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Retraction

Retracted: Basel III Liquidity Risk Measures and Bank Failure

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This article has been retracted as it is found to contain a substantial amount of material from the published article titled "The Information Value of Basel III Liquidity Risk Measures," by Dr. Deming Wu and Dr. Han Hong, which is published at The Social Science Research Network on November 19, 2012 without proper citation [1].

References

[1] L. N. P. Hlatshwayo, M. A. Petersen, J. Mukuddem-Petersen, and C. Meniago, "Basel III liquidity risk measures and bank failure," *Discrete Dynamics in Nature and Society*, vol. 2013, Article ID 172648, 19 pages, 2013.

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Research Article

Basel III Liquidity Risk Measures and Bank Failure

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Basel III banking regulation emphasizes the use of liquidity coverage and nett stable funding ratios as measures of liquidity risk. In this paper, we approximate these measures by using global liquidity data for 391 hand-selected, LIBOR-based, Basel II compliant banks in 36 countries for the period 2002 to 2012. In particular, we compare the risk sensitivity of the aforementioned Basel III liquidity risk measures to those of traditional measures such as the nonperforming assets ratio, return-on-assets, LIBOR-OISS, Basel II Tier 1 capital ratio, government securities ratio, and brokered deposits ratio. Furthermore, we use a discrete-time hazard model to study bank failure. In this regard, we find that Basel III risk measures have limited ability to predict bank failure when compared with their traditional counterparts. An important result is that a higher liquidity coverage ratio is associated with a higher bank failure rate. We also find that market-wide liquidity risk (proxied by LIBOR-OISS) was the major predictor of bank failures in 2009 and 2010 while idiosyncratic liquidity risk (proxied by other liquidity risk measures) was less. In particular, our contribution is the first to achieve these results on a global scale over a relatively long period for a variety of banks.

1. Introduction

Liquidity describes a bank's ability to fund asset increases and meet financial obligations, without incurring damaging losses. The role of banks in the maturity transformation of short-term deposits into long-term loans makes them vulnerable to liquidity risk, both of an idiosyncratic and market-wide nature (see, for instance, [1, 2]). The financial crisis that began in mid-2007 re-emphasized the importance of liquidity to financial market and banking sector functioning. Prior to the turmoil, financial markets were buoyant and funding was readily available at low cost. The subsequent reversal in market conditions leads to the evaporation of liquidity with the accompanying illiquidity lasting for an extended period of time. The banking system came under severe stress, which necessitated central bank support for both the functioning of money markets and individual institutions (see [2] for more details).

In response to deficiencies in financial regulation exposed by the recent spate of crises such as the subprime mortgage, global financial and ongoing Eurozone sovereign debt crises, on Sunday, 12 September 2010, the Basel Committee on Banking Supervision (BCBS) announced a strengthening of existing banking rules (see, for instance, [3–5]). More specifically, Basel III was touted as a regulatory standard on bank capital adequacy, stress testing (see, for instance, [6]), and market liquidity risk devised by the BCBS and its subgroup Working Group on Liquidity (WGL) (see, for instance, [7]). In essence, Basel III builds on Basel I and Basel II and is intended to improve the banking sector's ability to absorb shocks arising from financial and economic stress. This is intended to reduce the risk of spill-over from the financial sector to the real economy (see, [2] for further discussion). Another objective of Basel III regulation is to increase the quantity as well as the quality of capital, with adequate capital charges needed in the trading book. Also, the regulation aims to enhance risk management and disclosure, introduce a leverage ratio to supplement risk weighted measures, and address counter-party risk posed by over-the-counter (OTC) derivatives (see, for instance, [8–11]).

In Basel III, as in this paper, the maintenance of the global liquidity as well as the standards, the liquidity coverage ratio (LCR) and nett stable funding ratio (NSFR), underlying liquidity management are important. The LCR imposes a requirement 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 standard 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 institution's assets and activities over a one-year horizon." This standard should facilitate a diversification of liquid assets—hence discouraging a situation where they could be accumulated and susceptible to exposures such as those relating to sovereign debts (see, for instance, [12]). It will, however, be highlighted in subsequent sections of the paper that the two new Basel liquidity standards will probably not achieve their desired objectives where such standards are not coupled with other risk measures and leverage ratios (see, for instance, [3, 13]). To the best of our knowledge, no prior studies have attempted to calculate the LCR and NSFR using global public banking data.

This contribution also considers traditional liquidity risk measures such as the nonperforming 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 the traditional liquidity 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 [14, 15]). ROA relates to a bank's ability to generate a positive nett income from its investment in its assets. A positive correlation exists between ROA and bank liquidity (see, for instance, [16]). LIBOR is the rate at which banks indicate that they are willing to lend to other banks for a specified term of the loan. The 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 between 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 nett 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 [17] (see, also, [3]) while GSR (proxy for asset liquidity) and BDR (proxy for fund stability) are discussed in [14].

1.1. 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 (see, for instance, [2]). 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 [1] 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 [1] 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 (see, also, [2]).

1.1.1. Liquidity Coverage Ratio (LCR). 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, [3, 17]). 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 nett cash outflow (NCOF) over a 30-day horizon under a stress scenario specified by supervisors such that

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

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 nonfinancial 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

$$\begin{aligned} &\text{Market Value of L2As} \\ &\quad \leq 0.4 \times \text{Market Value of Total Stock of HQLA} \\ &0.15 \leq \text{Haircut Applied to L2A Current Market Value.} \end{aligned} \tag{2}$$

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

$$\begin{aligned} &\text{Total Nett Cash Outflows Over the Next 30 Calendar Days} \\ &\quad = \text{Expected Outflows} \\ &\qquad - \min\left[\text{Expected Inflows; 75\% of Expected Outflows}\right]. \end{aligned} \tag{3}$$

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

$$\begin{aligned} &\text{Total Expected Cash Inflows} \\ &\quad \leq 0.75 \times \text{Total Expected Cash Outflows.} \end{aligned} \tag{4}$$

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 nonfinancial 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 nonfinancial corporates, central banks, and public sector entities (10%) and credit and liquidity lines granted to retail clients (5%). For some derivatives outflows, national discretion applies. 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 nonfinancial corporates are capped at 50%. Full recognition of contractual inflows is granted to reverse repos in noneligible assets and performing wholesale loans to financial institutions.

An example of computing the LCR is given below. As we have seen, 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 nonfinancial 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

$$\text{HQLA} = \text{L1A} + \min\left(0.85 \times \text{L2A}, \frac{2}{3} \times \text{L1A}\right). \tag{5}$$

The stress scenario used for computation of nett 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 nett cash outflows (compared with (3)) are, therefore, given by

$$\text{NCOF} = \text{Outflows} - \min\left[\text{Inflows}, 75\% \times \text{Outflows}\right]. \tag{6}$$

As a first example, it is helpful to compute the LCR for Bank A. Bank A holds six types of assets, namely, cash, reserves, treasury securities, government and corporate bonds, and 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 (nonfinancial corporate with no operational relationship), overnight interbank borrowing, borrowings from the central bank, and equity. Table 1 presents the balance sheet item values.

Table 1: 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 ($\mathtt{T}$)	50	Unsecured wholesale funding (F^U)	210
Government bonds ($\mathtt{B}^G$)	100	Interbank borrowings (B^I)	80
Corporate bonds ($\mathtt{B}^C$)	50	Central bank borrowings (B^C)	50
Retail loans (Λ)	425	Equity (E)	60
Total	700	Total	700

The stock of HQLAs for LCR purposes is given by

$$\begin{aligned} A^{\mathrm{HQL}} &= C + R + \mathtt{T} + \mathtt{B}^G \\ &\quad + \min\left(0.85 \times \mathtt{B}^C, \frac{2}{3} \times \left(C + R + \mathtt{T} + \mathtt{B}^G\right)\right) = 267.5. \end{aligned} \tag{7}$$

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

$$\begin{aligned} O &= \Theta^{D^S} D^S + \Theta^{D^L} D^L + \Theta^{F^U} F^U + \Theta^{B^I} B^I + \Theta^{B^C} B^C + O^c \\ &= 0.075 \times 150 + 0.15 \times 150 + 0.75 \times 210 \\ &\quad + 1 \times 80 + 0.25 \times 50 + 10 = 306.25, \end{aligned} \tag{8}$$

where the run-off rate for stable retail deposits, less stable retail deposits, and unsecured wholesale 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

$$\begin{aligned} O^{\mathrm{NC}} &= 306.25 - \min(6, 0.75 \times 267.5) \\ &= 306.25 - \min(6, 200.625) = 300.25. \end{aligned} \tag{9}$$

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

$$C^{\mathrm{Lr}} = \frac{267.5}{300.25} = 0.89 < 1. \tag{10}$$

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.

1.1.2. Nett Stable Funding Ratio (NSFR). 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 (see, for instance, [12]). 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 is 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

$$\mathrm{NSFR} = \frac{\text{Available Stable Funding (ASF)}}{\text{Required Stable Funding (RSF)}} \geq 1. \tag{11}$$

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 <1 year. 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 nonfinancials 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 nonrenewable interbank loans receive a weight of 0; government bonds (including public sector entities, multilateral development banks, European Commission (EC), Bank for International Settlements (BIS) and central banks, and government guaranteed debt) with a 0% risk weight under Basel II are assigned a weight of 5%; corporate bonds and 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 nonfinancial 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 are assigned a 100% weight (see, for instance, [12]).

Table 2: 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
		Equity (E)	65
Total	575	Total	575

As a second example, we compute the NSFR for Bank B. This bank holds three types of assets, namely, cash, government bonds, and retail loans. Bank B funds itself using a combination of stable and less stable deposits, unsecured wholesale funding (nonfinancial corporate with no operational relationship), and equity. Table 2 presents the balance sheet item values.

The ASF, F^{AS}, 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

$$\begin{aligned} F^{\mathrm{AS}} &= \Phi^{D^S} D^S + \Phi^{D^L} D^L + \Phi^{F^U} F^U + \Phi^E E \\ &= 0.85 \times 150 + 0.70 \times 150 + 0.50 \times 210 \\ &\quad + 1 \times 65 = 402.5, \end{aligned} \tag{12}$$

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, F^{RS}, 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

$$\begin{aligned} F^{\mathrm{RS}} &= \Psi^C C + \Psi^{B^G} B^G + \Psi^{\Lambda} \Lambda \\ &= 0.0 \times 50 + 0.05 \times 100 + 0.85 \times 425 = 366.25, \end{aligned} \tag{13}$$

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

$$F^{\mathrm{NSr}} = \frac{402.5}{366.25} = 1.1 > 1. \tag{14}$$

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

1.2. Theoretical Perspectives on Bank Failure. In this subsection, we 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 insolvency and liquidity risks. In this model, the log-hazard, h^i_{t+1}, is specified as

$$h^i_{t+1} = \alpha^0 + \mathscr{R}^{Ii}_{t+1} + \mathscr{R}^{Li}_{t+1}, \tag{15}$$

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

1.2.1. Insolvency Risk Component. 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

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

The first component in (16) is the market valuation component, $(A^{bi}_t/(E^{ci}_t + R^i_t))(\Pi^i_t/r^{di}_t)$, where $A^{bi}_t/(E^{ci}_t + R^i_t)$ is the ratio of the book value of a bank's total assets, A^{bi}_t, to the sum of its tangible common equity, E^{ci}_t, and loan and lease loss reserves, R^i_t. Since the aforementioned sum can be regarded as the effective capital of a bank, $A^{bi}_t/(E^{ci}_t + R^i_t)$ is a measure of leverage. Also, Π^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 on 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 (see, for instance, [16]). The leverage term, $A^{bi}_t/(E^{ci}_t + R^i_t)$, serves as an amplifier for the effects of changes in Π^i_t and r^{di}_t.

The second component, $(K^{bi}_t - E^{ci}_t)/(E^{ci}_t + R^i_t)$, 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 equity, E^{ci}_t. Beforehand, we have no expectation about the sign of the coefficient α^2. On the one hand, $K^{bi}_t - E^{ci}_t$ increases the capital buffer, so one would expect it to reduce the hazard. On the other hand, intangible capital could overinflate the reported capital, which could lead to a positive sign on this coefficient.

The third component, $r^{\Lambda i}_t \Lambda^i{}_t/(E^{ci}_t + R^i_t)$, is the ratio of the interest income from loans, $r^{\Lambda i}_t \Lambda^i{}_t$, to effective capital, $E^{ci}_t + R^i_t$, where loan yields and total loans are denoted by $r^{\Lambda i}_t$ and $\Lambda^i{}_t$, respectively. We expect the loan interest income coefficient, α^3, to have a negative sign.

Similarly, the fourth component, $S^i_t r^{Si}_t/(E^{ci}_t + R^i_t)$, is the ratio of interest income from securities, $r^{Si}_t S^i_t$, to effective capital, $E^{ci}_t + R^i_t$. We expect their coefficient, α^4, to have a negative sign.

The fifth component, $X^{Ibi}_t/(E^{ci}_t + R^i_t)$, is the ratio of interest expense, X^{Ibi}_t, to effective capital, $E^{ci}_t + R^i_t$. We expect its coefficient, α^5, to have a positive sign.

The sixth component, $I^{nnbi}_t/(E^{ci}_t + R^i_t)$, is the ratio of nett noninterest income, I^{nnbi}, to effective capital, $E^{ci}_t + R^i_t$. Beforehand, we do not have any expectation about the sign of α^6. On the one hand, an income would reduce the hazard. On the other, if this income is associated with taking additional risk, it would increase the hazard.

The seventh component is the NPAR, $A_t^{ni}/(E_t^{ci}+R_t^i)$, that is the ratio of nonperforming assets, A^{ni}, to effective capital, $E_t^{ci}+R_t^i$. We expect its coefficient, α^7, to be positive.

The eighth component, $(A_t^{ni}/(E_t^{ci}+R_t^i))\Delta H_t^i$, is the interaction term between the NPAR, $A_t^{ni}/(E_t^{ci}+R_t^i)$, and the change in housing price indices, ΔH_t^i. We expect its coefficient, α^8, to be negative, as rising housing prices would reduce the loss severity.

We expect α^9 associated with $(A_t^{ni}/(E_t^{ci}+R_t^i))\Delta U_t^i$, the interaction term between the NPAR ratio and the change in unemployment rates, ΔU_t^i, to be positive because a high unemployment rate would increase the loss severity.

1.2.2. Liquidity Risk Component. 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

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

The LIBOR-OISS, O_t^s, 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 (16) and (17) into (15), we obtain that

$$\begin{aligned} h_{t+1}^i &= \alpha^0 + \alpha^1 \frac{A_t^{bi}}{E_t^{ci}+R_t^i}\frac{\Pi_t^i}{r_t^{di}} + \alpha^2 \frac{K_t^{bi}-E_t^{ci}}{E_t^{ci}+R_t^i} + \alpha^3 \frac{\Lambda_t^i r_t^{\Lambda i}}{E_t^{ci}+R_t^i} \\ &\quad + \alpha^4 \frac{S_t^i r_t^{Si}}{E_t^{ci}+R_t^i} + \alpha^5 \frac{X_t^{Ibi}}{E_t^{ci}+R_t^i} + \alpha^6 \frac{I_t^{nnbi}}{E_t^{ci}+R_t^i} \\ &\quad + \alpha^7 \frac{A_t^{ni}}{E_t^{ci}+R_t^i} + \alpha^8 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta H_t^i + \alpha^9 \frac{A_t^{ni}}{E_t^{ci}+R_t^i}\Delta U_t^i \\ &\quad + \alpha^{10}O_t^s + \alpha^{11}C_t^{Ri} + \alpha^{12}F_t^{Ri}, \\ &\qquad \alpha^1, \alpha^3, \alpha^4, \alpha^8, \alpha^{11}, \alpha^{12} < 0; \quad \alpha^5, \alpha^7, \alpha^9, \alpha^{10} > 0. \end{aligned} \tag{18}$$

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

Question 1 (Basel III liquidity risk measure estimations). Can we calculate an approximate value for the Basel III liquidity risk measures (viz., LCR and NSFR)? How do their values compare with traditional risk measures (for instance, NPAR, ROA, LIBOR-OISS, BIIT1KR, GSR, and BDR)? (see Section 4).

Question 2 (liquidity risk measure information values). How sensitive are Basel III liquidity risk measures by comparison to traditional ones? (see Section 5).

Question 3 (bank failure and liquidity). Is there a link between bank failures and liquidity risk? If so, how can this link be quantified? (see Section 5).

Question 4 (liquidity contribution to bank failure). Was idiosyncratic or market-wide liquidity risk the major contributor to bank failures during the 2007 to 2009 financial crisis? (see Section 5).

This paper is arranged as follows. Section 2 provides a literature review while Section 3 provides data and methodology. Also, Section 4 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 5 examines the sensitivity of these risk measures. Also, Section 5 presents the results and discussion of liquidity risk measures and its connection with Class I and II bank failure. Finally, Section 6 provides some concluding remarks and possible topics for future research.

2. Literature Review

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

2.1. 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 [14] 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, [14] proves that once a bank breaches the 100% mark, the chances of rehabilitation are a mere 5.06% (see, also, [15]). The connection between profitability in the form of ROA and liquidity is discussed in [23]. In particular, ROA as a liquidity measure is explained (see [16] for more discussions). The LIBOR-OISS is a measure of market-wide liquidity risk. The capital adequacy ratio BIIT1KR is described in [17] (see, also, [3]) while GSR (proxy for asset liquidity) and BDR (proxy for fund stability) are discussed in [14].

2.2. Literature Review of Basel III Liquidity Risk Measures. Although the "sound principles" in [1] 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

Table 3: Liquidity studies [18–22] for Group 1 and 2 banks.

Organization	BCBS			EBA	
Contribution	[18]	[19]	[20]	[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
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

activities. Since the "sound principles," guidance for supervisors has been augmented substantially. In particular, proposed Basel III liquidity regulation explained in [24, 25] 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, [24, 25]).

Some of the first results involving Basel III liquidity standards is to be found in [18–22]. A summary table of these contributions is presented later.

We have that the BCBS's [18–20] as well as [21, 22] from the European Banking Authority (EBA) represent five quantitative impact studies or monitoring exercises using nonpublic bank data reported in December 2009, June 2011, and December 2011. Table 3 summarizes the results of these studies. The most recent BCBS monitoring exercise was based on bank data reported on Thursday, 31 December 2011. This study covers a total of 209 banks across the world, including 102 Group 1 banks 6 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.

The contents of this paper is strongly related to [12] where Basel III liquidity measures are discussed. In particular, this paper computes the NSFR in accordance with Basel III prescripts. The study [12] finds that the funding ratio appears to have satisfied Basel III minimum liquidity standards for certain developing countries during this period. Our contribution also has connections with [26–28]. In the former, we use actuarial methods to discuss liquidity risk management focusing on cash inflows and securities allocation. The main objective in [26] is to minimize liquidity risk in the form of funding and credit crunch risk in an incomplete market (see, also, [2, 27, 28]). In order to accomplish this, we construct a stochastic model that incorporates reference processes. However, the current paper is an improvement on [26] in that it complies with Basel III liquidity regulation related to NSFRs (see Section 3).

2.3. Literature Review of Liquidity and Bank Failure. While recent research studies how liquidity risk causes or exacerbates the financial crisis (see, for instance, [29–32]), 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, [29, 32]).

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, [33] shows 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, [29–32]).

3. 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, namely, NPAR, LIBOR-OISS, BIT1KR, and ROA.

3.1. 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 [34]). 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 (T1 K) 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 Basel II compliant 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), 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), United Kingdom (8,5), and United States (35,66).

In particular, we neither considered subsidiaries, central banks, banks with incomplete records (e.g., with inconsistent noncontinuous information) nor bank-year observations with negative HQLA, NCO, ASF, RSF, or other values. Furthermore, we mostly use nonpermanent samples for regression analysis and investigation of cross-sectional patterns. By contrast to permanent samples, the nonpermanent 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 (see [34]).

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 [34]). When data is unavailable, this necessitates a reliance on specific interpolation and extrapolation techniques.

3.2. Methodology for Liquidity Risk Measures. In this subsection, we describe the methodologies related to calculating the approximate and information values of liquidity risk measures.

3.2.1. 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 that 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 matur ity 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 nett 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. 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.

3.2.2. 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 assessing such liquidity. In our case, we would like to know how we can assess the rationality and effectiveness of the measures' use 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

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

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.

4. Liquidity Risk Measure Dynamics

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

4.1. Liquidity Risk Measure Plots. Figure 1 plots the 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

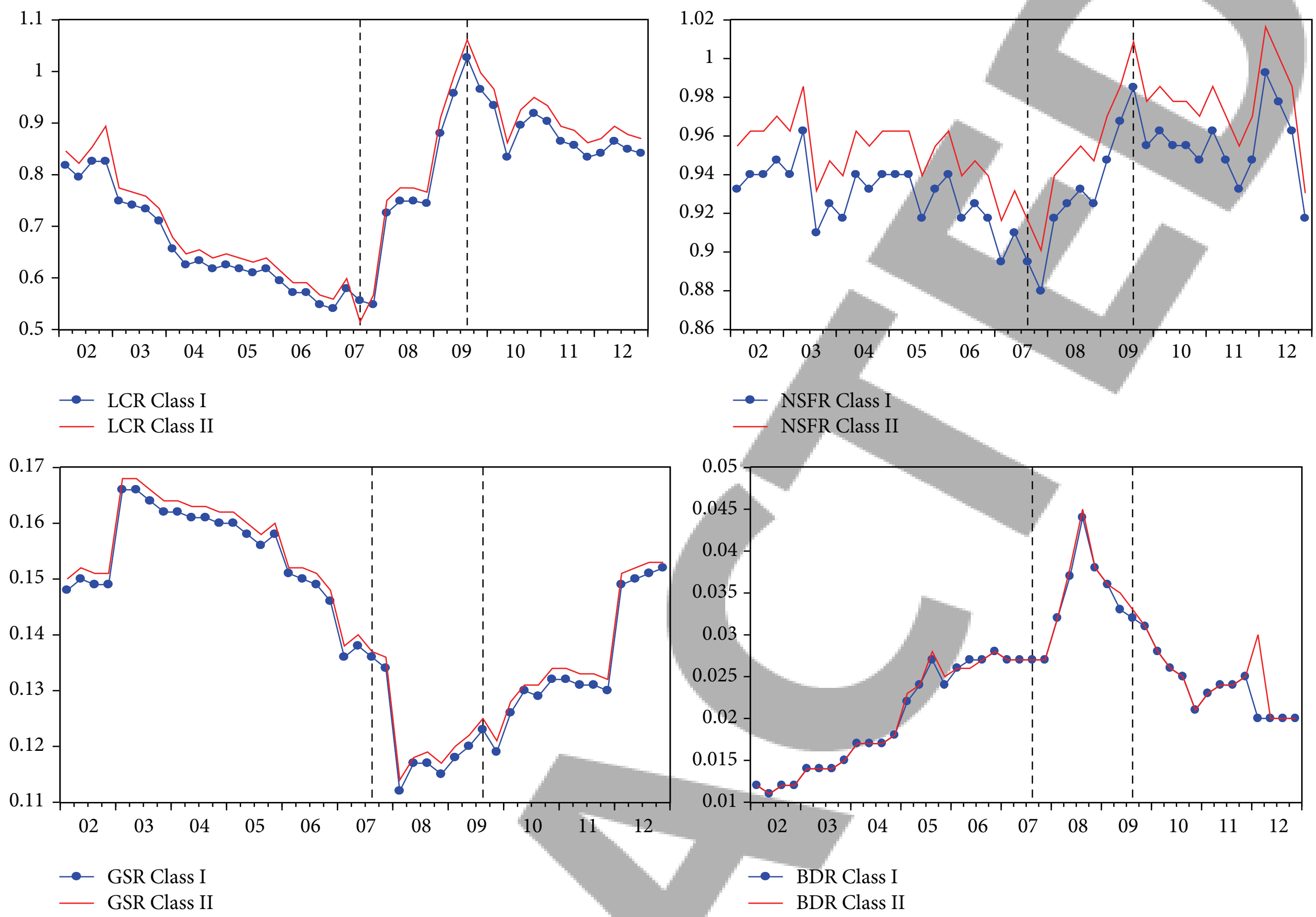

Figure 1: LCR, NSFR, GSR, and BDR for Class I and II banks.

an upward trend from 2001 through 2008, followed by a trend reversal. The general impression from Figure 1 is that the time series is nonstationary.

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

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.

4.2. Descriptive Statistics of Liquidity Risk Measures. The descriptive statistics of the LCR, NSFR, GSR, and BDR as well as NPAR, ROA, LIBOR-OISS, and BIIT1KR are presented later.

4.2.1. Descriptive Statistics of LCR, NSFR, GSR, and BDR. In Table 4, the mean, median, standard deviation, skewness, kurtosis, and Jarque-Bera statistics for LCR, NSFR, GSR, and BDR are described.

In Table 4, three out of four variables show positive skewness, namely, LCR, NSFR, and BDR while GSR is negatively skewed. This table also reports the summary statistics of the approximate measures of the LCR, NSFR, GSR, and BDR for Class I banks. It is clear that the mean for the LCR and NSFR is 74.96% and 93.76%, respectively. The value of the kurtosis for all the variables in Table 4 is equal to or less than 3, which means that the distribution is flat. All risk measures show forms of normality because the probability values in the said table have a P value greater than 5%. Nevertheless, the normality test is very sensitive to the number of observations and may only produce desirable and efficient results if observations are large. From Table 4, it is clear that the NSFR for most banks seem to have satisfied the Basel III minimum liquidity standard of 100% (compare with [2]). On the other hand, in the absence of empirical evidence, it is hard to conclude that the Basel III LCR standard had complied with these standards.

4.2.2. Descriptive Statistics of NPAR, ROA, LIBOR-OISS, and BIIT1KR. In Table 5, the mean, median, standard deviation,

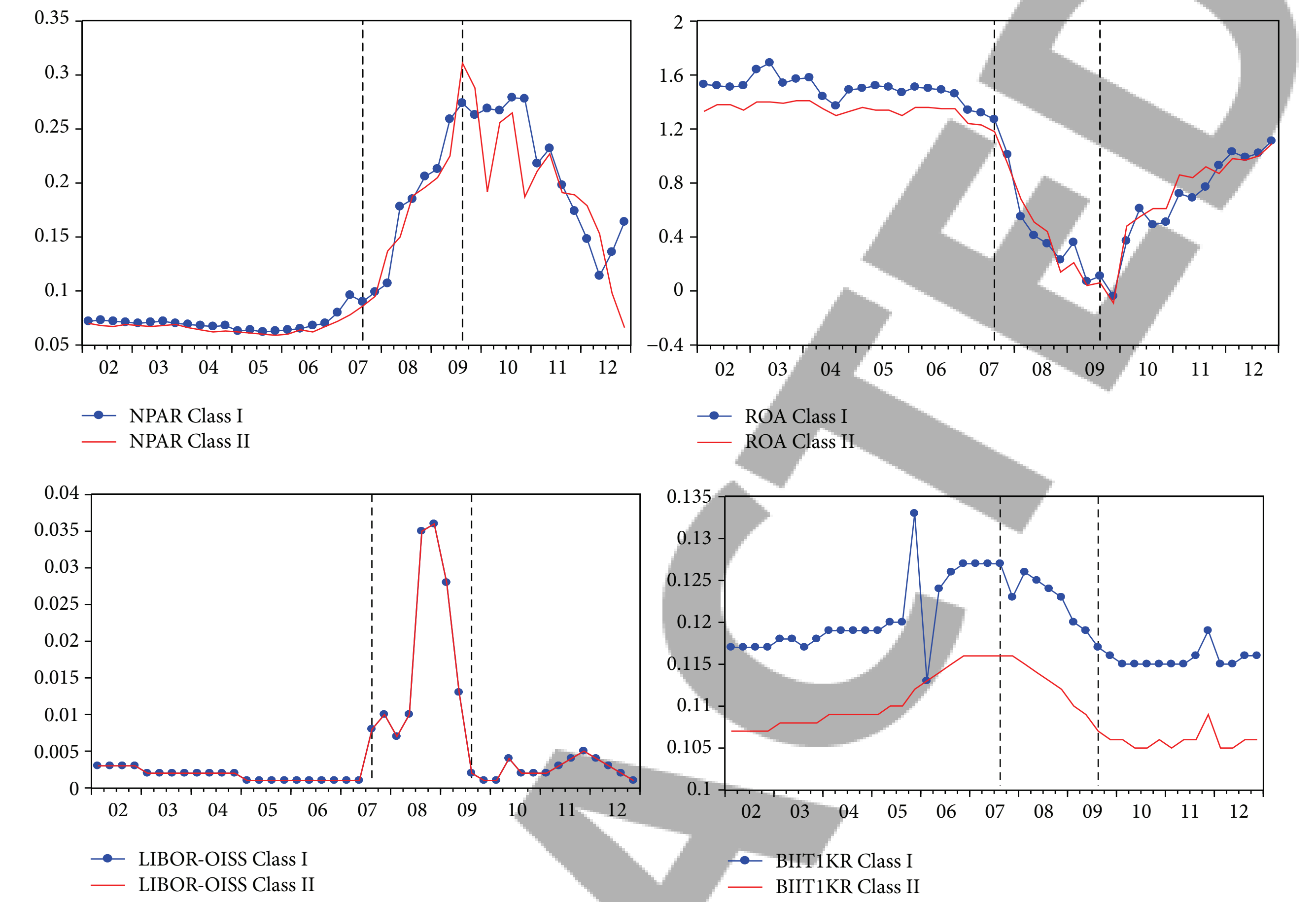

FIGURE 2: NPAR, ROA, LIBOR-OISS, and BIIT1KR for Class I and II banks.

TABLE 4: Descriptive statistics of LCR, NSFR, GSR, and BDR for Class I and II banks.

Parameter	Basel III liquidity standards		Traditional liquidity risk measures	
	LCR	NSFR	GSR	BDR
Mean	(0.748720, 0.773430)	(0.937550, 0.959670)	(0.142136, 0.144023)	(0.023750, 0.024136)
Median	(0.748840, 0.774060)	(0.940000, 0.962500)	(0.148500, 0.150500)	(0.024000, 0.025000)
Maximum	(1.026760, 1.061340)	(0.992690, 1.016400)	(0.166000, 0.168000)	(0.044000, 0.045000)
Minimum	(0.540400, 0.514560)	(0.879840, 0.900900)	(0.112000, 0.114000)	(0.011000, 0.011000)
Std. Dev.	(0.027670, 0.143466)	(0.023357, 0.023991)	(0.016247, 0.016286)	(0.007644, 0.007864)
Skewness	(0.027670, −0.029454)	(0.005426, −0.004725)	(−0.248100, −0.241821)	(0.333869, 0.304656)
Kurtosis	(1.825270, 1.855696)	(3.167401, 3.133101)	(1.782049, 1.782182)	(2.846654, 2.832527)
Jarque-Bera	(2.535599, 2.406985)	(0.051591, 0.032643)	(3.170968, 3.147815)	(0.860545, 0.732065)
Probability	(0.281450, 0.300144)	(0.974534, 0.983811)	(0.204849, 0.207234)	(0.650332, 0.693480)
Sum	(32.94368, 34.03091)	(41.25221, 42.22550)	(6.254000, 6.337000)	(1.045000, 1.062000)
Sum Sq. Dev.	(0.794993, 0.885043)	(0.023458, 0.024750)	(0.011351, 0.011405)	(0.002512, 0.002659)
Observations	(44, 44)	(44, 44)	(44, 44)	(44, 44)

skewness, kurtosis, and Jarque-Bera statistics for NPAR, ROA, LIBOR-OISS, and BIIT1KR are described.

Similar comments as those for the liquidity measures in Table 4 can be made about Table 5 involving NPAR, ROA, LIBOR-OISS, and BIIT1KR.

4.3. LCR and NSFR Shortfalls. In this subsection, we report the LCR and NSFR shortfalls for Class I and II banks (Figure 3).

The BCBS issued the full text of the revised LCR in [35] following endorsement by its governing body, the Group of

Table 5: Descriptive statistics of NPAR, ROA, LIBOR-OISS, and BIIT1KR for Class I and II banks.

Parameter	Basel III liquidity standards		Traditional liquidity risk measures	
	NPAR	ROA	LIBOR-OISS	BIIT1KR
Mean	(0.133841, 0.125932)	(1.058636, 0.989545)	(0.005023, 0.005023)	(0.119500, 0.109432)
Median	(0.093000, 0.075000)	(1.295000, 1.205000)	(0.002000, 0.002000)	(0.118500, 0.109000)
Maximum	(0.279000, 0.311000)	(1.690000, 1.410000)	(0.036000, 0.036000)	(0.133000, 0.116000)
Minimum	(0.062000, 0.059000)	(−0.040000, −0.090000)	(0.001000, 0.001000)	(0.113000, 0.105000)
Std. Dev.	(0.078458, 0.075746)	(0.519461, 0.447416)	(0.008168, 0.008168)	(0.004542, 0.003669)
Skewness	(0.713759, 0.822853)	(−0.601728, −0.939206)	(2.949292, 2.949292)	(0.967224, 0.607675)
Kurtosis	(1.927948, 2.345809)	(1.944343, 2.676113)	(10.78247, 10.78247)	(3.209685, 2.049259)
Jarque-Bera	(5.843023, 5.749916)	(4.698321, 6.661111)	(174.8269, 174.8269)	(6.941108, 4.365138)
Probability	(0.053852, 0.056419)	(0.095449, 0.035773)	(0.000000, 0.000000)	(0.031100, 0.112751)
Sum	(5.889000, 5.541000)	(46.58000, 43.54000)	(0.221000, 0.221000)	(5.258000, 4.815000)
Sum Sq. Dev.	(0.264696, 0.246713)	(11.60312, 8.607791)	(0.002869, 0.002869)	(0.000887, 0.000579)
Observations	(44, 44)	(44, 44)	(44, 44)	(44, 44)

Table 6: Minimum LCR requirements (2015–2019).

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

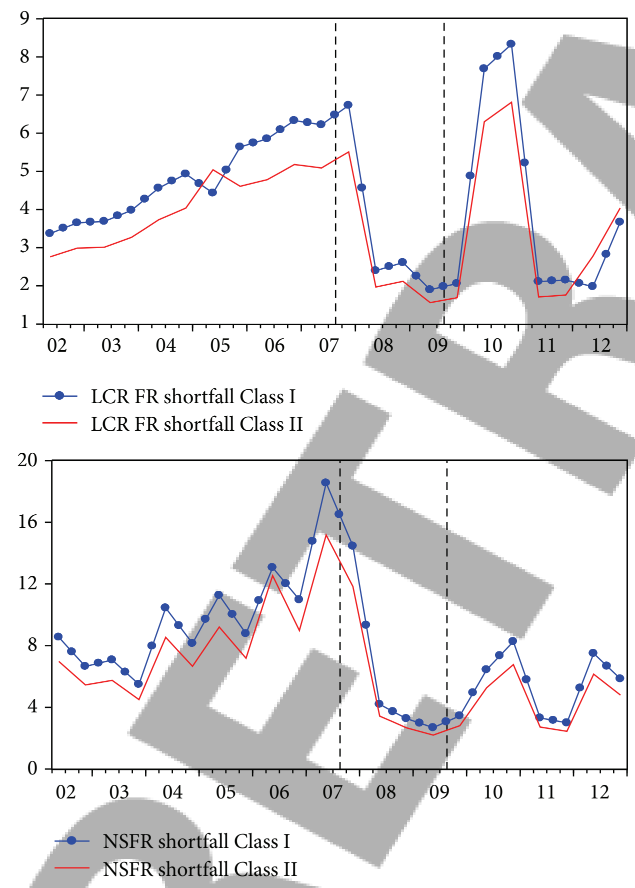

Figure 3: LCR and NSFR shortfalls for Class I and II banks.

Central Bank Governors and Heads of Supervision (GHOS). Specifically, the LCR will be introduced as planned on 1 January 2015, but the minimum requirement will begin at 60%, rising in equal annual steps of 10% to reach 100% on 1 January 2019 (Table 6). 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.

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.

5. Liquidity Risk Measures and Bank Failure

In this section, we present the results and discussion of liquidity risk measures and bank failure for both Class I and II banks.

5.1. 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 7 reports the information value of 8 liquidity risk measures.

As Table 7 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

Table 7: Information values of liquidity risk measures for Class I and II banks.

Rank	Liquidity risk measure	V^I
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)

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.

5.2. Class I and II Bank Failure. From Section 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

$$
\begin{aligned}
h^{Ai}_{t+1} = {} & \alpha^0 + \alpha^1 \frac{A^{bi}_t}{E^{ci}_t + R^i_t}\frac{\Pi^i_t}{r^{di}_t} + \alpha^2 \frac{K^{bi}_t - E^{ci}_t}{E^{ci}_t + R^i_t} + \alpha^3 \frac{\Lambda^i_t r^{\Lambda i}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^4 \frac{S^i_t r^{Si}_t}{E^{ci}_t + R^i_t} + \alpha^5 \frac{X^{Ibi}_t}{E^{ci}_t + R^i_t} + \alpha^6 \frac{I^{nnbi}_t}{E^{ci}_t + R^i_t} \\
& \alpha^7 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} + \alpha^8 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta H^i_t + \alpha^9 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta U^i_t \\
& + \alpha^{10} O^s_t + \alpha^{11} C^{Ri}_t + \alpha^{12} F^{Ri}_t, \\
& \alpha^1, \alpha^3, \alpha^4, \alpha^8, \alpha^{11}, \alpha^{12} < 0; \quad \alpha^5, \alpha^7, \alpha^9, \alpha^{10} > 0.
\end{aligned}
\tag{20}
$$

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

$$
\begin{aligned}
h^{Bi}_{t+1} = {} & \alpha^0 + \alpha^1 \frac{A^{bi}_t}{E^{ci}_t + R^i_t}\frac{\Pi^i_t}{r^{di}_t} + \alpha^2 \frac{K^{bi}_t - E^{ci}_t}{E^{ci}_t + R^i_t} + \alpha^3 \frac{\Lambda^i_t r^{\Lambda i}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^4 \frac{S^i_t r^{Si}_t}{E^{ci}_t + R^i_t} + \alpha^5 \frac{X^{Ibi}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^6 \frac{I^{nnbi}_t}{E^{ci}_t + R^i_t} + \alpha^7 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} + \alpha^8 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta H^i_t \\
& + \alpha^9 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta U^i_t + \alpha^{10} O^s_t, \\
& \alpha^1, \alpha^3, \alpha^4, \alpha^8 < 0; \quad \alpha^5, \alpha^7, \alpha^9, \alpha^{10} > 0,
\end{aligned}
\tag{21}
$$

$$
\begin{aligned}
h^{Ci}_{t+1} = {} & \alpha^0 + \alpha^1 \frac{A^{bi}_t}{E^{ci}_t + R^i_t}\frac{\Pi^i_t}{r^{di}_t} + \alpha^2 \frac{K^{bi}_t - E^{ci}_t}{E^{ci}_t + R^i_t} + \alpha^3 \frac{\Lambda^i_t r^{\Lambda i}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^4 \frac{S^i_t r^{Si}_t}{E^{ci}_t + R^i_t} + \alpha^5 \frac{X^{Ibi}_t}{E^{ci}_t + R^i_t} + \alpha^6 \frac{I^{\mathrm{nnbi}}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^7 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} + \alpha^8 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta H^i_t + \alpha^9 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta U^i_t \\
& + \alpha^{11} C^{Ri}_t + \alpha^{12} F^{Ri}_t,
\end{aligned}
\tag{22}
$$

$$
\begin{aligned}
h^{Di}_{t+1} = {} & \alpha^0 + \alpha^1 \frac{A^{bi}_t}{E^{ci}_t + R^i_t}\frac{\Pi^i_t}{r^{di}_t} + \alpha^2 \frac{K^{bi}_t - E^{ci}_t}{E^{ci}_t + R^i_t} + \alpha^3 \frac{\Lambda^i_t r^{\Lambda i}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^4 \frac{S^i_t r^{Si}_t}{E^{ci}_t + R^i_t} + \alpha^5 \frac{X^{Ibi}_t}{E^{ci}_t + R^i_t} + \alpha^6 \frac{I^{\mathrm{nnbi}}_t}{E^{ci}_t + R^i_t} \\
& + \alpha^7 \frac{A^{ni}_t}{E^{ci}_t + R^i_t} + \alpha^8 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta H^i_t + \alpha^9 \frac{A^{ni}_t}{E^{ci}_t + R^i_t}\Delta U^i_t,
\end{aligned}
\tag{23}
$$

respectively.

The bank failure rates for the 391 LIBOR-based, Basel II compliant banks from 36 countries for 2002 to 2012 included in our study are given in Table 8.

From Table 8, we note that 6 Class I and 17 Class II banks failed in the period 2002 to 2012.

Table 9 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.

5.3. 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 (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 Table 10.

As can be seen from Table 10, there is small differences in model statistics between Models A and B. On the other

Table 8: Class I and Class II bank failures (2002–2012).

Quarter	Total bank count	Total bank failures	Bank failure rate	Class I and II bank count	Class I and II failures	Class I and 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)
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)

Table 9: Bank failure rate by decile for Class I and II banks.

Decile	LCR	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, 0.0015)	(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)

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 provides 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.

5.4. Observed and Predicted Bank Failure Rates for Class I and II Banks. Models A to D observed and predicted bank failure rates are displayed in Table 11.

Table 11 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 11 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 Models A and B, which excludes the LCR and NSFR. The differences between the predictions of Models A and B are negligible. Since Model B excludes the approximate measures of the LCR and NSFR, the differences between the predicted values of Models A and B measure the marginal contribution of these approximate measures. As can be seen, the predicted failure rates of Models A and B are very similar, and both closely match the observed failure rate.

On the other hand, Table 11 also displays the marginal contribution of the LIBOR-OISS in predicting bank failures. Columns 2, 3, and 5 show 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 11 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 11 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 11, 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 11 suggest that 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.

6. Conclusions and Future Directions

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

6.1. Conclusions about Liquidity Risk Sensitivity 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 [34]). 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 (compared with Question 2).

Table 10: Models A to D estimation results for Class I and II banks.

(a) Model statistics

	Model A	Model B LCR and NSFR excluded	Model C LIBOR-OISS excluded	Model D Liquidity risk excluded
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)	(197.674, 196.0993)	(198.086, 199.773)
Log likelihood	(−85.379, −85.557)	(−87.657, −86.956)	(−91.816, −91.433)	(−93.886, −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)

(b) Parameter estimates

	Model A	Model B LCR and NSFR excluded	Model C LIBOR-OISS excluded	Model D Liquidity risk excluded
α^0	$(-0.0138^{***}, -0.0242^{***})$	$(0.0023^{***}, 0.0019^{***})$	$(-0.0230^{***}, -0.0290^{***})$	(0.0002, 0.0010)
	([0.003], [0.003])	([0.0011], [0.0013])	([0.0024], [0.0026])	([0.0013], [0.0011])
α^1	$(-0.0918^{***}, -0.0369^{***})$	$(-0.0888^{***}, -0.0354^{***})$	$(-0.0900^{***}, -0.0356^{***})$	$(-0.0834^{***}, -0.0322^{***})$
	([0.010], [0.011])	([0.009], [0.010])	([0.008], [0.009])	([0.0007], [0.0007])
α^2	(0.0140, 0.0157)	$(0.0143^{***}, 0.0165^{***})$	(0.0131, 0.0127)	$(0.0134^{***}, 0.0144^{***})$
	([0.0112], [0.0111])	([0.0087], [0.0086])	([0.0117], [0.0116])	([0.0097], [0.0096])
α^{3*}	(−0.0173, −0.0055)	$(-0.0218^{***}, -0.0109^{***})$	(−0.0121, −0.0026)	(−0.0205, −0.0116)
	([0.0218], [0.0221])	([0.0203], [0.0205])	([0.0216], [0.0219])	([0.0197], [0.0200])
α^4	(−0.0067, −0.0073)	(−0.0043, 0.0029)	(0.0003, −0.0011)	(0.0072, 0.0124)
	([0.0039], [0.0034])	([0.0037], [0.0041])	([0.0053], [0.0056])	([0.0055], [0.0066])
α^5	$(0.0993^{***}, 0.5733^{***})$	(0.0884, 0.8119)	$(0.1199^{***}, 0.6088^{***})$	$(0.1069^{***}, 0.9680^{***})$
	([0.0297], [0.0297])	([0.0285], [0.0286])	([0.0274], [0.0273])	([0.0246], [0.0247])
α^6	$(-0.1326^{***}, -0.7184^{***})$	$(-0.1095^{***}, -0.9477^{***})$	$(-0.1539^{***}, -0.7255^{***})$	$(-0.1054^{***}, -1.0600^{***})$
	([0.0490], [0.0490])	([0.0648], [0.0649])	([0.0250], [0.0251])	([0.0526], [0.0529])
α^7	$(0.0116^{***}, 0.0185^{***})$	$(0.0139^{***}, 0.0233^{***})$	$(0.0103^{***}, 0.0144^{***})$	$(0.0164^{***}, 0.0210^{***})$
	([0.0010], [0.0010])	([0.0009], [0.0010])	([0.0009], [0.0009])	([0.0008], [0.0009])
α^8	$(0.0013^{***}, 0.0006^{***})$	$(0.0010^{***}, 0.0002^{***})$	(0.0014, 0.0000)	(0.0009, −0.0007)
	([0.1362], [0.1698])	([0.1354], [0.1688])	([0.1535], [0.1914])	([0.1566], [0.1952])
α^9	(0.0001, 0.0005)	(0.0002, 0.0006)	(−0.0002, 0.0001)	(−0.0002, 0.0001)
	([0.0006], [0.0004])	([0.0008], [0.0008])	([0.0005], [0.0007])	([0.0007], [0.0006])
α^{10*}	$(0.0963^{***}, 0.1036^{***})$	$(-0.1226^{***}, -0.1243^{***})$	(–, –)	(–, –)
	([0.0091], [0.0092])	([0.0095], [0.0094])	([–], [–])	([–], [–])
α^{11}	(0.0024, 0.0015)	(–, –)	(0.0062, 0.0046)	(–, –)
	([0.0286], [0.0293])	([–], [–])	([0.0250], [0.0266])	([–], [–])
α^{12*}	$(0.0155^{***}, 0.0260^{***})$	(–, –)	$(0.0211^{***}, 0.0282^{***})$	(–, –)
	([0.0007], [0.0007])	([–], [–])	([0.0008], [0.0008])	([–], [–])

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

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 [34]), we cannot directly compare our results with those of the BCBS (see, in particular, [18–20]) and EBA

Table 11: Observed and predicted bank failure rates for Class I and II banks (2002–2012).

Model A to D bank failures (2002–2012)					
Parameter	Observed bank failure rates	Predicted bank 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)
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)

Table 12: Summary table of the nett stable funding ratio.

Available stable funding (sources)		Required stable funding (uses)	
Item	ASF factor	Item	RSF factor
(i) T1K and T2K instruments (ii) Other preferred shares and capital instruments in excess of T2K allowable amount having an effective maturity of 1 yr or >1 yr (iii) Other liabilities with an effective maturity of 1 yr or >1 yr	100%	(i) Cash (ii) Short-term unsecured actively-traded instruments (<1 yr) (iii) Securities with exactly offsetting reverse repo (iv) Securities with remaining maturity <1 yr (v) Nonrenewable loans to financials with remaining maturity <1 yr	0%
Stable deposits of retail and small business customers (nonmaturity or residual maturity <1 yr)	90%	Debt issued or guaranteed by sovereigns, central banks, BIS, IMF, EC, noncentral government, multilateral development banks with a 0% risk weight under Basel II standardized approach	5%
Less stable deposits of retail and small business customers (nonmaturity or residual maturity <1 yr)	80%	Unencumbered non-financial senior unsecured corporate bonds and covered bonds rated at least AA−, and debt that is issued by sovereigns, central banks, and PSEs with a risk-weighting of 20%; maturity ≥1 yr	20%
Wholesale funding provided by non-financial corporate customers, sovereign central banks, multilateral development banks, and PSEs (non-maturity or residual maturity <1 yr)	50%	(i) Unencumbered listed equity securities or non-financial senior unsecured corporate bonds (or covered bonds) rated from A+ to A−, maturity ≥1 yr (ii) Gold (iii) Loans to non-financial corporate clients, sovereigns, central banks, and PSEs with a maturity <1 yr	50%
All other liabilities and equity not included above	0%	Unencumbered residential mortgages of any maturity and other unencumbered loans, excluding loans to financial institutions with a remaining maturity of 1 yr or >1 yr that would qualify for the 35% or lower risk weight under Basel II standardized approach for credit risk	65%
		Other loans to retail clients and small businesses having a maturity <1 yr	85%
		All other assets	100%
		Off balance sheet exposures	
		Undrawn amount of committed credit and liquidity facilities	5%
		Other contingent funding obligations	National supervisory discretion

(see, more specifically, [21, 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.

6.2. Future Directions. As recent financial crises showed, the BCBS needs to recognize the inherent limitations and weaknesses of liquidity provisioning. The proposals at an international level to supplement Basel III liquidity risk measures with other internationally harmonized and appropriately calibrated liquidity standards have been welcomed and could lead to its adoption by a wide range of countries in the future. The LCR and NSFR cannot do the job alone; it needs to be complemented by other prudential tools or measures to ensure a comprehensive picture of the dissipation of liquidity in banks as well as the financial system. Additional measures to provide a comprehensive view of aggregate liquidity, including embedded liquidity, and to trigger enhanced surveillance by supervisors need to be developed.

There appears to be consensus that no single tool or measure would have prevented the financial crisis and that an adequate policy response requires a mix of macro- and microprudential 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.

Appendix

ASF and RSF Summaries

In Table 12, we represent a summary of the ASF and RSF components of the NSFR together with their multiplication factors.

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