.S. banking system. The financial crisis of 2007-2009 had devastating effects on the banking system worldwide. The feeble performance of financial institutions during the crisis heightened the necessity of understanding systemic risk exhibited the critical role of monitoring the banking system, and strongly necessitated quantification of the risks to which banks are exposed, for incorporation in policy formulation. In the aftermath of the crisis, US bank regulators focused on overhauling the then existing regulatory framework in order to provide comprehensive capital buffers against bank losses. In this context, the Basel Committee proposed in 2011, the Basel III framework in order to strengthen the regulatory capital structure as a buffer against bank losses. The reform under Basel III framework aimed at raising the quality and the quantity of regulatory capital base and enhancing the risk coverage of the capital structure. Separately, US bank regulators adopted the Dodd-Frank Wall Street Reform and Consumer Protection Act (2010) to implement stress tests on systemically important bank holding companies (SIBs).

Concerns about system-wide distress have broadened the debate on banking regulation towards a macro prudential approach. In this context, limiting bank risk and systemic risk has become a prolific research field at the crossroads of banking, macroeconomics, econometrics, and network theory over the last decade (Kuritzkes et al., 2005; Goodhart and Sergoviano, 2008; Geluk et al., 2009; Acharya et al., 2010, 2017; Tarashev et al., 2010; Huang et al., 2012; Browless and Engle, 2012, 2017 and Cummins, 2014). 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.” While US bank regulators and policy-makers have moved to strengthen the regulatory framework in the post-crisis period in order to prevent another financial crisis, a growing recent line of research has suggested that there is a significant link between monetary policy and bank distress (Bernanke, Gertler and Gilchrist, 1999; Borio and Zhu, 2008; Gertler and Kiyotaki, 2010; Delis and Kouretas, 2010; Gertler and Karadi, 2011; Delis et al., 2017). In my research, I examine the link between the monetary policy and bank distress.

In the first chapter, I investigate the impact of the federal funds rate (FFR) changes on the banking system distress between 2001 and 2013 within an unrestricted vector auto-regression model. The Fed used FFR as a primary policy tool before the financial crisis of 2007-2009, but focused on quantitative easing (QE) during the crisis and post-crisis periods when the FFR hit the zero bound. I use the Taylor rule rate (TRR, 1993) as an “implied policy rate”, instead of the FFR, to account for the impact of QE on the economy. The base model of distress includes three macroeconomic indicators—real GDP growth, inflation, and TRR—and a systemic risk indicator (Expected capital shortfall (ES)). I consider two model extensions; (i) I include a measure of bank lending standards to account for the changes in the systemic risk due to credit tightening, (ii) I replace inflation with house price growth rate to see if the results remain robust. Three main results can be drawn. First, the impulse response functions (IRFs) show that raising the monetary policy rate contributed to insolvency problems for the U.S. 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 extend models. Second, variance decomposition (VDs) analysis shows that up to ten percent of error variation in systemic risk indicator can be attributed to innovations in the policy rate in the extended model. Third, my results supplement the view that policy rate hikes led to housing bubble burst and contributed to the financial crisis of 2007-2009. This is an example for how monetary policy-making gets more complex and must be conducted with utmost caution if there is a bubble in the economy.

In the second chapter, I examine the prevalence and asymmetry of the effects on bank distress from positive and negative shocks to the target fed fund rate (FFR) in the period leading to the financial crisis (2001-2008). A panel model with three blocks of control variables is used. The blocks include: positive/negative FFR shocks, macroeconomic drivers, and bank balance sheet indicators. A distress indicator similar to Texas Ratio is used to proxy distress. Shocks to FFR are defined along the lines suggested by Morgan (1993). Three main results are obtained. First, FFR shocks, either positive or negative, raise bank distress over the following year. Second, the magnitudes of the effects from positive and negative shocks are unequal (asymmetric); a 100 bps positive (negative) shock raises the bank distress indicator (scaled from 0 to 1) by 9 bps (3 bps) over the next year. Put differently, after a 100 bps positive (negative) shock, the probability of bankruptcy rises from 10% to 19% (13%). Third, expanding operations into non-banking activities by FHCs does not benefit them in terms of distress due to unanticipated changes in the FFR as FFR shocks (positive or negative) create similar levels of distress for BHCs and FHCs.

In the third chapter, I explore the systemic risk contributions of U.S. bank holding companies (BHCs) from 2001 to 2015 by using the expected shortfall approach. Developed by analogy with the component expected shortfall concept, I decompose the aggregate systemic risk, as measured by expected shortfall, into several subgroups of banks by using publicly available balance sheet data to define the probability of bank default. The risk measure, thus, encompasses the entire universe of banks. I find that concentration of assets in a smaller number of larger banks raises systemic risk. The systemic risk contribution of banks designated as SIFIs increased sharply during the financial crisis and reached 74% at the end of 2015. Two-thirds of this risk contribution is attributed to the four largest banks in the U.S.: Bank of America, JP Morgan Chase, Citigroup and Wells Fargo. I also find that diversifying business operations by expanding into nontraditional operations does not reduce the systemic risk contribution of financial holding companies (FHCs). In general, FHCs are individually riskier than BHCs despite their more diversified basket of products; FHCs contribute a disproportionate amount to systemic risk given their size, all else being equal.

I believe monetary policy-making in the last decade carries many lessons for policy makers. Particularly, the link between the monetary policy target rate and bank distress and systemic risk is an interesting topic by all accounts due to its implications and challenges (explained in more detail in first and second chapters). The literature studying the relation between bank distress and monetary policy is fairly small but developing fast. The models I investigate in my work are simple in many ways but they may serve as a basis for more sophisticated models.

To my wife Ceyda, my daughter Asli Berrin and my son Hasan Altan

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1. THE LINK BETWEEN FEDERAL FUNDS RATE AND BANKING SYSTEM DISTRESS: AN EMPRICAL INVESTIGATION

1.1 Introduction

Since the financial crisis of 2007-2009, academics and practitioners 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 strong accommodative monetary policies 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

[1] See "A Survey of Systemic Risk Analytics", January, 2012, Working Paper, Office of Financial Research, Department of Treasury.

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, 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 chapter, 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 auto-regression (VAR) model from 2001 through 2013. The base model of distress includes a *systemic risk indicator* and three macroeconomic indicators as its determinants: the real GDP growth rate, inflation, and the primary monetary policy interest rate (FFR). These four variables represent a potentially *complete macro-economy* with demand (the monetary policy interest rate), 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).

In a second step, we expand the model to include a lending criteria indicator (senior loan officer survey; discussed in section 1.3.1) to account for the impact of these criteria on bank distress, and subsequently, we replace inflation with a house price index in both the base and extended models to investigate the robustness of the results. Changes in

[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.

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, while loosening credit standards (making it easy to obtain loans) may lighten the borrowers' burden. Regarding house prices, the period we investigate overlaps with the U.S. housing boom and bust years of 2001-2006 and 2007-2010, respectively. 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 extend the models to see if this alters the effect of a rate increase on systemic risk.

Our systemic risk indicator for the banking system (to be detailed later), 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 recession[3]. 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

[3] According to NBER definition, the recession started in December 2007 and ended in June 2009.

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 U.S. 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 on systemic risk in the extended model is that tighter lending policies lead to a surge in credit losses of banks, curtailing the contribution of TRR to systemic risk as a result. 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.

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. Our sample period runs from 2001 through 2013. This period covers both the housing boom (2001-2006) and the housing bust (2007-2010) periods. We have to account for these phases of the business cycle, especially that the housing market's contribution to U.S. GDP is significant. More importantly, the general consensus is that the bursting of housing bubble in 2007 triggered the credit crisis, which led to the Great Recession of

2007-2009 (Holt, 2009). Replacing inflation with a house-price index in both models, we observe similar but larger impacts from monetary policy on systemic risk: 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. Error variance due to innovations in output and inflation in total, initially rises to 15%, but declines to 8% over time. The effect of TTR 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. Our findings strengthen the view in the literature 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 U.S., as compared to others developed in the literature that include only a group of banks (Tarashev et al., 2010; Huang et al., 2012, and Cummins, 2014). To construct a systemic risk indicator, 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 (explained in section 1.3.2.2b). Our paper is the first to use such an indicator as 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 others such as Expected Default Frequency (EDF) used in Tarashev (2010) are available only for a number of banks. Employing a bank distress indicator enables us to create a systemic risk indicator that encompasses the entire banking system. Second, using our systemic risk indicator, we explore the effect of changes in the FFR on bank distress over a period that includes 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 1.2 is the literature review. Section 1.3 discusses the methodology, data and models. Section 1.4 analyzes the estimation results and section 1.5 concludes.

1.2 Literature Review

This section reviews the literature on the measurement of systemic risk and macro-finance as related to the current study. Systemic risk is difficult to define and measure due to the complexity of causal events and/or mechanisms. A survey of systemic risk literature prepared for the U.S. Treasury Department'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 found in the literature is a risk in which many market participants simultaneously suffer severe losses, which then spreads through the system (Benoit et al., 2015).

1.2.1 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 institutions take bets that are both large and correlated. In other words, it explains why financial institutions expose themselves to default and their counterparts to contagion. Some sources of risk 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 as a cornerstone of their business model, even though banks do not consciously seek that situation[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 institutions 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, 2017), Tarashev et al. (2010), Huang et al. (2012) and Cummins (2014). Measures of systemic risk in these papers have two common features. First, they all provide a *single* risk metric that can potentially encompass *all* institutions in the system[5]. Second, they can be applied to *any* subset of institutions 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

[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. (2010a).

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 the securities issued by financial institutions 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. (2010, 2017), 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].

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

8 Acharya et al. (2010, 2017) 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 Tarashev et al. (2010a) who also use the term ES. Both terms refer to the same concept. In chapter 3, we will discuss the concept of Marginal Expected Shortfall (MES) which is also proposed by Acharya et al. (2010, 2017) and compare it to the other ES concepts introduced in the literature.

1.2.2 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 is countercyclical with respect to risk: as capital increases, bank risk declines. Another strand of papers focuses on firms' 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 so than it increases 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 or value of assets.

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:

H$_1$: Systemic risk is positively associated with effective FFR: increases (reductions) in FFR are associated with greater (lesser) distress on banks.

1.3 Methodology, Data and Models

1.3.1 The Sample

This section describes data sources, variable selection, and variable construction. The sample runs from 2001Q1 to 2013Q4. We derive a systemic risk indicator based on U.S. BHC balance sheet data. In the rest of the text, we use the term banking system distress indicator interchangeably with systemic risk indicator. To maintain homogeneity in the data we do not go below the BHC level to consider subsidiaries separately. Moreover, most management decisions are made at the BHC level, rather than by subsidiaries. BHCs also switch (transfer) assets across subsidiaries for window dressing and tax purposes, making the subsidiary level data unreliable. The primary data source for balance sheet data is the Call Report available from the Chicago Fed's quarterly Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) database. BHC balance sheet data are acquired from Wharton Research Data Services (WRDS). Table 1.1 presents summary statistics for the bank distress indicator and its components.

Table 1.1: Summary Table for Bank Distress Indicator and Its Components

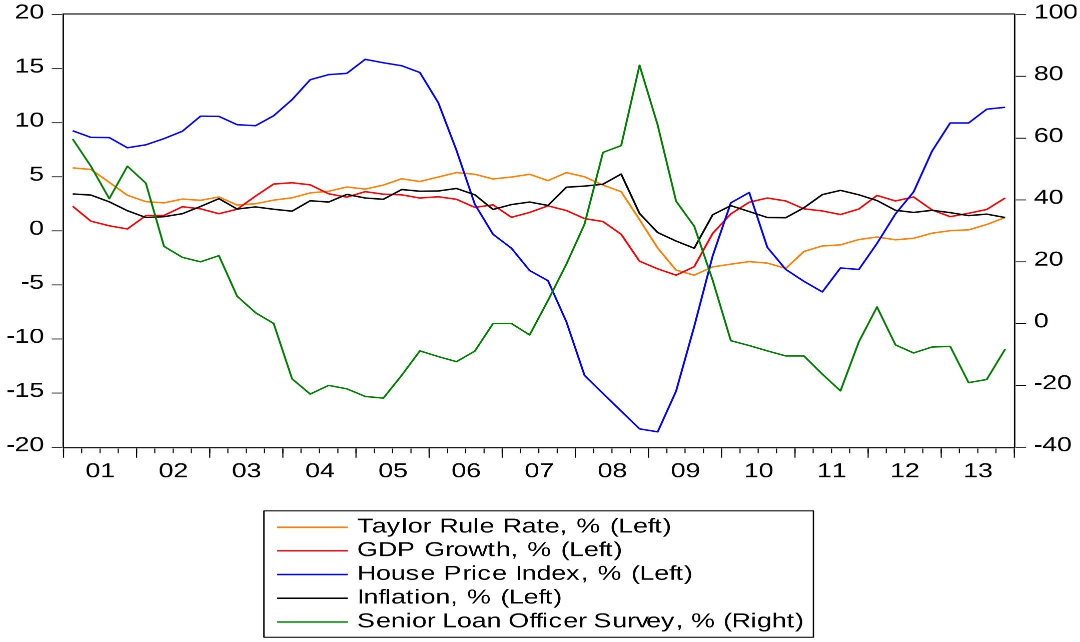
Variable Name	Min	10th	25th	Mean	Median	75th	90th	Max	Std. dev.
Bank Distress Indicator	0.000	0.014	0.032	0.073	0.115	0.129	0.247	1.000	0.176
Capital/Asset	0.006	0.064	0.077	0.094	0.091	0.107	0.128	0.275	0.028
Loan Loss Reserves/Assets	0.000	0.006	0.007	0.012	0.009	0.011	0.015	0.155	0.005
Non-Perf. Assets/Assets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

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.

For macroeconomic drivers, we use several sources. Gross Domestic Product (GDP) data are obtained from the U.S. Bureau of Economic Analysis' National Income and Product Accounts. These data are 2009 constant prices and seasonally adjusted annualized values. The U.S. 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 U.S. Board of Governors of the Fed System's H.15 interest rate release. We use effective FFR data[9]. Unemployment rate 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 1.1 shows the macroeconomic data (Taylor rule rate, real GDP growth rate, inflation, house price growth rate and senior loan officers survey, all in %) used in the models.

[9] The federal funds rate is the overnight, interbank lending rate among depository institutions. The weighted average of this rate across all transactions is the effective federal funds. 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. They become stable when converted to quarterly frequency and approach the target rate.

Figure 1.1: Macroeconomic Indicators Used in VAR Model



Our lending criteria indicator is from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices[10]. 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.

10 The sample data covers the housing boom and downturn periods. However, because surveys regarding 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.

1.3.2 Model Specification and Variable Construction

1.3.2.1 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. 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:

$$Z_t = \alpha + B_1 Z_{t-1} + \cdots + B_k Z_{t-k} + u_t \tag{1}$$

where, $Z_t = \begin{pmatrix} R \\ Y \\ P \\ S \end{pmatrix}_t$

where B_i 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 (see Appendix A) and look at impulse responses (IRFs) and variance decompositions (VDs) in the model. IRFs and VDs are discussed in detail in Section 1.4.

1.3.2.2 The Systemic Risk Indicator

1.3.2.2a 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[11]. 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

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[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.

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[12]. 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, and 100% to loans in nonaccrual status (write-offs) and other real estate owned (REO)[13]. Using these haircuts, Cole and White define the following ratio for bank distress:

$$Distress\ Indicator = (0.2 * 30 - 89d\ DEL + 0.5 * 90d\ plus\ DEL + WOF + REO)/(Equity + LLA) \quad (2)$$

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

[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)

[13] Cole and White separated non-performing assets into several components and assumed a different haircut for each component. They picked the one that has the highest predictive power for bank failures. They found 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.

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[14].

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 primary bank risks, one can observe sections of the balance sheet that have deteriorated and increased bankruptcy risk,

[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.

or improved, reducing bankruptcy risk[15]. Next, we develop a systemic risk indicator time series by employing the distress indicator as the probability of default for a particular bank.

1.3.2.2b Constructing a Systemic Risk Indicator

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, 2017; 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, 2017). A formal method of attributing systemic risk to institutions was proposed by Acharya, et al. (2010, 2017). 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, 2017). In this approach, we treat the banking system as a portfolio of banks. Tarashev et al. (2010a) define and use ES in a similar way,

[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.

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, 2017), but we use a numerical algorithm similar to the one used by Tarashev et al. (2010a).

In the ES approach, following Tarashev et al. (2010a), 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_α is the maximum level of the losses (system wide loss) associated with the default of banks with confidence level $(1-\alpha)$, e.g. α = 5%, such that probability of the total loss going over the VaR_α level is alpha, $\Pr(Loss > VaR_\alpha)$ = α, 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_α level. A systemic event is an extreme event that is assumed to occur when the system-wide loss exceeds the value specified by VaR_α. Specifically,

$$ES_\alpha = E[Loss|Loss \geq VaR_\alpha] \tag{3}$$

In other words, ES is the expectation of system-wide loss when the loss exceeds its VaR_α limit. VaR_α conveys the maximum level of losses exceeded with a given probability

16 Typically, α is selected as 1% or 5% and the VaR gives the most a bank can lose with 99% and 95% confidence, respectively.

alpha, and ES provides the mean over the range from VaR_α 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:

$$ES_\alpha = \sum_i E[l_i | Loss \geq VaR_\alpha] \tag{4}$$

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

$$l_i = s_i \, . LGD_i . I_i \tag{5}$$

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, $\sum_i s_i$ = 1. LGD_i is loss-given-default which shows how much of the losses are recovered if bank i defaults. The default indicator, I_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 1.3.2.2a. For deriving the default indicator, we employ a *model of stochastic losses* similar to Tarashev et al. (2009)[19]. The

[17] Acharya et al. (2010, 2017) 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. (2010a), Huang et al. (2012) and Cummins (2014).

[19] Tarashev et al. (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).

distribution of defaults $\{I_i\}_{i=1}^{n}$ is determined via Monte Carlo simulations[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, $\sum_i l_i$. 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[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)[22]. On the other hand, default probabilities constructed using market asset prices are known as *risk-neutral default*

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[20] Tarashev et al. (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.

[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%.

[22] Tarashev et al. (2010a) 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.

probabilities because they are composed of default risk and risk premia[23]. A physical default concept is superior to the risk-neutral default concept because the risk premia in market prices of assets (bonds, loans or CDs) 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, the 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[24]. 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 to the literature. 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),

[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; 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.

another physical default concept used by Tarashev et al. (2010a), is available only for a number of banks. Employing a bank distress indicator (explained in section 1.3.2.2b) enables us to create a systemic risk indicator that encompasses the entire banking system.

1.3.2.3 The Taylor Rule Rate (TRR)

The recession of 2007-2009 marked the sharpest downturn in the U.S. 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[25]. 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[26]. While no central bank

[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.

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; Meyer, 2009; Gagnon, 2010; Dudley, 2010; Neely, 2012; Bernanke, 2015) (further discussion of this issue is provided in Appendix B).

Several versions of the rule have been suggested over the years[27]. 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[28]. This version of the Taylor rule has the form:

$$i_t = constant + \beta(\pi_t - \bar{\pi}) + \gamma(ue_t - \overline{ue}) \tag{6}$$

[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, π_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 $(y_t - \bar{y}) = \mu(ue_t - \overline{ue})$.

[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.

where i_t is the effective FFR, π_t is the inflation rate, $\bar{\pi}$ is the inflation target, ue_t is the actual unemployment rate, and $\overline{ue}$ is the natural rate of unemployment. Equation (6) tells us that there is a "neutral" FFR, $constant$, 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, $constant$, 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[29].

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 1.2). 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.

[29]If $(\pi_t - \bar{\pi}) > 0$, the nominal fed funds rate should rise by β times the inflation gap. For example, assuming β 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 γ is -2 and the inflation gap is zero, if the unemployment rate exceeds the natural rate of unemployment by 1%, then the FFR should decline by 2 percentage points to lower the "real" FFR in order to accelerate domestic demand and gradually reduce the unemployment rate to its natural rate.

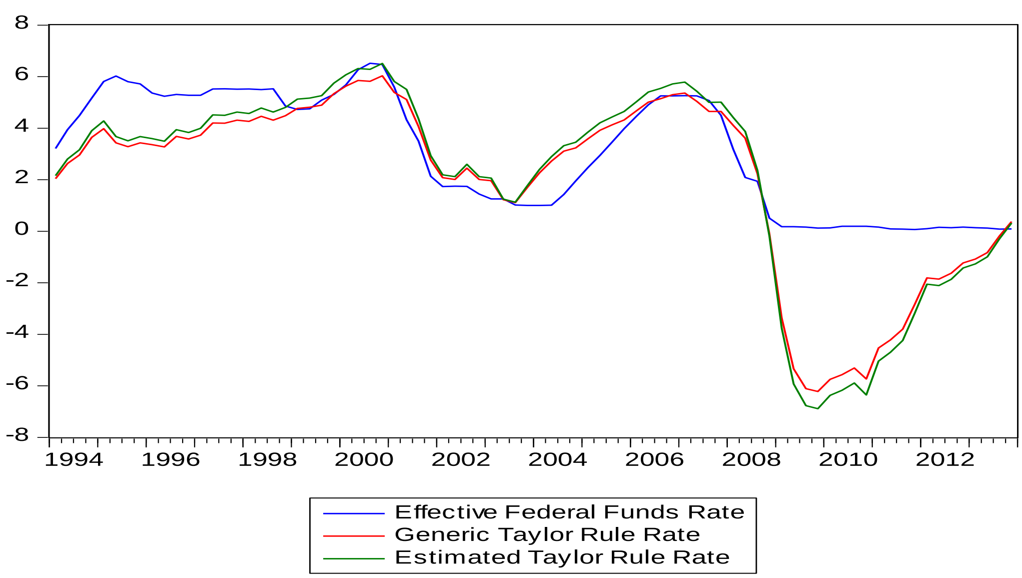
Estimation results are presented in Table 1.2 and "implied policy rate" is demonstrated in Figure 1.2.

Table 1.2: Taylor Rule Rate Estimation (Equation 6)

Dependent variable Federal Funds Rate, percentage points (ppt)	Coefficient	T-stat	P > |t|
Constant, α	3.740	17.50	0.000
Inflation gap, γ	1.106	2.52	0.015
Unemployment gap, β	-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 Breauch-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 1.2: Monetary Policy Rates: Federal Funds Rate vs Taylor Rule Rate, %



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 for discussion of the results).

1.4 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 1.4.1.2 and 1.4.1.3. Results from the models with house price index are reviewed in section 1.4.1.4. Since 13 years of quarterly data may be insufficient for a VAR model, in section 1.4.2, 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 1.4.3, 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[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 traditional approach of picking short lags, two lags and three lags for the basic models, and the extended model, respectively, for all

30 Sims (1980) describes the over-parametrization problem and calls it as "profligate parametrization."

components, and assume a short-term dynamic relation among the variables in the models[31]. The lag order is selected according to information criteria (IC) (see 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.

1.4.1 VAR Model of Macro Drivers and Systemic Risk Indicator

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

[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.

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).

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. Therefore, 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[32]. In the subsequent 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.

1.4.1.1 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[33]. 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

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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.

VD[34]. Transformation of a reduced form model to structural form requires identifying assumptions that establish causal links among variables[35]. 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 ordering justified by the adjustment speed of each variable to contemporaneous shocks[36]. We order the macro variables as the Taylor rule rate, GDP growth rate, and inflation, and then put systemic risk measures after macro variables in the base model[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 right. 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 need 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.

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[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 1.4.2).

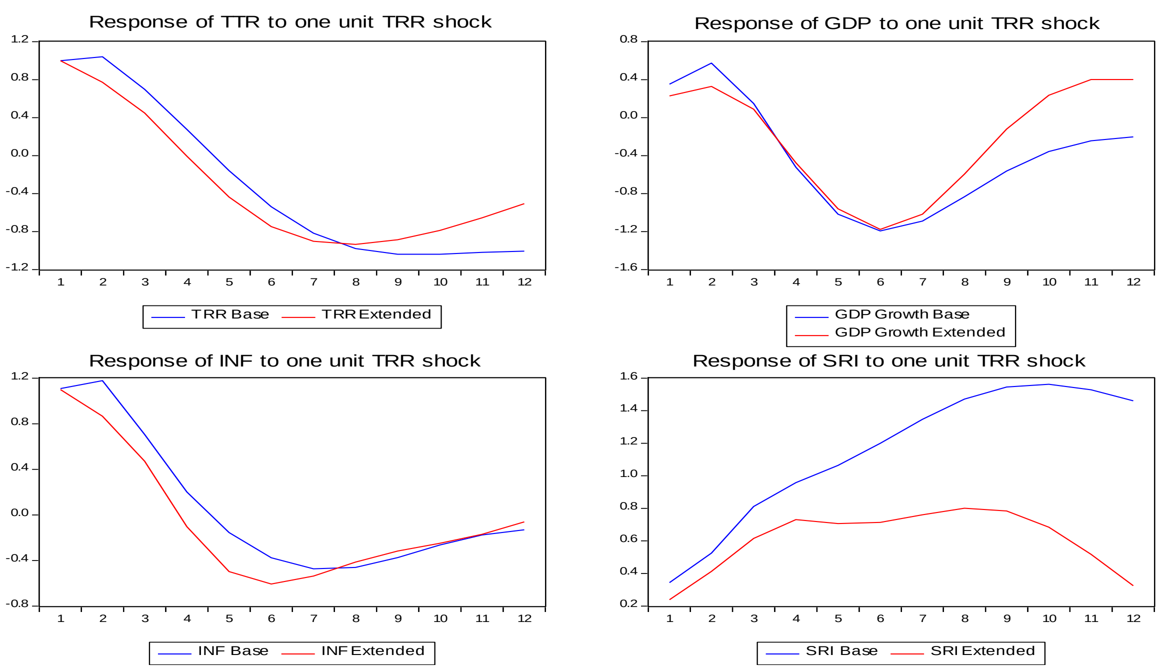
[36] Sims (1980) introduces the Cholesky decomposition and discusses the impacts of the variable ordering. A common application of Cholesky ordering is that the first variable should be selected such that it is the only one with potential immediate impact on all other variables. The second variable may 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.

[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.

1.4.1.2 The Base Model

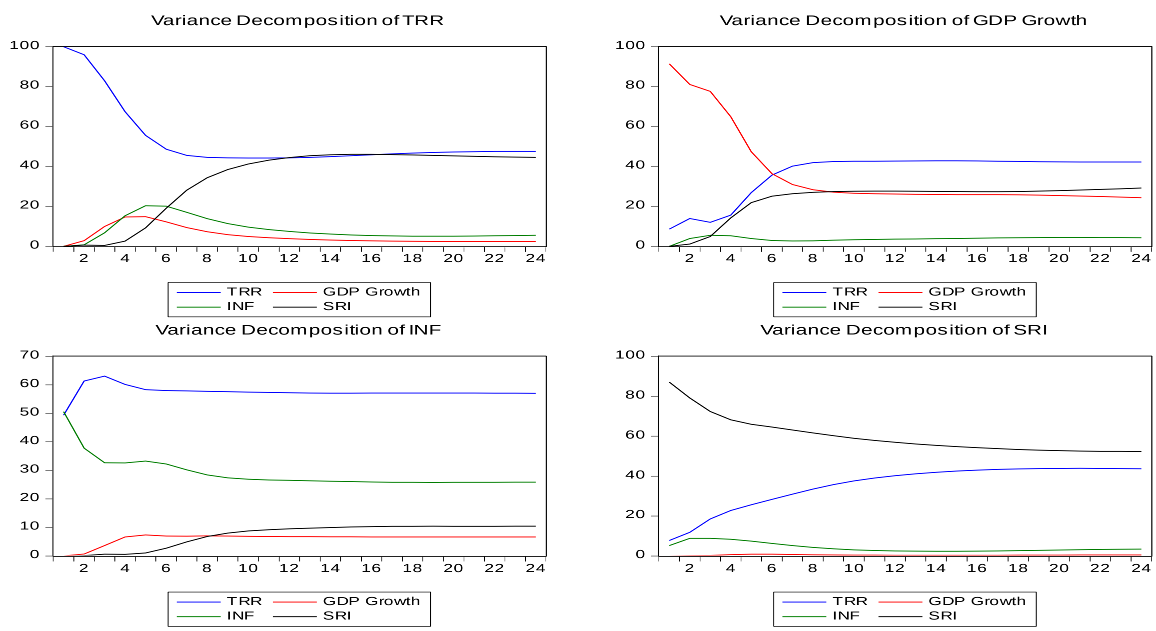
The results of the IRFs and VDs are presented in Figures 1.3 and 1.4, respectively. In the base model, we find that a one-unit (100bp) increase in the TRR *reduces* GDP growth and inflation until the end of a year and a half after the shock is introduced. More specifically, the impact of a rate increase on GDP growth peaks at -1.2 percentage points in the sixth quarter, subsiding thereafter and disappearing after twelve quarters (Figure 1.3, 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 1.3, 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.

Figure 1.3: Impulse Responses (IRF) - Models with Inflation (Base and Extended)



According to VDs, innovations in TRR account for 8% of error variance in output growth after one quarter and 45% after eight quarters (Figure 1.4, 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 1.4, 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.

Figure 1.4: Variance Decomposition - The Base Model with Inflation



In the base model, we find that one-unit increase in the TRR raises the systemic risk at varying degrees over the ten quarters after the shock is introduced (Figure 1.3, bottom-right panel). The impact peaks at 1.6 percentage points in the tenth quarter. 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 (GDP growth and inflation) considered. 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 1.4, 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 1.4.1.3, we discuss the model extended to include the lending standards.

We modify the VAR model with a different ordering of macroeconomic 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.

1.4.1.3 Expanding the Base Model to Account for Lending Standards

The results of IRFs and VDs are presented in Figures 1.3 and 1.5, respectively. The direction of the effects among the macro variables are captured well in the extended model

[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%.

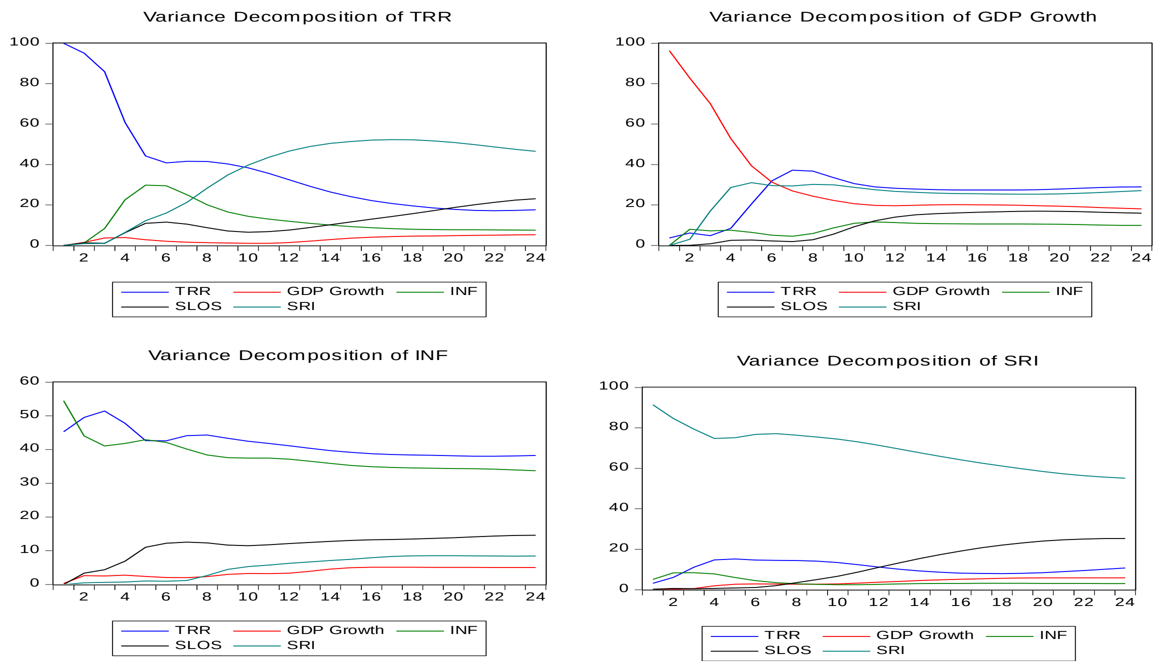
as well[40]. Once we introduce the lending-criteria indicator into the model, we find that it takes away some of the strength of TRR to constitute about 20% of the error variation in GDP. This suggests that the variations in economic activity do not come from the interest rate hike alone as lending criteria are also associated with changes in GDP to a considerable degree (Figure 1.3, 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 1.3, 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. The TRR continues to show a strong link with systemic risk in the banking industry, but the lending criteria indicator takes away some of its potency. 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 base model. More specifically, if the TRR rises 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 systemic risk in the base model in two ways. First, the impact from a unit shock to TRR lasts for a *shorter period* (it is less durable). Second, the magnitude of the impact *declines* to half

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 (Figure 1.4), 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.

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 1.5, bottom-right panel).

Figure 1.5: Variance Decomposition - The Models with Inflation – Extended Model



Movements in the senior loan officer survey account for less than 10% of 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 signified[41], suggesting that policy makers should focus on the short-term effects of the policy rate changes on bank distress.

1.4.1.4 Replacing Inflation with House Price Index

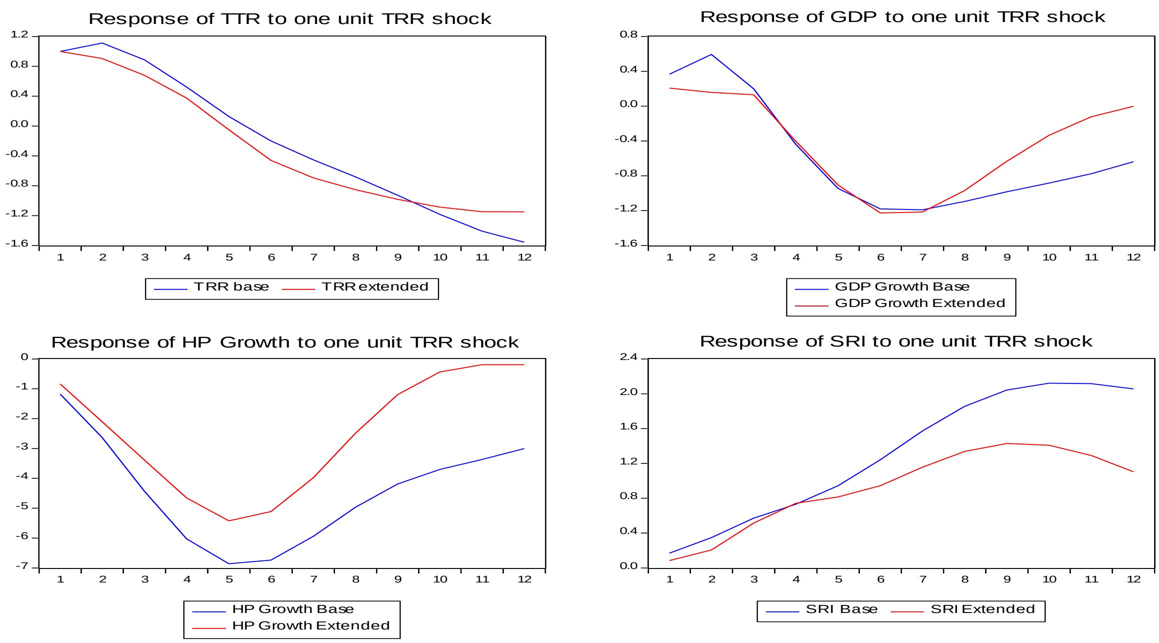
The results for IRFs are presented in Figure 1.6, and results for VDs are presented in Figures 1.7 and 1.8. The period we investigate overlaps with the U.S. housing boom and bust years of 2001-2006 and 2007-2010. Housing-related loans make up the largest share of household balance sheets and the housing 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 the interest rate changes and creates a

[41] See Lown and Morgan (2004) for the impact of lending standards on loan originations.

burden on homeowners. Moreover, an increase in rates reduces the demand for mortgage loans, and thereby home sales, and puts pressure on house prices[42].

Figure 1.6: Impulse Responses (IRF) – Models with House Price Growth (Base and Extended)



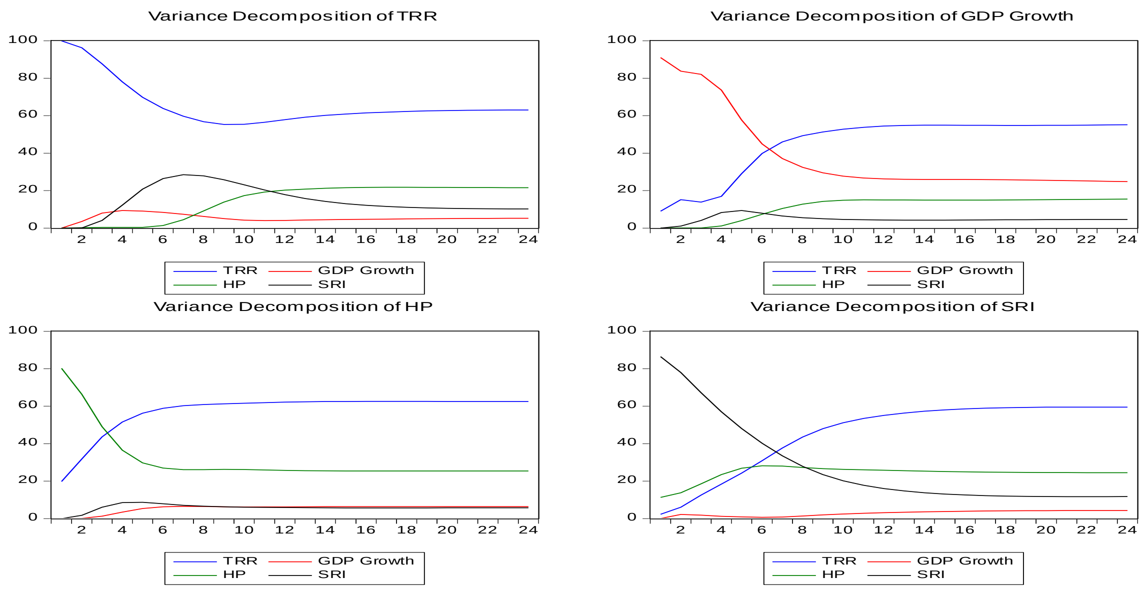
In the modified base model, a positive shock to TRR reduces house price growth until nearly a year and a half following the shock (Figure 1.6, bottom-left panel), two quarters sooner than its impact peaks on inflation. However, the magnitude of the effect is much larger: a 25 bps increase in the TRR starts reducing house price growth right away, the effect peaks at 1.7 percentage points (0.13 percentage points for inflation) in the sixth

42 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 https://www.bls.gov/opub/hom/pdf/homch17.pdf.

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 1.6, 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 1.7, 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 the 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 1.7, 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 1.7, 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.

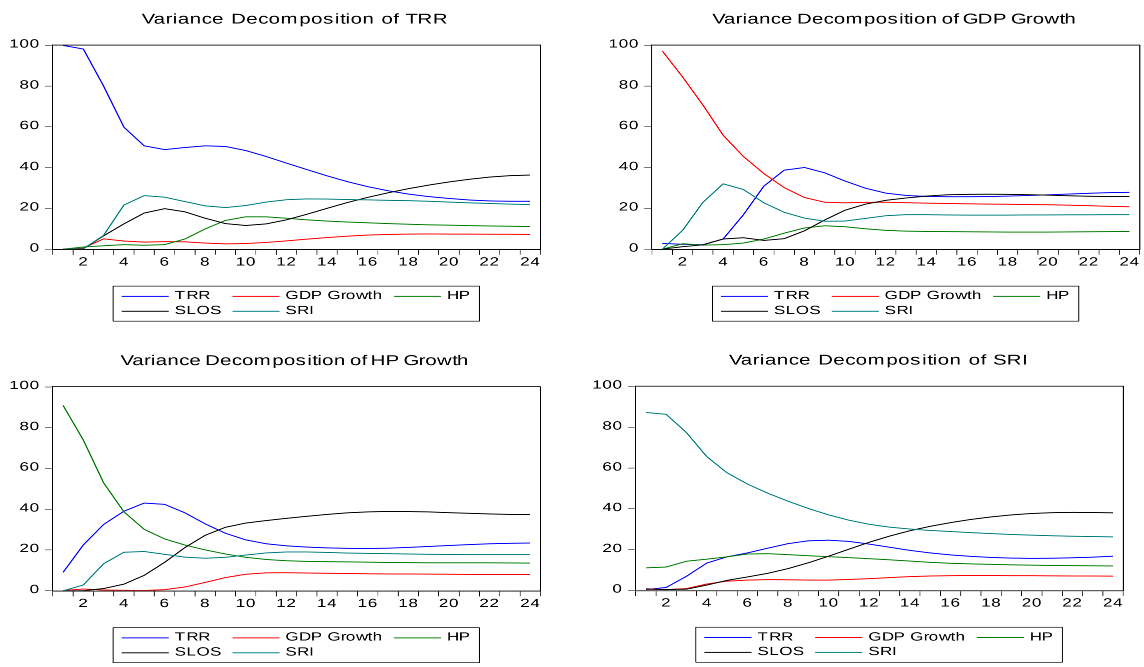
Figure 1.7: Variance Decomposition - The Base Model with House Prices



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 1.6, 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 modified 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 1.6, 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 1.7, 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 1.8, 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.

Figure 1.8: Variance Decomposition - The Extended Model with House Prices



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.

1.4.2 Robustness Check

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 monetary policy rate 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 (see 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 (Non-performing Assets + Real Estate Owned (REO))/(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 1.9 and 1.10. As can be seen from

[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 methodology 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.

these figures, the basic results continue to hold: A unit positive shock to implied policy rate creates distress on banks (Figure 1.9, the model with inflation; Figure 1.10, the model with house price).

Figure 1.9: Robustness Check I - Impulse Responses (IRFs) – Extended Model with Inflation

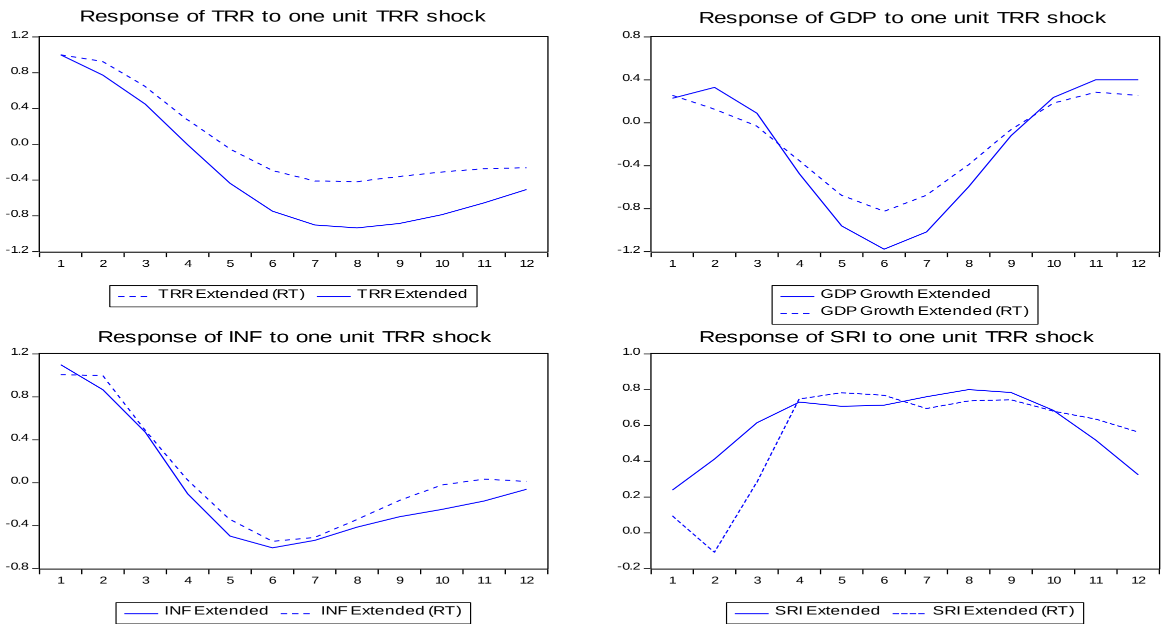
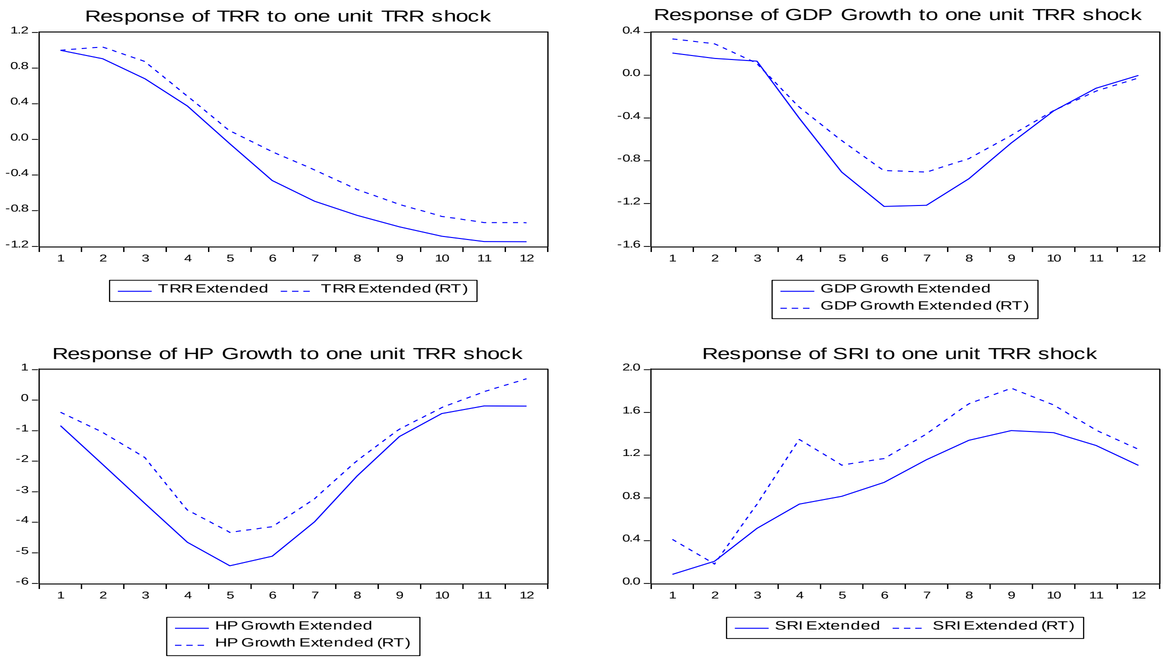


Figure 1.10: Robustness Check I - Impulse Responses (IRFs) – Extended Model with House Price Growth



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 1.11 and 1.12, are nearly identical to those from the Cholesky decomposition.

Figure 1.11: Robustness Check II - Generalized Impulse Responses (IRFs) – Extended Model with Inflation

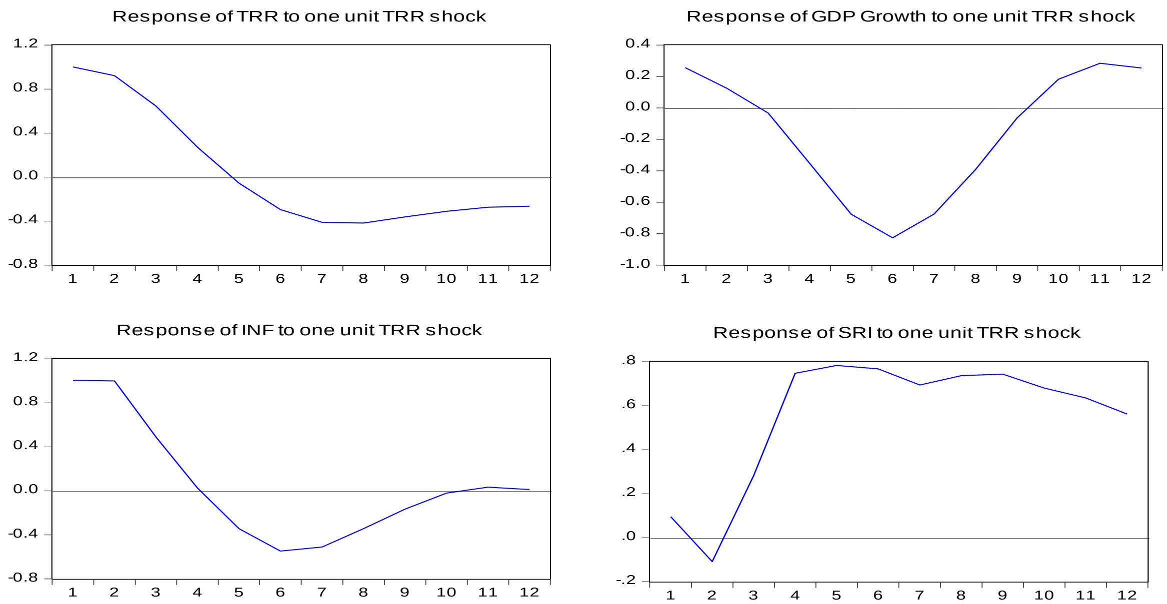
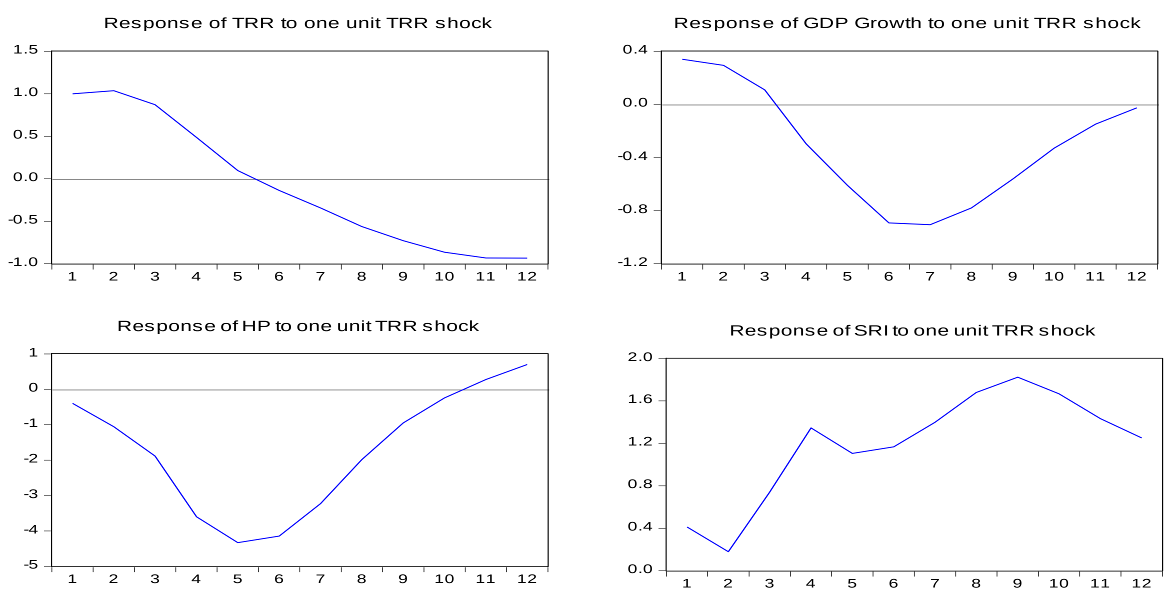


Figure 1.12: Robustness Check II - Generalized Impulse Responses (IRFs) – Extended Model with House Price Growth



1.4.3 Discussion of Results

The main takeaway from these results is that a rising monetary policy rate, all else being equal, creates distress on the banking system. This may sound somewhat counterintuitive if one considers the interest rate a primary source of income for banks[45]. In general, rising short-term interest rates create more revenue for banks because lenders pass the rate hikes to their new loans right away while deposit rates take time to rise (Driscoll and Judson, 2013)[46]. There is more rigidity and sluggishness in deposit rates. On the other hand, rate hikes make borrowing less attractive and reduce demand for new loans or even put more pressure on borrowers, whose liabilities are set to higher terms with rising rates, causing more loan payments to fall behind. Credit risk of the bank rises as borrowers cannot make payments[47]. These are the two main factors that broadly affect the banking system's distress level. However, one should also consider prevailing economic and credit market conditions between 2001 and 2013.

Pre-crisis period: The housing boom and bust characterizes our sample period. Therefore, bank lending (household borrowing) decisions and losses in housing-related loans lead to a positive elasticity of systemic risk with respect to short-term interest rates. The Federal Reserve started to lower overnight rates in January 2001. Falling short-term rates encouraged homebuyers to take out mortgages, particularly with adjustable rates, to buy homes and households began leveraging[48]. Lenders relaxed credit standards in

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[45] This depends whether deposit and loan rates are sticky and what kind of gap banks hold, but, in general, this statement holds.

[46] E.g., lenders raise rates for adjustable rate mortgages whenever the rate is reset. With respect to fixed-rate mortgages, rate hikes will affect new originations; existing loans will remain at the old low rates.

[47] Credit or default risk rises. Also fixed-rate loan commitments become more attractive to the businesses holding them, so they exercise them at the lenders' expense.

[48] Adjustable rates are popular for individuals who don't plan to stay in their homes for a long period; they can take advantage of the lower rate and not worry about affording higher payments after the loan adjusts. Adjustable-rate mortgages were very attractive when house prices were rising rapidly before the Great Recession.

response to rate cuts to shore up revenue. In an environment that became ever more competitive, they originated loans to many risky borrowers and the leveraging accelerated. Securitization allowed lenders to originate loans without paying much attention to their quality. In the pre-crisis period, the bank distress indicator shows a positive link with short-term rates because banks succeeded in issuing fresh loans and expanding their balance sheets in response to lower rates (low rates and low bank distress). Declining borrowing costs kept the housing market intact during and after the 2001 recession, but set the stage for disaster as the Fed kept the policy rate very low until late 2004 to ensure the economy gained momentum and slack in the labor market disappeared. This dynamic helped create a bubble in the housing market, while many lenders enjoyed income from exotic housing-related loan products.

Monetary tightening from June, 2004 to September, 2007 triggered a chain of events that eventually caused the housing crash[49]. When the Fed began raising the policy rate in 2004, housing demand was quite high. According to the Case-Schiller House Price Index, house prices increased more than 13% year-over-year nationwide in 2004. Losses on home mortgages began to surge in 2006 with continuing rate hikes, long before the Fed was done with the tightening cycle. Variable rate mortgages were reset much higher, precipitating loan defaults and foreclosures. The sharp tightening of monetary policy curbed economic growth and slowed income growth, curbing the appetite for housing. The year 2007 was a turning point for the housing market: Realizing the boom was over, many investors started to look for exits. This led to an unprecedented mortgage crisis as all real estate-related loans, including commercial mortgages and securities based on these loans,

[49] Fed raised the FFR target by 25 bps to 5.25% in June, 2006 meeting, and kept the target rate at 5.25% until September, 2007.

suffered surging delinquencies and heightened defaults. The U.S. economy weakened, prompting the Fed to begin its easing cycle in September 2007. Many real estate investors walked away from mortgages when they realized the downturn was underway and would be deep.

The monetary policy tightening period of June 2004 to September 2007 was associated with rising housing related losses, creating a positive correlation between short-term rates and the bank system's stress level: The higher the short-term rates, the greater the number of loans falling behind in payments. The positive relation between short-term rates and banking system stress before the financial 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 cards and auto loans, as well as commercial credit.

Crisis and post-crisis periods: The relation between the monetary policy rate and systemic risk became more complicated during the 2007-2009 recession and in the post-recession period because of the multifaceted nature of the policy implementation and the strong spillover potential of macroeconomic and policy shocks. Even though raising short-term rates may create more distress on lenders due to rate resets and lower demand[50], distress may also result from tightening credit standards as many borrowers are cut off and cannot refinance or roll over their outstanding debt.

Recessions accompanied by financial crisis are very costly in terms of lost output because business investment plunges amid a credit crunch (Jorda, Schularick and Taylor,

[50] Loan resets increase bank revenue (and limit bank IR risk), but if lower demand offsets the revenue increase, a rate increase creates a burden on households and causes loan defaults to increase.

2012)[51]. A credit crunch refers to a sudden decline in the supply of funds for lending, leading to a shortage of loans available. 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 financial 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 immediately after credit dried up and caused money and credit markets to freeze in the last quarter of 2008. The U.S. recession deepened to a level that, in several dimensions, 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 clearly it was not enough to counterbalance 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, and distress in the banking system surged. With lending standards, we believe the extended models underpin the effect of policy rate changes on banking distress better than the base models.

1.5 Concluding Remarks

In this paper, we investigate the relationship between the main U.S. monetary policy rate (the fed funds rate, or FFR) and systemic risk between 2001 and 2013, using the unrestricted reduced form VAR model. We build a systemic risk indicator based on an

[51] The links between lending standards, economic activity, and loan repayments have been widely investigated in the literature (Lown and Morgan, 2004).

insolvency criterion for bank holding companies 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 original 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. That is, easing monetary policy reduces the stress on bank balance sheets while tightening it adds stress. The sample period includes the U.S. credit boom era, which 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. 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 default and foreclosure. 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 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 financial crisis. The results discussed in this chapter show that if there is a bubble in the economy, monetary policy-making becomes more complicated and requires 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 previous decade carries many lessons for policymakers.

2. ASYMMETRIC EFFECTS OF POSITIVE VERSUS NEGATIVE FEDERAL FUNDS RATE SHOCKS ON U.S. BANK DISTRESS

2.1 Introduction

The poor performance of financial institutions during the 2008-2009 crisis elucidated the critical role of regulators and policymakers in monitoring the banking system and quantifying banks' individual and systemic risk exposures. To improve this function, after the crisis, U.S. bank regulators adopted the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA, 2010) and the proposed Basel III reform (2011). The DFA required stress tests to enhance the safety of the systemically important bank holding companies (SIBs) while Basel III aimed at raising both the quantity and quality of regulatory capital for the purpose of boosting risk coverage in banks' capital structure[52]. Moreover, both during and after the crisis, the Fed followed highly expansionary monetary policies by lowering the target fed funds rate (FFR) to zero and engaging in sustained quantitative easing (QE) for a long period.

It is notable that although expansionary monetary policy could lead to greater lending, as intended by regulators, it could also raise lending to riskier borrowers, elevating systemic risk. As suggested by Yellen (2011), "With interest rates at very low levels for a long period of time, and in an environment of low volatility, investors, banks, and other market participants may become complacent about interest-rate risk. Similarly, in such an environment, investors holding assets which entail exposure to greater credit risk may not

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52 The DFA establishes new minimum leverage and risk-based capital requirements for bank holding companies (BHCs) and systemically important nonbank finance companies. With DFA, minimum risk-based capital ratios for Tier 1 capital is set as 6.5% for "well capitalized" and 4.5% for "adequately capitalized" qualifications. Total capital ratio is set as 10% for "well capitalized" and 8% for "adequately capitalized". Minimum leverage ratio is set as 5% for "well capitalized" and 4% for "adequately capitalized", all to be established by Jan, 2019 (Congressional Research Service, July 27, 2016).

fully appreciate, or demand proper compensation for, potential losses." To elaborate, in such an environment, banks may seek higher interest rates, despite greater credit risk, in order to achieve, at least, a minimum threshold rate that they and their depositors and shareholders are used to. In general, when rates are low, banks' net interest margins (NIM) tend to shrink (Claessens et al., 2017). The rationale is that banks are reluctant to quickly lower deposit rates when interest rates decline, especially for retail depositors, while they must lower the rates on the existing loans through contractual repricing, and on the new loans through competition. The narrowing of interest rate margins raises bank incentives to switch to riskier assets offering higher expected yields (Delis et al., 2014). The risk-taking behavior of banks in periods of low interest rates will be exacerbated if banks expect the low interest rates to persist (Borio and Zhu, 2008). It follows that, the commitment of a central bank to low rates for a prolonged period, e.g., after an adverse shock to the economy, encourages banks to assume greater risk. If the increased risk taking due to interest rate reduction is of sufficiently large magnitude, it may lead to serious bank stress conditions and even bank failures (Apel and Claussen, 2012).

The objective of this chapter is to investigate the prevalence and asymmetry of the effects of unanticipated positive and negative shocks to the target FFR on US banks' distress conditions. The sample is chosen to run between 2001 and 2008 because the FFR hit the zero bound after 2008, and the Fed started using quantitative easing (QE) as a substitute policy tool. Quarterly data for all BHCs, including the financial holding companies (FHCs), are used. The terms banks and BHCs will be used interchangeably in the article. Bank distress is defined as a condition in which a bank's current or future ability to honor its commitments to its creditors is impaired (Altman et al., 2014). We gauge bank distress with two proxies; a bank distress indicator introduced by Cole and White (2012), which is similar to the so-called Texas ratio, and the non-performing asset ratio. Following Morgan (1993), the unanticipated shocks to the FFR are derived as residuals in a model where the FFR target is regressed on its lagged values, current and lagged values of output growth and inflation, a trend variable, and a constant term (eq.1, section 2.3.2.1). The shocks are sorted into positive and negative values, and their effects on bank distress are estimated while accounting for macroeconomic drivers and bank balance sheet indicators as controls (eq. 2, section 2.3.2.1).

The model (eq. 2) is estimated for positive and negative shocks separately for all banks and two subgroups separating BHCs and FHCs. The rationale for separating BHCs and FHCs is that they might be affected by interest rate shocks differently because their product diversities are very dissimilar. The Gramm-Leach-Bliley Act (GLBA) of 1999 enabled BHCs to register as FHCs, thus allowing them to engage in a broader range of nonbank activities such as securities underwriting and dealing, insurance underwriting, and merchant banking[53]. Since then, many large BHCs have registered as FHCs and expanded their nonbank subsidiaries (Avrahan, Selvaggi and Vickrey, 2012). Given the growth in their size, smaller share of loan revenues and product diversification into nonbank activities, FHCs may respond to interest rate shocks to a more limited (greater) extent than BHCs do as the gains due to diversification can counterbalance or add to the effect of interest rate shocks on loan revenues.

[53] See "Report to the Congress on Financial Holding Companies under the Gramm-Leach-Bliley Act", Nov, 2003, Board of Governors of the Federal Reserve System US Department of the Treasury.

We focus on 2001-2008 period for the effects of positive and negative FFR shocks on bank distress because this time period encompasses two major trends of policy rate changes that are argued to have caused the crisis of 2008-09. First, keeping interest rates too low and for too long in 2003 and 2004 following the 2001 recession to help raise employment and economic growth (Taylor, 2007). Second, the reversal of this over-accommodative monetary policy starting in 2004 in the form of a policy tightening that went too far and contributed to the housing market crash soon after (Holt, 2009). We explain the interest rate trends and the shocks in section 2.4.1. To the best of our knowledge, the asymmetry of the effects of positive and negative shocks to target FFR on bank distress have not been analyzed in the literature as these shocks have been assumed to display symmetric effects. This paper is the first to examine whether asymmetry exists in the effects of positive and negative shocks on bank distress and to assess the magnitudes of the effects.

We obtain several results. First, shocks, either positive or negative, raise bank distress over the following year. Second, the effects of positive or negative interest rate shocks on bank distress are asymmetric; an unanticipated positive interest rate shock of 100 bps brings about nearly three times as much distress as a 100 bps negative shock. If the distressed indicator is scaled between zero and one, a 100 bps positive shock raises the bank distress indicator by 9 bps over the next year (the probability of firm bankruptcy would rise from 10% before the shock to 19%) while a surprise 100 bps negative shock raises the bank distress only by 3 bps (the probability of firm bankruptcy rises from 10% before the shock to 13%). Third, the effects of positive or negative shocks on both BHCs and FHCs, are asymmetric. In both cohorts, positive and negative rate shocks create distress, with the impact of positive rate shock being nearly three times as large as the impact of negative rate shock. In this context, comparing the two cohorts, we do not find a significant difference between BHCs and FHCs from the view point of the effects of positive and negative shocks on distress. Specifically, positive (negative) shocks create as much distress on FHCs as on BHCs, despite their product mix dissimilarity (section 2.4.3). Fourth, models based on bank distress indicator have slightly greater explanatory powers (higher R^2) than those employing non-performing asset ratios. Fifth, the hedge ratio used to gauge whether interest-rate hedging helps reduce the impact of interest-rate shocks on distress is found to be significant and has the expected negative sign.

The rest of this paper is organized as follows: Section 2.2 reviews the literature on bank distress and risk-taking. Section 2.3 discusses methodology; the data, model specifications, and variable construction. Section 2.4 analyzes the estimation results and section 2.5 offers concluding remarks.

2.2 Literature Review

2.2.1 Bank Risk-Taking Literature

A number of studies have focused on bank risk-taking behavior in the prolonged low-interest rate environment in the run up to the 2008 crisis. Some of these studies consider this environment a main cause of the abundant liquidity that exacerbated bank risk-taking and distress (Taylor, 2009; Borio and Zhu, 2008) as it altered the risk perception and/or the risk tolerance of banks. Even though the bank risk-taking literature is vast, empirical evidence on a link between monetary policy and bank risk-taking is scarce. To remedy this shortcoming, a few theoretical papers study the role of monetary policy in banks' risk-taking behavior. Among these studies, Agur and Demeritez (2010) and Valencia (2011) have developed dynamic models, while and Dell'Ariccia et al. (2010) have used a static framework to investigate the impact of the prolonged lax monetary policy on bank risk-taking. Agur and Demeritez (2010) show that to ensure financial stability in a crisis, the central bank should reduce its target rate sharply but only for a short period, because if banks expect rates to remain low for long periods, they adjust their long-term asset portfolios towards riskier projects. Valencia (2011) shows that greater capital requirements can reduce the impact of banks' excessive risk-taking on financial stability. He proposes the use of counter-cyclical regulatory policies such as increased capital requirements and loan-to-value caps to contain risk. Dell'Ariccia et al. (2017) show that prolonged easy monetary environments increase bank risk. In particular, they find that the credit risk of bank loans is negatively associated with short-term interest rates and that this negative relationship is more pronounced for highly capitalized banks.

Empirical literature has used both aggregate and bank-level risk data for countries other than the U.S. to examine bank risk-taking behavior. Jimenez et al. (2008), Ioannidou et al. (2009), Delis and Kouretas (2011), and Maddaloni and Peydro (2011) take an international perspective on bank risk-taking. Specifically, using bank-level data from the Spanish Credit Register, Jimenez et al. (2008) find that expansionary monetary policy raises the riskiness of banks' portfolios due to the lower collateral values and the search by banks for higher yields in the medium term. Ioannidou et al. (2009) use Bolivian bank-level data to experiment with monetary policy changes. They find that when monetary policy becomes expansionary, banks increase their number of new risky loans.

2.2.2. Bank Distress and Failure Literature

A large stream of papers has focused on the predictability of bank failures with the aim of constructing an early warning system that identifies risky banks prior to failure. DeYoung and Torna (2012) give an excellent review of the literature on determinants of bank failures and the models developed to predict these risk factors. Wheelock and Wilson (2000), DeYoung (2003), Oshinsky and Olin (2005), and Schaeck (2008) are the most significant of these studies. These studies look into bank failures during the savings and loan crisis of the 1980s and 1990s, the 1987 U.S. stock-market crash, and bank failures in Europe in the 1990s. They identify a set of robust bank balance sheet covariates, such as the concentration of business loans or real estate loans, liquidity, asset growth, reliance on deposit funding, management skills, equity capital, and asset quality, as predictors of bank failures. A growing set of studies has applied the same measures to bank distress during the crisis of 2007-2009 (e.g., Altunbas, et al., 2011; Cole and White, 2012).

Another stream of studies has focused on nontraditional banking activities such as securitization to investigate bank failure risk. The evidence is mixed. Some argue that nontraditional activities such as securities underwriting or securities brokerage help to diversify risk (e.g., Uzun and Webb, 2007 and Jiangli and Pritsker, 2008), while others argue that such activities increase failure risk (e.g. Allen and Jagtiani, 2000; DeYoung and Roland, 2001; DeJonghe, 2010; Demirguc-Kunt and Huizinga, 2010). DeYoung and Torna (2012) separate fee-based activities (e.g., securities brokerage or insurance sales) from asset-based activities (e.g., asset securitization and investment banking) and show that bank failure risk declines with fee-based activities, but increases with asset-based activities. There is also a growing literature investigating how off-balance-sheet activities (OBSA) affect bank risk. Deng et al. (2016) find that banks reduce exposure to interest-rate risk via derivatives hedging in order to take greater credit risk in lending, where they have a niche. Most of these studies focus on the crisis periods.

Surprisingly few studies look at non-crisis periods or crisis periods over a long and continuous time span. To the best of our knowledge, Mayes and Stremmel (2014) was the first attempt to study the causes of bank distress in the U.S. over a longer period (1992 to 2012) using a logit model and discrete survival analysis. They find that the characteristics of banks that become distressed do not change over time. They also provide a review of bank distress literature, including a few important studies on European countries. De Graeve et al. (2008) investigate the German banking system between 1995 and 2004. They find that monetary tightening puts pressure on banks even during a non-crisis period, but they are silent regarding the effects of monetary loosening. A common feature of these studies is treating bank failure as a binary variable and using binary variable regression models (logit, probit etc.) to examine the causes of bank failure.

2.2.3. Hypotheses

Our work follows the literature on bank distress and failure. However, it differs from the main stream of research in this area in that we do not define bank distress in binary terms, as either "fail" or "survive". Instead, we develop a continuous indicator of distress by defining a "technical failure" condition for a bank similar to Cole and White (2012). For rate hikes, loan demand factors may increase the stress level. Specifically, borrowers facing higher rates will find it difficult to meet their obligations, raising loan default rate and the risk profile of the bank. Particular to the period of our investigation (2001-2008), rate hikes created payment pressures on borrowers who faced rate resets, thus reducing demand for loans and increasing the loan default rate. Therefore, we expect surprise rate hikes to create stress on banks for one year after the rate hike due to rising delinquencies on adjustable rate loan products. Thus, we propose:

H_1: Positive interest rate shocks create distress on banks.

The commitment of a central bank to keep interest rates low for some time after an adverse shock to the economy reduces the chances of large upside interest rate movements, encouraging banks to assume greater risk in their activities[54]. When interest rates are low for a long period, the margin between lending and deposit rates tend to shrink (Claessens et al., 2017)[55] as banks are reluctant to quickly lower deposit rates when interest rates decline, because they fear losing clientele, while they must pass the lower rates on the existing loans based on contractual repricing and on new loans due to competition. Consequently, banks switch to riskier assets with higher expected yields (Borio and Zhu, 2008), raising the chances of their own distress. Thus, we propose:

H_2: Negative interest rate shocks increase the level of distress on banks.

If not rejected, H_1 and H_2 point to rising bank distress due to unexpected rate changes. Combining H_1 and H_2, we examine which effect (the effect of positive or negative

[54] See the Fed statement in August, 2003

[55] In a cross country analysis of 47 countries from 2005 to 2013, Claessens et al. (2017) find that one percentage point interest rate drop implies an 8 bps lower NIM, with this effect being greater (20 bps) at low rates. For each additional year of "low for long", margins fall by another 9 bps.

shock) is greater. In other words, we examine if there is asymmetry in the effect of rate shocks on bank distress. This constitutes the basis of our paper. We form our next hypotheses to check the asymmetry:

$H_{3a\,(b)}$: The impact of positive interest rate shocks on bank distress is larger (smaller) than the impact of negative interest rate shocks on bank distress.

We examine the third hypotheses ($H_{3a\,(b)}$) also on both cohorts, BHCs and FHCs, because the effect of the interest rate shocks may be different according to their business models. It is critical to examine distress on BHCs and FHCs separately because FHCs engage in a range of financial activities that BHCs do not. These include securities underwriting and dealing, insurance underwriting, and merchant banking without limitations that BHCs are subjected to[56]. In particular, BHCs are allowed to acquire up to only 25% of their gross revenue from securities underwriting or dealing[57], they are restricted to a narrow scope of merchant banking activities and they are not allowed to acquire more than five percent of any class of voting securities, or more than 24.9% of the total equity, of a nonfinancial company. Similarly, BHCs are not allowed to underwrite or sell insurance as an agent.

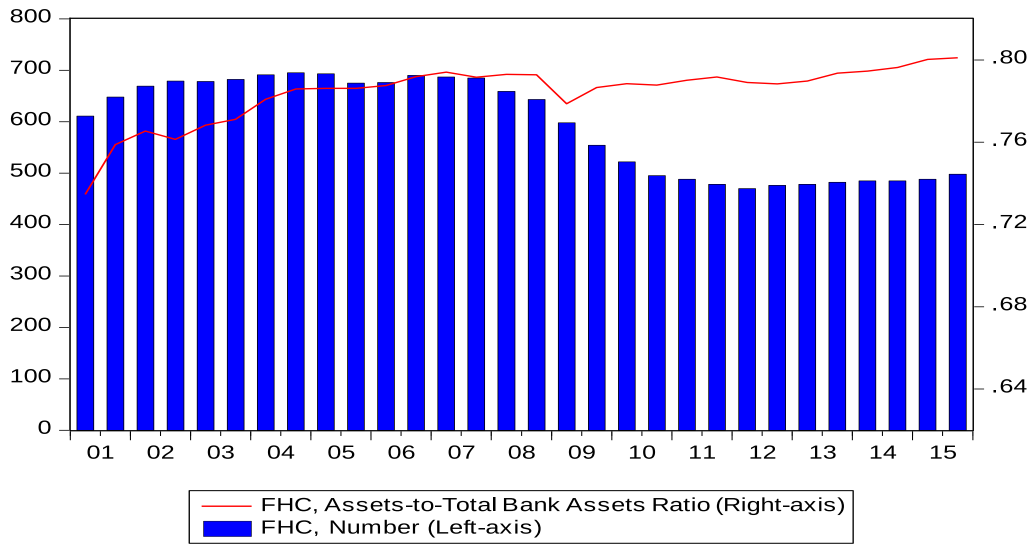
Most large BHCs have registered as FHCs. At the end of 2015, there were 498 FHCs in the US and they owned nearly 80% of all banking assets; the remaining 20% was

56 See "Report to the Congress on Financial Holding Companies under the Gramm-Leach-Bliley Act", Nov, 2003, Board of Governors of the Federal Reserve System, US Department of the Treasury.

57 See the reference in the last footnote.

owned by 4070 BHCs. There is a notable growth in the size and importance of nonbank subsidiaries after BHCs convert to FHCs (Figure 2.1).

Figure 2.1: Number of Financial Holding Companies and Their Asset Share in Total Bank Assets



Thus, FHCs may respond to interest rate shocks differently than do BHCs. In particular, non-traditional operations under FHCs may reduce or increase the impact of interest rate shocks on these firms. More specifically, even if these activities engender some risk reduction due to diversification, FHCs may exhibit greater risk because risk reduction could embolden them to take additional risk in other areas (risk shifting). Therefore, we propose

> $H_{4a\ (b)}$: Positive interest rate shocks have larger (smaller) effects on BHC distress, than negative interest rate shocks (asymmetry).

$H_{5a\ (b)}$: Positive interest rate shocks have larger (smaller) effects on FHC distress, than negative interest rate shocks on FHC distress (asymmetry).

We test hypotheses H_1 to H_5 within both static and dynamic panel fixed-effect models.

2.3 Data and Methodology

This section contains a description of data sources and construction of bank balance sheet indicators and the bank distress indicator. Data are quarterly from 2001 to 2008. We stop at 2008 because the FFR hit the zero bound in the last quarter of 2008. FFR is a nominal rate, and the Federal Reserve typically does not set it below zero. After the FFR hit the zero bound in December 2008, the Fed began using unconventional policy tools, such as quantitative easing (QE), instead of FFR[58]. We focus on U.S. BHCs because our main objective is to investigate the impact of the monetary policy rate on the U.S. banking system distress. Using BHC level data is preferred over individual banking subsidiary data because decision making occurs at the BHC level and BHCs transfer funds across their multiple subsidiaries for window dressing and tax reduction, rendering the individual bank data unreliable.

2.3.1 The Sample

The primary data source for BHCs is the Chicago Fed's Consolidated Financial Statements for Bank Holding Company (FR Y-9C) database. Our panels have 32 quarters of data points, from 2001Q1 to 2008Q4, and the dataset includes all BHCs and FHCs

[58] Extending the FFR beyond 2008 is possible but with an implied policy rate (Taylor rule rate) rather than actual FFR. We do not take this route because creating interest rate shocks based on an implied policy rate maybe far-fetched.

operating in the U.S. Thus, there is no selection (or survivorship) bias in our estimations. We use several sources for the macroeconomic drivers. Gross Domestic Product data are obtained from the U.S. Bureau of Economic Analysis' National Income and Product Accounts. It is in 2009 constant prices and seasonally adjusted annualized values. The U.S. Bureau of Labor Statistics is the source for Consumer Price Index data (CPI). CPI is a seasonally adjusted index tied to 100 at 1982-84. The federal funds rate (FFR) is the target rate as set by Federal Open Market Committee (FOMC) of the Board of Governors of the Federal Reserve System. The definitions for all control variables are provided in Table 2.1. Table 2.2 presents variable construction for distress proxies and bank-level indicators based on FR Y-9C codes.

Table 2.1: Data Description

Dependent Variable	*Definitions*[¥]
Distress Indicator	(0.3*30-89 day delinquent assets + 0.5*90 + day delinquent assets + assets in non-accrual interest status) / (equity capital+ loan loss allowance)
Non-performing Assets Ratio	(0.3*30-89 day delinquent assets + 0.5*90 + day delinquent assets + assets in non-accrual interest status) / total assets
Independent Variable	*Definitions*[¥]
Profitability (ratio)	Net income-to-total assets ratio
Efficiency (ratio)	Total operating (noninterest) expenses–to-total revenues
Size (log)	Size of Balance Sheet (logarithmic transformation of total assets)
Interest Rate Derivatives	Interest rate derivatives held for non-trading purposes
Hedging (ratio)	Interest rate derivatives-to-total assets ratio
Funding Gap - Assets (ratio)	The spread between interest sensitive assets and interest sensitive liabilities-to-total assets ratio
Real GDP Growth, %	Real Gross Domestic Product, Millions of Chained 2009 Dollars, Seasonally Adjusted Annual Growth Rate
Federal Funds Rate, %	Federal Funds Rate (Target Rate), percent, as announced by FOMC (converted into quarterly frequency)**
Inflation, %	Consumer Price Index, All-items, All-Urban Consumers (CPI-U), 1982-84=100, Year-ago change *

[¥]Bank Holding Company Database of Chicago Federal Reserve System:
[**]Board of Governors of the Federal Reserve System
[*]Bureau of Labor Statistics

Table 2.2: Variable Description with FR Y-9C Mnemonics

Dependent Variable	*Definitions*
Distress Indicator	(0.3*bhck5524 + 0.5*bhck5525 + bhck5526 + bhck2745)/(bhck2170 - bhck2948 + bhck3123)
Non-performing Assets Ratio	(0.3*bhck5524 + 0.5*bhck5525 + bhck5526 + bhck2745)/bhck2170
Independent Variable	*Definitions*
Profitability (ratio)	bhck4340/bhck2170
Efficiency (ratio)	(bhck4079 + bhck4107)/bhck4093
Size (log)	log(bhck2170)
Hedging (ratio)	bhck8725/bhck2170
Interest Rate Derivatives	bhck8725
Interest Sensitive Liabilities	bhck3296+bhck3296+bhck3409+bhck3408
Interest Sensitive Assets	bhck3197
Funding Gap - Assets (ratio)	(bhck3296+bhck3296+bhck3409+bhck3408-bhck3197)/bhck2170

Note: The variable descriptions are given in Consolidated Financial Statements (Files FR Y-9C) mnemonics.

Table 2.3 provides summary statistics for bank balance sheet indicators. Correlation coefficients for explanatory variables are presented in Table 2.4.

Table 2.3: Summary Statistics: All Dependent and Independent Variables

Variable Name	# of obs	Min	25th	Mean	Median	75th	90th	Max	Std. dev.
Distress Indicator (ratio)	54,020	0.000	0.026	0.078	0.051	0.093	0.159	1.000	0.098
Non-performing Assets (ratio)	54,020	0.000	0.003	0.008	0.005	0.009	0.015	0.087	0.009
Profitability (ratio)	61,162	0.007	0.005	0.010	0.009	0.014	0.019	0.032	0.007
Efficiency (ratio)	61,162	0.206	0.363	0.437	0.428	0.501	0.576	0.948	0.144
Size ($bil.)	61,162	0.026	0.238	7.350	0.428	0.948	3.296	2,360	66.20
Hedging (ratio)	59,776	0.000	0.000	0.020	0.000	0.000	0.031	13.89	0.165
Funding Gap-Assets (ratio)	59,259	0.721	0.052	0.069	0.067	0.192	0.317	0.784	0.206

Note: This table presents the summary statistics for the variables (and definitions) presented in the table 1. Summary statistics for Profit-Asset Ratio, Efficiency Ratio, Size of Balance Sheet and Hedge Ratio are given for 2000Q1-2008Q4 period due to 4-Q lag in the equations. These indicators are winsorized at 1%, except Hedge Ratio. For the rest of the indicators, stats are provided for 2001Q1–2008Q4 period. Distress Indicator is winsorized to keep all values between 0 and 1, included. Ratios are not percentages. All ratios are fraction of total assets, except efficiency.

Table 2.4: Correlation Coefficients Between Explanatory Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Profitability (1)	1.000							
Efficiency (2)	0.1992	1.000						
	(0.000)							
Size (3)	0.0226	0.0580	1.000					
	(0.000)	(0.000)						
Hedging (4)	0.0099	0.0456	0.1875	1.000				
	(0.005)	(0.000)	(0.000)					
GDP growth (5)	0.0442	0.0450	0.1491	0.0240	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)				
Positive Shocks (6)	0.0347	0.0808	0.0584	0.0031	0.0055	1.000		
	(0.000)	(0.000)	(0.000)	(0.444)	(0.039)			
Negative Shocks (7)	0.0150	0.1393	0.0978	0.0104	0.0232	0.5699	1.000	
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)		
Inflation (8)	0.0333	0.1573	0.0590	0.0175	0.5178	0.1522	0.2230	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: P-values are reported in parenthesis

2.3.2 The Model

Our primary focus is the effect of unexpected changes (shocks) in the main monetary policy rate (target FFR) on bank distress. We determine FFR shocks as described in section 2.3.2.1. Then, we sort the shocks into positive and negative shocks, and estimate the effects on bank distress within static and dynamic models as discussed in section 2.3.2.2.

2.3.2.1 Interest Rate Shocks

We use the method proposed by Morgan (1993) to identify the unanticipated changes in the target FFR (shocks) in two steps[59]. In step one, the target FFR (announced) is regressed on its own lagged values (lagged quarters), in addition to current and lagged values of output growth and inflation, a time trend and a constant term (eq.1). The announced FFR has two components, one component is determined by the control variables (predicted target rate as determined by macro drivers) and the other is a residual (shock)[60]. Specifically, we estimate the equation of the form:

$$ffr_t = \alpha + trend + \sum_{j=1}^{J} \beta_j ffr_{t-j} + \sum_{j=0}^{J} \rho_j y_{t-j} + \sum_{j=0}^{J} \gamma_j p_{t-j} + w_t \qquad (1)$$

In this model, ffr_t is the Fed's (announced) target rate, y_t is the output growth, p_t is inflation, and w_t is the residual. The residuals from this equation, which are essentially the variations in the FFR not explained by the current and lagged values of output growth and inflation and its own lags, are used to identify the stance of monetary policy. In step two, following Parker and Rothman (2004), we sort the residuals by sign to create positive and negative shocks. Specifically, the interest rate shock series are computed as w_t^+= max [0, w_t] and w_t^- = max[0, w_t]. Positive residuals ($w_t^+; w_t \geq 0$) indicate a tight monetary policy because they measure how much the current FFR exceeds the level predicted by

[59] Delis, Hasan and Mylonidis (2017) choose a different method of identifying unanticipated shocks. They employ an equation proposed by Romer and Romer (2004) which generates the interest rate shocks based on the expectations of macroeconomic variables. Specifically, they use the Real GDP and inflation *forecasts* provided by the Fed to generate the shocks. However, under the theory of the risk-taking channel, banks mostly develop their risk incentives based on perceptions about the observed level of interest rates given macroeconomic conditions. Therefore, we believe the shocks created based on expectations may be inferior to the shocks proposed by Morgan (1993).

[60] The announced target rate is nearly identical to observed (effective) target as the Fed achieves its targets. The two rates may differ slightly on a daily or even on a weekly basis, but they are (nearly) identical in quarterly frequency.

current and lagged values of output and inflation. Negative residuals ($w_t^-; w_t \leq 0$) indicate a loose policy because the current funds rate is lower than predicted level given current and lagged values of output and inflation. The discussion on the comparison of FFR shocks with announced FFR in the context of business cycles (and exogenous events, e.g. Sept. 11 attacks) is provided in Appendix D.

2.3.2.2 The Bank Distress Model

We introduce a panel fixed-effects model to describe bank distress. This framework was employed by Cover (1992), Morgan (1993), and Parker and Rothman (2004) to explore the asymmetric effects of interest rate shocks on output (the real sector). We use it for bank distress. The model can be described as:

$$distress\ proxy_{i,t} = \alpha + \mu_i d_i + \delta_k' bc_{i,t-4}^k + \sum_{j=1}^{J} \rho_j y_{t-j} + \sum_{j=1}^{J} \gamma_j p_{t-j} +$$

$$\sum_{j=1}^{J} (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) + u_{i,t} \tag{2}$$

where $distress\ proxy_{i,t}$ is distress proxy for bank *i* at time *t.* We gauge bank distress with two proxies; a distress indicator introduced by Cole and White (2012), which is similar to so-called Texas ratio, and a non-performing asset ratio defined as total non-performing assets as a fraction of total assets. In equation 2, bank distress is described as a function of k-dimension bank balance-sheet indicators bc_i^k, output growth y_t, inflation p_t, and interest rate shocks, $w_t^{+/-}$. μ_i is the individual bank fixed effect, d_i is the bank dummy and $u_{i,t}$ is the error term. Delis and Kouretas (2011) and Delis et al. (2017) use a similar model to examine bank risk-taking. The interest-rate shocks are estimated as outlined in the previous section. Interest-rate shocks in opposite directions are put into the equation with lags to capture the asymmetry. As a common application in the bank risk literature, we break down the explanatory variables into bank-specific factors and macroeconomic indicators. Macroeconomic effects are accounted for by lagged output growth rate (Delis and Kouretas, 2011; Mayes and Stremmel, 2014), and lagged inflation (De Graeve and Koetter, 2008; Blank and Dovern, 2010). To control for a number of factors that may possibly cause changes in bank distress, we include bank balance-sheet indicators in the model (Cole and White, 2012; Mayes and Stremmel, 2014; Antoniadis, 2015). Thus, the model has three blocks of control variables: positive/negative interest rate shocks, macroeconomic drivers, and bank balance sheet indicators. At the bank level we control for balance-sheet characteristics that indicate the capacity and the willingness of the bank to supply additional loans or cause changes in banks' risk appetite, and, thereby, in banks' stress level. These include profitability (net profit/total assets), efficiency (total operating expense/total revenue), hedging for interest-rate risk (interest rate derivatives held for non-trading purposes/total assets) and size (natural logarithm of total assets). All control variables are explained in more detail in section 2.3.4.

We consider two variants of the model presented in equation 2. In the first variant, we use the first difference of the bank distress proxy ($s_{i,t}$) for a bank i at time t as a dependent variable: $\Delta s_{i,t} = s_{i,t}$ - $s_{i,t-1}$. This is our static model. In the second variant, we move the lagged dependent variable, $s_{i,t-1}$, to the right-hand side, and estimate the equation with level distress proxy ($s_{i,t}$) as the dependent variable. This is a dynamic model because the values of distress proxy in period t, $s_{i,t}$, depend on the values of the lagged distress proxy, $s_{i,t-1}$, as well as other covariates in equation 2. We discuss both models and results in section 2.4.

A few identification limitations convince us to use the functional form in equation (2). First, the literature on bank default risk asks whether such risk can influence the stance of monetary policy, and whether both of these variables are affected by third factors such as macroeconomic conditions (Delis and Kouretas, 2011). If true, this will bias the estimation. We expect this type of endogeneity (simultaneity) problem not to be of much importance because the U.S. monetary authority has adopted a price-stability and maximum employment objective since 1977[61]. The Fed did not directly target financial stability (low bank failure risk), because price stability was considered sufficient to reach macroeconomic and financial stability before the recent financial crisis (Delis et al., 2017). The Fed may always choose to intervene at a time of financial market turbulence (e.g., Sept. 11 attacks) 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). This may arguably have changed with the crisis. However, because we consider only the pre-crisis period, we are less concerned about the simultaneity problem[62].

Second, the FFR changes cannot be directly used as a control variable next to macroeconomic variables (output growth and inflation) in a distress equation because monetary policy changes are endogenous to output growth or inflation. If put into same

[61] In 1977, Congress amended the Federal Reserve Act to improve monetary stability. The Federal Reserve Act, Section 2A, 1997 amendment: The Board of Governors of the Federal Reserve System and the Federal Open Market Committee shall maintain long run growth of the monetary and credit aggregates commensurate with the economy's long run potential to increase production, so as to promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates.

[62] See Delis and Kouretas (2011) for a similar discussion and treatment of endogeneity between bank risk and monetary policy.

equation, their estimated effects on bank distress will be in part due to the effect of the changes in output growth or inflation. This is not an issue in our model. We estimate the model that generates interest rate shocks (residuals) with the Ordinary Least Squares (OLS) procedure. Therefore, FFR shocks (residuals, w_t) are orthogonal to the changes in output growth and inflation[63]. The variations in the FFR not explained by output growth and inflation, namely the residuals, are used as a shock in the distress equations to identify the effect of the stance of policy on bank distress.

Third, bank-specific terms representing bank characteristics may be affected by FFR shocks. Therefore, they enter the model as lagged drivers, with four-quarter lags, to avoid endogeneity with FFR shocks[64]. We consider only four-quarter lags because the interest rate terms enter into the equation with one- to four-quarter lags. The first three lags do not show any clear correlation with bank balance-sheet terms. Thus, we assume the interest rate shocks do not affect bank balance sheet characteristics contemporaneously[65]. Separately, we do not add particular balance-sheet indicators with more than one lag because they can be highly persistent (autoregressive)[66].

2.3.3 Dependent Variable Construction: Distress Indicator and Non-Performing Asset Ratio

Our proxies for bank distress include a bank distress indicator (main proxy) and a non-performing asset ratio. Following Cole and White (2012), we define the distress

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63 A feature of the OLS technique is that the residuals are orthogonal to the regressors.

64 For similar bank-level controls see Laeven and Levine (2009), Delis and Kouretas (2011), Delis, Hasan and Mylonidis (2017).

65 Although with quarterly data there is some risk of simultaneity, with monthly data it will not be an issue.

66 See Delis, Hasan and Mylonidis (2017), Delis and Kouretas (2011) and Laeven and Levine (2009) for a similar set of bank balance sheet controls.

indicator as non-performing assets divided by the sum of equity capital and loan loss reserves. Non-performing assets are constructed by applying haircuts (i.e. percentage estimates of loss) to the assets reported as delinquent. More specifically, we consider a 20% haircut for loans that were past due 30-89 days and still accruing interest, a haircut of 50% for loans that were past due 90+ days and still accruing interest, and a haircut 100% for loans in nonaccrual status (write-offs) and other real estate owned. The write-offs were not assigned a haircut because loans in write-off status are terminated and considered as a loss. The haircuts are used to consider only the share of the assets expected to be lost and reported as write-off[67]. We write the distress indicator as:

$$Distress\ Indicator = (0.2 * (30 - 89d\ DEL) + 0.5 * (90d\ plus\ DEL) + WOF + REO)/(Equity + LLA) \quad (3)$$

Cole and White (2012) consider the distress indicator values equal to or greater than one as "technical default" because they use it as a binary variable (survive, fail) in their models. We use this ratio as a continuous variable where a rising distress indicator points to increased distress and vice versa. Among our 54,020 observations, in 206 observations, the distress indicator rises above one, and in 11 of them, it falls below zero[68]. In both cases, we set the indicator to 1 because falling below zero and rising above 1 shows extreme distress. Negative values are possible when denominator falls below zero, which happens when equity falls below zero, meaning that the value of assets falls below liabilities, and

[67] For example, assuming a haircut of 20% for the assets that are 30-89 days delinquent is another way of saying 20% of these assets will be eventually lost. See Cole and White (2012) for selection of haircuts.

[68] Values below zero and above one are rare but possible. They show extreme distress. Typically, the distress indicator starts rising when the bank comes under stress. We may see one or two quarters of below zero or above one values before the regulators take over the bank (Chernykh and Cole, 2015).

reserves for loan losses is insufficient to offset the gap. 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[69]. The main advantage of this indicator is that it accounts for the two primary banking risks, capital adequacy and asset quality, in a simple measure (Chernykh and Cole, 2015)[70]. The second proxy, the non-performing asset ratio, is calculated as non-performing assets to total assets ratio, often used as a credit-risk indicator[71, 72].

2.3.4 Control Variables

The control variables are chosen mostly based on Laeven and Levine (2009), Delis and Kouretas (2011), and Delis et al. (2017). We separate control variables into macroeconomic indicators and bank balance-sheet characteristics. As macroeconomic drivers, we use the year-over-year growth rate in GDP to gauge the business cycles and the year-over-year change in inflation (CPI) as an indicator for the price level. For bank balance-sheet characteristics, we introduce several indicators. To gauge bank's earning ability and strength, we use profitability (net income/total assets, ROA) in the equations.

69 Also see (Chernykh and Cole, 2015) for a discussion of this indicator outperforming other capital ratios.

70 Banks with extreme levels of non-performing assets and grossly insufficient loan-loss reserves, but with "adequate" equity capital can survive for several years before regulators take action. Similarly, a bank with a liquidity shortage may see its equity base and loan loss reserves melt while its assets still appear prudent. By accounting for the two primary bank risks, one could observe several sections of the balance sheet that deteriorated and raised bankruptcy risk or improved and reduced bankruptcy risk.

71 The non-performing asset ratio, is a credit-risk indicator. Holding poorly performing assets makes banks more vulnerable to financial distress because they require write-downs and curtail the capital cushion. Thus, a high value of this ratio is associated with higher credit risk. We define non-performing assets as in the bank distress indicator (eq. 3 above). The two proxies are highly correlated (rho = 0.81), but the distress indicator is superior to the non-performing assets ratio because it includes capital adequacy as well as asset quality while the latter only gauges the asset quality (Chernykh and Cole, 2015).

72 A measure of bank risk used in literature is the Z-index. We use distress indicator because it can be used as a probability of default, as it is bounded between 0 and 1 (except in extreme cases). The Z-index can take positive values over a wide range.

Reduced earnings lead to losses and distress. To control for management competence, we use the efficiency ratio (operating expenses/total revenue). The higher the management competence (efficiency), the lower the likelihood of losses. The interest rate-hedging ratio accounts for the effect of financial derivatives in reducing the interest-rate risk exposure of the BHCs. Hedging interest rate risk is likely to reduce bank distress. Derivative instruments used for hedging purposes are reported as "derivative contracts held for non-trading" in call reports data for BHCs[73]. For the interest-rate hedging ratio, we scale "interest rate derivatives for non-trading" with total assets (Deng et al., 2007; Choi and Elyasiani, 1997). We use total assets (with log transformation) to control for the size of the balance sheet.

2.3.5 Exploring BHC Subgroups: BHCs versus FHCs

Since the passage of the GLBA (1999), many large BHCs have registered as FHCs (Figure 2.1). There is also a notable growth in the size and importance of FHCs (Avrahan, Selvaggi and Vickrey, 2012). At the end of 2007, right before the crisis, there were 668 FHCs in operation, constituting 12% of all U.S. BHCs. These FHCs controlled nearly 80% of total banking assets. After the onset of the crisis, the number of FHCs declined to 477 at the end of 2012, but these FHCs continued to hold nearly 80% of all banking assets. The total assets of FHCs increased from \$10.7 trillion in 2007 to \$13.7 trillion in 2012, exhibiting a greater average size for FHCs after the recession. At the year-end 2015, 498 FHCs operated in the U.S. and controlled \$14.4 trillion worth of assets, nearly 80% of all

[73] The use of derivatives that are reported as "contracts held for non-trading" for risk-management purposes are verified for robustness by Purnanandam (2007). Also see Begenau, Piazzesi and Schneider (2015) and Deng et al., (2016) and refer to http://www.occ.ustreas.gov/ftp/deriv/dq202.pdf for more details.

banking assets. In our sample, there were 611 FHCs and 5,250 BHCs at the beginning of 2001. At the end of 2008, there were 643 FHCs and 4,959 BHCs. The sample size for BHC and FHC cohorts is, respectively, 41,170 and 12,850 bank-quarters.

2.4 Empirical Results

The model generating interest-rate shocks (eq.1) is estimated using the OLS. Results are presented in Table 2.5 and discussed in section 2.4.1. The model of distress using changes in distress proxies (static model; eq. 2', section 2.4.2.1) is estimated using the OLS and the model that uses distress proxies in level (dynamic model; eq. 2'', section 2.4.2.2) is estimated using the Generalized Method of Moments (GMM). We use the OLS for equation 1 because it creates orthogonal residuals (shocks). We need orthogonality for the shocks to distinguish their true effect on distress proxies from the effects of macroeconomic variables in the distress equations. We prefer the OLS for the static distress model (eq. 2') because it is the technique most commonly used for linear regression. GMM stands out as the estimation technique for the dynamic model (eq. 2'') as put forward by Arellano and Bond (1991) and discussed in section 2.4.2.2. The macroeconomic data and interest-rate shocks enter into distress equations with four lags. Therefore, we check the significance of the cumulative elasticities, the symmetry of negative and positive cumulative elasticities, and the equality of elasticities for FHCs versus BHCs using the Wald-tests. The results are presented in Tables 2.7 to 2.10 and discussed in sections 2.4.2 and 2.4.3.

Table 2.5: Generation of Unanticipated Interest Rate Shocks

$$ffr_t = \alpha + trend + \sum_{j=1}^{4} \beta_j ffr_{t-j} + \sum_{j=0}^{4} \rho_j y_{t-j} + \sum_{j=0}^{4} \gamma_j p_{t-j} + w_t$$

ffr_t is the target federal funds rate (FFR) as announced by Fed, y_t is the output growth, p_t is the inflation, w_t is the residual (shock), the difference between the actual target and fitted (predicted) target rates, $trend$ is time-trend and α is the intercept. The sample span is 1984Q1-2008Q4. The coefficients in the first column are for lagged target rates, current and lagged GDP growth rates, and current and lagged Inflation rate.

Dependent Variable: Federal Funds Rate (Target)

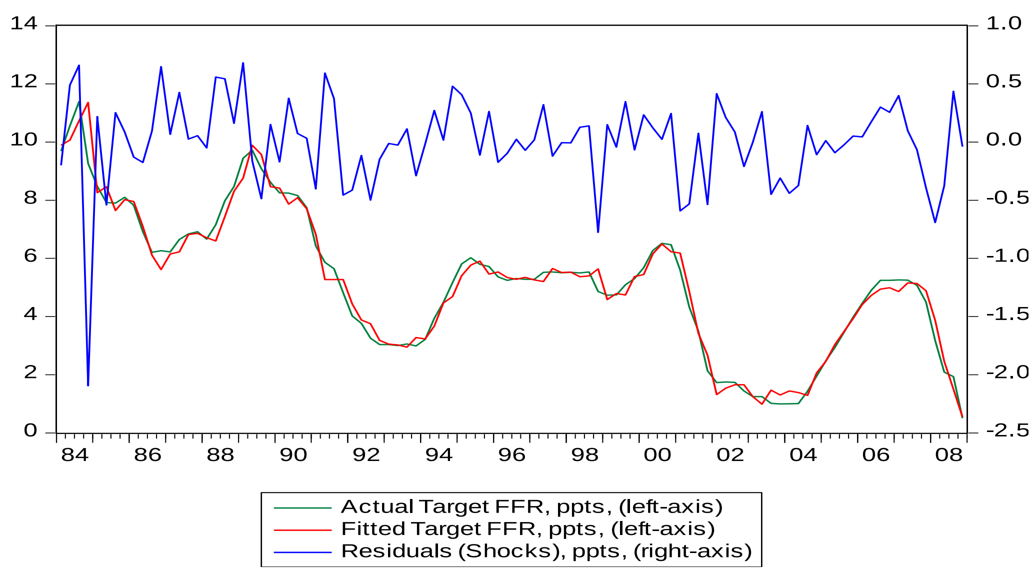
	coefficients	t-stat	p-value
constant	-0.61	-2.603	0.011
(Target FFR, β)			
β_1	1.362	13.00	0.000
β_2	-0.598	-3.354	0.001
β_3	0.253	1.380	0.171
β_4	-0.133	-1.311	0.193
(GDP growth rate, ρ)			
ρ_0	22.50	3.287	0.002
ρ_1	-5.051	-0.478	0.634
ρ_2	-7.141	-0.689	0.493
ρ_3	0.783	0.074	0.941
ρ_4	7.785	1.106	0.272
(Inflation, γ)			
γ_0	22.01	2.988	0.004
γ_1	-8.911	-0.829	0.409
γ_2	-2.949	-0.252	0.802
γ_3	-7.737	-0.662	0.510
γ_4	15.70	1.727	0.088

Note: The trend is insignificant and it is removed from the equation.

2.4.1 Generating FFR Shocks

We present the results of the model of interest rates (eq.1) in Table 2.5. The announced target FFR, the fitted values and the shocks are demonstrated in Figure 2.2. The model of interest rate is estimated using a sample of target FFR, real GDP growth and inflation from 1984Q1 to 2008Q4 to generate the FFR shocks. Morgan (1993) uses 8-Q lags for FFR, real GDP growth and inflation to estimate FFR shocks as residuals. We explore lags from 4 to 8 quarters, and find that the 4-Q lag specification works best based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) tests[74]. The residuals should satisfy two Gauss Markov error properties for having unbiased estimators: (i) zero average residuals and (ii) homoscedasticity. The average of the residuals is zero as needed. The residuals also pass the Shapiro-Wilk Test of normality (p= 0.134). The residuals show some heteroscedasticity according to Breauch-Pagan-Godfey Test (p=0.044), but have no heteroscedasticity (p=0.201) according to Harvey-Godfey Test. Figure 2.2 presents the "announced" target FFR, the predicted target FFR (the fitted values) and the residuals (shocks, w_t) from 1984Q1 to 2008Q4.

Figure 2.2: Estimation of Interest Rate Shocks (1984Q1-2008Q4), percentage points



Note: The Interest rate shocks (residuals) have a normal distribution. This distribution passes Shapiro-Wilk Test of normality with p= 0.134. The average of the residuals is zero. According to Harvey-Godfey Test, the residuals have no heteroscedasticity (p=0.201), but, according to Breauch-Pagan-Godfey Test, the residuals do show heteroscedasticity (p=0.044). Dates appear on the horizontal axis.

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[74] We also looked at 8 quarter lags. The results do not change materially.

In Table 2.6, we present the announced (actual) and "fitted" target FFR for the sample period (2001Q1-2008Q4) (columns I and II).

Table 2.6: Target Federal Funds Rates (Policy Rate) and Shocks

PERIOD	Actual Target Rate, % (I)	Fitted Target Rate, % (II)	Actual Target Rate, First diff. (ppts) (III)	Shocks, w_t (ppts) (IV)	(-) Shocks w_t^-=min[0, w_t] V	(+) Shocks w_t^+=max[0, w_t] VI
2000Q4	6.473	6.227				
2001Q1	5.593	6.185	-0.880	-0.591	-0.591	0
2001Q2	4.327	4.859	-1.267	-0.532	-0.532	0
2001Q3	3.497	3.421	-0.830	0.076	0	0.076
2001Q4	2.133	2.670	-1.363	-0.536	-0.536	0
2002Q1	1.733	1.318	-0.400	0.415	0	0.415
2002Q2	1.750	1.538	0.017	0.212	0	0.212
2002Q3	1.740	1.654	-0.010	0.086	0	0.086
2002Q4	1.443	1.653	-0.297	-0.209	-0.209	0
2003Q1	1.250	1.251	-0.193	-0.001	-0.001	0
2003Q2	1.247	0.986	-0.003	0.261	0	0.261
2003Q3	1.017	1.466	-0.230	-0.449	-0.449	0
2003Q4	0.997	1.306	-0.020	-0.310	-0.310	0
2004Q1	1.003	1.443	0.007	-0.440	-0.440	0
2004Q2	1.010	1.383	0.007	-0.373	-0.373	0
2004Q3	1.433	1.290	0.423	0.143	0	0.143
2004Q4	1.950	2.059	0.517	-0.109	-0.109	0
2005Q1	2.470	2.457	0.520	0.013	0	0.013
2005Q2	2.943	3.035	0.473	-0.092	-0.092	0
2005Q3	3.460	3.485	0.517	-0.025	-0.025	0
2005Q4	3.980	3.929	0.520	0.051	0	0.0508
2006Q1	4.457	4.412	0.477	0.045	0	0.0449
2006Q2	4.907	4.731	0.450	0.176	0	0.1760
2006Q3	5.247	4.945	0.340	0.302	0	0.3017
2006Q4	5.247	4.990	0.000	0.256	0	0.2565
2007Q1	5.257	4.858	0.010	0.399	0	0.3990
2007Q2	5.250	5.155	-0.007	0.095	0	0.0954
2007Q3	5.073	5.139	-0.177	-0.065	-0.065	0
2007Q4	4.497	4.891	-0.577	-0.394	-0.394	0
2008Q1	3.177	3.869	-1.320	-0.692	-0.692	0
2008Q2	2.087	2.462	-1.090	-0.375	-0.375	0
2008Q3	1.940	1.504	-0.147	0.436	0	0.436
2008Q4	0.507	0.546	-1.433	-0.040	-0.040	0

Note: ppts is percentage points.

The interest rate model in equation 1 predicts the target FFR as a level based on the four own quarterly lags, real GDP growth rate and inflation rate, both in the current and past four quarters. Since real GDP growth and inflation are essentially growth rates, they enter into the equation in levels. The variations in FFR not explained by these variables, the residuals (w_t), are used to identify the stance of policy. If the announced rate exceeds the predicted value based on the model, we have a positive shock ($w_t \geq 0$). This represents tight policy. If the announced FFR is lower than what would be expected given the current and lagged values of output and inflation, we would have a negative residuals ($w_t \leq 0$), indicating an easy policy. It is critical to note that the shocks generated in this method may not necessarily point to a rate hike or cut by the Fed. The model would generate a positive residual (tight monetary policy) for a period in which the target rate is kept unchanged but it still exceeds the rate pointed to by the underlying macroeconomic drivers. Similarly, a negative shock may occur when the announced policy rate is kept unchanged while the macroeconomic drivers point to a higher rate. For example, the policy rate may be kept flat at 4% in two consecutive quarters, while the model suggests that it should be 4.25% in the first quarter and 3.75% in the second quarter. In this case, the predicted rate points to looser monetary policy in the first quarter and to tighter policy in the second.

In Table 2.6, we present, respectively, the announced (actual) FFR and the predicted FFR in column I and II. The quarter-to-quarter change in the announced FFR is presented in column III for comparison with FFR shocks. The FFR shocks, (the residuals) are presented in column IV. Comparing quarter-to-quarter target rate change with FFR shocks help us to put the timing of FFR shocks in perspective with business cycles. For example, the target FFR was cut every quarter from 2001Q1 to 2002Q1 to fight the 2001 recession. However, the FFR shocks in this period tell us that the rate cuts were often too aggressive as they came as a surprise on the down side (negative shocks). We sort the interest rate shocks (w_t) into *positive shocks* ($w_t^+ = \max[0, w_t]$; $w_t \geq 0$) and *negative shocks* ($w_t^- = \min[0, w_t]$; $w_t \leq 0$) (columns V and VI). We use these shocks as explanatory variables in the distress models (discussed in detail in Appendix D).

2.4.2 The Effect of Unanticipated Rate Shocks on Bank Distress

We examine positive and negative policy shocks separately to investigate the asymmetry of their effects on bank distress. Our static model (eq. 2') uses the first difference ($\Delta s_{i,t}$) as the dependent variable while our dynamic model (eq. 2'') uses the distress proxy as a level. We estimate both models once using the bank distress indicator and again using the non-performing assets ratio as the dependent variable. The three blocks of control variables in the models include bank balance sheet indicators, macroeconomic drivers, and interest rate shocks. We initially estimate the models with FFR shocks and macroeconomic variables alone, and then include bank balance sheet indicators to examine to what extent balance sheet indicators add to the explanatory power of the model. We present the results of both specifications in Tables 2.7-2.10. We discuss the results of the full model including bank level indicators in the rest of this section and section 2.4.3. Results in Tables 2.7-2.10 are based on the bank distress indicator used as a distress proxy.

Interest rate shocks and macroeconomic indicators are flow measures, while the distress indicator proxies are stock measures: they show the distress level of a bank at a given point in time. We convert the distress level into a flow measure by taking the first difference, and probe the effect of exogenous variation in interest-rate shocks and macroeconomic indicators on the *change* in bank distress. This model (eq. 2') and the results are discussed in section 2.4.2.1. The third set of explanatory variables, namely bank balance sheet indicators (profitability, efficiency, size and interest rate hedge) are stock measures. Their potential impact on distress is better approximated when distress is expressed in levels which requires a dynamic formulation (Delis and Kouretas, 2011). The dynamic formulation (eq. 2'') and its advantages are discussed in section 2.4.2.2. Initially, we estimate the models with the panels of *all* banks. Then, we disaggregate the panel into bank type (BHCs versus FHCs) subgroups.

2.4.2.1 A Static Model of Bank Distress and Interest Rate Shocks

To assess the impact of interest rate shocks (w_t) on changes in bank distress, we estimate the static model below (eq. 2'), where $\Delta s_{i,t}$ is the quarterly change in bank distress, bc_i^k includes the k-dimensional bank balance sheet indicators, y_t is output growth, p_t is inflation, $w_t^{+/-}$ are positive and negative FFR shocks, $u_{i,t}$ is the error term, μ_i is individual bank effect and d_i is a set of dummies to capture individual bank effects. d_i is 1 for bank i and 0 for others[75]. α is the intercept.

[75] Individual bank effects account for unobserved bank heterogeneity such as company culture, internal risk management processes, or the focus of the operations. Heterogeneity in BHCs may arise from factors such as geography or a field of concentration in banking activities. For example, while some banks in certain geography focus on commercial loans, others concentrate on household loans (business model). Banks operating in areas with high homeownership may pay more attention to residential mortgages than do those in areas with low homeownership. Similarly, larger entities could diversify their operations, since they can, while smaller entities may concentrate on less risky activities. Unless these trends are controlled for, they will reside in the error term and create endogeneity. Accounting for individual bank effects with dummy variables to capture unobserved heterogeneity, the model takes the form of fixed-effect models. We cluster for the groups in the panel to allow for intragroup correlation, relaxing the requirement that the observations be independent. Put differently, the observations are independent across banks but not necessarily within the bank groups.

$$\Delta s_{i,t} = \alpha + \mu_i d_i + \delta_k' bc_{i,t-4}^k + \sum_{j=1}^4 \rho_j y_{t-j} + \sum_{j=1}^4 \gamma_j p_{t-j} + \sum_{j=1}^4 (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) + u_{i,t} \qquad (2')$$

The framework of regressing output growth on lagged inflation, output growth and FFR shocks were employed by Cover (1992), Morgan (1993), and Parker and Rothman (2004) to explore the asymmetric effects of interest rate shocks on output. We employ the same framework for bank distress. Our model is also similar to the bank-risk taking models used by Delis and Kouretas (2011) which regress *changes* in bank risk variables on macroeconomic and bank-level control variables, and changes in monetary policy rates.

The estimation results of the static model with bank distress indicator are reported in columns I and II of Table 2.7. Column I reports the results from the model that has interest rate shocks and macroeconomic variables as control variables. Column II reports the results from the model that includes balance sheet indicators in addition to interest rate shocks and macroeconomic variables. The coefficients for interest rate shocks and macroeconomic drivers are cumulative over four quarters (lag1 to lag4). We check the joint significance of the coefficients by Wald-tests, and report the results in the lower part of Table 2.7. Positive shocks enter into the model with positive sign and negative shocks enter with negative sign. Therefore, the dimension of the effect of a shock is determined by both signs of the shocks and the coefficients; a positive shock with a positive coefficient and a negative shock with a negative coefficient both indicates rising distress.

Table 2.7: The Static Model of Distress (Equation 2'): All BHCs 2001-2008

Dept. variable (Distress Indicator)	(I)	(II)
	All	All
Positive shock	0.123***	0.093***
Negative shock	-0.039***	-0.031***
GDP growth	-0.002***	-0.001***
Inflation	0.014***	0.011***
Profitability		-0.177***
		(-3.86)
Efficiency		-0.051***
		(-9.41)
Size		0.011***
		(6.68)
Hedging		-0.0034**
		(-2.30)
Constant	-0.047***	-0.165***
	(-16.76)	(-7.76)
Wald-tests for Interest Rate Shocks and Macro Drivers		
(1) $\sum_{j=1}^{4}\beta_j^{+}=0$	0.000	0.000
(2) $\sum_{j=1}^{4}\beta_j^{-}=0$	0.000	0.000
(3) $\lvert\sum_{j=1}^{4}\beta_j^{+}\rvert-\lvert\sum_{j=1}^{4}\beta_j^{-}\rvert=0$	0.000	0.000
(4) $\sum_{j=1}^{4}\rho_j=0$	0.000	0.003
(5) $\sum_{j=1}^{4}\gamma_j=0$	0.000	0.000
# of obs	50142	48302
R-sq	0.110	0.121

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses. Cluster-robust standard errors. Walt-tests are conducted to measure the joint significance of the coefficients.

$$\Delta s_{i,t} = \alpha + \mu_i d_i + \delta_k' \, bc_{i,t-4}^{k} + \sum_{j=1}^{4}\rho_j y_{t-j} + \sum_{j=1}^{4}\gamma_j p_{t-j} + \sum_{j=1}^{4}(\beta_j^{+} w_{t-j}^{+} + \beta_j^{-} w_{t-j}^{-}) + u_{i,t}$$

This is the static equation (eq 2'). Column I shows the results from the model without bank-level indicators. Column II shows results from the full model. $s_{i,t}$ is distress indicator, Δ is the first difference, $bc_{i,t-4}^{k}$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term. β_j^{+} is the coefficient for positive shocks and β_j^{-} is the coefficient for negative shocks. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, rows (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. Row (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are similar. Rows (4) and (5) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively

According to the figures in col II in Table 2.7 (rows 1 and 2) positive shocks have a positive coefficient and negative shocks have a negative coefficient. This indicates that both positive and negative shocks to target FFR ($w_t \geq 0$ and $w_t \leq 0$) raise the distress on banks in the sample containing all BHCs. In terms of magnitude, we find that a 100 bps positive shock, e.g. target FFR being raised from 4% to 5% unexpectedly, when the GDP growth rates and inflation suggest that it should remain flat at 4%, raises the bank distress indicator by 9 bps (sum of 4 lags, $\sum_{j=1}^{4} \beta_j^{+} = 0.093$) over one year. The impact is smaller if the shock is negative: a negative shock of 100 bps raises the bank distress indicator by 3 bps (sum of 4 lags, $\sum_{j=1}^{4} \beta_j^{-} = -0.031$). Both results are significant at 1%. In Table 2.7, the Wald-test results for significance of the effect over four quarterly periods are reported in column II, row (1) for positive shocks and row (2) for negative shocks. Because the distress indicator is scaled between 0 and 1, 9 bps increase in distress indicator points to a typical bank's rising probability of bank failure (explained in section 2.3.3), e.g. from 10% to 19%. The dissimilar magnitudes of the effects for positive and negative shocks indicate *asymmetry* between the effects of these shocks. The Wald-test results reject the symmetry of the effects (Table 2.7, Wald-tests, column II, row (3)). The magnitude of the impact of a positive shock is nearly three times that of a negative shock.

As for the channel of the effect, as discussed earlier, a positive interest rate shock ($w_t \geq 0$) raises delinquency and default on borrowers as they are unable to make payments on their loans at the new higher rate, and, thereby, it elevates the distress on the banks' balance sheets. During the housing downturn of 2007, when interest rates rose, many homeowners with adjustable rate mortgages (ARMs) could not refinance their loans because the declining home prices left many of them with negative or insufficient equity to qualify. Similarly, when positive interest rate shocks led to higher rates on ARMs, the monthly payments were no longer manageable for the borrowers, leading to non-payments and eventually to foreclosure (Holt, 2009).

Conversely, although a negative shock lowers borrower delinquency and defaults; it also causes more risk-taking by banks and elevates their distress over time. The rationale is that banks may consider, e.g. a surprise rate cut, as a sign for persistence of low rates and feel encouraged to chase higher returns, in order to achieve a minimum threshold rate, even at the cost of greater risk-taking. These riskier assets create distress over time. In our sample, the three blocks of negative shocks, each has three to four consecutive quarters of rates below the model-determined targets ($w_t \leq 0$), likely to cause perceptions of persistence in rate cuts. Our results show that even though negative shocks reduce the stress on borrowers and lead to lower loan delinquency and default rates, the distress generated by increased risk-taking due to persistence of rate cuts more than offsets this effect; creating more distress on the banks[76]. In terms of magnitude, the net effect of a negative shock is nearly one third of the effect of a positive shock of the same size due to counterbalancing effects[77].

Macroeconomic control variables have the expected signs. The cumulative coefficient of real GDP growth has a negative sign (sum of 4 lags, $\sum_{j=1}^{4} \rho_i$=-0.001) and inflation has a positive sign (sum of 4 lags, $\sum_{j=1}^{4} \gamma_i$=0.011), both significant at 1% (Table 2.7, Wald-tests, column II, row (4) and (5)). This indicates that rising GDP growth curtails

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[76] Rate changes by the Fed can be persistent. In response to the 911 terrorist attacks, the Fed lowered rates 11 times. During the 2004-2006 period, it raised rates 17 times in reaction to inflation concerns.

[77] Gauging risk-taking with credit risk indicators such as non-performing loans ratio (Delis and Kouretas, 2011), Z-index (Delis et al., 2017) and expected default frequency *over one year* (Altunbas et al., 2014) is a common practice. Our results are consistent with those of these authors. Thus, they are complementary to the risk-taking literature.

and rising inflation strengthens distress on banks. In terms of magnitude, if GDP growth rises from 2% to 3%, the distress indicator declines 0.1 percentage points. This provides support for tax cuts, such as the ones legislated by the Trump administration, given that they are indeed effective in promoting significant economic growth. Similarly, if inflation rises 25 bps, e.g. from 1.5% to 1.75%, bank distress rises 0.3 percentage points. Thus, the low inflation environment prevailing in the recent decades is likely to have been helpful in limiting distress in the banking system.

As to the balance sheet indicators, profitability (ROA) has a negative sign and it is significant at 1%; an indication that it reduces bank distress. Rising profitability indicates that bank assets are performing well, suggesting smaller levels of current and expected future non-performing assets and lower bank distress[78]. Efficiency (total operating expense/total revenue) has a negative sign and it is significant at 1%. The higher the management competence, the lower the likelihood of wrong decisions and losses. Good management raises costs because of higher compensation and monitoring costs, and at the same time lowers the losses and distress. Bank *size* is positively associated with bank distress. Large banks are organizationally more complex (opaque) and tend to have less-stable funding and more aggressive management. Thus, they are riskier and subject to greater distress[79]. The coefficient for the hedge ratio is negative and significant, indicating that hedging interest rate risk does curtail bank distress.

[78] Profitability is considered endogenous because it is affected by risky asset level; it enters the estimated equations lagged once.

[79] Proponents of large banks, in particular banks which are too-big-to-fail (TBTF), argue that they should be bailed out when in distress because their failure would generate liquidity risk in the banking system. Our results provide valuable input for this issue as we find that in the run-up to the crisis, larger banks became even more distressed than smaller ones.

2.4.2.2 A Dynamic Model of Bank Distress and Interest Rate Shocks

The static model uses change in distress proxy ($\Delta s_{i,t} = s_{i,t} - s_{i,t-1}$) as a dependent variable. It can be converted into a dynamic model by taking the level, $s_{i,t}$, as a dependent variable and moving the lagged proxy, $s_{i,t-1}$, to right-hand side. Thus, our dynamic model takes the following form[80].

$$s_{i,t} = \alpha + \mu_i + \lambda s_{i,t-1} + \delta_k' bc_{i,t-4}^k + \sum_{j=0}^{4} \rho_j y_{t-j} + \sum_{j=0}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) + u_{i,t} \qquad (2'')$$

We estimate eq. (2'') using the GMM method proposed by Arellano and Bond (1991) for dynamic panel data. In linear dynamic panel-data models, a lagged dependent variable, $s_{i,t-1}$, and unobservable fixed panel-level effects, μ_i, are, by construction, correlated which makes the standard estimators inconsistent. The Arellano and Bond's (1991) method addresses this problem and produces consistent estimators. Arellano and Bond (1991) estimators have two other advantages. First, they do not break down in the presence of unit roots (Binder et al., 2003). Second, and more importantly, they accommodate the possible endogeneity between the distress and some of the right-hand side variables by means of appropriate instruments (Delis and Kouretas, 2011). In this dynamic model, coefficient of the lagged distress variable (λ) is the speed of adjustment to equilibrium. A zero value of λ implies that bank distress adjusts to its equilibrium value

[80] This dynamic equation is a generic form that is converted from the static equation (eq. 2'). When we estimate the dynamic models, we add a second lagged dependent variable, $s_{i,t-2}$, to the model (and it is significant) because the distress proxies are highly persistent.

instantaneously, while a value of 1 indicates no adjustment. A value between zero and 1 suggests that distress persists, but will eventually return to its normal (average) level.

Empirical results for the dynamic model (eq. 2'') are presented in Table 2.8. The Arellano and Bond's (1991) estimator requires that there be no autocorrelation in the idiosyncratic errors. When the idiosyncratic errors are independently and identically distributed (i. i. d.), the first differenced errors are first-order serially correlated (Arellano and Bond, 1991). The serial correlation in the first-differenced errors of order of 2, however, implies that the moment conditions used by the estimator are not valid; and, hence, the model is misspecified. In all our dynamic models, we look at first- and second-order autocorrelation, AR (1) and AR (2), in the first differenced errors. We find that in both models, the results exhibit strong evidence against the null hypothesis of zero autocorrelation in the first-differenced errors at order 1, but cannot reject it at order 2, indicating that the models are not misspecified. We report AR (1) and AR (2) statistics at the bottom of Table 2.8. We initially put one lag for the dependent variable, $s_{i,t-1}$, into model, which turns out to be highly significant with a very high coefficient of λ_1 = 0.82 (Table 2.8, column II). Then, we add the second and the third lags. The second lag, $s_{i,t-2}$ is significant with a small coefficient of $\lambda_2 = 0.07$ (Table 2.8, column II). The third lag is insignificant, so it is dropped from the equation. Note that λ_1, λ_2 range between -1 and 1, and thus $s_{i,t}$ is stable. This means $s_{i,t}$ will converge to equilibrium (discussed below).

The estimation results for dynamic models are broadly in line and directionally similar with those based on the static model, with only one exception: the hedge ratio becomes insignificant in the model with bank distress indicator (Table 2.8, column II).

Table 2.8: The Dynamic Model of Distress (Equation 2'') All BHCs: 2001-2008

Dept. variable (Distress Indicator)	(I)	(II)
	All	All
Lagged dependent variable (-1)	0.81***	0.82***
	(25.21)	(33.77)
Lagged dependent variable (-2)	0.074***	0.07***
	(3.68)	(4.38)
Positive shock	0.158***	0.133***
Negative shock	-0.057***	-0.047***
GDP growth	-0.0039***	-0.0025***
Inflation	0.0180***	0.0160***
Profitability		-0.239***
		(-5.34)
Efficiency		-0.068***
		(-6.42)
Size		0.0233***
		(5.56)
Hedging		-0.002
		(-0.38)
Constant	-0.050***	-0.325***
	(-9.73)	(-5.88)
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers		
(1) $\sum_{j=1}^{4} \beta_j^+ = 0$	0.000	0.000
(2) $\sum_{j=1}^{4} \beta_j^- = 0$	0.000	0.000
(3) $\lvert \sum_{j=1}^{4} \beta_j^+ \rvert - \lvert \sum_{j=1}^{4} \beta_j^- \rvert = 0$	0.000	0.000
(4) $\sum_{j=1}^{4} \rho_j = 0$	0.000	0.000
(5) $\sum_{j=1}^{4} \gamma_j = 0$	0.000	0.000
# of obs	47285	45157
Wald-test	3674.1	3796.6
p-value	0.000	0.000
AR1	0.000	0.000
AR2	0.692	0.524

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses. Cluster-robust standard errors. Walt-tests are conducted to measure the joint significance of the coefficients.

$$s_{i,t} = \alpha + \mu_i + d_{gr} + \lambda_1 s_{i,t-1} + \lambda_2 s_{i,t-2} + \delta_k^{'} \, bc_{i,t-4}^{k} + \sum_{j=1}^{4} \rho_j y_{t-j} + \sum_{j=1}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) + u_{i,t}$$

This is the static equation (eq. 2''). Column I shows the results from the model without bank-level indicators. Column II shows from the full model. $s_{i,t}$ is distress indicator, $bc_{i,t-4}^{k}$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term. λ_1 and λ_2 are coefficients for the lagged dept. variables, β_j^+ is the coefficient for positive shocks and β_j^- is the coefficient for negative shocks. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, rows (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. Row (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are similar. Rows (4) and (5) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

In the panel with bank distress indicator, the impact of shocks to target FFR on bank distress is positive for both positive and negative shocks (both raise the distress on banks) (Table 2.8, column II), and they are both significant at 1% (Table 2.8, Wald-tests, column II, row (1) and (2)). The magnitude of the impact of a positive shock is nearly three times that of a negative shock indicating *asymmetry* in the effects of these shocks. Wald-test results reject the hypothesis of similarity of the shock effects (Table 2.8, column II, row (3)). All the macro drivers have the expected signs, similar to the ones in the static model. The results for the non-performing assets ratio are given in Appendix E [81].

Next, we examine the long-term equilibrium condition (steady state) for the dynamic model. For equilibrium, we assume that distress proxy reaches steady state where all the past values become identical to the current value, $s_{i,t-2} = s_{i,t-1} = s_{i,t} = s^*$. Similarly, in steady state the lagged independent variables are assumed to be equal[82]. Re-arranging equation 2'' by moving the lagged distress proxies, $(\lambda_1 + \lambda_2)s^*$, to left-hand side and dividing the coefficient of the independent variables by (1- λ_1 - λ_2), the model 2'' takes the form,

$$s^* = \tilde{\alpha} + \tilde{\delta}_k' bc^{k,*} + \tilde{\rho} y^* + \tilde{\gamma} p^* + \tilde{\beta}^+ w^{+,*} + \tilde{\beta}^- w^{-,*} \qquad (2''')$$

81 Results based on non-performing assets ratio are directionally similar to those based on bank distress indicator. Specifically, both positive and negative interest rate shocks create added distress, but the impact magnitude of a positive shock is nearly three times that of a negative shock, indicating asymmetry (as it was the case for the bank distress indicator). Both effects are significant at 1%. The macroeconomic drivers (real GDP and inflation) have the correct signs, negative and positive respectively, and they are significant at the 1% level.

82 That's, $y_{t-1} = y_{t-2} = y_{t-3} = y_{t-4} = y^*$ for Real GDP growth rate, and $p_{t-1} = p_{t-2} = p_{t-3} = p_{t-4} = p^*$ for inflation. Similarly, lags for all positive and negative shocks are assumed to be equal to $w^{+,*} = w_{t-1}^{+} = w_{t-2}^{+} = w_{t-3}^{+} = w_{t-4}^{+}$ and $w^{-,*} = w_{t-1}^{-} = w_{t-2}^{-} = w_{t-3}^{-} = w_{t-4}^{-}$. The balance sheet indicators exist in the model with only one lag, therefore, $bc^{k,*} = bc^k$.

where $s^*, y^*, p^*, bc^{k,*}, w^{+,*}$ and $w^{-,*}$ are variables at steady state. The very high coefficient for the first lag (λ_1 = 0.82) and statistically significant second lag ($\lambda_2 = 0.07$) of distress proxy in equation 2''' point to a very slow adjustment of the distress proxy to equilibrium in the dynamic model. This means the effects of the macro variables and the interest rate shocks on distress proxy in the equilibrium (eq. 2''') are much higher than their short-term effects in equation 2''.

The long-term effect of output growth, $\tilde{\rho}$, is -0.023 (versus 0.0025 for short-term effect), for inflation, $\tilde{\gamma}$, it is 0.145 (versus 0.016), for positive shocks, $\tilde{\beta}^+$, it is 1.209 (versus 0.133), and for negative shocks, $\tilde{\beta}^-$, it is -0.427 (versus 0.047). The coefficients for bank balance sheet indicators are computed similarly. After determining the steady state condition for bank distress proxy, we check the equilibrium with numerical values. For bank balance sheet indicators, we use median values for profitability (0.009), efficiency (0.43) and size (log of $ 428M) as presented in Table 2.1. For macroeconomic variables, we use 2% for output growth (long-term potential growth rate for U.S. economy) and 2.5% for inflation (Fed's target inflation rate). The long-term equilibrium equation includes the steady state conditions for negative and positive shocks. However, positive and negative shocks cannot affect bank distress concurrently. There will be either (i) a positive or (ii) a negative shock, or (iii) there will be no shock. We check all three conditions. Assuming there is no shock, the equilibrium equation predicts steady state distress proxy to stand at 0.03, which is between the 25th percentile value (0.026) and the median value (0.051) of the distress indicator (Table 2.1). If we assume a positive shock ($w_t^{+,*}$) equal to the average of positive shocks from 2001Q1 to 2008Q4, namely 0.09 (or 9 bps), equation 2''' predicts the distress proxy to be at 0.13. For a negative shock ($w_t^{-,*}$) equal to the average negative shocks, -0.16 (-16 bps), the model predicts the distress proxy to be at 0.09. Put differently, for a representative bank that has the median total assets of $0.43 billion, profitability of 0.009 and efficiency of 0.43, the steady state distress indicator is 0.03 if the economy is growing at 2% and inflation rate is 2.5%. In case of a positive shock of 9 bps (e.g. if the Fed announces the target rate 9 bps higher than what macroeconomic indicators suggest), the distress indicator rises from 0.03 to 0.13. In case of a negative shock of 16 bps, the distress indicator rises from 0.03 to 0.09. These results show that our dynamic model captures the relation between distress proxy and independent variables well[83].

2.4.3 Sample Disaggregation: Bank Holding Companies versus Financial Services Holding Companies

We disaggregate the sample into two subgroups according to bank type (BHC and FHC) in order to contrast the magnitudes of the effects of positive and negative shocks across the subgroups. We estimate the static and dynamic models (4a-4b) below using a dummy variable (d_{gr}) to separate the two groups:

$$\Delta s_{i,t} = \alpha + \mu_i d_i + d_{gr} + \delta_k' bc_{i,t-4}^{k} + \textstyle\sum_{j=1}^{4} \rho_j y_{t-j} + \sum_{j=1}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^{+} w_{t-j}^{+} + \beta_j^{-} w_{t-j}^{-}) + d_{gr} * (\sum_{j=1}^{4} (\beta_{d,j}^{+} w_{t-j}^{+} + \beta_{d,j}^{-} w_{t-j}^{-})) + u_{i,t} \qquad (4a)$$

[83] The average of all positive shocks (Table 2.6, col V) and all negative shocks (Table 2.6, col VI), from 2001Q1 to 2008Q4, are respectively, 0.09 and -0.16. When there is no positive or negative shock, the model predicts steady state distress at 0.03, a value which falls in between the 25 percentile distress indicator value of 0.026 and median distress indicator value of 0.051 (Table 2.3, row one). If we assume average positive shock of 0.09, the model predicts the distress indicator at 0.13 (up from steady state prediction of 0.03). If we assume average negative shock of -0.16, the model predicts the distress indicator at 0.09 (up from steady state prediction of 0.03). These predictions, 0.13 and 0.09, are located, respectively, near 75th percentile and between 75th and 90th percentiles (Table 2.3, row one). Thus, we can argue that our dynamic model captures the relation between distress proxy and independent variables well.

$$s_{i,t} = \alpha + \mu_i + d_{gr} + \lambda s_{i,t-1} + \delta_k' bc_{i,t-4}^k + \sum_{j=1}^4 \rho_j y_{t-j} + \sum_{j=1}^4 \gamma_j p_{t-j} + \sum_{j=1}^4 (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) + d_{gr} * (\sum_{j=1}^4 (\beta_{d,j}^+ w_{t-j}^+ + \beta_{d,j}^- w_{t-j}^-)) + u_{i,t} \quad (4b)$$

where d_i is the dummy for individual bank *i* and α is the intercept. The other variables are as defined earlier. The bank group dummy (d_{gr}) takes the unit value for FHCs and zero for BHCs. If significant, this variable reflects a shift due to organizational dissimilarities between the two groups. This variable is also interacted with interest rate shocks to estimate the effect of the shocks for FHCs and BHCs separately (slope shift). The results contrasting BHCs and FHCs in static and dynamic models are reported, respectively, in Tables 2.9-2.10 and discussed below. Results for full model (interest rate shocks, macroeconomic drivers and bank level indicators) are presented in column II.

2.4.3.1 Changes in Bank Distress and Unexpected Shocks (Static Model)

In the static model, the coefficient of cohort dummy (d_{gr}) is negative (-0.004) and significant at 5%, suggesting that FHCs, on average, have less distress than BHCs (Table 2.9, column II.b). For BHCs, positive and negative FFR shocks have the opposite signs, $\sum_{j=1}^4 \beta_j^+$= 0.093 for positive shocks and $\sum_{j=1}^4 \beta_j^-$=-0.029 for negative shocks (Table 2.9, column II.a). Similarly, for FHCs, positive and negative shocks have opposite signs, $\sum_{j=1}^4 \beta_j^+$= 0.092 and $\sum_{j=1}^4 \beta_j^-$=-0.035 (Table 2.9, column II.b). All coefficients are significant at 1% (Table 2.9, Wald-tests, column II.a and II.b, rows (1) and (2)). These results indicate that positive and negative shocks both raise distress on banks for both BHCs and FHCs and that the effects are asymmetric in both cases.

In terms of magnitude, for both cohorts, BHCs and FHCs, the effect of a positive shock is nearly three times as large of that of a negative shock of the same size. Wald-tests reject the similarity of the shock effects (Table 2.9, column II.a and II.b, row (3)). It is notable, however, that a positive shock ($w_t \geq 0$) creates the same level of distress BHCs (0.093) and FHCs (0.092) (Table 2.9, column II.a and II.b). The equality of these effects for the two sub-groups cannot be rejected according the Wald-tests (p = 0.834, Table 2.9, column II, row (4)). Similarly, the effect of negative shock ($w_t \leq 0$) on BHCs (-0.029) is not substantially different from the one on FHCs (-0.035). The Wald-test also verifies that the difference in the effects is not significant (p = 0.166, Table 2.9, column II, row (4)). Thus, according to the static model results, expanding into financial (nonbank) activities by FHCs does not alter the effect of the interest rate shocks (positive or negative) on their distress to be distinct from that on the BHCs.

Table 2.9: Sorting the Sample According to Bank Type (BHC vs FHC): Static Model

Dept. variable (Distress Indicator)	(I.a)	(I.b)	(II.a)	(II.b)
	BHC	FHC	BHC	FHC
Group dummy		-0.0004		-0.004**
		(-0.13)		(-2.06)
Positive shock	0.124***	0.121***	0.093***	0.092***
Negative shock	-0.038***	-0.042***	-0.029***	-0.035***
GDP growth	-0.0021***		-0.0008***	
Inflation	0.0145***		0.011***	
Profitability			-0.236***	
			(-5.28)	
Efficiency			-0.066***	
			(-6.36)	
Size			0.024***	
			(5.59)	
Hedging			-0.0015	
			(-0.33)	
Constant	-0.044***		-0.332***	
	(-13.51)		(-5.93)	
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers				
(1) $\sum_{j=1}^{4}\beta_j^{+} = 0$	0.000	0.000	0.000	0.000
(2) $\sum_{j=1}^{4}\beta_j^{-} = 0$	0.000	0.000	0.000	0.000
(3) $\lvert\sum_{j=1}^{4}\beta_j^{+}\rvert - \lvert\sum_{j=1}^{4}\beta_j^{-}\rvert = 0$	0.000	0.000	0.000	0.000
(4) $\lvert\sum_{j=1}^{4}\beta_{BHC,j}^{+}\rvert - \lvert\sum_{j=1}^{4}\beta_{FHC,j}^{+}\rvert = 0$	0.639		0.834	
(5) $\lvert\sum_{j=1}^{4}\beta_{BHC,j}^{-}\rvert - \lvert\sum_{j=1}^{4}\beta_{FHC,j}^{-}\rvert = 0$	0.429		0.166	
(6) $\sum_{j=1}^{4}\rho_j = 0$	0.000		0.003	
(7) $\sum_{j=1}^{4}\gamma_j = 0$	0.000		0.000	
# of obs	50142		48302	
R-sq	0.110		0.121	

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses. Cluster-robust standard errors. Walt tests are conducted to measure the joint significance of the coefficients

$$\Delta s_{i,t} = \alpha + \mu_i d_i + d_{gr} + \delta_k' bc_{i,t-4}^{k} + \sum_{j=1}^{4}\rho_j y_{t-j} + \sum_{j=1}^{4}\gamma_j p_{t-j} + \sum_{j=1}^{4}(\beta_j^{+} w_{t-j}^{+} + \beta_j^{-} w_{t-j}^{-}) +$$

$$d_{gr} * (\textstyle\sum_{j=1}^{4}(\beta_{d,j}^{+} w_{t-j}^{+} + \beta_{d,j}^{-} w_{t-j}^{-})) + u_{i,t}$$

This is the static equation (eq. 4a). Column I shows the results from the model without bank-level indicators. Column II shows the results from the full model. $s_{i,t}$ is distress indicator, Δ is the 1st difference, $bc_{i,t-4}^{k}$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term and d_{gr} is the group dummy (indicator variable) for bank type cohort: 0 for BHC and 1 for FHC, and d_i is the individual bank dummy. β_j^{+} is the coefficient for positive shocks and β_j^{-} is the coefficient for negative shocks. $\beta_{d,j}^{+}$ is the coefficient for positive shock interacted with group dummy. $\beta_{d,j}^{-}$ is the coefficient for negative shock interacted with group dummy. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are equal. In tests (4) and (5), $\beta_{BHC,j}^{+}$=β_j^{+} and $\beta_{FHC,j}^{+}$=β_j^{+}+$d_{gr} * \beta_{d,j}^{+}$ and $\beta_{BHC,j}^{-}$=β_j^{-} and $\beta_{FHC,j}^{-}$=β_j^{-}+$d_{gr} * \beta_{d,j}^{-}$. (4) and (5) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks on banks with positive gap and negative gap are equal. (6) and (7) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

2.4.3.2 Dynamic Model of Bank Distress and Interest Rate Shocks

The estimation results from dynamic models, presented in Table 2.10, are quite similar to the ones from the static model. These results show that the effects of positive and negative shocks are asymmetric for both BHCs and FHCs (Table 2.10, Wald-tests, column II.a and II.b, row (3)) and in both cases, the effect of a positive shock is nearly three times that of a similar negative shock. In addition, similar to static models, FHCs and BHCs are not affected differently in terms of distress by shocks of either sign. Negative shocks create as much distress on FHCs as they do on BHCs as evidenced by the Wald-test ($p = 0.330$, Table 2.10, column II.a, row (5)). In case of positive shocks, the statistical evidence for the similarity of the effects for BHCs and FHCs is weaker but still convincing. Wald-tests show that the similarity of the effects on BHCs and FHCs can be rejected at 10%, but not at 5% ($p = 0.075$) (Table 2.10, Wald-tests, columns II.b, row (4)).

These results, in general, point to the inadequacy of portfolio diversification through formation of FHCs in reducing bank distress. In other words, expanding banking operations into nontraditional activities such as underwriting and distributing securities or insurance business do not benefit FHCs in terms of reducing the failure risk (Allen and Jagtiani, 2000; DeYoung and Roland, 2001; DeJonghe, 2010; Demirguc-Kunt and Huizinga 2010). One way to see the extent of the portfolio diversification of bank activities is to look at the sources of non-interest income including all income streams that functionally-diversified banks generate by providing a broad array of nontraditional banking activities. Shifting to nontraditional banking might actually reduce banking system stability (raise bank failure risk) because bank interest income is less risky than all other (noninterest) revenues (DeJonghe, 2010).

Table 2.10: Sorting the Sample According to Bank Type (BHC vs FHC): Dynamic Model

Dept. variable (Distress Indicator)	(I.a)	(I.b)	(II.a)	(II.b)
	BHC	FHC	BHC	FHC
Lagged dependent variable (-1)	0.81***		0.82***	
	(25.36)		(33.97)	
Lagged dependent variable (-2)	0.073***		0.066***	
	(3.56)		(4.36)	
Group dummy		0.0037		-0.0021
		(0.61)		(-0.65)
Positive shock	0.165***	0.145***	0.138***	0.116***
Negative shock	-0.056***	-0.061***	-0.049***	-0.054***
GDP growth	-0.004***		-0.0025***	
Inflation	0.0180***		0.0159***	
Profitability			-0.237***	
			(-5.42)	
Efficiency			-0.067***	
			(-6.39)	
Size			0.0239***	
			(5.62)	
Hedging			-0.0015	
			(-0.34)	
Constant	-0.054***		-0.33***	
	(-8.92)		(-5.93)	
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers				
(1) $\sum_{j=1}^{4}\beta_j^+ = 0$	0.000	0.000	0.000	0.000
(2) $\sum_{j=1}^{4}\beta_j^- = 0$	0.000	0.000	0.000	0.000
(3) $\lvert\sum_{j=1}^{4}\beta_j^+\rvert - \lvert\sum_{j=1}^{4}\beta_j^-\rvert = 0$	0.000	0.000	0.000	0.000
(4) $\lvert\sum_{j=1}^{4}\beta_{BHC,j}^+\rvert - \lvert\sum_{j=1}^{4}\beta_{FHC,j}^+\rvert = 0$	0.096		0.075	
(5) $\lvert\sum_{j=1}^{4}\beta_{BHC,j}^-\rvert - \lvert\sum_{j=1}^{4}\beta_{FHC,j}^-\rvert = 0$	0.350		0.330	
(6) $\sum_{j=1}^{4}\rho_j = 0$	0.000		0.000	
(7) $\sum_{j=1}^{4}\gamma_j = 0$	0.000		0.000	
# of obs	47285		45155	
Walt-test	3757.6		3850.9	
p-value	0.000		0.000	
AR1	0.000		0.000	
AR2	0.726		0.533	

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses. Cluster-robust standard errors. Walt tests are conducted to measure the joint significance of the coefficients

$$s_{i,t} = \alpha + \mu_i + d_{gr} + \lambda_1 s_{i,t-1} + \lambda_2 s_{i,t-2} + \delta_k' bc_{i,t-4}^k + \sum_{j=1}^{4} \rho_j y_{t-j} + \sum_{j=1}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) +$$

$$d_{gr} * (\sum_{j=1}^{4} (\beta_{d,j}^+ w_{t-j}^+ + \beta_{d,j}^- w_{t-j}^-)) + u_{i,t}$$

This is the dynamic equation (eq. 4b). Column I shows the results from the model without bank-level indicators. Column II shows the results from the full model. $s_{i,t}$ is distress indicator, $bc_{i,t-4}^k$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term and d_{gr} is the group dummy (indicator variable) for bank type cohort: 0 for BHC and 1 for FHC, and d_i is the individual bank dummy. λ_1 and λ_2 are coefficients for the lagged dept. variables, β_j^+ is the coefficient for positive shocks and β_j^- is the coefficient for negative shocks. $\beta_{d,j}^+$ is the coefficient for positive shock interacted with group dummy. $\beta_{d,j}^-$ is the coefficient for negative shock interacted with group dummy. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are equal. In tests (4) and (5), $\beta_{BHC,j}^+$=β_j^+ and $\beta_{FHC,j}^+$=β_j^++$d_{group} * \beta_{d,j}^+$ and $\beta_{BHC,j}^-$=β_j^- and $\beta_{FHC,j}^-$=β_j^-+$d_{gr} * \beta_{d,j}^-$. (4) and (5) test whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks on BHCs and FHCs are equal. (6) and (7) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

There could be some gains for FHCs from portfolio diversification, e.g., from scope economies due to serving the same core customer base with a variety of products (department store set up) or sharing account maintenance costs (input reutilization), or lower cash flow volatility (Gandhi, et. al., 2016). But these gains are typically offset by increased exposure to noninterest activities that generate noninterest income. These activities are more volatile but not necessarily more profitable than lending activities (Stiroh and Rumble, 2006; Laeven & Levine, 2007). The positive effects of the diversification are limited to "good" times and reverse exactly when they are needed most. In other words, banks that rely on income generated by diversified business units – noninterest income – can breakdown precisely when these revenues are needed most (DeJonghe, 2010; Gandhi, et. al., 2016). Many of the synergies generated by expanding into nonbanking activities, or even in banks' core businesses, broke down during the time of financial distress in 2007-2009 crisis (Acharya and Mora, 2015). On the liabilities side too, banking strategies typical to FHCs rely prominently on attracting non-deposit, wholesale funding, that are riskier compared to deposits, resulting in elevated bank fragility (Demirguc-Kunt and Huizinga, 2010). In particular, banks that rely more on wholesale funding see more stress building with a tightening monetary policy (Choi, 2016).

These arguments beg the question why BHCs convert into FHCs or why FHCs are moving steadily into non-bank activities. One explanation is that FHC managers may have a misguided notion of diversification so they are operating under a false sense of security. For example, FHC managers may target cross-selling, selling multiple products to the same core customer base in the hopes of reaping scope economies and diversification benefits. Although this does open new revenue streams, these streams may be riskier and/or the different streams can be exposed to the same types of shocks. Examples are an industry slowdown or changing consumer preferences (Stiroh and Rumble, 2006). With a similar false sense of security, more diversified banks may offset risk-reducing diversification benefits by engaging in riskier activities (more so when the monetary policy is overly accommodative), particularly maintaining riskier lending lines and operating on lower capital ratios (Demsetz and Strahan, 1997). The largest banks in U.S., which have more diversified portfolios (most are FHCs) tend to take additional risk by holding derivative positions for trading purposes, though this strategy does not lead to greater risk-adjusted performance (Kim and Kim, 2013). Our results reinforce the consensus in the literature that converting into FHCs is not rewarding and that portfolio diversification does not necessarily lead to a higher level of performance, especially when it is needed most. Therefore, FHCs do not respond to interest rate shocks differently than BHCs.

2.5 Concluding Remarks

The crisis of 2007-2009 propelled policymakers to more closely examine the links between monetary policy and bank distress. The prolonged period of low interest rates in the first half of the 2000s is often seen as a main reason for excessive risk buildup in the U.S. banking industry in the run-up to the crisis. We attempt to shed light on the effects of monetary policy on bank distress by investigating the impact of interest rate shocks (changes in the target fed funds rate) on bank distress from 2001 to 2008. We explore positive and negative rate changes separately to examine whether the effects of these changes are asymmetric in nature. We estimate our models for a pooled sample of BHCs and FHCs and for these two subgroups separately.

Our empirical results show a strong relationship between bank distress and shocks to the main monetary policy interest rate over the year following the shock. If the change in the target interest rate (monetary policy) is a surprise, distress builds for banks, regardless of whether the shock is positive or negative, although positive shocks create considerably more distress than negative shocks. The channels of the effect are the following. With a positive shock, borrowers of adjustable-rate loans find it difficult to service their debts. As a result, delinquency and default rates rise, and bank balance sheets come under stress. A negative surprise shock, may cause expectations of a sustained low interest rate, emboldening and encouraging banks to make riskier loans and investments in order to seek higher returns, which in turn creates distress. The results for negative shocks are complementary to the bank risk-taking literature suggesting that risk-taking activities increase in a sustained low interest-rate environment (Borio and Zhu, 2008).

The evidence on the impact of interest rate shocks on BHCs and FHCs as separate groups demonstrates that the direction of the effect on distress and the asymmetry in magnitude of the effects found for the pooled sample continue to hold. In addition, the findings suggest that diversifying operations into non-traditional banking, through reorganization of BHCs as FHCs does not necessarily make them better able to absorb surprise rate changes; if there is some benefit from diversification of the portfolio, it is counterbalanced by more risk taking on the part of the FHCs. After a positive shock, rising delinquencies on existing loans and declining demand for new loans raise the level of distress on both BHCs and FHCs as the borrowers simply cannot afford the higher rates. After a negative shock, both BHCs and FHCs seek higher returns exposing themselves to higher distress.

Our results suggest that monetary policy should be considered as an integral part of macro-prudential supervision, particularly bank supervision and regulation. In our view, bank regulators should take into account monetary policy effects, while the Fed should be concerned with banks' risk behavior in a low interest-rate environment. This was partially achieved with the Dodd-Frank Act of 2010 which gives Fed a new mandate of financial stability, in addition to implementing monetary policy. With the Dodd-Frank Act, Fed conducts stress tests periodically to assess larger banks' ability to weather stress under hypothetical macroeconomic scenarios. Bank supervision was integrated into the macroeconomic policy framework of the Federal Reserve. However, much work is needed to better understand the sources of bank distress and banks' changing risk profiles according to macroeconomic policies.

3. THE SYTEMIC RISK CONTRIBUTION OF U.S. BANK HOLDING COMPANY SUBGROUPS

3.1 Introduction

The performance of U.S. bank holding companies (BHCs) during the financial crisis of 2007-2009 increased the need to understand systemic risk in the banking industry. The failure of individual BHCs sent shocks across the banking system and beyond. Since then policy makers and regulators have focused on building defenses against systemic risk and promoting financial stability. Defending against systemic risk requires understanding which measures of systemic risk can capture economic trends and gauge the changing risk profile of the banking system over time. Over the last two decades, the U.S. banking system has been transformed, with financial intermediation shifting from banks to financial services holding companies (FHCs). Large U.S. banks have also grown larger through acquisitions, increased branching, and asset growth. Policy makers and regulators need to better understand how this transformation alters the risk profile of banks and systemic risk.

In this chapter, we examine individual risk levels and systemic-risk contributions of subgroups of BHCs according to balance sheet size and organization type (FHC versus BHC), using an expected shortfall (ES) approach that has become common in the systemic-risk literature. Our main goal is to quantify the systemic-risk contributions of bank subgroups and examine how it has evolved over time. Systemic-risk analysis for banks is closely related to portfolio-risk analysis (Acharya et al., 2010, 2017). The logic is same: it consists of determining the contribution of a given asset (respectively, a bank) to the risk of the portfolio (respectively, the banking system). The ES concept measures the conditional expectation of a bank loss due to a default under extreme conditions (systemic events). The "shortfall" refers to the shortage of capital (or a hypothetical insurance premium) needed to offset the losses. We define "systemic event" as an extreme event in which system-wide losses exceed a certain threshold, determined using a Value-at-Risk (VaR) framework. For a "loss," we use bank liabilities that are not recovered after the collapse of a bank: by accounting identity, bank liabilities are the assets of bank creditors; e.g. households and businesses. Thus, ES is the loss incurred by households and businesses that is not covered in case of a bank failure. To determine individual bank default, we employ a stochastic model of losses in a Monte Carlo simulation framework similar to the one proposed by Tarashev (2010a, 2013). ES quantifies the contribution of each bank to the overall risk of the system, and the contribution of each bank is added up to obtain the expected shortfall in the subgroup or the whole system. The building block of systemic risk contribution is the individual bank's probability of default. To determine probability of default, we use a bank distress indicator, similar to an insolvency criterion formally known as the Texas Ratio (detailed later). Different versions of the Texas Ratio can be used to gauge bank distress. We use the version offered by Cole and White (2012). In addition to systemic risk contribution, we investigate the risk level of individual institutions (banks) by constructing a systemic risk *indicator*. The systemic risk indicator is the ratio of ES to total liabilities (bank credit). More specifically, it is the probability-weighted bank credit loss per one unit of bank credit.

We obtain several interesting results. First, our results show that the largest banks as a group (those in the top 1% or 5% by asset size) pose a significantly bigger systemic risk than the group of smaller banks (those in the bottom 50%) and the group of midsize banks (those in the 50%-99% or 50%-95% cohorts). The systemic-risk contribution of the banks in the top 1% by asset size was 85% of the total systemic risk in 2015. That is, 85% of the total systemic risk is created by the banks in the top 1% (46 banks in 2015) according to asset size. The corresponding figure for banks in the top 5% (230 banks in 2015) is 94%. Midsize and small size banks contribute the rest. The largest banks contribute the most because they are large and also because they are individually riskier: the systemic risk indicator shows that, in general, larger banks are also individually riskier than midsize and small banks. In other words, large banks contribute to systemic risk proportionately more than do small banks. These results show that consolidation in the banking sector may raise systemic risk: A banking system made up of a large number of small banks may pose less systemic risk than one with an equal amount of aggregate assets shared by fewer banks. Next, we look at the banks designated as Systemically Important Financial Institutions (SIFIs) and the four largest banks in U.S. according to asset size as of 2015[84]. Our results show that the 34 SIFIs contributed nearly 50% to systemic risk in 2001, and this share increased to 80% by the end of the financial crisis. This shows that the SIFI designation correctly identifies the source of fourth-fifth of the systemic risk seen during the crisis. Applying the ES approach to the four largest U.S. banks (JPMorgan Chase, Bank of America, Wells Fargo, and Citigroup), we find that the aggregate risk contribution of the "Big Four" increased steadily since 2001 and reached nearly 50% in 2015. We also find that the aggregate risk contributions of the SIFIs and the big four banks are larger than their asset shares in the banking system: these banks are systemically more important than their

[84] The "Big Four," group of U.S. banks by asset size, has no official designation. We consider this category because the asset sizes of these banks far exceed those of the next largest institution. As of 2018, Citigroup holds $1.84 trillion in assets while Goldman Sachs, the fifth largest bank, holds $0.9 trillion.

asset share indicates. The opposite is true for small and midsize banks; they are systemically less important than their asset shares indicate. Our findings show that the "too big to fail" perception will persist as the largest banks have grown even larger, and are systemically more important than their asset size indicates: a future collapse of these banks would pose a larger threat to the financial system than those that occurred during the financial crisis.

Our results also show that FHCs, in general, are individually riskier and contribute to systemic risk proportionately more than do BHCs. However, the financial crisis of 2008-2009 affected BHCs more severely than FHCs, in part, because small and midsize community banks were hit hard by the housing downturn. FHCs were affected as well, but the government bail-outs (e.g. TARP and loan guarantees) of large FHCs in 2009 masked the real burden that might have developed on these institutions without such help. One implication of this finding is that diversifying into nontraditional operations (e.g. securities underwriting and dealing, insurance underwriting and merchant banking) without the limitations that govern BHCs, do not make FHCs more risk-proof in a financial crisis. FHCs are, in general, larger than BHCs, and the share of the banking industry assets held by FHCs has been increasing. Combined with the findings from the bank size cohort examination, our results point to the potential future risk created by the concentration of assets in a smaller number of larger banks. Consequently, policy makers will have to consider disallowing mergers among bigger banks or limiting the number of branches to prevent further consolidation in the banking system. Our results also suggest that policy makers should reconsider some Gramm-Leach-Bliley Act (GLBA, 1999) provisions that allow BHCs to convert themselves to FHCs and enter nontraditional banking operations without limitations. Shifting to nontraditional banking might actually lessen the stability of the banking system and increase failure risk, as bank interest income is less risky than all other (noninterest) revenues (DeJonghe, 2010). The positive effect of product diversification through FHCs is limited to good times and reverses exactly when it is needed most, namely during crises. Banks that rely on noninterest income generated by diversified business units may see this source of revenue break down precisely when it is needed most (DeJonghe, 2010; Gandhi, et. al., 2016).

3.2 Literature Review

This section reviews the literature on the measurement of systemic risk related to this article. Systemic risk is difficult to define or measure. A survey of systemic-risk literature prepared for the U.S. Treasury Department'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." Others define systemic risk as the chance that many market participants will suffer severe losses simultaneously, losses that then spread through the system (Benoit et al, 2015).

Systemic risk has become a prolific research field over the last decade, as in encompasses banking, macroeconomics, econometrics, and network theory. A survey by Benoit, Colliard, Hurlin, and Preignon (2010) gives an excellent review of the theoretical and empirical literature on systemic risk. According to this survey, one strand of research focuses on global measures of systemic risk and is statistical in nature. This literature has developed along two distinct approaches. The first focuses on the sources of systemic risk, such as contagion, bank runs, and liquidity crises. This "source-specific approach" explains why many financial institutions take bets that are both large and correlated, thus exposing themselves to default and their counterparts to contagion. The 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 and, thus, permit clear identification of the source of risk. The second approach, the so-called "global approach", does not take a particular stand on the causes of systemic risk, but rather aims to quantify it. These studies commonly treat the financial system as a portfolio of institutions. Examples include Kuritzkes et al. (2005), Goodhart and Sergoviano (2008), Geluk et al. (2009), Acharya et al. (2010, 2017), Tarashev et al. (2010a, 2013), Huang et al. (2012), Cummins (2014), Banulescu and Dumitrescu (2015), Browless and Engle (2012, 2017).

Measures of systemic risk in these papers have two common features. First, they all provide a *single* risk metric that can potentially encompass *all* institutions in the system[85]. Second, they can be applied to *any* subset of institutions in the system such as money-center banks (MCBs), systemically important financial institutions (SIFIs), or large, mid-size, and small banks. Given these two features, the systemic risk implied by the measure can be allocated across institutions using attribution methodology[86]. Some papers in this strand propose replacing a host of macro-prudential tools (such as identifying

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

86 See Tarashev, Borio, and Tsatsaronis (2010a). The method to estimate the systemic-risk contribution has an additive property. The contribution of each bank or a group of banks may be added to compute the systemic (aggregate) risk. This is desirable from an operational perspective, because it allows macro-prudential tools to be implemented at the level of individual banks.

systemically important financial institutions) and allocating capital requirements on individual banks 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).

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 indicators are the marginal expected shortfall (MES), introduced by Acharya et al. (2010, 2017), and delta conditional value-at-risk (CoVaR), put forward by Adrian and Brunnermeier (2014)[87]. MES and CoVaR are conceptually different measures: MES gauges the marginal contribution of a bank (sensitivity to a unit change in a firm’s weight in the financial system) to the risk of the financial system measured by expected shortfall (ES). “Shortfall” refers to the capital needed to offset the loss incurred by banks conditional on the system being in distress. The delta conditional value-at-risk (CoVaR) measures the system losses conditional on each bank being in distress. Neither MES nor CoVaR can be consistently aggregated across subgroups for different reasons. MES measures cannot be aggregated across subgroups because it measures only the marginal contributions of each bank while it fails to include the size of the bank. CoVaR cannot be aggregated due to the lack of an additive property. Browless and Engle (2012, 2017) extend the MES to a more comprehensive measure, called SRISK, by taking into account the size and the leverage of the financial institution. SRISK measures the capital shortfall of a financial institution during a crisis in the financial system. Banulescu and Dumitrescu (2015) introduce a new

[87] A survey by the U.S. Treasury Department’s Office of Financial Research discusses 31 quantitative measures of systemic risk in the economics and finance literature. See “A Survey of Systemic Risk Analytics”, January, 2012, Working Paper, Office of Financial Research, Department of Treasury.

measure, called component expected shortfall (CES), which measures the "absolute" contribution of a firm rather than the marginal contribution (MES), to systemic risk. The main advantage of CES is that it has an additive property: Absolute contributions of individual banks can be added up to compute the aggregate (systemic) risk. Our method is similar to CES in the sense that it measures absolute contributions, and the systemic event (or financial distress) is defined with ES. However, our method differs from CES in the way we define the probability of a bank default. The CES method uses bank and market equity returns while we use balance-sheet indicators. Using balance-sheet indicators enables us to define bank default in a way that expands coverage of systemic-risk estimations to all banks.

3.3 Methodology

3.3.1 Data and Sample

This section describes data sources, variable selection, and calculations. All data are quarterly. We derive systemic risk contributions of banks based on U.S. BHC balance sheet data. We do not go below the BHC level to consider subsidiaries separately because we want to avoid volatility in the data series. Moreover, most management decisions are made at the BHC level, rather than by subsidiaries. BHCs also transfer assets across subsidiaries for window-dressing and tax purposes, making the subsidiary level data unreliable. The primary data source for balance-sheet data is the Chicago Fed's quarterly Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) database. BHC balance-sheet data is acquired from Wharton Research Data Services (WRDS).

Figure 3.1 presents the number of banks (BHCs and FHCs) and their total assets from 2001 to 2015. There were 4,568 banks operating in the U.S. at the end of 2015, with total assets of $18 trillion, down from 5,861 at the beginning of 2001 with total assets of $7.5 trillion.

Figure 3.1: Bank Holding Companies and Asset Size ($bil., left-axis; number, right-axis)

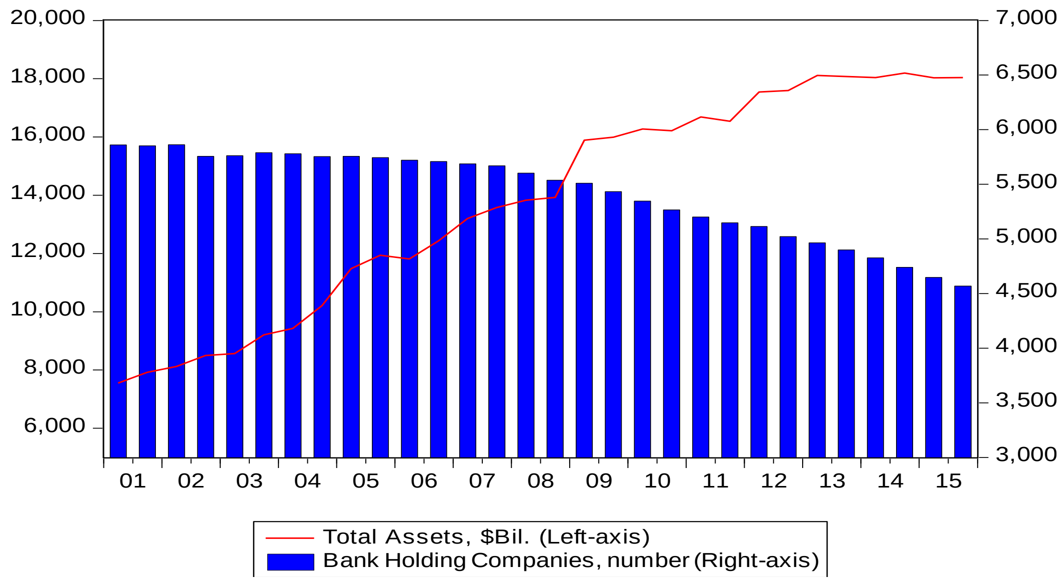
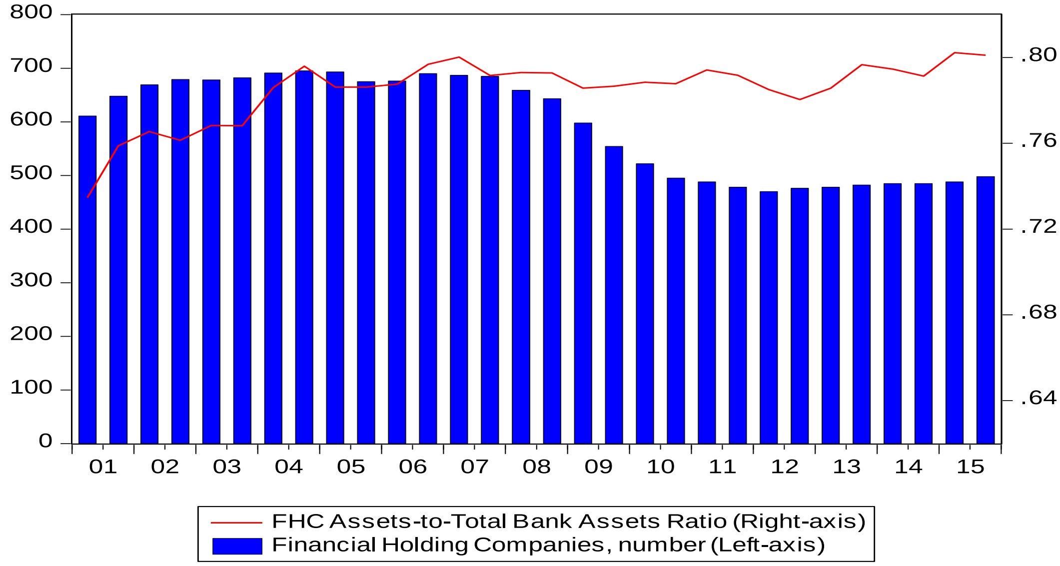


Figure 3.2 demonstrates the number and asset share of FHCs from 2001 to 2015. The FHC sector has also consolidated over time. There were 611 FHCs operating in U.S. at the beginning of 2001 with total assets of $5.5 trillion, compared to 498 at the end of 2015 with total assets of $14.4 trillion.

Figure 3.2: Financial Holding Companies and Assets Ratio (number, left-axis; ratio, right-axis)



3.3.2 Variable Construction

3.3.2.1 The Bank Distress Indicator

Following Cole and White (2012), we use a book-value insolvency measure, defined as non-performing assets divided by the sum of equity capital and loan-loss reserves, for each bank in our sample to build our systemic risk indicator[88]. Cole and White (2012) classify banks that do not have enough equity capital and loan loss reserves to cover non-performing assets as being "in technical failure" (or insolvent). Holding poorly performing assets makes banks more vulnerable to financial distress. Banks are required to hold a loan-loss allowance account to absorb losses both from loans currently identified as bad and from loans that will later prove uncollectable. This account acts as a cushion

88 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). The Texas Ratio was developed by Gerrard Cassidy and his colleagues at RBC Capital (see Barr, Alistair, May 23, 2008) for the purpose of analyzing troubled banks during the 1980s. Our measure differs from that of Cassidy in one respect: In the original form, Cassidy defines non-performing assets as those that are delinquent more than 90-days while Cole and White (2012) include early delinquencies in the ratio with some haircuts.

against losses: If a bank's loan-loss allowance account exceeds its expected credit losses, the bank can absorb more unexpected losses without failing and imposing costs on the Federal Deposit Insurance Corporation (FDIC). Conversely, loan-loss allowances that prove to be less than actual losses ultimately reduce the bank's equity capital, moving it closer to insolvency. If equity capital falls below a certain level, the bank can be closed by regulators[89].

Non-performing assets are defined as those more than 90 days past due and in accrual status. 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 interest, and 100% to loans in nonaccrual status (write-offs) and other real estate owned (REO)[90]. Using these haircuts, Cole and White define the following indicator ratio for bank distress:

$$Distress\ Indicator = (0.2 * 30 - 89d\ DEL + 0.5 * 90d\ plus\ DEL + WOF + REO) / (Equity + LLA) \quad (1)$$

If the distress indicator is equal to one, the bank is considered to be in technical default. As such, a rising ratio indicates that stress is building up. To derive the ES of each bank, a "probability of default" must be assigned to the bank for each time period (detailed in the next section). We use the distress indicator to create probability-of-default proxies

[89] 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.

[90]Cole and White separated non-performing assets into several components and assumed a different haircut for each component. They pick the haircuts that have the highest predictive power for bank failures. The authors found that at the end of 2009 there were 347 banks that satisfied this definition of technical failure based on the haircut assumption (the assumption that produces the highest prediction power). Of the 74 banks that failed in the first half of 2010, 68 (92%) were in this group of 347.

for all banks in the U.S. This measure serves our purpose best because (i) it defines distress as a proportion in the $[0,1]$ interval, except in very rare extreme stress periods, and (ii) it enables us to create a continuous distress indicator time series. Next, we develop a systemic risk indicator time series by using the distress indicator as the probability of default for a particular bank.

3.3.2.2 Constructing Systemic Risk Measures

In developing a systemic risk measure, treating the financial system explicitly as a portfolio of institutions has become a common approach (Acharya et al., 2010, 2017; Banulescu and Dumitrescu, 2015; Huang et al., 2012). One concept widely used in this approach is expected shortfall (ES). ES is essentially a standard measure of firm-level risk that refers to portfolio credit losses under extreme conditions and the capital needed to offset those losses. 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 institutions (Acharya et al., 2010, 2017; Cummins, 2014; Tarashev et al., 2010a, 2013).

A formal method of attributing systemic risk to institutions was initially proposed by Acharya, et al. (2010, 2017). For a particular firm, ES measures the potential loss incurred by the firm as a whole in an extreme event. Company-wide losses are broken down into contributions from individual groups within the company. For BHC or FHC subsidiaries can be treated as an example of these individual groups. Acharya et al., proposes that a similar approach can be used to determine systemic risk; the financial system consists of a number of firms, similar to a firm that consists of a number of subsidiaries. A systemic event occurs when the financial system's expected loss exceeds a certain threshold; that is, when the financial system's return falls below a certain level (see Appendix F for the expected shortfall approach proposed by Acharya and others)[91].

3.3.2.2a. Systemic Risk Contribution of Banks: Expected Shortfall Approach

We leverage the ES approach to develop our systemic risk measures along the lines defined by Acharya, but our approach differs from Acharya in two ways. First, Acharya proposes a concept of *marginal* expected shortfall (*MES*) to identify how a particular bank's risks add to the financial system's overall risk. This systemic risk measure captures the marginal contribution of a bank to the risk of the financial system as measured by ES. More specifically, *MES* refers to the change in the financial system's ES engendered by a unit increase in the weight of the i^{th} institution in the system, *e.g.* relative size. The marginal approach has one major inconvenience as a systemic risk measure: It does not account for the level of firm's characteristics, e.g. size, leverage, etc. If the objective is the identification of SIFIs, for example, a major consequence is that a small, unlevered firm can appear more systematically risky than a big, levered one. To overcome this inconvenience, we develop a measure that determines the whole (absolute) contribution, rather than the marginal contribution, from an institution. Our approach is similar to the ones taken by Tarashev et al. (2010a, 2013), Banulescu and Dumitrescu (2015).

Second, Acharya uses bank *return* as a building block of the MES measure. More specifically, *MES* is the shortfall (loss) in *bank's return* in an extreme event in which the *market return* falls below a certain threshold. It also refers to the *capital* needed to offset

[91] Acharya et al, 2010 uses equity return data to define capital loss. That is, expected capital shortfall is the amount that equity falls below target level. $ES_\alpha = E(r_m | r_m < VaR_\alpha)$, where r_m is the market return which is sum of the returns of all institutions.

bank's losses from an extreme event. We use bank *credit* instead of *return* as a building block (see Tarashev et al. (2010a, 2013) for a similar treatment). Two factors convince us to use bank credit. First, defining the loss on bank credit (debt) instead of bank return enables us to expand the systemic risk measure coverage to the whole universe. Bank balance sheet (bank liabilities) data are readily available for all BHCs. On the contrary, bank return (market data) is available only for banks whose equities are publicly traded. In simplified terms, a bank's debt (liabilities) is the funding (or credit) available to the bank to continue its operations, more specifically, to finance its assets (or lending). Typically, banks' main creditors are households and firms. In case of a bank default, losses on a bank's liabilities are essentially the losses of households and firm's assets. If the losses are large enough (an extreme event), it may impair the financial intermediation and potentially damage the real economy. From a creditor perspective, a loss occurs when the bank fails and the assets are not collected. However, from a bank's perspective, if the probability of failure rises, creditors can pull their assets and may leave the bank in funding shortage. In either case, financial intermediation can be impaired and economic activity can be affected with banks' providing less funding to the households and firms. We define the ES as a shortfall in bank's credit (losses on bank's debt) which may deplete equity and impair a bank's functioning in a systemic event. It also refers to the *capital* needed to offset the bank's loss in a systemic event. A systemic event is defined as an extreme event, in which the sum of all banks' credit losses surges above a certain threshold to impair financial intermediation, and potentially damages the real economy (see Appendix F for derivation of ES).

Our approach is quite similar to Tarashev et al. (2010a, 2013) in the way ES is defined and in the use of bank credit rather than bank return as a building block. It differs, however, according to the way the probability of default is defined. Tarashev et al. (2010a, 2013) uses expected default frequency (EDF) as the probability of default[92]. We use the bank distress indicator described in section 3.3.2.1 as a bank default probability. Defining the bank distress indicator as a proxy for probability of default enables us to expand the coverage of systemic risk measures to include all banks. Expected default frequency (EDF) is available only for a number of large banks. The bank distress indicator, on the other hand, is built by balance sheet data and it is available for all banks.

3.3.2.2b. Individual Riskiness of Banks: Systemic Risk Indicator

To this end, we define the concept of systemic risk contribution (or systemic importance) of banks. ES is the measure of systemic risk which shows the systemic risk *contribution* of a particular bank or a group of banks in a certain time period. To evaluate the "riskiness" or "risk level" of a group of banks or the whole banking system, we scale the ES with sum of bank liabilities (debt) and call it the systemic risk *indicator*. The systemic risk indicator represents the riskiness of the group or the whole banking system in the sense that it provides a ratio of the total bank credit (assets of households and businesses) that are at risk of being lost in a systemic event. Put differently, systemic risk *contribution* (ES) is the probability-weighted average (expected) of losses incurred by households and firms associated with bank failures conditional on a systemic event. The

[92] EDF is a product of Moody's KMV 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. This is a physical (actual) default measure that is developed based on the structural definition of default, similar to the bank distress indicator we develop in this paper, e.g. based on balance sheet measures rather than market prices.

systemic risk indicator (the ratio of ES to total bank debt) shows the amount of bank credit at risk of being lost per one unit of credit available. The systemic risk indicator serves as a proxy for the riskiness of a bank cohort or the banking system: the higher the systemic risk indicator, the greater the distress in the banking system. In the rest of this paper, we use systemic risk contribution to demonstrate the absolute risk contribution of a bank cohort in volume. The systemic risk indicator, on the other hand, enables us to provide an analysis for the proportionality of the risk contribution among the bank cohorts. For example, in a banking system with two cohorts, if one cohort's risk contribution is twice as much as the others' while the two cohorts are equal in size, the first cohort is said to contribute to the systemic risk more than proportionately due to its higher individual risk level. More precisely, the first cohort's systemic risk indicator is twice as high as the second cohort's risk indicator.

3.3.2.2c. Drivers of Systemic Importance

According to our ES approach, systemic risk contribution (or systemic importance) has three drivers: bank size (debt), unconditional probability of default (PD), and bank exposure to systemic risk (propensity to default with other banks). The first driver is the size of a bank's debt. Systemic risk contribution is a bank's share in systemic risk. We define this share to be equal to the expected losses of the bank's creditors (household and business assets) in a systemic event (Tarashev et al., 2010a, 2013). According to this definition, the sum of systemic importance of each bank is exactly equal to the system-wide risk. Systemic importance increases with the magnitude of the losses that are likely to occur in case of a bank default. More specifically, the larger the bank's debt, the greater the losses it imposes on its creditors. Thus, a bank of a larger size would be of greater systemic importance, all else the same. The second driver is the unconditional probability of default (PD). A bank with a higher (unconditional) probability of default, or PD, is more likely to default in a systemic event, all else being the same. The third driver is the banks' exposure to common risk factors or common-factor loading which shows the tendency to default with others. The likelihood of an individual bank's default increases further to the extent that the bank is connected to other banks, and that an extreme adverse shock to the banking system will affect this bank. In other words, the likelihood of an individual bank's default increases with its tendency to default with others. This tendency arises either because financial institutions are similar to each other (e.g. lend to similar sectors) or because they are interconnected[93]. In brief, higher exposures to the common risk factor result in a higher probability of joint failures in the system. In turn, a higher probability of joint failures translates into higher average losses in a systemic event, which leads to a higher level of systemic risk, as measured by the expected shortfall. The contribution of each individual bank to the systemic risk is mostly determined by its size, but the contagion effect of individual bank's failure on the whole banking system is more heavily affected by its interconnectedness with other banks than by its size. Importantly, the probability of default and the size can be constructed on the basis of institution-specific characteristics alone, but the common-factor loading relates to characteristics of the system as a whole. In the next section, we discuss the systemic risk measures of several bank cohorts by referring to these three drivers.

[93] Bank i's exposure to bank j, in particular, and the banking system, in general, can be determined from the correlation between banks' asset returns, which is approximated by the correlation between banks' equity returns (Tarashev et al., 2010a, 2013; Huang et al., 2012; Banulescu and Dumitrescu, 2015).

3.4. Discussion of Results

In this section, we review the aggregate risk contribution of several bank subgroups as represented by ES and the risk level (individual riskiness) by the systemic risk indictor. The results are presented in Figures from 3.1 to 3.20 and Tables from 3.1 to 3.4. Building systemic risk measures that encompass all or a subgroup of banks requires some simplification in the ES framework[94]. The first simplification is the assumption of a single Loss-Given-Default (LGD) in equation 6. Altman and Kishore (1996) show that LGD can vary over the credit cycle; it tends to be higher when credit conditions deteriorate (pro-cyclical). More specifically, recoveries on the losses are smaller during the recessions when credit conditions deteriorate, and higher during the expansions when the credit conditions improve and credit becomes easier to obtain. Andersen (2011) model LGD as changing over the economic cycle (economic growth versus non-growth periods). However, according to Huang et al. (2012), the magnitude of fluctuation during the economic cycle is very small. Estimating LGD for each bank and each time period is computationally very difficult. Therefore, we assume LDG to be constant as recommended in Basel II and also as used by (Tarashev et al., 2010a, 2013)[95]. The second and more important simplification is assuming constant exposure to the common (systemic) risk factors, ρ_{it} (Appendix I, equation 4). A common risk factor defines the correlation between a particular bank and the banking system. It influences the propensity (or tendency) of bank i to default with other banks. If the banking system is going through a systemic event in which several banks are collapsing, a bank with a pristine balance sheet may suffer from the losses of failing banks due to interconnectedness. We assume that all banks have identical common-factor

[94] See the examples for the large banks only (Tarashev et. al., 2010; Huang et al., 2012; Cummins 2014).

[95] Basel II recommends to assume LDG constant at 0.55.

loading due to data limitations: the data that may be approximated for the bilateral exposure for each bank is difficult to find, if not impossible. Assuming a single common-factor loading for all banks may potentially cause over- or underestimations of ES. We examine the range of over- and underestimation and show that the distortion on ES values due to a single common-factor loading assumption is small, thus it is tolerable (section 3.4.2).

We start our analysis by explaining ES with stylized examples in section 3.4.1. As a hypothetical measure, it is critical to evaluate ES values within the limits of its definition. Next, we discuss the limitations of a single common-factor loading assumption for all banks on the ES estimations in section 3.4.2. Then we discuss the expected shortfall in BHC subgroups according to the asset-size breakdown in section 3.4.3 and organization type (BHC versus FHC) breakdown in section 3.4.4. In section 3.4.5, we examine how the systemic importance of SIFIs has changed over time. Finally, we review the contribution of the four largest U.S. banks to systemic risk and compare our results with the findings of Banulescu and Dumitrescu (2015) in section 3.4.6. Before discussing the systemic risk in bank subgroups in detail, we provide a short explanation for how to evaluate ES estimations for bank cohorts.

3.4.1 Expected-Shortfall: Stylized Examples

ES refers to the conditional expectations of losses under extreme conditions. It is the probability-weighted average (expected) loss incurred by a bank's creditors (households and firms) associated with bank failures during a systemic event. At the same time, we can read it as the capital (or a hypothetical insurance premium) needed to offset the losses associated by the failure of banks. It is important to note that ES is a hypothetical concept that depends on how the systemic event (or financial distress) is defined. In our approach, a systemic event occurs when the hypothetical aggregate losses exceed the threshold set by *VaR*. Thus, there is a systemic event attributed to all time periods regardless of business cycles. However, the severity of the events changes greatly from one period to another because the distribution of the aggregate losses depends on the probability of default, which changes from one period to another due to business cycles or bank characteristics[96]. For example, in a non-crisis (crisis) period, the probabilities of defaults are low (high). Therefore, the aggregate losses are low (high) and the expected loss beyond *VaR* (*%5*) is small (large). More precisely, the ES figures estimated by Monte Carlo simulations are the losses that will occur in the extreme case with 5% probability. For example, if the banking system has one period *VaR (5%)* of $500 billion losses, then we are 95% confident that over a given period the aggregate losses will not exceed $500 billion. If it does, it is an extreme event (a systemic event), and we start worrying about the total losses in the banking system. Then, ES (e.g. $1 trillion) is the expected aggregate loss conditional on the occurrence of an extreme event that can be realized with only 5% probability. ES is critical in the sense that it helps to determine policy measures (e.g. insurance premiums for the banks) according to the occurrence of the systemic event.

ES figures are hypothetical for a particular bank and they may change by a large amount from one period to another. For example, suppose bank A faces two different systemic events in two periods, in which the bank size remains constant, e.g., liabilities remain unchanged, but the probability of default (PD) changes because of the economic conditions. Period one is a non-crisis period, and the ES for this bank is $50 billion. Period

[96] The distribution of losses also depends on the liabilities, too, however, the volatility in PDs is much higher than the liabilities; thus it is the PD that derives the aggregate losses to a great extent.

two is a crisis period, and ES is much larger at $300 billion. If the bank fails, it will actually face the same amount of losses in both periods because the liabilities are identical. However, expected shortfalls (capital to offset the households and firms' hypothetical losses) associated with the bank in two periods are different because bank A faces a higher PD in the crisis period than the non-crisis period. In addition, a systemic event reflects a different severity condition in a particular period. The severity condition is defined by the same rule for both periods, in which the aggregate losses exceed occurrence threshold of 95%. However, 95% thresholds are different because the loss distributions are generated based on the probability of defaults of all banks in each period separately. In a non-crisis period, lower PDs across the banking system point to a smaller loss distribution while in crisis periods, high PDs point to larger distribution. Therefore, the 95% occurrence thresholds are different, and thus the systemic events are defined differently. An ES of $50 billion reflects the hypothetical probability weighted bank loss in a systemic event, which occurs in on-crisis period; an ES of $300 billion reflects the same in crisis period. The six-fold difference reflects the likelihood of bank A's failure (PD) in two different systemic events in two different periods. Next, we review the results from the bank cohort simulations. We start with explaining the assumption of a single common-loading factor.

3.4.2 Single Common-Factor Loading

A common-factor loading, ρ_i, affects a particular bank to the degree that the bank has exposure to other banks in the banking system (Appendix I, equation 4). Following Tarashev et al. (2010a, 2013) and Huang et al. (2012), bank i's exposure to bank j can be determined from the correlation between the banks' asset returns, which can be approximated by the correlation between the banks' equity returns (stock market return); call it ρ_{ij}[97]. Tarashev et al. (2010a, 2013) use a correlation matrix of the bilateral exposures of the "large" 60 U.S. banks for a common-factor loading ranging from 0.13 to 0.76, with an average of 0.58[98]. More specifically, if a shock hits the banking system (the system of 60 banks), the asset value of bank i will be affected at the scale of ρ_i. In particular, the correlation between the equity returns of two banks can be negative, however, the correlation between bank i and the rest of the banks in the system is positive (Tarashev et al., 2010a, 2013). For example, declining house prices affects banks that rely heavily on housing-related loans (mortgage, HELOCS etc.) negatively, but at a varying degrees depending on the weight of the loans in the balance sheets. Therefore, the correlation of bank i with others can hardly be negative. Huang et al. 2012 find that the correlation of equity returns of each of 74 Asian banks with the rest of the banks in the banking system is all positive and changes from 0.1 to 0.8. The equity-return data to define bilateral exposure for all banks is difficult to find, if not impossible, because not all bank equities are publicly traded. Moreover, estimating the correlations for thousands of banks also requires an enormous amount of work and time. For N number of banks, there are N (N-1) correlations between the equity returns for each time period. Tarashev et al. (2010a, 2013) and Huang et al. 2012 work with less than 100 banks[99]. Expanding their method to encompass the whole banking universe can be very cumbersome. Therefore, we assume

[97] Quantitatively, a one-standard-deviation increase in average PDs (0.0053) moves up the indicator by 11 basis points, and a one-standard-deviation increase in average correlations (0.0681) increases the indicator by 2 basis points. It suggests that changes in PDs have a dominant effect on the indicator; the correlation impact exists but plays a secondary role. (Huang, Zhou, and Zhu, 2009)

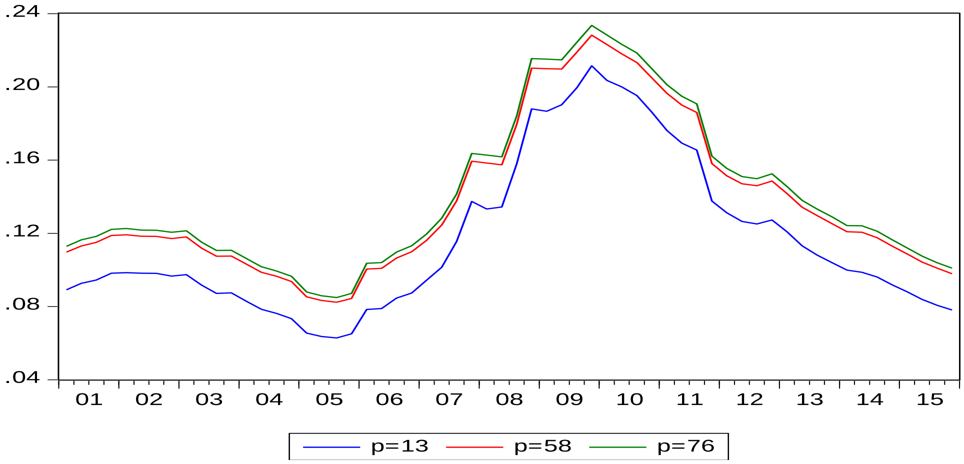
[98] Tarashev et al. (2010a, 2013) investigates the ES of 60 large banks. It does not comment on how the 60 banks were selected or whether they are the largest 60.

[99] The common-factor loadings in their work are estimated by applying the factorization methodology outlined in Tarashev and Zhu (2008) to the correlation matrix of assets returns.

the exposure of banks to the banking system over time is unique and does not change over time. This is a strong assumption and may potentially lead to an over- or under-estimation of ES in simulations. Therefore, we conduct a deeper examination of single common-factor loading assumption.

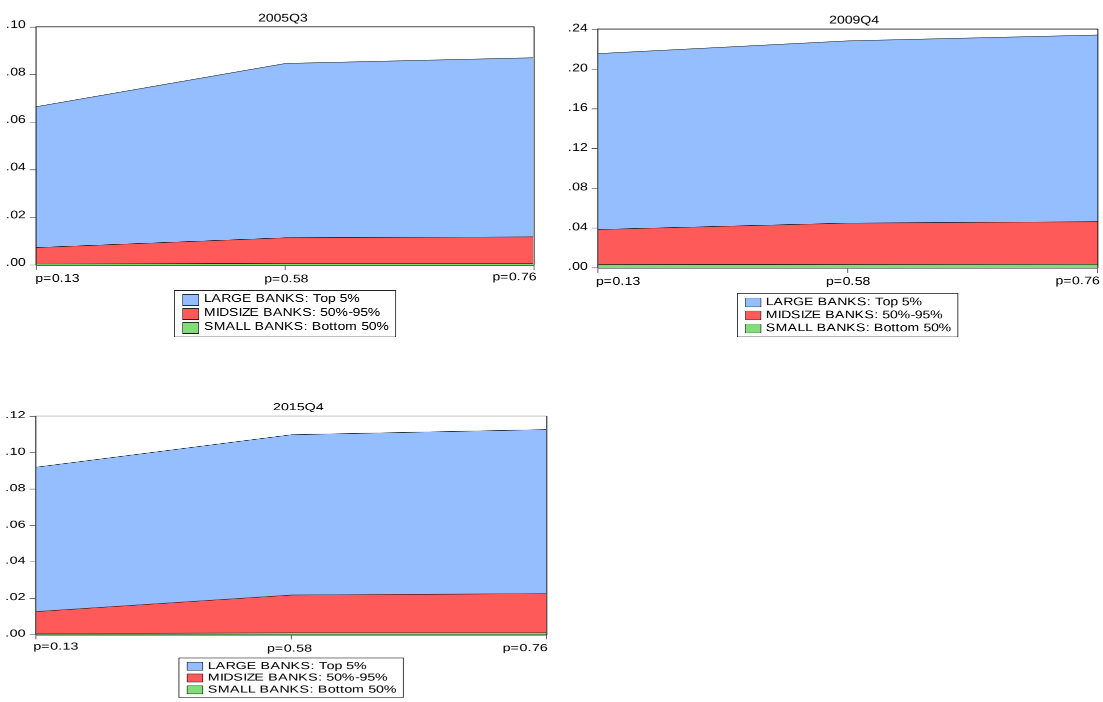
In this section, we provide an analysis for the systemic risk contribution of banks on the basis of different common-factor loading assumptions and examine the error margin caused by the varying assumptions. More specifically, we consider the boundary common factor loadings (minimum and maximum p-values) conditions for 60 banks in Tarashev et al. (2010a, 2013) and examine how sensitive the ES is to the factor loadings. In other words, we examine how much the ES estimations change if we assume minimum or maximum values of common factor loadings in Tarashev et al. (2010a, 2013) instead of the average value for all banks. We show that the deviation in ES due to the varying assumption of common factor loadings is very small and, thus, tolerable. For this exercise, initially, we derive systemic risk indicators for the banking system by assuming the common-factor loading for all banks and time periods as 0.58, the average of 60 large banks. Then, we repeat the estimations by assuming loadings as 0.13 (min) and 0.76 (max) for all banks and all time periods. The results are presented in Figure 3.3. The loading factor ρ_i enters into the stochastic loss model as a scalar. Therefore, assuming minimum and maximum values for the loading factor causes a parallel upward or downward shift in the indicator: the systemic risk is highest when we use 0.76 and lowest when we use 0.13. This is quite intuitive; rising banks' exposure to each other (and to the banking system) pulls up the likelihood of joint defaults in the banking system and poses more systemic risk.

Figure 3.3: Comparing Systemic Risk Indicators According to Common-Factor Loadings Assumptions: ρ_i = 0.13, 0.58, 0.76 (ratio, left-axis), (2001-2015)



To see this more clearly, we pick three data points on the systemic risk indicator in Figure 3.3: 2005Q3, 2009Q4 and 2015Q4. Systemic risk indicator declines to its lowest level in 2005Q3 and rises to its highest level in 2009Q4. 2015Q4 is the most recent data point. We want to examine the lowest and the highest systemic risk indicator estimations if we assume minimum and maximum factor loadings instead of the average. The rest of the data points fall in between. Thus, we can determine the boundary values for the errors caused by a single common-factor loading assumption. We also look at the error margin in the last data point which is neither a minimum nor a maximum point (see Appendix G for more detailed discussion). The results are demonstrated in Figure 3.4 and also presented in Table G.1 in Appendix G. The results of these exercises show that (i) the impact of the assumed average common-factor loading on the systemic risk indicator is limited, and (ii) the error is more pronounced for the small banks as the smaller bank size causes the impact of common-factor loading to be amplified in ES estimation. However, this is not a big concern because small banks' (those in the bottom 50% by asset size) contribution to the aggregate risk is less than 1%. Besides, upward bias creates conservative assumptions. The results also show that (iii) the error margin declines during the crisis periods as the probability of default increases and become more important in ES estimations. In the next four subsections, we examine the systemic risk contribution (systemic importance) and systemic risk levels of several bank subgroups.

Figure 3.4: Systemic Risk by Common Risk Exposure by Bank Size (Top 5%, Midsize 50%- 95%, Bottom 50%), Ratio, y-axis; ρ_{size}, x-axis



In Figure 3.4, systemic risk indicators for bank size cohorts (top 5%, midsize 50%-95% and bottom 50%) were derived for three common factor loadings, ρ_{size}, separately: 0.13, 0.58 and 0.76. The systemic risk indicators for size cohorts are Expected Shortfall for *each* cohort scaled by the sum of *all* liabilities in the banking system: $ES_K(Loss \geq VaR_\alpha)/S$, where K is bank size cohort (e.g. top 5%) and S is sum of the liabilities of all banks. The cross sections for 2005Q3, 2009Q4 and 2015Q4 are presented to demonstrate the contribution of each size cohort to the topline systemic risk indicators. The systemic event in all charts is defined on the whole banking system: $Loss \geq VaR_\alpha$.

3.4.3 Small Banks versus Large Banks

The banking system has consolidated considerably over the last fifteen years, leaving fewer banks holding larger levels of assets (Figure 3.1). For policy makers concerned about controlling systemic risk, it is imperative to understand how the systemic importance of a bank changes if its asset size gets larger. In this section, we explore the systemic importance of large, midsize, and small banks by grouping banks according to asset size. First, we group them as large (top 5%), midsize (50%–95%) and small (bottom 50%) banks. More specifically, we define banks as large if they rank within the top 5th percentile, and small if they rank in the bottom 50th percentile, according to asset size. We then label the rest midsize banks. At the end of 2015, BHCs with assets above $8.91 billion are classified as large banks. There are 230 large banks in the top 5% cohort. The BHCs with assets below $0.31 billion are classified as small banks. There are 2,284 banks in this cohort. The rest are grouped as midsize banks (2,056 banks). We group the banks according to asset size for each time period separately. More specifically, if a bank is classed as large in one period, it may fall into the midsize cohort if its balance sheet shrinks. Conversely, a bank that is classed as midsize in one period may become a large bank if its balance sheet grows in the next period. Then, to examine how much the risk contribution changes from the top 5% to the top 1%, we change the cutoff for the largest size cohort to 1% and midsize to 50%-99%: the bottom 50% remains same. In this case, the asset size cutoff for the largest bank cohort rises to $37.6 billion and the number of large banks decline to 46 banks. A total of 4,568 U.S. BHCs hold nearly $18 trillion worth of assets at the end of 2015, up from $7.5 trillion owned by 5,861 banks in 2001 (Figure 3.1). The results for systemic risk contributions using both classification schemes are presented as the ES amount in Figure 3.5, and as a ratio on a scale from 0 to 1 in Figure 3.6.

Figure 3.5: Expected Shortfall (ES) by Bank Size, $bil. (2001-2015)

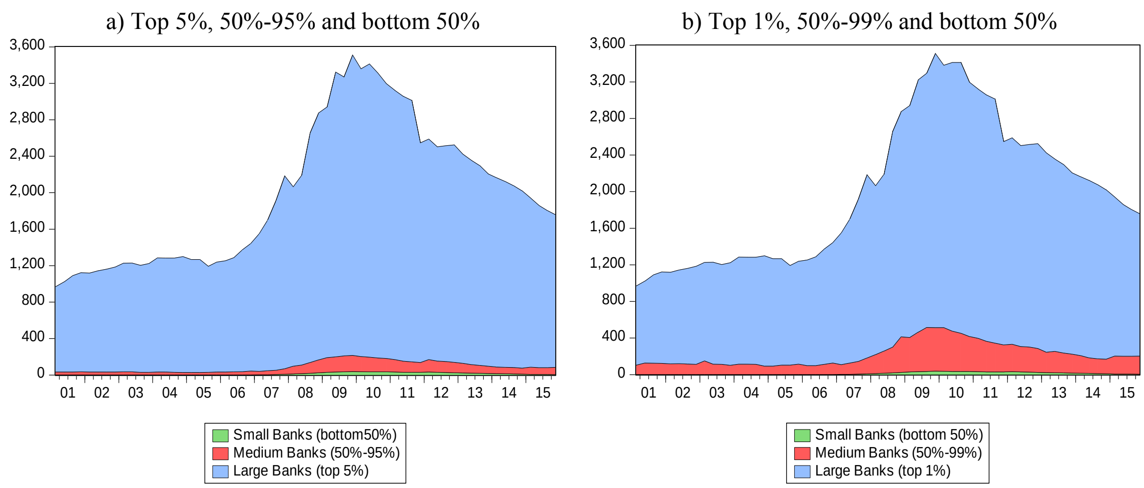


Figure 3.5 compares the Expected Shortfall ($bil.) for large, midsize and small cohorts. Expected Shortfall is $ES_K(Loss \geq VaR_\alpha)$, where K is bank size cohort (e.g. top 5%). Figure a) presents the ES for the bank asset size distribution of top 5%, 50%-95% and 50%. Figure b) presents the ES for the bank asset size distribution of top 1%, 50%-99% and 50%.

Figure 3.6: Contribution to Aggregate Risk by Bank Size, Ratio: scale 0 to 1 (2001-2015)

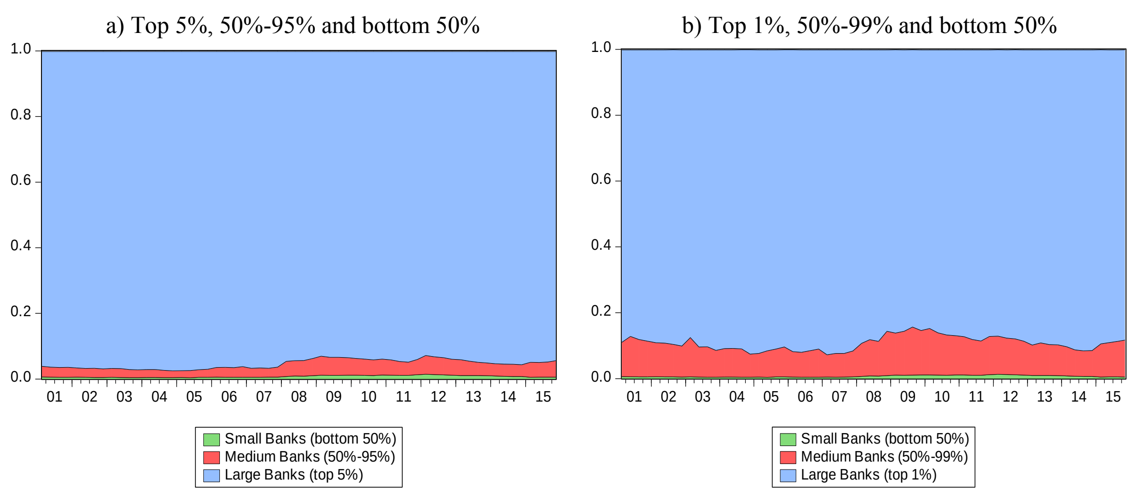


Figure 3.6 compares the Expected Shortfall share for large, midsize and small cohorts in the banking system. Expected Shortfall for each cohort is $ES_K(Loss \geq VaR_\alpha)$, where K is bank size cohort (e.g. top 5%). The total Expected Shortfall is $ES(Loss \geq VaR_\alpha)$. The cohort ES share is $ES_K(Loss \geq VaR_\alpha)/ES(L \geq VaR_\alpha)$ ratio, scaled from 0 to 1. Figure a) presents the ES share for each bank asset size cohort of top 5%, 50%-95% and 50%. Figure b) presents the ES share for each bank asset size cohort of top 1%, 50%-99% and 50%.

We obtain two important results. First, the aggregate risk as measured by the ES in the U.S. banking system reaches its peak in 2009Q4. During the Great Recession, the U.S. economy contracted most sharply in 2009Q1, shrinking 5.4% q/q (annualized), but it took three quarters for the impact of the shock on the U.S. banking system to peak. This was due to the lagged effects of the shock on household and firm balance sheets. Borrowers do not default on their all loan obligations right after the crisis; most continue to pay until their income flow is fully disrupted or they lose hope for an economic turnaround. There is a phase difference between the shock on the economy and its peak effect on bank balance sheets due to the deteriorating job market following the economic shock: the U.S. unemployment rate continued to rise after the shock and peaked at 9.9% in 2009Q4. Second, the largest banks pose a very high systemic risk due to their size, proportionally more than midsize and small banks. More specifically, when the size cohorts are divided into the top 5%, middle 5%-50% and bottom 50%, in the same period, the contribution of the largest banks to systemic risk is $3.28 trillion (Figure 3.5a), which is 94% of total systemic risk (Figure 3.6a). The rest comes from midsize and small banks: ES is $0.18 billion and $0.046 billion, respectively, for these two bank groups. Alternatively, when the banks are broken down into the top 1%, 1%-50% and bottom 50%, the contribution of the largest banks to aggregate risk at the time when the systemic risk is highest (2009Q4) is $2.97 trillion (Figure 3.5b), which is 85% of total systemic risk (Figure 3.6b). The rest comes from midsize and small banks: ES is $0.48 billion and $0.046 billion, respectively. These results highlight the systemic importance of the largest U.S. banks. We observe that the largest banks contribute to aggregate risk more substantially not only during the crisis periods, but also during the non-crisis periods, which points to the necessity of imposing tighter supervision on the largest institutions in order to preserve the stability of the financial system (Banulescu and Dumitrescu, 2015). The largest banks have been formally designated as SIFI and brought under close scrutiny by the Fed, with stress tests after the passage of the Dodd-Frank Act (2010).

Expected shortfall patterns show the contribution of a particular bank or a group of banks to the systemic risk, however, they do not directly show the riskiness of the bank or the group of banks. More specifically, a bank may pose a higher risk to the banking system due to its size even though its probability of default is not high, while a smaller bank may pose a lower risk even though it is severely distressed. To examine the riskiness of the bank size cohorts, we use systemic risk indicators. Figure 3.7 presents the systemic risk indicators for bank size cohorts. Systemic risk indicators show that the largest U.S. BHCs are, in general, individually riskier than midsize and small size banks, which leads larger banks to contribute to systemic risk disproportionately. We also observe that risk levels among the U.S. BHCs grossly increased during the 2007-2009 financial crisis. We also observe that banks in the top 1% cohort are riskier than those in the top 5% (Figures 3.7a versus 3.7b). Our results also show that medium-size banks contribute to systemic risk less than proportionately. Small size banks are, in general, individually riskier than medium size banks in the sense that they have a greater probability of default [100]. In particular, they have higher ratios of nonperforming loans to total loans due to less efficient credit-risk evaluation and loan monitoring. To elaborate, increases in regulatory compliance and technological burdens have disproportionately increased community banks' costs (Hughes

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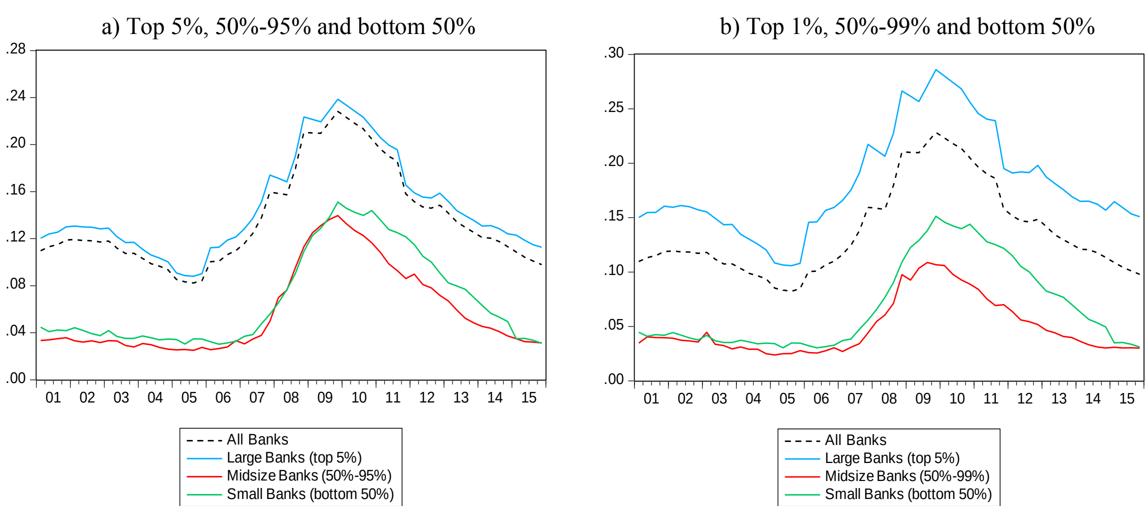
[100] From 2011 to 2015, the probability of default as measured by the bank distress indicator for small banks (banks in the bottom 50%) is 0.066; for midsize banks it is 0.059. In 2009Q4, when stress on U.S. banks peaked according our systemic risk measures, the median probability of default for small banks was 0.19, while for midsize banks it was 0.23.

et al., 2018). Small community banks traditionally had a comparative advantage in small-business lending, but advanced technology has allowed midsize banks (and nonbank alternative lenders) to become more important providers of small-business loans since the latter part of the 2000s (Jagtiani and Lemirex, 2016, 2018). Hughes et al., (2018) finds that midsize banks have a higher return on assets than do smaller banks, due not to more profitable investment opportunities, but to greater efficiency at exploiting them; small banks experience higher overall average operating and corporate overhead costs than midsize banks. Figures 3.7a and 3.7b demonstrate that the banks at the top and bottom of the size spectrum were affected by the financial crisis more intensively than were midsize banks.

Figure 3.7: Systemic Risk Indicators by Bank Asset Size, Ratio: scale 0 to 1 (2001-2015)



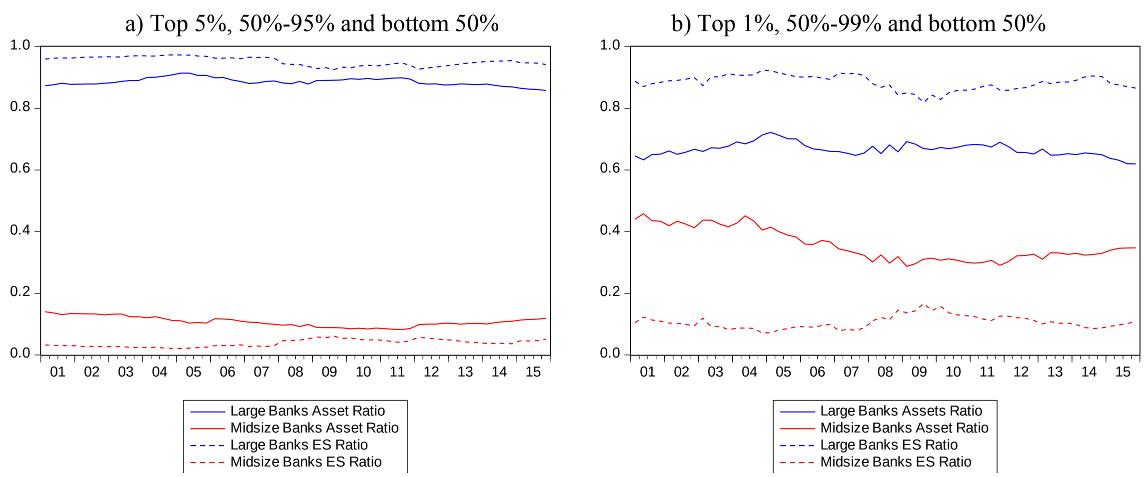
In Figure 3.7, systemic risk indicators for all BHCs (banking system) and asset size cohorts. The systemic risk indicators for size cohorts are Expected Shortfall for *each* cohort scaled by the sum of liabilities in *each* cohort the banking system: $ES_K(Loss \geq VaR_\alpha)/S_K$, where K is bank size cohort. The systemic risk indicator for the banking system is $ES(Loss \geq VaR_\alpha)/S$. Figure a) presents the ES share for each bank asset size cohort of top 5%, 50%-95% and 50%. Figure b) presents the ES share for each bank asset size cohort of top 1%, 50%-99% and 50%.

We find that a typical large bank makes a greater contribution to systemic risk than does a midsize or small bank, with size being an important factor. This is a critical result because over the years the U.S. banking system has become more consolidated. After reviewing the systemic importance (risk contribution) and risk level of the different bank cohorts, we examine how their systemic importance compares to their asset size. Balance-sheet size is a common way to rank banks according to size. Naturally, a bank that holds more assets is more critical to the system than a smaller one; the larger the asset size, the more credit a bank provides to the economy. The natural question is whether a bank's beneficial role in the economy outweighs the systemic risk it poses. More precisely, we ask how the asset share of a particular bank compares to its systemic risk contribution, and compare the asset shares of large and midsize banks with their ES shares. Results for the two alternative size breakdowns (with large banks defined as those in the top 5% and top 1%, respectively) are presented in Figure 3.7a and Figure 3.7b. Our results show that the banks in the top 1% cohort disproportionately contribute to systemic risk. The share of total assets of banks in the top 1% stays slightly above 60%, from 2001 to 2015, while the systemic risk contribution of this cohort remains above 80% in the same period, and there are times when it rises to 90%. On the contrary, the asset share of midsize banks is nearly flat around 40%, whereas their systemic risk contribution remains less than 20%[101]. The systemic risk contribution of banks in the top 1% declined from 0.90 in 2007 to 0.80 in 2009 as the smaller banks became more distressed during the crisis. We observe that disproportionality in systemic risk contribution continues if we expand the largest BHCs cohort to 5%. Banks in the top 5% cohort account for nearly 90% of all bank assets. On

[101] For the smallest banks (bottom 50%), the asset share and systemic risk share is very small. The asset share is between 2-3% and systemic risk share is between 1-2%.

the other hand, the contribution of this cohort to systemic risk is more than 95% of the total. Midsize banks constitute only 10%-15% of total assets, but their contribution to systemic risk is less than 5%. In brief, banks in the top 5% account for nearly 90% of all assets but contribute 95% to the aggregate risk. Banks in the top 1%, on the other hand, account for nearly 70% of all assets but contribute 90%, which shows that larger institutions pose a disproportionate threat to the financial system during systemic events (Figure 3.8).

Figure 3.8: Comparing Assets-to-Total Assets Ratio with Expected Shortfall (ES)-to-Total Expected Shortfall (ES), Ratio: scale 0 to 1 (2001-2015)



In Figure 3.8, the asset ratio is the ratio of total assets in the size cohort (e.g. large banks cohort) to sum of bank assets in two cohorts (large and midsize cohorts). The Expected Shortfall (ES) ratio for a bank size cohort is the ratio of the ES of the cohort to sum of ES of two cohorts. The cohort ES share is $ES_{K1}(Loss \geq VaR_{\alpha})/(ES_{K1}(L \geq VaR_{\alpha})+ ES_{K2}(Loss \geq VaR_{\alpha}))$ ratio, where $K1,\ K2$ are large and midsize cohorts.

These results suggest that regulators' focus should be on larger banks to prevent systemic risk threatening banking stability, and that regulators should be concerned about encouraging banks to grow even larger. Our results also highlight the importance of diversification (with assets held by larger numbers of smaller banks) in the banking system. Asset consolidation in the banking system raises systemic risk; therefore, the trend of fewer but larger banks carries a potential of higher systemic risk in a financial crisis. Our results are complementary to the findings of (Tarashev et al., 2010a, 2013) that systemic importance (contribution to systemic risk or expected shortfall) increases with individual riskiness (probability of default) and institutions' relative sizes, and that the systemic importance of financial institutions increases faster than their size.

3.4.4 Bank Holding Companies versus Financial Services Holding Companies

Next, we investigate the systemic risks of BHCs and FHCs because of the removal of restrictions on certain financial activities when banks convert to the FHC structure[102]. The Gramm-Leach-Bliley Act (GLBA) of 1999 enabled BHCs to register as FHCs, allowing them to engage in a broad range of financial (nonbank) activities without limitations, including securities underwriting and dealing, insurance underwriting and merchant banking activities. The GLBA allowed BHCs to be converted formally into FHCs without actually engaging in these activities. However, FHCs generally engage in such activities without the restrictions that apply to BHCs or that BHCs tend to avoid[103]. In particular, BHCs are allowed to obtain only 25% of their gross revenue from securities underwriting or dealing. Their merchant-banking activities are also limited. BHCs are not allowed to acquire more than five percent of any class of voting securities, or more than 24.9% of the total equity, of a nonfinancial company. Similarly, BHCs are not allowed to underwrite or sell insurance as an agent. Without such limitations, FHCs may potentially

[102] See "Report to the Congress on Financial Holding Companies under the Gramm-Leach-Bliley Act", Nov, 2003, Board of Governors of the Federal Reserve System U.S. Department of the Treasury.

[103] See "Report to the Congress on Financial Holding Companies under the Gramm-Leach-Bliley Act", Nov, 2003, Board of Governors of the Federal Reserve System U.S. Department of the Treasury.

respond to business cycles differently than do BHCs[104]. Most large BHCs have registered as FHCs since the passage of the GLBA.

At the end of 2015, there were 498 FHCs in the U.S. and they owned nearly 80% of all banking assets; the remaining 20% was owned by 4,070 BHCs. There is a notable growth in the size and importance of FHCs since the passage of GLBA as the U.S. banking system has consolidated over time, with more assets held by fewer banks (Avraham, Selvaggi and Vickrey, 2012; Figure 3.1 and 3.2). There were 611 FHCs and 5,250 BHCs in the U.S. at the beginning of 2001. By the end of 2008, the number of FHCs increased to 643 while the number of BHCs shrank to 4,959. The number of FHCs and BHCs declined to 498 and 4,070 at the end of 2015.

In addition to consolidation via mergers and acquisitions, the asset size of banks under FHCs' control has grown steadily over time. The average size of balance sheets as measured by total assets increased from \$1.43 billion in 2001 to \$3.83 billion in 2015. Expanding into nontraditional operations, FHCs may potentially respond to financial crises differently than BHCs do. For example, removing restrictions on nontraditional activities such as securities underwriting or securities brokerage may potentially help FHCs diversify credit risk and reduce systemic risk (Uzun and Webb, 2007; Jiangli and Pritsker, 2008). Similar to bank size cohorts, we examine the systemic importance (systemic risk) of BHCs and FHCs as measured by ES and individual riskiness (risk level) measured by the systemic risk indicator. Figure 3.9 demonstrates the systemic risk contribution for each cohort: Figure 3.9a presents ES in volume and Figure 3.9b shows the ratio in scale from 0 to 1.

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[104] The Gramm-Leach-Bliley Act (GLBC) of 1999 allowed BHCs to convert themselves into FHCs and conduct a much wider range of "financial in nature" activities, including unlimited securities dealing and underwriting as well as general insurance business. The GLBC also allows FHCs to conduct "non-financial activities" such as physical commodity trading. However, there are limitations to such activities. In general, an FHC may directly engage in any non-financial activity if the Federal Reserve determines it is "complementary" to a financial activity.

Figure 3.9: Comparing Expected Shortfall by Bank Type: Bank Holding Companies versus Financial Services Holding Companies (2001-2015)

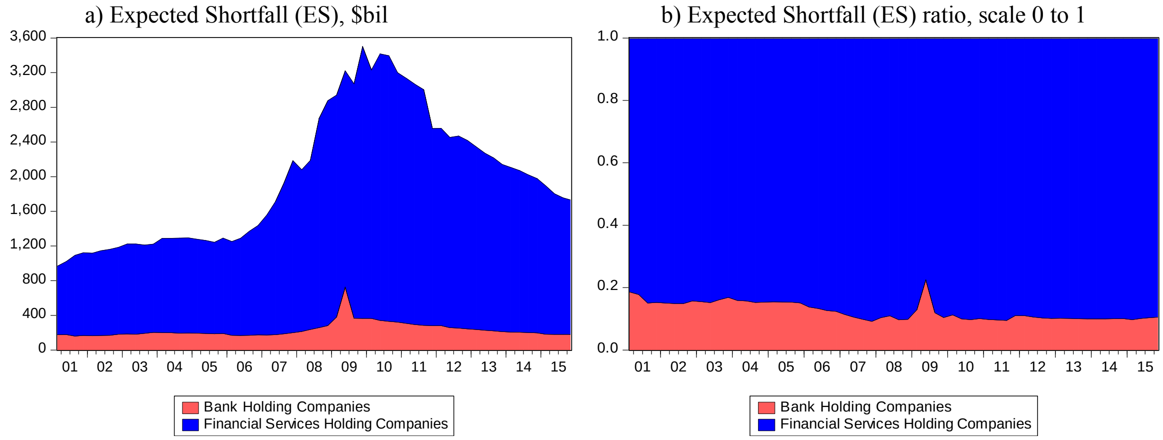


Figure 3.9a compares the Expected Shortfall ($bil.) for bank organization type cohorts: BHC and FHC. Expected Shortfall is $ES_K(Loss \geq VaR_\alpha)$, where K is bank cohort (e.g. BHC). Figure 3.9b compares the Expected Shortfall share for BHC and FHC cohorts in the banking system. Expected Shortfall for each cohort is $ES_K(Loss \geq VaR_\alpha)$, where K is bank cohort (e.g. BHC) The total Expected Shortfall is $ES(Loss \geq VaR_\alpha)$. The cohort ES share is $ES_K(Loss \geq VaR_\alpha)/ES(Loss \geq VaR_\alpha)$ ratio, scaled from 0 to 1.

We find that most of the systemic risk is concentrated in the FHC cohort: nearly 80%-90% of aggregate risk can be attributed to FHCs. In only one quarter, 2009Q2, does FHCs' risk contribution fall below 0.8 (Figure 3.9b). In this quarter, the contribution of BHCs to aggregate risk jumps due to the impact of the financial crisis. More precisely, the contribution of BHCs to systemic risk rises more than twofold, from 0.10 to 0.22 in this period. Rapidly surging distress (as reflected in default probabilities) in the BHC cohort due to the unfolding financial crisis causes the ES of BHCs jump in this period (explained below). The effect of the financial crisis on the BHC cohort is clearer if we compare systemic risk indicators (Figure 3.10).

Figure 3.10: Systemic Risk Indicator by Bank Type: Bank Holding Companies vs Financial Services Holding Companies, Ratio: scale 0 to 1 (2001-2015)

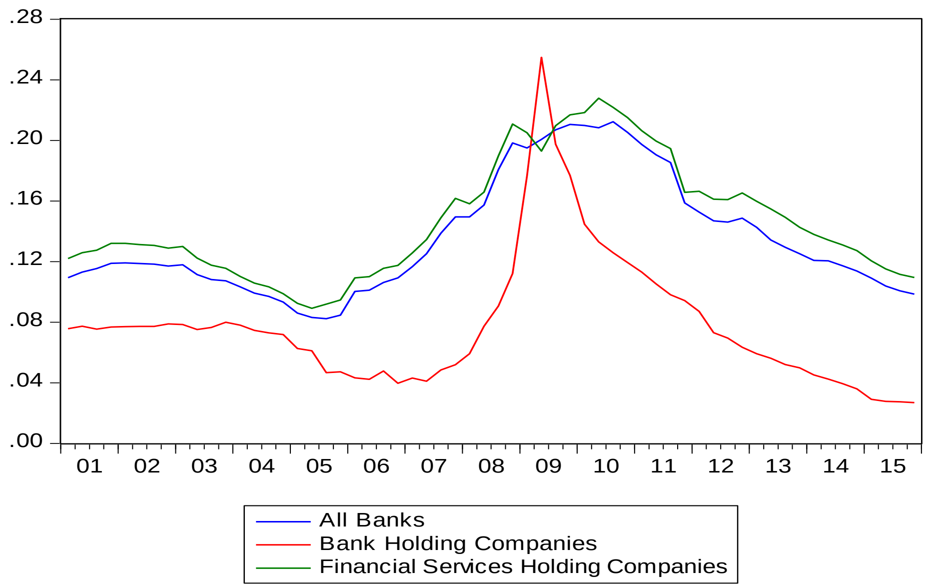


Figure 3.10 presents systemic risk indicators for all banks (banking system) and organization type cohorts. The systemic risk indicators for organization type cohorts are Expected Shortfall for *each* cohort scaled by the sum of liabilities in *each* cohort: $ES_K(Loss \geq VaR_\alpha)/S_K$, where K is bank organization type cohort. The systemic risk indicator for the banking system is $ES(Loss \geq VaR_\alpha)/S$.

FHCs, in general, have been riskier than BHCs. The risk level of BHCs was lower than FHCs until the financial crisis. The FHC cohort systemic risk indicator rises to nearly 14% in the period following the 2001 recession, and then declines to 8% in 2005 as the economy recovers from the recession and low interest rates fuel a credit expansion. The risk indicator changes course in 2006 when the housing market takes a pause and impaired loans begin to take a toll on their balance sheets; the risk level of FHCs starts rising in 2006 and peaks at 23% in 2010. The risk level of BHCs remains lower than that of FHCs, but follows a similar pattern until the financial crisis: the effect of business cycles on BHCs and FHCs are quite similar until 2007. The stress on BHCs begins rising with the onset of the recession at the end of 2007, but the rate of increase in BHCs' risk level is much steeper than for FHCs: the risk level in the BHC cohort rises rapidly from 11% in 2008Q4 to 27%

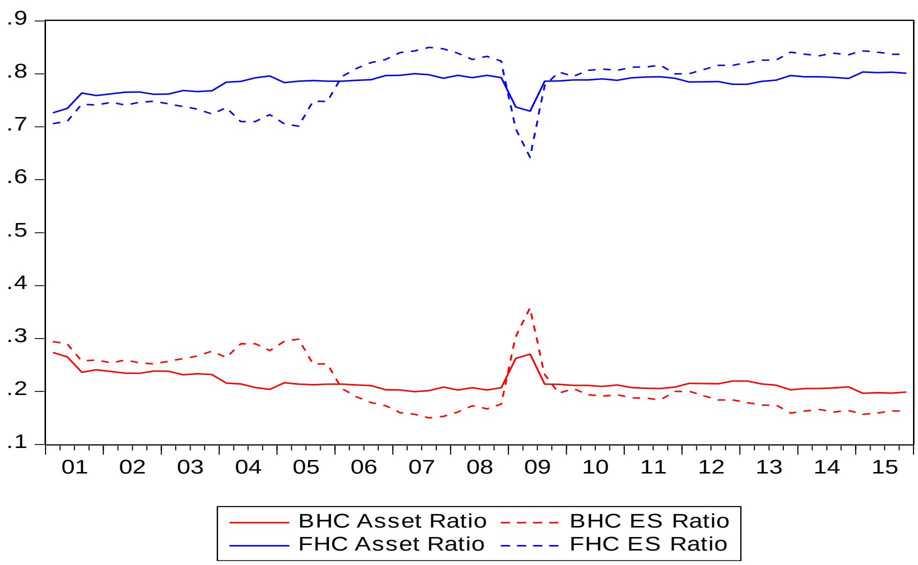
in 2009Q2, a level higher than that of the FHC cohort, before declining below the FHC cohort in the post-recession period (Figure 3.10). BHCs, most of which are small or medium-sized community banks, had heavily engaged in real estate and industrial lending in the years running up to the financial crisis. They used their advantage in relationship lending compared with larger banks, and expanded their balance sheets with these loans. The housing downturn, however, caused many community banks to struggle as impaired residential mortgage loans mounted on their balance sheets. Their pain intensified when a sharp drop in economic activity reduced the demand for commercial real estate and industrial loans. Thus the risk level (individual riskiness) of BHCs, in general, increased much faster than that of FHCs during the financial crisis. This does not necessarily mean that converting to an FHC makes a bank less risky. Our results show that in the non-crisis periods, the risk level as measured by systemic risk indictor in the FHC cohort has been higher than for the BHCs. Several large FHCs received government bailouts in 2008-2009, in the form of loan guarantees and cash injections, to remain buoyant during the financial crisis[105]. Without government bailouts, large FHCs could have failed and sent systemic shock waves to the global financial system. Because government intervention masks the true risk levels of large FHCs during the financial crisis, systemic risk indicators are likely underestimating the riskiness of FHCs. The high risk levels of FHCs point to the inadequacy of portfolio diversification in reducing bank distress or the inadequacy of the choices FHCs made in that diversification. In other words, expanding banking operations into nontraditional activities such as underwriting and distributing securities or insurance

[105] Signed into a law October 3, 2008, the Troubled Asset Relief Program (TARP) program enabled the U.S. government to purchase "toxic" assets and equity from financial institutions to strengthen its financial sector. The program was revised multiple times as the crisis evolved; the four largest U.S. banks each had to participate. Citigroup and Bank of America agreed to receive preferred stock investments from the Treasury in the amount of $45 billion, and JPMorgan Chase and Wells Fargo agreed to receive $25 billion.

policies do not reduce FHC failure risk (Allen and Jagtiani, 2000; DeYoung and Roland, 2001; DeJonghe, 2010; Demirguc-Kunt and Huizinga, 2010; Akcay and Elyasiani, 2018).

Next, we compare the asset shares of BHCs and FHCs with their shares of systemic importance for the proportionality of their risk contribution. Put differently, we explore whether BHCs and FHCs' systemic importance changes in tandem with their asset size (Figure 3.11).

Figure 3.11: Systemic Risk Indicator by Bank Type: Comparing Assets-to-Total Assets ratio with Expected Shortfall (ES)-to-Total Expected Shortfall (ES), Ratio: scale 0 to 1 (2001-2015)



In Figure 3.11, the asset ratio is the ratio of total assets in the organization type cohort (e.g. FHC) to sum of total bank assets in two cohorts. The Expected Shortfall (ES) ratio for a bank organization type cohort is the ratio of the ES of the cohort to sum of ES of two cohorts. The cohort ES share is $ES_{K1}(Loss \geq VaR_{\alpha})/(ES_{K1}(Loss \geq VaR_{\alpha})+ ES_{K2}(Loss \geq VaR_{\alpha}))$ ratio, where $K1, K2$ are BHC and FHC cohorts.

Our results show that the rising riskiness of BHCs during the financial crisis is also evident from asset ratio-ES ratio comparison. FHCs hold substantially more assets than BHCs, but their contribution to overall systemic risk was lower than their asset share until 2006. In other words, FHCs were systemically less important than their asset share indicated. An overly accommodative monetary policy caused a credit boom and let households and businesses borrow cheaply to finance spending and investment. Fresh loans flowing onto banks' balance sheets inflated FHC assets. The impaired assets were very low initially due to low interest rates. FHCs grew larger but did not pose a threat to the financial system because of their pristine balance sheets. Excessive risk-taking due to low interest rates (and low interest-rate margins) led to more impaired loans over time. Impaired assets continued to mount after the Fed changed course and began tightening monetary policy in the second half of 2004; many borrowers faced higher interest rates and began to default. Rising interest rates from 2005 to 2007, the housing market downturn and a financial crisis from 2007 to 2009 created a lot of trouble for borrowers. The systemic contribution of FHCs increased rapidly and remained high until 2009. In this period, FHCs posed a larger threat to the systemic risk than their asset share would indicate. In 2009, the risk contribution of FHCs declined rapidly relative to BHCs; thus, the ES share declined below the asset share (Figure 3.11). The reason for this reversal was not that the FHCs' riskiness as measured by the systemic risk indicator declined; on the contrary, the risk level of FHCs increased during the crisis period (Figure 3.11). However, because the risk level of BHCs rose much faster, FHCs' contribution to aggregate risk declined and caused the ES share to decline compared to the asset share. For about one year, the risk contribution of BHCs exceeded their asset share due to the struggles of small and midsize community banks. The ES share of FHCs (contribution to systemic risk) rose back above their asset share in 2009Q4 and remained above it until the end of 2015. We also note that the too-big-to Fail (TBTF) protection created for large firms may have possibly led them to carry more risk than did smaller banks. In the next section, we examine the contribution of SIFIs to aggregate risk and compare their ES share to their asset share to better evaluate the TBTF paradigm and draw policy implications.

3.4.5 Systemically Important Financial Institutions (SIFI)

In studying systemic risk and macro-prudential policies to limit system wide distress, the key is to identify the so-called Systemically Important Financial Institutions (SIFI). The Financial Stability Board (2010) defines SIFIs as financial institutions "whose disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity." The Federal Reserve identifies 34 SIFIs (Table 3.1), also called Domestic Systemically Important Banks (D-SIBs), considered U.S. banks required to perform stress tests. As a regulator of the large banks, the Federal Reserve develops the list of the banks subject to stress testing every year[106].

Several systemic risk measures are developed to identify SIFIs, e.g., MES, CES and SRISK. The ES method used in this paper also has the potential to identify SIFIs, but we take SIFIs as given and estimate their total systemic risk contribution[107]. We examine how their systemic risk contribution has changed over time. In the next section, we show that most of the systemic risk is concentrated in a small number of very large institutions, which are also designated as SIFIs.

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[106] For the United States, the D-SIB list includes financial institutions considered too small for Global Systemically Important Banks (G-SIB) status, but important enough to require stringent annual stress testing by the Federal Reserve. Strictly speaking, the Financial Stability Oversight Council (FSOC) does not designate any banks or bank holding companies as systemically important, but the Dodd-Frank Act imposes heightened supervision standards (including the annual stress test) on any bank holding company with a balance sheet larger than $50 billion. Despite the lack of any official D-SIB designation, the banks subject to U.S. stress tests can be considered D-SIBs.

[107] According to the Basel III agreements, these institutions should face a capital 'surcharge' based on the 'negative externalities' they generate, i.e. their contribution to the aggregate risk of the financial system.

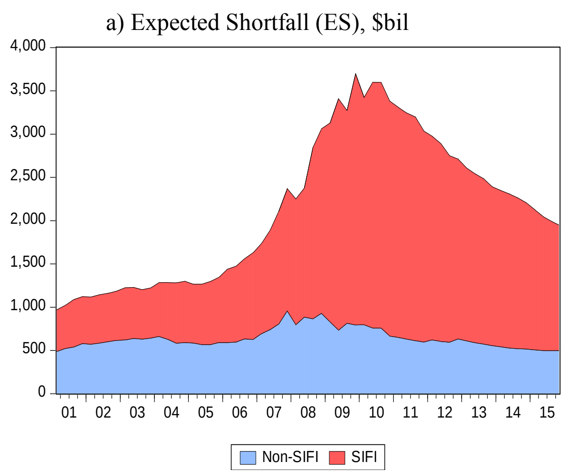
Table 3.1: List of 34 Systemically Important Financial Institutions (SIFI)[108]

	SIB Name	Designation
1)	Ally Financial Inc.	D-SIB (D for Domestic)
2)	American Express Company	D-SIB
3)	BancWest Corporation	D-SIB
4)	Bank of America Corporation	G-SIB (G for Global)
5)	The Bank of New York Mellon Corporation	G-SIB
6)	BB&T Corporation	D-SIB
7)	BBVA Compass Bancshares, Inc.	D-SIB
8)	BMO Financial Corp.	D-SIB
9)	Capital One Financial Corporation	D-SIB
10)	CIT Group Inc.	D-SIB
11)	Citigroup Inc.	G-SIB
12)	Citizens Financial Group, Inc.	D-SIB
13)	Comerica Incorporated	D-SIB
14)	Deutsche Bank Trust Corporation	D-SIB
15)	Discover Financial Services	D-SIB
16)	Fifth Third Bancorp	D-SIB
17)	The Goldman Sachs Group, Inc.	G-SIB
18)	HSBC North America Holdings Inc.	D-SIB
19)	Huntington Bancshares Incorporated	D-SIB
20)	JPMorgan Chase & Co.	G-SIB
21)	KeyCorp	D-SIB
22)	M&T Bank Corporation	G-SIB
23)	Morgan Stanley	G-SIB
24)	MUFG Americas Holdings Corporation	D-SIB
25)	Northern Trust Corporation	D-SIB
26)	The PNC Financial Services Group, Inc.	D-SIB
27)	Regions Financial Corporation	D-SIB
28)	Santander Holdings USA, Inc.	D-SIB
29)	State Street Corporation	G-SIB
30)	SunTrust Banks, Inc.	D-SIB
31)	TD Group US Holdings LLC	D-SIB
32)	U.S. Bancorp	D-SIB
33)	Wells Fargo & Company	G-SIB
34)	Zions Bancorporation	D-SIB

[108]The Systemically Important Banks (SIB) that participated in 2017 Stress Tests: https://www.federalreserve.gov/newsevents/pressreleases/bcreg20170203a.htm

The results from ES estimations of SIFI and non-SIFI banks are provided in Figures 3.12-3.14. Figure 3.12a presents the ES of SIFIs and non-SIFIs by volume. Figure 3.12b demonstrates the contribution of SIFIs and non-SIFIs to the aggregate risk ratio, on a scale from 0 to 1. The ES of SIFIs and non-SIFIs increased substantially between 2001 and the 2008-2009 financial crisis (Figure 3.12a). The rate of increase is much steeper in the SIFI cohort than in the non-SIFI cohort. At the beginning of 2001, the ES of SIFIs and non-SIFIs were nearly equal at around \$500 billion: SIFI and non-SIFI banks were equally systemically important. The ES of SIFIs increased five-fold to \$2.9 trillion in 2009Q4, while the ES of non-SIFIs barely doubled to \$1 trillion in 2008Q4. The SIFIs' contribution to aggregate risk, which was around 0.5 at the beginning of 2001 (Figure 12b), trended up to nearly 0.8 until the end of the financial crisis, and remained nearly flat till 2015.

Figure 3.12: Comparing Expected Shortfall by Bank Designation: Systemically Important Financial Institutions (SIFI) versus Others (non-SIFI) (2001-2015)



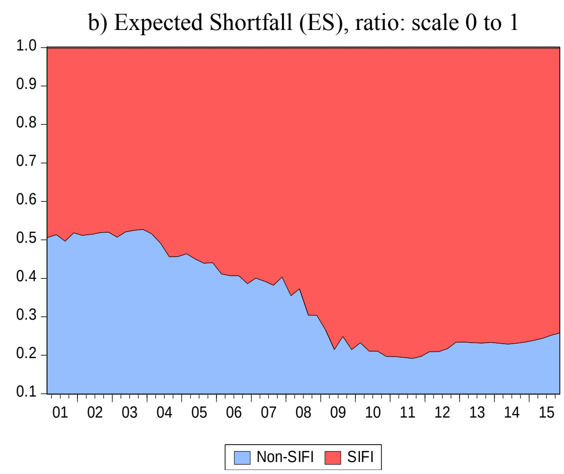
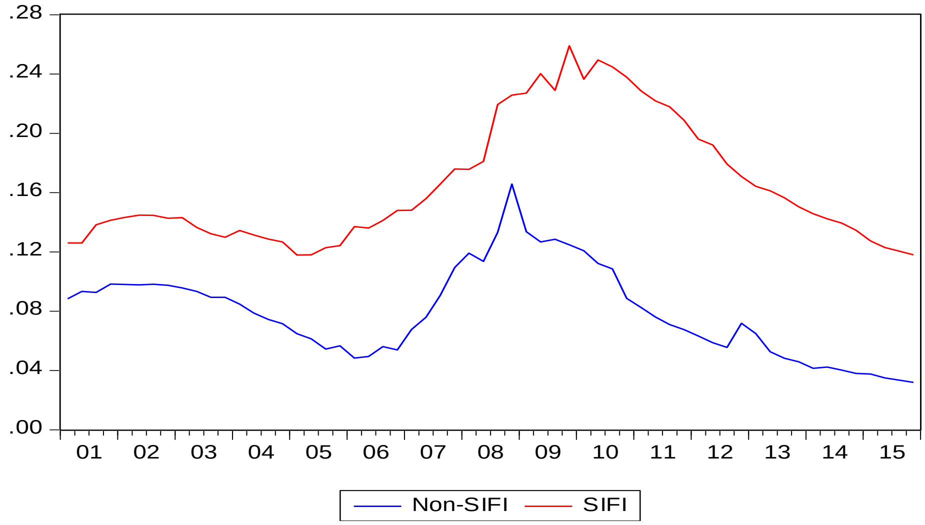


Figure 3.12a compares the Expected Shortfall (\$bil.) for bank cohorts: SIFI and non-SIFI. Expected Shortfall is $ES_K(Loss \geq VaR_\alpha)$, where K is bank cohort (e.g. SIFI). Figure 3.12b compares the Expected Shortfall shares for SIFI and non-SIFI cohorts in the banking system. Expected Shortfall for each cohort is $ES_K(Loss \geq VaR_\alpha)$, where K is bank cohort (e.g. SIFI) The total Expected Shortfall is $ES(Loss \geq VaR_\alpha)$. The cohort ES share is $ES_K(Loss \geq VaR_\alpha)/ES(Loss \geq VaR_\alpha)$ ratio, scaled from 0 to 1.

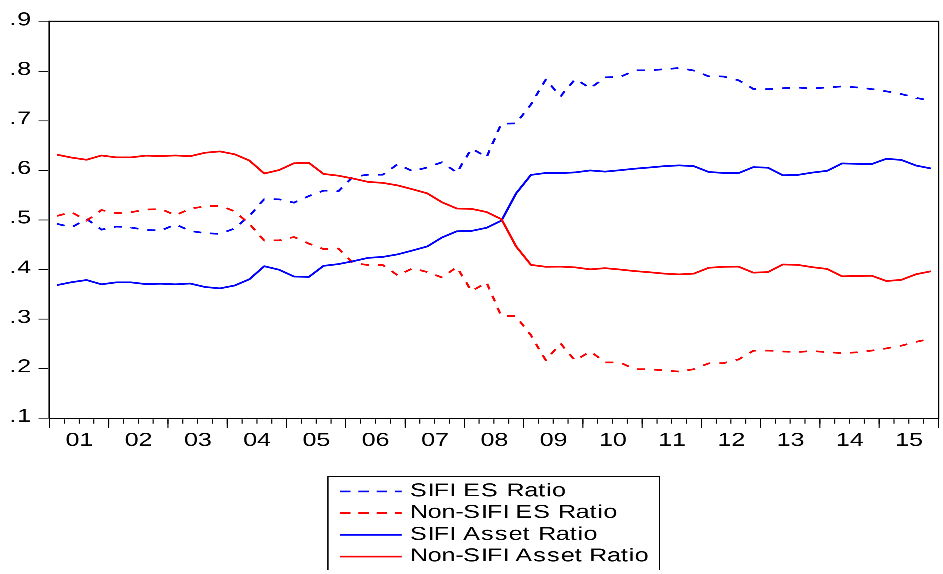
Two factors drove this drastic change. The first factor was balance-sheet growth. Banks classified as systemically important grew rapidly following the 2001 recession, when interest rates were cut to stimulate the economy and help the labor market recover. Low interest rates led to a credit boom, and SIFIs expanded their balance sheets via asset growth as well as through acquisitions. As SIFIs grew larger, their risk contribution increased. The increase in risk contribution (or systemic importance) was disproportional to asset growth, due to the rising individual riskiness of SIFIs. The second factor was increased individual riskiness. The risk level of SIFIs, as measured by the systemic risk indicator, has been continually higher than the risk level of non-SIFI banks, but it increased even further after monetary tightening started in the second half of 2004. The systemic risk indicator, the probability-weighted loss per one unit of bank credit, increased from 0.12 in 2005 to 0.24 in 2009 (Figure 3.13). The 80% contribution to systemic risk from 34 institutions shows that large institutions in the U.S. pose a significant threat to the banking system and have to be monitored closely.

Figure 3.13: Systemic Risk Indicator: Systemically Important Financial Institutions (SIFI) versus others (non-SIFI), Ratio: scale 0 to 1 (2001-2015)



In Figure 3.13, systemic risk indicators for all banks (banking system) and SIFI/Non-SIFI cohorts are compared. The systemic risk indicators for cohorts are Expected Shortfall for *each* cohort scaled by the sum of the liabilities in *each* cohort: $ES_K(Loss \geq VaR_\alpha)/S_K$, where K is bank cohort (e.g. SIFI).

Figure 3.14: Comparing Assets-to-Total Assets Ratio with Expected Shortfall (ES)-to-Total Expected Shortfall (ES), Ratio: scale 0 to 1 (2001-2015)



In Figure 3.14, the asset ratio is the ratio of total assets in the bank cohort (e.g. SIFI) to sum of bank assets in two cohorts (SIFI + Non-SIFI). The Expected Shortfall (ES) ratio for a bank cohort is the ratio of the ES of the cohort to sum of ES of two cohorts. The cohort ES share is $ES_{K1}(Loss \geq VaR_\alpha)/(ES_{K1}(Loss \geq VaR_\alpha)+ ES_{K2}(Loss \geq VaR_\alpha))$ ratio, where $K1,\ K2$ are SIFI + Non-SIFI bank cohorts.

The systemic importance of SIFIs is greater than their asset share in the banking system (Figure 3.14). SIFIs hold substantially more assets than non-SIFIs, but their contribution to overall systemic risk is even greater. The asset share of SIFIs trended up from 2004 to 2007 as they acquired more assets and expanded their balance sheets, but it dramatically increased during the crisis through mergers. Wells Fargo acquired Wachovia, JPMorgan acquired Bear Sterns and Washington Mutual, and Bank of America acquired Merrill Lynch (discussed in section 3.4.5). When the subprime crisis hit the U.S. financial system in mid-2007, SIFIs held nearly 45% of all bank assets (Figure 3.14). Their asset share jumped to 59% in 2009Q1. Larger SIFIs pose a significant risk to the U.S. banking system. The ES of SIFIs has been always higher than their asset share, underscoring how SIFIs contribute disproportionately to aggregate risk. The ES share of SIFIs steadily increased from 50% to nearly 60% from 2004 to 2007, and then jumped to nearly 80% in 2009Q2. The ES of SIFIs declined to 75% in 2015 while their asset share remained at 60%.

Since the Great Recession, the ES of both cohorts have been trending down as the probability of bank defaults has declined amid an improving economy. Yet the rapidly rising systemic risk of SIFIs during the financial crisis period shows that classifying 34 institutions as SIFI and requiring them to conduct annual stress testing is the right policy decision. It is possible that the "too big to fail" (TBTF) protection that was created to highlight the systemic importance of large firms is leading them to carry more risk than smaller banks. In the next section, we examine the aggregate risk contribution of the four largest U.S. banks and compare their total ES share to their asset share to better evaluate the TBTF paradigm.

3.4.6 The "Big Four"

After observing that the systemic importance of large banks has increased over time, and that they pose a large systemic risk to the banking system, we expand our analysis to consider the four largest banks in U.S.: Bank of America (BAC), JP Morgan Chase (JPM), Citigroup (Citi) and Wells Fargo (WFC). The results are presented in Figures 3.15 to 3.18. Similar to SIFIs, there is no formal regulatory designation for the "Big Four." Their common feature is that their balance sheets are materially larger than those of the next largest banks. The asset sizes of the "Big Four" range from \$2.5 trillion to \$1.8 trillion, far above the fifth largest U.S. bank (Goldman Sachs) which holds \$0.9 trillion in assets as of 2018. Three factors convince us to explore the systemic importance of these "Big Four" U.S. banks after examining the systemic risk contribution of banks in the top 1% and 5% by asset size and of SIFIs. First, we wish to enrich our analysis and further support our conclusion that larger banks contribute to systemic risk disproportionately. Second, these banks were either involved in critical acquisitions encouraged by regulators to calm the financial system – e.g., JPM acquired Bear-Sterns and WFC acquired Wachovia Corp. – or else they themselves neared collapse due to poor balance-sheet performance during the financial crisis and required a government bailout (e.g. Citi and BAC). In section 3.4.6.1, we show how the ES approach handles mergers, using the example of WFC's acquisition of Wachovia. Third, and most importantly, in section 3.4.6.2, we analyze the robustness of our ES approach by comparing the systemic risk contribution of the four largest banks with systemic risk measures estimated through two other approaches: SRISK and CES.

Our results show that the systemic importance of the "Big Four" as measured by ES increased from a probability-weighted average expected loss of \$500 billion in 2001 to nearly \$2 trillion in 2009 (Figure 3.15a). Their share of banking system risk, increased from 40% in 2001 to 55% in 2009 (Figure 3.15b). Rising bank distress (the probability of default) of the four banks and their expanding balance during the Great Recession (2007-2009) contributed to their surging risk contribution. The assets of JPM, BAC and WFC surged during the recession, while Citigroup's size declined with asset sales. The systemic risk contribution of each member of the "Big Four" is discussed in Appendix H.

Figure 3.15: Expected Shortfall (ES): The Big-Four versus Others (2001-2015)

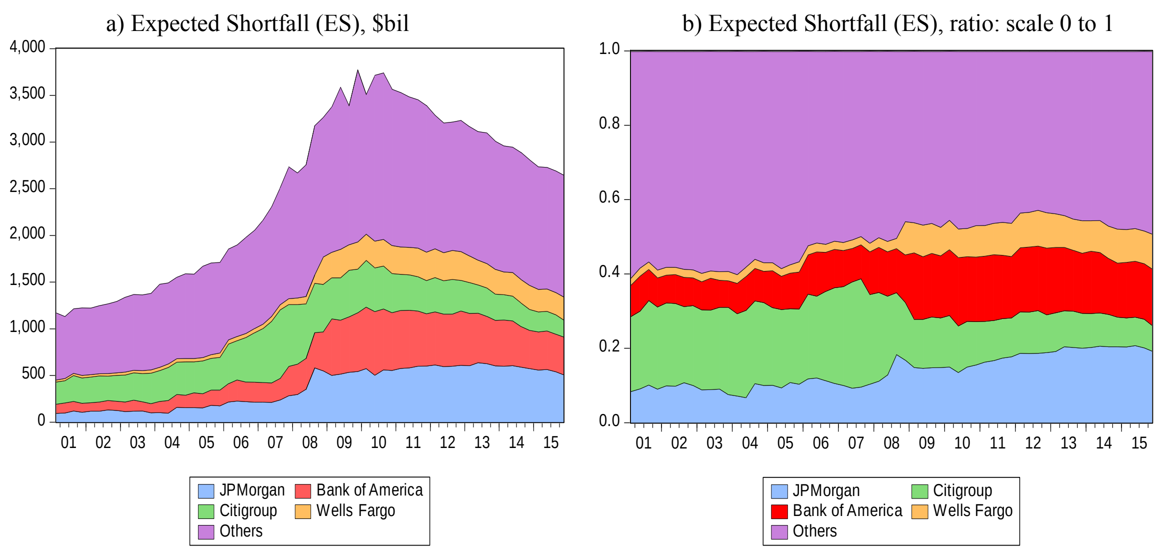
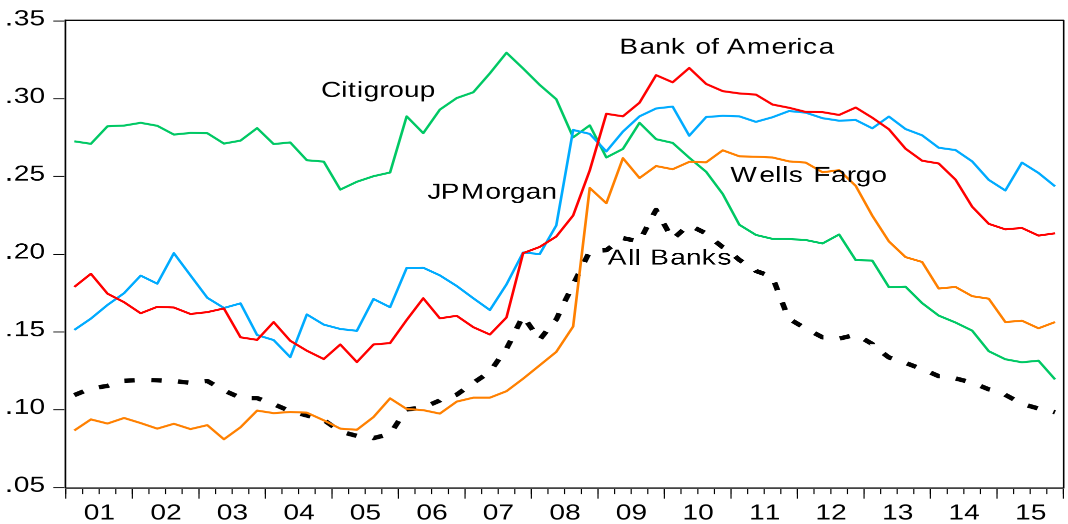


Figure 3.15a compares the Expected Shortfall (\$bil.) for bank cohorts: Big Four (Citigroup, Bank of America, JP Morgan and Wells Fargo). Expected Shortfall is $ES_K(Loss \geq VaR_\alpha)$, where K is a bank (e.g. Citigroup). Figure 3.15b compares the Expected Shortfall shares of Big Four banks. Expected Shortfall for each bank is $ES_K(Loss \geq VaR_\alpha)$, where K is a bank (e.g. Citigroup) The total Expected Shortfall is $ES(Loss \geq VaR_\alpha)$. The individual bank ES share is $ES_K(Loss \geq VaR_\alpha)/ES(Loss \geq VaR_\alpha)$ ratio, scaled from 0 to 1.

The systemic risk contribution of the group as measured by ES has trended down since 2009 as each bank's distress ebbed; a recovering economy and tighter lending standards helped put their balance sheets in order. We present the individual riskiness of each bank as measured by the systemic risk indicator in Figure 3.16. Our results show that the risk level of the big four banks is generally higher than the banking system average. The individual riskiness of each one, except Citigroup, surged sharply during the recession due to rising bank distress. Citigroup's risk level was the highest of the four until 2008, but it has declined since then with distressed asset sales. The risk level of each bank trended down since the recession, but stayed above the banking system average.

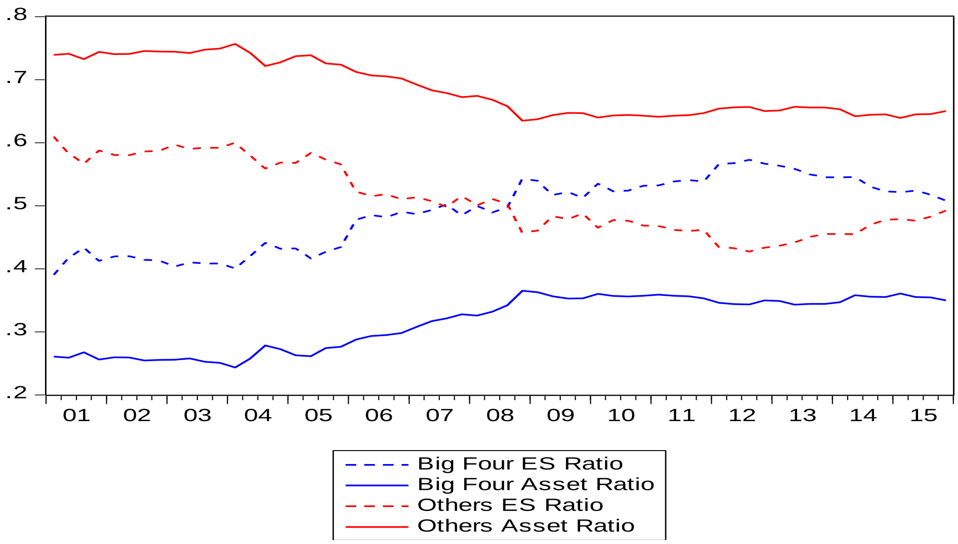
Figure 3.16: Systemic Risk Indicators: The Big-Four versus All Banks, Ratio: scale 0 to 1 (2001-2015)



In Figure 3.16, systemic risk indicators of Big Four banks are compared. The systemic risk indicators of banks are Expected Shortfall for *each* bank scaled by the sum of the liabilities of *each* bank: $ES_K(Loss \geq VaR_\alpha)/S_K$, where K is a bank (e.g. Citigroup)

The growing systemic importance of the big four is also evident from the asset ratio-ES ratio comparison (Figure 3.17). Our results show that the four largest U.S. banks' contribution to systemic risk among all banks has been greater than their assets share since 2001. Put differently, the big four have been always systemically more important than their asset sizes indicate. At the beginning of 2001, the four largest banks' asset- and systemic-risk shares were, respectively, 0.26 and 0.40. These figures grew to 0.35 and 0.50 by the end of 2015Q4, which shows that these banks became larger and their systemic importance increased in tandem over time (Figure 3.17). Our results also show that nearly half of the systemic risk is created by the largest four banks, and supports their close monitoring by regulators.

Figure 3.17: Comparing Assets-to-Total Assets ratio with Expected Shortfall (ES)-to-Total Expected Shortfall (ES), Ratio: scale 0 to 1: Big Four vs Others (2001-2015)



In Figure 3.17, the asset ratio is the ratio of total assets of the Big Four (Citigroup, Bank of America, JP Morgan and Wells Fargo) to sum of all bank assets (Big Four plus Others). The Expected Shortfall (ES) ratio of Big Four is the ratio of the ES of the Big Four to total ES in the banking system. The Big Four ES share is $ES_K(Loss \geq VaR_\alpha)/ES(Loss \geq VaR_\alpha)$ ratio, where K represents Big Four.

3.4.6.1 Acquisitions & Mergers in the Expected-Shortfall Approach

The additive property of the expected-shortfall approach makes it useful in aggregating the ES of banks in a group to generate totals. Aggregation is done across a group of banks for a particular time period. Thus, data discontinuity due to acquisitions and mergers in the banking sector does not pose a problem. In this section, we show how acquisitions and mergers are handled in the ES approach, using WFC's acquisition of

Wachovia Corporation (Wachovia) as an example. Wachovia, a financial holding company, was the fourth largest banking organization in the United States (after BAC, JPM and Citi), ahead of Wells Fargo Corp. with slightly over $800 billion in holding company assets in June, 2008. Wachovia's subsidiary banks were the nation's largest holders of payment-option adjustable-rate mortgages (ARMs) and were suffering from the housing market downturn in mid-2008[109]. In September 2008, the nation's second largest holder of payment-option ARMs, Washington Mutual Inc. (WaMu), filed for Chapter 11 bankruptcy protection, a move driven by its holdings of payment-option ARMs. Its failure added to existing concerns among Wachovia's depositors and creditors. Wachovia's financial condition deteriorated rapidly through the rest of 2008, largely because of losses in its portfolio of payment-option ARMs, and it was acquired by WFC in December, 2008[110].

WFC's assets and liabilities nearly doubled with its Wachovia acquisition (Figure 13.18a): WFC acquired a company as large as itself. However, because Wachovia was distressed and struggling to stay buoyant, with this acquisition, WFC's systemic risk contribution as measured by ES increased 150%, from $78 billion to $280 billion in 2008Q4 (Figure 13.18b). More specifically, in 2008Q3, right before the acquisition, WFC's systemic risk contribution was $78 billion. Wachovia's systemic risk contribution, on the other hand, was nearly twice WFC's at $160 billion in the same period. Thus, the sum of ES in both banks was $238 billion. With the acquisition, WFC's ES increased to $280 billion in 2008Q4, some $40 billion (or 15%) higher than the sum of the two banks'

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109 A payment-option ARM is a monthly adjusting adjustable rate mortgage (ARM), which allows the borrower to choose between several monthly payment options, including a fully amortizing payment, an interest-only payment or a payment of any amount at or above the minimum. See "Crisis and Reponses: An FDIC History, 2008-2013," FDIC report, 2017.

110 Crisis and Reponses: An FDIC History, 2008-2013, FDIC report, 2017.

ES in 2008Q3 (Figure 13.18b). Even though the acquisition saved Wachovia from a brutal collapse, the combined balance sheet continued to suffer amid a rapidly deteriorating financial system in 2008Q4 (Figure 13.18b). The acquisition also significantly raised WFC's individual riskiness as measured by the systemic risk indicator, from 15% to 24% (Figure 13.18c). The increase in the risk indicator is smaller than the increase in the sum of the two company's ES because scaling the ES with total liabilities (the sum of the liabilities of the two companies) led to some of the ES in Wachovia being absorbed by WFC. These results show that the ES approach handles mergers and acquisitions quite well, due to its additive property.

Figure 3.18: Change in Wells Fargo's Balance Sheet and Systemic Risk Components (2001-2015)

Figure 3.18a: Assets vs Liabilities, $bil.

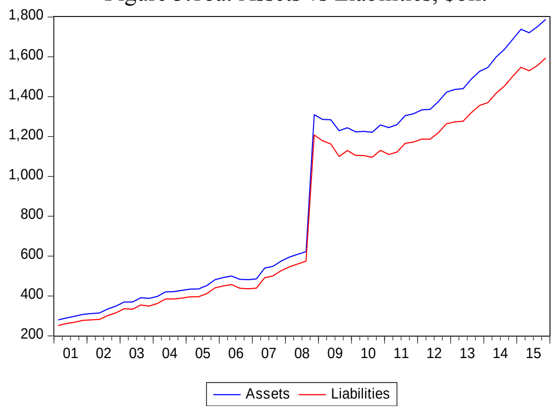


Figure 3.18b: Expected Shortfall (ES), $bil.

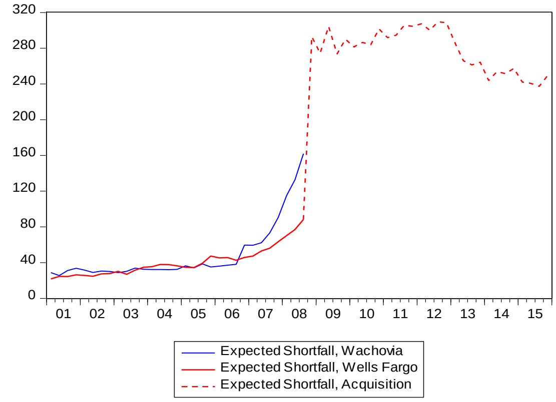
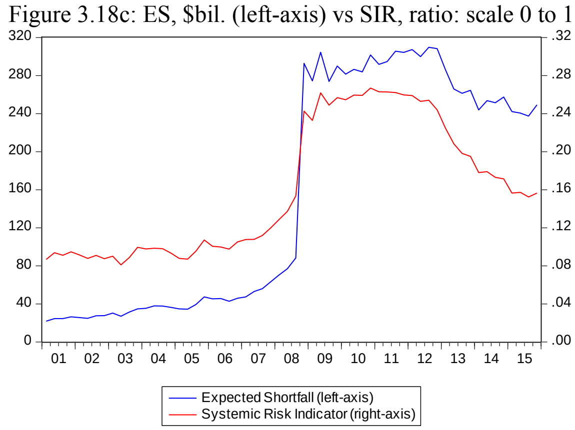


Figure 3.18c: ES, $bil. (left-axis) vs SIR, ratio: scale 0 to 1 (right-axis)



In Figure 3.18a, Assets and Liabilities in $bil. In Figure 3.18b shows Expected Shortfall (*ES*), $ES(Loss \geq VaR_{\alpha})$, for Wells Fargo and Wachovia before Wells Fargo's acquisition of Wachovia, and the *ES* after the acquisition. In Figure 3.18c, *ES* is $ES(Loss \geq VaR_{\alpha})$ and systemic risk indicator (SIR) is $ES(Loss \geq VaR_{\alpha})/S$, where *S* is total bank liabilities.

3.4.6.2 Comparing the ES Approach with Other Systemic Risk Methods for the "Big Four"

Next, we compare our results for the big four with results of other methods proposed in literature to identify systemic risk contributions. The comparison shows that our estimations are broadly in line with other methods' outcomes. The results are presented in Tables 3.3 and 3.4. Table 3.3 presents the systemic risk contribution of the four largest banks based on the ES approach that we use in this paper and the CES method proposed in Banulescu and Dumitrescu (2015), in seven time periods. The time periods are selected according to Banulescu and Dumitrescu (2015). The ES approach puts the systemic risk contribution of the four largest banks at 43%-44% before the financial crisis (Table 3.3: col 2007Q2, 2007Q4, ES). According to the CES method, the aggregate risk contribution of the four largest bank is 31%-34% (Table 3.3: col 2007Q2, 2007Q4, CES). There is a ten-percentage point gap between the outputs of these models in the pre-crisis period. However, in the crisis period (Table 3.3: col 2008Q3, 2009Q1), both methods show nearly the same amount of systemic risk contribution, around 45%. The results are also quite similar in the post-crisis period (2010Q2). Comparing both methods according to individual bank systemic risk contribution shows that Citi poses the highest total risk before the crisis period (Table 3.3: col 2007Q2, 2007Q4, row one). The risk contributions of BAC and JPM rose during the crisis while Citi's share declined (Table 3.3: col 2008Q1-2009Q1, row one). WFC's contribution remained lowest during the period from 2007 to 2010.

Table 3.2: Systemic Risk Contribution of Four Largest Banks in US, by Two Methods: Expected Shortfall (ES) and Component Expected Shortfall (ES), %

	2007Q2		2007Q4		2008Q1		2008Q2		2008Q3		2009Q1		2010Q2	
	ES	CES	ES	CES	ES	CES	ES	CES	ES	CES	ES	CES	ES	CES
BAC	8%	8%	10%	10%	11%	11%	11%	10%	11%	15%	16%	10%	16%	13%
C	25%	13%	22%	9%	21%	8%	19%	9%	15%	9%	11%	5%	11%	12%
JPM	8%	9%	9%	8%	10%	10%	12%	10%	17%	11%	13%	15%	12%	12%
WFC	2%	5%	2%	5%	2%	7%	3%	6%	3%	7%	7%	16%	7%	11%
Total	44%	34%	43%	31%	44%	35%	44%	35%	44%	40%	48%	46%	46%	47%

The ES is the systemic risk contribution of a bank, which is Expected Shortfall for a bank, $ES(Loss \geq VaR_{\alpha})$, as a share of total Expected Shortfall in the banking system. CES figures show the systemic contribution of a bank, and estimated by (Banulescu and Dumitrescu, 2015).

Next, we include another systemic risk method, SRISK, into our comparison with results for the big four from Banulescu and Dumitrescu (2015). More specifically, we rank the four banks according to their contributions to aggregate risk as estimated by three systemic risk measurement methods: ES, CES and SRISK (Table 3.3). The comparison shows that while no method perfectly matches another, some common results can be deduced from the outcomes of all methods (Table 3.3). WFC turns out to be the lowest systemic-risk contributor using all the measures during both crisis and non-crisis periods. Citi was the highest risk contributor until 2008Q3, then its contribution declined. JPM's systemic risk contribution surged with the acquisitions of Bear Sterns and WaMu in the second and third quarters of 2008, and remained high thereafter. The results for BAC are somewhat elusive. However, we can still argue that all methods point to the increasing risk contribution of BAC in the post-crisis period (2010Q2). Only our ES approach shows BAC as the highest risk contributor in 2009Q1, a period when BAC was struggling to digest the losses from Merrill Lynch, which it acquired in the previous quarter, while still bearing losses from the failed mortgage lender, Countrywide. The cross comparison of our ES approach with other methods proposed in the literature shows that results from our method for the four largest banks line up well with the results from other methods. The benefit of our method is that coverage can be expanded to include all banks in the universe. It may therefore give a better assessment of aggregate systemic risk.

Table 3.3: Ranking the Systemic Risk Contribution of Four Largest Banks in US according to three Systemic Risk Methods: ES, CES and SRISK

2007Q2			2007Q4			2008Q1			2008Q2			2008Q3			2009Q1			2010Q2		
ES	CES	SRISK	ES	CES	SRISK	ES	CES	SRISK	ES	CES	SRISK	ES	CES	SRISK	ES	CES	SRISK	ES	CES	SRISK
C	C	C	C	BAC	C	C	BAC	C	C	JPM	C	JPM	BAC	C	BAC	WFC	C	BAC	BAC	BAC
JPM	JPM	BAC	BAC	C	BAC	BAC	JPM	JPM	JPM	BAC	JPM	C	JPM	JPM	JPM	JPM	JPM	JPM	JPM	C
BAC	BAC	JPM	JPM	JPM	JPM	JPM	C	BAC	BAC	C	BAC	BAC	C	BAC	C	BAC	BAC	C	C	JPM
WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	WFC	C	WFC	WFC	WFC	WFC

The ES is the systemic risk contribution of a bank, which is Expected Shortfall for a bank, $ES(Loss \geq VaR_{\alpha})$, as a share of total Expected Shortfall in the banking system. CES and SRISK figures show the systemic contribution of a bank, and estimated by (Banulescu and Dumitrescu, 2015).

3.5 Policy Implications and Concluding Remarks

The systemic importance of financial institutions is the key input for policy makers whose objective is preserving financial stability. In this chapter, we shed light on the systemic risk profile of subgroups of bank holding companies and try to demonstrate how systemic risk has evolved within the banking industry as the sector has become more consolidated. The analysis in this chapter delivers four important messages: (i) Diversification in terms of asset ownership reduces systemic risk in the banking system. Put differently, the concentration of assets in a small number of large banks elevates systemic risk. Our results show that large banks, in general, are riskier and contribute proportionately more to systemic risk than do small banks. This is true particularly when they are not well capitalized and have unstable funding. However, becoming less risky does not mean that their systemic risk contribution necessarily declines, because aggregate risk contribution also depends on the size of the bank. Therefore, micro-prudential regulation, which focuses on individual bank risk, may not fully reflect the systemic ramifications of large banks' risk-taking: the same capital or funding deficiencies create more systemic risk when they occur in large banks (Laeven et al. 2016). This requires more stringent capital and liquidity standards for large banks (due to systemic risk, i.e., macro-prudential reasons) in line with the approach of imposing capital surcharges on systemically important banks taken by Basel III. To strengthen the liquidity positions of large financial institutions, the U.S. Federal Reserve adopted a “liquidity coverage ratio” rule in April, 2017. This rule proposes standard minimum liquidity requirements for large and systemically important banking institutions. With this rule, these institutions are required to hold minimum amounts of high-quality, liquid assets, such as central-bank reserves and government and corporate debt, that can be converted quickly and easily into cash. With this liquidity cushion, large banks are expected to be able to continue daily operations during a liquidity shortage. To strengthen capital positions, the Fed adopted capital rules under the Basel III accord in January, 2014. The objective of the capital rules is to ensure that banks maintain strong capital positions that will enable them to continue lending to creditworthy households and businesses even after unforeseen severe downturns. These measures constitute a big improvement over the previous regulatory framework; however, their effectiveness can only be tested during crisis periods. (ii) Financial services holding companies are generally riskier and pose a proportionately larger systemic risk than do bank holding companies. Diversifying business operations by expanding into nontraditional operations without limitation does not reduce the systemic risk created by FHCs. The risks of large banks are especially high when they engage in more market-based activities or are organizationally complex (Laeven et al., 2016). (iii) Regulators’ recommendation that SIFIs face capital surcharges according to their contributions to aggregate risk in the financial system is a sound policy (Banulescu and

Dumitrescu, 2015). SIFIs are larger than they were during the financial crisis, and their systemic risk has steadily increased since 2001. (iv) A negative impact of consolidation in the banking system is a rising systemic-risk contribution. Nearly half the systemic risk in the U.S. banking system is created by the four largest banking institutions, supporting the notion of too-big-to-fail. Large banks, on average, are riskier and create more systemic risk than do smaller banks, but the case for economies of scale in large banks cannot be dismissed (Laeven et al., 2016). Therefore, an "optimal" bank size is highly uncertain, and regulations that restrict outright bank size may be imprecise and difficult to implement. Nevertheless, our results suggest that policy makers should be concerned about the recent trend of consolidation in the banking system.

In this chapter, we provide a survey of systemic risk profiles for several U.S. bank holding company cohorts at a high level with an approach that has recently gained attention in the literature. One path to expanding our findings involves improving systemic-risk measures by incorporating more precise common-factor loadings (the tendency to fail with other banks) and loss-given default metrics into estimations. Our results can also be improved by exploring the link between bank characteristics and systemic-risk measures. After investigating the systemic- risk contributions and individual risk profiles of bank cohorts, a natural question involves the bank characteristics that lead to systemic risk. We believe that further research on these two fronts will yield valuable contributions to the systemic-risk literature.

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APPENDICES

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, I 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 fairly 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.

B. TAYLOR RULE DISCUSSION (RELATED TO LITERATURE)

Negative Taylor Rule Rate (Related to Literature): A strand of papers in the literature claims that the Fed's 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 intend to use the TRR for the period that FFR remained at zero bound: if the Taylor rule 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 quantitative easing 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 1.2).

Discussing Estimation Results: According to the results, reported in Table 1.2, 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 R^2 of 0.59[111]. 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 TTR 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

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111 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.

positive territory in the last quarter of 2013. Figure 1.2 compares our estimate with the actual FFR and the generic TTR. The model estimate closely follows the generic rule rate constructed according to Rosenberg (2010). Therefore, we use the estimated TRR in our model.

C. LIST OF 34 SYSTEMICALLY IMPORTANT BANKS (SIB)[112]

	SIB Name	Designation
1)	Ally Financial Inc.	D-SIB
2)	American Express Company	D-SIB
3)	BancWest Corporation	D-SIB
4)	Bank of America Corporation	G-SIB
5)	The Bank of New York Mellon Corporation	G-SIB
6)	BB&T Corporation	D-SIB
7)	BBVA Compass Bancshares, Inc.	D-SIB
8)	BMO Financial Corp.	D-SIB
9)	Capital One Financial Corporation	D-SIB
10)	CIT Group Inc.	D-SIB
11)	Citigroup Inc.	G-SIB
12)	Citizens Financial Group, Inc.	D-SIB
13)	Comerica Incorporated	D-SIB
14)	Deutsche Bank Trust Corporation	D-SIB
15)	Discover Financial Services	D-SIB
16)	Fifth Third Bancorp	D-SIB
17)	The Goldman Sachs Group, Inc.	G-SIB
18)	HSBC North America Holdings Inc.	D-SIB
19)	Huntington Bancshares Incorporated	D-SIB
20)	JPMorgan Chase & Co.	G-SIB
21)	KeyCorp	D-SIB
22)	M&T Bank Corporation	G-SIB
23)	Morgan Stanley	G-SIB
24)	MUFG Americas Holdings Corporation	D-SIB
25)	Northern Trust Corporation	D-SIB
26)	The PNC Financial Services Group, Inc.	D-SIB
27)	Regions Financial Corporation	D-SIB
28)	Santander Holdings USA, Inc.	D-SIB
29)	State Street Corporation	G-SIB
30)	SunTrust Banks, Inc.	D-SIB
31)	TD Group US Holdings LLC	D-SIB
32)	U.S. Bancorp	D-SIB
33)	Wells Fargo & Company	G-SIB
34)	Zions Bancorporation	D-SIB

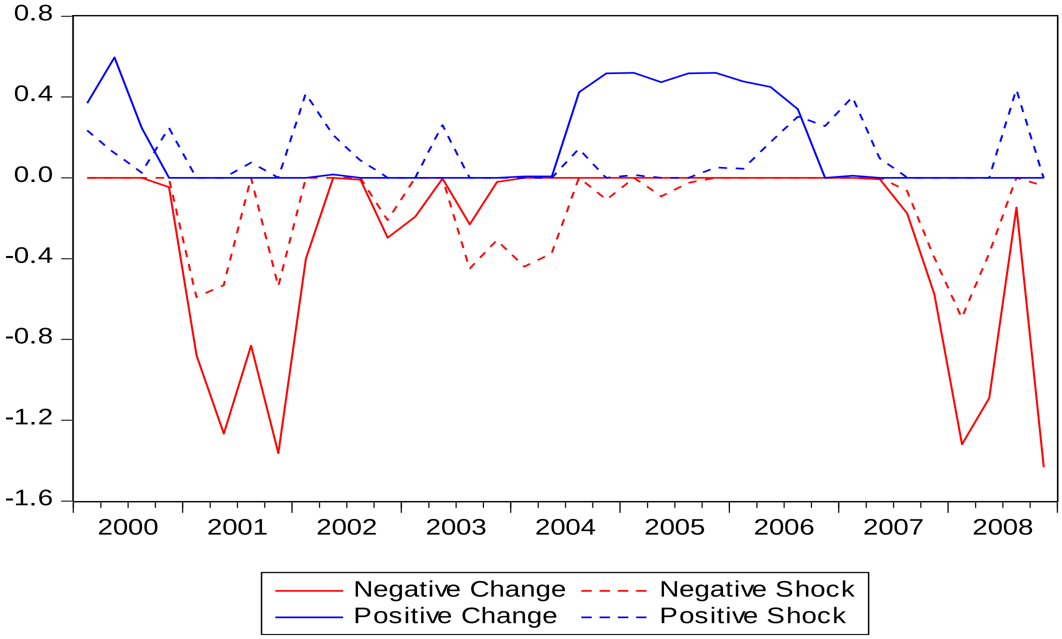
[112] "D" stands for domestic and "G" stands for global. We included 21 banks (highlighted above) in our robustness tests. All Systemically Important Banks (SIB) that participated in 2017 Stress Tests: https://www.federalreserve.gov/newsevents/pressreleases/bcreg20170203a.htm

D. INTEREST RATE SHOCKS DURING THE SAMPLE PERIOD

Negative Shocks ($w_t^- = \min[0, w_t]; w_t \leq 0$): There are three main blocks of negative shocks ($w_t \leq 0$) during the sample period: 2001Q1-Q4, 2003Q3-2004Q2, and 2007Q3-2008Q2 (Table 2.6, column V; Figure D.1). Two of these blocks overlap with recessionary periods while the third is in an expansionary period. Specifically, the Fed cut the FFR target in every quarter from 2001Q1 to 2002Q1. This first block of shocks overlaps with this monetary easing period. We observe three large quarterly negative shocks (Table 2.6, column V): 59 bps in 2001Q1, 53 bps in 2001Q2, and 54 bps in 2001Q4. These shocks are residuals from equation (1). By comparison, the Fed reduced the target FFR 88 bps in 2001Q1, 126 bps in 2001Q2, and 136 bps 2001Q4 (Table 2.6, column III). This suggests that the Fed's rate cuts were very aggressive: e.g., the Fed cut the rate by 88 bps in 2001, but 59 bps of it came as a surprise; the other 29 bps was determined by macro factors. The 2001 recession was a small recession; output shrank only for two, non-consecutive quarters and in each, the rate of contraction was barely larger than 1% (-1.1% in 2001Q1 and -1.3% in Q3). However, the Fed swiftly responded to rapidly eroding confidence in the economy as a result of "tight" conditions in some segments of the financial markets due to falling prices of high-tech stocks[113]. The negative shock in 2001Q4 was due to the Fed's aggressive action to ease anxiety in financial markets following the 911 attacks. The FOMC lowered the FFR target by 175 bps in the three months following the attacks.

113 FOMC Statement (Press Release) January 2001.

Figure D.1: Federal Funds Rate Changes (quarter-over-quarter) versus Shocks, percentage points (2000Q1-2008Q4)



Note: Federal funds rate is the target rate as announced by Fed. The shocks are the difference between the announced target and the fitted target (residuals). We sort the residuals by sign to create positive and negative shocks. Similarly, the rate changes are sorted by sign to create positive and negative changes.

The second block of negative shocks, from 2003Q3 to 2004Q2, overlaps with the expansion period from 2002Q1-2007Q3[114]. The level of the target FFR is on average 40 bps lower than it should be in this period, according to our model (eq.1)[115]. The target FFR remained flat at 1% from 2003Q3 to 2004Q2, but our model results point to an overly loose monetary policy for this period and suggest that the target FFR should have been 1.4%, instead of 1%. This indicates that the residual or the negative shock was -40 bps. The U.S. economy grew at 3.8% and 3.1%, yearly, in 2003 and 2004, respectively. However, the slow growth of the labor market in 2003, and, particularly, the perceived deflationary

114 According to the NBER, 2002Q1 to 2007Q3 is an expansion period.

115 Many researchers argue that the Fed kept the policy rate too low for too long after the 2001 recession, see (Taylor 2007).

pressures in 2003 and 2004, prompted policymakers to keep rates low[116]. Separately, the Fed adopted a communication strategy as part of its monetary policy in this period. The FOMC noted in August 2003 meeting that policy was likely to remain accommodative for a "considerable period", and removed the strategy later in its May 2004 meeting. The central role of this strategy regarding the future path of the monetary policy was low rates of inflation. In June 2003, the Fed estimated a probability that economy would experience price deflation over 2004 and 2005 of about 40 percent (Dokko et al., 2009)[117].

The third block coincides with the Great Recessionary period of 2007-2009. The target FFR was reduced in each quarter from 2007Q3 to 2008Q4 (Table 2.6, column III). There are four quarterly negative shocks in this period, from 2007Q3 to 2008Q2, of which the largest was -69 bps in 2008Q1. The Fed cut the target FFR by132 bps in this quarter. The rest of the negative shocks in this block were relatively small. These findings again suggest that target FFR cuts were very aggressive in response to recessions. The 5% unemployment rate and 2.5% inflation prevailing in 2007 did not require sharp rate cuts, yet the Fed acted swiftly to "forestall" adverse effects of (i) the tightening of credit conditions since the summer of 2007 when the subprime crisis began and (ii) the "intensifying" housing market correction (FOMC Statement; Sept, 2007). The economy formally entered a recession in December, 2007, but the economy's fundamentals did not deteriorate sharply: The Fed's actions in the first half of 2008 aimed at alleviating anxiety

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116 The unemployment rate declined only 20 bps in 2003 to 5.8%. More importantly, the FOMC inflation forecast was in the range of 1.25-1.5% in the beginning of 2003, and 1-1.25% in the beginning of 2004. Realized inflation at 3.0% in 2004 was mostly due to rising oil prices. Another reason for keeping interest rates low was the housing market: "Greenspan realized the only way out was to push interest rates even lower to ignite a housing boom" (Zandi, 2008).

117 Dokko et al., 2009 acknowledge that the motivation for a communication strategy involved settings in which risks to the outlook or the perceived costs of missing an objective are markedly asymmetric. Under such conditions, policymakers may respond by adjusting policy in a way that would not be justified solely by the modal outlook for output and inflation gaps; instead, policy actions may be guided by the entire distribution of potential outcomes and associated costs. As a result, the policy stance in such circumstances is likely to differ appreciably from what would be chosen if policy were guided solely by the modal outlook.

in financial markets and preventing it from spilling over to the broader economy. Therefore, our model points to negative shocks in this period.

Positive Shocks ($w_t^+ = \max[0, w_t]; w_t \geq 0$): We observe two main blocks of positive shocks: 2002Q1-2002Q3 and 2006Q2-2007Q2 (Table 2.6, column VI). The first block reflects Fed's response to 911 attacks. To reduce volatility in financial markets following the attacks, the Fed acted aggressively to cut the target rate from 3.50% in September to 1.75% until January, 2002, by a sharp 175 bps, then, kept the target rate flat until 2002Q3. This created a positive shock. More specifically, our model predicts target rates that are 71 bps (cumulative) lower than the actual rate of 1.75 from 2002Q1-2002Q3 (Table 2.6, column VI). This implies a *tight* policy because macroeconomic conditions suggest a rate cut while the actual target was kept unchanged. We attempt to explain the tight policy in this period with extra measures that the Fed took in response to 911 attacks. In addition to its sharp rate cut (from Sep 2001 to Jan 2002), the Fed took measures to restore confidence in the financial system by providing liquidity in a number of ways: (i) direct lending through the discount window; (ii) repurchase agreements by the New York Fed desk; (iii) extension of float; and (iv) swap lines to permit foreign central banks to meet their liquidity needs in US dollars (Neely, 2002; Lacker, 2003). Inflation remained subdued, below 1.5% in 2002. Therefore, it is likely that the Fed saw its liquidity measures as sufficiently bold, and decided not to cut the target rate further[118].

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[118] The US economy grew 2% in 2002, which is not strong enough for a recovery following a recession. However, the Fed's main concern was inflation. Because inflation expectations remained weak, the Fed cut the policy rate further to 1% in 2003.

The second, larger, block coincides with the monetary tightening period. The target rate was raised from 4.9% in 2006Q2 to 5.25% in 2006Q3, and kept flat until the second half of 2007 (Table 2.6, column I). In this block, the positive shock is nearly, on average, 25 bps, which suggests that given the pace of output growth and inflation, monetary policy was tighter than our model points to. Inflation remained the Fed's main concern in 2006 and 2007 as it increased from 2.1% in 2006Q1 to 2.7% in 2006Q4[119]. The Fed kept its target FFR at 5.25% in 2007, but continued to worry about inflation. In the first FOMC meeting of 2007 Fed chairman Bernanke said: "My recommendation also is to take no action and to maintain a bias toward further tightening". However, the Fed refrained from hiking rates further in 2007 because of concerns about the housing market. House prices mildly declined in the second and third quarters of 2006 (according to the Case-Shiller price index), and resumed weak growth in the fourth quarter. This was considered a sign that the housing market was stabilizing, not the start of a crash: "The housing market has looked a bit more solid, and the worst outcomes have been made less likely", Bernanke said in the meeting. In the same meeting, Bernanke also said that policymakers thought a further rate hike could put pressure on the housing market. The Fed did not tighten monetary policy further (did not raise the target rate) after setting the target rate at 5.25%. However, our model predicts to a lower target rate based on the underlying macroeconomic conditions implying that the announced rate was too high in 2006Q2-2007Q2 period ($w_t \geq 0$).

[119] The economy grew 2.6% in 2006 and 2.5% in 2007, and the unemployment rate remained flat at 4.6% in both years.

Downward Bias in Fed's Monetary Policy Decisions: Figure D.1 presents the interest rate shocks and compares them with policy rate changes. The scale of rate shocks, positive and negative, suggests that surprises (w_t) were skewed to the negative side; the average negative shock during the sample period of 2001-2008 was 16 bps while the average positive rate shock was less than 9 bps, showing that the Fed's policy decisions in the 2001–2008 period were biased downward. Two recessions and deflation fears drove the downward bias. The Fed has been blamed for cutting rates too much and keeping them too low for too long in the run-up to the recent recession (Taylor, 2009). Our model results support this claim. In particular, 2003Q3-2004Q2 is a negative shock period where the model estimates 40 bps tighter monetary policy (w_t = -40bps) for each quarter. That's, the policy rate remained 40 bps lower than what would the macroeconomic conditions demanded in each quarter in this period.

The high correlation of the policy rate cuts with negative shocks (Rho = 0.63) also points to downward bias in Fed decisions (Figure D.1). A high positive correlation between policy rate cuts and negative shocks in a particular period shows that the timing of Fed's target policy rate cuts was broadly in line with the timing of our FFR model (eq.1) predicting a lower level of target rate, though rate cuts were excessive and created surprises on the down side (because our model predicts negative shock). More precisely, the FFR model predicts a lower policy rate, but Fed cuts the target rate for that period to a lower level than our model predicts, which creates negative shocks[120]. The policy rate decisions

[120] If the Fed does not change target policy rate while our model predicts a lower rate or the Fed cuts the rate to a level that is higher than our model predicts, it will point to a positive shock. If the Fed cuts the rate to exactly what our model predicts, then the shock is zero and correlation is nil. Therefore, a positive correlation with target policy rate cut occurs only if there is a negative shock.

in 2001Q1-Q4, and 2007Q3-2008Q2 periods are good examples. They create negative shocks and a positive correlation between shocks and the policy decisions.

On the contrary, the correlation between positive shocks ($w_t \geq 0$) and rate hikes is almost nil: the two main blocks of positive shocks occurred when either the Fed kept rates flat or cut rates to a level that is higher than our model predicts. More specifically, the monetary tightening cycle (raising the target rate) in 2001-2008 period took 9 quarters: it began in 2004Q3 and ended in 2006Q3. The target policy rate was either reduced or kept unchanged in the rest of the time. The zero correlation between the rate hikes and positive shocks suggest that rate hikes put the target rate to a level that is broadly in line with what our FFR model (eq.1) predicts both in timing and the magnitude of the hike (except 06Q2 and 06Q3 in which the rate hike is excessive and puts the target rate to a level above the predicted value). However, it is either the rate cuts that came in short, or the rate left unchanged while the economic conditions demanded a lower rate than actual, e.g. 2001Q1 to 2001Q3 or 2006Q4 to 2007Q2, which created positive shocks.

It is important to note that there are two exceptions: one negative (2003Q3-2004Q2) and one positive (2006Q4 to 2007Q2). Both shocks occurred when the Fed kept the target policy rate flat. In these periods, correlation of shocks with the policy rate change is nil. However, we can still conclude that the Fed's policy actions adopted a downward bias between 2001Q1 and 2008Q4; it cut the rates too much during the monetary easing cycles (2001Q1-Q4 and 2007Q3-2008Q2), while the rate hikes (2004Q3-2006Q3) put the target policy rate roughly to the levels as predicted by our model.

E. ROBUSTNESS CHECK: NON-PERFORMING ASSETS RATIO (PROXY FOR DISTRESS)

All Bank Holding Companies: Static and Dynamic models: We estimate our models by replacing bank distress indicator with non-performing assets ratio as a robustness check. The estimation results for the *static* model are presented in Table E.1 and for dynamic model in Table E.2. In both tables, the results for the model without bank balance sheet indicators are presented in column I and those for the full model (that includes bank balance sheet indicators) in column II. The non-performing asset ratio essentially measures credit risk and it is commonly used in literature as an asset quality indicator: a high value of this ratio indicates higher credit risk. However, it is also used in risk-taking papers as a dependent variable based on the truism that high risk-taking results in high losses (Delis and Kouretas, 2011). Therefore, we use it for a robustness check for our models as a distress proxy, but caution that it is not as a good a distress proxy as the distress indicator used in our main models.

Results based on non-performing assets ratio are directionally similar to those based on bank distress indicator, with one exception in the sample disaggregation (detailed in the next section). Specifically, both positive and negative interest rate shocks create added distress, but the impact magnitude of a positive shock is nearly three times that of a negative shock, as it was the case for the bank distress indicator): $\sum_{j=1}^{4} \beta_j^{+}$= 0.0085 vs $\sum_{j=1}^{4} \beta_j^{-}$= -0.0025. Both effects are significant at 1% (Table E.1, column II, rows (1) and (2)). The macroeconomic drivers (real GDP and inflation) have the correct signs, negative and positive respectively, and they are significant at the 1% level (Table E.1, column II, rows

(4) and (5)). The dissimilar magnitudes of the effects for positive and negative shocks indicate *asymmetry* between the effects of these shocks. The Wald-test results reject the symmetry of the effects (Table E.1, Wald-tests, column II, row (3)). The results on the impact of bank balance sheet indicators on non-performing assets ratio are also directionally similar to the ones from the model with a bank distress indicator, except for the hedge ratio. The coefficients for profitability and efficiency ratio all have negative signs and asset size has a positive sign, all significant at varying levels. The hedge ratio is found to be insignificant. Observing similar results, with one exception (hedge ratio), in the model with a non-performing asset ratio serves as a robustness test for the bank distress indicator. However, the models using the bank distress indicator yield slightly higher measures of goodness of fit (R^2) than those with non-performing asset ratio. This may indicate that the former is a better gauge for bank distress than the latter. The statistically significant coefficient for the hedge ratio with the correct sign (negative) also strengthens the view that the bank distress indicator is superior.

The estimation results for *dynamic* models are broadly in line with those we reported from the static model and similar to the ones from the models that use bank distress indicator as a distress proxy (Table E.2, column II). The impact of shocks to target FFR on bank distress is positive for both positive and negative shocks (both raise the distress on banks), and they are both significant at 1% (Table E.2, Wald-tests, column II, row (1) and (2)). The magnitude of the impact of a positive shock is nearly three times that of a negative shock indicating *asymmetry* in the effects of these shocks. Wald-test results reject the hypothesis of similarity of the shock effects (Table E.2, column II, row (3)). All the macro drivers have the expected signs, similar to the ones in the static model and the ones from the models that use bank distress indicator as a distress proxy.

Table E.1: All Bank Holding Companies: Static Model

Dept. variable (Non-performing Assets Ratio)	(I)	(II)
	All	All
Positive shock	0.0113***	0.0085***
Negative shock	-0.0033***	-0.0025***
GDP growth	-0.0002***	-0.00007**
Inflation	0.0012***	0.00095***
Profitability		-0.0124***
		(-2.79)
Efficiency		-0.0053***
		(-10.76)
Size		0.0011***
		(6.78)
Hedging		0.0002
		(0.64)
Constant	-0.0041***	-0.014***
	(-17.57)	(-7.68)
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers		
(1) $\sum_{j=1}^{4} \beta_j^{+} = 0$	0.000	0.000
(2) $\sum_{j=1}^{4} \beta_j^{-} = 0$	0.000	0.000
(3) $\lvert\sum_{j=1}^{4} \beta_j^{+}\rvert - \lvert\sum_{j=1}^{4} \beta_j^{-}\rvert = 0$	0.000	0.000
(4) $\sum_{j=1}^{4} \rho_j = 0$	0.000	0.018
(5) $\sum_{j=1}^{4} \gamma_j = 0$	0.000	0.000
# of obs	50142	48302
R-sq	0.102	0.113

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses.
Cluster-robust standard errors. Walt tests are conducted to measure the joint significance of the coefficients.

$$\Delta s_{i,t} = \alpha + \mu_i d_i + \delta_k' bc_{i,t-4}^{k} + \sum_{j=1}^{4} \rho_j y_{t-j} + \sum_{j=1}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^{+} w_{t-j}^{+} + \beta_j^{-} w_{t-j}^{-}) + u_{i,t}$$

This is the static equation (eq 2’). Column I shows the results from the model without bank-level indicators. Column II shows the results from the full model. $s_{i,t}$ is distress indicator, Δ is the 1st difference, $bc_{i,t-4}^{k}$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term. β_j^{+} is the coefficient for positive shocks and β_j^{-} is the coefficient for negative shocks. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, rows (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. Row (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are similar. Rows (4) and (5) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

Table E.2: All Bank Holding Companies: Dynamic Model

Dept. variable (Non-performing Assets Ratio)	(I)	(II)
	All	All
Lagged dependent variable (-1)	0.80***	0.81***
	(22.52)	(29.14)
Lagged dependent variable (-2)	0.053***	0.04***
	(2.73)	(3.16)
Positive shock	0.0142***	0.0117***
Negative shock	-0.0048***	-0.004***
GDP growth	-0.0004***	-0.00025***
Inflation	0.0015***	0.0014***
Profitability		-0.021***
		(-5.13)
Efficiency		-0.008***
		(-8.14)
Size		0.0015***
		(4.07)
Hedging		0.0001
		(0.12)
Constant	-0.0037***	-0.019***
	(-10.8)	(-4.07)
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers		
(1) $\sum_{j=1}^{4} \beta_j^{+} = 0$	0.000	0.000
(2) $\sum_{j=1}^{4} \beta_j^{-} = 0$	0.000	0.000
(3) $\lvert \sum_{j=1}^{4} \beta_j^{+} \rvert - \lvert \sum_{j=1}^{4} \beta_j^{-} \rvert = 0$	0.000	0.000
(4) $\sum_{j=1}^{4} \rho_j = 0$	0.000	0.000
(5) $\sum_{j=1}^{4} \gamma_j = 0$	0.000	0.000
# of obs	47285	45157
Walt-test	3691.3	3893.6
p-value	0.000	0.000
AR1	0.000	0.000
AR2	0.876	0.753

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses.
Cluster-robust standard errors. Walt tests are conducted to measure the joint significance of the coefficients.

$$s_{i,t} = \alpha + \mu_i + d_{gr} + \lambda_1 s_{i,t-1} + \lambda_2 s_{i,t-2} + \delta_k' bc_{i,t-4}^{k} + \sum_{j=1}^{4} \rho_j y_{t-j} + \sum_{j=1}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^{+} w_{t-j}^{+} + \beta_j^{-} w_{t-j}^{-}) + u_{i,t}$$

This is the static equation (eq. 2’’). Column I shows the results from the model without bank-level indicators. Column II shows the results from the full model. $s_{i,t}$ is distress indicator, $bc_{i,t-4}^{k}$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term. λ_1 and λ_2 are coefficients for the lagged dept. variables, β_j^{+} is the coefficient for positive shocks and β_j^{-} is the coefficient for negative shocks. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, rows (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. Row (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are similar. Rows (4) and (5) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

Sample Disaggregation: BHCs versus FHCs (Static and Dynamic Models): In this section, we review the results from the models that contrast the magnitudes of the effects of positive and negative shocks within the bank type subgroups: BHCs vs FHCs. The results from the *static* model (eq. 4a) that uses non-performing assets ratio as a distress proxy are broadly similar to the ones from the models that uses bank distress indicator as a distress proxy (Table E.3, columns II.a and II.b) with one exception: the hedge ratio turns insignificant. Positive and negative shocks both raise distress on banks for both BHCs and FHCs and the effects are asymmetric. For both cohorts, BHCs and FHCs, the effect of a positive shock is nearly three times that of a negative shock of the same magnitude. Wald-tests reject the similarity of the shock effects (Table E.3, columns II.a and II.b, row (3)). A positive shock ($w_t \geq 0$) creates the same level of distress across cohorts, namely on BHCs (0.085) and FHCs, (0.079) (Table E.3, column II). The similarity of the positive shock effects for the two sub-groups cannot be rejected according the Wald-tests (p-value = 0.343, Table E.3, column II, row (4)). The evidence for the similarity of the effects of negative shocks is less compelling (compared to the models with bank distress indicator). However, it is still clear: the similarity of the effects of negative shock ($w_t \leq 0$) on BHCs (-0.023) and on FHCs (-0.030) can be rejected at 10%, but cannot be rejected at 5% significance by Wald-tests (p-value = 0.073, Table E.3, column II, row (5)). The sings of the coefficients of macroeconomic drivers are same as the ones in the model with bank distress indicator.

The results from the dynamic model are also broadly in line with the same model that uses bank distress indicator as distress proxy except the magnitudes of impact of the negative shocks. Dynamic models' results also show that positive and negative shocks both raise distress on banks for both BHCs and FHCs, and the effects are asymmetric. For both cohorts, BHCs and FHCs, the effect of a positive shock is nearly three times that of a negative shock. Wald-tests reject the similarity of the shock effects (Table E.4, column II.a and II.b, row (3)). A negative shock ($w_t \leq 0$) creates the same level of distress across cohorts, namely on both BHCs (-0.0038) and FHCs, (-0.0045) (Table E.4, column II). The similarity of the positive shock effects for the two sub-groups cannot be rejected according the Wald tests (p-value = 0.200, Table E.4, column II, row (5)). However, in a stark contrast to the static model, the effect of a positive shock to FHCs (0.0101) is materially less than the effect on BHCs (0.0123): Wald-tests (p-value = 0.029, Table E.4, column II, row (4)). The similarity of the effects of the negative and positive shocks cannot be rejected at 5% significance level in the dynamic model that uses banks distress indicator as a distress proxy. We note that while the dynamic models provide some evidence for the positive shock taking a smaller toll on FHCs than BHCs (0.01 vs 0.012), we also caution that the non-performing assets ratio is not a good indicator for distress; it is essentially a credit risk indicator. The main conclusion from our results is that both positive and negative shocks create distress on both BHCs and FHCs, and that the effects are asymmetric. We also underline the conclusion that converting to FHC does not make the institution risk proof.

Table E.3: Sorting the Sample According to Bank Type (BHC vs FHC): Static Model

Dept. variable (Non-performing Assets Ratio)	(I.a)	(I.b)	(II.a)	(II.b)
	BHC	FHC	BHC	FHC
Group dummy		-0.0001		-0.00034**
		(-0.55)		(-1.99)
Positive shock	0.0115***	0.0108***	0.0085***	0.0079***
Negative shock	-0.0031***	-0.0037***	-0.0023***	-0.0030***
GDP growth	-0.0002***		-0.00006**	
Inflation	0.0013***		0.00095***	
Profitability			-0.0122***	
			(-2.75)	
Efficiency			-0.0052***	
			(-10.88)	
Size			0.0010***	
			(6.89)	
Hedging			0.0002	
			(0.65)	
Constant	-0.004***		-0.015***	
	(-17.6)		(-7.73)	
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers				
(1) $\sum_{j=1}^{4}\beta_j^+ = 0$	0.000	0.001	0.000	0.000
(2) $\sum_{j=1}^{4}\beta_j^- = 0$	0.000	0.000	0.001	0.000
(3) $\lvert\sum_{j=1}^{4}\beta_j^+\rvert - \lvert\sum_{j=1}^{4}\beta_j^-\rvert = 0$	0.000	0.000	0.000	0.000
(4) $\lvert\sum_{j=1}^{4}\beta_{BHC,j}^+\rvert - \lvert\sum_{j=1}^{4}\beta_{FHC,j}^+\rvert = 0$	0.275		0.343	
(5) $\lvert\sum_{j=1}^{4}\beta_{BHC,j}^-\rvert - \lvert\sum_{j=1}^{4}\beta_{FHC,j}^-\rvert = 0$	0.102		0.073	
(6) $\sum_{j=1}^{4}\rho_j = 0$	0.000		0.015	
(7) $\sum_{j=1}^{4}\gamma_j = 0$	0.000		0.000	
# of obs	50142		48302	
R-sq	0.102		0.114	

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses. Cluster-robust standard errors. Walt tests are conducted to measure the joint significance of the coefficients.

$$\Delta s_{i,t} = \alpha + \mu_i d_i + d_{gr} + \delta_k' bc_{i,t-4}^k + \sum_{j=1}^{4}\rho_j y_{t-j} + \sum_{j=1}^{4}\gamma_j p_{t-j} + \sum_{j=1}^{4}(\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) + d_{gr} * (\sum_{j=1}^{4}(\beta_{d,j}^+ w_{t-j}^+ + \beta_{d,j}^- w_{t-j}^-)) + u_{i,t}$$

This is the static equation (eq. 4a). Column I shows the results from the model without bank-level indicators. Column II shows the results from the full model. $s_{i,t}$ is distress indicator, Δ is the 1st difference, $bc_{i,t-4}^k$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term and d_{gr} is the group dummy (indicator variable) for bank type cohort: 0 for BHC and 1 for FHC, and d_i is the individual bank dummy. β_j^+ is the coefficient for positive shocks and β_j^- is the coefficient for negative shocks. $\beta_{d,j}^+$ is the coefficient for positive shock interacted with group dummy. $\beta_{d,j}^-$ is the coefficient for negative shock interacted with group dummy. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are equal. In tests (4) and (5), $\beta_{BHC,j}^+=\beta_j^+$ and $\beta_{FHC,j}^+=\beta_j^+ + d_{gr} * \beta_{d,j}^+$ and $\beta_{BHC,j}^-=\beta_j^-$ and $\beta_{FHC,j}^-=\beta_j^- + d_{gr} * \beta_{d,j}^-$. (4) and (5) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks on banks with positive gap and negative gap are equal. (6) and (7) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

Table E.4: Sorting the Sample According to Bank Type (BHC vs FHC): Dynamic Model

Dept. variable (Non-performing Assets Ratio)	(I.a)	(I.b)	(II.a)	(II.b)
	BHC	FHC	BHC	FHC
Lagged dependent variable (-1)	0.80***		0.81***	
	(22.51)		(29.08)	
Lagged dependent variable (-2)	0.053***		0.044***	
	(2.70)		(3.15)	
Group dummy		0.0002		-0.0003
		(0.31)		(-0.79)
Positive shock	0.0150***	0.0118***	0.0123***	0.0101***
Negative shock	-0.0043***	-0.0051***	-0.0038***	-0.0045***
GDP growth	-0.0004***		-0.0003***	
Inflation	0.0015***		0.0014***	
Profitability			-0.0206***	
			(-5.05)	
Efficiency			-0.008***	
			(-8.02)	
Size			0.0015***	
			(4.17)	
Hedging			0.00009	
			(0.13)	
Constant	-0.0031***		-0.020***	
	(-4.76)		(-4.17)	
Wald-tests for Interest Rate Shocks and Macroeconomic Drivers				
(1) $\sum_{j=1}^{4} \beta_j^+ = 0$	0.000	0.000	0.000	0.000
(2) $\sum_{j=1}^{4} \beta_j^- = 0$	0.000	0.000	0.000	0.000
(3) $\lvert \sum_{j=1}^{4} \beta_j^+ \rvert - \lvert \sum_{j=1}^{4} \beta_j^- \rvert = 0$	0.000	0.000	0.000	0.000
(4) $\lvert \sum_{j=1}^{4} \beta_{BHC,j}^+ \rvert - \lvert \sum_{j=1}^{4} \beta_{FHC,j}^+ \rvert = 0$	0.002		0.029	
(5) $\lvert \sum_{j=1}^{4} \beta_{BHC,j}^- \rvert - \lvert \sum_{j=1}^{4} \beta_{FHC,j}^- \rvert = 0$	0.460		0.200	
(6) $\sum_{j=1}^{4} \rho_j = 0$	0.000		0.000	
(7) $\sum_{j=1}^{4} \gamma_j = 0$	0.000		0.000	
# of obs	47285		45157	
Walt-test	3814.3		3976.5	
p-value	0.000		0.000	
AR1	0.000		0.000	
AR2	0.883		0.762	

*, **, *** Denote significance at the 10%, 5% and 1% level, respectively, t-statistics in parentheses. Cluster-robust standard errors. Walt tests are conducted to measure the joint significance of the coefficients.

$$s_{i,t} = \alpha + \mu_i + d_{gr} + \lambda_1 s_{i,t-1} + \lambda_2 s_{i,t-2} + \delta_k' bc_{i,t-4}^k + \sum_{j=1}^{4} \rho_j y_{t-j} + \sum_{j=1}^{4} \gamma_j p_{t-j} + \sum_{j=1}^{4} (\beta_j^+ w_{t-j}^+ + \beta_j^- w_{t-j}^-) +$$
$$d_{gr} * (\sum_{j=1}^{4} (\beta_{d,j}^+ w_{t-j}^+ + \beta_{d,j}^- w_{t-j}^-)) + u_{i,t}$$

This is the dynamic equation (eq. 4b). Column I shows the results from the model without bank-level indicators. Column II shows the results from the full model. $s_{i,t}$ is distress indicator, $bc_{i,t-4}^k$ is the vector of bank balance sheet indicators, y_t is the output growth, p_t is the inflation, w_{t-j} are interest rate shocks (positive and negative), u_t is the error term and d_{gr} is the group dummy (indicator variable) for bank type cohort: 0 for BHC and 1 for FHC. λ_1 and λ_2 are coefficients for the lagged dept. variables, β_j^+ is the coefficient for positive shocks and β_j^- is the coefficient for negative shocks. $\beta_{d,j}^+$ is the coefficient for positive shock interacted with group dummy. $\beta_{d,j}^-$ is the coefficient for negative shock interacted with group dummy. ρ_j is the coefficient of real GDP growth and γ_j is the coefficient of inflation. With respect to Wald-tests, (1) and (2) test the significance of sum (from lag1 to lag4) of the coefficients of positive and negative shocks. (3) tests whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks are equal. In tests (4) and (5), $\beta_{BHC,j}^+$=β_j^+ and $\beta_{FHC,j}^+$=β_j^++$d_{group} * \beta_{d,j}^+$ and $\beta_{BHC,j}^-$=β_j^- and $\beta_{FHC,j}^-$=β_j^-+$d_{gr} * \beta_{d,j}^-$. (4) and (5) test whether the magnitude of the effects (in absolute terms) of the sum (from lag1 to lag4) of positive and negative shocks on BHCs and FHCs are equal. (6) and (7) test the significance of sum (from lag1 to lag 4) of the coefficients of real GDP growth and inflation, respectively.

F. CONSTRUCTING SYSTEMIC RISK MEASURES BY EXPECTED SHORTFALL

Acharya, et al. (2010, 2017) proposes an expected shortfall (ES) approach to determine systemic risk. ES measures the potential loss incurred by a firm in case of an extreme event. A systemic event occurs when the financial system's expected loss exceeds a certain threshold; that is, when the financial system's return (market return) falls below a certain level[121]. Acharya et al, (2010, 2017) employ value-at-risk (VaR) concept to determine the threshold and define an extreme event. Specifically, VaR is the most that the market return falls within a time period with confidence level α. Then, the probability of the market losing more than VaR (market return falling below *VaR)* within a time period is α: $\Pr(market\ return < VaR_\alpha)$ = α. Put differently, with $1-\alpha$ confidence, the market return will be greater than *VaR*. The parameter α is typically taken to be 1% or 5%. For example, the total market return in period *t* is $100, and the probability of the market return declining to $60 next period due to slowing economic growth is 5%. Then, VaR_α is $60 and α is 5%. The *ES* is then defined as the expected market loss conditional on the return being less than the VaR_α level:

$$ES_\alpha = -E[r_m | r_m \le VaR_\alpha] \tag{1}$$

where, r_m is the market return of the banking system and equal to the sum of all weighted bank returns in the market: $r_m = \sum_{i=1}^{n} w_i r_i$. Put differently, the expected shortfall is the

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[121] Acharya et al, 2010 uses equity return data to define capital loss. That is, expected capital shortfall is the amount that equity falls below target level. $ES_\alpha = E(r_m | r_m < VaR_\alpha)$, where r_m is the market return which is sum of the returns of all institutions.

average of market returns in a period when the market loss exceeds its *VaR* limit. Based on this definition, Acharya et al, (2010, 2017) proposed the concept of *Marginal Expected Shortfall* (*MES*) to identify how a particular bank's risk taking adds to the financial system's overall risk. Formally,

$$MES_{\alpha} = \frac{dES_{\alpha}}{dw_i} = -E(r_i | r_m \leq VaR_{\alpha}) \tag{2}$$

This systemic risk measure captures the marginal contribution of a bank to the risk of the financial system as measured by ES. It corresponds to the change in the financial system's ES engendered by a unit increase in the weight of the ith institution in the system, *e.g.* relative size. Banulescu and Dumitrescu (2015) expand on *MES* and propose a concept of *Component Expected Shortfall* (*CES*) to address the main drawback of *MES*,

$$CES_{i,\alpha} = w_i \frac{dES_{\alpha}}{dw_i} = -w_i E(r_i | r_m \leq VaR_{\alpha}) \tag{3}$$

CES determines the *absolute* contribution of an institution to the systemic risk as measured by the ES of the financial system. It is set out in the same measurement unit as ES*, e.g.* U.S. dollars. More specifically, *CES* corresponds to the product of *MES* and the weight of the bank in the system, e.g. relative market capitalization. The larger the contribution, the more systemically important the institution is. One important feature of CES is that, by construction, the sum of all the financial institution's CES is equal to the *ES* of the financial system: $ES_{\alpha} = \sum_{i=1}^{n} CES_{i,\alpha}$.

In Acharya et al, (2010, 2017) and Banulescu and Dumitrescu (2015), ES is defined by return (firm and market return). More specifically, ES is the shortfall (loss) in *firm's return* in an extreme event in which the *market return* falls below a certain threshold. It also refers to the *capital* needed by a firm to offset the firm's losses from an extreme event. Tarashev et al. (2010a, 2013) define and use the ES approach along the lines suggested by Banulescu and Dumitrescu, (2015), but take a different perspective on the definition of "loss". Tarashev et al. (2010a, 2013) defines the "loss" as the bank's debt (liabilities) and equate the systemic risk with the expected credit losses on banks' debt in systemic events. In Tarashev et al. (2010a, 2013), a systemic event is defined as one in which the aggregate credit losses exceed a certain threshold. We follow the approach of Tarashev et al. (2010a, 2013) to derive our systemic risk measures, but supplement it with different data and assumptions to make it more functional, and expand the coverage of risk measures to include small banks. In addition, Banulescu and Dumitrescu (2015) estimates bank i's expected return conditional on a systemic event, $E(r_i|r_m \leq VaR_\alpha)$, directly[122]. Replacing bank return with bank liability and estimating the expected loss for thousands of banks creates a computational burden. Tarashev et al. (2010a, 2013) define a condition for a systemic event based on bank failures where the sum of all liabilities exceeds a certain threshold and derives ES for each bank or group of banks with a Monte Carlo simulation. Our approach is quite similar to the one taken by Tarashev et al. (2010a, 2013). We define ES as,

$$ES_\alpha = E[Loss|Loss \geq VaR_\alpha] \qquad (4)$$

[122] Acharya et al, (2010, 2017) and Banulescu and Dumitrescu, (2015) estimate the expected returns in a bivariate GARCH model for each bank.

More technically, ES is the expectation of system-wide credit loss when the loss exceeds its *VaR* limit. *VaR* conveys the maximum level of losses exceeded with a given probability α, and ES provides the mean over the range from *VaR* to the greatest possible loss[123]. Put differently, systemic risk *contribution* ES is the probability-weighted average (expected) of credit losses incurred by households and firms associated by bank failures conditional on a systemic event. More formally, let the banking system be composed of n banks, indexed by i = {1,2,…,n}, where n ∈ N. Then, the set of losses associated with the failure of banks in the banking system at any point in time is $\{loss_i\}_{i=1}^{n}$, where $loss_i$, is the size of bank creditors' (households and firms) assets that are lost if bank i fails in a particular period. Then, aggregate losses in the system can be obtained by summing the losses across the banks[124]. Thus, equation 5 can be written as,

$$E[Loss|Loss \geq VaR_\alpha] = \sum_i E[loss_i|\sum_i loss_i \geq VaR_\alpha] \qquad (4')$$

where $loss_i$ is nil if bank i survives or equal to the size of the loss net of recovery if it fails. Formally,

$$loss_i = s_i \,.\, LGD_i . I_i \qquad (5)$$

[123] Typically, α is selected as 1% or 5% and the VaR gives the most a bank can lose with 99% and 95% confidence, respectively. In a slight deviation from this definition, Huang et al. (2012) used the concept of the distress insurance premium (DIP) which defines systemic event by a threshold: a systemic event occurs if the total losses exceed a certain threshold L_{min} instead of VaR_α.

[124] Look for a similar treatment in Tarashev et al. (2010a, 2013), Huang et al. (2012) and Cummins (2014). The support from FDIC is assumed to be zero for the bank losses.

In this expression, s_i is the size of the bank *i*'s liabilities (i.e., the book value of its liabilities, equity is not considered a liability). LGD_i is loss-given-default which shows the actual losses after recoveries are netted out if bank i defaults. The default indicator, I_i, is either 0 (bank survives) or 1 (bank fails) and determined for each bank and time period in a model of *stochastic losses* (discussed in detail in Appendix I). In this definition, systemic risk is equal to the sum of systemic risk contributions of all banks, $ES_\alpha = \sum_{i=1}^{n} ES_{i,\alpha}$. Tarashev et al. (2010a, 2013) calls systemic risk contribution as *systemic importance*. Systemic importance is a bank's share in system-wide risk: a bank is systemically important to the financial system as much as it contributes to the total systemic risk in a systemic event. We use the same terminology in our study and call ES systemic risk contribution or systemic importance, interchangeably, in the rest of the paper.

Expected shortfall is a bottom-up approach that enables adding the systemic importance (systemic risk contribution) of individual banks to a group of banks or to the whole banking system. The additive property of the ES approach is used by Banulescu and Dumitrescu, (2015) and Tarashev et al. (2010a, 2013). We utilize this feature of ES to determine the systemic importance and the riskiness of a subset of BHCs in the banking system[125]. For concreteness, let a subset of the banking system be composed of k banks, indexed by j = $\{1,2,\ldots,k\}$, where $k \in N^{sub}$ and $N^{sub} \subseteq$ N. The vector of losses due to bank

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[125] In contrast with expected shortfall, alternative systemic risk measure CoVaR of Adrian and Brunnermeier (2014) cannot be consistently aggregated across subgroups due to the lack of the additive property. CoVaR focuses directly on individual institutions (or groups of institutions), too, however, it does not deliver components that add up to the total. In other words, adding the CoVaRs of all the banks in a system will not deliver the system-wide VaR. This is the biggest weakness of the CoVaRs. Therefore, we prefer the expected shortfall method.

failures in this subset is measured as $\{loss_j\}_{j=1}^{k}$. Then, the ES in the subset can be determined as

$$ES_K(Loss \geq VaR_\alpha) = \sum_j^k E\left[loss_j \middle| Loss \geq VaR_\alpha\right] \quad (4'')$$

where $Loss = \sum_j loss_j$, sum of bank losses in the banking system. A systemic event occurs when the system-wide loss goes above a certain threshold: $Loss \geq VaR_\alpha$, and conditional on systemic event, the expected shortfall in the subset, ES_K, is determined by adding the losses of the banks in the subset.

G. SINGLE COMMON-FACTOR LOADING ASSUMPTION

In 2005Q3, the systemic risk indicator for all banks is estimated to be 0.097 if the average ρ_i value is used (Table G.1, col 2005Q3, Total). The risk indicator declines to 0.076 if we assume minimum ρ_i value of 0.13, and rises to 0.100 for maximum ρ_i value of 0.76. According to these results, the systemic risk indicator is biased to the downside with only -3.0% (0.097/0.100-1, -3.0%) if all banks are exposed to each other with the highest common-loading, and biased to the upside with 27.6% (0.097/0.076-1, 27.6%) if the bank exposure is at its minimum. In 2009Q4, when the risk indicator reaches its peak, the risk indicator is estimated at 0.232 if the average ρ_i value is used. Repeating the same calculations, the risk indicator estimations are 0.215 for the minimum ρ_i value of 0.13 and 0.238 for the maximum ρ_i value of 0.76. These results show that the peak value of the risk indicator may be biased in a range of -2.5% to 7.9%. The error margin on systemic risk indicator due to assuming different loading factors is larger during the non-crisis period (e.g. in 2005Q3), than the crisis period (e.g. in 2009Q4): ([-3.0%, 27.6%] in 2005Q3 versus [-2.5%, 7.9%] in 2009Q4). Higher exposure to the common-loading factor results in a higher likelihood of default in the banking system, but the increment in the contribution of an institution to systemic risk is smaller in the stress periods than in the non-stress periods (Figure 3.3). It is the unconditional probability of default (PD) that drives the institution's contribution to systemic risk during the stress period. Empirical evidence in literature suggests that PD is a dominant factor in determining the systemic risk: the common-factor loading also matters, but to a lesser extend (Huang et al. 2012, Tarashev et al. 2010a, 2013).

When the economy is growing, borrowers are less likely to fall behind in their loan obligations. Therefore, the probability of bank default is low during the expansion periods.

Table G.1: Expected Shortfall (*ES*) as a Share of Total Liabilities, by Asset Size and Common-Factor Loading: Ratio, scale 0 to 1

	2005Q3				2009Q4				2015Q4			
	Large	Midsize	Small	Total	Large	Midsize	Small	Total	Large	Midsize	Small	Total
ρ=0.13	0.067	0.0089	0.0006	0.076	0.180	0.032	0.0017	0.215	0.092	0.015	0.0011	0.108
ρ=0.58	0.085	0.0116	0.0008	0.097	0.191	0.0384	0.0021	0.232	0.110	0.0223	0.0014	0.133
ρ=0.76	0.087	0.012	0.0009	0.100	0.196	0.0393	0.0022	0.238	0.113	0.0230	0.0017	0.137

The "Total" column reports systemic risk indicators for all banks: $ES(Loss \geq VaR_{\alpha})/S$, where S is sum of the liabilities of all banks. The "Large", "Midsize" and "Small" columns report Expected Shortfall (ES_K) for each cohort as a share of total liabilities in the banking system (S): $ES_K(L \geq VaR_{\alpha})/S$. Bank size cohorts are top 5%, midsize 50%-95% and bottom 50%. Common factor loadings, ρ_{size}, are: 0.13, 0.58 and 0.76. The cross sections for 2005Q3, 2009Q4 and 2015Q4 are presented to demonstrate the contribution of each size cohort to the topline systemic risk indicators.

When the growth slows or the economy enters into recession, on the other hand, rising unemployment and falling income cause many borrowers struggle to stay current on their loan obligations and probability of bank failure rises. Repeating the same exercise for 2015Q4 gives an error range of [-2.9%, 20%]). Next, we deepen our analysis to BHC bank size subgroups[126]. We split the banks into three asset size cohorts as large (top 5%), midsize (50%-95%) and small (bottom 50%) banks and repeat the same experiment for each asset size cohort. The results are presented in Table G.1.

Our results show that selecting a wrong ρ_i causes the largest deviation in the risk contribution of the *small* banks cohort due to small asset size. The total systemic risk indicator in 2005Q3 stands at 0.097 if ρ_i is selected to be 0.58. The share of smallest banks in total systemic risk is 0.0008, less than 1% of the total indicator (Table G.1, col

[126] We pick asset size subgroups for this exercise because all subgroups that we estimate the systemic risk contribution in this paper are essentially created according to the bank size: large, midsize, small banks cohort, SIFIs, 4 largest BHCs, and BHC versus FHC (FHCs are in general larger than BHCs).

2005Q3-Small, row 2). If all small banks have an actual ρ_i of 0.13 (min exposure), assuming 0.58 distorts the risk contribution of small banks cohort by 33% (0.0006 vs 0.0008; Table G.1, col 2005Q3-Small, row 1, 2). For midsize banks, the distortion is lower than the small banks at 29% (0.0089 vs 0.0116; Table G.1, col 2005Q3-Midsize, row 1, 2). These results point to a material distortion in terms of percentage change in risk indicator; however, because the risk shares of small and midsize banks in the aggregate systemic risk are very low; the impact of using a different ρ_i is limited. The total share of the small and midsize banks in the aggregate risk indicator is 12.8% ((0.0008+0.0116)/0.097). If all the small and midsize banks actually have the highest exposure at the ρ_i of 0.76, assuming average ρ_i of 0.58 distorts the risk share of small and midsize banks by much less: -3.3% (0.0120 vs 0.0116) for midsize banks, and -11% (0.0009 vs 0.0008) for small banks (Table G.1, col 2005Q3, row 2, 3).

Next, we examine large banks, the top 5% cohort. If all the large banks have an actual ρ_i of 0.76, using 0.58 distorts the risk contribution by only -2.3% (0.087 vs 0.085) (Table G.1, col 2005Q3-Large, row 2 and 3). On the contrary, if all the large banks have an actual ρ_i of 0.13, using 0.58 distorts the risk contribution by 26.3% (0.067 vs 0.085) (Table G.1, col 2005Q3-Large, row 1 and 2). In summary, if the actual ρ_i is 0.13 for all bank size cohorts, assuming average ρ_i of 0.58 causes the distortion of 26.3% for largest banks, 29% for midsize banks and 33% for small banks in the time period of 2005Q3. If the actual ρ_i is 0.76, the distortion will be much less at -2.3% for large banks, -3.3% for midsize banks and -11% for small banks. The distortion in the risk share of the largest bank cohort is high in level, but small in percentage because large banks' contribution to systemic risk is much higher than the midsize and small banks due to their size. We can refine some of the assumptions for common-factor loading and our findings by leveraging some of the results from related work in the literate. For example, there is compelling evidence in the literature that the bigger banks often have stronger inter-linkages with the rest of the banking system and tend to have higher common-factor loading (Huang et al. 2012)[127]. Therefore, for large banks, checking for the error margin according to the maximum exposure assumption, 0.76, is more relevant than the minimum, 0.13. Secondly, our midsize cohort contains the banks that have asset size above the median (upper 5%-50% percentile), which essentially means that checking the error margin according to the upper boundary of 0.76 is more relevant than the lower boundary of 0.13 for the midsize banks as well. If we assume the lower boundary of 0.13 for the smallest banks, our maximum error for the systemic risk shares of size cohorts becomes -2.3% for large banks, -3.3% for midsize banks, and 33% for smallest banks. These results show that the estimations for systemic risk contributions of the largest and midsize banks based on a single average common-factor loading have a very small error margin. Our estimations may generate an error as much as 33% in the smallest banks cohort. However, because the contribution of the smallest banks to aggregate systemic risk is very low, less than 1%, due to the bank size, single common-factor loading assumption does not cause a big distortion in the aggregate systemic risk contribution. Besides, 2005Q3 is a non-stress period where the aggregate systemic risk indicator declines to its lowest point and the error margins rises to the highest. In all other periods, systemic risk indicator rises either because PD or the

[127] Huang et al. 2012 also shows that the median exposure of the banks as reflected by the correlation of the equity returns in their work remained flat throughout a long time period. This result states a change in one banks exposure maybe offset by an other's exposure in the opposite direction; therefore, the median remains flat. This result also suggests that the exposure range, e.g. [0.13-0.76] in Tarashev et al. 2010a, 2013) does not change significantly over time.

bank size increases while common-factor loading is held constant. Thus, indeed the 33% is the maximum error that our estimations may suffer for the smallest banks cohort. To verify this argument, we repeat the same exercise for 2009Q4 and 2015Q4 data points. In 2009Q4, when the systemic risk indicator is at its peak, assuming the minimum ρ_i of 0.13 for the smallest bank cohort and the maximum ρ_i of 0.76 for the midsize and largest banks cohorts generates the error margins at 17.8% for smallest banks cohort, -2.3% for midsize banks and -1.5% for the largest banks. In 2015Q4, with the same assumptions, we get 29.3% for the smallest banks, -3.0% for the midsize banks and -2.2% for the largest banks.

H. THE CRISIS STORY OF "BIG FOUR"

A rapid growth in the four largest banks in the U.S. had occurred prior to the financial crisis. A combination of deregulations, particularly through the GLBA of 1999, had provided banks with the ability to consolidate and expand across service lines, which continued to happen until the crisis. Paired with generally robust economic growth, the deregulation of the financial sector enabled the largest banks to post double-digit growth rates right up to the onset of the crisis. The balance sheets of JPM, BAC and WFC expanded even faster during the Great Recession with acquisitions. To ensure that financial markets continue to operate properly as the financial crisis unfolded in 2008, the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Department of the Treasury, facilitated a number of major transactions among the largest financial institutions. With some combination of financial support and regulatory persuasion, the federal government facilitated BAC's merger with Merrill Lynch and its acquisition of Countrywide Financial, JPM's acquisition of Bear Stearns, and WFC's acquisition of Wachovia. The results are demonstrated in Figures 3.15 to 3.17. Our results show that while the risk level of the Big Four increased during the recession due to rising bank distress, only the systemic risk contribution of JPM, BAC and WFC went up during the recession while Citi's risk contribution indeed declined due to its asset sales that led to a shrinkage of its balance sheet (Figures 3.15a, Figures 3.15b). Growing bank size and rising bank distress (probability of bank default) inflated the systemic risk contributions of JPM, BAC and WFC.

Until the financial crisis, Citi's contribution to the systemic risk was highest among the largest four banking institutions (Figure 3.15a, 3.15b). The ES of Citi steadily increased from \$240 bil. in 2001Q1 to \$730 bil. in 2007Q3, until when the Subprime crisis hit the financial markets in mid-2008, as its balance sheet expanded with credit boom and economic expansion following the 2001 recession (Figure 3.15a) [128]. With assets sales and portfolio cleansing (old bad loans defaulting and dropping from balance sheets while high quality new loans leading to better balance sheets), the contribution of Citi's to aggregate risk declined starting in 2007Q4. At the end of 2009, Citi's ES declined to \$470 bil. The decline in ES was facilitated by declining liabilities (asset sales), rather than declining riskiness as measured by systemic risk indicator (Fig 3.16). The systemic risk indicator (*ES* scaled by liabilities) remained elevated until end of 2009. In the post-crisis period, Citi improved its balance sheet. Its contribution to aggregate risk and risk level are the lowest among the largest four banks in 2015.

BAC's systemic importance as measured by ES steadily increased from 2001Q1 to2007Q3. With risky acquisitions such as Countrywide and Merrill-Lynch, the ES nearly tripled from \$230 bil. in 2007Q3 to \$630 bil. in 2009Q4 (Figure 3.15a). The share of BAC's aggregate risk contribution increased from 0.09 to 0.17 in the same period (Figure 3.15b). The sharp increase in the aggregate risk contribution is due to rising riskiness as measured by systemic risk indicator in addition to expanding balance sheet with acquisitions (Figure 3.16). The systemic risk indicator was flat around 15% from 2001 to 2007, but it doubled during the financial crisis and increased to 30% in 2009. In the post crisis period, BAC's contribution to systemic risk remained flat around 0.17 for three years following the crisis

[128] There is no formal definition for "Subprime Crisis", thus there is no formal starting date, however, French investment bank PNB Paribas' announcement that it suspends three investment funds which invested in subprime mortgage debt due to a "complete evaporation of liquidity" in the market on August 9th, 2007 is the first of many credit-loss and write-down announcements by banks, mortgage lenders and other institutional investors, as subprime assets went bad can be considered as a starting date of Subprime Crisis.

period, then declined slightly to 0.15 in 2015. According to the systemic importance, BAC is ranked the second after JPM.

JPM is another financial holding company whose aggregate risk contribution increased during the recession and remained high in the post-recession period. JPM's risk contribution as measured by ES was nearly $100 bil. in 2001Q1, and it gradually increased to $245 bil. in 2007Q3 with expanding balance sheet. In this period, the total risk contribution of JPM remained flat at 0.10 (Figure 3.15b). Its risk contribution as measured by ES increased much faster during the recession with rising individual riskiness and acquisitions of WaMu and Bear Sterns, and reached $580 bil. in 2010Q1, 0.15 by ratio. The ES gradually declined to $550 bil in 2015, but by share of contribution, JPM's ES corresponds to a whopping 19% of the total systemic risk. The long portfolio cleansing of impaired mortgage loans kept JPM's ES elevated in the post-recession period. This is also evident in the systemic risk indicator. The individual riskiness as measured by systemic risk indicator fluctuated between 15%-20% from 2001 to 2007 (Figure 3.16). With the onset of the housing market downturn, the risk indicator increased from 16% in 2007Q2 to 29% in 2009Q4, and then gradually declined to 24% in 2015. According to the risk indicator, JPM remains as the riskiest bank among the Big Four, and also ranked on the top of the list of systemic importance according to its contribution to the aggregate risk.

WFC is another bank whose systemic risk contribution increased during the financial crisis. Before the crisis, WFC was the smallest of big four banks. Its contribution to aggregate risk was smallest not because of its size only, but also because of its risk level. Our results show that, from 2001 to 2004, WFC's systemic risk indicator was lower than the U.S. average and with a slight increase, it remained around U.S. average until 2007

(Figure 3.16). Similar to JPM, WFC's individual risk level began to increase with housing market downturn in 2007. In 2008Q4, WFC acquired a failing financial holding company, Wachovia. This acquisition raised the individual risk level and also risk contribution of WFC dramatically. The individual risk level as measured by systemic risk indicator increased from 15% to 24% in one quarter after this acquisition in 2008Q4 (Figure 3.16). Its systemic risk contribution as measured by ES increased from $45 bil. in 2006Q4 to $90 bil. in 2008Q3 because of impaired housing related loans (Figure 3.15a). The acquisition, however, raised the aggregate risk contribution to $290 bil in 2008Q4. The portfolio cleansing of impaired assets from Wachovia acquisition took several years: the individual riskiness remained elevated at 25% until 2013. WFC's systemic risk contribution also remained elevated around $300 bil. until 2013. With improving housing market, both the individual riskiness and the systemic risk contribution of Wells Fargo steadily declined until the end of 2015 (Figure 3.15a and 3.16).

The surging systemic importance of "Big Four" is also evident from the asset ratio. ES ratio comparison (Figure 3.17). Our results show that the largest four U.S. banks' contribution to systemic risk among all banks has been greater than their assets share since 2001. Put differently, the Big Four have been always more systemically important than their asset size indicate. At the beginning 2001, the largest four banks' asset and systemic risk shares were, respectively, 0.26 and 0.40. These figures have grown to 0.35 and 0.50 at the end of 2015Q4, which shows that these banks have become larger, and their systemic importance have increased in tandem over time (Figure 3.17). Our results also show that nearly half of the systemic risk is created by the largest four banks, and provides a justification for why they should be monitored closely.

I. MODEL OF STOCKHASTIC LOSSES

The default indicator, I_i, is either 0 or 1 and determined for each bank and time period as a function of its *probability of default.* As the *probability of default*, we use the bank distress indicator, $PD_{i,t}$ developed in section 3.2.2.1. To determine default indicator, I_i, we employ a variant of portfolio credit risk model introduced by Vasicek (1991). Similar versions of this model have been used for bank credit risk by Tarashev (2010a, 2010b, 2013), Huang (2012) and Cummins 2014. More specifically, we assume that there is a single period of length t and bank *i*, which starts with an asset value of A_0 and faces an asset return of $r_{i,t}$. Then, the value of bank assets and the asset return at period t is defined as,

$$A_{i,t} = A_0 + r_{i,t}$$

$$r_{i,t} = \sigma_v(t, A_0)\rho_{i,t}\epsilon_{m,t} + \sigma_v(t, A_0)\sqrt{1 - \rho_{i,t}^2}\xi_{i,t} \quad (1)$$

The asset return at period t is determined by a volatility of assets $\sigma_v(t, A_0)$, one common risk factor, $\epsilon_{m,t}$, which is a shock to the market that affects all banks and idiosyncratic factors, $\xi_{i,t}$ for all $i \in \{1,2, \dots, N\}$. The risk factors are assumed to be mutually independent standard normal distributions. $\rho_i \in [0,1]$ is the *common-factor loading* of bank *i* that shows correlation of bank returns with the market return. The common factor loading influences the propensity of bank *i* to default with other banks.

Separately, we define a risk profile of bank *i* by its *probability of default* $PD_{i,t}$:

$$PD_{i,t} = \Phi\left(\frac{DP_{i,t}-A_0}{\sigma_v(t,A_0)}\right) \tag{2}$$

$DP_{i,t}$ is a default point and assumed to be lower than the initial value of assets, $DP_{i,t} < A_0$. The tem Φ is the cumulative distribution function. Equation (2) tells us that there is a single value of a default point associated with a given *probability of default*: the lower the default point, the lower the probability of default[129]. Or, if the default point is set equal to the starting value of assets, A_0, the probability of default is 0.5: when the volatility of assets is set to unity, the value of bank assets in the next period will be less than the default point with 50% probability. Re-organizing equations 1 and 2, the asset returns scaled by asset volatility is given by

$$\frac{A_{i,t}-A_0}{\sigma_v(t,A_0)} = \rho_{it}.\epsilon_{m,t} + \sqrt{1-\rho_{it}^2}\xi_{i,t} \tag{3}$$

Then, we are ready to define a bank failure condition. In this framework, bank *i* is assumed to default when its assets $A_{i,t}$ falls below a default point, $A_{i,t} < DP_{i,t}$: bank starts the period with a sufficiently high level of assets and defaults only if the value of its assets falls below a threshold. Specifically, this happens when

[129] For example, for a given bank (initial asset value, A_0 and asset volatility, $\sigma_v(t, A_0)$), the failure risk for the bank rises (e.g. *probability of default*, $PD_{i,t}$ rises from 0.2 to 0.3), if the default point $DP_{i,t}$ is set higher. Similarly, e.g. assuming a default point equal to initial level of assets makes *probability of default* equal to 0.5 for a standard normal distribution. That is by 50% probability; the value of assets will be lower than the initial value of assets in the next period.

$$\rho_{it}.\epsilon_{m,t} + \sqrt{1-\rho_{it}^2}\xi_{i,t} < \Phi^{-1}(PD_{i,t}) \qquad (4)$$

Equation (4) tells us that it is sufficient to determine the asset return, $r_{i,t}$, in equation (1) and compare it to the *inversed* risk profile distribution in equation (2), $\Phi^{-1}(PD_{i,t})$ to decide whether the bank defaults or survives, I_i = 1 or 0. As a *probability of default*, we use the bank distress indicator, $PD_{i,t}$ developed in section 3.2.2.1. Once a fail/survive condition for a bank is specified as in equation 4, the distribution of failures, $\{I_i\}_{i=1}^n$, is determined via Monte Carlo simulations (see Appendix J for the MC procedure). Applying size of bank debt, $\{s_i\}_{i=1}^n$, and loss-given-default, LGD_i, to the distribution of defaults, we determine the distribution of individual banks' losses, $\{l_i\}_{i=1}^n$ for a particular time period. Aggregate loss is the sum of all simulated losses across the banks, $Loss = \sum_i l_i$. It is then straightforward to obtain the ES of the banking system as in equation (Appendix F, equation 4'). Repeating these steps for each quarter, time series of ES_t is created for the 2001-2015 period.

J. MONTE CARLO SIMULATIONS FOR EXPECTED SHORTFALL (ES) APPROACH

Suppose there are *N* banks in the portfolio. Following Tarashev and Zhu (2009), we use a Monte Carlo simulation to create the systemic risk measure. We specify this probability distribution as follows. System-wide losses equal to $\sum_{i=1}^{N} s_i \, . LGD_i . I_i$, where s_i is the size of the liabilities of institution *i*, LGD (loss-given-default) is the share of s_i that is lost if that institution defaults, and *I* is an indicator variable that equals 1 if institution *i* defaults and 0 otherwise. Without loss of generality, the overall size of the system is set to unity, $\sum_i s_i$ = 1 and, for simplicity, it is assumed that LGD_i = 55% for all institutions. This method estimates the probability distribution of defaults in a portfolio of N banks, $\{I_i\}_{i=1}^{n}$, when a default is driven by separate draws of two random variable.

1. Let N be the number of BHCs in period t and ρ is the common loading for all banks.
2. Generate N random draws for Z_i and one draw for M from independent standard normal distributions and determine $V_i = \rho . M + \sqrt{1-\rho^2} Z_i$, where $i = 1, \dots, N$.
3. Denoting the $i - th$ member of N and associated unconditional probability of default by pd_i, entity i is said to default if and only if $V_i < \Phi^{-1}(pd_i)$. Probability of default is *bank distress indicator*. Φ^{-1} is the inverse standard normal distribution.
4. Repeat steps 2 and 3 hundred thousand times to create the distribution of I_i for each bank i.