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Xi Yang

UMR 7235

Université de Paris Ouest Nanterre La Défense
(bâtiment G)
200, Avenue de la République
92001 NANTERRE CEDEX

Tél et Fax : 33.(0)1.40.97.59.07
Email : nasam.zaroualete@u-paris10.fr

université Paris Ouest Nanterre La Défense

Predicting bank failures:

The leverage versus the risk-weighted capital ratio[1]

Xi Yang[a]

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Abstract

This paper investigates the efficiency of leverage ratios and risk-weighted capital ratios as bank failure predictors during the global financial crisis. Analyzing 417 bank failures between 2008 and 2012, we find that the predictive power of different capital ratios is not homogeneous across banks. The simple leverage ratio outperforms the risk-weighted ratio in predicting failures of large banks, while both capital ratios are important in predicting the failure of smaller banks. The better performance of the leverage ratio in the case of large banks is especially important during the crisis period of 2008-2010. The findings support the regulatory reforms proposed by Basel Committee on Banking Supervision on the adoption of a supplementary minimum leverage ratio in order to strengthen the resilience of the bank sector.

JEL classification: G21, G28, G33
Keywords: leverage ratio, risk-weighted capital ratio, bank failure, CAMELS, Logit model

[a] Université Paris Ouest-Nanterre La Défense, EconomiX-CNRS, 200 Avenue de la République, 92001 Nanterre, France. E-mail address: xiyang92@gmail.com.

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1. Introduction

Capital ratios have been used as a tool for evaluating the safety and soundness of banks since a long time. In the United States, the minimum capital ratio requirements were formally introduced in banking regulation in 1981 (Gilbert et al., 1985). Since the enactment of the Basel Accord in 1988, risk-based capital ratios have been the central of international capital regulation. Regulators as well as researchers have continuously made efforts in assessing and improving the capital regulation standards to ensure that banks hold enough capital to deal with credit and market risks in the unstable financial environment.

The recent global financial crisis revealed the problems associated with the risk-based capital framework (Brei and Gambacorta, 2015). Besides the well-known pro-cyclical effects (Gordy and Howells, 2006; Repullo and Suarez, 2008), the risk-weighted capital framework has been criticized for its complexity and the opacity of the risk weighting methods and potential manipulation of bank's internal risk assessments (Mariathasan and Merrouche, 2014). In fact, to the extent that risks are measured with historical data and that past experience is a good guide for the future, a risk-weighted ratio should be the best tool for matching a firm's capital requirements. However, in reality, historical data are not sufficiently large to calibrate risk models. The models themselves are simplifications of reality and therefore modelling uncertainty is unavoidable in risk measuring (Gordy, 2003; Bank of England, 2014). Moreover, complexity and lack of transparence in the risk weighting framework impede market participants to distinguish adequately between strong and weak banks. Mariathasan and Merrouche (2014) find that reported riskiness declines for banks that adopted the internal rating-based approach for calculating their risk-weighted assets. The effect is even stronger among weakly capitalized banks. However, introducing a leverage ratio into the regulation framework seems to help getting around the drawbacks of risk-weighting models. It is argued that, provided that there exists information asymmetry between banks and regulators, a risk-independent leverage ratio restriction can put a floor on the risk-weighted ratio and induce banks to declare honestly their risk taking via the internal rating based approach (Blum, 2008; Brei and Gambacorta, 2015; Dermine, 2015).

In the wake of the global financial crisis, the Basel Committee on Banking Supervision (BCBS) puts forward a non-risk based leverage ratio (see Section 2) to complement the existing capital framework in order to discourage leverage building up and to remedy flaws of the risk-weighted capital requirements. As a part of Basel III package, the primary proposal on leverage ratio was published in 2010. Then the final rules came out in January 2014. Although similar unweighted leverage ratios were included in banking regulation of several countries prior to 2010, this is the first time that a leverage ratio is taking account of both on- and off-balance assets which applicable worldwide. It is worth examining the role of the leverage ratio in bank regulation. To be successful in any of these roles, capital ratios should bear a significant negative relationship to the risk of subsequent bank failure (Estrella et al., 2000).

Against this backdrop, the present paper studies the efficacy of the leverage ratio in predicting bank failure comparing it with the risk-based capital ratio. More specifically, we try to answer the following questions: (i) Does the leverage ratio outperform the risk-weighted ratio as a predictor of bank failure?; and (ii) Is there a difference in the performance of the leverage ratio across small and large banking institutions?

A number of studies have investigated the effectiveness of the leverage ratio and risk-weighted ratio in predicting bank risks and performance. Blundell-Wignall and Roulet (2013) and Demirguc-Kunt et al. (2013) both use international data on banks from advanced economies surrounding the global financial crisis. Blundell-Wignall and Roulet (2013) find evidence that the risk-weighted capital does not significantly predict default risk as measured by the distance-to-default. The non-weighted leverage ratio, on the contrary, found strong support. Demirguc-Kunt et al. (2013) study the relationship between the stock returns and the level of capital ratios. They find that during the crisis, a stronger capital position was associated with better stock market performance, and this relationship is stronger when capital is measured by the leverage ratio rather than by the risk-adjusted capital ratio. Other papers have used data on US banks. Estrella et al. (2000) study the predictive power of capital ratios in the case of bank failures during 1989 and 1993. Their findings indicate that the simple leverage ratio and the risk-weighted ratio predict equally well the failure of banks over short horizons of less than two years, while the risk-weighted ratio is more effective over long term. Mayes and Stremmel (2014) compare the performance of the simple leverage ratio and risk-weighted ratio as a predictor for failed banks for the period from 1992 to 2012. They find that the leverage ratio performs slightly better than risk-weighted ratio. However, Haldane and Madouros (2012) conducting a simple analysis on predictive power of capital ratios in bank failures since 2007 find different results: the risk-based capital ratio is a significant predictor while leverage ratio is not. Contrary to the intuition, the papers using the US data did not find evidence that leverage ratio is more effective than risk-weighted ratio, rather they reached different and contradictory conclusions. This can be due to the difference in sample periods or the negligence of the heterogeneity of individual banks, since the econometric analyses are done for the full sample of banks without considering the fact that large and small banks have managed capital ratios differently. This is an issue we will deal with in the present paper.

Our study uses a quarterly database on the financial statements of US commercial banks, from small regional banks to global systemically important banks (G-SIBs). The econometric analysis is based on the early warning system which explains bank failures by CAMELS ratios: Capital adequacy, Asset quality, Management competence, Earning ability, Liquidity and Sensitivity to market risk. We estimate logit regressions with a binary failure indicator as dependent variable over 2008-2012. Alternating risk-weighted ratio and leverage ratio as capital adequacy variables in the regressions, we compare their predictive power with regard to bank failures. Moreover, assuming that large banks might adopt riskier and more aggressive business models than small regional banks and that they have different risk-weighting methods (internal versus standard approach), we split the sample according to the size of banks. Thus, it allows us to gauge whether the predictive effectiveness similar across different types of banks. The main findings suggest that the leverage ratio outperforms the risk-weighted ratio for large banks and the relation is the opposite for small banks.

The remainder of the paper is organized as follows. Section 2 presents the Basel III proposals on the strengthened capital regulation and their implementation in the United States. The formula to calculate the leverage ratio is given at the end of the section. Section 3 describes the data and stylized facts about the capital ratios and then discusses the econometric approach. Section 4 reports the main results of baseline estimations along with robustness checks. Section 5 gives concluding remarks.

2. Leverage ratios in the US Basel III regulatory capital regime

In order to address the market failure revealed by the global financial crisis and to promote a more resilient banking sector, the Basel Committee introduces a number of fundamental reforms to the international regulatory framework, the Basel III package. The reforms strengthen micro-prudential regulation at the bank level by raising both the quality[2] and the quantity of the regulatory capital base and enhance the risk coverage of the capital framework: Basel III introduces for the first time a minimum common equity Tier 1 (CET 1) capital ratio set at 4.5 percent of risk-weighted assets and a capital conservation buffer of 2.5% (to be implemented from 2019); and the minimum Tier 1 capital ratio is revised and increased to 6%. The reforms also have a macro-prudential focus. Basel III proposes a

[2] Basel III improves the regulatory capital quality through a stricter definition of capital, properly focused on common equity (common shares plus retained earnings).

countercyclical capital buffer to protect the whole banking sector in period of excess aggregate credit growth. In addition, to contain systemic risks arising from the interconnection of financial institutions, capital surcharges of 2.5 percent of a bank's risk-weighted assets will be applied to G-SIBs. To ensure that banks meet the new capital standard through reasonable earnings retention and capital raising while still supporting lending to the economy, transitional arrangements will be put in place from 2013 to 2018. That is, during this period, the minimum capital ratios (especially capital buffers) banks should meet will increase gradually to the level required by Basel III (BCBS, 2010).

Much of the vulnerabilities that led to the global financial crisis are related to the fact that financial institutions had built up excessive on- and off-balance sheet leverage (Aglietta and Scialom, 2010). In many cases, banks were excessively leveraged while maintaining strong risk-based capital ratios (Brei and Gambacorta, 2015). The downward pressure on asset prices during the crisis triggered a vicious deleveraging process, causing declines in bank capital and further amplifying the crisis. In response, the Basel III framework has introduced a leverage ratio requirement to complement the risk-based regulatory framework. Leverage does not rely on assumptions such as the correlation or volatility of assets and does not assume any mitigating effects of diversification. Thus, the leverage ratio constitutes a protection against "the illusion of the measurability of risks" that the risk weight methodology conveys (Hellwig, 2010). It therefore protects individual banks against the underestimation of their risks caused by rare events or the weaknesses of risk models in capturing endogenous risk. The leverage ratio is intended to achieve two objectives: constraining the built-up of leverage in the banking sector and reinforcing the risk-based capital requirements with a simple, transparent and non-risk based backstop measure (BCBS, 2010; BCBS, 2014a).

The Basel III leverage ratio is defined as Tier 1 capital divided by an exposure measure, where total exposure is the sum of (1) on-balance sheet exposures; (2) derivative exposures; (3) securities financing transaction (SFT) exposures; and (4 off-balance sheet (OBS) items[3]. The minimum requirement for leverage ratio is set at 3% for the period from 1 January 2013 to 1 January 2017 and banks are required to publicly disclose their leverage ratio on 1 January 2015. The Basel Committee will adjust the definition and carry out the final calibration of leverage ratio by 2017, with a view to migrating to a Pillar 1 treatment on 1 January 2018.

The Basel III regulatory capital regime is adopted by US federal banking agencies[4] at the same time. Despite some modifications to comply with the Dodd-Frank Act, the US version generally mirrors Basel III and respects the same transitional period calendar. In terms of risk-based capital requirements, the final US Basel III is applied to all US banking organizations, including banks, savings associations, US domiciled Bank Holding Companies (BHCs) with assets of $500 million and greater and Savings and Loan Holding Companies (SLHCs), irrespective of size (FRB, 2013). The minimum capital requirements for CET 1, Tier 1 and total capital ratios and buffers in Basel III remain in the US standards, while some components of regulatory capital are redefined and the rules for calculating risk-weighted assets are revised to enhance risk sensitivity and address weaknesses in the current US framework (FRB, 2013).

Compared to the risk-weighted capital framework, the US leverage ratio framework differs from the original Basel III. This is because there has been a non-risk-weighted leverage ratio in the US capital regime since 1980s (Brei and Gambacorta, 2015). This ratio is defined as the Tier 1 capital divided by the average of daily or weekly total assets over one quarter. The leverage ratio requirement is applied to all US

[3] Concrete definitions are provided in BCBS (2014a).
[4] Federal banking agencies refer to Federal Reserve System, Federal Deposit Insurance Corporation and the Office of the Comptroller of the Currency.

banking organizations. This ratio is one of the capital criteria of the US prompt corrective action (PCA[5]) framework. An "adequately-capitalized" bank should maintain a leverage ratio of 4 percent[6] at minimum and 5 percent for a "well-capitalized" bank.

As the existing leverage ratio only takes account of the on-balance sheet assets, but not the OBS exposures, the US Basel III framework introduces also the Basel III leverage ratio which equals to the Tier 1 capital divided by the total on- and off- balance sheet exposures with slight modifications. To distinguish the two ratios, the leverage ratio proposed by Basel Committee is called supplementary leverage ratio in the US capital framework. The supplementary leverage ratio will be only applied to banking organizations subject to the advanced approaches risk-based capital rules[7]. The minimum requirement is set at 3 percent as the Basel leverage ratio. Moreover, a more restrictive requirement will be applied to US G-SIB and their insured depository institution subsidiaries. That is, the G-SIB should hold a supplementary leverage ratio of at least 5 percent to avoid restriction on dividend distributions and discretionary bonus payments to executive officers and the depository institution subsidiaries should maintain a 6% supplementary leverage ratio to be considered well-capitalized (FRB, 2014). Therefore, the US supplementary leverage ratio is a complement to capital standards with a macro-prudential goal. It can be an effective instrument to achieve Dodd-Frank Act's objective of curbing "Too-big-to-fail" as well. The supplementary leverage ratio provides for systemically important banks a capital buffer to improve their loss absorbing capacity. The fact that higher ratio puts more private capital at risk is expected to shift banks' risk-taking incentives so as to raise their resilience.

This paper aims to investigate the efficacy of different capital ratios to forecast bank failures. While the components of risk-based capital ratios and the US leverage ratio are reported in banks' financial statements, it is challenging to obtain the denominator of the supplementary leverage ratio. The relative final rules for supplementary leverage ratio were only issued in 2014. Some elements necessary to calculate the total leverage exposure are new items disclosed for the first time in 2015, as a result of the enhancement of risk coverage of the Basel III capital framework. Some other elements are modified compared to their old definition prior to 2015[8]. As our database goes from 2001 to 2012, what we can do is to calculate a proxy for the exposure measure with available on- and off-balance sheet assets categories. The total leverage exposure is the sum of 1) on-balance sheet assets net of amounts deductible from Tier 1 capital, 2) potential future exposure for derivatives contracts and 3) credit equivalent amounts of OBS exposures excluding repo-style transactions. The potential future exposure (PFE) equals the notional principal amount for each derivative contract multiplied by a conversion factor and the credit equivalent of OBS which is equal to the notional amount multiplied by a credit conversion factor. Table 1 provides a summary of the elements to calculate the leverage exposure proxy. In fact, we have to give up SFT exposure (Repo-style transaction exposure) which should be added in the total leverage exposure, because

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[5] The PCA has been adopted with the Federal Deposit Insurance Corporation Improvement Act of 1991. The Act specifies five capital categories according to bank's capital/asset ratios (risk-weighted or non-weighted) from well capitalized to critically under-capitalized. Each category is associated with both mandatory and discretionary provisions. When a bank is downgraded to a lower level of capital zone (from undercapitalized category), the regulatory constraint is consequently reinforced. Supervisors are authorized to close down a bank within 90 days after it has crossed the threshold of critical undercapitalization. See Spong (2000) Tables 5, 6 and 7 on pages 91, 93 and 94.

[6] Prior to the introduction of US Basel III framework, an adequately capitalized bank may have a leverage ratio of 3 percent if its most recent examination rating (CAMELS rating) was the highest rating and it is not experiencing or anticipating significant growth. This exemption is eliminated by the US Basel III proposal.

[7] Advanced approaches institutions generally refer to banking organizations with total consolidated assets higher than $250 billion or with on-balance sheet foreign exposures higher than $10 billion.

[8] For example, the unconditionally cancelable commitments and off-balance sheet repo-style transaction are new items and the item of notional principal amounts of credit derivative contracts is redefined.

of lack of information. However, the proxy will still be reliable. We observe in previous studies, such as Brei and Gambacorta (2015), the SFT exposures in total leverage exposure represent only 6 percent in the total leverage exposure for 105 large banks from 14 advanced economies. We can deduce that the share of SFT exposure will be much smaller for most US banking organizations. Moreover, the initial US Basel III proposals released in 2012 did not require special treatment on SFT: SFT exposure is recognized as the on-balance sheet amounts and OBS SFTs are not included in leverage exposure. The SFT exposures are added in final leverage ratio framework for the purpose of the harmonization with Basel III framework.

In summary, using the information reported in banks' financial statements, we calculate the two leverage ratios for all banking organizations in our database as following:

$$Leverage\ ratio = \frac{Tier\ 1\ Capital}{Average\ total\ assets}$$

$$Supplementary\ Leverage\ ratio = \frac{Tier\ 1\ Capital}{Total\ leverage\ exposure}$$

3. Data and methodology

3.1. Sample selection

This paper compares the performance of different capital ratios in the prediction of bank failures. Data for the empirical study are collected from multiple sources. The failed bank list is available on the official websites of FDIC and/or Federal Reserve Bank of Chicago. We get the list of banks recapitalized by the US Department of the Treasure from the CNN Money website. The quarterly data for the bank-specific characteristics are extracted from Consolidated Reports of Condition and Income (Call reports) which provide detailed balance sheet and income information. The reports are published at the Federal Reserve Bank of Chicago website until 2010 and the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution site since March 2011. The unconsolidated financial statements data for parent companies (bank holding companies) can be found at Chicago Fed's website. Finally, we complete the dataset with two macroeconomic indicators, the House Price Index by state and the personal income by state released, respectively, by Federal Housing Finance Agency and U.S. Bureau of Economic Analysis (BEA).

The dataset covers all FDIC-insured commercial banks[9] active between 2001 and 2012. We excluded banks with a lifespan of less than 8 quarters and voluntarily liquidated banks[10]. Finally, we obtain an unbalanced panel of 9456 banks, of which 7719 (82 percent) have been owned by holding companies. 6272 banks

[9] Our dataset consists of federally charted and state-chartered commercial banks, state-charted thrifts (saving banks) and cooperative companies. National banks (federally charted banks) are regulated by the Office of the Comptroller of the Currency (OCC), state member banks regulated by the Federal Reserve System (FRS) and state non-member banks, state saving banks and cooperative companies by the Federal Deposit Insurance Corporation (FDIC). All these banks are insured by FDIC. However, federal saving banks and saving & loans associations initially regulated by the Office of Thrift Supervision (abolished and merged with OCC in 2010) are not included in the dataset, because they began to complete Call Reports only in 2011 and the available data series are not long enough.

[10] Different from bank failure, in the voluntary liquidation, shareholders can retire or transfer the assets voluntarily and progressively. The total assets can approach zero in the end. This results in an artificial evolution of bank financial ratios over time, which is not expected. So we decide to drop these voluntarily liquidated banks. In fact, they are not included as failures in the FDIC failed bank list.

have been still active at the end of 2012 with $13.5 trillion of assets in total, $1.5 trillion of equity capital and $1.2 trillion of Tier 1 capital. Their aggregated risk-weighted assets were $9 trillion.

During the period 2001-2012, 431 banks, as Table 2 shows, have failed and entered bankruptcy procedure with the FDIC assistance (deposit insurance), representing 4.55 percent of total number of commercial banks (431/9456=0.0455). The percentage was slightly higher in the largest 10 percent banks (56/945=0.0593) than in the smallest 90 percent banks (375/8511=0.0441), if we split the sample at the 90^{th} percentile of banks' average size (defined as the logarithm of a bank's average assets during the sample period). However, there were hardly failures among the largest 100 banks. In fact, they were beneficiaries of the famous "too big to fail" rule. The government rescue program TARP aimed at restoring the liquidity and stability to the financial system and bailed out firstly systemically important banks (Bayazitova and Shivdasani, 2012; Cornett et al., 2013; Li, 2013). Moreover, most of bank failures (417 out of 431 and in terms of involved assets $236 billion out $238 billion) occurred during the financial crisis.

Then, we conduct a statistical analysis on our principal variables of interest, the capital ratios. We observe that the risk-weighted capital ratios are often extremely high for new banks, especially in the first year after their foundation. This is comprehensible. At the beginning of its lifetime, a bank has neither developed money earning activities nor built customer/depositor loyalty. To have a more homogenous database, we drop these observations of the first four quarters of newly founded banks. We drop also 0.5 percent of extreme values at the right tail of distribution of total risk-weighted capital ratio and risk-weighted Tier 1 ratio.

3.2. Overview on capital ratios

Figure 1 shows the evolution over time of five capital ratios: total risk-weighted capital ratio, risk-weighted Tier 1 ratio, ratio of total equity over total assets on balance sheet, Tier 1 capital over total average assets (leverage ratio) and Tier 1 capital over total exposure (supplementary leverage ratio). Graphs are drawn respectively for large and small banks defined as above. In Panel A we see that small banks are better capitalized than large banks and capital ratios are less volatile in small banks than large one, implying that large banks are accessible to multiple funding sources. Both of them fulfill the minimum requirement of 8 percent for total regulatory capital ratio. For both kinds of banks, the difference between total capital ratio and Tier 1 capital ratio is not remarkable, meaning that US banks are generally funded by high-quality capital. The leverage ratio line is obviously different from the supplementary ratio line for large banks, while they almost coincide for small banks. This means off-balance sheet activities in the US banking sector are operated by large banks. Small banks hardly engage in these activities. This inference is confirmed by the graphs on the right-hand side: the large banks hold a total of $12 trillion on balance sheet assets and near $3 trillion off-balance sheet assets.

The Panel B shows the capital ratios evolution of two sub-sample of the large banks group, the G-SIBs[11] identified by the G20 Financial Stability Board (FSB) in Graph c) and other large banks (no G-SIBs) with average assets higher than $10 billion in Graph d). The situation of no G-SI large banks is close to that of the whole large banks group. However, G-SIBs which hold half of total assets in the banking sector (see

[11] G-SIBs are JP Morgan, Citigroup, Bank of America, Wells Fargo, Goldman Sachs, Morgan Stanly, State Street and Bank of New York Mellon. Here we take the largest commercial bank in each group, including Wachovia bank and Merrill Lynch bank which are large banking institutions acquired by G-SIBs during the crisis. Goldman Sachs and Morgan Stanly are excluded, because they changed status in 2008 and this made their financial condition incomparable with others'.

graph on the right side) seem to be significantly less capitalized and rely more heavily on lower quality capital. In particular, we see that for a long period prior to the crisis, their supplementary leverage ratio was below 6 percent which is the minimum level for a well-capitalized bank according to the new strengthened capital requirement. Moreover, the risk-weighted ratios increased in response to 2007 *subprime* crisis, while the non-weighted ratios continued decreasing. Thus, the risk-weighted ratios risk hiding banks' real capital losses through the manipulation of risk-weights. This observation adds to the accumulating evidence which suggests that banks do use model complexity and non-verifiable assumptions to increase their benefits (Haldane, and Madouros, 2012; Mariathasan and Merrouche, 2014), as the Internal Ratings Based Approach enables them to reduce capital charge. Hence, Basel III framework is intended to stress the role of leverage ratios in the capital requirements, especially for large banks.

Figure 2 plots the relationship between banks' capitalization and their destiny (failure, rescue or surviving). Graphs show the evolution of risk-weighted Tier 1 ratio, leverage ratio and supplementary leverage ratio over 24 quarters prior to the events[12]. All three capital ratios are powerful predictors of bank failure: failures are accompanied with a significant decrease in capital ratios which starts three or four years prior to the failures. The difference is, that using risk-weighted ratio as the criterion, failed banks seem to be always less capitalized compared to surviving banks, even though it is far ahead the failure date. On the contrary, the failed banks' non-weighted ratios begin deviating from the average of surviving banks only 10 or 12 quarters before the failures. Therefore, the risk-weighted ratio appears to be a good failure predictor over longer horizons than non-weighted ratios. This observation is consistent with the findings of Estrella et al. (2000. If a bank's risk-weighted capital ratio were lower than the sector average, this would be a signal of danger in the future in general. However, if a bank's leverage ratio were lower than the sector average, it could be in danger in two or three years. We put the evolution of the three capital ratios together in the Graph d) and see that the two leverage ratios are close to each other, reflecting the characteristics of small banks, which constitute the most part of failed banks sample.

On the other hand, capital ratios of rescued banks evolve in similar way to surviving banks. The obvious difference of risk-weighted Tier 1 ratio between the two types is rather explained by the difference in capitalization manner between large and small banks, because most rescued banks belong to the group of large bank.

3.3. The empirical model

We investigate the capacity of different capital ratio to predict bank failure, using an early warning model. Following existing literatures (Cole and White, 2012; Berger and Bouwman, 2013; DeYoung and Torna, 2013; Bouvatier et al., 2014) we will estimate various version of the basic cross-sectional Logit model below:

$$prob(Y_{it} = 1) = \frac{1}{1 + \exp(-\beta_1 K_{it-4} - \beta_2 X_{it-4} - \beta_3 Z_{it} - \beta_4 B_{it-4})}$$

Where *Y* is a failure indicator which equals to one in the quarter of bank failure and zero otherwise[13]. Here a failure means the bank fails and ceases to exist. Depositors are paid by the deposit insurance funds

[12] For failed banks, t=0 is set in the quarter when the last call report is available, i.e. one quarter prior to the failure. In the case of surviving banks, t=0 is Q4/2012. For rescued banks, we do not have exact rescue date for each bank. In fact, the recapitalization took place in Q4/2008 for G-SIBs and through all the year 2009 for other banks. We set t=0 for G-SIBs at Q3/2008, the last quarter prior to the rescue, and at Q4/2008 for other rescued banks.

[13] We might have several ways to increase the failed bank sample. The first is to integrate weakly capitalized acquired banks, as Bouvatier et al. (2014) did. However, the objective of this paper is to study the efficiency of capital ratio as

managed by FDIC and assets may be distributed or sold to other entities with assistance of FDIC. *K* denotes our principal variables of interest: the risk-weighted Tier 1 capital ratios, the Tier 1 capital over total average assets ratio and the Tier 1 capital over total exposure ratio. As Figure 1 shows, the two risk-weighted ratios have the same trend and so do the three non-weighted ratios. Therefore, we keep three ratios with the same numerator in order to make the results more comparable. In the different econometric regressions, we estimate the ratios one by one or together. *X*, *Z* and *B* denote respectively control variables of three kinds: bank-specific financial ratios, variables indicating macroeconomic condition and bank holding company level variables. We discuss in detail in next subsection the choice of control variables based on the CAMELS rating system.

We lag the explanatory variables for four quarters in the econometric model. In fact, a good failure prediction model should reveal the signals of vulnerability correctly and as early as possible. It would be ideal if thanks to the model the failures could be forecasted two or three years in advance. However, some empirical studies found evidence that the forecasting ability of balance sheet based indicators is likely to increase when the bank goes close to the failure. The further ahead the forecasted period, the lower the prediction quality is and the higher the forecasting errors are (Mayes and Stremmel, 2014). After several experiments, we decided to put four lags for bank and bank holding company level variables. On the contrary, macroeconomic variables are not lagged, because banks' destiny is influenced by today's economic environment rather than that of one year ago.

The early warning models will be estimated for bank failures that took place between 2008 and 2012. As Table 2 shows, there were few bank failures prior to the *subprime* crisis. We plot in Figure 3 the quarterly number of failures from 2001 to 2012. After a long period of almost zero failure, the failure wave arrived suddenly with the outbreak of the financial crisis. The number of failures by quarter stayed at a high level until 2010. Even if the US economic growth had been restored by the beginning of 2010[14], the number of failures reacted with delay. The situation has calmed down gradually from 2011. Therefore, we also estimate the model for the period 2008-2010 to investigate the capital ratios' failure predicting efficiency during the darkest days of the crisis. Unfortunately, the regressions on the period 2011-2012 may not be reliable because of insufficient number of failures.

Our regression sample contains 137,559 quarterly observations for 7686 banks active during 2008-2012 in total, of which 710 banks are classified in the category of large banks as defined in the previous section and 6976 in the group of small banks.

3.4. Explanatory variables

To avoid omitted variables problems, our regressions contain a broad set of control variables, besides the variables of interest. Following previous work on the determinants of bank failures, the choice of control

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failure predictor. It seems less appropriate to adjust failure definition using a criterion relative to capital level. Cole and White (2012) propose to define a "technical failure" when banks report that the sum of equity plus loan loss reserve is less than half of the value of its nonperforming assets. We drop this idea for the same reason indicated above. A third way is to include rescued banks as failed banks. In fact, the TARP aims at helping temporarily unhealthy banks out of a period of financial distress rather than saving banks that were economically unviable in the long term (Cornett et al., 2013). This implies rescued banks might have different characteristics from failed banks. We have to give up this idea to privilege the homogeneity of our failure sample.

[14] According to data from U.S. Bureau of Economic Analysis, after the negative growth of one year, the US GDP restarted growing in Q3/2009. And in Q1/2010 the GDP came back to its level of 2007. Some studies on the crises also take Q4/2009 as the end of the banking crisis (Berger and Bouwman, 2013).

variables is inspired by the CAMELS components (Wheelock and Wilson, 2000; Oshinsky and Olin, 2006; Cole and White, 2012). The CAMELS rating is a supervisory rating system developed by the U.S. banking regulators to classify a bank's overall condition. Since the rating system is designed to take into account all bank-specific financial and operational factors examiners assess in their evaluation of an institutions performance, CAMELS components constitute essential variables in bank failure prediction models. Moreover, we include in our models several bank holding company level variables indicating intra-group organizational structure to control for complexity and interconnection within a banking group. Almost all variables are expressed as a ratio over the bank's total assets. The names and brief definitions are provided in Table 3.

Asset quality is represented by annual assets growth rate, non-performing assets ratio and loan portfolio structure. A high asset growth rate can be an indicator of aggressive business strategy with looser monitoring. This can be an adverse factor to bank health. Non-performing loans are loans that are in default or close to being in default and other real estate owned (OREO) is most frequently a result of foreclosure on real property as a result of default by the borrower who used the property as collateral for the loan. These are non-earning and poor quality assets which is likely to increase likelihood of a bank's failure. As the most important activity for commercial banks, loans represent over 50 percent of banks' total assets. The loan portfolio structure can be a signal of banks' credit risk. According to Cole and White (2012), residential mortgages were generally considered to be safe prior to the *subprime* crisis, whereas this proposition is doubtful today. Since commercial mortgages[15] and commercial & industrial loans are linked to riskier commercial activities and investments in enterprises, they might expose banks to more risks and incertitude.

The management competence is reflected by banks' cost management efficiency. We use a non-interest expense (which mainly encompasses fix costs, like salaries and rents) over total assets ratio to proxy it. Earning ability is represented by the return on assets measured as annual net income over total assets. A bank that is profitable and does well in cost control is expected to survive with more chance.

Liquidity of a bank can be considered from two angles. On the on hand, liquidity is a property of assets. Liquid assets, i.e. cash and assets easy to convert into cash, help banks to repay short-term debts and cope with unexpected withdrawals of deposits and liquidity shocks on financial market. On the other hand, the lessons from the financial crisis showed that the funding liquidity risk could put a well-capitalized bank into difficulties. Therefore a stable funding profile is intended to reduce the likelihood that disruptions to a bank's regular sources of funding will erode its liquidity position in a way that would increase the risk of its failure and potentially lead to broader systemic stress (BCBS, 2014b). We use the ratio of core deposits[16] over total assets as the funding stability indicator (FDIC, 2011) and expect it to influence negatively the probability of failure.

Since a great number of banks in our database are small local banks, the sensitivity to market risk is difficult to capture with accounting data. Economic cycle tends to influence financial market risk as well as

[15] The definition of commercial mortgages in OCC's handbooks includes loans secured by construction and (land) development and loans secured by nonresidential properties. A multifamily residential property is frequently an apartment complex. So the multifamily residential mortgages are classified as commercial mortgages. Moreover, OCC' definition of residential real estate lending comprises only loans secured by properties designed to house 1-4 families (http://www.occ.gov/publications/publications-by-type/comptrollers-handbook/index-comptrollers-handbook.html).

[16] Core deposits consist of transaction deposits, saving deposits, FDIC-insured time deposits less than $100,000, then minus insured brokered deposits less than $100,000. The FDIC deposit insurance coverage for each category has been set to $250,000 permanently through Dodd-Frank Act. In order to keep the consistency of calculation method, we take $100,000 as the ceiling of deposit insurance for whole sample.

individual banks' health. Some macroeconomic variables are therefore included in our regression model. The state-level personal income growth rate is a general indicator of macroeconomic condition in which banks operate[17]. A higher income growth implying a favorable economic environment is likely to decrease the probability of bank's failure. A second macro variable is the house price index growth which captures credit cycle driving asset prices (Blundell-Wignall and Roulet, 2013). As nearly 20 percent of banks' assets are residential mortgages (see Table 3), changes in real estate prices could affect bank performance and risk. Following Berger and Bouwman (2013), we calculate the house price index growth rate from the quarterly state-level "purchase only" indices[18].

Finally, we control for parent company level characteristics. Over 80 percent of US commercial banks are affiliated with a bank holding company, whether the latter is a multi-bank holding company (MBHC) or a one-bank holding company[19]. A well-capitalized and profitable holding company can be a source of strength. Especially, distressed affiliated banks of MBHCs are also more likely to receive capital injections, and thereby recover more quickly (Ashcraft, 2008; Bouvatier et al., 2014). Moreover, during the crisis, the complex and opaque organizational pattern of large banks has impeded information disclosure and provoked moral hazard problems, which in turn exacerbated the distresses and even threatened the stability of finance system. The investigation at the BHC level allows revealing organizational structure and strategy of banking groups and seeing whether the heavy interconnection within group affects commercial bank health. The size of BHC unconsolidated assets give a global vision on the parent companies. A large size is generally associated with better assets diversification, more funding sources and even implicit government guarantees. From the source-of-strengthen viewpoint, a large holding company might support the subsidiaries to better resist financial distresses. The short-term funding ratio reflecting BHC's funding instability is to indicate its ability to withstand liquidity crises. At last, we use the BHC's investment in nonbank subsidiaries and its funding source from nonbank subsidiaries as proxies of the intra-group interconnection. Nonbank entities (investment bank, brokers and dealers etc.) often engage in more volatile market activities. However, they are subject to different prudential regulation rules from banks. The linkage with nonbank subsidiaries represents the most dangerous part of intra-group relationship. We expect the interconnection proxies to be positively associated with failure probability.

Table 3 provides the summary statistics on all explanatory variables across the regression sample period. Panel B compares bank-specific and parent company characteristics across different types of banks. The difference between failed and non-failed banks is always statistically significant and confirms our expectation on impacts of financial characteristics on failure probability. On average, failed banks are less capitalized, less cost efficient, less profitable, less liquid with more non-performing assets and more engagement in risky loans categories. Their holding companies seem more fragile as well, with less stable funding and closer interconnection with nonbank subsidiaries. Moreover, large banks show different characteristics compared to small banks. Thus, we think to split the data according to bank size and investigate them separately.

[17] We can also use real GDP growth or unemployment instead of personal income growth. As the most widely used macro variables, all the three variables tend to evolve jointly. The variables substitution does not affect our results.

[18] There are two types of house price indices available on the Federal Housing Finance Agency website, ''purchase only'' index (built on purchases) and an ''all transactions'' index (built on purchases and appraisals). Berger and Bouwman (2013) argue that bank behavior is affected by purchases, but not by mere appraisals, the purchase only index is most appropriate.

[19] A multi-bank holding company is a company that owns or controls two or more banks while a one-bank holding company is a company that owns or controls only one bank.

4. Results

4.1. Baseline model

Like previous studies, we investigate as the first step all the banks in the sample together, expecting to reach some general findings for the whole commercial bank sector. Table 4 provides the results of the estimates with all banking organizations active between 2008 and 2012. In specifications 1, 2 and 3, the probability of bank failure is regressed on risk-weighted Tier 1 capital ratio, leverage ratio and supplementary leverage ratio respectively, as well as the control variables. As coefficients estimated by Logit model are not directly interpretable, we calculate and report in the table the marginal effect of each independent variable for the average failed bank.

Overall, the results show that all three capital ratios predict accurately bank failures during and after the 2008 financial crisis: the relationship between capital ratios and the failure probability is negative and statistically significant at the 1 percent level. Looking at the marginal effect of capital ratios on the failure, we observe that the probability of failure seems more sensitive to leverage ratios than to the risk-weighted ratio[20]. All other things remaining equal, a 1 percent higher Tier 1 risk-weighted ratio at the average failed bank decreases the probability of failure by 1.081 percent. In contrast, the decrease induced by the increase of 1 percent of leverage ratio (and supplementary leverage ratio) rises to 1.418 percent (and 1.444 percent).

Most of the control variables are also significant with the expected signs. Consistent with the findings of Cole and White (2012) and DeYoung and Torna (2013) who used the CAMELS rating system, distressed banks are likely to hold more assets of lower quality and loans of riskier categories that tend to perform poorly during economic downturns. Higher earnings and stable funding sources like core deposits help banks to survive in the crisis. Moreover, weak regional macroeconomic condition is an important risk factor that heightens the probability of failure. Finally, we find evidence that banks' ability to resist failure can be influenced by parent companies behaviors. The probability of failure is significantly higher for banks owned by a holding company which invests massively in non-bank activities and in which activities are funded with less stable sources.

To compare the overall predictive power of the early warning models with different capital ratios, we look at the number of true and false prediction resulting from each model. There are several ways to achieve this. One method is to classify banks in descending order according to the estimated probability of failure. As we have 417 failed banks in the data, we consider the first 417 banks with the highest estimated probability of failure as banks predicted to fail. Another method to compare the correct and false prediction is to use the area under the receiver operating characteristic curve (AUROC) that is a mapping of the true positive rate to the false positive rate at various threshold settings. The AUROC is a convenient and interpretable summary measure of the signaling quality of a binary signal (Drehmann and Juselius, 2014). It gives the probability that the model ranks correctly a randomly chosen pair of observations, one with Y=1 and one with Y=0. The value of AUROC ranges from 0.5 to 1 and the higher the value, the better is the predictive power of the model. At the bottom of Table 4 are reported the AUROC value, the number

[20] The marginal effect of an independent variable is calculated for its increase of one percent one year prior to the failure, holding other variables at the average level of all failed banks in the regression sample. Here, the reference point is Tier1 risk-weighted ratio=0.085, leverage ratio=0.067, supp. leverage ratio=0.066, asset growth=0.062, Nonperforming assets=0.117, Residential mortgage=0.142, Commercial real estate lending=0.463, Co.& ind. loans =0.035, Cost inefficiency=0.037, ROA=-0.026, liquid assets=0.089, core deposits=0.541, House price index growth= -0.057, Personal income growth=0.012, BHC size=0.083, BHC short-term borrowing=0.046, BHC invest. in nonbank subs.=0.017 and BHC money due to nonbank subs.=0.155.

of correct prediction (the number of real failures in the estimated failures), the number of false alarm (the number of non-failed banks among the predicted failures) as well as the number of banks that have received the public recapitalization. As shows in the table, these parameters are similar across the three predictive models and the AUROC is as high as 0.96, suggesting that all three capital ratios are efficient failure predictive indicators.

However, containing large G-SIFs and small regional banks, the commercial bank sector is not a homogenous set. The study at the whole sector level may hide some interesting individual characteristics. Hence, in the next step, we will distinguish the sub-sample consisting of large banks from that of small banks to further reveal the role of different capital ratios.

4.2. Large banks vs. small banks

In this section, we estimate failure predicting models respectively with the 10 percent largest banks in the whole sample and the 90 percent smaller banks, as defined in Section 3.1. The regression results of models based on Tier 1 risk-weighted ratio, leverage ratio and supplementary ratio are provided in Specifications 1, 2 and 4 of Table 5 for large banks and Table 6 for small banks. Comparing these results with corresponding models in Table 4, we see that the regressions on small banks give close results to the full sample based regressions, in terms of the variable significance, the estimated marginal effects and model overall predictive power measured by the AUROC value. However, different patterns emerge for large banks sample. While the leverage ratio and supplementary leverage ratio are still negatively associated with probability of failure with high significance, the risk-weighted ratio is significant at only 5 percent level. The marginal effect of leverage ratios (-3.088 and -3.029) is remarkably higher than that of the risk-weighted ratio (-1.546). The AUROC value and the numbers of true and false prediction tend to suggest the model based on the simple non risk-weighted ratios outperform the risk-weighted ratio based model, although the difference remains slight.

As did Estrella et al. (2000) and Haldane and Madouros (2012), we include the risk-weighted and leverage ratios together in the same regression to investigate which of them bring more information to the failure prediction. The Specification 3 (and 5) of Table 5 report the results of the model combining Tier 1 risk-weighted ratio and leverage ratio (supplementary leverage ratio) for large banks sub-sample. It is shown that the leverage ratios remain highly significant with expected sign, while the risk-weighted ratio loses the significance.

Next, we check whether the leverage ratios, as failure indicators, provide more information than the risk-weighted ratio, using the likelihood ratio (LR) test. The likelihood ratio test is commonly used to evaluate the difference between nested models and to test whether adding an explanatory variable to an existing regression increases significantly the fit of the model[21]. The likelihood ratio test statistic is built with the difference of log likelihoods of two models and should be distributed chi-squared. Table 7 summarizes the statistics necessary to compare our models based on different capital ratios. For instance, to compare whether the leverage ratio can add useful information to a risk-weighted ratio based model for large banks, we can perform a likelihood ratio test on the difference of log likelihood of Specifications 1 and 3 in Table 5. The result shows the statistic is statistically significant at 1 percent level (statistic=10.02 and associated p-value=0.0015), suggesting that adding the leverage ratio as a predictor variable results in significant improvement in model fit. On the contrary, applying the same test to compare Specifications 2

[21] A model is nested in another if the first model can be generated by making one or more parameters of the second equal zero.

and 3, the statistic is not significant (statistic=0.02 and p-value=0.9024). This means that the model with leverage ratio being the basic model, adding the risk-weighted ratio cannot improve the model fit. At the bottom left-hand corner of Table 7 is shown the LR test to compare the Tier 1 risk-weighted ratio and the supplementary leverage ratio, which implies similar results. Hence, it is confirmed that the non-weighted leverage ratio and supplementary leverage ratio are better indicators to predict failures of large banks, compared to the risk-weighted capital ratio.

We conduct the same analyses on the small bank sub-sample. Specification 3 and 5 in Table 6 indicates that Tier 1 risk-weighted ratio outperforms non-weighted ratios in predicting failures of small banks. The likelihood ratio tests for models based on different capital ratios (see the right hand side of Table 7) confirm that leverage ratios bring no longer supplementary information, when the risk-weighted ratio has been included in the early warning model.

In summary, although both risk-weighted capital ratios and simple leverage ratios are efficient predictor of bank failures in general, we find evidence that their roles are quite different for large banks and small banks. While the regulatory risk-weighted ratios are significantly associated with the probability of small banks' going bankruptcy, they may fail to give warning of failure for large banks. This can be explained by different business models of large and small banks and the regulatory conditions they face. In contrast to small regional banks concentrating in less risky local deposit collecting and loan granting, large banks tend to run more diversified and more complex banking and trading portfolios. Therefore, it is relatively more difficult to assess risks in large banks. On the other hand, large banks are more likely to adopt the internal rating-based approach for calculating their risk-weighted assets. The potential manipulation of risk-weights may help to hide certain risks and thereby make the risk-weighted ratio inefficient to reflect the banks' real risk-taking. Our results suggest that non-weighted leverage ratios that are less easily manipulated work well in predicting failures of large banks, supporting the current capital regulation reforms to complement risk-weighted capital ratios with leverage ratios, especially for large banks.

After investigating bank failures post *subprime* crisis, in the section, we are interested in how the capital ratios performed in forecasting the failures during the darkest period of the crisis, 2008-2010. To this end, we apply the logit model to active banks in 2008-2010, including 701 large banks and 6946 small banks, in which 298 banks (48 large banks and 250 small banks) have failed, representing 70 percent of the total number of failures after the crisis broke.

We observe in Table 8 that the Tier 1 risk-weighted ratio loses completely the significance in the regression on large bank sub-sample while the leverage ratios remain significant at 1 percent level. In terms of estimated marginal effect, the increase of the leverage ratio (or supplementary leverage ratio) by 1 percent, one year prior the failure, will decrease the probability of failure by nearly 5 percent. With regard to the small banks, no difference has been found on the predictive power of the three capital ratios and the marginal effect of each capital ratio on the probability of failure is comprised between -1.5 and -1.1 and closed to each other. The results are consistent with the findings discussed in the last sub-section. Furthermore, they tend to emphasize the deficiency of risk-weighted ratios in capturing banks' real risk-taking during a period of economic distress. In other words, the prescribed supervisory risk weights may be inefficiency to cover unexpected losses related to the sudden deterioration of financial condition. In contrast, taking in account the leverage building on and/or off balance sheet, the non-weighted ratios perform stably across economic and financial cycle in signaling the risk of failure.

4.3. Robustness test

A potential challenge that our econometric models face is that the bank failures are rare events. For instance, among over 130,000 observations in the baseline regression on the whole sample, there are only 417 failures. The rare event effects may result in biased logit coefficients (King and Zeng, 2001). To deal with this problem, we estimate the following logit model:

$$prob(Y_i = 1) = \frac{1}{1 + \exp(-\beta_1 K_i - \beta_2 X_i - \beta_3 Z_i - \beta_4 B_i)}$$

where the dependent variable Y_i equal one if a bank i failed after the crisis broke; K_i, X_i, Z_i and B_i denote respectively the one-year averages (from Q4/2007 to Q3/2008) of the three variables of interest and the control variables, including bank-specific financial ratios, macro variables and holding company level variables for the bank i. Economically, using the average around the deterioration of the financial crisis resulting from the Lehman Brothers' bankruptcy, the model checks the influence of the banks' capitalization at the beginning of the global financial crisis on the probability of failure during the crisis. In this model, we consider as failures only banks that went bankruptcy during 2008-2010 instead of 2008-2012, because it is hardly relevant to attribute a failure in 2011 and 2012 to the inadequate capitalization four or five years before the event. This model is expected to mitigate the rare event problem, since the total number of observations reduces by 90 percent while the number of observations with failure indicator equal to one remains unchanged[22].

The regressions have been done for large banks and small banks separately and the results are given in Table 9. In general, the results confirm the robustness of previous regressions. In the small banks sub-sample, both estimated coefficients and marginal effects of the three capital ratios are associated with negative and highly significant signs. In the large bank sub-sample, it is proved that the Tier 1 regulatory ratio has no significant effect on the bank failure and higher leverage ratio and/or supplementary leverage ratio are likely to reduce the probability of bank failure. Moreover, it appears that the supplementary leverage ratio is more efficient than the leverage ratio, as the former is significant at the 5 percent level while the latter is significant at only 10 percent level.

5. Conclusion

We have investigated in this paper the efficiency of non-weighted leverage ratios and risk-weighted regulatory ratios as bank failures predictors during and after the global financial crisis. Analyzing 417 bank failures between 2008 and 2012 with logit models, we find that the predictive power of different capital ratios is not homogeneous across banks. The simple leverage ratios outperform risk-weighted ratios in predicting the failures of the 10 percent largest banks of the banking sector, while the two types of ratios are both relevant for smaller banks. A further study on failures of large banks shows that the difference of predictive power is more remarkable during the crisis period (2008-2010).

Our study reveals the deficiency of risk-weighted capital ratios in signaling the risk-takings of large banks and suggests that the non-weighted leverage ratios could be useful prudential regulation tools to remedy the default of risk-weighted ratios. As said Haldane and Madouros (2012), the simpler the environment, the more robust are likely to be sophisticated regulatory rules, we also find that the risk-weighted capital

[22] Compared to the regressions on active banks in 2008-2010 concerning 84933 observations and 7647 banks, in which 298 banks failed (Table 8), the regression sample for this robustness check covers 7504 observations (active banks from the beginning of 2008 until Q/2008) and 297 failures.

ratios are stably efficient failure predictor for small banks. Our findings go in line with recent regulatory reforms mainly destined to large financial institutions, aiming at enhancing the regulatory capital framework by adding leverage ratios as complementary prudential tools. However, it is worth noting that the leverage ratios are not perfect. As the leverage ratios are insensitive to risk, they are likely to require banks to use the same amount of capital to fund high-risk assets as low-risk assets (Bank of England, 2014). Consequently, they might encourage banks to take on riskier but more profitable assets. Hence, a good capital regulatory framework should rely on strengthened risk-weighted capital ratios based on high quality equity and the leverage ratios play a supporting role.

Moreover, we did not find strong evidence on the difference between the efficiency of the leverage ratio and the supplementary leverage ratio. This might be explained by the fact that the off-balance sheet activities, which distinguish one ratio from the other, are concentrated in a small number of systemically important banks. Nevertheless, the descriptive statistics show that for about largest one hundred banks, the supplementary leverage ratio was closed to or even lower than the current minimum requirement during a long time prior to the financial crisis. This implies that the supplementary leverage ratio can be an important and informative tool in the regulation framework for large banks.

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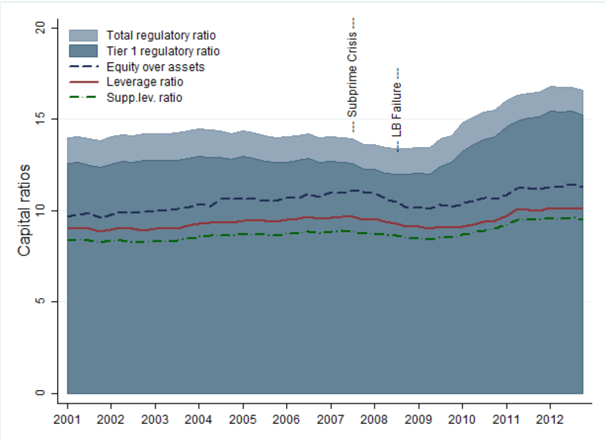
Appendix

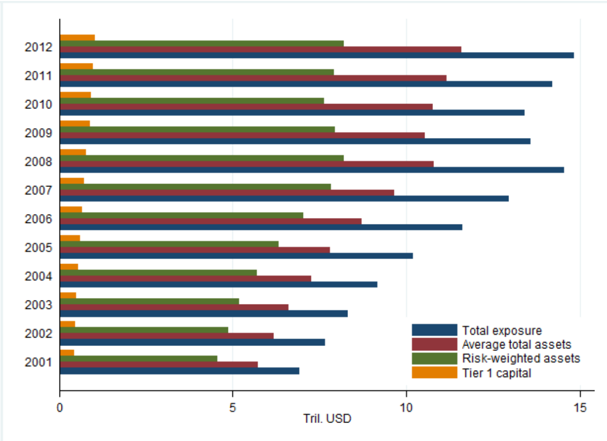
Figure 1: capital ratio decomposition, a comparison by bank size

Panel A: Large banks vs. small banks

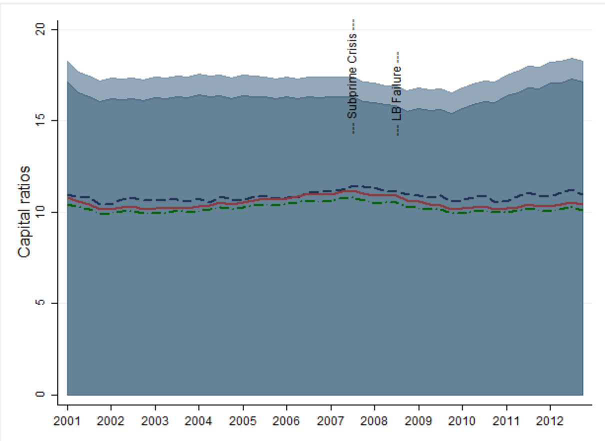
a) Large banks: Capital ratios



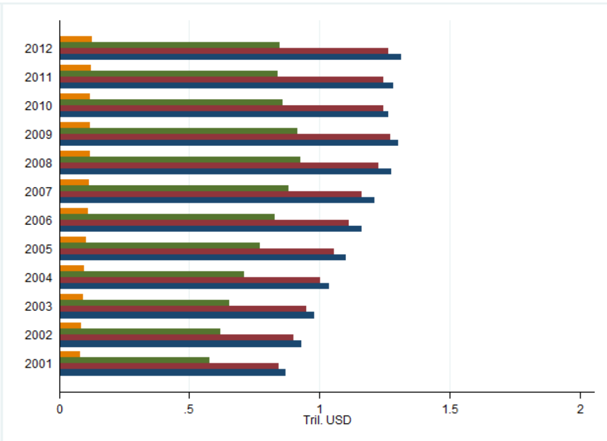
Denominators of ratios
(compared to Tier1 capital)



b) Small banks: Capital ratios



Denominators of ratios

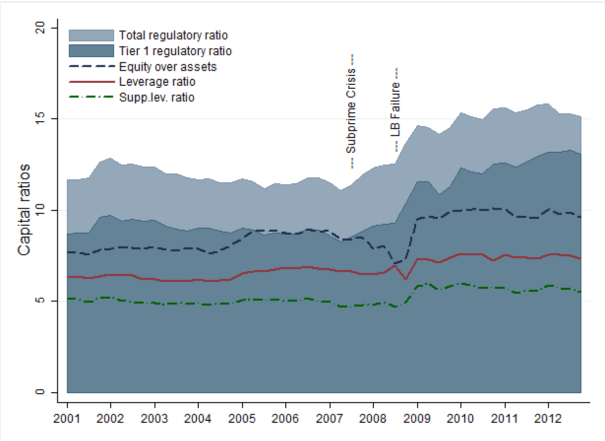


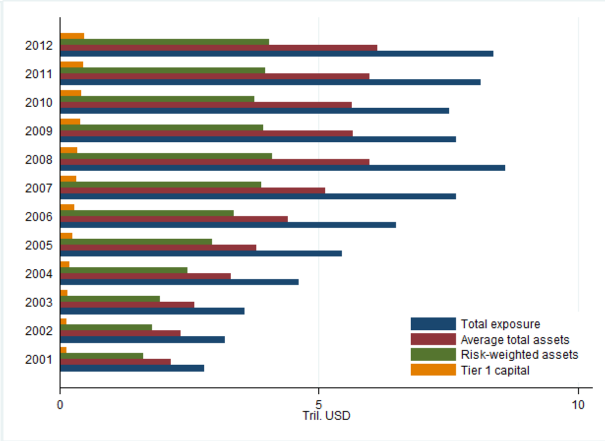
Panel B: Sub-samples of large banks

c) G-SIBs:

Capital ratios

Denominators of ratios

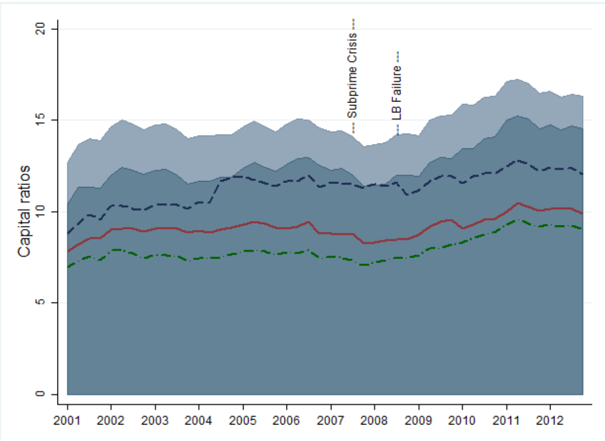




d) Banks (non G-SIBs) with assets higher than $10 billion

Capital ratios

Denominators of ratios



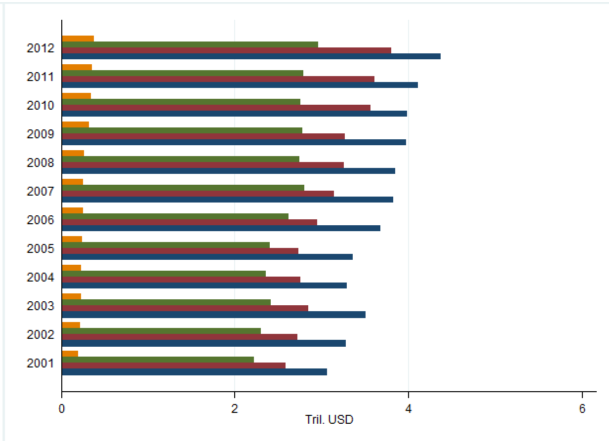
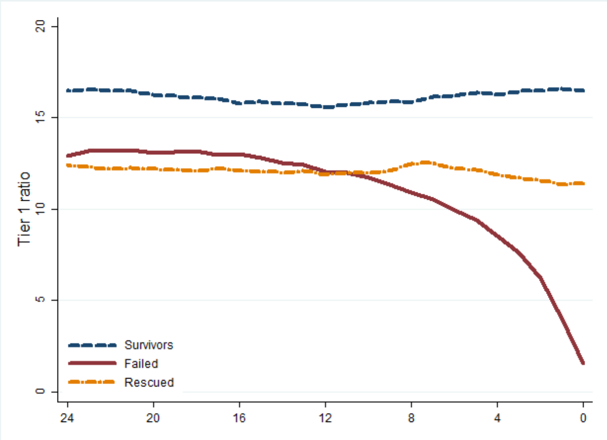
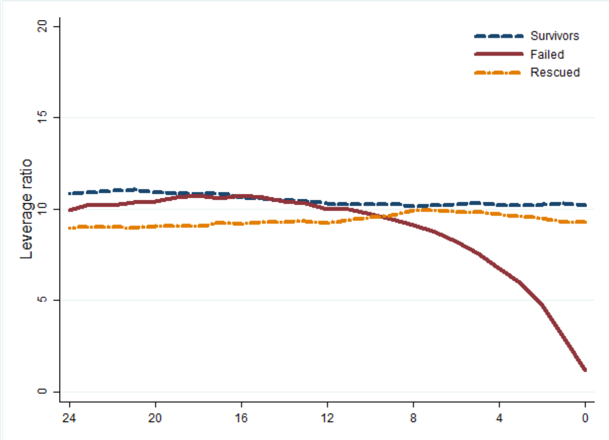


Figure 2: Capital ratios evolution at failed, rescued and non-rescued surviving banks

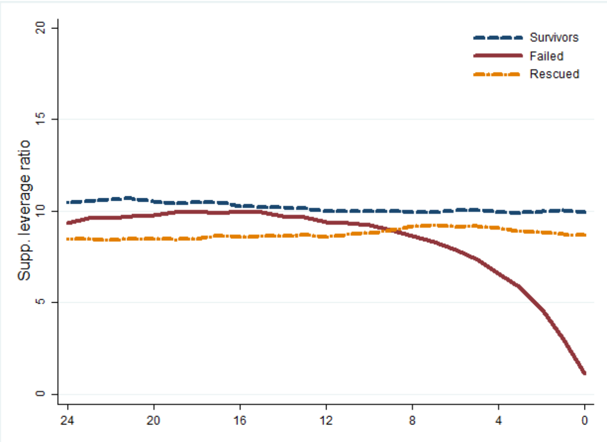
a) Tier 1 capital ratio



b) Leverage ratio



c) Supplementary leverage ratio



d) comparing capital ratios for failed banks

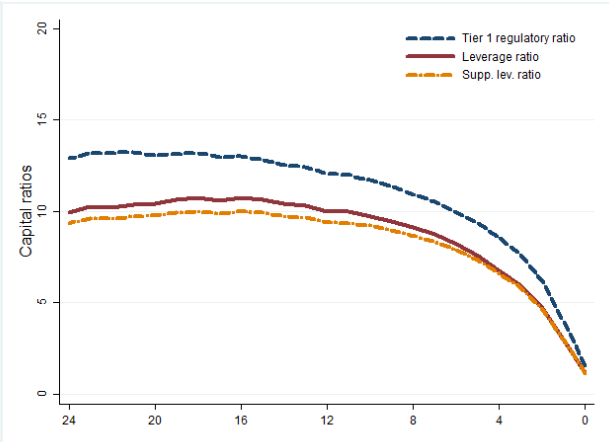


Figure 3: Number of failures, Q1/2001-Q4/2012

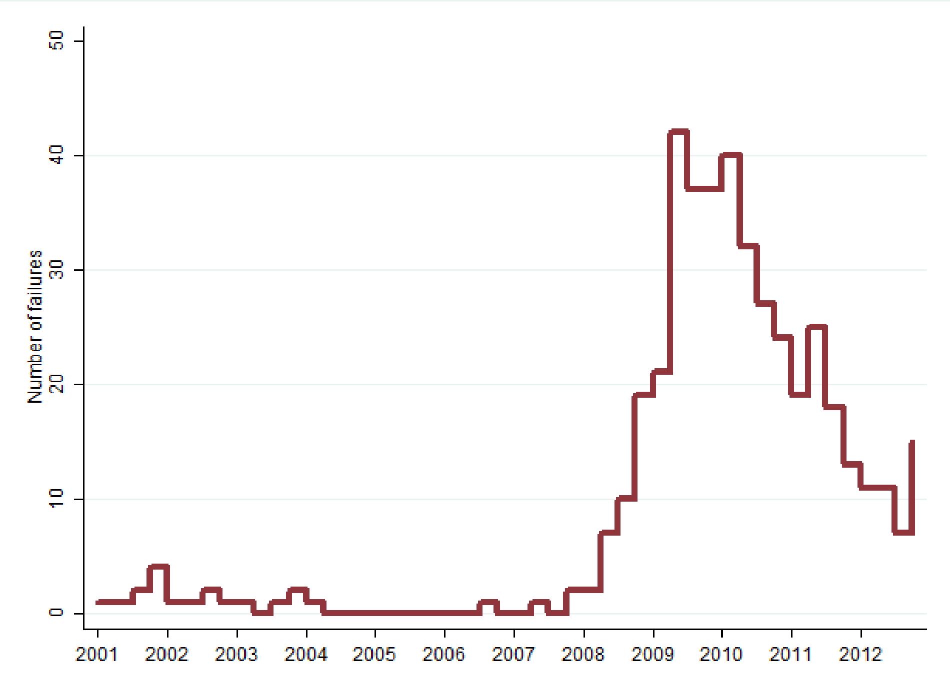


Table 1: Calculation of the total leverage exposure

Items	Conversion factor[1]	Memo
On-balance sheet exposures		
On-balance sheet assets	1	
Amounts deductible from Tier 1 capital[2]	-1	
Derivative exposures		
Interest rate contracts, NPA (< 1 year / 1-5 years / > 5 years)[3]	0 / 0.005 / 0.015	
Foreign exchange contracts, NPA (< 1 year / 1-5 years / > 5 years)	0.01 / 0.05 / 0.075	
Gold contracts, NPA (< 1 year / 1-5 years / > 5 years)	0.01 / 0.05 / 0.076	
Other precious metals contracts, NPA (< 1 year / 1-5 years / > 5 years)	0.07 /0.07 / 0.08	
Other, NPA (< 1 year / 1-5 years / > 5 years)	0.10 / 0.12 / 0.15	
Equity derivative contracts, NPA (< 1 year / 1-5 years / > 5 years)	0.06 / 0.08 / 0.10	
credit derivative contracts (investment grade), NPA (< 1 year / 1-5 years / > 5 years)	0.05 / 0.05 / 0.05	
credit derivative contracts (sub-investment grade), NPA (< 1 year / 1-5 years / > 5 years)	0.10 / 0.10 /0.10	
Repo-style transaction exposures	-	Not reported
Other off-balance sheet exposures		
Financial standby letters of credit, NA	1	
Performance standby letters of credit, NA	0.5	
Commercial and similar letters of credit, NA	0.5	
Retained recourse on small business obligations sold with recourse, NA	1	
All other off-balance sheet liabilities, NA	1	
Unused commitments with an original maturity exceeding one year, NA	0.5	
Unused commitments with an original maturity less than one year or ABCP conduits, NA	0.2	
Unconditionally cancelable commitments, NA	0.1	Not reported

Note: NPA stands for notional principal amounts. NA stands for notional amounts. (1) The column of conversion factor reports add-on factor applied to NPA of derivative contract to calculate PFE. (2) Amounts deductible from Tier 1 capital refer to goodwill, intangible assets and deferred tax assets. (3) Remaining maturities for derivative contracts are indicated in parenthesis.

Table 2: Failed and rescued banks

	Large		Small	Total
		Banks with assets > $10 bil.		
Nb. of banks, 2001-12	945	119	8511	9456
Total assets Dec. 2012 (in bil. USD)	12182	10704	1293	13475
Nb. of failures, 2001-12	56	1	375	431
- among which failed in 2008-12	55	1	362	417
Total assets at failure (in bil. USD), 2001-12	147	26	91	238
- among which involved in 2008-12	146	26	90	236
Nb. of banks rescued by TARP	202	35	419	621
Capital injected (in bil. USD)	182	167	4	186[23]
Nb. of failure and closure after rescue	5	0	18	23

[23] The total amount of capital injected by TARP is $205 billion. Some beneficiaries (like federal saving banks) are not covered by our dataset.

Table 3: Descriptive statistics

Panel A: Overview on the regression sample, 2008-2012

Variables	Description	Obs.	Mean	Std. Dev.	Min	Max
Risk-weighted ratio, Tier 1	Tier 1 capital over risk-weighted assets	137559	15.87	8.29	-13.52	147.65
Leverage ratio, Tier 1	Tier 1 capital over average total assets in balance sheet	137559	10.55	4.13	-7.43	97.12
Supp. Leveraga ratio, Tier 1	Tier 1 capital over total exposure	137559	10.23	3.92	-8.48	95.80
Asset growth	Annual assets growth	137559	9.99	28.73	-92.40	500.00
Non-performing assets	30 days past due, nonaccrual loans and OREO over total assets	137559	2.70	3.13	0.00	43.63
Residential mortgages	Loans secured by 1-4 family residential properties over TA	137559	17.69	12.57	0.00	100.83
Commercial real estate lending	Commercial real estate lending (sum of multifamily residential mortgages, loans secured by construction, land development and nonresidential properties) over total assets	137559	23.98	16.89	0.00	95.96
Co.& ind. loans	Commercial & industrial loans over total assets	137559	2.50	5.76	0.00	96.15
Cost inefficiency	Non interest expense over total assets	137559	3.12	1.76	-35.68	78.85
ROA	Net income over total assets	137559	0.51	1.48	-34.37	29.96
Liquid assets	Sum of cash and federal funds sold over total assets	137559	9.64	8.48	0.00	97.59
Core deposits	Core deposits over total assets	137559	64.06	12.58	0.00	94.09
House price index growth	Annual growth rate of house price index, by state	137559	-2.48	5.01	-32.29	19.31
Personal income growth	Annual growth rate of personal income, by state	137559	3.33	4.19	-11.36	21.30
BHC size	Log of holding company unconsolidated total assets (UTA)	137559	8.01	4.39	0.00	19.95
BHC short-term borrowing	BHC's borrowing with maturity less than one year over UTA	137559	1.11	4.62	0.00	98.78
BHC invest. in nonbank subs.	BHC's direct investments in nonbank subs. over UTA	137559	0.84	3.84	-8.87	99.42
BHC money due to nonbank subs.	BHC's balance due to nonbank subsidiaries over UTA	137559	5.51	11.42	0.00	100.00

Note: all ratios and growth rates are in percentage.

Panel B: Summary statistics across different types of banks, 2008-2012

Variables	Large	Small	Difference	Failed	Surviving	Difference
Risk-weighted ratio, Tier 1	13.16	16.14	-2.98***	10.94	16.03	-5.09***
Leverage ratio, Tier 1	9.55	10.65	-1.11***	9.07	10.60	-1.53***
Supp. Leveraga ratio, Tier 1	8.92	10.36	-1.44***	8.65	10.28	-1.63***
Asset growth	12.37	9.76	2.61***	17.05	9.78	7.28***
Non-performing assets	2.74	2.70	0.04	6.50	2.59	3.92***
Residential mortgages	17.58	17.70	-0.12	14.14	17.80	-3.66***
Commercial real estate lending	29.63	23.42	6.21***	47.41	23.25	24.15***
Co.& ind. loans	10.58	1.70	8.88***	3.31	2.48	0.83***
Cost inefficiency	3.06	3.13	-0.07***	3.22	3.12	0.09***
ROA	0.50	0.51	-0.01	-0.75	0.55	-1.30***
Liquid assets	6.95	9.91	-2.96***	7.38	9.71	-2.33***
Core deposits	57.84	64.68	-6.84***	54.36	64.36	-10.00***
BHC size	10.85	7.73	3.12***	8.22	8.00	0.22***
BHC short-term borrowing	1.09	1.11	-0.02	2.70	1.06	1.64***
BHC invest. in nonbank subs.	2.61	0.67	1.94***	1.12	0.83	0.28***
BHC Money due to nonbank subs.	9.43	5.12	4.31***	12.79	5.28	7.51***
Number of banks	710	6976		417	7269	
Number of observations	12354	125205		4112	133447	

Note: all ratios and growth rates are in percentage. ***, **, * indicate that means are significantly different across two groups of banks at the 1%, 5%, and 10% level, based on a t-test.

Table 4: Logit regression results for bank failures, full sample, 2008 - 2012

	Spec. 1: R.-weighted ratio		Spec. 2: Leverage ratio		Spec. 3: Supp. lev. ratio	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Tier 1 Risk-weighted ratio	-1.081***	0.139				
Leverage ratio			-1.418***	0.164		
Supp. Leveraga ratio					-1.444***	0.169
Asset growth	0.007	0.007	0.011*	0.006	0.007	0.006
Non-performing assets	0.452***	0.054	0.435***	0.055	0.450***	0.057
Residential mortgages	-0.009	0.026	-0.023	0.025	-0.022	0.025
Commercial real estate lending	0.078***	0.016	0.118***	0.018	0.119***	0.018
Co.& ind. loans	-0.002	0.034	0.016	0.037	0.006	0.037
Cost inefficiency	-0.022	0.177	0.013	0.163	0.018	0.165
ROA	-0.391***	0.127	-0.352***	0.123	-0.379***	0.124
Liquid assets	0.010	0.048	-0.038	0.045	-0.044	0.044
Core deposits	-0.081***	0.018	-0.085***	0.018	-0.081***	0.018
House price index growth	-0.157***	0.035	-0.168***	0.035	-0.162***	0.034
Personal income growth	-0.529***	0.069	-0.563***	0.070	-0.557***	0.070
BHC size	-0.156***	0.051	-0.156***	0.050	-0.156***	0.050
BHC short-term borrowing	0.069***	0.018	0.071***	0.018	0.071***	0.018
BHC invest. in nonbank subs.	-0.038	0.069	-0.033	0.067	-0.036	0.070
BHC money due to nonbank subs.	0.030***	0.012	0.029**	0.012	0.030***	0.012
Observations	137559		137559		137559	
Pseudo R^2	0.353		0.353		0.352	
Log likelihood	-1834.4		-1835.1		-1835.5	
AUROC	0.9616		0.9608		0.9608	
Nb. of banks	7686		7686		7686	
Nb. of failures	417		417		417	
Correct prediction	211		207		211	
False alarms	206		210		206	
- among which rescued banks	21		20		21	

Note: This table reports marginal effect of each variable on the probability of failure. The marginal effect of a variable is calculated by setting other variables at their average level four quarters before bank failure. Bank-specific and holding company-specific variables are lagged for 4 quarters. ***, **, * indicate significance on the 1%, 5%, 10% level.

Table 5: Logit regression results for large banks, 2008-2012

	Spec. 1		Spec. 2		Spec. 3		Spec. 4		Spec. 5	
	Risk-weighted ratio		Leverage ratio		Risk-weighted ratio + Leverage ratio		Supp. lev. ratio		Risk-weighted ratio + Supp. lev. ratio	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Tier 1 Risk-weighted ratio	-1.546**	0.753			-0.046	0.264			0.101	0.251
Leverage ratio			-3.088***	0.988	-3.029***	0.989				
Supp. Leverage ratio							-2.982***	0.972	-3.129***	1.039
Asset growth	-0.007	0.022	0.010	0.022	0.010	0.022	-0.007	0.023	-0.007	0.023
Non-performing assets	0.910**	0.356	0.987***	0.318	0.988***	0.320	1.029***	0.352	1.031***	0.349
Residential mortgages	-0.208	0.213	-0.246	0.224	-0.245	0.226	-0.231	0.223	-0.231	0.220
Commercial real estate lending	0.243***	0.079	0.352***	0.101	0.351***	0.099	0.347***	0.100	0.351***	0.098
Co.& ind. loans	-0.214	0.169	-0.083	0.189	-0.086	0.190	-0.104	0.178	-0.097	0.178
Cost inefficiency	-0.585	0.707	-0.393	1.009	-0.378	0.996	-0.308	0.996	-0.323	0.979
ROA	-0.847*	0.497	-0.504	0.670	-0.494	0.670	-0.542	0.662	-0.554	0.657
Liquid assets	0.444**	0.198	0.344**	0.174	0.355*	0.209	0.317	0.195	0.295	0.207
Core deposits	-0.186**	0.094	-0.227**	0.099	-0.227**	0.099	-0.213**	0.097	-0.212**	0.096
House price index growth	-0.179	0.136	-0.238	0.150	-0.238	0.152	-0.211	0.147	-0.209	0.148
Personal income growth	-1.560***	0.412	-1.807***	0.458	-1.806***	0.457	-1.752***	0.447	-1.755***	0.447
BHC size	0.314	0.363	0.232	0.389	0.228	0.388	0.223	0.375	0.227	0.369
BHC short-term borrowing	0.403*	0.207	0.458*	0.239	0.459*	0.240	0.430**	0.218	0.428**	0.217
BHC invest. in nonbank subs.	-0.484	0.315	-0.463	0.340	-0.466	0.345	-0.552	0.369	-0.550	0.370
BHC money due to nonbank subs.	0.172**	0.080	0.163*	0.086	0.163*	0.086	0.171**	0.083	0.171**	0.083
Observations	12354		12354		12354		12354		12354	
Pseudo R^2	0.407		0.421		0.422		0.419		0.419	
Log likelihood	-209.0		-204.0		-204.0		-204.8		-204.8	
AUROC	0.9510		0.9606		0.9606		0.9608		0.9610	
Nb. of banks	710		710		710		710		710	
Nb. of failures	55		55		55		55		55	
Correct prediction	29		30		30		30		30	
False alarms	26		25		25		25		25	
- among which rescued banks	9		9		9		10		10	

Note: This table reports marginal effect of each variable on the probability of failure. The marginal effect of a variable is calculated by setting other variables at their average level four quarters before bank failure. The marginal effect is evaluated at Tier1 risk-weighted ratio=0.088, leverage ratio=0.071, supp. leverage ratio=0.068, asset growth=0.068, Nonperforming assets=0.090, Residential mortgage=0.093, Commercial real estate lending=0.524, Co.& ind. loans =0.076, Cost inefficiency=0.029, ROA=-0.020, liquid assets=0.079, core deposits=0.460, House price index growth=-0.078, Personal income growth=-0.006, BHC size=0.112, BHC short-term borrowing=0.052, BHC invest. in nonbank subs.=0.018 and BHC money due to nonbank subs.=0.250. Bank-specific and holding company-specific variables are lagged for 4 quarters. ***, **, * indicate significance on the 1%, 5%, 10% level.

Table 6: Logit regression results for small banks, 2008-2012

	Spec. 1 Risk-weighted ratio		Spec. 2 Leverage ratio		Spec. 3 Risk-weighted ratio + Leverage ratio		Spec. 4 Supp. lev. ratio		Spec. 5 Risk-weighted ratio + Supp. lev. ratio	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Tier 1 Risk-weighted ratio	-1.091***	0.136			-0.805***	0.231			-0.899***	0.269
Leverage ratio			-1.345***	0.164	-0.401	0.288				
Supp. Leverage ratio							-1.371***	0.169	-0.269	0.338
Asset growth	0.010	0.007	0.013**	0.007	0.011	0.007	0.010	0.007	0.010	0.007
Non-performing assets	0.443***	0.055	0.419***	0.055	0.438***	0.055	0.433***	0.057	0.442***	0.055
Residential mortgages	0.004	0.026	-0.008	0.024	-0.003	0.027	-0.009	0.025	-0.000	0.027
Commercial real estate lending	0.065***	0.017	0.104***	0.018	0.074***	0.019	0.104***	0.018	0.071***	0.019
Co.& ind. loans	0.036	0.041	0.041	0.041	0.037	0.042	0.038	0.042	0.036	0.041
Cost inefficiency	0.043	0.165	0.045	0.150	0.053	0.158	0.047	0.154	0.049	0.161
ROA	-0.373***	0.129	-0.350***	0.122	-0.357***	0.128	-0.374***	0.123	-0.368***	0.128
Liquid assets	-0.022	0.047	-0.065	0.043	-0.035	0.048	-0.071	0.044	-0.032	0.049
Core deposits	-0.069***	0.019	-0.070***	0.019	-0.071***	0.019	-0.068***	0.019	-0.070***	0.019
House price index growth	-0.160***	0.038	-0.166***	0.037	-0.165***	0.038	-0.163***	0.037	-0.163***	0.038
Personal income growth	-0.480***	0.070	-0.496***	0.069	-0.493***	0.071	-0.491***	0.069	-0.487***	0.071
BHC size	-0.196***	0.054	-0.187***	0.051	-0.198***	0.054	-0.185***	0.052	-0.197***	0.054
BHC short-term borrowing	0.058***	0.019	0.061***	0.018	0.059***	0.018	0.060***	0.018	0.059***	0.018
BHC invest. in nonbank subs.	-0.014	0.064	-0.009	0.061	-0.014	0.064	-0.009	0.062	-0.014	0.064
BHC money due to nonbank subs.	0.023*	0.012	0.022*	0.012	0.022*	0.012	0.023*	0.012	0.023*	0.012
Observations	125205		125205		125205		125205		125205	
Pseudo R^2	0.354		0.350		0.354		0.350		0.354	
Log likelihood	-1601.6		-1610.4		-1600.3		-1610.9		-1601.2	
AUROC	0.9636		0.9617		0.9636		0.9617		0.9635	
Nb. of banks	6976		6976		6976		6976		6976	
Nb. of failures	362		362		362		362		362	
Correct prediction	184		184		185		185		186	
False alarms	178		178		177		177		176	
- among which rescued banks	12		12		12		13		12	

Note: This table reports marginal effect of each variable on the probability of failure. The marginal effect of a variable is calculated by setting other variables at their average level four quarters before bank failure. The marginal effect is evaluated at Tier1 risk-weighted ratio=0.084, leverage ratio=0.067, supp. leverage ratio=0.068, asset growth=0.061, Nonperforming assets=0.121, Residential mortgage=0.149, Commercial real estate lending=0.454, Co.& ind. loans =0.029, Cost inefficiency=0.038, ROA=-0.027, liquid assets=0.091, core deposits=0.554, House price index growth=-0.053, Personal income growth=0.015, BHC size=0.078, BHC short-term borrowing=0.046, BHC invest. in nonbank subs.=0.016 and BHC money due to nonbank subs.=0.140. Bank-specific and holding company-specific variables are lagged for 4 quarters. ***, **, * indicate significance on the 1%, 5%, 10% level.

Table 7: Likelihood ratio (LR) test

	Large banks		Small banks	
	LR statistic	Prob > chi2	LR statistic	Prob > chi2
Tier 1 risk-weighted ratio vs. Leverage ratio				
Spec. 1 vs. Spec. 3	10.02	0.0015	2.65	0.1036
Spec. 2 vs. Spec. 3	0.02	0.9024	20.32	0.0000
Tier 1 risk-weighted ratio vs. Supp. lev. ratio				
Spec. 1 vs. Spec. 5	8.47	0.0036	0.84	0.3582
Spec. 4 vs. Spec. 5	0.06	0.8017	19.45	0.0000

Note: Specification numbers correspond to those used in Tables 5 and 6. Spec. 1 represents the estimation with the risk-weighted Tier 1 capital ratio, Spec. 2 with the leverage ratio, Spec. 3 with the risk-weighted ratio and the leverage ratio, Spec. 4 with the supplementary leverage ratio and Spec. 5 with the risk-weighted ratio and the supplementary leverage ratio. LR statistic is given by the following formula: $LR = 2[ll(Spec.B) - ll(Spec.A)]$, where Spec. A and Spec. B denote the estimations to compare and ll(.) represents the log likelihood of the relative specification.

Table 8: Logit regression results for bank failures, 2008-2010

	Spec. 1		**Spec. 2**		**Spec. 3**		**Spec. 4**		**Spec. 5**		**Spec. 6**	
	Large banks						**Small banks**					
	Risk-weighted ratio		Leverage ratio		Supp. lev. ratio		Risk-weighted ratio		Leverage ratio		Supp. lev. ratio	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Tier 1 Risk-weighted ratio	-2.418	1.698					-1.139***	0.199				
Leverage ratio			-4.742***	1.331					-1.361***	0.235		
Supp. Leverage ratio					-4.855***	1.360					-1.440***	0.242
Asset growth	-0.015	0.034	0.014	0.031	-0.015	0.034	0.015***	0.005	0.018***	0.005	0.015***	0.005
Non-performing assets	1.075**	0.514	1.273**	0.499	1.369**	0.551	0.521***	0.084	0.497***	0.080	0.516***	0.081
Residential mortgages	-0.158	0.243	-0.181	0.254	-0.159	0.259	-0.009	0.032	-0.026	0.030	-0.027	0.031
Commercial real estate lending	0.267***	0.094	0.460***	0.131	0.459***	0.131	0.063***	0.021	0.102***	0.023	0.102***	0.023
Co.& ind. loans	-0.341	0.224	-0.138	0.255	-0.166	0.250	0.032	0.044	0.034	0.044	0.031	0.045
Cost inefficiency	-0.475	0.778	0.047	1.241	0.125	1.231	0.119	0.108	0.113	0.100	0.128	0.092
ROA	-0.727	0.654	-0.079	0.886	-0.079	0.872	-0.321**	0.151	-0.289**	0.147	-0.302**	0.145
Liquid assets	0.505**	0.234	0.445*	0.255	0.377	0.300	0.005	0.053	-0.045	0.047	-0.054	0.048
Core deposits	-0.210*	0.120	-0.256**	0.119	-0.239**	0.119	-0.077***	0.023	-0.080***	0.023	-0.077***	0.023
House price index growth	-0.150	0.151	-0.201	0.187	-0.157	0.184	-0.119**	0.046	-0.125***	0.045	-0.121***	0.045
Personal income growth	-1.502***	0.483	-1.791***	0.541	-1.766***	0.541	-0.462***	0.100	-0.464***	0.098	-0.464***	0.096
BHC size	0.356	0.443	0.217	0.491	0.207	0.477	-0.196***	0.063	-0.182***	0.061	-0.180***	0.061
BHC short-term borrowing	0.238	0.272	0.288	0.310	0.240	0.284	0.077***	0.023	0.078***	0.022	0.077***	0.022
BHC invest. in nonbank subs.	-0.457	0.320	-0.419	0.355	-0.540	0.391	0.036	0.038	0.037	0.040	0.042	0.040
BHC money due to nonbank subs.	0.186	0.115	0.180	0.125	0.194	0.121	0.046***	0.018	0.043**	0.017	0.044**	0.017
Observations	7761		7761		7761		77172		77172		77172	
Pseudo R^2	0.387		0.408		0.406		0.350		0.347		0.349	
Log likelihood	-178.89		-172.87		-173.43		-1093.2		-1098.5		-1095.8	
AUROC	0.9434		0.9498		0.9495		0.9555		0.9541		0.9544	
Nb. of banks	701		701		701		6946		6946		6946	
Nb. of failures	48		48		48		250		250		250	
Correct prediction	28		27		28		129		128		128	
False alarms	20		21		20		121		122		122	
- among which rescued banks	7		7		7		9		9		8	

Note: Marginal effects are reported. For the large bank sample, the marginal effect is evaluated at Tier1 risk-weighted ratio=0.092, leverage ratio=0.076, supp. leverage ratio=0.071, asset growth=0.092, Nonperforming assets=0.083, Residential mortgage=0.090, Commercial real estate lending=0.540, Co.& ind. loans =0.075, Cost inefficiency=0.028, ROA=-0.016, liquid assets=0.070, core deposits=0.446, House price index growth=-0.084, Personal income growth=-0.015, BHC size=0.113, BHC short-term borrowing=0.045, BHC invest. in nonbank subs.=0.019 and BHC money due to nonbank subs.=0.225. For the small bank sample, the marginal effect is evaluated at Tier1 risk-weighted ratio=0.092, leverage ratio=0.075, supp. leverage ratio=0.073, asset growth=0.121, Nonperforming assets=0.103, Residential mortgage=0.145, Commercial real estate lending=0.467, Co.& ind. loans =0.030, Cost inefficiency=0.007, ROA=-0.022, liquid assets=0.078, core deposits=0.533, House price index growth=-0.068, Personal income growth=-0.004, BHC size=0.082, BHC short-term borrowing=0.047, BHC invest. in nonbank subs.=0.017 and BHC money due to nonbank subs.=0.142. ***, **, * indicate significance on the 1%, 5%, 10% level.

Table 9: Robustness checks

	Spec. 1		Spec. 2		Spec. 3		Spec. 4		Spec. 5		Spec. 6	
	Large banks						Small banks					
	Risk-weighted ratio		Leverage ratio		Supp. lev. ratio		Risk-weighted ratio		Leverage ratio		Supp. lev. ratio	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Tier 1 Risk-weighted ratio	-6.253	4.351					-4.411***	0.905				
Leverage ratio			-7.420**	3.580					-4.550***	0.864		
Supp. Leverage ratio					-7.487**	3.168					-5.320***	0.993
Asset growth	-0.211	0.286	-0.113	0.239	-0.152	0.240	0.114***	0.033	0.136***	0.031	0.120***	0.031
Non-performing assets	11.197***	1.936	11.402***	1.815	11.623***	1.858	5.171***	0.703	4.985***	0.687	5.196***	0.711
Residential mortgages	-0.772	0.748	-0.873	0.742	-0.877	0.746	-0.248	0.186	-0.297*	0.180	-0.321*	0.184
Commercial real estate lending	1.203***	0.261	1.345***	0.269	1.306***	0.279	0.483***	0.123	0.687***	0.122	0.680***	0.124
Co.& ind. loans	-0.390	0.801	-0.154	0.720	-0.213	0.724	0.109	0.244	0.141	0.238	0.091	0.244
Cost inefficiency	1.425	1.264	2.761*	1.430	1.826*	1.046	0.027	0.972	0.059	0.911	0.135	0.888
ROA	1.332	3.342	2.404	3.510	1.904	3.583	-4.803***	1.695	-4.918***	1.654	-4.761***	1.671
Liquid assets	1.732	1.113	0.917	0.693	0.970	0.858	0.074	0.453	-0.282	0.421	-0.276	0.433
Core deposits	-0.823**	0.388	-0.903**	0.363	-0.837**	0.366	-0.570***	0.137	-0.573***	0.140	-0.572***	0.140
House price index growth	-0.354	0.665	-0.263	0.661	-0.243	0.665	-0.567*	0.300	-0.607**	0.297	-0.613**	0.300
Personal income growth	-0.679	2.377	-1.031	2.374	-0.855	2.383	-2.569**	1.057	-2.281**	1.023	-2.342**	1.032
BHC size	-0.210	1.571	-0.180	1.527	-0.147	1.560	-1.130***	0.396	-0.992**	0.390	-1.038***	0.394
BHC short-term borrowing	2.638***	0.906	3.044***	0.920	2.682***	0.892	0.959***	0.230	0.992***	0.227	0.991***	0.230
BHC invest. in nonbank subs.	-4.166***	1.423	-4.101***	1.367	-4.084***	1.355	-0.082	0.743	-0.058	0.733	-0.075	0.751
BHC money due to nonbank subs.	1.328**	0.553	1.286**	0.562	1.309**	0.559	0.344***	0.129	0.344***	0.129	0.350***	0.130
Observations	698		698		698		6806		6806		6806	
Pseudo R^2	0.503		0.503		0.503		0.403		0.397		0.400	
Log likelihood	-86.9		-86.9		-86.9		-637.4		-644.5		-641.2	
AUROC	0.9493		0.9494		0.9498		0.9356		0.9319		0.9328	
Nb. of failures	48		48		48		249		249		249	
Correct prediction	31		31		31		125		120		122	
False alarms	17		17		17		124		129		127	
- among which rescued banks	3		3		3		2		4		3	

Note: Independent variables are averages over Q4/2007 and Q3/2008. Marginal effects are reported. For the large bank sample, the marginal effect is evaluated at Tier1 risk-weighted ratio=0.100, leverage ratio=0.088, supp. leverage ratio=0.081, asset growth=0.114, Nonperforming assets=0.059, Residential mortgage=0.087, Commercial real estate lending=0.556, Co.& ind. loans =0.083, Cost inefficiency=0.027, ROA=-0.001, liquid assets=0.054, core deposits=0.440, House price index growth=-0.097, Personal income growth=0.043, BHC size=0.113, BHC short-term borrowing=0.035, BHC invest. in nonbank subs.=0.019 and BHC money due to nonbank subs.=0.206. For the small bank sample, the marginal effect is evaluated at Tier1 risk-weighted ratio=0.107, leverage ratio=0.075, supp. leverage ratio=0.073, asset growth=0.181, Nonperforming assets=0.069, Residential mortgage=0.136, Commercial real estate lending=0.486, Co.& ind. loans =0.031, Cost inefficiency=0.034, ROA=-0.007, liquid assets=0.066, core deposits=0.532, House price index growth=-0.079, Personal income growth=0.040, BHC size=0.082, BHC short-term borrowing=0.031, BHC invest. in nonbank subs.=0.012 and BHC money due to nonbank subs.=0.125. ***, **, * indicate significance on the 1%, 5%, 10% level.