“Basel III, liquidity and bank failure”

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Basel III, liquidity and bank failure

Abstract

Liquidity coverage and net stable funding ratios are liquidity risk measures highlighted by Basel III banking regulation. This paper estimates these measures by using 2002 to 2012 global liquidity data for LIBOR-based banks in 36 countries. Furthermore, the paper compares the aforementioned Basel III liquidity risk measures to the more traditional non-performing assets ratio, return-on-assets, LIBOR-OISS, Basel II Tier 1 capital ratio, government securities ratio and brokered deposits ratio. Moreover, we use a hazard model to show that Basel III liquidity risk measures have low predicting power in relation to bank failure. Also, their traditional counterparts are better in this respect. In fact, we prove that higher liquidity coverage and net stable funding ratios are associated with higher bank failure rates. We also find that LIBOR-OISS (proxy for market-wide liquidity risk) accurately predicted 2009 and 2010 bank failures while other liquidity risk measures (proxies for idiosyncratic liquidity risk) were not as reliable.

Keywords: Basel III, liquidity risk, liquidity coverage ratio, net stable funding ratio, bank failure, hazard model.
JEL Classification: G13, G32.

Introduction

Bank liquidity measures the ease with which banks' asset funding is able to be increased and financial obligations met. In transforming deposits into loans, banks become susceptible to idiosyncratic and market-wide liquidity risk (see, for instance, [14]). Incidences of such risks proliferated during the 2007-2009 financial crisis in both the financial markets and banking industry. The worsening of market conditions in this period caused a lack of liquidity in various financial sectors including the banking sector. In order to counteract this on September 12, 2010, the Basel Committee on Banking Supervision (BCBS) and its subgroup Working Group on Liquidity (WGL) (see, for instance, [3]) announced amendments to existing banking regulation with the introduction of Basel III (see, for instance, [4], [9] and [28]). This regulation involves liquidity, capital adequacy and stress testing (see, for instance, [33]) and is intended to improve banks' ability to absorb shocks arising from financial and economic stress in order to reduce the risk contagion in the financial sector. Other objectives of Basel III regulation is to increase the quality of capital and enhance risk management and disclosure, introduce a leverage ratio to supplement risk weighted measures as well as address counter-party risk (see, for instance, [16], [18] and [26]).

In Basel III, the risk measures, the liquidity coverage ratio (LCR) and net stable funding ratio (NSFR), underly liquidity management. The LCR requires that banks maintain an adequate level of "unencumbered, high-quality liquid assets that can be converted to cash to meet its liquidity needs for a 30 calendar day time horizon under severe liquidity stress conditions specified by supervisors." On the other hand, the NSFR is designed to "promote longer-term funding of the assets and activities of banking organizations by establishing a minimum acceptable amount of stable funding based on the liquidity of an institution's assets and activities over a one-year horizon". These standards should facilitate liquid asset diversification, thus discouraging their accumulation and susceptibility to risky exposures. It will however be clear that the LCR and NSFR, will probably not achieve their aims without considering other factors (see, for instance, [9] and [13]). To the best of our knowledge, no prior studies have attempted to estimate the LCR and NSFR using global public banking data.

This contribution also considers traditional liquidity risk measures such as the non-performing assets ratio (NPAR), return-on-assets (ROA), London Interbank Offered Rate-Overnight Indexed Swap Spread (LIBOR-OISS), Basel II Tier 1 capital ratio (BIIT1KR), government securities ratio (GSR) and brokered deposits ratio (BDR). Furthermore, we note that risk measures for asset liquidity include the GSR and LCR while funding stability is measured by the BDR and NSFR. NPAR (known as the Texas ratio under certain circumstances) exhibits robust bank failure predictive power (see, [19] and [27]). ROA refers to banks' ability to generate positive net income from asset investment with a positive correlation existing between ROA and bank liquidity. LIBOR is the rate at which banks indicate they are willing to lend to other banks for a specified term of the loan. The Overnight Indexed Swap (OIS) rate is the rate on a derivative contract on the overnight rate. In the US, the overnight rate is the effective federal funds rate. In such a contract, two parties agree that one will pay the other a rate of interest that is the difference be-

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tween the term OIS rate and the geometric average the overnight federal funds rate over the term of the contract. The OIS rate is a measure of the market's expectation of the overnight funds rate over the term of the contract. There is very little default risk in the OIS market because there is no exchange of principal; funds are exchanged only at the maturity of the contract, when one party pays the net interest obligation to the other. The LIBOR-OISS is assumed to be a measure of bank health because it reflects what banks believe is the risk of default associated with lending to other banks. It is a measure of market-wide liquidity risk. The capital adequacy ratio BIIT1KR is described in [8] (see, also, [9]) while GSR (proxy for asset liquidity) and BDR (proxy for fund stability) are discussed in [19].

Main questions and outline. The main questions addressed in this chapter about liquidity and bank failure are listed below.

Question 1: Approximate values for Basel III liquidity risk measures. How do estimates for the Basel III liquidity risk measures compare with values for traditional risk measures? (see section 3).

Question 2: Information values for liquidity risk measures. Are Basel III liquidity risk measures more sensitive than traditional ones? (see section 4).

Question 3: Liquidity and bank failure. How can the link between bank failures and liquidity risk be quantified? (see section 4).

Question 4: Contribution of liquidity to bank failure. To what extent did idiosyncratic or market-wide liquidity risk contribute to bank failures subsequent to the 2007 to 2009 financial crisis? (see section 4).

This paper is organized as follows. Section 1 provides a literature review while section 2 provides data and methodology. Also, section 3 describes the dynamics of liquidity risk measures from Basel III (viz., LCR and NSFR) and traditional risk measures (for instance, NPAR, ROA, LIBOR-OISS, BIIT1KR, GSR and BDR) while section 4 examines the sensitivity of these risk measures. Also, section 4 presents the results and discussion of liquidity risk measures and its connection with Class I and II bank failure. The final section provides some concluding remarks, considers policy implications and possible topics for future research.

1. Literature review

In this section, we review literature about traditional liquidity risk measures, Basel III liquidity standards as well as liquidity and bank failure.

1.1. Literature review of traditional liquidity risk measures. As we have seen before, NPAR, ROA, LIBOR–OISS, BIIT1KR, GSR and BDR are measures of an individual bank's liquidity risk. It was shown in [19] that the NPAR exhibits robust bank failure predictive power. The idea is that when a bank's ratio goes above 100 %, it is at risk of failure. In fact, [19] proves that once a bank breaches the 100 % mark, the chances of rehabilitation are a mere 5.06 % (see, also, [27]). The connection between profitability in the form of ROA and liquidity is discussed in [24]. In particular, ROA as a liquidity measure is explained.

1.2. Literature review of Basel III liquidity risk measures. Although the "Sound Principles" in [14] focuses on liquidity risk management at medium and large complex banks, it has broad applicability to all types of banks. The implementation of these principles by both banks and supervisors was tailored to the size, nature of business and complexity of banking activities. Since the "Sound Principles", guidance for supervisors has been augmented substantially. In particular, proposed Basel III liquidity regulation explained in [10] and [12] has added a great deal. These prescripts emphasize the importance of supervisors assessing the adequacy of a bank's liquidity and the associated risk management framework. Also, it suggests steps that supervisors should take if these are deemed inadequate. The BCBS expects banks and supervisors to implement the revised principles promptly and thoroughly and that the BCBS will actively review progress in implementation (see, for instance, [10] and [12]).

Our contribution has connections with [29], [31] and [32]. In the former, we use actuarial methods to discuss liquidity risk management focussing on cash inflows and securities allocation. The main objective in [29] is to minimize liquidity risk in the form of funding and credit crunch risk in an incomplete market (see, also, [31] and [32]). In order to accomplish this, we construct a stochastic model that incorporates reference processes. However, the current article is an improvement on [29] in that it complies with Basel III liquidity regulation related to NSFRs (see section 2).

Some of the first results involving Basel III liquidity standards is to be found in [6], [7], [11], [21] and [22]. A summary table of these contributions is presented below.

Table 1. Liquidity studies [6], [7], [11], [21] and [22] for Group 1 and 2 banks

Organization	BCBS			EBA	
Contribution	[6]	[7]	[11]	[21]	[22]
Report date	Sep-12	Apr-12	Dec-10	Sep-12	Apr-12
Bank data date	12/31/2011	06/30/2011	12/31/2009	12/31/2011	06/30/2011

Table 1 (cont.). Liquidity studies [6], [7], [11], [21] and [22] for Group 1 and 2 banks

Organization		BCBS			EBA
Bank count	(102,107)	(103,102)	(NA,NA)	(44,112)	(NA,NA)
Total assets (Euro trillions)	61.40	58.50	NA	31.00	31.00
Weighted Average LCR	(0.91, 0.98)	(0.90, 0.83)	(0.83, 0.98)	(0.72, 0.91)	(0.71, 0.70)
LCR Shortfall ($ Trillions)	2.33	2.28	2.24	1.52	1.55
Weighted average NSFR	(0.98, 0.95)	(0.94, 0.93)	(0.93, 1.03)	(0.93, 0.94)	(0.89, 0.90)
NSFR shortfall ($ Trillions)	3.24	3.60	3.74	1.81	2.46

We have that the BCBS's [6], [7] and [11] as well as [21] and [22] from the European Banking Authority (EBA) represent five quantitative impact studies or monitoring exercises using non-public bank data reported in December 2009, June 2011 and December 2011. Table 1 summarizes the results of these studies. The most recent BCBS monitoring exercise was based on bank data reported on December 31, 2011. This study covers a total of 209 banks across the world, including 102 Group 1 banks 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.

1.3. Literature review of liquidity and bank failure. While recent research studies show liquidity risk causes or exacerbates the financial crisis (see, for instance, [1], [17], [20] and [25]), few empirical investigations have probed the relationships between bank failures and liquidity risk. One obvious reason for this is that there had been few bank failures globally between 1995 and 2007. The massive number of bank failures subsequently provides us with a costly opportunity to improve our understanding of bank failures and liquidity risk (see, for instance, [1] and [25]).

While the new liquidity standards aim at strengthening individual banks liquidity risk management, it remains to be seen whether idiosyncratic liquidity risk was the major contributor to bank failures during the 2007-2009 financial crisis. Furthermore, [22] show that tight risk management of individual financial firms could lead to market illiquidity at the aggregate level. While an individual firm appears to benefit from tightening its risk management, it becomes more reluctant to provide liquidity to other firms. As a consequence, the aggregate market liquidity declines. Therefore, further investigations are needed to assess the effectiveness of Basel III liquidity standards on reducing bank failures (see, for instance, [1], [17], [20] and [25]).

2. Liquidity risk data and methodology

In this section, we consider the public data and methodology used to probe the liquidity risk measures on asset liquidity (LCR and GSR) and capital stability (NSFR and BDR) in both the traditional and proposed Basel III paradigm. Also, we consider 4 other liquidity risk measures, viz., NPAR, LIBOR-OISS, BIT1KR and ROA.

2.1. Data for liquidity risk measures. We use EMERG global liquidity data that consist of observations for LIBOR-based banks for the period 2002 to 2012 (see [30]). In particular, we use databases consisting of individual banks' income statements as well as on- and off-balance sheet items. We study liquidity for Class I banks that have Tier 1 capital (T1K) in excess of US$4 billion and are internationally active and Class II banks that do not satisfy these conditions. Of course, there are Class II banks that could have been classified as Class I if they were internationally active. These banks contributed greatly to the total assets of the Class II banks.

A total of 391 LIBOR-based banks from 36 countries were included in the study, including 157 Class I and 234 Class II banks. These banks (with the number of Class I and Class II banks in parenthesis for each jurisdiction) are located in Australia (5,2), Austria (2,6), Belgium (1,2), Brazil (3,1), Canada (7,3), China (7,1), Czech Republic (4,3), Denmark (1,3), Finland (0,14), France (5,5), Germany (8,25), Hong Kong (1,8), Hungary (1,2), India (6,6), Indonesia (1,3), Ireland (3,1), Italy (2,11), Japan (14,5), Korea (6,4), Luxembourg (0,1), Malta (0,3), Mexico (1,8), the Netherlands (3,13), Norway (1,6), Poland (0,5), Portugal (3,3), Russia (0,3), Saudi Arabia (4,1), Singapore (5,0), South Africa (4,5), Spain (2,4), Sweden (4,0), Switzerland (3,5), Turkey (7,1), the United Kingdom (8,5) and the United States (35,66).

In particular, we did not consider subsidiaries, central banks, banks with incomplete records (e.g., with inconsistent, non-continuous information) nor bank-year observations with negative HQLA, NCO, ASF, RSF or other values. Furthermore, we mostly use non-permanent samples for regression analysis and investigation of cross-sectional patterns. By contrast to permanent samples, the non-permanent ones do not suffer from survivorship bias. Bank failure data for the period 2002 to 2012 were obtained from deposit insurance schemes in the aforementioned countries. For instance, for the US, bank failure data was obtained from the Federal Insurance Corporation (FDIC) and matched with call report data. We choose the period 2002-2012 because EMERG global liquidity data does not allow us to accurately calculate the LCR and NSFR prior to 2002 [30].

It must be emphasized that there are difficulties in calculating the LCR and NSFR using the available public data. Firstly, the prescripts related to Basel III liquidity risk standards are ambiguous and constantly changing. Therefore, we have to use our discretion in applying the aforementioned guidelines. Secondly, the data available is limited and incomplete in terms of format and granularity between EMERG global banking data and the information required for determining Basel III LCR and NSFR (see [30]). When data is unavailable, this necessitates a reliance on specific interpolation and extrapolation techniques.

2.2. Methodology for liquidity risk. In this subsection, we provide theoretical perspectives on Basel III liquidity risk measures and bank failure, a consideration of approximate methods to estimate liquidity risk measures as well as a methodology for finding information values for such measures.

2.2.1. Theoretical perspectives on Basel III liquidity risk measures. The difficulties experienced by some banks during the financial crisis despite adequate capital levels were due to lapses in basic principles of liquidity risk management. In response, as the foundation of its liquidity framework, the BCBS in 2008 published "Principles for Sound Liquidity Risk Management and Supervision" known as "Sound Principles" for short (see [14] for more details). These principles provide detailed guidance on the management and supervision of liquidity risk and is intended to promote improved liquidity risk management in the case of full implementation by banks and supervisors. As such, the BCBS coordinates follow-ups by supervisors to ensure that banks adhere to "Sound Principles" (see [14] for more details). To complement these principles, the BCBS has further strengthened its liquidity framework by developing two minimum standards for funding liquidity. They are described in the ensuing discussions.

The LCR aims at increasing the resilience of banks under severe stress over a 30-day period without special government or central bank support (see, for instance, [8] and [9]). The LCR is a minimum requirement and, as such, pertains to large internationally active banks on a consolidated basis. The severe stress scenario referred to earlier combines market-wide and idiosyncratic stress including a three notch rating downgrade, the run-off of retail and wholesale deposits, the stagnation of primary and secondary markets (repo, securitization) for many assets and large cash-outflows due to off-balance sheet items (OBS). The LCR embellishes traditional liquidity "coverage" methodologies used internally by banks to assess exposure to stress events. This liquidity standard requires that a bank's stock of unencumbered high quality liquid assets (HQLAs) be larger than the projected net cash outflow (NCOF) over a 30-day horizon under a stress scenario specified by supervisors such that:

$$LCR = \frac{Total\ Stock\ of\ High\ Quality\ Liquid\ Assets\ (HQLAs)}{Total\ Nett\ Cash\ Outflows\ (NCOF)\ Over\ the\ Next\ 30\ Calendar\ Days} \geq 1, \quad (1)$$

Cash, excess central bank reserves (to the extent that these deposits can be withdrawn in times of stress; i.e., reserves exceeding the minimum reserve requirements), and government bonds with 0% risk weight under Basel II (including government guaranteed bonds, debt of central banks and public sector entities etc.) are considered Level 1 assets (L1As). Level 2 assets (L2As) mainly consist of government bonds with a 20 % risk weight under Basel II, covered and non-financial corporate bonds (rating at least AA-). L2As are further classified into Level 2A assets (L2AAs) and Level 2B assets (L2BAs). The latter are subject to higher haircuts and a limit. These include corporate debt securities rated A+ to BBB with a 50% haircut, certain unencumbered equities subject to a 50% haircut and certain residential mortgage-backed securities rated AA or higher with a 25% haircut. However, additional conditions concerning the debt and breadth of the underlying markets, a haircut of at least 15%, and a maximum ratio of 40% of HQLAs (after haircuts) apply to L2As. Symbolically this means that:

$$Market\ value\ of\ L2As \leq 0.4 \times Market\ value\ of\ total\ stock\ of\ HQLA 0.15 \leq Haircut\ applied\ to\ L2A\ current\ market\ value. \quad (2)$$

inflow for the ensuing 30-calendar days. While calculating total net cash outflow, total expected cash inflow is considered up to an aggregate cap of 75 % of total expected cash outflow. Symbolically, we have

$$Total\ nett\ cash\ outflows\ over\ the\ next\ 30\ calendar\ days = Expected\ outflows - min[Expected\ inflows; 75\%\ of\ expected\ outflows]. \quad (3)$$

Total expected cash inflows are calculated by multiplying the outstanding balances of various categories of contractual receivables by the rates at which they are expected to flow in under the stress scenario. In order to prevent banks' from relying solely on these inflows for its liquidity an upper cap of 75% of total expected cash outflows is set. This ensures that banks hold a minimum stock of HQLAs equal to 25 % of cash outflows. Symbolically, we have that

$$\textit{Total expected cash inflows} \leq 0.75 \times \textit{Total expected cash outflows.} \quad (4)$$

NCOF is calculated by applying binding run-off parameters to the contractual outflows of liabilities as well as OBS items and roll-over assumptions to the contractual inflows from assets. Repos in L1As (0% run-off), stable retail (including SMEs) deposits (3% run-off) and less stable retail deposits (10 % run-off) are considered the most stable funding sources under severe stress. Repos with L2As and with central banks (also in non-LCR-eligible assets) are assigned run-off rates of 15% and 25%, respectively. The latter also applies to operational balances irrespective of the counterparty (but for the part of these balances covered by deposit insurance the CRD IV foresees a 5% run-off rate). Other unsecured wholesale funding from non-financial corporates, central banks and public sector entities (PSEs) receives a 75% run-off rate.

Contractual outflows from most other balance sheet positions are assumed to run-off completely as are all OBS items except credit lines granted to non-financial corporates, central banks, and public sector entities (10%) and credit and liquidity lines granted to retail clients (5%). For some derivatives outflows, national discretion apply. Contractual cash-inflows over the 30-day period are capped by 75% of total outflows. No inflows are recognized from operational balances at other banks, receivables from reverse repos in L1As, and undrawn liquidity lines and similar facilities. Reverse repos in L2As are treated symmetrically as well, so that 15% of the contractual inflows effectively count as inflows. Planned inflows from performing retail loans and loans to non-financial corporates are capped at 50%. Full recognition of contractual inflows is granted to reverse repos in non-eligible assets and performing wholesale loans to financial institutions.

An example of computing the LCR if given below. As we have seen in the above, two levels of assets can be applied towards the HQLA pool in the numerator of a bank's LCR. L1As include cash, central bank reserves and debt securities issued or guaranteed by public authorities with a 0% capital risk weight under Basel III. L2As include debt securities issued by public authorities with a 20% risk weight plus highly rated non-financial corporate bonds and covered bonds. Moreover, L2As may comprise no more than 40% of a bank's total HQLA stock. In other words, the quantity of L2As included in the HQLA calculation can be at most 2/3 of the quantity of L1As. In addition, L2As are subject to a 15% haircut when added to HQLA. All assets included in the calculation must be unencumbered (e.g., not pledged as collateral) and operational (e.g., not used as a hedge on trading positions). A bank's stock of HQLAs (compared with (2)) can then be written as:

$$HQLA = L1A + \min(0.85 \times L2A, 2/3 \times L1A). \quad (5)$$

The stress scenario used for computation of net cash outflows envisions a partial loss of retail deposits, significant loss of unsecured and secured wholesale funding, contractual outflows from derivative positions associated with a three-notch rating downgrade, and substantial calls on OBS exposures. The calibration of scenario run-off rates reflects a combination of the experience during the recent financial crisis, internal stress scenarios of banks, and existing regulatory and supervisory standards. From these outflows, banks are permitted to subtract projected inflows for 30 calendar days into the future. However, the fraction of outflows that can be offset this way is capped at 75%. The expected net cash outflows (compared with (3)) are, therefore, given by

$$NCOF = Outflows - \min[Inflows, 75\% \times Outflows]. \quad (6)$$

As a first example, it is helpful to compute the LCR for Bank A. Bank A holds six types of assets, viz., cash, reserves, Treasury securities, government and corporate bonds as well as retail loans. In particular, reserves and Treasuries are L1As and we suppose that corporate bonds are L2As. Bank A funds itself using a combination of stable and less stable deposits, unsecured wholesale funding (non-financial corporate with no operational relationship), overnight interbank borrowing, borrowings from the Central Bank and equity. Table 2 presents the balance sheet item values.

Table 2. Illustrative balance sheet for computing LCR

Assets		Liabilities	
Cash (C)	50	Stable retail deposits (D^S)	150
Reserves (R)	25	Less stable retail deposits (D^L)	150
Treasuries (T)	50	Unsecured wholesale funding (F^U)	210
Government bonds (B^G)	100	Interbank borrowings (B^I)	80
Corporate bonds (B^C)	50	Central bank borrowings (B^C)	50

Table 2 (cont.). Illustrative balance sheet for computing LCR

Assets		Liabilities	
Retail loans (Λ)	425	Equity (E)	60
Total	700	Total	700

The stock of HQLAs for LCR purposes is given by

$$AHOL = C + R + T + B^G + \min(0.85 \times B^C, 2/3 \times \times(C + R + T + B^G)) = 267.5. \quad (7)$$

The outflow of funds associated with the stress scenario depends on the run-off rates specified in the LCR rules for the different types of liabilities. Using Θ^j to denote the run-off rate for liabilities of type j and letting $O^c = 10$ denote contractual outflows, we have that

$$O = \Theta^D SD^S + \Theta^D LD^L + \Theta^F UF^U + \Theta^B IB^I + +\Theta^B CB^C + O^c = 0.075 \times 150 + 0.15 \times 150 + +0.75 \times 210 + 1 \times 80 + 0.25 \times 50 + 10 = 306.25, \quad (8)$$

where the run-off rate for stable retail deposits, less stable retail deposits and unsecured whole sale funding are taken to be 7.5%, 15% and 75%, respectively. Also, the run-off rate on overnight interbank borrowing is 100 % and the run-off for secured transactions with the central bank against non-HQLA is 25 %. Assuming contractual inflows of 6, the expected nett cash outflow is given by

$$O^{NC} = 306.25 - \min(6, 0.75 \times 267.5) = = 306.25 - \min(6, 200.625) = 300.25. \quad (9)$$

Hence, the LCR, C^{Lr}, of the bank is given by

$$C^{Lr} = \frac{267.5}{300.25} = 0.89 < 1. \quad (10)$$

As the LCR is below 100 %, this bank would need to make changes to its balance sheet in order to comply with the new liquidity standards.

The NSFR is the quotient of the amount of available stable funding (ASF) and required stable funding (RSF) over a 1-year stress period. Clearly, the objective of the NSFR is to reduce the maturity mismatch between assets and liabilities with remaining contractual maturities of one year or more. Stable funding is defined as the type of equity and liability financing expected from reliable sources during a stress scenario. It is important to note that in order to avoid reliance on Central Banks, funding from such banks are not considered in the evaluation of the NSFR liquidity standard. The ratio is defined as the available stable funding (ASF) over required stable funding (RSF). This standard is required to be greater than 100 % by Basel III to ensure that the available funding meets the required funding over the evaluated period. Thus, we have that:

$$NSFR = \frac{Available\ Stable\ Funding\ (ASF)}{Required\ Stable\ Funding} = \geq 1. \quad (11)$$

ASF is defined as the total amount of bank capital, preferred stock with maturity ≥ 1 year, liabilities with effective maturities ≥ 1 year, demand deposits and/or term deposits with maturities < 1 year and wholesale funding with maturities < 1year. In order to determine the actual ASF, the aforementioned capital and liability types have to be multiplied by a specific ASF factor assigned to each type. In the ASF calculation, capital and hybrids, and liabilities with a residual maturity of more than 1 year have a 100% weight, stable deposits and less stable deposits are weighted by 90 and 80%, respectively. Wholesale funding from non-financials is weighted by 50%; the rest is not recognized as stable funding.

Required stable funding (RSF) is defined as the weighted sum of the value of assets held and funded by the bank multiplied by a specific RSF factor assigned to each particular asset type. The weights are loosely linked to the run-off rates in the LCR: Cash, Commercial Paper, bonds with a maturity of below 1 year and non renewable interbank loans receive a weight of 0; government bonds (incl. Public Sector Entities, multilateral development banks, European Commission (EC), Bank for International Settlements (BIS) and central banks as well as government guaranteed debt) with a0%riskweight under Base II are assigned a weight of 5%;corporate bond sand covered bonds with a rating of AA- or better with a residual maturity of one year or more have a 20% weight; corporate bonds and covered bonds with a rating of below AA- but at least A- and a residual maturity of at least 1 year as well as loans to non-financial corporates with a residual maturity less than one year get a 50% weight; unencumbered mortgages with a risk weight of up to 35% under Basel I receive a 65% RSF weight; retail loans with a residual maturity of less than 1 year get a 85% weight; the rest a 100% weight.

As a second example, we compute the NSFR for Bank B. This bank holds three types of assets, viz., cash, government bonds and retail loans. Bank B funds itself using a combination of stable and less stable deposits, unsecured wholesale funding (non-financial corporate with no operational relationship) and equity. Table 3 presents the balance sheet item values.

Table 3. Illustrative Balance Sheet for Computing NSFR

Assets		Liabilities	
Cash (C)	50	Stable retail deposits (D^S)	150
Government bonds (B^G)	100	Less stable retail deposits (D^L)	150
Retail loans (Λ)	425	Unsecured wholesale funding (F^U)	210
Assets		Liabilities	
		Equity (E)	65
Total	575	Total	575

The ASF, FAS, depends on the ASF factors specified in the NSFR rules for the different types of liabilities. Using Φ^j to denote the ASF factor for liabilities of type j, we have that

$$F^{AS} = \phi^{D^S} D^s + \phi^{D^L} D^l + \phi^{F^U} F^U + \phi^E E = 0.85 \times \times 150 + 0.70 \times 150 + 0.50 \times 210 + 1 \times 65 = 402.5, \quad (12)$$

where the ASF factors for stable retail deposits, less stable retail deposits, unsecured wholesale funding and equity are 85%, 70%, 50% and 100%, respectively.

The RSF, FRS, relies on the factors given in the NSFR specifications for the different asset types. Using Ψ_j to denote the RSF factor for liabilities of type j, we have that

$$F^{RS} = \psi^C C + \psi^{B^G} B^G + \psi^\Lambda \Lambda = 0.0 \times 50 + 0.05 \times 100 + + 0.85 \times 425 = 366.25, \quad (13)$$

where the RSF factors for cash, government bonds and retail loans are 0%, 5% and 85%, respectively. Hence, the NSFR, F^{NSr}, of the bank is given by

$$F^{NSr} = \frac{402{,}5}{366{,}25} = 1{,}1 > 1. \quad (14)$$

As the NSFR is above 100%, Bank B complies with the new liquidity standards.

2.2.2. Theoretical perspectives on bank failure. In these subsection the authors discuss issues related to the relationship between liquidity risk and bank failures. In this regard, we estimate a discrete-time hazard model, in which the conditional bank failure rate is linked to the insolvency and liquidity risks. In this model, the log – hazard h^i_{t+1}, is specified as:

$$h^i_{t+1} = \alpha^0 + R^{Ii}_{t+1} + R^{Li}_{t+1}, \quad (15)$$

which consists of a constant α^0, a component associated with involvency risk R^{Ii}_{t+1}, and a part attributed to liquidity risk, R^{Li}_{t+1}.

It is well-known that variables affecting bank insolvency risk include capital adequacy, asset quality, profitability and local economic conditions. In this case, we specify the insolvency component as

$$\begin{aligned} R^{Ii}_{t+1} &= \alpha^1 \frac{A^{bi}_t}{E^{ci}_t + R^i_t} \frac{\Pi^i_t}{r^{di}_t} + \alpha^2 \frac{K^{bi}_t - E^{ci}_t}{E^i_t + R^i_t} + \alpha^3 \frac{\Lambda^i_t r^{\Lambda i}_t}{E^{ci}_t + R^i_t} + \\ &+ \alpha^4 \frac{S^i_t r^{Si}_t}{E^{ci}_t + R^i_t} + \alpha^5 \frac{X^{Ibi}_t}{E^{ci}_t + R^i_t} + \alpha^6 \frac{I^{nnbi}_t}{E^{ci}_t + R^i_t} + \\ &+ \alpha^7 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} + \alpha^8 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} \Delta H^i_t + \alpha^9 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} \Delta U^i_t. \end{aligned} \quad (16)$$

The first component in (16) is the market valuation component, $\frac{A^{bi}_t}{E^{ci}_t + R^i_t} \frac{\Pi^i_t}{r^{di}_t}$, where $\frac{A^{bi}_t}{E^{ci}_t + R^i_t}$ is the ratio of the book value of a banks total assets, A^{bi}_t, to the sum of its tangible common equality, E^{ci}_t, and loan and lease loss reserves, R^i_t. Since the aforementioned sum can be regarded as the affective capital of a bank, $\frac{A^{bi}_t}{E^{ci}_t + R^i_t}$, is a measure of a leverage. Also, $\frac{\Pi^i_t}{r^{di}_t}$, is the ratio of ROA, Π^i_t, to the market discount rate r^{di}_t. We expect the coefficient of the market valuation component α^1, to be negative, with increases in ROA reducing the hazard, while an increase in the market discount rate increases the hazard. The leverage term, $\frac{A^{bi}_t}{E^{ci}_t + R^i_t}$, serves as an implifier for the effects of changes in Π^i_t and r^{di}_t.

The second component, $\frac{K^{bi}_t - E^{ci}_t}{E^{ci}_t + R^i_t}$, is the ratio of intangible capital, $K^{bi}_t - E^{ci}_t$, to effective capital, $E^{ci}_t + R^i_t$, with the book value of capital, K^{bi}_t, and tangible common equality, E^{ci}_t. Beforehand, we have no *r*

We expect α^9 associated with $\frac{A^{ni}_t}{E^{ci}_t + R^i_t} \Delta U^i_t$, the interaction term between the NPAR ratio and the change in unemployment rates, ΔU^i_t, to be positive because a high unemployment rate would increase the loss severity.

The liquidity risk consists of two components. The first is the idiosyncratic component that differentiates between banks with strong and weak liquidity risk management practice. For example, a bank with more rigorous liquidity risk management is less exposed to idiosyncratic risk. The second component is the market-wide liquidity risk that affects every bank. For example, a severe liquidity disruption in the market could cause a shortage of funding for many banks. In this case, the component attributed to liquidity risk is specified as

$$R_{t+1}^{Li} = \alpha^{10} O_t^s + \alpha^{11} C_t^{Ri} + \alpha^{12} F_t^{Ri} \tag{17}$$

The LIBOR-OISS, O^t, measures the market-wide liquidity risk. We expect the coefficient on the LIBOR-OISS, α^{10}, to be positive, as a rise in the LIBOR-OISS would increase the market funding liquidity risk. The LCR and NSFR measure the idiosyncratic liquidity risk. We expect the coefficient of the LCR, α^{11}, to be negative, as banks with more liquid assets are less likely to encounter liquidity difficulties. Finally, the coefficient on the NSFR, α^{11}, is expected to be negative, as banks with more stable funding are less likely to run into funding problems. Substituting equations (16) and (17) into equation (15), we obtain the equation

$$h_{t+1}^{i} = \alpha^0 + \alpha^1 \frac{A_t^{bi}}{E_t^{ci}+R_t^i}\frac{\Pi_t^i}{r_t^{di}} + \alpha^2 \frac{K_t^{bi}-E_t^{ci}}{E_t^{ci}+R_t^i} + \alpha^3 \frac{\Lambda_t^i r_t^{\Lambda i}}{E_t^{ci}+R_t^i} + \alpha^4 \frac{S_t^i r_t^{Si}}{E_t^{ci}+R_t^i} + \alpha^5 \frac{X_t^{Ibi}}{E_t^{ci}+R_t^i} + \alpha^6 \frac{I_t^{nnbi}}{E_t^{ci}+R_t^i} +$$

$$+\alpha^7 \frac{A_t^{ni}}{E_t^{ci}+R_t^i} + \alpha^8 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta H_t^i + \alpha^9 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta U_t^i + \alpha^{10} O_t^s + \alpha^{11} C_t^{Ri} + \alpha^{12} F_t^{Ri}, \tag{18}$$

$$\alpha^1, \alpha^3, \alpha^4, \alpha^8, \alpha^{11}, \alpha^{12} < 0; \alpha^5, \alpha^7, \alpha^9, \alpha^{10} < 0.$$

2.2.3. Approximate value of liquidity risk measures. We use extrapolation (and interpolation) techniques to approximate LCR and NSFR with an acceptable degree of accuracy.

In the first instance, calculating the LCR requires information about liabilities with a remaining maturity of less than one month. However, the quarterly data we use only reports information about liabilities with a remaining maturity of less than three months. So we have to extrapolate the liabilities with a remaining maturity of one month. There are two approaches to doing this. Firstly, we can assume the maturity schedule is evenly distributed, such 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. This is the approach adopted in this paper. Second, as a robustness check, one can assume an extreme case such that all liabilities with a remaining maturity within three months mature within the first month. Secondly, the guidelines require dividing liabilities into subcategories of retail deposits, unsecured wholesale funding, and secured funding with different run-off rates. However, the information available from the call report data lacks 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 all OBS items, such as the increased liquidity needs related to downgrade triggers embedded in financing transactions, derivatives and other contracts, etc. Our calculations of the LCR and NSFR are partial measures that capture a bank's liquidity risk as reflected by both its on- and off-balance sheet items.

2.2.4. Information value of liquidity risk measures. Each of the aforementioned liquidity risk measures (NPAR, ROA, LIBOR-OISS, BIIT1KR, GSR, BDR, LCR and NSFR) contains information on bank liquidity. It is to be expected that some measures are

less informative than others for the purpose of assess ing such liquidity. In our case, we would like to know how we can assess the rationality and effectiveness of the measures' used in the process of determining liquidity. For that purpose, we use the information value (IV) criterion. We calculate the information value, V^I, of the aforementioned risk measures for predicting bank failures in one year via the formula

$$V^I = \sum_{k=1}^{m} (p^k - q^k)\log\left(\frac{p^k}{q^k}\right), \tag{19}$$

where p^k and q^k are probability distributions associated with liquid and illiquid banks, respectively. In general, our investigations will show that the information value of the two approximate Basel III risk measures, LCR and NSFR, are very low.

3. Liquidity risk measure dynamics

In this section, we provide liquidity risk measure plots as well as LCR and NSFR shortfalls for Class I and II banks.

3.1. Liquidity risk measure plots. Figure 1 plots the LCR, NSFR, GSR and BDR for Class I and II banks.

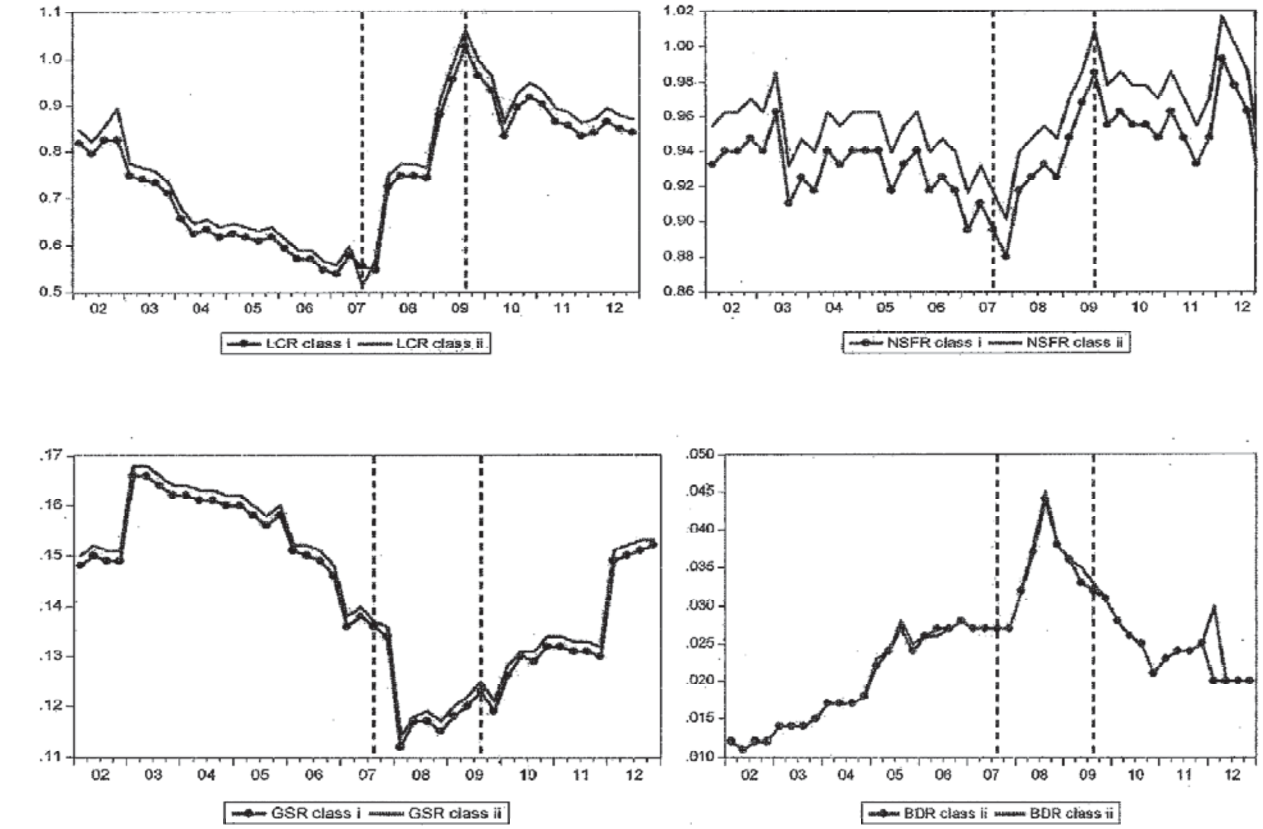

Fig. 1. LCR, NSFR, GSR and BDR for Class I and II banks

It shows that LCR and NSFR had been in downward trends from 2002 through 2007. The average LCR had risen sharply from 2007 to 2009 and peaked in 2009. On the other hand, the average NSFR had risen sharply from 2007 to 2010 and peaked in 2010. The same figure presents the average GSR and BDR. The GSR declined until 2008, when this trend reversed. On the other hand, the average BDR had been in an upward trend from 2001 through 2008, followed by a trend reversal. The general impression from Figure 1 is that the time series is non-stationary.

Analogous to Figure 1, we can represent NPAR, ROA, LIBOR-OISS and BIIT1KR for Class I and II banks as follows.

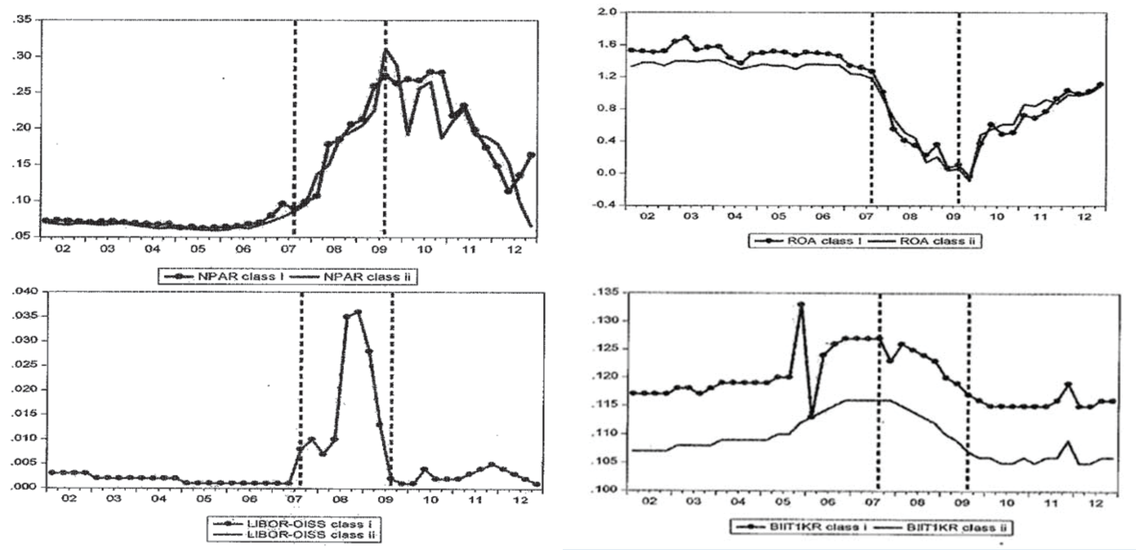

Fig. 2. NPAR, ROA, LIBOR-OISS and BIIT1KR for Class I and II banks

Figure 2 shows that the NPAR, ROA, LIBOR-OISS and BIIT1KR for Class I and II banks had exhibited varying behavior in the period from 2002 to 2007. The NPAR had risen sharply from 2007 to 2009 and peaked in 2009. On the other hand, the average NSFR had risen sharply from 2007 to 2010 and peaked in 2010. The same figure presents the average GSR and BDR. The GSR declined until 2008, when this trend reversed. On the other hand, the average BDR had been in an upward trend from 2001 through 2008, followed by a trend reversal.

3.2. LCR and NSFR shortfalls. In this subsection, we report the LCR and NSFR shortfalls for Class I and II banks.

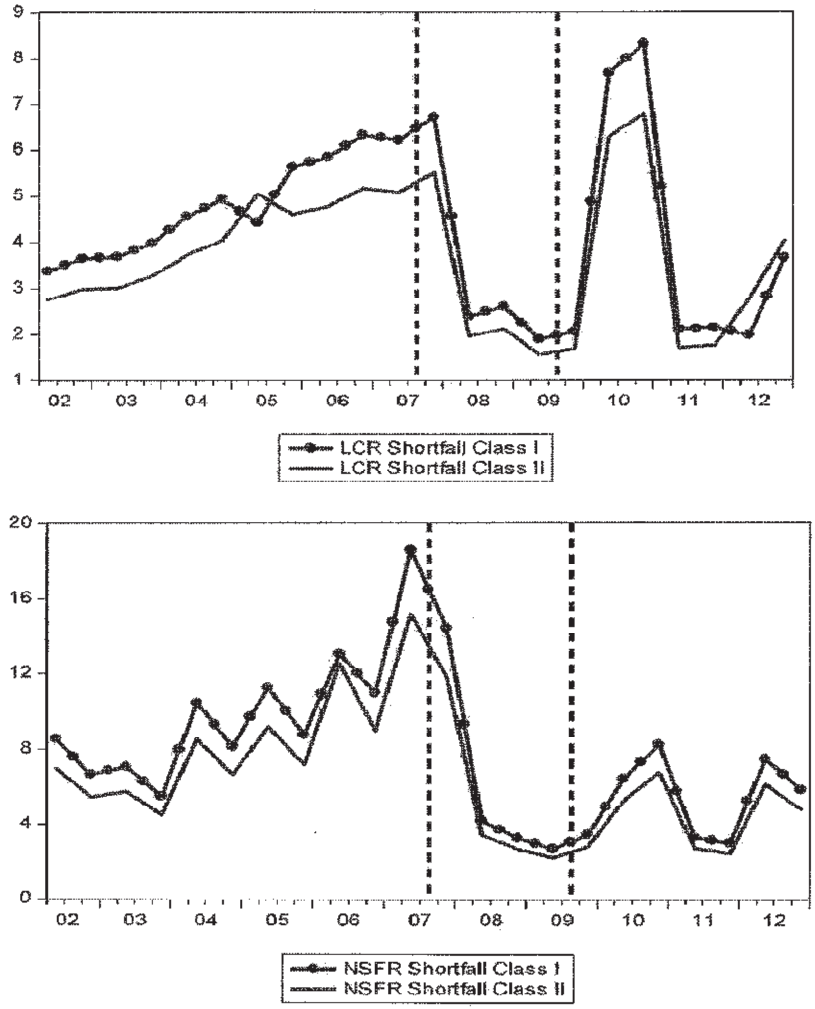

Fig. 3. LCR and NSFR shortfalls for Class I and II banks

The BCBS issued the full text of the revised LCR in [5] following endorsement by its governing 16 body, the Group of Central Bank Governors and Heads of Supervision (GHOS). Specifically, the LCR will be introduced as planned on January 1, 2015, but the minimum requirement will begin at 60%, rising in equal annual steps of 10% to reach 100% on January1, 2019. This graduated approach is designed to ensure that the LCR can be introduced without disruption to the orderly strengthening of banking systems or the ongoing financing of economic activity.

Table 4. Minimum LCR Requirements (2015-2019)

Years	2015	2016	2017	2018	2019
Minimum LCR requirements	60%	70%	80%	90%	100%

To meet the standards, banks can scale back business activities which are most vulnerable to a significant short-term liquidity shock or by lengthening the term of their funding beyond 30 days. Banks may also increase their holdings of HQLAs. The GHOS agreed that, during periods of stress it would be entirely appropriate for banks to use their stock of HQLA, thereby falling below the minimum. Moreover, it is the responsibility of bank supervisors to give guidance on usability according to circumstances.

4. Liquidity risk measures and bank failure

In this section, we present the results and discussionof liquidity risk measures and bank failure forboth Class I and II banks.

4.1. Liquidity risk measure sensitivity for class I and II banks. In this subsection, we examine the sensitivity of the approximate liquidity risk measures from Basel III. A risk measure is more risk sensitive if it has higher predicting power of bank failures than other variables. Therefore, we compare the predictive power of different risk measures for predicting bank failures within one year. To do this, we divide each variable into 10 deciles and calculate its information value for predicting bank failures in one year. Table 5 reports the information value of 8 liquidity risk measures.

Table 5. Information values of liquidity risk measures for Class I and II banks

Rank	Liquidity risk measure	V^1
1	NPAR	(6.40507, 6.15319)
2	ROA	(5.35271, 5.68749)
3	LIBOR-OISS	(5.03623, 4.76481)
4	BIIT1KR	(3.06038, 3.25412)
5	GSR	(1.66051, 1.49787)
6	BDR	(1.28143, 1.12909)
7	LCR	(0.83371, 0.69743)
8	NSFR	(0.38681, 0.49621)

As Table 5 has shown, the LCR and NSFR rank very low in terms of risk sensitivity. In this regard, their information values – (0.83371, 0.69743) and (0.38681, 0.49621), respectively – are much lower than those of the six traditional liquidity risk measures. The Class I bank liquidity risk measures, NPAR, LIBOR-OISS, GSR, BDR and LCR have information values that are greater than their Class II counterparts.

4.2. Class I and II bank failure. From subsection 1.2, we recall that the discrete-time hazard model – hereafter known as Model A that we will use to investigate bank failure can be represented by:

$$h^{Ai}_{t+1} = \alpha^0 + \alpha^1 \frac{A_t^{bi}}{E_t^{ci}+R_t^i}\frac{\Pi_t^i}{r_t^{di}} + \alpha^2 \frac{K_t^{bi}-E_t^{ci}}{E_t^{ci}+R_t^i} + \alpha^3 \frac{\Lambda_t^i r_t^{\Lambda i}}{E_t^{ci}+R_t^i} + \alpha^4 \frac{S_t^i r_t^{Si}}{E_t^{ci}+R_t^i} + \alpha^5 \frac{X_t^{Ibi}}{E_t^{ci}+R_t^i} + \alpha^6 \frac{I_t^{nnbi}}{E_t^{ci}+R_t^i} +$$
$$+\alpha^7 \frac{A_t^{ni}}{E_t^{ci}+R_t^i} + \alpha^8 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta H_t^i + \alpha^9 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta U_t^i + \alpha^{10} O_t^s + \alpha^{11} C_t^{Ri} + \alpha^{12} F_t^{Ri}, \tag{20}$$

$\alpha^1, \alpha^3, \alpha^4, \alpha^8, \alpha^{11}, \alpha^{12} < 0;\ \alpha^5, \alpha^7, \alpha^9, \alpha^{10} > 0.$

From this model we can derive Model B, Model C and Model D where LCR and NSFR are excluded, the LIBOR-OISS and liquidity risk is excluded, respectively. In essence, this means that Models B to D can be represented by the equations (21) and (22), respectively. he bank failure rates for the 391 banks from 36 countries for 2002 to 2012 included in our study are given in the table below.

$$h^{Bi}_{t+1} = \alpha^0 + \alpha^1 \frac{A_t^{bi}}{E_t^{ci}+R_t^i}\frac{\Pi_t^i}{r_t^{di}} + \alpha^2 \frac{K_t^{bi}-E_t^{ci}}{E_t^{ci}+R_t^i} + \alpha^3 \frac{\Lambda_t^i r_t^{\Lambda i}}{E_t^{ci}+R_t^i} + \alpha^4 \frac{S_t^i r_t^{Si}}{E_t^{ci}+R_t^i} + \alpha^5 \frac{X_t^{Ibi}}{E_t^{ci}+R_t^i} + \alpha^6 \frac{I_t^{nnbi}}{E_t^{ci}+R_t^i} +$$
$$+\alpha^7 \frac{A_i^{ni}}{E_t^{ci}+R_t^i} + \alpha^8 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta H_t^i + \alpha^9 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta U_t^i + \alpha^{10} O_t^s + \alpha^{11} C_t^{Ri} + \alpha^{12} F_t^{Ri}, \tag{21}$$

$\alpha^1, \alpha^3, \alpha^4, \alpha^8, \alpha^{11}, \alpha^{12} < 0;\ \alpha^5, \alpha^7, \alpha^9, \alpha^{10} > 0.$

$$h^{Ci}_{t+1} = \alpha^0 + \alpha^1 \frac{A_t^{bi}}{E_t^{ci}+R_t^i}\frac{\Pi_t^i}{r_t^{di}} + \alpha^2 \frac{K_t^{bi}-E_t^{ci}}{E_t^{ci}+R_t^i} + \alpha^3 \frac{\Lambda_t^i r_t^{\Lambda i}}{E_t^{ci}+R_t^i} + \alpha^4 \frac{S_t^i r_t^{Si}}{E_t^{ci}+R_t^i} + \alpha^5 \frac{X_t^{Ibi}}{E_t^{ci}+R_t^i} + \alpha^6 \frac{I_t^{nnbi}}{E_t^{ci}+R_t^i} +$$
$$+\alpha^7 \frac{A_i^{ni}}{E_t^{ci}+R_t^i} + \alpha^8 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta H_t^i + \alpha^9 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta U_t^i + \alpha^{11} C_t^{Ri} + \alpha^{12} F_t^{Ri}. \tag{22}$$

$$h^{Di}_{t+1} = \alpha^0 + \alpha^1 \frac{A_t^{bi}}{E_t^{ci}+R_t^i}\frac{\Pi_t^i}{r_t^{di}} + \alpha^2 \frac{K_t^{bi}-E_t^{ci}}{E_t^{ci}+R_t^i} + \alpha^3 \frac{\Lambda_t^i r_t^{\Lambda i}}{E_t^{ci}+R_t^i} + \alpha^4 \frac{S_t^i r_t^{Si}}{E_t^{ci}+R_t^i} + \alpha^5 \frac{X_t^{Ibi}}{E_t^{ci}+R_t^i} + \alpha^6 \frac{I_t^{nnbi}}{E_t^{ci}+R_t^i} + \alpha^7 \frac{A_t^{ni}}{E_t^{ci}+R_t^i} +$$
$$+\alpha^8 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta H_t^i + \alpha^9 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta U_t^i. \tag{23}$$

Table 6. Class I and Class II bank failures (2002-2012)

Quarter	Total bank count	Total bank failures	Bank failure rate	Class I & II bank count	Class I & II failures	Class I & II bank failure rate
02Q1	391	0	0.000	(157, 234)	(0, 0)	(0.000, 0.000)
02Q2	391	1	0.003	(157, 234)	(0, 1)	(0.000, 0.004)
02Q3	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
02Q4	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
03Q1	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
03Q2	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
03Q3	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
03Q4	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)

Table 6 (cont.). Class I and Class II bank failures (2002-2012)

Quarter	Total bank count	Total bank failures	Bank failure rate	Class I & II bank count	Class I & II failures	Class I & II bank failure rate
04Q1	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
04Q2	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
04Q3	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
04Q4	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
05Q1	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
05Q2	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
05Q3	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
05Q4	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
06Q1	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
06Q2	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
06Q3	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
06Q4	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
07Q1	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
07Q2	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
07Q3	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
07Q4	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
08Q1	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
08Q2	390	0	0.000	(157, 233)	(0, 0)	(0.000, 0.000)
08Q3	390	1	0.003	(157, 233)	(0, 1)	(0.000, 0.004)
08Q4	389	2	0.005	(157, 232)	(1, 1)	(0.006, 0.004)
09Q1	387	1	0.003	(156, 231)	(0, 1)	(0.000, 0.004)
09Q2	386	2	0.005	(156, 230)	(1, 1)	(0.006, 0.004)
09Q3	384	4	0.010	(155, 229)	(1, 3)	(0.006, 0.013)
09Q4	380	4	0.010	(154, 226)	(2, 2)	(0.013, 0.009)
10Q1	376	3	0.008	(152, 224)	(1, 2)	(0.007, 0.009)
10Q2	373	2	0.005	(151, 222)	(0, 2)	(0.000, 0.009)
10Q3	371	0	0.000	(151, 220)	(0, 0)	(0.000, 0.000)
10Q4	371	0	0.000	(151, 220)	(0, 0)	(0.000, 0.000)
11Q1	371	0	0.000	(151, 220)	(0, 0)	(0.000, 0.000)
11Q2	371	1	0.003	(151, 220)	(0, 1)	(0.000, 0.005)
11Q3	370	0	0.000	(151, 219)	(0, 0)	(0.000, 0.000)
11Q4	370	0	0.000	(151, 219)	(0, 0)	(0.000, 0.000)
12Q1	370	0	0.000	(151, 219)	(0, 0)	(0.000, 0.000)
12Q2	370	1	0.003	(151, 219)	(0, 1)	(0.000, 0.005)
12Q3	369	1	0.003	(151, 218)	(0, 1)	(0.000, 0.005)
12Q4	368	0	0.000	(151, 217)	(0, 0)	(0.000, 0.000)

From Table 6, we note that 6 Class I and 17 Class II banks failed in the period 2002 to 2012.

Table 7. Bank failure rate by decile for Class I and II banks

Decile	LSR	NSFR	GSR	BDR	BIIT1KR	NPAR	ROA
0	(0.0030, 0.0030)	(0.0070, 0.0070)	(0.0210, 0.0210)	(_ , _)	(0.0435, 0.0435)	(0.0000, 0.0000)	(0.0470, 0.0470)
1	(0.0020, 0.0020)	(0.0070, 0.0070)	(0.0120, 0.0120)	(_ , _)	(0.0025, 0.0025)	(0.0000, 0.0000)	(0.0015, 0.0015)
2	(0.0010, 0.0010)	(0.0070, 0.0070)	(0.0070, 0.0070)	(_ , _)	(0.0015, 0.0015)	(0.0007, 0.0007)	(0.0005, 0.0005)
3	(0.0030, 0.0030)	(0.0090, 0.0090)	(0.0050, 0.0050)	(0.0015, 0.0012)	(0.0015, 0.0015)	(0.0005, 0.0005)	(0.0000, (0.0000)
4	(0.0020, 0.0020)	(0.0060, 0.0060)	(0.0040, 0.0040)	(_ , _)	(0.0010, 0.0010)	(0.0000, 0.0000)	(0.0000, 0.0000)
5	(0.0030, 0.0030)	(0.0040, 0.0040)	(0.0030, 0.0030)	(_ , _)	(0.0005, 0.0005)	(0.0007, 0.0007)	(0.0003, 0.0003)
6	(0.0040, 0.0040)	(0.0040, 0.0040)	(0.0020, 0.0020)	(0.0040, 0.0040)	(0.0010, 0.0010)	(0.0015, 0.0015)	(0.0001, 0.0001)
7	(0.0060, 0.0060)	(0.0030, 0.0030)	(0.0010, 0.0010)	(0.0060, 0.0060)	(0.0000, 0.0000)	(0.0010, 0.0010)	(0.0005, 0.0005)
8	(0.0080, 0.0080)	(0.0020, 0.0020)	(0.0010, 0.0010)	(0.0115, 0.0115)	(0.0000, 0.0000)	(0.0015, 0.0015)	(0.0003, 0.0003)
9	(0.0200, 0.0200)	(0.0010, 0.0010)	(0.0000, 0.0000)	(0.0240, 0.0240)	(0.0000, 0.0000)	(0.0465, 0.0465)	(0.0010, 0.0010)

Table 7 provides the bank failure rate by decile for Class I and II banks in the case of the LCR, NSFR and 6 other liquidity risk measures. Both the LCR and NSFR have very low discriminatory power. It is interesting to note that, contrary to popular belief, the higher LCR is associated with the higher bank failure rate. This result is not surprising because of the following facts. Firstly, as we have seen in Figures 1 and 2, the average LCR has risen sharply since 2007. Secondly, Table 8 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.

4.3. Estimating discrete-time hazard models for Class I and II banks. In this subsection, we estimate four discrete-time hazard models. The first model is based on equation (18), which is the benchmark model. We call it Model A. In Model B, we exclude the LCR and NSFR from Model A but keep the LIBOR-OISS. Therefore, we can estimate the contribution of the LCR and NSFR for predicting bank failures by comparing Models B and A. For Model C, we exclude the LIBOR-OISS from Model A but keep the LCR and NSFR. Comparison of Models A and C allows us to measure the contribution of market-wide liquidity risk. Finally, Model D excludes idiosyncratic and market-wide liquidity risk measures (i.e., the LCR, NSFR and LIBOR-OISS). The model statistics include the number of observations, *N*, Pseudo *R*2, AIC, BIC, Log Likelihood, AUC Statistic, HL Statistic and HL p-value. The estimation results are reported in the following table.

Table 8. Models A to D estimation results for Class I and II banks

	Model A	Model B LSR & NSFR excluded	Model C LIBOR-OISS excluded	Model D liquidity risk excluded
Panel A: Model statistics				
N	(2.978, 4.413)	(2.978, 4.413)	(2.978, 4.413)	(2.978, 4.413)
Psuedo R^2	(0.642, 0.645)	(0.639, 0.635)	(0.618, 0.620)	(0.610, 0.609)
AIC	(172.967, 173.5180)	(175.113, 176.073)	(183.980, 184.036)	(188.973, 189.256)
BIC	(184.877, 185.496)	(186.347, 186.096)	(197.678, 196.0993)	(198.086, 199.773)
Log likelihood	(-85.379, -85.557)	(-87.657, -86.956)	(-91.816, -91.433)	(-83.886, -94.004)
AUC Statistic	(0.9823, 0.9821)	(0.9832, 0.9829)	(0.9807, 0.9809)	(0.9842, 0.9839)
HL Statistic	(19.841, 19.983)	(6.464, 6.089)	(21.747, 20.947)	(24.963, 25.072)
HL p-value	(0.011, 0.011)	(0.063, 0.062)	(0.007, 0.007)	(0.002, 0.002)
Panel B: Parameter estimates				
α^0	(-0.0138 ***, -0.0242 ***) ([0.003] [0.003])	(0.0023 ***, 0.0019 ***) ([0.0011], [0.0013])	(-0.0230***, -0.0290***) ([0.0024], [0.0026])	(0.0002, 0.0010) ([0.0013], [0.0011])
α^1	(-0.0918 ***, -0.0369 ***) ([0.010], [0.011])	(-0.0888 ***, -0.0354 ***) ([0.009], [0.010])	(-0.0900 ***, -0.0356 ***) ([0.008], [0.009])	(-0.0834 ***, -0.0332 ***) ([0.0007], [0.0007])
α^2	(0.0140, 0.0157) ([0.0112], [0.111])	(0.0143 ***, 0.0165 ***) ([0.0087], [0.0086])	(0.0131, 0.0127) ([0.0117], [0.0116])	(0.0134***, 0.0144***) ([0.0013], [0.0011])
α^3	(-0.0173, -0.0055) ([0.0218], [0.0221])	(-0.0218 ***, 0.0109 ***) ([0.0203], [0.0205])	(-0.0121, -0.0026) ([0.0216], [0.0219])	(-0.0205***, -0.0116***) ([0.0197], [0.0200])
α^4	(-0.0067, -0.0073) ([0.0039], [0.0034])	(2.978, 4.413) (2.978, 4.413)	(0.0003, -0.0011) ([0.0053], [0.0056])	(0.0072, 0.0124) ([0.0055], [0.0066])
α^5	(0.0993 ***, 0.5733 ***) ([0.0297],[0.0297])	(-0.0043 ***,0.0029) ([0.0037], [0.0041])	(0.1199***, 0.6088***) ([0.0274], [0.0273])	(0.1069***, 0.9680***) ([0.0246], [0.0247])
α^6	(-0.1326 ***, -0.7184 ***) ([0.0490], [0.0490])	(-0.1095 ***, -0.9477 ***) ([0.0648], [0.0649])	(-0.1539 ***, -0.7255 ***) ([0.0250], [0.0251])	(-0.1054***, -1.0600***) ([0.0526], [0.0529])
α^7	(0.0116 ***, 0.0185 ***) ([0.0010], [0.0010])	(0.0139 ***, 0.0233 ***) ([0.0009], [0.0010])	(0.0113 ***, 0.0144***) ([0.0009], [0.0009]])	(0.0164***, 0.0210***) ([0.0008], [0.0009])
α^8	(0.0013 ***, 0.0006 ***) ([0.0362], [0.1698])	(0.0010 ***, 0.0002 ***) ([0.1354], [0.1688])	(0.0014, 0.000) ([0.1535], [0.1914]])	(0.0009, -0.0007) ([0.1566], [0.1952])
α^9	(0.0001, 0.0005) ([0.0006], [0.0004])	(0.0002, 0.0006) ([0.0008], [0.0008])	(- 0.0002, 0.0001) ([0.0005], [0.0007]])	(-0.0002, 0.0001) ([0.0007], [0.0006])
α^{10}	(0.0963 ***, 0.1036 ***) ([0.0091], [0.0092])	(0.1226 ***, 0.1243 ***) ([0.0095], [0.0094])		
α^{11}	(0.0024, 0.0015) ([0,0286], [0,0293])		(0.0062, 0.0046) ([0.0250], [0.0266]])	
α^{12}	(0.0155 *** 0.0260 ***) ([0.0007], [0.0007])		(0.0211***, 0.0282***) ([0.0008], [0.0008]])	

As can be seen from Table 8, there are small differences in model statistics between Models A and B. On the other hand, there are substantial differences between Model A and C that excludes the market-wide liquidity risk measures. Furthermore, the coefficient of LCR in Model A is positive and insignificant, suggesting that the LCR has little predictive power of bank failures. On the other hand, the coefficient of the LIBOR-OISS is statistically significant and positive, which implies that market-wide liquidity risk is a significant predictor of bank failures. Table 10 also provides information about ROC curves that measure rank-ordering power for Models A to D. These ROC curves are similar with Model D having the highest AUC statistic. This statistic is represented by the area under the ROC curves.

4.4. Observed and predicted bank failure rates for Class I and II banks. Table 9 in the Appendix provides information about the observed conditional failure rate and predicted values from Models A to D as well as the marginal contribution of the LCR and NSFR approximate measures for Class I and II banks. Also, Table 6 displays the observed one-year conditional bank failure rates against the predicted values from Models A to D. Columns 2, 3 and 4 display the observed one-year conditional bank failure rates against the predicted values from Model A and B, which excludes the LCR and NSFR. The differences between the predictions of Model A and B are negligible. Since Model B excludes the approximate measures of the LCR and NSFR, the differences between the predicted values of Model A and B measure the marginal contribution of these approximate measures. As can be seen, the predicted failure rates of Model A and B are very similar, and both closely match the observed failure rate. On the other hand, Table 9 also displays the marginal contribution of the LIBOR-OISS in predicting bank failures. Columns 2, 3 and 5 shows the observed one-year conditional bank failure rates against the predicted values from Model A and Model C, which excludes the LIBOR-OISS. The differences between the predictions of these two models are substantial for 2009 and 2010. As can be seen from the aforementioned columns, there are significant differences between the predicted failure rates of Models A and C in 2009 and 2010. The predicted failure rate of Model C is lower than that of Model A in 2009, while it is higher than that of Model A in 2010. We offer the following explanation. First, by looking at Table 9 again, we can see that the LIBOR-OISS was extremely high in 2008 and was extremely low in 2009. The former caused more banks to fail in 2009. On the other hand, the extremely low LIBOR-OISS (perhaps because of central banks interventions) in 2009 helped reduce the number of bank failures in 2010.

Columns 2, 3 and 6 in Table 9 display the observed one-year conditional bank failure rates against the predicted values from Model A and Model D that excludes liquidity risk. The differences between the predictions of these two models are substantial for 2009 and 2010. Because Model C excludes the LIBOR-OISS, the differences between the predicted values of Models A and C measure the marginal contribution of the LIBOR-OISS. Furthermore, as can be seen from Table 9, the predicted values of Models C and D are very close to each other, suggesting that the LIBOR-OISS accounts for a majority of the marginal contribution of liquidity risk. In summary, the results of Table 9 suggest the LIBOR-OISS was a major predictor of bank failures in 2009 and 2010. On the other hand, the approximate LCR and NSFR measures had very little information value in predicting bank failures.

Conclusions, policy implications and future directions

In this section, we draw the most important conclusions arrived at in our analysis, consider policy implications and suggest possible topics for future research.

Conclusions about Basel III, liquidity and bank failure. New Basel III banking regulation emphasizes the liquidity risk measures LCR and NSFR. In this paper, we approximated these measures by using global banking data for 391 LIBOR-based banks in 36 countries for the period 2002 to 2012 (see [30]). To the best of our knowledge, no prior studies have attempted to approximate the LCR and NSFR using global public data (see Question 1). In addition, we compare the information values of LCR and NSFR to traditional measures in terms of their power to predict bank failures. We find that the new liquidity measures have relatively low information values when compared with traditional liquidity risk measures, such as the NPAR, ROA, LIBOR-OISS, BIIT1KR, GSR and BDR (compare with Question 2).

An important result is that the higher LCR is associated with the higher bank failure rate. If this result is not caused by the inaccuracy of our approximate LCR measure, it would imply that the LCR is poor in predicting bank failures (see Question 3). Also, we estimate a bank failure model that differentiates between idiosyncratic and market-wide liquidity risks. We find that market-wide liquidity risk as encapsulated by LIBOR-OISS 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 individual and market-wide levels. This explanation provides an answer to Question 4.

Because our study is based on EMERG global liquidity data (see [30]), we cannot directly compare our results with those of the BCBS (see, in particular, [6], [7] and [11]) and EBA (see, more specifically, [21] and [22]). As was mentioned before, there are gaps between the call report data and the data required for calculating the new liquidity risk ratios. It is likely that our results are less accurate. Nevertheless, our study covers a relatively long period between 2002 and 2012, 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 300 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.

There, clearly highlight a need for a better understanding of the business models and their evolutions. For these reasons, more policy-oriented research and monitoring is necessary to better align the regulatory initiatives with the inherent risks of different models.

There appears to be consensus that no single tool or measure would have prevented the financial crisis and that an adequate policy response re-quires a mix of macro- and micro-prudential policy tools. The LCR and NSFR can be useful prudential tools, and can be relatively easy to implement, for jurisdictions that do not want to rely solely on risk-sensitive capital requirements. Combining the LCR and NSFR with Basel-type capital rules can reduce the risk of depleted liquidity in banks. As the findings in this paper showed, however, policy makers need to be cognizant of the inherent limitations and weaknesses of the LCR and NSFR.

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Appendix

Table 9. Observed and predicted bank failure rates for Class I and II banks (2002-2012)

Model A to D bank failures (2002-2012)					
		Observed bank		Predicted bank failure rates	
Parameter	Failure rates	Model A	Model B	Model C	Model D
02Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
02Q2	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)
02Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
02Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
03Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
03Q2	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
03Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
03Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
04Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
04Q2	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
04Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
04Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
05Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
05Q2	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
05Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
05Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
06Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
06Q2	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
06Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
06Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
07Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
07Q2	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
07Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
07Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
08Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
08Q2	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
08Q3	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)
08Q4	(0.006, 0.004)	(0.006, 0.004)	(0.006, 0.004)	(0.003, 0.002)	(0.003, 0.002)
09Q1	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.004)	(0.000, 0.003)	(0.000, 0.003)

Table 9 (cont.). Observed and predicted bank failure rates for Class I and II banks (2002-2012)

Model A to D bank failures (2002-2012)					
		Observed bank		Predicted bank failure rates	
09Q2	(0.006, 0.004)	(0.006, 0.004)	(0.006, 0.004)	(0.005, 0.003)	(0.004, 0.003)
09Q3	(0.006, 0.013)	(0.006, 0.013)	(0.006, 0.013)	(0.006, 0.013)	(0.006, 0.013)
09Q4	(0.013, 0.009)	(0.013, 0.009)	(0.013, 0.009)	(0.014, 0.010)	(0.014, 0.011)
10Q1	(0.007, 0.009)	(0.007, 0.009)	(0.007, 0.009)	(0.008, 0.011)	(0.006, 0.010)
10Q2	(0.000, 0.009)	(0.000, 0.009)	(0.000, 0.009)	(0.000, 0.010)	(0.000, 0.010)
10Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.003, 0.004)	(0.002, 0.003)
10Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.002, 0.003)	(0.003, 0.004)
11Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
11Q2	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.007)	(0.000, 0.006)
11Q3	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
11Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
12Q1	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)
12Q2	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.007)	(0.000, 0.006)
12Q3	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.005)	(0.000, 0.006)
12Q4	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)	(0.000, 0.000)