The Information Content of Basel III Liquidity Risk Measures

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Abstract

The Basel III liquidity coverage ratio (LCR) is measure of asset liquidity, and the net stable funding ratio (NSFR) is a measure of funding stability. We find the probability of failure of U.S. commercial banks is negatively correlated with the NSFR, while it is positively correlated with the LCR. The positive correlation between bank failure and the LCR highlights the negative externality of liquidity hoarding. Both the NSFR and the LCR have limited effects on bank failures. In contrast, the systemic funding liquidity risk was a major contributor of bank failures in 2009 and 2010. We also shed light on the assumptions on net cash outflow rates in the new liquidity standards.

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Key words: Basel III; Liquidity risk; Bank failure; Insolvency risk; Information value; Liquidity hoarding

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1. Introduction

The length and severity of the liquidity disruption during the financial crisis of 2007–2009 has prompted regulators to emphasize the importance of sound liquidity risk management. In December 2010, the Basel Committee on Banking Supervision (BCBS) (2010a) strengthened its liquidity framework by proposing two standards for liquidity risk. The liquidity coverage ratio (LCR) standard requires that banks have sufficient high-quality liquid assets to survive a significant stress scenario over one month, while the net stable funding ratio (NSFR) standard induces banks to fund their activities with more stable sources of funding. The LCR is measure of asset liquidity and is defined as the ratio of the stock of high-quality liquid assets to the total net cash outflows over the next 30 calendar days under a significantly severe liquidity stress condition. The NSFR is a measure of funding stability and is defined as the ratio of available stable funding (ASF) to required stable funding (RSF). Therefore, the objective of the LCR standard is to increase individual banks' liquidity buffers, while the objective of the NSFR standard is to enhance their funding stability.

Will the new liquidity standards achieve their intended goal of reducing liquidity risk in the banking sector? To the best of our knowledge, few studies have examined the new liquidity risk measures proposed in Basel III.[1] Therefore, it is our goal to contribute by providing some early empirical evidence on this issue. Specifically, we examine the effectiveness of the new liquidity standards in reducing bank failures. Obviously, bank failure reduction may not be the sole

[1] Two recent studies (International Monetary Fund (IMF), 2011; Vazquez and Federico, 2012) attempt to calculate and evaluate the NSFR using a coarse classification of asset and liabilities. These studies also made assumptions on the weights of available stable funding (ASF) and required stable funding (RSF). The IMF pointed out that "data issues remain a challenge in the analysis of NSFR". Neither study evaluates the LCR because of data limitations.

purpose of the new liquidity measures of Basel III. However, regulators and policy makers do not act randomly. It is highly likely that reducing bank failures is among their top objectives when proposing the new liquidity standards. Therefore, examining the link between the new liquidity risk measures and bank failure is crucial in understanding their overall effectiveness.

While the new liquidity standards aim at strengthening individual banks' liquidity buffers and lowering their maturity mismatches, it remains to be seen whether idiosyncratic liquidity risk was a major contributor to bank failures during the 2007–2009 financial crisis. Since the seminal work of Diamond and Dybvig (1983) on liquidity risk and bank runs, a growing body of theoretical literature has underscored the systemic nature of liquidity risk and the important role of contagion in financial crisis (Allen and Gale, 2000; Diamond and Rajan, 2005). For this reason, the IMF questioned that the new liquidity standards can only play a limited role in managing systemic liquidity risk (International Monetary Fund (IMF), 2010, 2011).

On the empirical side, recent studies have identified systemic liquidity disruptions in multiple short-term funding markets.[2] However, few empirical studies have directly linked bank failures to both systemic and idiosyncratic liquidity risks. One obvious reason for the lack of empirical studies is that there had been few bank failures in the United States between 1995 and 2007. The massive number of bank failures during the recent financial crisis offers us a costly opportunity to improve our understanding of bank failures and liquidity risk.

We examine this issue in three stages. First, we calculate the approximate measures of LCR and NSFR using call reports data of U.S. banks. To the best of our knowledge, our study is the

[2] These disruptions include the collapse of the asset-backed commercial paper (ABCP) market in 2007 (Covitz, Liang, and Suarez, 2013), the run on the repurchase agreement market (the repo market) (Gorton and Metrick, 2012), and the strains in the interbank market (International Monetary Fund (IMF), 2010).

first large effort to calculate the LCR and the NSFR of U.S. commercial banks.

In the second stage, we examine the links between the new liquidity risk measures and bank failures. We employ a bank failure model that links bank failure to insolvency and liquidity risks. We postulate that liquidity risk affects banks through both idiosyncratic and systemic channels, which can have varied impacts on bank failures. Our approach is consistent with the theoretical model of Allen, Carletti, and Gale (2009), who divide liquidity risk into idiosyncratic and aggregate liquidity risk. Therefore, this model allows us to estimate the contributions of different channels. Since the new liquidity ratios target an individual bank's liquidity risk management, their effects are largely contained in the idiosyncratic channel. By comparing the contributions of these different channels, we can assess the effectiveness of the new liquidity risk standards.

Bank failure is a complicated process in which other factors, such as regulatory forbearance, government intervention, and other political considerations, can also play important roles. However, the scope of this paper is to examine the links between liquidity risk and bank failures. We follow the literature and include a list of control variables to control for the missing variable bias.[3] Again, regulators and policy makers do not act randomly, and we believe the variables included in our models have strong influence in their decision-making process. However, finding all possible factors that affect bank failure is out of the scope of this study.[4]

Our empirical results confirm the negative externality of liquidity hoarding. More specifically, we find the probability of failure of U.S. commercial banks is positively correlated

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[3] See King, Nuxoll, and Yeager (2006) for a survey of the literature of bank failure models. Our model is an extension to the Moody's RiskCalc™ U.S. banks model (Dwyer, Guo, and Hood, 2006).

[4] It is perhaps also impossible in any kind of empirical study, as one can always argue that there are missing variables in any specification of the empirical model.

with the LCR, which is a measure of asset liquidity. To reduce the liquidity risk, a bank can increase the liquidity buffer by hoarding liquidity. However, liquidity hoarding of individual banks can have negative externality effects, leading to market illiquidity at the aggregate level (Gârleanu and Pedersen, 2007; Allen, Carletti, and Gale, 2009; Acharya and Skeie, 2011). Similar to the prisoner's dilemma in the game theory, when each bank tries to hoard liquidity, it reduces the liquidity provision to other institutions. As a consequence, the aggregate market liquidity declines, thereby making everyone worse off.

Finally, a crucial component of the Basel III LCR standard is its assumptions on the rates of cash outflows and inflows of different liability categories under stressed conditions. To the best of our knowledge, these assumptions are largely untested. While this paper cannot directly test these assumptions because of data limitations, we calculate two additional measures of the LCR using the 90th and 99th percentiles of net cash outflow rates of different funding categories. Therefore, we can compare these measures with the measure of the LCR based on the assumptions in the Basel III LCR standard. It is our hope that our results will stimulate efforts to establish the empirical evidence regarding the rates of net cash outflows of different liability categories under stressed conditions.

The remainder of this paper is organized as follows. Section 2 describes the data and calculates the approximate measures of the Basel III LCR and NSFR. Section 3 examines the links between the new liquidity risk measures and bank failures and provides some empirical evidence on the rates of net cash outflows of different liability categories. Section 4 concludes.

2. Data and the approximate measures of LCR and NSFR

2.1. Data

Our sample period spans the period from 2001 to 2011.[5] We build a quarterly panel data set from the quarterly income statements and balance-sheet data of U.S. commercial banks (i.e., call reports data) obtained from the Federal Reserve Bank of Chicago. To prevent the possibility of outlier driving the results, we exclude all bank-quarters when total assets, total loans, total deposits, and total liabilities are either missing or below one million U.S. dollars. The final quarterly data set includes 334,365 bank-quarter observations. It is used for calculating the net cash outflow rates of different funding categories.

Bank failure data since 2001 are obtained from the Federal Deposit Insurance Corporation (FDIC) and are matched with call reports data. Table 1 lists the distribution of failed banks by year in our sample between 2002 and 2011. FDIC defines three categories of transactions in its failures and assistance transactions data. The first category consists of assistance transactions, in which the charter of the failed / assisted institution survives the resolution process in most cases. The second category includes different types of purchase and assumption transactions, in which the failed/assisted institution's charter is terminated, its insured deposits plus some assets and other liabilities are transferred to a successor charter. The third category consists of payoff transactions, in which the failed / assisted institution's charter is closed, and there is no successor institution. The deposit insurer (i.e., the FDIC or the former Federal Savings and Loan Insurance Corporation) pays insured depositors in payoff transactions. All categories of failure and

[5] One reason for choosing the period from 2001 to 2011 is because of the limitation of the U.S. bank data we collected through call reports data, which prevents us from calculating the LCR and NSFR with a reasonable level of accuracy for data before 2001.

assistance transactions are treated as failure in this study.

When analyzing the relationship between new liquidity risk measures and bank failures, we define a binary performance variable to indicate whether a bank will fail within the next 12 months. In each year, if a bank fails within the next 12 months, it is flagged as "bad" and is assigned the binary value of 1. Otherwise, it is flagged as "good" and is assigned the binary value of 0.

We choose the time interval of the performance variable to be one year in our analyses for several reasons. First, because we employ a discrete-time hazard model in our analysis, the time interval should be consistent with the practical use of the model. For capital calculation purposes, banks typically use credit risk models to predict default in the next 12 months.[6] Second, while one can estimate the hazard model using a shorter interval such as a quarter, we are concerned that such a short interval could pick up random error or noise instead of the underlying relationship. For instance, reporting delay, information withholding, and even personnel shortages could delay the closure of a bank from one quarter to the next. Third, using a short interval would introduce a substantial serial correlation among explanatory variables because of the way these variables are constructed. For instance, variables such as ROA, loan yields, security yields, and interest expense are constructed using the trailing 12 months data. Even though one could model the time series property of these explanatory variables, it is not clear whether such an approach would introduce misspecification errors in addition to the complexity. On the other hand, if we construct these variables using a shorter interval, it would subject them to seasonal effects. Finally, using quarterly data to predict the conditional failure rate over a

[6] Shorter prediction intervals could be useful for stress testing or other purposes, which are not directly relevant to the scope and purpose of this paper.

longer interval would also subject the dependent variable to serial correlation because of the overlapping of time intervals over consecutive quarters.

Therefore, we use an annual data set in our analyses, based on the fourth quarter of each year. The final annual data set includes 82,853 bank-year observations. We report the summary statistics of bank-level variables using the annual data set.

2.2. The approximate measures of LCR and NSFR

The Basel III LCR standard was designed to ensure that a bank maintains an adequate level of unencumbered, high-quality liquid assets that can be converted into cash to meet its liquidity needs for 30 days under a significantly severe liquidity stress scenario. The LCR is defined as the ratio of the stock of high-quality liquid assets to the total net cash outflows over the next 30 calendar days under a significantly severe liquidity stress condition:

$$\text{LCR} = \frac{\text{Stock of high-quality liquid assets}}{\text{Total net cash outflows over the next 30 days}} . \tag{1}$$

This ratio is required to be above 100%. The calculation of LCR depends on assumptions in the calculations of the stock of high-quality liquid assets and the total net cash outflows. These assumptions include the classification of “Level 1” and “Level 2” assets, the weights assigned to these asset categories, the classification of different liability categories, and the rates of cash outflow and inflow for different liability categories. It should be noted that most of these expert-judgment-based assumptions are largely untested against empirical evidence.

The NSFR standard was developed to promote medium and long-term funding stability. The NSFR is the ratio of available stable funding (ASF) to required stable funding (RSF):

$$\text{NSFR}=\frac{\text{Available stable funding (ASF)}}{\text{Required stable funding (RSF)}} . \tag{2}$$

This ratio is required to be greater than 100%. The calculation of the NSFR depends on assumptions in the calculations of ASF and RSF, such as classifications of different assets and liabilities categories, and the weights assigned to these categories. Similar to the LCR, most of these assumptions are based on expert judgment and are largely untested.

Tables A.1 and A.2 in Appendix A summarize the categories and weights used in the calculations of LCR and NSFR. We need to overcome several obstacles in these calculations. First, there are ambiguities in certain guidelines of Basel III liquidity risk standards. Therefore, we have to use our judgment when applying these guidelines. Second, there are gaps in data format and granularity between existing public data and the information required for calculating the LCR and the NSFR under the Basel III guidelines. Therefore, we have to rely on interpolation and extrapolation techniques when the required data are not readily available.

We highlight in the following discussion some extrapolation and interpolation techniques employed in this paper. In the first example, calculating the LCR requires information about liabilities with a remaining maturity of less than one month. The quarterly call report data, however, only report information about liabilities with a remaining maturity of less than three months. Therefore, we have to extrapolate the liabilities with a remaining maturity of one month. We assume the maturity schedule is evenly distributed so that the amount of liabilities with a remaining maturity of less than one month equals one-third of the amount of liabilities with a remaining maturity within three months. As a robustness check, we can also assume an extreme case when all liabilities with a remaining maturity within three months mature within the first month.

In the second example, the guidelines require dividing liabilities into subcategories of retail deposits, unsecured wholesale funding, and secured funding with different run-off rates. The call reports data, however, lack such granularity. In this case, we have to make assumptions on the distribution of subcategories within their parent category. Without additional information, we generally assume equal distribution of subcategories within the parent category.

Finally, except for unused commitments, letters of credit, and the net fair value of derivatives, we do not have the information required for calculating the liquidity needs of other off-balance sheet items, such as the increased liquidity needs related to downgrade triggers embedded in financing transactions and derivatives contracts. Therefore, our calculations of the LCR and NSFR are partial measures that capture a bank's liquidity risk as reflected by its balance sheet rather than by its off-balance-sheet items.

Table 2 reports the summary statistics of the approximate measures of the LCR and NSFR along with other bank-level variables. As Table 2 shows, the average LCR is 87.96% while the average NSFR is 121.39% for the entire period of 2001–2011. Fig. 1 plots the average LCR and NSFR over time, which shows that both ratios were in a downward trend from 2001 through 2007. Having reached the bottom at the end of 2007, both ratios increased sharply. The average LCR reached its peak in 2009 while the average NSFR reached its peak in 2010.

2.3. Comparison with existing studies

To the best of our knowledge, no published studies have attempted to calculate the LCR and NSFR using the public data by following the exact definitions of Basel III. On the other hand, the Basel Committee on Banking Supervision (2010b, 2012a, 2012b) and the European Banking Authority (EBA) (2012a, 2012b) have conducted five quantitative impact studies or monitoring exercises using non-public bank data reported in December 2009, June 2011 and December 2011.

Table 3 summarizes the results of the BCBS and EBA studies. The most recent BCBS monitoring exercise was based on bank data reported in December 31, 2011. This study covers 209 banks across the world, including 102 Group 1 banks[7] and 107 Group 2 banks. This study finds that the weighted-average LCR is 91% for Group 1 banks, and 98% for Group 2 banks. It also reports an aggregate LCR shortfall of $2.33 trillion. The weighted-average NSFR is 95% for Group 1 banks, and 94% for Group 2 banks. The aggregate NSFR shortfall is $3.24 trillion.

Because our study is based on call reports data of U.S. banks, we cannot directly compare our results with the results of the BCBS and the EBA studies. As was mentioned before, there are gaps between call reports data and the data required for calculating the new risk ratios. It is likely that our results are less accurate. Nevertheless, our study covers a relatively long period between 2001 and 2011, while the BCBS and EBA studies cover only three reporting dates. Because the banks participating in the BCBS studies are large international banks, they tend to be more similar to each other. On the other hand, there is more variation in our sample, which includes more than 8,343 banks over a 10-year period. The large sample size and the long sample period allow us to perform additional analyses that cannot be performed in the BCBS and EBA studies.

In Table 4, we report the sum of high-quality liquid assets, the sum of 30-day net cash outflows, and the sum of LCR shortfalls of U.S. banks in the fourth quarter of each year. As Table 4 shows, the sum of 30-day net cash outflows exceeds the sum of high-quality liquid assets every year. For instance, the sum of LCR shortfalls in 2007 is $2.48 trillion. It declined to $1.12 billion in 2009, and then climbed back to $1.93 trillion in 2010. It stood at $917 billion at the

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[7] Group 1 banks are those that have Tier 1 capital in excess of €3 billion and are internationally active. All other banks are considered Group 2 banks.

end of 2011. Therefore, for U.S. banks as a whole, there has always been less liquid asset than required under the Basel III LCR standard.

While we cannot directly compare our results with the results of the BCBS and EBA studies because each study uses a different sample, our results are qualitatively similar to theirs. For instance, we can perform an indirect comparison on bank data reported in December 2011. For December 2011, the sum of LCR shortfalls of all banks participating in the BCBS study (2012b) is \$2.33 trillion, while the sum of LCR shortfalls of European banks participating in the EBA study (2012b) is \$1.52 trillion. If we assume both studies include the same sample of European banks, we can obtain the sum of LCR shortfalls of all other banks as \$2.33 trillion − \$1.52 trillion = \$810 billion. On the other hand, the sum of LCR shortfalls of all US banks in our study is \$917 billion (see Table 4). Therefore, while we cannot perform an apples-to-apples comparison, our results are largely in line with those of the BCBS studies.

Table 5 reports the sum of available stable funding, the sum of required stable funding, and the sum of NSFR shortfalls.

As this table shows, the sum of required stable funding exceeded the sum of available stable funding before 2008. Since 2009, there has been more available stable funding than required stable funding. This surplus grew to \$441 billion at the end of 2011. The NSFR surplus in the U.S banking system may have been partially caused by a series of large-scale asset purchases (LSAP) by the Federal Reserve, which began in late 2008.

3. The new liquidity risk measures and bank failures

This section examines the link between the new liquidity risk measures and bank failures. We first examine the risk sensitiveness of the new liquidity risk measures. A risk measure is more risk sensitive if it has higher predictive power of bank failures than other variables. In the second stage, we employ a bank failure model that links bank failure to insolvency and liquidity risks.

3.1. The risk sensitiveness of the new liquidity risk measures

We use the information value[8] to measure the predictive power of each risk measure. The information value is a measure of a variable's ability to discriminate between two performance outcomes in prediction modeling (Thomas, Edelman, and Crook., 2002). We divide the value of each risk measure into 10 deciles and calculate its information value as follows:

$$\mathrm{IV}=\sum_{i=1}^{10}\left(\left(P\_Bad_i - P\_Good_i\right)\bullet \log\left(\frac{P\_Bad_i}{P\_Good_i}\right)\right). \tag{3}$$

In the above equation, the variable $P\_Bad_i = \frac{N_i^b}{N^b}$ is the proportion of the number of "bad" banks in interval i (N_i^b) to the total number of "bad" banks in the entire sample (N^b). Likewise the variable $P\_Good_i = \frac{N_i^g}{N^g}$ is the proportion of the number of "good" banks in interval i (N_i^g) to the total number of "good" banks in the entire sample (N^g). This definition is very intuitive. For instance, if we have $P\_Bad_i = P\_Good_i$ for interval i, then the contribution of this interval to the information value of the risk measure will be zero. A risk measure with low information value will have little predictive powers of bank failures.

[8] The information value is a variant form of the Kullback–Leibler divergence statistics (which is also called information divergence or relative entropy) in information theory and statistics (Kullback, 1959), which is a measure of the difference between two probability distributions.

Table 6 reports the rankings of the average information value of 16 risk measures using an annual sample from 2001 to 2010 that predicts bank failures from 2002 to 2011. In each year, we calculate the information value of each risk measure in predicting bank failures within the next 12 months. Therefore, a risk measure with a higher ranking has higher predictive power of bank failures for the entire period from 2002 to 2011. As it appears, the LCR and NSFR rank very low in the list. Their information values (0.0650 and 0.0435, respectively) are lower than the information values of two traditional liquidity risk measures: the government securities ratio (0.1562) and the brokered deposits ratio (0.1237).

Fig. 2 and Fig. 3 plot the bank failure rate by decile for LCR and NSFR. Both the LCR and NSFR have very low discriminatory power. It is interesting to note that, contrary to common belief, a high LCR is associated with a higher bank failure rate. However, the positive correlation between bank failure and the LCR is consistent with the theoretical prediction of Gârleanu and Pedersen (2007), who show that tight liquidity risk management of one institution can have negative externality effects. As each institution tries to hoard liquidity, it provides less liquidity to other institutions. As a consequence, the aggregate market liquidity declines, thus making everyone worse off. As we have seen in Fig. 1, the average LCR has risen sharply since 2007. Second, Table 1 shows that there have been a large number of bank failures since 2007. As a result, a higher LCR is associated with a higher bank failure rate.

3.2. A model of bank failure prediction

Most bank failure models are accounting-ratio models pioneered by Altman (1968). These models are typically built by searching through a large number of accounting-ratio variables covering capital adequacy, asset quality, earnings, liquidity, and sensitivity to market risk.

Commercially successful models in this category include Zeta® and Moody's RiskCalc™ U.S. banks model. Among recent studies, Berger and Bouwman (2013) employ an accounting-ratio model to examine how capital affects a bank's probability of survival and market share, while Jin, Kanagaretnam and Lobo (2011) examine the ability of selected accounting and audit quality variables to predict bank failures.

A second group of corporate default models comprises the structural models of default (Black and Scholes, 1973; Merton, 1974), which link a firm's probability of default to its distance to default: a volatility-adjusted measure of firm leverage. Despite the successful commercialization by Moody's KMV, these models suffer from the limitation that two key inputs of the model, the market value and the volatility of a firm's assets, are not directly observed and have to be calibrated under certain assumptions. As a result, only firms with publicly traded securities can be calibrated. Since as much as 95% of U.S. commercial banks are not publicly traded, there is hardly any bank failure model based on this approach. Contrasted with the structural models, the accounting-ratio models are also called the reduced-form models.

Empirical tests on the prediction power of accounting-ratio and structural models are inconclusive. For instance, Hillegeist et al. (2004) find that structural models perform better than accounting-ratio models. On the other hand, Bharath and Shumway (2008) conclude that a firm's conditional default probability is not completely determined by its distance to default. Using a sample of U.K. non-financial firms during the period of 1985–2001, Agarwal and Taffler (2008) find that accounting-ratio models perform slightly better than structural models.

3.2.1. Econometric model

One commercially successful bank failure prediction model is the Moody's RiskCalc™ U.S.

banks model (Dwyer, Guo, and Hood, 2006; Dwyer and Eggleton, 2009), which consists of two components: the financial statement only (FSO) component and the credit cycle adjustment (CCA) component. The FSO component uses nine variables as its inputs: capital ratio, return on assets, net interest margin, loan mix, commercial loan charge-off ratio, consumer loan charge-off ratio, other real estate owned ratio, size, and government securities ratio. The government securities ratio is measure of liquidity risk in this model.

To have a better understanding of the relationship between liquidity risk and bank failures, we develop a new model that has two enhancements over the Moody's RiskCalc model. First, we enhance the modeling methodology by employing a dynamic discrete-time hazard model, in which the bank failure hazard consists of two major components:

$$\lambda_{i,t+1} = \exp\left(U_{i,t+1} + V_{i,t+1}\right) . \tag{4}$$

The hazard is also called the default intensity, which is the conditional probability that bank i fails at time $t+1$ given it has not failed at time t. Estimation and applications of discrete-time hazard model can be found in Kalbfleisch and Prentice (2002), Allison (1995), and Shumway (2001).

Eq. (4) can be rewritten in the form of log-hazard:

$$h_{i,t+1} = \log(\lambda_{i,t+1}) = U_{i,t+1} + V_{i,t+1} . \tag{5}$$

We call the first component ($U_{i,t+1}$) the insolvency component, which consists of the first eight variables used in the Moody's RiskCalc model. A predictor of $U_{i,t+1}$ is defined as

$$\begin{aligned}\widehat{U}_{i,t+1} &= \beta_0 + \beta_1 \bullet cap_{i,t} + \beta_2 \bullet roa_{i,t} + \beta_3 \bullet nim_{i,t} + \beta_4 \bullet loan\_mix_{i,t} + \beta_5 \bullet oreo\_r_{i,t} \\ &+ \beta_6 \bullet size_{i,t} + \beta_7 \bullet cons\_co\_r_{i,t} + \beta_8 \bullet ci\_co\_r_{i,t} .\end{aligned} \tag{6}$$

The second component is the liquidity risk component. In Moody's RiskCalc model, the liquidity risk component consists of a single bank-specific liquidity risk measure: the government securities ratio. We modify the liquidity risk component so that it consists of bank-specific liquidity risk measures and a measure of systemic funding liquidity risk. The bank-specific funding liquidity risk is the consequence of an individual bank's liquidity mismanagement. On the other hand, the systemic funding liquidity risk affects every bank in the market. Our approach is consistent with Allen, Carletti, and Gale (2009), who divide liquidity risk into idiosyncratic liquidity risk and aggregate liquidity risk.

Theoretic studies did not result in a generally accepted methodology for measuring either bank-specific funding liquidity risk or systemic funding risk. Although there are several indirect measures for bank-specific liquidity risk, each emphasizes a different aspect of funding liquidity risk and is subject to various measurement errors (Koch and MacDonald, 2003). The indirect measures of bank-specific funding risk can be divided into two major groups: asset liquidity and funding stability. Asset liquidity measures include net liquid asset ratio, current ratio, and government securities ratio. Funding stability measures include brokered deposits ratio, core deposits ratio, and non-core funding ratio. According to this classification, LCR is a measure of asset liquidity, while NSFR is a measure of funding stability. Two recent empirical studies attempt to estimate bank-specific funding liquidity risk using bidding and borrowing rates of some European banks in repos with the European Central Bank (ECB) (Fecht, Nyborg, and Rocholl, 2011; Drehmann and Nikolaou, 2013). Unfortunately, these data are not publicly available and only cover a very short period.

There is no commonly accepted definition of systemic liquidity risk. The IMF defines it as the risk of simultaneous liquidity difficulties at multiple financial institutions (International Monetary Fund (IMF), 2011) and has proposed a systemic liquidity risk index. Since our focus is on bank's funding risk, we choose a simple measure that is based on interbank interest rate spreads, the TED spread, as the measure of systemic funding liquidity risk. The TED spread is the spread between the three-month London offered interbank rate (LIBOR) and the three-month U.S. Treasury bills rate. Interbank spreads are widely used by practitioners and regulators to measure the stress in the interbank market. Other popular interbank rate spreads include the LIBOR-OIS spread, which is the spread of three-month LIBOR over the three-month Overnight Indexed Swap (OIS). There is usually very little difference between the TED spread and the LIBOR-OIS spread. However, Rodríguez-Moreno and Peña (2013) show that there was a remarkable difference between these two spreads during the recent financial crisis. They suggest that while both spreads reflect default risk[9] and liquidity risk, the TED spread also contains the "flight to quality" effects. Since our focus is on measuring the overall stress in the interbank market, we do not need to differentiate between these subcomponents.

The interbank spreads are regarded as ex-ante systemic risk measures according to the taxonomy of Bisias et al. (2012), which can act as an early-warning indicator to gauge the funding liquidity in the general market. Despite the recent controversy over the accuracy of LIBOR during the recent crisis, LIBOR was an important benchmark rate even during the crisis because many existing financial contracts use it as the reference rate. As a result, banks' revenue and expenses are very sensitive to it. In addition, these spreads are also widely used by other researchers to study the financial crisis. For instance, Gorton and Metrick (2012) use the changes in the LIBOR-OIS spread to measure counterparty risk in repo transactions, while Cornett et al. (2011) use the time variation of the TED spread as the measure of liquidity strains on the banking system in their study of liquidity risk management in the financial crisis. Fig. 4 plots the one-year conditional bank failure rate with the TED spread of the preceding year, which shows

[9] It is also called counter party risk in Gorton and Metrick (2012) and Cornett et al. (2011).

that a rise in the TED spread is followed by a rise in the conditional bank failure rate.

Therefore, the liquidity risk component of the log-hazard is specified as:

$$\widehat{V}_{i,t+1} = \beta_9 \bullet TED_t + \beta_{10} \bullet LCR_{i,t} + \beta_{10} \bullet NSFR_{i,t} \ . \tag{7}$$

Combining Eqs. (5), (6), and (7), the predictor of log hazard is specified as

$$\begin{aligned} \hat{h}_{i,t+1} &= \beta_0 + \beta_1 \bullet cap_{i,t} + \beta_2 \bullet roa_{i,t} + \beta_3 \bullet nim_{i,t} + \beta_4 \bullet loan\_mix_{i,t} + \beta_5 \bullet oreo\_r_{i,t} \\ &+ \beta_6 \bullet size_{i,t} + \beta_7 \bullet cons\_co\_r_{i,t} + \beta_8 \bullet ci\_co\_r_{i,t} \\ &+ \beta_9 \bullet Ted_t + \beta_{10} \bullet LCR_{i,t} + \beta_{11} \bullet NSFR_{i,t} \ . \end{aligned} \tag{8}$$

Table 7 summarizes the explanatory variables used in Eq. (8).

3.2.2. The estimation results

We estimate four models. The first model is based on Eq. (8), which is the benchmark model. We call it Model 1. In Model 2, we exclude the LCR and NSFR from Model 1 but keep the TED spread. Therefore, we can estimate the contribution of LCR and NSFR for predicting bank failures by comparing Model 2 and Model 1. For Model 3, we exclude the TED spread from Model 1 but keep the LCR and the NSFR. Comparison of Models 1 and 3 allows us the gauge the contribution of the systemic funding liquidity risk. Finally, Model 4 excludes idiosyncratic and systemic funding liquidity risk measures (i.e., the LCR, the NSFR and the TED spread).

Model fit statistics are reported in Table 8, while parameter estimates are reported in Table 9. As Table 8 and Table 9 show, the differences in model statistics between Model 1 and Model 2 are very small. On the other hand, there are substantial differences between Model 1 and Model 3, which excludes the systemic funding liquidity risk measures. Furthermore, the TED spread has a large, positive, and statistically significant coefficient, which implies that the systemic funding liquidity risk is a significant predictor of bank failures.

Consistent with Fig. 3, the coefficient on the NSFR in Model 1 is negative and statistically significant, suggesting that a higher NSFR is associated with a lower probability of bank failure. However, the coefficient on the LCR in Model 1 is positive and statistically significant, suggesting that a higher LCR is associated with a higher bank failure rate. This result is consistent with Fig. 2 and is consistent with the negative externality of liquidity hoarding. Because the LCR is a measure of asset liquidity, while the NSFR is a measure of funding stability, these results suggest that there is a distinct difference between roles of asset liquidity and funding stability in bank failures. In other words, increasing funding stability reduces the probability of bank failure, while liquidity hoarding has the negative externality that increases the probability of bank failure.

Fig. 5 plots the observed conditional failure rate and the predicted values from Models 1–4, Since Model 2 excludes the LCR and the NSFR, the differences between the predicted values of Model 1 and Model 2 measure the marginal contribution of the LCR and the NSFR. As can be seen, the predicted failure rates of Model 1 and Model 2 are very similar, and both closely match the observed failure rate. On the other hand, the differences between the predicted values of Model 1 and Model 3 measure the marginal contribution of the TED spread. As shown in Fig. 4, there are large differences between the predicted failure rates of Model 1 and 3 in 2009 and 2010. The predicted failure rate of Model 3 is lower than that of Model 1 in 2009, while it is higher than that of Model 1 in 2010.

We offer the following explanation. First, Fig. 4 plots the one-year conditional bank failure rate with the TED spread of the preceding year, which shows that a rise in the TED spread is followed by a rise in the conditional bank failure rate. In addition, we can see that the TED spread was extremely high in 2008 and was extremely low in 2009. The extremely high TED spread in 2008 caused more banks to fail in 2009. On the other hand, the extremely low TED spread (perhaps because of central banks interventions) in 2009 helped reduce the number of bank failures in 2010. Furthermore, as shown in Fig. 5, the predicted values of Models 3 and 4 are very close to each other, suggesting that the TED spread accounts for a majority of the marginal contribution of liquidity risk. Overall, the results suggest the TED spread was a major predictor of bank failures in 2009 and 2010, while the approximate measures of the LCR and NSFR had very little information value in predicting bank failures.

We have also performed collinearity checks and correlation analysis among explanatory variables and found the conditional number and variance inflation factor are below their corresponding rule-of-thumb thresholds (e.g., 30 and 10). Therefore, we conclude that multicollinearity is not significant in the regression. Correlation analysis shows that the correlation between the LCR and the NSFR is 0.38.

3.3. Robustness test on the LCR

The Basel III LCR standard has made assumptions on the rates of cash outflows and inflows under a significant severe liquidity stress scenario. These assumptions are mainly based on expert judgment and are largely untested. It is not clear how this "significantly severe liquidity stress scenario" is defined. In statistical terminology, does this stress scenario correspond to the extreme events at the 99th or the 90th percentiles? The guidelines prescribe the rates of cash outflows of different funding sources. For instance, less stable deposits have a "run-off rate of 10% or higher," while the run-off rates for unsecured wholesale funding provided by small business customers are "5%, 10%, and higher," It is difficult to tell whether these run-off rates correspond to the tail events at the 99th or the 90th percentiles.

This section provides some empirical evidence on the rates of net cash outflows of several liability categories based on call reports data. We are unable to test directly the assumptions in the Basel III guidelines because of several limitations. First, the classification of assets and liabilities in the Basel III guidelines is different from the classification used in call reports data. As a result, we could not match all the liabilities categories defined in Basel III. Second, Basel III specifies both cash inflow and outflow rates, while we can only estimate the net cash outflow rates using call reports data. Finally, Basel III guidelines require monthly cash flow data, while we only have quarterly data. As a result, we have to apply linear interpolation to calculate monthly net cash outflow rates.

Table B.1 of Appendix B reports the median, and the 90th, 95th, and 99th percentiles of quarterly net cash outflow rates of major funding categories. As this table shows, the 99th percentiles of the net cash outflow rates for total liabilities, total deposits, REPO and other borrowed money are 11.1%, 11.7%, 100%, and 100%, respectively. If we look at the subcategories of deposits, we can see that the 99th percentiles of net cash outflows rates for transaction deposits, non-transaction deposits, demand deposits, saving deposits, and money market deposits are 41.8%, 13.8%, 48.4%, 27%, and 42.6%, respectively. These numbers could serve as empirical evidence regarding the assumptions in the Basel III guidelines. Table B.2 of Appendix B reports the summary statistics on net cash outflow rates of additional subcategories of funding.

Fig. 6 plots the average values by year of three measures of LCR. The first measure of LCR (LCR) is calculated using the net cash outflow rates specified in the Basel III LCR standard. The second measure of LCR (LCR2_P90) is calculated using the 90th percentile of the monthly net cash outflow rate of each funding category. The third measure of LCR (LCR2_P99) is calculated using the 99th percentile of the monthly net cash outflow rate of each funding category. The monthly net cash outflow rates are calculated using linear interpolation. This figure shows that LCR lies between LCR2_P90 and LCR2_P99, and it is closer to LCR2_P90 than to LCR2_P99. Therefore, this figure suggests that the net cash outflow rates in the Basel III LCR standard are close to the 90th percentiles of net cash outflow rates calculated using call report data of U.S. banks. We hope our preliminary results would stimulate future efforts to establish the empirical evidence on the net cash outflow rates of different funding categories.

4. Conclusions

This paper makes four contributions. First, we calculate the approximate measures of the Basel III LCR and NSFR. This is a challenging task given the evolving nature of the Basel III liquidity risk standards. Nevertheless, our study is the first large effort to obtain reasonable approximations of these ratios. Our results are largely consistent with the results of five BCBS and EBA studies. While our results may be less accurate than the results of the BCBS and EBA studies, the large sample size and the long sample period in our study allow us to perform additional analyses that cannot be performed in the BCBS and EBA studies.

Second, we examine the links between the new liquidity risk measures and bank failures. Our empirical results show that the probability of failure of U.S. commercial banks is negatively correlated with the NSFR, while it is positively correlated with the LCR. Because the LCR is a measure of asset liquidity, while the NSFR is a measure of funding stability, these results highlight the subtle difference between asset liquidity and funding stability: high funding stability reduces the probability of bank failure, while liquidity hoarding has the negative externality that increases the probability of bank failure.

Third, we estimate a bank failure model that differentiates between idiosyncratic and systemic funding liquidity risks. We find that systemic funding liquidity risk was the major predictor of bank failures in 2009 and 2010, while idiosyncratic liquidity risk played only a minimal role. This finding implies that an effective liquidity risk management framework needs to target banks at both the individual level and the system level.

Finally, we provide some indirect empirical evidence on the net cash outflow rates of certain liability categories based on call reports data. Since the assumptions on the rates of cash inflow and outflow of different funding sources under “a significantly severe liquidity stress scenario” are largely untested, we hope our preliminary results will motivate further research to establish the empirical evidence on the net cash outflow rates of different liability categories under severely stressed conditions.

Appendix A. Additional tables in LCR and NSFR calculation

Table A.1

Summary of liquidity coverage ratio calculation

Item	Weight
Panel 1: Stock of high-quality liquidity assets	
A. Level 1 assets	100%
Cash	
Securities in 0% risk weight category	
Repos in 0% risk weight category	
B. Level 2 assets	85%
Securities in 20% risk weight category	
Repos in 20% and 100% risk weight categories	
Panel 2: Cash Outflows	
Small time deposits with a remaining maturity less than one month	5%
25% of saving deposits	
Unused commitments of home equity line of credit	
Unused commitments of credit cards	
50% of transaction deposits of individuals, partnerships, and corporation	10%
50% of large time deposits with a remaining maturity less than one month	
25% of saving deposits	
Foreign deposits with a remaining maturity of less than one month	
Unused commitments of commercial real estate	
50% of other unused commitments	
50% of transaction deposits of individuals, partnerships, and corporations	15%
Securities lent in 0% risk weight category	
Transaction deposits of domestic banks	25%
50% of large time deposits with a remaining maturity of less than one month	
25% of savings deposits	
50% of repos	
Securities lent in 20% risk weight category	
Subordinate note with a remaining maturity less than one year	
Transaction deposits of U.S. government	75%
Transaction deposits of states and political subdivisions in the United States	
Transaction deposits of foreign governments and official institutions	
25% of savings deposits	
50% of repos	100%
Other liabilities	
Net negative fair value of CDS	
Unused commitments for securities underwriting	
50% of other unused commitments	
Securities lent in 50% and 100% risk categories	
Trading liabilities	
Other borrowed money with a remaining maturity of less than one year	
Panel 3: Cash Inflows	
50% of loans with a remaining maturity less than one month	100%
Derivatives with a positive fair value for purpose other than trading	

Table A.2
Summary of net stable funding ratio calculation

Available stable funding (Sources)		Required stable funding (Uses)	
Item	Weight	Item	Weight
Tier 1 capital Tier 2 capital Time deposits with a remaining maturity of over one year Other borrowed money with a remaining maturity of over one year	100%	Unused commitments Letter of credit Securities in 0% risk weight category	5%
50% of transaction deposits of individuals, partnerships, and corporations Small time deposits with a remaining maturity of less than one year 50% of savings deposits	90%	Securities in 20% risk weight category	20%
50% of transaction deposits of individuals, partnerships, and corporations 50% of large time deposits with a remaining maturity of less than one year 50% of foreign deposits 50% of savings deposits	80%	Securities in 50% risk weight category Loans in 0% risk weight category Trading securities in 0% risk weight category Other assets in 0% risk weight category	50%
50% of large time deposits with a remaining maturity of less than one year Other borrowed money with a remaining maturity of less than one year Transaction deposits of U.S. government Transaction deposits of states and political subdivisions in the United States Transaction deposits of foreign governments and official institutions	50%	Loans in 20% risk weight category Trading securities in 20% risk weight category Other assets in 20% risk weight category	65%
		Loans in 50% risk weight category Trading securities in 50% risk weight category Other assets in 50% risk weight category	85%
		Securities in 100% risk weight category and no risk weight Loans in 100% risk weight category and no risk weight category Trading securities in 100% risk weight category and no risk weight category Other assets in 100% risk weight category and no risk weight category	100%

Appendix B. Calculation of quarterly net cash outflow rates

Table B.1
Quarterly net cash outflow rates of major funding categories, 2001–2011

This table reports the median, the 90th, 95th, and 99th percentiles of the net cash outflow rate of major funding categories.

Funding category	N	Median	90th percentile	95th percentile	99th percentile
Total liabilities	332,984	-1.35	3.64	5.57	11.11
Total deposits	332,984	-1.31	3.92	5.91	11.73
Repo	130,029	2.99	100.00	100.00	100.00
Other borrowed money	210,068	0.00	35.42	67.78	100.00
Transaction deposits	331,223	-1.68	11.21	17.10	41.84
Non-transaction deposits	332,637	-1.07	4.38	6.65	13.81
Demand deposits	330,748	-1.85	14.61	21.91	48.37
Saving deposits	331,163	-1.73	8.40	12.98	26.99
Money market deposits	317,944	-1.67	14.01	21.33	42.62
Other saving deposits	326,176	-1.43	7.60	12.17	32.73
Time deposits	331,871	-0.43	5.91	8.84	17.72
Core deposits	332,622	-1.07	5.32	8.00	17.20
Non-maturity deposits	332,677	-1.78	6.57	9.79	18.87
Brokered deposits	108,355	0.00	38.53	66.81	100.00
Uninsured deposits	138,580	-1.92	31.78	100.00	100.00
Insured deposits	332,977	-1.10	4.85	8.30	22.51
Insured brokered deposits	101,594	0.00	44.09	77.34	100.00
Preferred deposits	62,504	100.00	100.00	100.00	100.00
IRA deposits	319,111	-0.87	3.43	6.15	22.67

Table B.2
Quarterly net cash outflow rates of selected subcategories of funding, 2001–2011

This table reports the median, the 90th, 95th, and 99th percentiles of the net cash outflow rate of selected subcategories of funding.

Subcategory of funding	N	Median	90th percentile	95th percentile	99th percentile
Large time deposits	292,841	-0.82	15.24	29.13	100.00
Small time deposits	331,047	0.00	5.84	9.27	21.57
Time deposits, maturity within 1 year	331,763	-0.11	11.67	18.58	51.46
Large time deposits, maturity within 1 year	266,345	-0.83	21.44	38.37	100.00
Small time deposits, maturity within 1 year	329,480	0.06	11.63	19.57	66.79
Other borrowed money, maturity within 1 year	138,923	0.00	100.00	100.00	100.00
Time deposits, less than $100k, maturity or repricing within 3 months	329,940	0.09	32.74	44.09	68.34
Time deposits, less than $100k, maturity or repricing within 1 year	330,881	0.30	9.65	14.20	28.22
Time deposits, $100k or more, maturity or repricing within 3 months	325,630	-0.89	51.53	65.64	94.44
Time deposits, $100k or more, maturity or repricing within 1 year	327,212	-1.56	45.24	58.79	86.17
Transaction deposits, individual, partnership, business	322,448	-1.74	11.37	18.01	48.52
Transaction deposits, domestic governments	170,672	6.67	98.03	100.00	100.00
Transaction deposits, local governments	277,087	-0.14	39.42	56.36	92.17
Transaction deposits, domestic banks	68,399	0.00	75.39	99.65	100.00
Non-transaction deposits, individual, partnership, business	323,818	-0.96	4.37	6.82	15.09
Non-transaction deposits, domestic governments	18,386	0.00	100.00	100.00	100.00
Non-transaction deposits, local governments	295,929	-0.02	28.01	44.25	87.01
Non-transaction deposits, domestic banks	103,605	0.00	50.00	90.39	100.00
Brokered deposits, maturity within 1 year	97,803	0.00	63.37	98.97	100.00
Large brokered deposits, maturity within 1 year	43,538	0.00	100.00	100.00	100.00
Small brokered deposits, maturity within 1 year	76,633	0.00	73.31	100.00	100.00
Insured brokered deposits, less than $100k	81,147	0.00	51.34	90.33	100.00
Insured brokered deposits, $100k or more	62,817	0.00	72.42	100.00	100.00

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Table 1
Number of failed banks by year between 2002 and 2011

This table lists the distribution of failed and total banks by year from 2002 to 2011 in the sample. The data are collected from Federal Financial Institutions Examination Council (FFIEC) call reports of condition and income found on the website of the Federal Reserve Bank of Chicago. Bank failure data since 2002 are obtained from the Federal Deposit Insurance Corporation (FDIC) and are matched with call reports.

Year	Number of failed banks	Number of total banks
2002	8	8,304
2003	3	8,136
2004	3	8,011
2005	0	7,845
2006	0	7,746
2007	1	7,620
2008	24	7,504
2009	122	7,313
2010	135	7,074
2011	86	6,769
All	382	76,322

Table 2

Summary statistics of select bank-level variables, annual data, 2001–2011 (%)

This table reports the number of observations (N), the mean, the median, the standard deviation, the 10th and the 90th percentiles of LCR, NSFR and other variables for the sample period of 2001–2011. All values are expressed in percent, except for size, which is the natural (base e) logarithm of total assets (expressed in thousands of U.S. dollars).

Ratio	N	Mean	Median	Standard deviation	10th percentile	90th percentile
LCR	82,853	87.96	59.55	90.03	21.80	184.36
NSFR	82,853	121.39	113.51	35.38	95.50	154.17
Capital ratio	82,853	10.80	9.80	3.81	7.46	15.37
Return on assets	82,853	0.74	0.93	1.19	-0.32	1.77
Net interest margin	82,853	3.72	3.69	0.82	2.80	4.67
Loan mix	82,853	47.88	46.51	23.43	17.49	81.11
Other real estate owned ratio	82,853	0.33	0.03	0.75	0.00	0.93
Size	82,853	11.83	11.69	1.31	10.35	13.38
Consumer loan charge off ratio	82,853	0.06	0.02	0.09	0.00	0.15
Commercial loan charge off ratio	82,853	0.08	0.01	0.15	0.00	0.25
Government securities ratio	82,853	14.29	11.41	12.12	1.32	31.08
Non-performing assets ratio	82,853	1.33	0.64	1.97	0.01	3.30
Texas ratio	82,853	12.98	6.13	21.78	0.10	30.63
Loss reserve to assets ratio	82,853	0.95	0.85	0.52	0.46	1.50
Tangible capital ratio	82,853	10.36	9.36	3.74	7.14	14.81
Brokered deposits ratio	82,853	2.24	0.00	4.88	0.00	8.40
Non-core funding ratio	82,853	7.99	4.80	9.41	0.00	21.33
Net liquid assets ratio	82,853	20.98	18.11	15.26	4.21	42.10
Net short-term assets ratio	82,853	-21.96	-22.38	19.13	-46.66	2.09
Core deposits ratio	82,853	58.10	59.78	12.19	41.28	71.97

Table 3
Summary of existing studies by the BCBS and the EBA

This table summarizes the results of three quantitative impact studies by the Basel Committee on Bank Supervision (BCBS) and two studies by the European Banking Authority (EBA).

	BCBS			EBA	
Report date	Sep-12	Apr-12	Dec-10	Sep-12	Apr-12
Bank data date	12/31/2011	6/30/2011	12/31/2009	12/31/2011	6/30/2011
Group 1 bank count	102	103	NA	44	NA
Group 2 bank count	107	102	NA	112	NA
Total assets (trillions of euro)	€ 61.40	€ 58.50	NA	€ 31.00	€ 31.00
Group 1 weighted-average LCR	91%	90%	83%	72%	71%
Group 2 weighted-average LCR	98%	83%	98%	91%	70%
Group 1 weighted-average NSFR	98%	94%	93%	93%	89%
Group 2 weighted-average NSFR	95%	94%	103%	94%	90%
Exchange rate used (dollar/euro)	1.2952	1.2952	1.2952	1.2952	1.2952
LCR shortfall (trillion of USD)	$2.33	$2.28	$2.24	$1.52	$1.55
NSFR shortfall (trillion of USD)	$3.24	$3.60	$3.74	$1.81	$2.46

Table 4
LCR shortfall by year, 2001–2011 ($ billions)

This table reports the sum of high-quality liquid assets, the sum of 30-day net cash outflows and the LCR shortfall, which is defined as the difference between the sum of 30-day net cash flows and the sum of high-quality liquid assets. All dollar amounts are expressed in billions of U.S. dollars

Quarter	Bank count	High-quality liquid assets	30-day net cash outflows	LCR shortfall
2001-12-31	8,304	$826	$2,160	$1,334
2002-12-31	8,136	$999	$2,552	$1,554
2003-12-31	8,011	$1,040	$2,700	$1,660
2004-12-31	7,845	$983	$2,909	$1,927
2005-12-31	7,746	$986	$3,139	$2,153
2006-12-31	7,620	$1,093	$3,401	$2,308
2007-12-31	7,504	$1,254	$3,728	$2,475
2008-12-31	7,317	$2,030	$3,546	$1,515
2009-12-31	7,081	$2,245	$3,364	$1,120
2010-12-31	6,772	$2,470	$4,395	$1,925
2011-12-31	6,517	$2,832	$3,749	$917

Table 5
NSFR shortfall by year, 2001–2011 ($ billions)

This table reports the sum of available stable funding, the sum of required stable funding and the NSFR shortfall, which is defined as the difference between the sum of required stable funding and the sum of available stable funding. All dollar amounts are expressed in billions of U.S. dollars.

quarter	Bank count	Available stable funding	Required stable funding	NSFR shortfall
2001-12-31	8,304	$4,544	$4,924	$380
2002-12-31	8,136	$4,930	$5,358	$428
2003-12-31	8,011	$5,362	$5,717	$356
2004-12-31	7,845	$5,688	$6,209	$521
2005-12-31	7,746	$6,035	$6,603	$568
2006-12-31	7,620	$6,664	$7,378	$714
2007-12-31	7,504	$7,418	$8,334	$915
2008-12-31	7,317	$8,456	$8,637	$181
2009-12-31	7,081	$8,474	$8,404	$-70
2010-12-31	6,772	$8,607	$8,432	$-175
2011-12-31	6,517	$8,718	$8,277	$-441

Table 6
The average information value of liquidity risk measures, sample period: 2001–2010

This table reports the average information value of each explanatory variable for predicting the one-year conditional bank failure.

Rank	Variable name	Information value
1	Non-performance assets ratio	0.6388
2	Texas ratio	0.5713
3	ROA	0.5696
4	TED spread	0.4925
5	Tangible capital ratio	0.3234
6	Capital ratio	0.3172
7	Loss reserve ratio	0.3114
8	Government securities ratio	0.1562
9	Net interest margin	0.1539
10	Broker deposits ratio	0.1237
11	Non-core funding ratio	0.0719
12	LCR	0.0650
13	Net liquid assets ratio	0.0539
14	NSFR	0.0435
15	Net short-term assets ratio	0.0095
16	Core deposits ratio	0.0082

Table 7
Summary of explanatory variables in the bank failure prediction model
This table summarizes the explanatory variables in the bank failure prediction model in Eq. (8).

Name	Math notation	Description
Capital ratio	$cap_{i,t}$	Capital to total asset ratio
ROA	$roa_{i,t}$	Return on assets
Net interest margin	$nim_{i,t}$	Net interest income to total asset ratio
Loan mix	$loan\_mix_{i,t}$	Sum of commercial and industry loans, and commercial real estate loans to total assets ratio
OREO ratio	$oreo\_r_{i,t}$	Other real estate owned to total assets ratio
Size	$size_{i,t}$	Natural logarithm of total assets
Consumer loan charge-off ratio	$cons\_co\_r_{i,t}$	Consumer loan charge-offs to total assets ratio
Commercial loan charge-off ratio	$ci\_co\_r_{i,t}$	Commercial loan charge-offs to total assets ratio
TED spread	Ted_t	Spread of the three-month LIBOR over the three-month Treasury rate
LCR	$LCR_{i,t}$	Basel III liquidity coverage ratio
NSFR	$NSFR_{i,t}$	Basel III net stable funding ratio

Table 8

Model fit statistics of discrete-time hazard models

This table reports the model fit statistics of four discrete-time hazard models that predict bank failure from the period of 2002–2011 using annual data for the period of 2001–2010. Model 1 is based on the log-hazard specified in Eq. (8). Model 2 is Model 1 excluding the LCR and the NSFR; Model 3 is Model 1 excluding the TED spread; Model 4 is Model 1 excluding the LCR, the NSFR and the TED spread.

	Model 1	Model 2 Excluding the LCR and the NSFR	Model 3 Excluding the TED spread	Model 4 Excluding liquidity risk measures
Observations	76,322	76,322	76,322	76,322
Pseudo R^2	0.620	0.612	0.596	0.587
AIC	1,853.700	1,887.053	1,966.377	2,004.510
BIC	1,964.613	1,979.480	2,068.047	2,087.695
Log likelihood	-914.850	-933.526	-972.189	-993.255
AUC statistic	0.970	0.968	0.967	0.965

Table 9
Parameter estimates of discrete-time hazard models

This table reports the parameter estimates of four discrete-time hazard models that predict bank failure from the period of 2002–2011 using annual data for the period of 2001–2010. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Model 1 is based on the log-hazard specified in Eq. (8). Model 2 is Model 1 excluding the LCR and the NSFR; Model 3 is Model 1 excluding the TED spread; Model 4 is Model 1 excluding the LCR, the NSFR and the TED spread.

	Model 1	Model 2 Exclude the LCR and the NSFR	Model 3 Exclude the TED spread	Model 4 Exclude liquidity risk measures
Constant	-1.364	-4.771***	-0.926	-4.867***
	[1.204]	[1.095]	[1.185]	[1.080]
Capital ratio	-63.564***	-63.793***	-55.002***	-55.381***
	[6.264]	[6.073]	[5.645]	[5.493]
ROA	-63.161***	-63.634***	-70.736***	-70.866***
	[5.119]	[4.930]	[4.982]	[4.766]
Net interest margin	-23.127*	-20.696*	-29.557**	-22.557**
	[12.202]	[11.831]	[11.969]	[11.478]
Loan mix	1.191**	1.744***	1.427***	1.901***
	[0.495]	[0.455]	[0.494]	[0.454]
OREO ratio	22.610***	25.000***	13.627***	15.939***
	[4.416]	[4.432]	[4.431]	[4.430]
Size	0.188***	0.203***	0.198***	0.232***
	[0.062]	[0.063]	[0.062]	[0.062]
Consumer loan charge-off	167.332**	185.141***	126.534*	140.566**
ratio	[68.040]	[68.062]	[67.993]	[67.697]
Commercial loan charge-off	29.743	28.327	-19.600	-22.544
ratio	[30.295]	[29.990]	[30.372]	[30.079]
TED spread	80.076***	80.376***		
	[7.404]	[7.301]		
LCR	0.191***		0.125**	
	[0.054]		[0.054]	
NSFR	-2.702***		-2.839***	
	[0.502]		[0.478]	

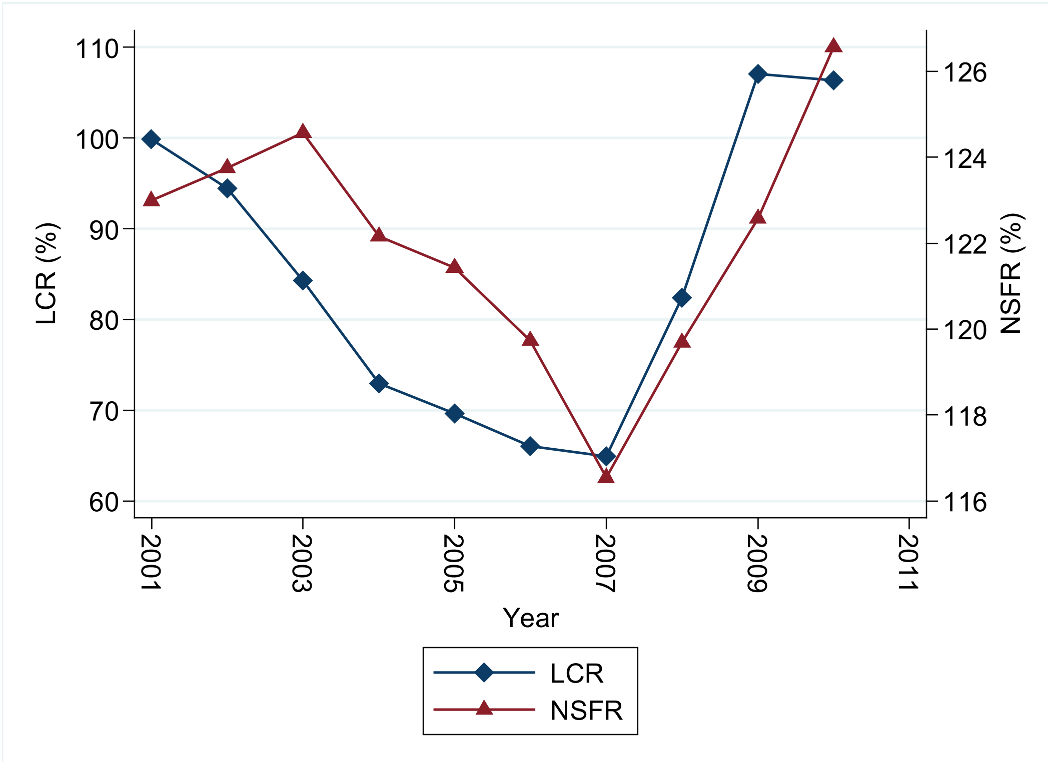

Fig. 1. The average LCR and NSFR of U.S. commercial banks over time: 2001–2010. This figure shows that both ratios were in downward trends from 2001 through 2007. The average LCR rose sharply from 2007 to 2009 and peaked in 2009, while the average NSFR sharply increased from 2007 to 2010 and peaked in 2010.

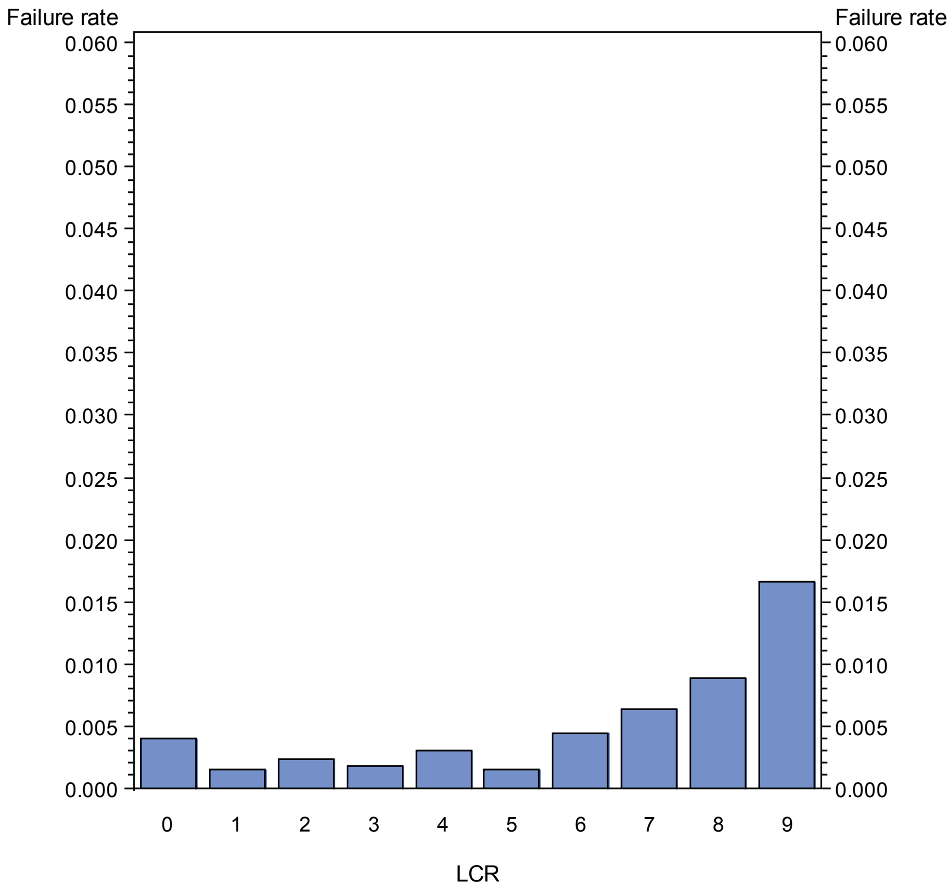

Fig. 2. Bank failure rate by decile of LCR (2002-2011). This figure plots the one-year conditional bank failure rate by the LCR deciles, which shows that a higher LCR is associated with a higher probability of failure.

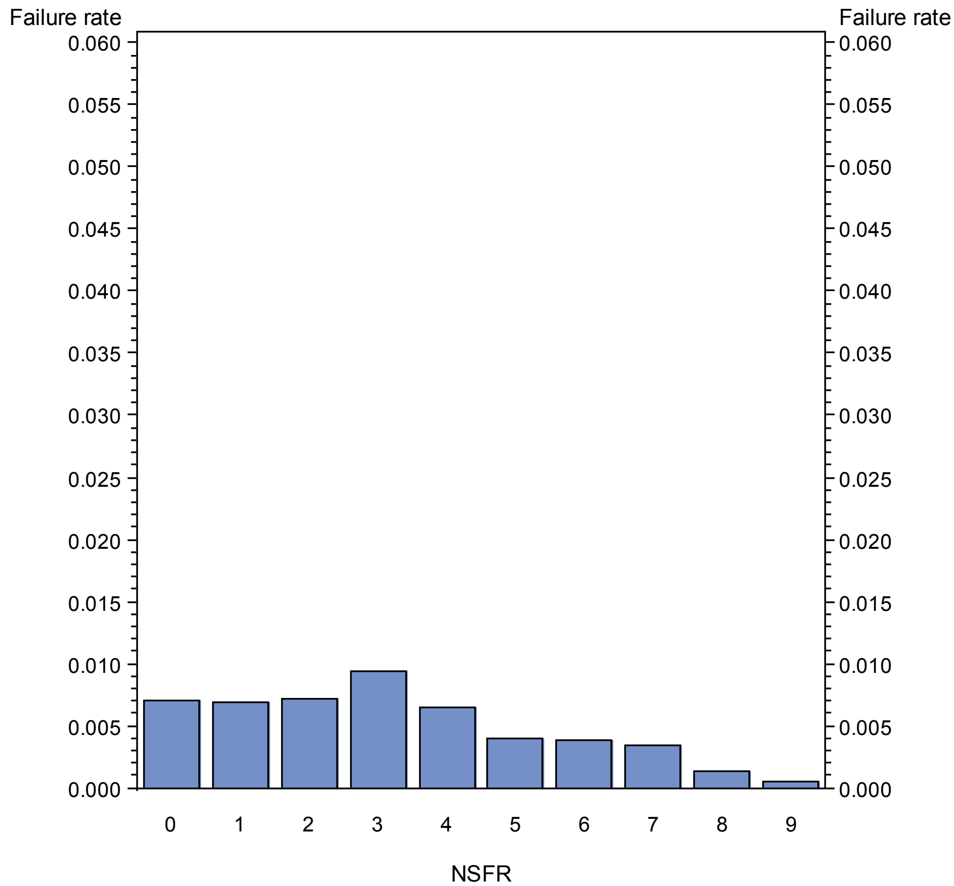

Fig. 3. Bank failure rate by decile of NSFR (2002–2011). The figure plots the one-year conditional bank failure rate by the NSFR deciles. It shows that a higher NSFR is associated with a low probability of failure for the third to the ninth deciles of the NSFR. This relationship does not hold for the lowest three deciles of the NSFR.

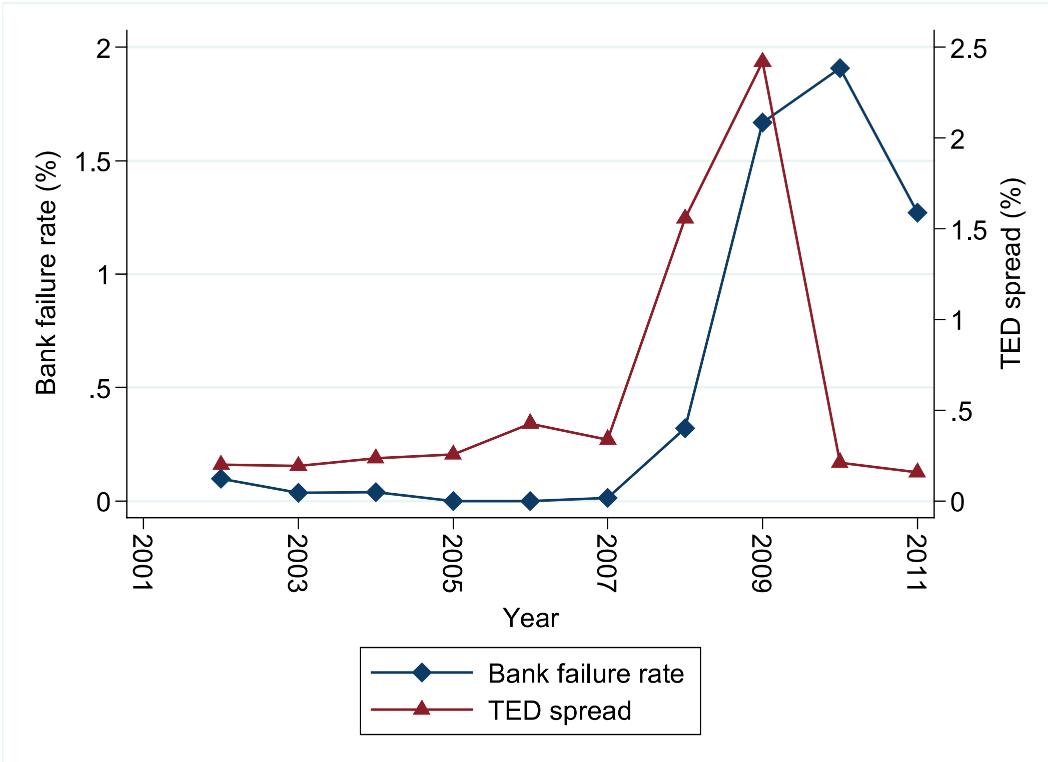

Fig. 4. Bank failure rate and the TED spread: 2002–2011. This figure plots the one-year conditional bank failure rate with the TED spread of the preceding year, which shows that a rise in the TED spread is followed by a rise in the conditional bank failure rate.

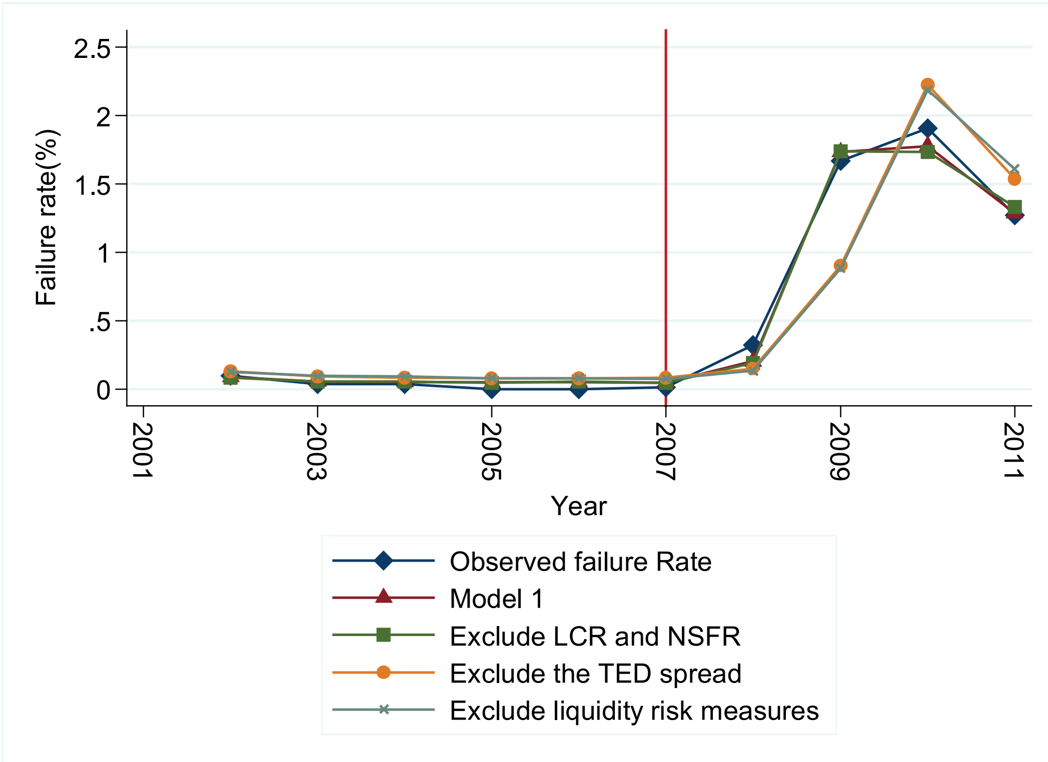

Fig. 5. Observed and predicted one-year conditional bank failure rates, 2002–2011. This figure plots the observed one-year conditional bank failure rates against the predicted values from models 1–4. The differences between the predictions of Model 1 and Model 2 are very small, which indicates that the marginal contribution of the LCR and the NSFR in predicting bank failure is minimal. On the other hand, there is substantial difference between the predicted values of Model 1 and Model 3.

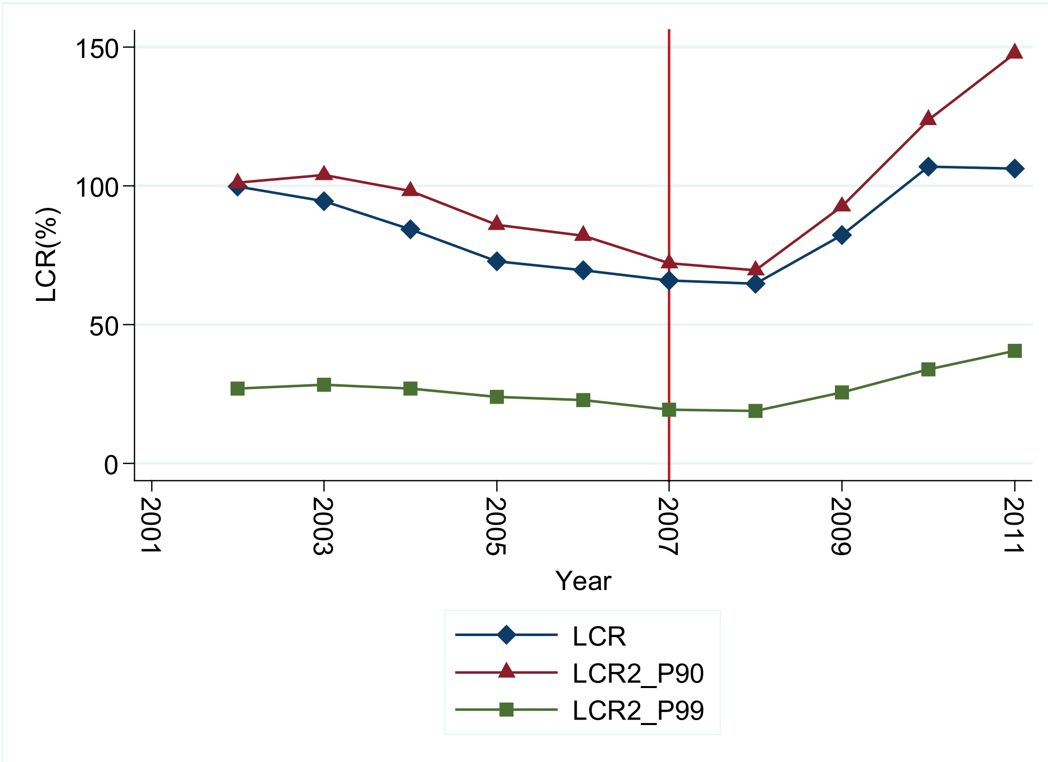

Fig. 6. The robustness test of the LCR, 2002–2011. This figure plots the average values by year of three measures of LCR. The first measure of LCR (LCR) is calculated using the net cash outflow rates specified in the Basel III LCR standard. The second measure of LCR (LCR2_P90) is calculated using the 90th percentile of the monthly net cash outflow rate of each funding category. The third measure of LCR (LCR2_P99) is calculated using the 99th percentile of the monthly net cash outflow rate of each funding category. The 90th and the 99th percentiles of net cash outflow rate of each funding category are calculated using call report data between 2001 and 2011. The 90th and the 99th percentiles of quarterly net cash outflow rates of different funding categories are reported in Tables B.1 and B.2 of Appendix B. The monthly net cash outflow rates are calculated using linear interpolation. This figure shows that LCR lies between LCR2_P90 and LCR2_P99, where it is closer to LCR2_P90 than to LCR2_P99. Therefore, this figure suggests that the net cash outflow rates in the Basel III LCR standard are close to the 90th percentiles of net cash outflow rates calculated using the call report data of U.S. banks.