Are "too big to fail" banks just different in size? – A study on risk-taking and tail risk

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Abstract

This study explores how different bank characteristics affect general risk-taking and tail risk of Too-Big-to-Fail (TBTF) and non-TBTF banks. We show that TBTF banks' investment decisions drive their risks, while sources of funding drive risks of other banks. Contradicting the general belief, we find that non-TBTF banks together generate larger contagion risk to the real economy. Regulations designed to limit tail risk, such as raising core capital, do not lower banks' general risk-taking, especially for TBTF banks. Furthermore, after the Global Financial Crisis, tail risk becomes more sensitive to liability-side activities only among non-TBTF banks, implying that post-crisis banking regulations further enhanced the "Too-Big-to-Fail" privilege of the largest banks.

Keywords: Risk-Taking; Tail Risk; Systemic Risk; Banking Regulation; Too-Big-to-Fail (TBTF) banks

JEL Classification: G21; G28; G32

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1. Introduction

The Global Financial Crisis is a vivid example of how the failure of a few systemically important financial institutions (SIFIs), which are usually also the Too-Big-to-Fail (TBTF) financial institutions, could destabilize the entire financial system and dampen the real economic growth. Consequently, regulatory bodies require the few largest financial institutions[1] to follow additional requirements on liquidity coverage ratio, supplementary leverage ratio and countercyclical capital requirements. By October 2019, all Basel Committee on Banking Supervision member jurisdictions (except China) have fully adopted the additional requirements for global systemically important banks and for domestically systemically important banks, whichever applicable (Basel Committee on Banking Supervision, 2019). The Federal Reserve Board also classifies bank organizations into three categories — large and complex banking organizations, large and noncomplex banking organizations, and the rest — and regulate them in descending priority and stringency.

This paper aims at answering two issues on the effectiveness of the post-crisis regulations, at least in the case of the U.S.. First, we analyze if regulating a few bank characteristics to mitigate tail risk can simultaneously spill over to controlling bank general risk-taking. Second, because risks of TBTF banks and those of non-TBTF banks are driven by different characteristics, we ask whether TBTF and non-TBTF banks should be regulated differently. We do so by measuring tail risk with Marginal Expected Shortfall (MES) and SRISK, and general risk with accounting risk measures.

Two strands of literature on regulating banks are in order. The first strand focuses on general risk and uses accounting-based risk indicators, such as Z-score, Merton distance to

[1] These institutions are, for example, on the list of "global systemically important banks" published by the Financial Stability Board, "other systemically important institutions" published by the European Banking Authority, and "required participants" in the Comprehensive Capital Analysis Program and Review program and the Dodd-Frank stress tests.

default, and volatility of ROA, to screen out key characteristics that drive bank risk-taking (see for example, Beltratti and Stulz, 2012; Bhagat, et al., 2015; Demirguc-Kunt and Huizinga, 2010). The second strand emphasizes on tail risk, especially systemic risk, by measuring the expected capital shortfall of the bank conditional on a prolonged market decline (Brownlees and Engle, 2017), the expected amount of undercapitalization of the bank conditional on a systemic event (Acharya, et al., 2017), or the tail co-movement between the bank and the equity market (Adrian and Brunnermeier, 2016). Adopting these systemic risk measures, Weiß et al. (2014) and Altunbas, et al. (2017) study why banks with certain characteristics have imposed larger pressure than others on the overall banking industry during financial crises.

Studies have drawn non-conclusive and sometimes conflicting conclusions about how bank size affects bank risks. For example, Deng and Elyasiani (2008) find that size expansion leads to more diversified funding resources and loan portfolio, thus reducing bank general risk. Wheelock and Wilson (2012) find that size boosts profitability. On the other hand, since monitoring cost increases with size, Laeven and Leving (2007) argue that managers in more geographically diversified banks are more likely to act on their own interest. Goetz, et al. (2013) also show that managers in banks with diversified loan portfolios tend to provide loans to insiders and reduce loan quality. As Altunbas et al. (2017) stress, one main reason for these conflicting results is because different risk proxies tend to capture different dimensions of bank risk. This leads to a rarely explored question of whether regulations on various bank characteristics for the purpose of reducing tail risk could also mitigate bank general risk-taking.

Our study is also related to the literature about the differences between TBTF and non-TBTF banks. Among other differences (see, for example, Stein, 2002, about the use of soft and hard information, Rossi et al., 2009, on geographically diversified funding resources, and Laeven and Levine, 2007, on agency problem), TBTF banks are expected to be bailed out in case of financial distress (Stern and Feldman, 2004), and thus tend to take excessive risk

(Cordella and Yeyati, 2003) while enjoying low cost of funds (Jacewitz and Pogach, 2018) and low tail risk (Gandhi and Lustig, 2015). Despite those differences in characteristics, the same regulations are still applicable to non-TBTF banks, albeit less stringent.

We investigate how different bank characteristics (size, capital structure, funding structure, asset structure and income structure) drive bank general risk-taking and tail risk. In particular, we test how the 20 largest banks, which hold around 80% of total assets and are therefore considered as TBTF banks, take on risks differently from others. After finding that they are indeed different, we further study whether regulating non-TBTF banks separately could enhance the stability of the entire financial system, by examining whether a stress event among non-TBTF banks could impose pressure on the real economy like their TBTF peers. Without loss of generality, the banks in our study is the sample of all deposit-taking and loan-making bank holding corporations (BHCs), which have relatively higher transparency and simpler asset-liability structure than other financial intermediaries.

We find that risks of TBTF banks are mostly due to their investment decisions (loan investments and income diversification), while those of non-TBTF banks are driven by their sources of funding (core capital, deposits, and leverage). Specifically, we first observe that while an increasing returns to scale effect among non-TBTF banks, size expansion further boosts general risk and tail risk among TBTF banks, indicating that size expansion brings more side effects, such as agency problem (Laeven and Leving, 2007), than diversification benefits when banks are of mega scale. Second, for non-TBTF banks, core capital could absorb tail risk but not influence general risk-taking behavior until the core capital is below the regulatory threshold of 6%. On the contrary, risks of TBTF banks are not sensitive to capital structure at all. This difference between TBTF and non-TBTF banks becomes more prominent after the Global Financial Crisis when capital requirements are tightened. Third, the tail risk of non-TBTF banks in the post-crisis period is positively associated with the level of deposits due to the risk of bank run, whereas the tail risk of TBTF banks is insensitive to the level of deposits. Fourth, although increases in loan investments and income diversification could enhance TBTF banks' credibility and reduce tail risk, this phenomenon is weakened after the Global Financial Crisis. Fifth, during an unexpected system-wide liquidity shock, TBTF banks tend to experience less debtor withdrawals and are more likely to be bailout when they are undercapitalized. Finally, contradicting the general belief that financial risk contagion is usually caused by TBTF banks, non-TBTF banks actually impose larger contagion risk to the overall real economy when collectively considered (especially for material, energy, real estate and health care sectors).

This paper contributes to the banking literature by pointing out two noteworthy situations that regulatory bodies should alert. First, risks of the TBTF banks versus others come from different sources. Therefore, different regulatory approaches should be taken. Specifically, our findings verify that post-crisis banking regulations in response to the Global Financial Crisis actually strengthened the special position of the "Too-Big-to-Fail" banks, which are less financially constrained and less worried about capital sufficiency than other banks. Second, non-TBTF banks collectively have larger impacts on the economy in general, while TBTF banks have larger impacts during the Crisis. Hence, regulatory bodies should particularly focus on the liability-side (i.e., capital structure and funding structure) of non-TBTF banks rather than simply implementing a slimmed-down version of TBTF regulatory policies on non-TBTF banks.

The remainder of the study is organized as follows. Section 2 describes measures of bank risks and characteristics. Section 3 explains the empirical models and data used. Section 4 provides the results on the relationship between bank characteristics and different risk dimensions (tail risk and general risk), and differences between TBTF and non-TBTF banks. Section 5 explains the results of the influence of those two size groups to the real economy.

Section 6 concludes.

2. Definitions of Risk Measures and Bank Characteristic Variables

2.1. Measures on tail risk

In this paper, we use two market-based tail risk proxies. Marginal Expected Shortfall (*MES*) captures the expected individual tail risk, while SRISK ratio (*SRISK*) measures the systemic risk and is defined as the tail risk conditional on a prolonged market decline.

2.1.1. Marginal Expected Shortfall

Proposed by Acharya et al. (2017), $MES_{i,\alpha}$ is defined as the expected daily return of bank i in the worst α (5%) cases. For each quarter, we estimate the time-varying *MES* by averaging the 5% worst daily returns in the most recent calendar year. We take the opposite sign of the previously estimated value so that an increase in *MES* represents an increase in the expected loss. The *MES* of bank i at the risk level of 5% for quarter t is

$$MES_{i,5\%,t} = -\left(\frac{1}{\sum_{j=0}^{N-1} I(r_{i,d-j} \leq -VaR_{i,5\%,t})} \sum_{j=0}^{N-1} I(r_{i,d-j} \leq -VaR_{i,5\%,t}) r_{i,d-j} \right) \times 100 \tag{1}$$

where t denotes the current quarter, d denotes the last trading day of the most recent year (between quarter t–3 and t); N is the number of trading days between quarter t–3 and t; $r_{i,d-j}$ is the daily return of bank i at day $d–j$; $VaR_{i,5\%,t}$ is the Value at Risk of bank i at the 5% significance level at quarter t; and $I(r_{i,d-j} \leq -VaR_{i,5\%,t})$ equals one if $r_{i,d-j}$ is one of the 5% worst returns between quarter t-3 and t, and zero otherwise.

2.1.2. SRISK

Due to Brownlees and Engle (2017), *SRISK* represents the expected required additional capital injection from existing shareholders to fulfill the capital need during a prolonged market decline. To ensure comparability to *MES*, *SRISK* is normalized by market capitalization as:

$$
\begin{aligned}
SRISK_{i,t} &= \mathrm{E}_t\left(Capital\ Shortfall_{i,d+1,d+22} \mid r_{m,d+1,d+22} < -10\%\right) \big/ Equity_{i,d} \times 100 \\
&= \left(8\% \times E_t(Assets_{i,d+22} \mid r_{m,d+1,d+22} < -10\%) - E_t(Equity_{i,d+22} \mid r_{m,d+1,d+22} < -10\%)\right) \\
&\quad \times 100 \big/ Equity_{i,t} \\
&= \left(8\% \times Debt_{i,d} - (1-8\%) \times Equity_{i,d} \times (1 - LRMES_{i,t})\right) \big/ Equity_{i,d} \times 100
\end{aligned}
\tag{2}
$$

where d denotes the last trading day of quarter t. $Capital\ Shortfall_{i,d+1,d+22}$ is the capital shortfall of bank i between day d+1 and d+22, $r_{m,d+1,d+22}$ equals the market return between day d+1 and d+22, and $Debt_{i,d}$ and $Equity_{i,d}$ are book value of debt and market value of equity at day d, respectively. $LRMES_{i,t}$ estimates the expected monthly loss of bank i in quarter t, conditional on a prolonged market decline which is defined as more than 10% drop on the equity market in a month (detailed calculation is shown in Appendix A).[2] That “8%” in the expression is the prudential capital level ratio as in Brownlees and Engle (2017).

2.2. Measures on general risks and profitability

2.2.1. Z-score

Z-score evaluates the distance from insolvency. Considering that Z-scores are highly skewed, we follow Houston et al. (2010) and Bhagat et al. (2015) to use the log transformation of Z-score (*ln_Z score*) to capture the level of risk-taking behavior of banks:

$$
ln\_Z\ score_{i,t} = \ln\left(\frac{ROA_{i,t} + CAR_{i,t}}{\sigma_i(ROA)}\right) \tag{3}
$$

where $ROA_{i,t}$ denotes return on assets of bank i at quarter t, $CAR_{i,t}$ (capital asset ratio) equals total assets minus total liabilities over total assets of bank i at quarter t, and $\sigma_i(ROA)$ is standard deviation of *ROA* of bank i over the entire sample period.

2.2.2. Other measures

[2] *LRMES* is also commonly used as a measure for systemic risk. Since we applied *SRISK*, which has embedded *LRMES*, we will not analyze it separately.

In here, we cover two accounting-based proxies: the loan allowance margin (*Allw Margin*) and the Net Interest Margin (*NI Margin*). The former reflects the level of banks' self-estimated loan loss provisions and is defined as the total loan allowance over gross loans. That is $Allw\,Margin_{i,t} = Loan\ Allowance_{i,t} / Total\ Loans_{i,t}$, where $Loan\ Allowance_{i,t}$ and $Total\ Loans_{i,t}$ are loan allowance and total loans of bank *i* at quarter *t*, respectively.

Net Interest Margin (*NI Margin*) is defined as the net interest income over earning assets (following Nguyen, 2012) to reflect the profitability of banks' traditional business. That is, $NI\ Margin_{i,t} = Net\ Interest\ Income_{i,t} / Earning\ Assets_{i,t}$, where $Earning\ Assets_{i,t}$ equals the sum of net loans and total investment securities of bank *i* at quarter *t*.

2.3. Measures on bank characteristics

Following Altunbas et al. (2017), we group bank characteristics into four categories: capital structure, asset structure, funding structure and income structure, each showing the bank's "health" structure from different perspective. Table 1 lists the sources and definitions of the variables.

2.3.1. Size

We use the natural logarithm of total assets to capture the size effect (*Size*). Even though systemic risk increases with size (Laeven et al., 2016), the influence of size on bank general risk is still debatable. In principle, large banks are able to reduce their general risk by diversifying their funding sources and loan investments geographically (Deng and Elyasiani, 2008) and across different industries (Acharya et al., 2006). Nevertheless, because monitoring cost also grows with bank size, increasing bank size could also intensify agency problem between corporate insiders and shareholders, which could offset the benefits of diversification. For example, Goetz et al. (2013) show that a more complex geographically diversified bank is more likely to lend to corporate insiders and has worse loan quality.

2.3.2. Capital structure

Demirguc-Kunt and Huizinga (2010) and Berger and Bouwman (2013) show that increased core capital as a buffer against potential losses could lower tail risk. In addition, since equity is technically a call option on banks' value, we also expect a non-linear relationship between capital ratio and general risk-taking (as in Morrison and White, 2005). Following Altunbas et al. (2017), we use *Tier 1 Ratio* to measure the sufficiency of core capital, and a dummy variable, *Under Cap*, which equals one if tier one capital covers less than 6% of risk-weighted assets and zero otherwise, to capture the possible non-linear effect.

2.3.3. Asset structure

Altunbas et al. (2017) state that the ratio of total bank loans to total assets is positively correlated with systemic risk during the Global Financial Crisis, but not correlated with idiosyncratic risk. On the contrary, Papanikolaou and Wolff (2014) suggest that higher ratio of total bank loans to total assets leads to lower general risk in the form of larger distance to insolvency and lower total market risk. We use *Loan to Asset* to represent the ratio of total loans written to total assets.

Real estate as loan collateral is a major source of illiquidity and is therefore a significant risk factor for bank stocks since 1990 (Carmichael and Coen, 2018). Altunbus et al. (2017) also unveil that banks' exposure in the real estate sector contributes to systemic risk. We further decompose banks' loan structure into real estate loans versus the other types of loans.

2.3.4. Funding structure

Because of deposit insurance and government guarantees, deposit is a stable and reliable funding source; and deposits to assets ratio is positively correlated with risk-taking (see, for example, Gatev and Trahan, 2006, and Khan et al., 2017). We define *Deposit Funding* as deposit to assets ratio to reflect funding stability. Besides, unlike depositors who are covered by deposit insurance, debtholders do not have explicit government guarantees, and thus are motivated to require collaterals, set debt covenants, and inhibit banks from taking excessive risk (Danisewicz et al., 2018). Acharya et al. (2017), Beltratti and Stulz, (2012), and Weiß et al. (2014), for example, show that a higher level of pre-crisis leverage led to higher bank risks during the Global Financial Crisis. Following Weiß et al. (2014), we employ the debt to asset ratio, denoted as *Debt Funding*, to represent banks' debt leverage. Note that debt in here excludes deposits, to separate the impact of debts from that of deposits.

2.3.5. Income structure

Since non-interest income is not perfectly correlated with interest income, commercial banks could benefit from diversification by expanding their business into trading activities, fee-based business, and other non-interest activities (Elsas et al., 2010). De Jonghe et al. (2015) find that increasing income diversification could reduce systemic risk in large banks, but raise such risk in small ones. Following Beltratti and Stulz (2012), we use the ratio of non-interest income to total revenue, denoted as *Non-Interest Income*, to represent income diversity.

We define *Excess Loan Growth* as the growth in gross loans and leases minus the growth in total assets to represent aggressiveness of lending strategy, and hence it is expected to be positive correlated with bank risk (Foos et al., 2010).

3. **Empirical Models and Data**

3.1. Effects of bank characteristics on risk proxies

3.1.1. Basic test

Following Altunbas et al. (2017), we regress risk proxies on lagged bank characteristics as the following equation shows:

$$
\begin{aligned}
Y_{i,t} = \beta_0 + \beta_1 Size_{i,t-1} &+ \underbrace{\beta_2 Tier\ 1\ Ratio_{i,t-1} + \beta_3 Under\ Cap_{i,t-1}}_{\text{Capital Structure}} \\
&+ \underbrace{\beta_4 Loan\ to\ Assets_{i,t-1} + \beta_5 Real\ Estate\ Loan_{i,t-1}}_{\text{Assets Structure}} \\
&+ \underbrace{\beta_6 Deposit\ Funding_{i,t-1} + \beta_7 Debt\ Funding_{i,t-1}}_{\text{Funding Structure}} \\
&+ \underbrace{\beta_8 Excess\ Loan\ Growth_{i,t-1} + \beta_9 Non\text{-}Interest\ Income_{i,t-1}}_{\text{Income Structure}} + v_i + u_t + \varepsilon_{i,t}
\end{aligned} \tag{4}
$$

where the dependent variables ($Y_{i,t}$) are risk proxies specified in Sections 2.1 and 2.2. Because of data availability and supported by the results of previous empirical studies discussed in Section 2.3, three of nine BHCs' characteristics (*Real Estate Loan*, *Debt Funding* and *Excess Loan Growth*) are different from the original work of Altunbas et al. (2017). Independent variables are lagged one period to tackle the problem of endogeneity. We include the time fixed effect, u_t, to control for macroeconomic uncertainties, and the cross-sectional fixed effect, v_i, to control for unidentified heterogeneity among BHCs.

3.1.2. TBTF versus non-TBTF banks

To see whether risk-taking and tail risk exposures of TBTF banks are different from the rest of the BHCs, we split the 20 largest depository BHCs (henceforth top 20 BHCs) from the rest of the sample. We consider the top 20 BHCs as TBTF banks for the following reasons. First, as Figure 1 exhibits, the top 20 BHCs make up 80% of total assets and deposits in the US banking industry, and contribute most of the systemic risk during the Global Financial Crisis.

Second, regulatory bodies use size as the major determinant to designate SIFIs (Irresberger et al., 2017). To ensure large banks have enough capital as a cushion against unexpected losses, the Federal Reserve Board conduct stress tests on large US BHCs regularly, through the Supervisory Capital Assess Program (SCAP) in 2009 and through annual Comprehensive Capital Analysis and Review (CCAR) afterward. Even though, strictly speaking, the Federal Reserve Board has not designated any banks as TBTF, literature commonly considers the 19

BHCs included by 2009 SCAP as TBTF BHCs (e.g., Balasubramnian and Cyree, 2014; Jacewitz and Pogach 2018; Huang et al., 2012). Among all these 19 BHCs, 14 are depository BHCs and are included in the group of top 20 depository BHCs. In addition, the top 20 BHCs have already covered all depository BHCs under the supervision of the Large Institution Supervision Coordinating Committee, and all large and complex (depository) banking organizations (with consolidated total assets of $250 billion or more). As a result, 70 to 80% of the top 20 BHCs in this study are subject to the previously mentioned TBTF regulations.

Third, the ranks of BHCs change overtime. For example, Wachovia and National City Corporation were top 10 BHCs before the Global Financial Crisis but were respectively acquired by Well Fargo and PNC Financial Services Group Inc. in late 2008. Similarly, the list of BHCs covered by annual stress tests is also time-varying. For example, all 19 BHCs on the list of 2009 SCAP were covered by 2011 CCAR, but only 10 of them were still tracked by 2019 CCAR. Hence, a dynamic TBTF list is more appropriate in this study.

We therefore add interaction terms between *Top20* dummy and bank characteristics in Equation (4) and get:

$$Y_{i,t} = \alpha + \sum_{k=1}^{9} \beta_k X_{i,k,t-1} + \sum_{k=1}^{9} \eta_k Top\,20_{i,t-1} \times X_{i,k,t-1} + v_i + u_t + \varepsilon_{i,t} \tag{5}$$

where $X_{i,1,t-1}$ to $X_{i,9,t-1}$ denote nine bank characteristics of bank *i* at quarter *t-1*. *Top20* is used to identify TBTF banks, which equals one if the BHC is ranked as one of the top 20 BHCs based on its lagged total assets and zero otherwise. As robustness tests, we also repeat the tests using the 10 largest depository BHCs as TBTF banks, and add interaction terms between size and other bank characteristics to examine the differences between TBTF and non-TBTF banks.

3.1.3. Influence of unexpected liquidity shock on bank characteristics during crisis

We next use the Global Financial Crisis as an example of unexpected system-wide liquidity shortage to analyze how banks react to this exogeneous event, as below:

$$X_{i,k,post} - X_{i,k,pre} = \beta_{0,k} + \beta_{1,k} X_{i,k,pre} + \beta_{2,k} Top20_{i,pre} \times X_{i,k,pre} + \varepsilon_i \quad (6)$$

where $X_{i,k,pre}$ and $X_{i,k,post}$ are average levels of *k*th bank characteristic for BHC *i* during the year before the Global Financial Crisis (2006Q4 to 2007Q3) and during the Global Financial Crisis (2007Q4 to 2009Q2), respectively.

3.2 ΔCoVaR model specification for risk contagion

Following Bernal et al. (2014), we define risk contagion from portfolio *i* to market *j* as the difference between the conditional tail risk (1st percentile) of market *j*, when portfolio *i* experiences a severe loss (1st percentile) and when it is in normal status (50th percentile). That is,

$$\Delta CoVaR_{1\%}^{j|i} = CoVaR_{1\%}^{j|R^i=-VaR^i_{1\%}} - CoVaR_{1\%}^{j|R^i=-VaR^i_{50\%}} \quad (7)$$

where R_j and R_i denote weekly return on the market *j* and on the portfolio *i*, respectively, while VaR_α^i denotes the Value at Risk of the portfolio *i* with a significance level of α (α-th quantile of the return distribution of the portfolio *i*) and $CoVaR_{1\%}^{j|R^i=-VaR^i_\alpha}$ is the 1st quantile *loss* of the market *j* conditional on $R_i = -VaR_\alpha^i$.

To capture risk contagion from different bank groups to the real economy in this study, market performance (R_j) is captured by weekly returns of either the overall equity market (represented by the S&P 500 index, or S&P 500 excluding financials & real estate index), or a stock market sector (represented by S&P sector indices) [3]. The performance of TBTF and non-

[3] We use the S&P 500 index to represent the performance of the overall real economy, and use S&P 500 excluding financials & real estate index as an alternative proxy of the system to mitigate the concern of spurious correlation. Companies are classified into 11 categories based on the Global Industry Classification Standard. Since "bank" is the major component of the S&P 500 Financials sector index, we exclude the economic sector of financials and focus on the impact of the tail risk of bank industrial on the rest 10 economic sectors.

TBTF banks (R_i) are reflected by value-weighted portfolio consisting of the top 20 banks (*Index_top*) and non-top banks (*Index_non*), respectively. At the beginning of each quarter, banks are assigned into top 20 BHCs and non-top BHCs based on their total assets in the last quarter.

Finally, we follow the two-step procedure proposed by Adrian, and Brunnermeier (2016) to estimate risk contagion of bank group i on the market j at week w ($\Delta CoVaR_w^{j|i}$), use the kernel density estimations introduced by Silverman (1986) to draw probability density function of each $\Delta CoVaR_w^{j|i}$, and use the bootstrap Kolmogorov-Smirnov (KS) test due to Abadie (2002) as the dominance test (see Appendix C for details).

3.3 Description of data

We use data of US bank holding companies (BHCs) which (i) are/were listed on New York Stock Exchange (NYSE), American Stock Exchange (AMES) or NASDAQ after January 1, 2002, (ii) have valid trading data, and (iii) have a primary SIC code of 60, to represent "banks". To merge market information from Worldscope with financial statement information from Federal Reserve Banks, we utilize the list of Center for Research in Security Prices – Federal Reserve Banks (CRSP-FRB) link published by Federal Reserve Bank of New York, and exclude those BHCs that are not on the list. In addition, as we focus on traditional deposit-taking and loan-making BHCs, we follow Beltratti and Stulz (2012) to include only BHCs with deposits to assets ratio of above 20% and ratio of total bank loans to total assets of above 10%.

Based on the report of the Business Cycle Dating Committee of the National Bureau of Economic Research (2010), the Global Financial Crisis period is defined as 2007Q4-2009Q2, *Post-Crisis* is between 2009Q3 and 2017Q4. The Pre-Crisis period is 2002Q1-2007Q3. There are 364 valid depository BHCs between 2002Q1 and 2017Q4 in total. Data frequency is on quarterly basis.

4. Influence of bank characteristics on bank risk-taking behavior and tail risk

4.1 Summary Statistics

Panel A of Table 2 reports the summary statistics of key variables. Since the residuals are heteroskedastic and autocorrelated, we use the robust standard errors (Arellano, 2003; Wooldridge, 2013). In addition, because all independent variables except *Size* are either ratios or growth rates, we expect them to be stationary. Unit root test results in Appendix B support this argument. Since most correlation coefficients are moderate (Panel B of Table 2) and the maximum variance inflation factor (VIF) equals 3.03 (much smaller than the threshold of 10), multicollinearity among independent variables is not a concern.

4.2 Preliminary results

Table 3 shows the results of regressing risk/profit measures on lagged bank characteristics following Equation (4).[4] Table 3 shows that controlling for other factors, systemic risk (*SRISK*) increases with bank size. Regarding general risk measures, our finding supports the increasing return to scale effect (Wheelock and Wilson, 2012) in that larger banks show higher profitability (lagged *Size* is positively associated with Net Income Margin) without additional risk-taking (*Size* is not significantly correlated with Z score or Allowance Margin).

4.2.1 On capital structure

As the function of core capital is to absorb losses, reduced *Tier 1 Ratio* would increase individual tail risk (*MES*) and systemic risk (*SRISK*). On the contrary, lagged *Tier 1 Ratio* is

[4] As the deadline of BHCs' quarterly financial reports is 45 calendar days after the report date, we can safely assume that investors have enough time to realize accounting information and to adjust their portfolio accordingly.

not correlated with general risk, suggesting that the level of tier 1 capital will not directly influence banks' risk-taking behavior. Undercapitalized BHCs (with tier 1 capital ratios below the threshold of 6%) tend to be more aggressive in risk-taking, resulting in lower Z scores and higher allowance margin (the coefficients of lagged *Under Cap* are −0.3969 and 0.4478 for ln_*Z score* and *Allw Margin*, respectively). That is, they have higher chance of insolvency and needing more allowance for writing off bad loans. The positive coefficient of *Under Cap*(*t*-1) for individual tail risk (*MES*) also suggests that investors have been aware of this moral hazard problem.

4.2.2 On funding structure

According to Beltratti and Stulz (2012) and Weiß et al. (2014), increased leverage could induce more outcome uncertainties. As Table 3 depicts, *MES*, *SRISK* and *Allw Margin* are positively associated with lagged *Debt funding* (coefficients of 0.0841, 0.2874 and 0.0211 respectively), while ln_*Z score* is negatively associated with it (coefficient of −0.0183). This indicates that increased sources of funding through leverage induce higher tail risk (higher *MES* and *SRISK*) and general risk (lower distance to insolvency and higher allowance margin). Intuitively, having been secured by deposit insurance and government guarantees, deposits are considered as a stable funding source and could be used to hedge against liquidity risk from loan demand shocks (Gatev and Trahan, 2006). However, a high deposit ratio could cause a depository bank vulnerable to bank run in extreme cases, even if the run is driven by depositors' self-filling beliefs (as in Diamond and Dybvig, 1983). Banks with more deposits, and hence lower funding liquidity risk, can afford to be more aggressive in risk-taking (higher allowance margin, *Allw Margin*, lower distance to insolvency, *ln_Z score*, and also higher profitability, *NI Margin*), but they are also more prone to higher tail risk (*MES* and *SRISK*).

4.2.3 *On asset structure*

Results in Table 3 shows that more loan investments, in terms of higher *Loan to Asset*, not only do not increase tail risk, but actually reduce the chance of default (0.0029 for ln_*Z score*) and increase profitability (0.0074 for *NI Margin*). The coefficient of *Real Estate Loan* is positive for *MES* (0.0145), and the coefficients of *Loan to Asset* are insignificant for all tail risk measures (*MES* and *SRISK*). These results imply that banks have better performances by having good quality loans; only higher investments in real estate loans are associated with higher tail risk.

4.2.4 *On income structure*

Table 3 shows that an increase in *Non-Interest Income* leads to larger distance away from insolvency (coefficient of 0.0001 for Z score) and lower allowance margin (–0.0002), which shows the positive effect of income diversification as in Beltratti and Stulz (2012). Besides, excess loan growth has negligible effect on tail risk and general risk in the following quarter. One of possible explanation is that prepayment rate (Kang and Zenios, 1992) and default rate (Esaki et al., 1999) of mortgage loans usually increase over the first three years after origination. Thus, banks with excessive loan growth tend to create higher risk in the longer run and would not be associated with risker financial outcomes in the short run.

4.3 *TBTF and non-TBTF banks*

After the Global Financial Crisis, regulatory bodies proposed a three-tier hierarchical regulatory structure for banks. The small group of top tier biggest BHCs includes several large and complex TBTF banking organizations (with total consolidated assets of $250 billion or more, or with on-balance sheet foreign exposures of $10 billion or more), which are mandatory to follow most stringent regulatory policies. The second tier consists of dozens of large and noncomplex banking organizations (with total consolidated assets of at least 50 billion but less than \$250, or with on-balance sheet foreign exposures of less than \$10 billion), which are exempt from some regulatory policies such as supplementary leverage ratio and countercyclical capital buffer, and have more flexibility than top ones in terms of most other regulatory policies such as liquidity coverage ratio, net funding reserve and stress testing. The rest (the majority of banking organizations) belong to the third tier and are subject to similar but least stringent regulatory policies.

In this section, we ask whether TBTF and non-TBTF banks should be subject to similar banking regulations by testing whether risks of the 20 largest banks and other banks are influenced by similar characteristics. Panel A of Table 4 reports the baseline results of Equation (5) which includes the dummy for the top 20 BHCs, and Panel B exhibits the corresponding aggregate coefficients of the top 20 BHCs (based on Wald Tests) for easy comparison. Table 5 shows results of the two robustness tests by (1) only considering the 10 largest BHCs as TBTF banks and (2) multiplying bank size to the bank characteristics.

Results from Table 4 are in general consistent with those in Section 4.2, especially for non-top BHCs. For the same unit increase in size, non-top BHCs have higher profitability without being exposed to additional general risk. However, top BHCs are found to take additional risk and have worse loan quality (lagged *Top20×Size* is negatively associated with the distance to insolvency and positively associated with allowance margin). This result holds even if we only consider the 10 largest BHCs as TBTF banks as in Panel A of Table 5.

The coefficients of lagged *Tier 1 Ratio* in Table 4 and the coefficients of lagged *Top20×Tier 1 Ratio* have similar magnitudes but opposite signs. This suggests that tier 1 capital works as an effective capital buffer against potential losses for non-top BHCs but not for the top BHCs. Similarly, the impact of lagged *Top20×Deposit Funding* on risk measures could offset that of *Deposit Funding* on risk measures, which supports the argument of Stern and

Feldman's (2004) that investors in general believe that TBTF banks would be bailed out in case of financial distress (i.e., deposit run in this case). Again, unlike non-top BHCs, the top 20 BHCs are not exposed to higher tail risk even if they are undercapitalized (the aggregative coefficients of lagged *Under Cap* are insignificant for *MES* and *SRISK*), and are less likely to exploit the equity option by adopting overly aggressively risk-taking strategies (the coefficient of lagged *Top20*×*Under Cap* is positive for Z score and negative for allowance margin).

In terms of income structure and asset structure, income diversification brings more benefits for top BHCs than non-top ones (the coefficients of lagged *Top20*×*Non-Interest Income* are negatively significant for *MES*, *SRISK* and Allowance margin). Even though Table 4 shows that loan to asset ratio and real estate loan to total loan ratio have similar influences on top and non-top BHCs, when we only consider the 10 largest BHCs as TBTF banks, the coefficients of the interaction term, *Top10*×*Loan to Asset*(t-1), are negatively significant for tail risk measures (*MES* and *SRISK*) and allowance margin (*Allw Margin*). Besides, Panel B of Table 5 shows that large banks could not screen new borrowers as efficient as small ones (as can be seen from $\partial MES/\partial Loan\ to\ Asset = -0.1259 + Size(t-1) \times 0.0078$ and $\partial Allw\ Margin/\partial Loan\ to\ Asset = -0.0463 + Size(t-1) \times 0.0031$). The above results indicate that increases in loan investments and income diversification enhance TBTF banks' credibility.

In sum, the flexibility on risk measures of the top BHCs being "Too-Big-to-Fail" is much clearer when they are separated from others. Non-top BHCs are more likely to be financially constrained, and their general and tail risks are highly dependent on funding and capital structures. The large sizes of the top BHCs generate high systemic risks. As such, their risks are less sensitive to their individual characteristics, and they are more likely to grab benefits from income diversification and loan investments. Simply put, risks of TBTF banks are more sensitive to the asset side of the balance sheet, while those non-TBTF banks are more prone to changes on the liability side.

4.4 Changes due to Post-Crisis regulations

Because of lessons learnt from the Global Financial Crisis and the introduction of Basel III Accord, regulatory bodies have updated banking regulations after the Crisis. Considering those post-crisis regulation changes are mostly targeted on TBTFs, we allow coefficients of characteristic variables to be different before and after the Crisis to check whether the differences between TBTFs and the rest are widened in the post-crisis period. Panel A of Table 6 reports the differences in coefficient values between top and non-top BHCs for both periods, and the significance of those differences based on Wald tests (detailed regression results are available upon request). The income structure and asset structure account for most of the differences between top and non-top BHCs in the pre- and crisis period, while funding structure and debt structure account for most of the differences in the post-crisis period. This suggests that the post-crisis changes in banking regulations designed to rein in risk-taking of largest banks and reduce systemic risk actually further strengthen the "too big to fail" privilege of the largest banks.

As shown in Panel A of Table 6, the impact of bank characteristics on bank risks could change over time. We further allow coefficients of bank characteristics to be time-varying (using a 5-year rolling window) and analyze the average impact of bank characteristics on bank risks.[5] Panel B presents the average coefficient for each characteristic and *p*-values based on Fama-MacMech regression (Fama and French, 2008). The magnitude and signs of coefficients are mostly consistent with our baseline regression in Table 4. This suggest that our main results

[5] Since we need to estimate nine interaction terms between *Top20* and bank characteristics in Equation (5), we have employed a 5-year rolling window to ensure each regression have enough observations for the test.

correctly reflect the impact of bank characteristics on bank risks.

4.5 Bank reactions to unexpected liquidity shortage

We use the Global Financial Crisis as an unexpected system-wide shortage to test whether non-top BHCs are more likely to be financially constrained, and whether top BHCs are more able to adjust their income and asset structure. On the liability side, Models (1) to (4) in Table 7 confirm that banks in general are financially constrained during the crisis. Non-top BHCs need to reduce their deposits and debts (the coefficients are respectively −0.149 and −0.175), whereas the top 20 BHCs are less likely to be squeezed by debtholders (coefficient of −0.175+0.099) and are more likely to be bailout when they are undercapitalized (that is, the coefficients of pre-crisis *UnderCap* is −0.363−0.270 for *Top20* and is higher in absolute value than −0.270 for other banks). On the asset-side, for Models (5) to (8), the aggregate coefficient of pre-crisis *Excess Loan Growth* is −0.562 (−0.967+0.405) for top 20 banks but is −0.967 for other banks; the aggregate coefficient of pre-crisis *Real Estate Loan* is −0.104 (−0.049−0.055) for top 20 banks but is −0.049 for other banks. This suggests that non-top banks reacted to the Crisis by cutting back credit supply as well as other non-interest income, while the top 20 BHCs had reduced less loan growth but had conducted a bigger cut on real estate loans. All these show that banks in general have to be more prudential by adjusting liabilities and, consequently, credit supply downwards amid unexpected system-wide financial shortage. This however has less effect on changes in risk-taking strategies of the top 20 BHCs. Moreover, the finding that non-top BHCs are more financially constrained than top BHCs during financial crises also echoes the existence of "Too-Big-to-Fail" subsidies. Since largest BHCs are vital to the real economy and to the financial system, they are bound to receive government support when facing difficulties (aka, TBTF subsidies). Therefore, they are able to raise funds at low costs (Jacewitz and Pogach, 2018), have low tail risk (Gandhi and Lustig, 2015) and subject to loose market discipline (Voelz and Wedow, 2011). All these benefits alleviate financial constraints of TBTF BHCs.

5 Banks and the economy

As discussed in the previous section, the regulatory rules for non-top BHCs are similar to, albeit weaker than, those for top-BHCs even though risks of top and non-top BHCs are driven by difference characteristics. In here, we further ask whether regulating non-top BHCs with less stringent regulations is enough in maintaining stability of the financial system.

We construct two value-weighted portfolios (*Index_top* and *Index_non*) to reflect the overall performance of the top 20 BHCs and the rest, and employ ΔCoVaR discussed in Section 3.2 to quantify risk contagion from these two groups to the real economy. Panel A of Table 7 provides the descriptive statistics of $\Delta CoVaR$, and Panel B shows the results of significance tests proposed by Castro and Ferrari (2014) (detailed regression results are available upon request).

5.1 Tests of Contagion

Panel A of Table 8 shows that when the top 20 BHCs suffer a distress event (1% distress level), the overall real economy needs to undertake on average 4.2872% more tail risk. For the non-top BHCs group, a distress event among them contributes to around the same amount (4.0843%) of Value at Risk to the real economy. During the Global Financial Crisis (2007Oct - 2009Jun), both top 20 and non-top BHCs have imposed double the amount of pre-crisis tail risk on the overall real economy. Excluding the financials and real estate firms from the overall economy (denoted as “Ex-Financials”), the impacts from the top 20 and non-top BHCs on the overall real economy are both lower (1.8506% and 2.1144%, respectively) before the Crisis (2002Jan - 2007Sep), but are then tripled (6.4196% and 6.3255%, respectively) during the

Crisis.[6]

Panel B shows that both the top 20 and non-top BHCs could influence the overall real economy. The significant risk spillover from non-top BHCs to the real economy is also supported by the literature. Comparing with TBTF banks, non-TBTF banks have more flat organizational structures (i.e., fewer layers of management), thus could better utilize soft information that is hard to store and transmit (Stein, 2002). By exploiting the comparative advantage in collecting and using soft information, these small banks could effectively alleviate financial constraints of informationally opaque firms (Berger et al. 2005) and small firms (Berger et al. 2017) . As a result, small banks could better facilitate local economic growth than large banks (Hakenes et al., 2015) and the failure of small banks could lead to a bigger decline in local income than that of large banks (Ashcraft, 2005). Besides, Kashyap and Stein (2000) show that fluctuations of bank loans are driven by small banks.

At the economic sector level, significance tests suggest that a distress event in top and non-top BHCs could both propagate to material, energy, real estate, health care, industrial, discretionary goods and communication service sectors. This can be explained by the fact that depository BHCs offer commercial and industrial loans to producers (e.g., agriculture, manufacturing, and other companies) on one side, and consumer loans (e.g., auto installment loans and credit card loans) and mortgage loans to consumers on the other. During the Crisis, the BHCs tightened credit due to liquidity shortage, and the financial difficulties eventually spilt over to related sectors. Meanwhile, only the risk from top BHCs could significantly spread to essential goods and information technology sectors, while only the stress event from non-top BHCs could build up the tail risk of utilities sector. This shows that banks of various sizes tend to support different sectors of the economy, which are therefore subject to different

[6] Because of the data availability, ΔCoVaR Ex-Financials is estimated between November 2005 and December 2017, while the rest ΔCoVaRs are estimated from January 2002 through December 2017.

impacts of credit shortages during the Crisis.

5.2 The dominance tests and distributions

We further employ the bootstrap Kolmogorov-Smirnov (KS) test as the dominance test for the impact on the economy. The economic meanings of the null hypotheses of the three KS tests are respectively whether a stress event among the top 20 banks could impose less, more, or similar pressure on the real economy than the non-top banks. Panel C of Table 8 shows that the hypothesis that impact from the top banks on the overall economy are larger than or similar to that of the non-top banks can be rejected (*p*-values for ΔCoVaR Top20>ΔCoVaR non-Top20 and ΔCoVaR Top20=ΔCoVaR non-Top20 for "Market" are 0.0189 and 0.0378, respectively). That is, a distress event among non-top BHCs imposes greater tail risk to the overall economy than a stress event among top 20 BHCs; and this holds even when excluding the financials and real estate companies (denoted as "Ex-Financials"). Risk contagion at the sectoral level, except from the utilities sector, echoes the findings in the previous section that top and non-top BHCs serve different market segments, and therefore exert different influences on them.

Figure 2 depicts the probability density function of each ΔCoVaR. The distributions of ΔCoVaR for both top 20 and non-top BHCs are positively skewed; and the distributions of ΔCoVaR for the top 20 BHCs have fatter tails (especially right tails) than non-top BHCs. Hence, our results indicate that non-top BHCs are systemically risker to the overall real economy than the 20 top BHCs, although they have less influences on utilities and information technology sectors. Besides, the positive skewness suggests that the influences from depository BHCs, especially largest ones, on the real economy would rise sharply in extreme events.

6 Conclusions

After the Global Financial Crisis, regulatory bodies have imposed more stringent requirements targeting on a few TBTF banks, and a similar but weaker version on the rest of the banking system. The primary objective of this paper is to explore whether TBTF and non-TBTF banks should be regulated differently. Splitting the data of the US bank holding companies (BHCs) into top 20 BHCs and non-top BHCs for the sample period of 2002 to 2017, we find that regulations such as raising core capital designed to limit tail risk have no effect on banks' general risk-taking as long as banks have enough core capital. Both tail risk and general risk of non-top banks are more sensitive to sources of funding, while risks of top banks are mostly due to their investment decisions. This is because the top banks could benefit more from income diversification and loan investments while not worrying about downside risks as they are too big to fail and will be bailed out when insolvent.

In addition, contradicting general belief that financial risk contagion is usually caused by TBTF banks, we find that non-top banks as a whole could exert more contagious pressure on the real economy. Hence, this study provides further insight that exerting higher scrutiny only on TBTF banks is not enough in protecting the overall economy. TBTF banks need to be bailed out, if any, not because they are short of funding *per se*, but because they take riskier investments; and they are not as contagious as always perceived. Our empirical results are in favor of an independent set of regulations governing non-top banks, rather than a slimmed-down version of regulatory policies, especially because the risks of top and non-top banks come from different sources, and they serve and influence different sectors of the economy.

It is worth noting that, this study only includes depository BHCs (aka, commercial banks), which mostly focus on deposit-taking and loan-making business, to reduce heterogeneity between BHCs. Investment banks are excluded because they could be involved in a heterogeneous set of activities such as underwriting services, advisory services, trading and brokerage, and so on (Iannotta, 2010). Nevertheless, major investment banks, such as Goldman Sachs and Morgan Stanley, have also become banking holding companies since 2008, and are subject to stress tests targeting on TBTF financial institutions. Therefore, future research is needed to answer the question of whether risk of investment BHCs and risk of depository BHCs are driven by similar bank characteristics. This question is also important, since investment banks are closely connected with each other and other commercial banks. A typical example is the collapse of Lehman Brothers that rippled throughout the financial system.

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Table 1 Data sources and variable definitions

Variables	Description	Source
Panel A: Risk/profit proxy		
Marginal Expected Shortfall (*MES*)	MES (Acharya et al. 2017) equals the equal-weighted average loss of 5% worst days in the preceding four quarters ×100. The detailed method is described in section 2.1. Banks with higher *MES* have higher tail risk.	Worldscope and Author's Calculation
SRISK Ratio (*SRISK*)	SRISK Ratio equals SRISK over the market cap ×100. SRISK (Brownlees and Engle, 2017) equals the expected capital shortfall conditional on a prolonged market decline. The detailed method is described in section 2.1. Banks with higher *SRISK* have higher tail risk.	Worldscope and Author's Calculation
ln_Z Score	*ln_Z score* is defined as the log transformation of Z-score. Z- score equals the sum of return on assets and capital asset ratio over the standard deviation of return on assets. Banks with lower ln_*Z score* have higher risk-taking.	Y-9C report and Author's Calculation
Allowance Margin (*Allw Margin*)	Allowance over gross loans and leases × 100. Banks with higher *Allw Margin* have higher risk-taking.	Y-9C report
Net Interest Margin (*NI Margin*)	Net interest income over earning assets ×100.	Y-9C report
Panel B: BHCs' characteristics		
Size	Log transformation of total assets (in real term)	Y-9C report
Tier 1 Ratio	Tier 1 capital to risk-weighted assets ×100	Y-9C report
Under Cap	Equals one if *Tier 1 Ratio* below 6% and zero otherwise	Author's Calculation
Loan to Asset	Net loans and leases to total assets ×100	Y-9C report
Real Estate Loan	Real estate backed loans to gross loans and leases ×100	Y-9C report
Deposit Funding	Total deposits to total assets ×100	Y-9C report
Debt Funding	Total debts to total assets ×100	Y-9C report
Excess Loan Growth	Growth in loans and leases minus growth in total assets ×100	Y-9C report
Non-Interest Income	Non-interest income to total revenue×100	Y-9C report
Panel C: State variables for CoVaR		
Term Spread	Ten-year Treasury rate minus three-month Treasury rate ×100	CEIC
TED Spread	Three-month LIBOR minus three-month Treasury rate ×100	CEIC
Credit Spread	Moody's Baa rated bond rate minus ten-year Treasury rate ×100	CEIC and Federal Reserve Bank of St. Louis
VIX	CBOE volatility index	DataStream
3M Yield	Three-month Treasury bill rate ×100	CEIC
Real Estate Excess	Weekly return on S&P 500 real estate sector index minus weekly return on S&P 500 index ×100	DataStream
Market	Weekly return on S&P 500 index ×100	DataStream

(*Continued…*)

(Table 1 Continued)

Variables	Description	Source
Panel D: Other factors		
Ex-Financials	Weekly return on S&P 500 Excluding Financials & Real Estate ×100	DataStream
Industrials	Weekly return on S&P 500 Industrials (sector) index ×100	DataStream
Discretionary	Weekly return on S&P 500 Consumer Discretionary (sector) index ×100	DataStream
Essentials	Weekly return on S&P 500 Consumer Staples (sector) index ×100	DataStream
Real Estate	Weekly return on S&P 500 Real Estate (sector) index ×100	DataStream
Energy	Weekly return on S&P 500 Energy (sector) index×100	DataStream
Health Case	Weekly return on S&P 500 Health Care (sector) index×100	DataStream
Information	Weekly return on S&P 500 Information technology (sector) index×100	DataStream
Materials	Weekly return on S&P 500 Material (sector) index×100	DataStream
Utilities	Weekly return on S&P 500 Utilities (sector) index×100	DataStream
Communication	Weekly return on S&P 500 Communication Service (sector) index×100	DataStream
Index_top	Weekly return on a value-weighted portfolio consisting of 20 largest depository BHCs, which is rebalanced quarterly.	DataStream and Author's Calculation
Index_non	Weekly return on a value-weighted portfolio consisting of non-top depository BHCs which is rebalanced quarterly.	DataStream and Author's Calculation

Table 2 Data description

Panel A shows the descriptive statistic of our sample. Panel B shows the correlation coefficients between major variables. All values are reported in percentages except *Under Cap* which is a dummy variable.

Panel A: Data description					
	Mean	Median	Std. Dev.	P5	P95
Risk/ Profit Proxies					
MES	5.05	4.03	3.27	2.31	12.28
SRISK	-73.97	-75.71	11.27	-85.20	-58.74
ln_Z Score	4.15	4.30	0.98	2.47	5.48
Allw Margin	1.51	1.33	0.77	0.68	2.92
NI Margin	1.10	1.03	0.38	0.72	1.71
Capital Structure					
Tier 1 Ratio	9.68	9.24	10.47	6.71	13.30
Under Cap	0.02	0.00	0.14	0.00	0.00
Asset Structure					
Loan to Asset	65.85	67.67	12.57	41.87	82.37
Real Estate Loan	72.90	75.39	17.82	41.84	97.09
Funding Structure					
Deposit Funding	76.01	77.55	8.93	59.98	87.49
Debt Funding	7.72	6.39	6.46	0.00	19.98
Income Structure					
Excess Loan Growth	0.17	0.30	5.11	-5.24	5.16
Non-Interest Income	23.48	21.99	41.97	6.16	47.14

Panel B: Correlation Matrix									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) *Size*	1								
(2) *Tier 1 Ratio*	-0.0349	1							
(3) *Under Cap*	0.1203	-0.0588	1						
(4) *Loan to Asset*	-0.2887	0.0347	-0.1412	1					
(5) *Real Estate Loan*	-0.4602	0.0013	-0.0932	0.2528	1				
(6) *Deposit Funding*	-0.4452	0.0075	-0.0856	0.2445	0.1025	1			
(7) *Debt Funding*	0.2127	-0.0339	0.0517	-0.0022	0.0599	-0.7662	1		
(8) *Excess Loan Growth*	-0.0126	0.0110	-0.0291	0.0795	0.0025	-0.0280	0.0206	1	
(9) *Non-Interest Income*	0.1356	-0.0052	0.0269	-0.1196	-0.0946	-0.0561	0.0130	-0.0147	1

Table 3 Market perception and risk-taking

Panel A reports the results of bank characteristics on tail risk and general risk, as in Equation (4). All independent variables are defined in Table 1. Standard errors are clustered by bank and are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% respectively.

Dependent variable	(1) *MES*	(2) *SRISK*	(3) ln_*Z score*	(4) *Allw Margin*	(5) *NI Margin*
Size(*t*-1)	0.1203 (0.1296)	4.3426*** (0.6603)	-0.0126 (0.0270)	-0.0571 (0.0617)	0.0895*** (0.0244)
Tier 1 Ratio(*t*-1)	-0.0016** (0.0006)	-0.0068*** (0.0026)	0.0009 (0.0008)	-0.0002 (0.0002)	0.0001 (0.0001)
Under Cap(*t*-1)	1.5781*** (0.5569)	1.5580 (3.1283)	-0.3969*** (0.0595)	0.4478*** (0.1715)	-0.0189 (0.0444)
Deposit Funding(*t*-1)	0.0841*** (0.0151)	0.2874*** (0.0765)	-0.0183*** (0.0036)	0.0211*** (0.0060)	0.0084** (0.0036)
Debt Funding(*t*-1)	0.0736*** (0.0162)	0.7900*** (0.0940)	-0.0212*** (0.0034)	0.0187*** (0.0063)	0.0033 (0.0031)
Loan to Asset(*t*-1)	-0.0071 (0.0058)	-0.0128 (0.0243)	0.0029** (0.0012)	-0.0004 (0.0022)	0.0074*** (0.0011)
Real Estate Loan(*t*-1)	0.0145** (0.0061)	-0.0073 (0.0211)	-0.0010 (0.0009)	0.0012 (0.0021)	0.0031*** (0.0010)
Excess Loan Growth(*t*-1)	-0.0022 (0.0045)	0.0193 (0.0186)	-0.0004 (0.0005)	-0.0060*** (0.0012)	-0.0016 (0.0011)
Non-Interest Income(*t*-1)	-0.0011 (0.0007)	-0.0081 (0.0050)	0.0001* (0.0001)	-0.0005* (0.0003)	-0.0002** (0.0001)
Constant	-4.8493* (2.5541)	-175.6313*** (13.9348)	5.7751*** (0.5521)	0.4467 (1.1910)	-1.4606*** (0.5094)
Observations	12,235	11,430	16,196	16,196	16,196
Number of quarters	364	362	364	364	364
Adj. R-squared	0.7618	0.3910	0.2696	0.4230	0.2374
BHC FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Table 4 Top 20 versus the rest depository BHCs

Panel A presents regression results of Equation (5). All independent variables are defined in Table 1. Variables below *Top20×* are cross products with *Top20*. Standard errors are clustered by bank and are reported in parentheses.

Panel B reports the aggregate coefficients of characteristics of Top 20 BHCs. Significances of coefficients are due to Wald tests. e.g., H_0 : coefficient of $size_{t-1}$ + coefficient of $TOP20 \times size_{t-1} = 0$.

P-values based on Wald tests are reported in square brackets.

*, **, *** indicate statistical significance at 10%, 5% and 1% respectively.

Panel A: Baseline regression					
Dependent Variable	(1) *MES*	(2) *SRISK*	(3) ln_*Z Score*	(4) *Allw Margin*	(5) *NI Margin*
Constant	-3.6482	-158.7438***	5.8407***	0.7400	-1.4479***
	(2.7403)	(14.2767)	(0.5714)	(1.2031)	(0.5306)
Size(*t*-1)	0.0632	3.5930***	-0.0156	-0.0655	0.0890***
	(0.1331)	(0.7070)	(0.0269)	(0.0620)	(0.0246)
Tier 1 Ratio(*t*-1)	-0.0033*	-0.0133**	0.0025	0.0002	0.0005
	(0.0018)	(0.0066)	(0.0026)	(0.0004)	(0.0006)
Under Cap(*t*-1)	2.7890***	6.8639***	-0.4484***	0.7452***	-0.0330
	(0.6953)	(2.1622)	(0.0783)	(0.1708)	(0.0639)
Deposit Funding(*t*-1)	0.0810***	0.2310***	-0.0186***	0.0195***	0.0087**
	(0.0162)	(0.0650)	(0.0040)	(0.0062)	(0.0040)
Debt Funding(*t*-1)	0.0612***	0.6693***	-0.0210***	0.0148**	0.0030
	(0.0174)	(0.0758)	(0.0037)	(0.0062)	(0.0035)
Loan to Asset(*t*-1)	-0.0069	-0.0112	0.0028**	-0.0001	0.0072***
	(0.0059)	(0.0226)	(0.0011)	(0.0022)	(0.0011)
Real Estate Loan(*t*-1)	0.0132**	-0.0193	-0.0012	0.0005	0.0029***
	(0.0064)	(0.0197)	(0.0009)	(0.0023)	(0.0010)
Excess Loan Growth(*t*-1)	0.0012	0.0227	-0.0003	-0.0062***	-0.0015
	(0.0054)	(0.0171)	(0.0006)	(0.0013)	(0.0012)
Non-Interest Income(*t*-1)	-0.0009	-0.0066	0.0001*	-0.0004*	-0.0002**
	(0.0006)	(0.0043)	(0.0001)	(0.0003)	(0.0001)
Top20×					
Size(*t*-1)	0.4659*	2.5679*	-0.0490**	0.1283*	-0.0106
	(0.2398)	(1.5291)	(0.0242)	(0.0762)	(0.0298)
Tier 1 Ratio(*t*-1)	0.0032*	0.0133**	-0.0025	-0.0004	-0.0005
	(0.0019)	(0.0067)	(0.0026)	(0.0005)	(0.0006)
Under Cap(*t*-1)	-2.8652***	-7.9518	0.2167**	-0.8768***	0.0802
	(0.9058)	(4.8456)	(0.0852)	(0.2698)	(0.0735)
Deposit Funding(*t*-1)	-0.0837**	-0.1724	0.0119**	-0.0186	0.0002
	(0.0391)	(0.2596)	(0.0049)	(0.0155)	(0.0057)
Debt Funding(*t*-1)	-0.0133	0.4178	0.0095	0.0044	0.0084
	(0.0474)	(0.4307)	(0.0059)	(0.0208)	(0.0067)
Loan to Asset(*t*-1)	-0.0003	-0.2142	-0.0020	-0.0100	0.0024
	(0.0152)	(0.1386)	(0.0023)	(0.0085)	(0.0029)
Real Estate Loan(*t*-1)	-0.0120	-0.0895	0.0043**	0.0004	-0.0003
	(0.0163)	(0.0870)	(0.0018)	(0.0045)	(0.0024)
Excess Loan Growth(*t*-1)	-0.0247	-0.0770	-0.0008	0.0003	-0.0008
	(0.0191)	(0.0523)	(0.0008)	(0.0044)	(0.0017)
Non-Interest Income(*t*-1)	-0.0421***	-0.5231***	-0.0010	-0.0173***	-0.0025*
	(0.0110)	(0.1377)	(0.0016)	(0.0048)	(0.0013)
Observations	12,235	11,430	16,196	16,196	16,196
Number of BHCs	364	362	364	364	364
Adj. R-squared	0.7667	0.4201	0.2818	0.4369	0.2392
BHC FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel B: Aggregate coefficients of Top 20 BHCs (Wald tests)					
Dependent Variable	(1) *MES*	(2) *SRISK*	(3) ln_*Z Score*	(4) *Allw Margin*	(5) *NI Margin*
Size(*t*-1)	0.5291*	6.1609***	-0.0646*	0.0628	0.0784*
	[0.0516]	[0.0003]	[0.0781]	[0.5220]	[0.0520]
Tier 1 Ratio(*t*-1)	-0.0001	0.0000	0.0000	-0.0002	0.0000
	[0.7730]	[0.9690]	[0.6280]	[0.1450]	[0.6370]
Under Cap(*t*-1)	-0.0762	-1.0879	-0.2317***	-0.1316	0.0472
	[0.8970]	[0.8010]	[0.0000]	[0.5380]	[0.1790]
Deposit Funding(*t*-1)	-0.0027	0.0586	-0.0067**	0.0009	0.0089**
	[0.9430]	[0.8210]	[0.0385]	[0.9500]	[0.0424]
Debt Funding(*t*-1)	0.0479	1.0871**	-0.0115**	0.0192	0.0114*
	[0.2870]	[0.0118]	[0.0220]	[0.3400]	[0.0516]
Loan to Asset(*t*-1)	-0.0072	-0.2254	0.0008	-0.0101	0.0096***
	[0.6270]	[0.1010]	[0.7240]	[0.2260]	[0.0008]
Real Estate Loan(*t*-1)	0.0012	-0.1088	0.0031*	0.0009	0.0026
	[0.9370]	[0.2030]	[0.0650]	[0.8160]	[0.2440]
Excess Loan Growth(*t*-1)	-0.0235	-0.0543	-0.0011**	-0.0059	-0.0023**
	[0.1980]	[0.2610]	[0.0480]	[0.1570]	[0.0462]
Non-Interest Income(*t*-1)	-0.0430***	-0.5297***	-0.0009	-0.0177***	-0.0027**
	[0.0001]	[0.0001]	[0.5940]	[0.0002]	[0.0415]

Table 5 Robustness tests of Table 4

Panel A is to consider the 10 largest BHCs as TBTF banks and employ the following equation:

$$Y_{i,t} = \alpha + \sum_{k=1}^{9} \beta_k X_{i,k,t-1} + \sum_{k=1}^{9} \eta_k Top10_{i,t-1} \times X_{i,k,t-1} + v_i + u_t + \varepsilon_{i,t}$$

where $X_{i,1,t-1}$ to $X_{i,9,t-1}$ denote nine bank characteristics of bank i at quarter $t-1$. *Top10* equals one if the BHC is ranked as one of the top 10 BHCs based on its lagged total assets, and zero otherwise. All variables below $Top10\times$ are cross products with *Top10*.

Panel B lists results of alternative test

$$Y_{i,t} = \alpha + \sum_{k=1}^{9} \beta_k X_{i,k,t-1} + \sum_{k=1}^{9} \eta_k Size_{i,t-1} \times X_{i,k,t-1} + v_i + u_t + \varepsilon_{i,t}$$

All variables below $Size\times$ are cross products with *Size*. Standard errors are clustered by bank and are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% respectively.

Panel A: Top 10 BHCs versus the rest					
	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*MES*	*SRISK*	ln_*Z Score*	*Allw Margin*	*NI Margin*
Constant	-4.6929*	-166.2366***	5.8183***	0.6001	-1.4601***
	(2.6849)	(13.2960)	(0.5647)	(1.1953)	(0.5246)
Size(*t*-1)	0.1061	3.9602***	-0.0133	-0.0582	0.0902***
	(0.1320)	(0.6651)	(0.0272)	(0.0618)	(0.0246)
Tier 1 Ratio(*t*-1)	-0.0016***	-0.0065***	0.0009	-0.0001	0.0001
	(0.0006)	(0.0022)	(0.0007)	(0.0002)	(0.0001)
Under Cap(*t*-1)	2.5082***	6.3579***	-0.4378***	0.7119***	-0.0253
	(0.6506)	(1.9535)	(0.0724)	(0.1589)	(0.0582)
Deposit Funding(*t*-1)	0.0826***	0.2362***	-0.0186***	0.0191***	0.0084**
	(0.0158)	(0.0628)	(0.0039)	(0.0060)	(0.0038)
Debt Funding(*t*-1)	0.0684***	0.7115***	-0.0213***	0.0151**	0.0030
	(0.0170)	(0.0739)	(0.0036)	(0.0060)	(0.0033)
Loan to Asset(*t*-1)	-0.0051	0.0002	0.0028**	0.0003	0.0074***
	(0.0058)	(0.0218)	(0.0011)	(0.0021)	(0.0011)
Real Estate Loan(*t*-1)	0.0155**	-0.0098	-0.0011	0.0009	0.0030***
	(0.0062)	(0.0192)	(0.0009)	(0.0022)	(0.0010)
Excess Loan Growth(*t*-1)	0.0000	0.0113	-0.0003	-0.0065***	-0.0017
	(0.0050)	(0.0165)	(0.0005)	(0.0013)	(0.0011)
Non-Interest Income(*t*-1)	-0.0010	-0.0068	0.0001*	-0.0005*	-0.0002**
	(0.0006)	(0.0044)	(0.0001)	(0.0003)	(0.0001)
Top10×					
Size(*t*-1)	0.5283**	4.2838**	-0.0762***	0.1780*	-0.0093
	(0.2200)	(1.6852)	(0.0231)	(0.0946)	(0.0251)
Tier 1 Ratio(*t*-1)	0.1950*	-0.9051	0.0345***	-0.0208	-0.0057
	(0.1047)	(0.8369)	(0.0100)	(0.0422)	(0.0167)
Under Cap(*t*-1)	-2.5427***	-10.9927*	0.2928***	-1.1083***	0.0363
	(0.8640)	(5.8897)	(0.0811)	(0.2688)	(0.0651)
Deposit Funding(*t*-1)	-0.1095**	-0.2731	0.0151***	-0.0238	0.0030
	(0.0478)	(0.3136)	(0.0055)	(0.0207)	(0.0063)
Debt Funding(*t*-1)	-0.0472	0.2112	0.0164**	0.0192	0.0129
	(0.0735)	(0.5932)	(0.0067)	(0.0282)	(0.0087)
Loan to Asset(*t*-1)	-0.0387*	-0.4319**	-0.0046**	-0.0266**	-0.0013
	(0.0221)	(0.1727)	(0.0023)	(0.0113)	(0.0022)
Real Estate Loan(*t*-1)	0.0013	-0.1030	0.0034**	0.0088	0.0001
	(0.0240)	(0.1663)	(0.0017)	(0.0093)	(0.0020)
Excess Loan Growth(*t*-1)	-0.0276**	-0.0693	0.0003	0.0038	0.0002
	(0.0139)	(0.0608)	(0.0013)	(0.0038)	(0.0017)
Non-Interest Income(*t*-1)	-0.0409***	-0.7020***	0.0013	-0.0184***	-0.0029**
	(0.0109)	(0.1373)	(0.0012)	(0.0054)	(0.0013)
Observations	12,235	11,430	16,196	16,196	16,196
Number of BHCs	364	362	364	364	364
Adj. R-Squared	0.7655	0.4203	0.2748	0.4377	0.2385
BHC FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel B: Interaction Terms between Size and Bank Characteristics					
Dependent Variable	(1) *MES*	(2) *SRISK*	(3) ln_*Z Score*	(4) *Allw Margin*	(5) *NI Margin*
Constant	-4.6137	-128.9890*	12.5461***	6.5284	2.3375
	(14.1898)	(76.6906)	(1.7365)	(5.0735)	(1.6589)
Size(*t*-1)	0.1497	1.7860	-0.4534***	-0.4402	-0.1580
	(0.9062)	(5.0027)	(0.1071)	(0.3229)	(0.1049)
Tier 1 Ratio(*t*-1)	-0.0140*	-0.0455**	0.0087	-0.0000	0.0013
	(0.0081)	(0.0207)	(0.0099)	(0.0022)	(0.0018)
Under Cap(*t*-1)	12.6342***	46.5367**	-1.1104***	3.2029***	-0.0621
	(3.2798)	(18.3598)	(0.3010)	(0.8119)	(0.2029)
Deposit Funding(*t*-1)	0.2072	0.3318	-0.0864***	0.0151	0.0023
	(0.1358)	(0.7182)	(0.0171)	(0.0502)	(0.0142)
Debt Funding(*t*-1)	0.1238	-1.3437	-0.0599***	-0.0388	-0.0159
	(0.1741)	(1.2061)	(0.0180)	(0.0586)	(0.0163)
Loan to Asset(*t*-1)	-0.1259**	-0.4233	-0.0147*	-0.0463**	-0.0278***
	(0.0597)	(0.3266)	(0.0077)	(0.0216)	(0.0099)
Real Estate Loan(*t*-1)	-0.0267	-0.2030	-0.0026	-0.0324**	-0.0091
	(0.0528)	(0.2782)	(0.0050)	(0.0154)	(0.0074)
Excess Loan Growth(*t*-1)	0.1141**	0.3836**	0.0090***	0.0144	0.0123**
	(0.0560)	(0.1708)	(0.0033)	(0.0142)	(0.0060)
Non-Interest Income(*t*-1)	0.0279	0.2736	0.0019*	0.0117**	0.0033*
	(0.0193)	(0.2286)	(0.0010)	(0.0057)	(0.0020)
Size×					
Tier 1 Ratio(*t*-1)	0.0007*	0.0024**	-0.0005	-0.0000	-0.0001
	(0.0004)	(0.0011)	(0.0005)	(0.0001)	(0.0001)
Under Cap(*t*-1)	-0.6457***	-2.5261**	0.0456***	-0.1680***	0.0028
	(0.1799)	(1.1254)	(0.0161)	(0.0476)	(0.0108)
Deposit Funding(*t*-1)	-0.0084	-0.0067	0.0044***	0.0002	0.0004
	(0.0085)	(0.0468)	(0.0010)	(0.0032)	(0.0008)
Debt Funding(*t*-1)	-0.0039	0.1340*	0.0025**	0.0036	0.0012
	(0.0110)	(0.0789)	(0.0011)	(0.0038)	(0.0010)
Loan to Asset(*t*-1)	0.0078**	0.0263	0.0012**	0.0031**	0.0023***
	(0.0039)	(0.0216)	(0.0005)	(0.0014)	(0.0007)
Real Estate Loan(*t*-1)	0.0026	0.0114	0.0001	0.0022**	0.0008
	(0.0034)	(0.0179)	(0.0003)	(0.0010)	(0.0005)
Excess Loan Growth(*t*-1)	-0.0074**	-0.0232**	-0.0006***	-0.0013	-0.0009**
	(0.0035)	(0.0107)	(0.0002)	(0.0010)	(0.0004)
Non-Interest Income(*t*-1)	-0.0020	-0.0193	-0.0001*	-0.0008**	-0.0002*
	(0.0013)	(0.0157)	(0.0001)	(0.0004)	(0.0001)
Observations	12,235	11,430	16,196	16,196	16,196
Number of BHCs	364	362	364	364	364
Adj R-Squared	0.7665	0.4115	0.2954	0.4389	0.2457
BHC FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Table 6 Changes in effects due to Post-Crisis Regulations and time-varying robustness checks

In Panel A, the impact of banks characteristics on risk measure are allowed to differ after the Global Financial Crisis:

$$Y_{i,t} = \alpha + \sum_{k=1}^{9} \eta_k Top\,20_{t-1} \times X_{i,k,t-1} + \sum_{k=1}^{9} \rho_k Post - Crisis \times Top\,20_{t-1} \times X_{i,k,t-1}$$
$$+ \sum_{k=1}^{9} \beta_k X_{i,k,t-1} + \sum_{k=1}^{9} \delta_k Post - Crisis \times X_{i,k,t-1} + v_i + u_t + \varepsilon_{i,t}$$

where $X_{i,1,t-1}$ to $X_{i,9,t-1}$ denote nine bank characteristics of bank *i* at quarter *t-1*. *Post-Crisis* is a dummy variable, which equals one between 2009Q3 and 2017Q4 and zero otherwise. Panel A exhibits the differences between top and non-top banks in different periods (detailed regression results are available upon request). To be specific, for *k*th characteristic, the coefficient difference between top and non-top banks in the pre and crisis period equals η_k, and that in the post crisis period equals $\eta_k+\rho_k$. *P* values based on Wald tests are reported in square brackets.

Panel B reports results of running Equation (5) with variables on a 5-year rolling window and perform Fama-MacBech regression (as in Fama and French, 2008) to obtain the average coefficient of each bank characteristic. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% respectively.

Panel A: *The aggregate coefficients for Top 20 BHCs minus coefficients for non-Top BHCs in different periods (Wald tests)*

	(1) *MES*	(2) *SRISK*	(3) *ln_Z score*	(4) *Allw Margin*	(5) *NI Margin*
Pre and Crisis Period (2002Q1-2009Q2)					
Size(*t*-1)	0.2712	3.0589**	-0.0445**	0.0244	0.0033
	[0.2899]	[0.0414]	[0.0231]	[0.7885]	[0.9088]
Tier 1 Ratio(*t*-1)	0.1785	0.0014	0.0265**	0.0162	-0.0097
	[0.1273]	[0.9978]	[0.0464]	[0.6957]	[0.6467]
Under Cap(t-1)	-1.0333	-15.1355	0.0689	-0.2385	-0.0288
	[0.1893]	[0.1999]	[0.3075]	[0.2020]	[0.6597]
Deposit Funding(*t*-1)	-0.0256	0.3492	0.0058	0.0031	0.0038
	[0.5841]	[0.2609]	[0.1362]	[0.8586]	[0.5597]
Debt Funding(*t*-1)	0.0404	0.7925	0.0085	0.0024	0.0055
	[0.5486]	[0.1634]	[0.1185]	[0.9086]	[0.4664]
Loan to Asset(*t*-1)	-0.0326	-0.6835***	-0.0008	-0.0031	0.0015
	[0.1091]	[0.0058]	[0.7745]	[0.7043]	[0.6075]
Real Estate Loan(*t*-1)	-0.0025	-0.1685**	0.0044**	-0.0034	-0.0032
	[0.8833]	[0.0370]	[0.0292]	[0.5396]	[0.1740]
Excess Loan Growth(*t*-1)	-0.0263	0.0064	-0.0017	-0.0025	-0.0023
	[0.2312]	[0.9567]	[0.1238]	[0.5155]	[0.2868]
Non-Interest Income(*t*-1)	-0.0669***	-0.8975***	0.0001	-0.0164***	-0.0056***
	[0.0000]	[0.0000]	[0.9555]	[0.0000]	[0.0002]
Post-Crisis Period (2009Q3-2017Q4)					
Size(*t*-1)	0.1437	1.8499	-0.0456*	0.0192	-0.0071
	[0.5810]	[0.2620]	[0.0488]	[0.8380]	[0.8290]
Tier 1 Ratio(*t*-1)	0.0756*	0.2950*	-0.0497***	-0.0031	-0.0031
	[0.0663]	[0.0504]	[0.0000]	[0.7820]	[0.5840]
Under Cap(*t*-1)	-5.4417***	-7.9514*	0.2216***	-1.2501***	0.0350
	[0.0000]	[0.0806]	[0.0092]	[0.0000]	[0.7600]
Deposit Funding(*t*-1)	-0.0675	-0.5114*	0.0116**	-0.0006	0.0037
	[0.1140]	[0.0653]	[0.0104]	[0.9660]	[0.5700]
Debt Funding(*t*-1)	0.0111	-0.1205	0.0055	0.0453	0.0036
	[0.8640]	[0.7290]	[0.3680]	[0.2050]	[0.6480]
Loan to Asset(*t*-1)	0.0158	0.0751	0.0018	-0.0180*	-0.0023
	[0.5130]	[0.5310]	[0.4610]	[0.0968]	[0.5340]
Real Estate Loan(*t*-1)	0.0132	-0.0007	0.0051***	0.0163*	-0.0001
	[0.6210]	[0.9950]	[0.0052]	[0.0601]	[0.9570]
Excess Loan Growth(*t*-1)	-0.0089	-0.0583	0.0000	0.0043	0.0016
	[0.6120]	[0.1470]	[0.9980]	[0.4250]	[0.4180]
Non-Interest Income(*t*-1)	-0.0121	-0.0845	0.0002	-0.0147*	-0.0018
	[0.3500]	[0.1900]	[0.9240]	[0.0184]	[0.3870]
Observations	12,235	11,430	16,196	16,196	16,196
Number of BHCs	364	362	364	364	364
Adj R-Squared	0.778	0.450	0.405	0.467	0.254
BHC FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Panel B: Fama-Machbech regression on a 5-year rolling window and average coefficients					
	(1)	(2)	(3)	(4)	(5)
Dependent Variable	*MES*	*SRISK*	ln_*Z Score*	*Allw Margin*	*NI Margin*
Constant	0.6385	-162.0619***	4.9440***	2.9080***	-3.5572***
	(1.7663)	(9.6603)	(0.2532)	(0.3390)	(0.5764)
Size(*t*-1)	-0.1316	4.4158***	0.0176**	-0.1670***	0.2086***
	(0.1560)	(0.6421)	(0.0101)	(0.0367)	(0.0302)
Tier 1 Ratio(*t*-1)	-0.0570***	-0.1416***	0.0280***	-0.0132***	0.0061***
	(0.0117)	(0.0255)	(0.0037)	(0.0038)	(0.0013)
Under Cap(*t*-1)	2.3156***	6.3949***	-0.2328***	0.4928***	-0.1001***
	(0.2530)	(0.5193)	(0.0226)	(0.0443)	(0.0177)
Deposit Funding(*t*-1)	0.0799***	0.2137***	-0.0152***	0.0142***	0.0086***
	(0.0110)	(0.0265)	(0.0014)	(0.0029)	(0.0012)
Debt Funding(*t*-1)	0.0574***	0.5929***	-0.0179***	0.0094***	0.0048***
	(0.0070)	(0.0285)	(0.0013)	(0.0023)	(0.0012)
Loan to Asset(*t*-1)	-0.0063**	0.0012	0.0003*	-0.0002	0.0082***
	(0.0029)	(0.0082)	(0.0002)	(0.0010)	(0.0008)
Real Estate Loan(*t*-1)	0.0261***	-0.0110	-0.0009***	0.0031***	0.0045***
	(0.0043)	(0.0085)	(0.0002)	(0.0004)	(0.0003)
Excess Loan Growth(*t*-1)	-0.0004	0.0154***	0.0002*	-0.0051***	-0.0022***
	(0.0011)	(0.0033)	(0.0001)	(0.0004)	(0.0002)
Non-Interest Income(*t*-1)	-0.0011***	-0.0099***	0.0001**	-0.0005***	-0.0002***
	(0.0002)	(0.0016)	(0.0000)	(0.0001)	(0.0000)
***Top20*×**					
Size(*t*-1)	-0.1935	3.1029***	-0.0799***	-0.0064	-0.0203*
	(0.2124)	(0.6391)	(0.0118)	(0.0579)	(0.0148)
Tier 1 Ratio(*t*-1)	0.1767***	-0.6949***	-0.0090**	0.0100	-0.0208***
	(0.0411)	(0.0988)	(0.0050)	(0.0082)	(0.0032)
Under Cap(*t*-1)	-2.2263***	-11.4991***	0.1132***	-0.6765***	0.0527***
	(0.2614)	(1.7862)	(0.0218)	(0.0810)	(0.0218)
Deposit Funding(*t*-1)	-0.0086	-0.1931***	0.0087***	0.0089***	0.0008
	(0.0129)	(0.0626)	(0.0018)	(0.0022)	(0.0012)
Debt Funding(*t*-1)	0.0466***	0.1959***	0.0069***	0.0246***	0.0005
	(0.0187)	(0.0656)	(0.0018)	(0.0047)	(0.0011)
Loan to Asset(*t*-1)	0.0191*	0.0420	-0.0012***	-0.0132***	0.0024**
	(0.0127)	(0.0468)	(0.0005)	(0.0015)	(0.0013)
Real Estate Loan(*t*-1)	0.0330**	-0.0755*	0.0048***	0.0114**	-0.0027**
	(0.0138)	(0.0578)	(0.0003)	(0.0051)	(0.0013)
Excess Loan Growth(*t*-1)	-0.0120***	-0.0754***	-0.0010***	0.0026***	0.0006***
	(0.0030)	(0.0139)	(0.0001)	(0.0006)	(0.0002)
Non-Interest Income(*t*-1)	-0.0300***	-0.4428***	-0.0003***	-0.0126***	-0.0033***
	(0.0039)	(0.0557)	(0.0001)	(0.0013)	(0.0004)
Ave. observations	3,826.267	3,534.800	5,097.178	5,097.178	5,097.178
Ave. number of BHCs	259.356	247.778	292.511	292.511	292.511
Ave. adj. R-squared	0.675	0.384	0.293	0.417	0.181
BHC FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES

Table 7 Unexpected liquidity shocks on changes in bank characteristics

These are regression results of Equation (6). We use the Global Financial Crisis as an unexpected system-wide liquidity shock, and regress ΔX_k – which equals the average level of kth bank characteristic during the Crisis (2007Q4 and 2009Q2) minus the average level of this characteristic during the year before the Crisis (2006Q4 and 2007Q4) – on the average pre-crisis level of this bank characteristic, $X_k(pre)$. For example, in Model (1) Δ*Tier 1 Ratio* denotes the difference between average levels of *Tier 1 Ratio* during the Crisis and the year before the Crisis, $X_k(pre)$ represents the average level of *Tier 1 Ratio* in the year before the Crisis, and $X_k(pre)\times Top20$ is the interaction term between $X_k(pre)$ and *Top20*. Standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% respectively.

	(1) Δ*Tier 1 Ratio*	(2) Δ*Under Cap*	(3) Δ*Deposit Funding*	(4) Δ*Debt Funding*
Intercept	3.740* (2.224)	0.012** (0.005)	9.757*** (1.877)	2.887*** (0.314)
$X_k(pre)$	-0.363 (0.241)	-0.270*** (0.044)	-0.149*** (0.025)	-0.175*** (0.032)
$X_k(pre)\times Top20$	-0.040 (0.200)	-0.363*** (0.073)	-0.018 (0.014)	0.099** (0.048)
Adj. R-squared	0.001	0.375	0.123	0.097
Observation	256	256	256	256
	(5) Δ*Loan to Assets*	(6) Δ*Real Estate Loan*	(7) Δ*Excess Loan Growth*	(8) Δ*Non-Interest Income*
Intercept	4.572*** (1.511)	3.964*** (1.201)	-0.386*** (0.098)	1.174 (3.352)
$X_k(pre)$	-0.060*** (0.022)	-0.049*** (0.016)	-0.967*** (0.069)	-0.247** (0.124)
$X_k(pre)\times Top20$	-0.015 (0.015)	-0.055*** (0.016)	0.405*** (0.151)	0.003 (0.128)
Adj. R-squared	0.023	0.054	0.453	0.013
Observation	256	256	256	256

Table 8 Impact of a distress event in BHCs on the real economy.

Panel A reports summary statistics of ΔCoVaR for top BHCs and non-top BHCs on the entire real economy and each economic sector. Panel B presents results of test of ΔCoVaR statistical significance. Panel C shows results of test of whether ΔCoVaR for top BHCs dominates that for non-top BHCs. Market and Ex-Financials denote S&P 500 and S&P 500 excluding financials and real estate indices, respectively. Discretionary, Essentials, Industrials, Real Estate, Energy, Health Case, Information, Materials, Utilities and Communication denote ten S&P 500 economic sector indices.

Panel A: Summary statistics of ΔCoVaR (1% distress level)

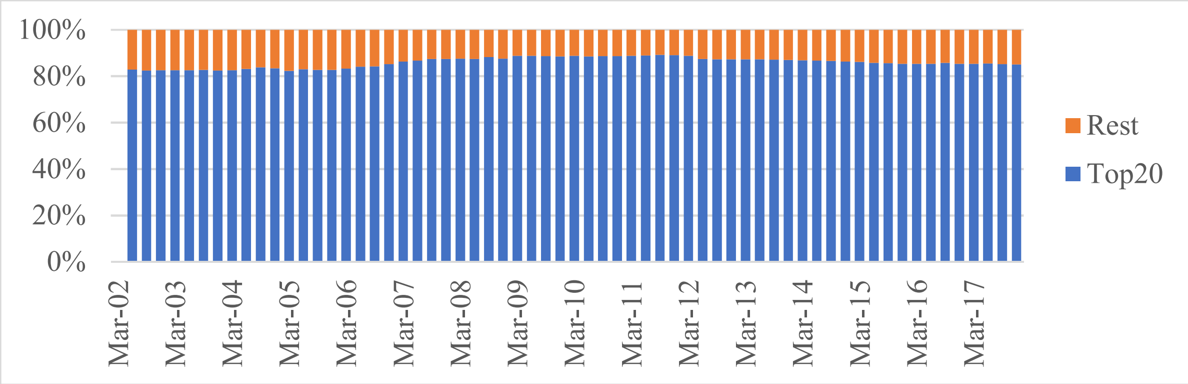
	Entire Sample 02Jan-17Dec		Pre-Crisis 02Jan-07Sep		Crisis 07Oct-09Jun		Post-Crisis 09Jul-17Dec	
In Percentage	mean	std.	mean	std.	mean	std.	mean	std.
Top 20 BHCs								
Market								
ΔCoVaR Market	4.2872	2.9731	3.9543	2.3300	8.3306	4.7844	3.6811	2.1135
ΔCoVaR Ex-Financials	3.1556	2.4814	1.8506	1.1074	6.4196	3.7725	2.7566	1.6752
Sectors								
ΔCoVaR Material	4.8442	3.3593	4.4680	2.6327	9.4129	5.4060	4.1593	2.3880
ΔCoVaR Energy	4.6717	3.2397	4.3089	2.5390	9.0777	5.2135	4.0112	2.3030
ΔCoVaR Real Estate	6.2780	4.3536	5.7905	3.4119	12.1989	7.0060	5.3904	3.0948
ΔCoVaR Health Care	3.4685	2.4053	3.1991	1.8850	6.7397	3.8707	2.9781	1.7098
ΔCoVaR Industrial	4.9465	3.4302	4.5624	2.6883	9.6117	5.5201	4.2472	2.4384
ΔCoVaR Discretionary	5.6221	3.8987	5.1855	3.0555	10.9244	6.2741	4.8273	2.7715
ΔCoVaR Essentials	1.7625	1.2222	1.6256	0.9579	3.4248	1.9669	1.5133	0.8689
ΔCoVaR Information	3.0024	2.0821	2.7693	1.6317	5.8341	3.3506	2.5780	1.4801
ΔCoVaR Communication	3.6372	2.5223	3.3548	1.9767	7.0676	4.0590	3.1230	1.7930
ΔCoVaR Utilities	2.7588	1.9131	2.5445	1.4993	5.3606	3.0787	2.3687	1.3600
Non-top BHCs								
Market								
ΔCoVaR Market	4.0843	2.4186	3.8133	1.9047	7.3402	3.9636	3.5983	1.6934
ΔCoVaR Ex-Financials	3.3247	2.3640	2.1144	1.1661	6.3255	3.6283	2.9601	1.6155
Sectors								
ΔCoVaR Material	5.3008	3.1390	4.9490	2.4720	9.5264	5.1442	4.6701	2.1978
ΔCoVaR Energy	4.8807	2.8902	4.5568	2.2761	8.7714	4.7365	4.2999	2.0236
ΔCoVaR Real Estate	6.4631	3.8272	6.0341	3.0141	11.6151	6.2721	5.6940	2.6797
ΔCoVaR Health Care	3.3098	1.9600	3.0902	1.5436	5.9483	3.2120	2.9160	1.3723
ΔCoVaR Industrial	4.5660	2.7038	4.2630	2.1294	8.2058	4.4311	4.0227	1.8931
ΔCoVaR Discretionary	4.9400	2.9253	4.6122	2.3038	8.8780	4.7940	4.3522	2.0482
ΔCoVaR Essentials	1.5281	0.9049	1.4267	0.7126	2.7462	1.4830	1.3463	0.6336
ΔCoVaR Information	2.4495	1.4505	2.2870	1.1424	4.4022	2.3772	2.1581	1.0156
ΔCoVaR Communication	2.8688	1.6988	2.6784	1.3379	5.1557	2.7841	2.5275	1.1894
ΔCoVaR Utilities	2.0420	1.2092	1.9064	0.9523	3.6697	1.9816	1.7990	0.8466

Panel B: Significance tests of ΔCoVaR

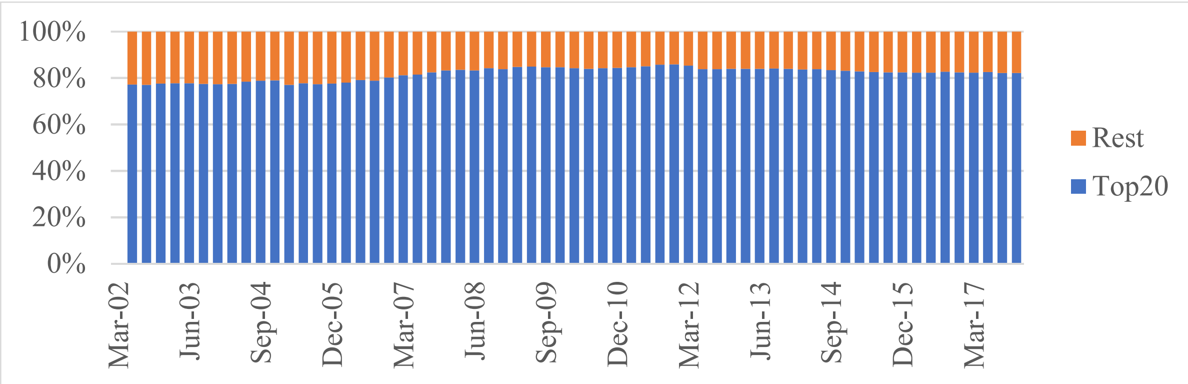
	Top 20 BHCs			non-Top 20 BHCs		
	Coefficient	*t*-statistic	*p*-Value	Coefficient	*t*-statistic	*p*-Value
Market						
ΔCoVaR Market	0.3627	5.2568	0.00%	0.4422	4.5475	0.00%
ΔCoVaR Ex-Financials	0.2700	2.9140	0.37%	0.3634	3.2544	0.12%
Sectors						
ΔCoVaR Material	0.4099	4.2499	0.00%	0.5740	3.4610	0.06%
ΔCoVaR Energy	0.3953	4.1232	0.00%	0.5285	4.4164	0.00%
ΔCoVaR Real Estate	0.5312	4.4318	0.00%	0.6998	4.6972	0.00%
ΔCoVaR Health Care	0.2935	4.7723	0.00%	0.3584	2.7748	0.57%
ΔCoVaR Industrial	0.4185	5.2042	0.00%	0.4944	8.9356	0.00%
ΔCoVaR Discretionary	0.4757	11.5737	0.00%	0.5349	9.9034	0.00%
ΔCoVaR Essentials	0.1491	2.8843	0.40%	0.1655	1.4171	15.69%
ΔCoVaR Information	0.2540	1.9799	4.81%	0.2652	1.4480	14.80%
ΔCoVaR Communication	0.3077	3.4342	0.06%	0.3106	2.4610	1.41%
ΔCoVaR Utilities	0.2334	1.6261	10.43%	0.2211	2.3983	1.67%

Panel C: Dominance tests

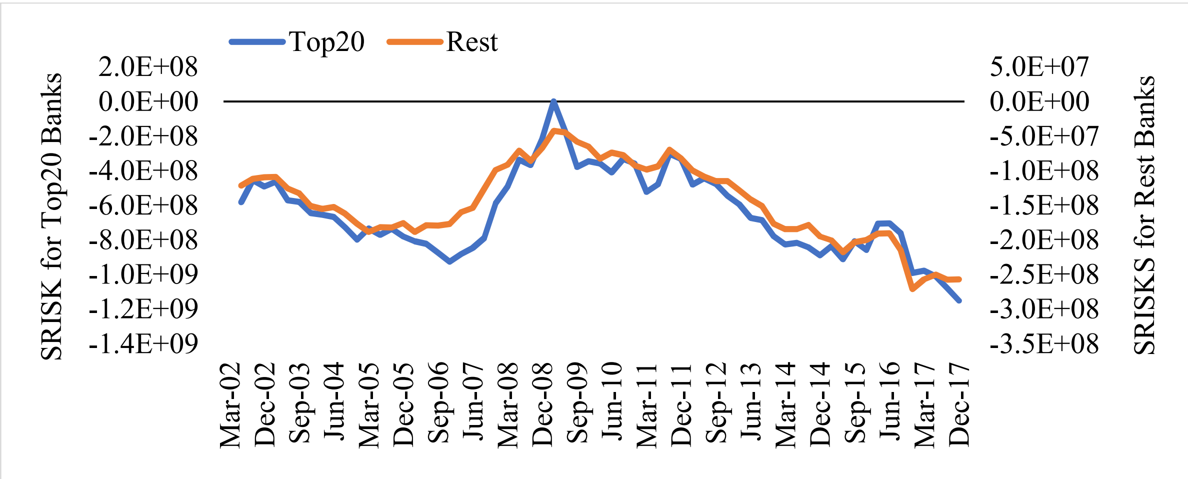
BHCs & Market						
	Market		Ex-Financials			
Null Hypothesis	Stat.	*p*-value	Stat.	*p*-value		
ΔCoVaR Top20<ΔCoVaR non-Top20	0.0499	0.1503	0.0193	0.8087		
ΔCoVaR Top20>ΔCoVaR non-Top20	0.0722	0.0189	0.0860	0.0148		
ΔCoVaR Top20=ΔCoVaR non-Top20	0.0722	0.0378	0.0860	0.0296		
BHCs & Sectors						
	Material		Energy		Real Estate	
Null Hypothesis	Stat.	*p*-value	Stat.	*p*-value	Stat.	*p*-value
ΔCoVaR Top20<ΔCoVaR non-Top20	0.0092	0.9377	0.0157	0.8278	0.0184	0.7732
ΔCoVaR Top20>ΔCoVaR non-Top20	0.1299	0.0000	0.1011	0.0004	0.0932	0.0013
ΔCoVaR Top20=ΔCoVaR non-Top20	0.1299	0.0000	0.1011	0.0008	0.0932	0.0027
	Health Care		Industrials		Discretionary	
Null Hypothesis	Stat.	*p*-value	Stat.	*p*-value	Stat.	*p*-value
ΔCoVaR Top20<ΔCoVaR non-Top20	0.0499	0.1503	0.0696	0.0251	0.0984	0.0006
ΔCoVaR Top20>ΔCoVaR non-Top20	0.0722	0.0189	0.0630	0.0486	0.0486	0.1659
ΔCoVaR Top20=ΔCoVaR non-Top20	0.0722	0.0378	0.0696	0.0501	0.0984	0.0012
	Essentials		Information		Communication	
Null Hypothesis	Stat.	*p*-value	Stat.	*p*-value	Stat.	*p*-value
ΔCoVaR Top20<ΔCoVaR non-Top20	0.1063	0.0002	0.1509	0.0000	0.1745	0.0000
ΔCoVaR Top20>ΔCoVaR non-Top20	0.0442	0.2194	0.0223	0.6844	0.0171	0.8011
ΔCoVaR Top20=ΔCoVaR non-Top20	0.1063	0.0004	0.1509	0.0000	0.1745	0.0000
	Utilities					
Null Hypothesis	Stat.	*p*-value				
ΔCoVaR Top20<ΔCoVaR non-Top20	0.2192	0.0000				
ΔCoVaR Top20>ΔCoVaR non-Top20	0.0118	0.8992				
ΔCoVaR Top20=ΔCoVaR non-Top20	0.2192	0.0000				



Panel A: The composition of total assets in the banking industry



Panel B: The composition of total deposits in the banking industry



Panel C: SRISK in dollar terms

Figure 1. Market power of Top depository BHCs.

Panel A and B depict the composition of assets and deposits in the depository banking industry respectively. Panel C reports total systemic risk (SRISK in dollar terms proposed by Brownlees and Engle in 2017) of bank group. The Top20 BHCs are depository BHCs whose total assets are ranked as the 20 largest depository BHCs in the previous quarter.

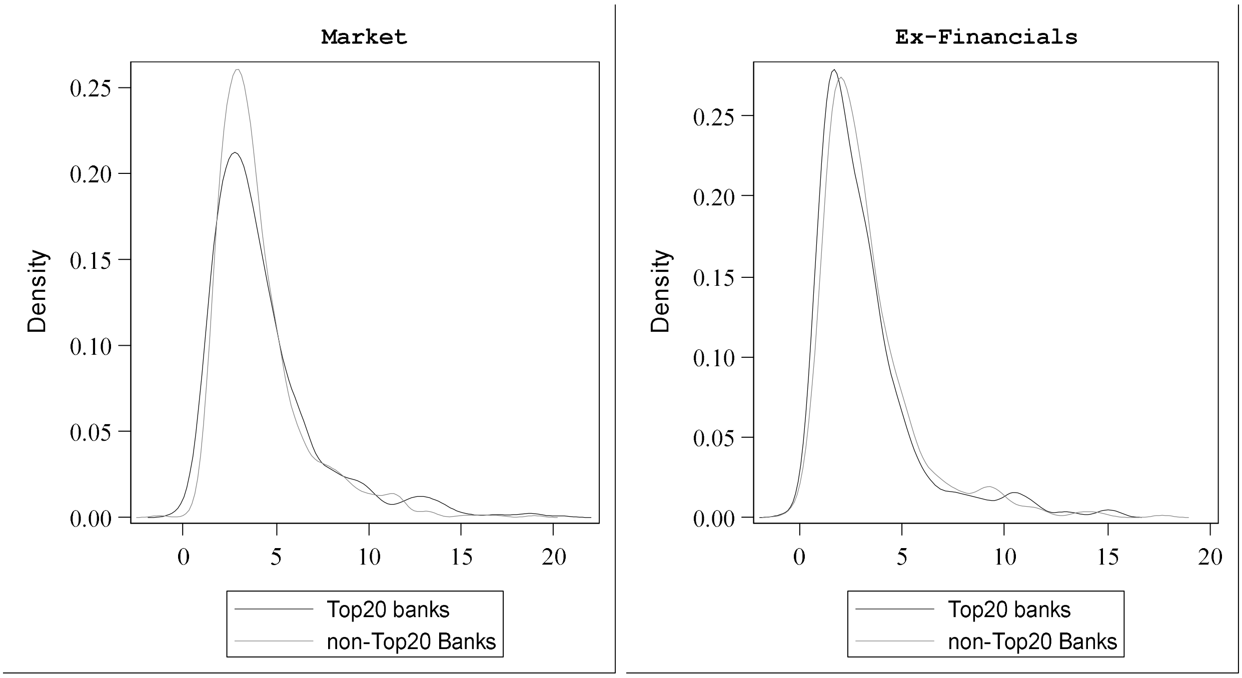


Figure 2. Kernel density of ΔCoVaR

These are the Probability Density Functions of ΔCoVaR for top 20 and non-top BHCs on the overall economy, using the kernel density estimation. S&P 500 index represents the performance of the overall real economy (Market), and S&P 500 excluding financials and real estate index represents is an alternative proxy for the overall real economy (Ex-Financial).

Appendices

Appendix A: Long-Run Marginal Expected Shortfall (*LRMES*)

LRMES is estimated by the following steps. First, for each quarter, we use a fixed-sized rolling window of two years (between quarter *t*-7 and *t*) and implement the DCC-TGARCH (due to Engle, 2002, and Zakoian, 1994, respectively) model to estimate daily covariance matrix between bank *i* and the equity market *m* as Equation (A1) below shows:[7]

$$\begin{cases} r_d = \varepsilon_d \quad \text{where } \varepsilon_d \sim i.i.d.N(0, D_d R_d D_d) \\ D_d{}^2 = diag\{w_j\} + diag\{k_j\} \circ \varepsilon_{d-1}\varepsilon_{d-1}' + diag\{\gamma_j\} \circ I_{\varepsilon_{j,d-1<0}} \varepsilon_{d-1}\varepsilon_{d-1}' + diag\{\lambda_j\} \circ D_{d-1}{}^2 \\ v_d = D_d{}^{-1}\varepsilon_d \\ Q_d = S(1-a-b) + av_{d-1}v_{d-1}' + bQ_{d-1} \\ R_d = diag\{Q_d\}^{-1} Q_d diag\{Q_d\}^{-1} \end{cases} \tag{A1}$$

where $r_d = (r_{i,d}, r_{m,d})'$ is the vector of daily returns of bank *i* and equity market *m* at day *d*, both of which are assumed to follow a joint normal distribution with a covariance matrix of $D_dR_dD_d$.. $\varepsilon_d = (\varepsilon_{i,d}, \varepsilon_{m,d})'$ is the residual vector. The diagonal matrix D_d^2 denotes conditional variance matrix at day *d*, and is estimated by TGARCH (1,1,1) model. Diagonal matrices $diag\{w_i\}$, $diag\{k_i\}$, $diag\{\gamma_i\}$ *and* $diag\{\lambda_i\}$ contain univariate TGARCH parameters. $I_{\varepsilon_{i,d-1<0}}$ includes all indicator functions at day *d*, and each indicator function equals one if $\varepsilon_{i,d-1} < 0$ and zero otherwise. The notation $\circ$ stands for element by element multiplication.

Then, for quarter *t*, we calculate the average correlation coefficients ($\rho_{i,t}$) between returns of bank *i* and equity market *m*, that is, $\rho_{i,t} = \sum_{j=0}^{N-1} \widehat{\rho}_{i,d-j}$, where *d* denotes the last trading day of quarter *t*, and *N* equals the number of trading days in that quarter. The same rationale applies

[7] Hwang and Valls Pereira (2006) suggest that, to avoid estimation bias in the Maximum Loglikelihood procedure, the minimal sample size is 250 for an ARCH(1) model and 500 for a GARCH(1,1) model. Hence, we set the size of rolling window to be two years instead of one year used by Brownlees and Engle's (2017).

to the average standard deviations of daily returns of bank i and the equity market m ($\sigma_{i,t}$ and $\sigma_{m,t}$).

Finally, the quarterly *LRMES* equals:

$$
\begin{aligned}
&LRMES_{i,t} = -\sqrt{22}\beta_{i,t}E(r_{m,d+1} \mid r_{m,d+1} < c) \times 100 \\
&\text{where } \beta_{i,t} = \rho_{i,t}\frac{\sigma_{i,t}}{\sigma_{m,t}}, \quad E(r_{m,d+1} \mid r_{m,d+1} < c) = -\sigma_{m,t}\frac{\phi(c/\sigma_{m,d})}{\Phi(c/\sigma_{m,d})}, \\
&\qquad c = \log(1-10\%)/\sqrt{22}
\end{aligned}
\tag{A2}
$$

where d denotes the last trading day of quarter t. $E(r_{m,d+1}|r_{m,d+1}<c)$ is the expected daily loss of the equity market when market returns are smaller than a threshold c. $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density function (PDF) and cumulative density function (CDF) of the standard normal distribution, respectively. The "22" in the last term is because it is assumed to have twenty-two trading days in one calendar month.

Appendix B: Panel unit roots tests.

The LLC test employs a null hypothesis of a common unit root, and the IPS, Panel ADP and Panel PP tests employ a null hypothesis of individual unit root. LLC, IPS, Panel ADF and Panel PP tests are proposed by Levin et al., (2002), Im et al., (2003), Maddala and Wu (1999) and Choi (2001), respectively. Lag length are selected based on SIC between 0 and 10. We have not tested the stationarity of *Undercapitalization*, as it is a dummy variable.

	LLC test		IPS test		Panel ADF test		Panel PP test	
	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
Dependent Variables								
MES	-11.79	0.00%	-9.66	0.00%	1288.84	0.00%	944.91	0.00%
LRMES	-12.35	0.00%	-11.21	0.00%	1381.95	0.00%	1478.09	0.00%
SRISK	-33.69	0.00%	-8.38	0.00%	1276.47	0.00%	1443.56	0.00%
ln_Z Score	-220.96	0.00%	-86.42	0.00%	2807.16	0.00%	2720.86	0.00%
Allw Margin	-6.43	0.00%	-2.99	0.14%	1030.16	0.00%	777.92	6.62%
NI Margin	-15.79	0.00%	-23.54	0.00%	2137.35	0.00%	2812.07	0.00%
Independent Variables								
Size	-7.89	0.00%	5.96	100.00%	814.68	0.80%	973.29	0.00%
Tier 1 Ratio	-8.20	0.00%	-11.44	0.00%	1405.08	0.00%	1548.18	0.00%
Loan to Asset	-5.05	0.00%	-1.02	15.43%	811.87	0.96%	807.59	1.26%
Real Estate Loan	-7.83	0.00%	-2.53	0.57%	931.34	0.00%	922.39	0.00%
Deposit Funding	-11.82	0.00%	-11.11	0.00%	1208.64	0.00%	1287.06	0.00%
Debt Funding	-13.74	0.00%	-11.65	0.00%	1397.35	0.00%	1340.77	0.00%
Excess Loan Growth	-99.98	0.00%	-95.93	0.00%	8934.64	0.00%	10917.10	0.00%
Non-Interest Income	-25.70	0.00%	-32.39	0.00%	3019.53	0.00%	3768.85	0.00%

Appendix C: Risk Contagion Measure and Test

Two-Step Procedure to Estimate ΔCoVaR

Following Adrian, and Brunnermeier (2016), we first regress the weekly return of index i ($R_{i,w}$) on a set of lagged state variables (M_{w-1}), using a α-th quantile regression.

$$R_{i,w} = \beta_i^{\alpha} + M_{w-1}\gamma_i^{\alpha} + \varepsilon_{i,w} \tag{C1}$$

where M_{w-1} is a vector of all lagged state variables: Δ*Term Spread*, Δ*TED Spread*, Δ*Credit Spread*, *VIX*, Δ*3M Yield* (changes in three-month treasury yield), *Real Estate Excess* (excess real estate returns) and *market* (return of S&P 500 index). Then, the α-th quantile of Value at Risk of the index i at week w equals the fitted value of Equation (C1) $\widehat{VaR}_{\alpha,w}^{i} = -\left(\hat{\beta}_i^{\alpha} + M_{w-1}\hat{\gamma}_i^{\alpha}\right)$.

We then regress the weekly returns of the real economy j ($R_{j,w}$) on lagged state variables along with the weekly return of index i ($R_{i,w}$), using q-th quantile regression.

$$R_{j,w} = \beta_j^{q} + M_{w-1}\gamma_j^{q} + R_{i,w}\delta_j^{q} + \varepsilon_{j,w} \tag{C2}$$

$\Delta CoVaR_{q,w}^{j|i}(\alpha)$ is then computed by:

$$\Delta CoVaR_{q,w}^{j|i}(\alpha) = \hat{\delta}_j^{q}\left(\widehat{VaR}_{\alpha,w}^{i} - \widehat{VaR}_{50\%,w}^{i}\right) \tag{C3}$$

Equation (C3) follows Castro and Ferrari (2014) and Adrian and Brunnermeier (2016) in eliminating the influence of the lagged state variables from ΔCoVaR estimation.[8] As we focus on extreme distress events (α = q = 1%), we use $\Delta CoVaR_{w}^{j|i}$ to denote $\Delta CoVaR_{1\%,w}^{j|i}(1\%)$ for simplicity in the rest of this study. The significance test is such that *ΔCoVaR* is significant if

[8] Bernal et al. (2014) propose an alternative measure, which first estimate $\widehat{CoVaR}_{q,t}^{j|i}(\alpha) = \hat{\beta}_j^{q} + M_{t-1}\hat{\gamma}_j^{q} + \widehat{VaR}_{\alpha,t}^{i}\widehat{\delta}_j^{q}$ and then calculate $\Delta\widehat{CoVaR}_{q,t}^{j|i} = \widehat{CoVaR}_{q,t}^{j|i}(1\%) - \widehat{CoVaR}_{q,t}^{j|i}(50\%)$. We have not considered the alternative measure since $\Delta\widehat{CoVaR}_{q,t}^{j|i}$ has not excluded influence from the changes in macro uncertainty.

and only if $\hat{\delta}_j^q$ is statistically different from zero. The covariance matrices are estimated by the Sparsity function method proposed by Koenker and Machado (1999), since our sample size of around 800 is far less than 5000 required by the resampling method to generate stable estimations.

Dominance Tests

We also employ the dominance test to evaluate whether top 20 BHCs have a significantly larger impact on the real economy than the rest non-top banks together. We use the bootstrap Kolmogorov-Smirnov (KS) test proposed by Abadie (2002) as the dominance test. The two-sample KS test statistic is:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{1/2} \sup_x \left|A_m(x) - B_n(x)\right| \tag{C4}$$

where $A_m(x)$ and $B_n(x)$ denote cumulative density functions of the $\Delta CoVaR$ for top and non-top bank indexes, respectively; and m and n are sample size of previous mentioned $\Delta CoVaR$s. The null hypothesis is:

$$H_0 : \Delta CoVaR_w^{j|i} > \Delta CoVaR_w^{j|k} \tag{C5}$$

for group i versus group k.