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Does liquidity affect the financial health of Indian banks?

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ABSTRACT

The dynamic and volatile economic environment impacts the bank's performance and raises the risk of bankruptcy. This study deepens the understanding of financial distress in the Indian banking sector through liquidity. Furthermore, the study aims to analyse and understand the relationship between liquidity, liquidity measures and financial distress. The study evaluated the short- and long-term liquidity ratios from 2012 to 2022. Quantile panel discussion analysis (QPDA) was incorporated into this study. Linear and non-linear relationships measure the impact of liquidity on financial distress. The study comprises data from 23 Indian banks and represents the Indian banking landscape. The study investigates the effect of Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) on bank stability. The findings highlight that the LCR improves short-term liquidity but excessive levels can increase bank distress. On the other hand, NSFR raises stress initially but improves stability and reduces distress beyond a certain limit. The results show the need to balance short-term liquidity with long-term funding stability in regulatory policies. The implications of this study contribute to risk management strategies and better decision-making within the baking sector. This study proposes significant insights to the banks, policymakers, regulators and various banking institutions.

Contribution/Originality: The study excludes the qualitative factors that can impact liquidity and financial distress. The meticulous analysis of how the impacts of LCR and NSFR on bank stability, understanding of regulatory measures' long-term effects on financial distress, and enhancing the understanding to strengthen the Indian banking sector contribute to the originality of this study.

1. INTRODUCTION

The Indian banking industry is critical to the country's economy, providing a foundation for financial stability and prosperity. Bank failures, often more costly to resolve than non-bank failures can substantially impact important stakeholders, including taxpayers (El Diri, King, Spokeviciute, & Williams, 2021). The risk of bank failure poses significant economic costs and societal burdens globally impacting the economic performance of nations and potentially jeopardizing domestic and global economies (Sharma, 2013). The banking sector in India faces bankruptcy risk due to the unique characteristics of the sector including regulatory frameworks, market structures, and economic conditions (Das et al., 2020). The Indian banking scenario has faced intense transformations due to global and domestic factors. Banking operations are impacted by economic uncertainty with technological advancements, regulatory norms and continuously changing customer preferences. It is a great challenge to monitor the financial health of a financial institution. Bank regulators must forecast financial distress accurately to mitigate the risk, reduce financial loss, and take the necessary actions. This also helps improve the resource allocation parameter, manage resources effectively and focus on instant bank evaluation (Flannery, 1998).

After the worldwide financial crisis in 2008, the curiosity to understand the reasons and aspects that led to financial distress in banks has risen. Advanced warning technologies have been developed to detect financial distress, raise the alarm to the concerned authorities, and avoid any financial crisis-like situations (Soenen & Vander Vennet, 2022). Traditional forecasting models use accounting data from past information which is not relevant in the current times as they may not forecast the future trend (Agarwal & Taffler, 2008). The financial health of banks and forecasting accuracy can be developed by considering the microeconomic indicators, market information, and non-financial factors (Flannery & Bliss, 2019). A study noted the macroeconomic factors and market details (Männasoo & Mayes, 2009) reflecting less information on how non-financial factors impact the bank default risk (Chiaramonte & Casu, 2017). Hence, this study examines how liquidity can predict financial distress in banks. The Basel Committee on Banking Supervision (BCBS) was set up in 1974. It aims to maintain the financial stability of banks worldwide for over fifty years. BCBS has formulated policies and regulations that improve global banking systems. The financial crisis of 2007-09 was caused by excessive borrowings, poor governance, lack of risk management strategies, and inadequate liquidity, after which the Basel III framework was introduced. Therefore, the Basel III norms focus on Liquidity Risk (LR) management to support the banking system. These norms have introduced the key measures which are the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), which evaluate the liquidity and enhance the LR management in the banks (Pinto, Rastogi, & Agarwal, 2024).

Financial distress is a complex issue (Kebede, Tesfaye, & Erana, 2024). Financial distress is the bank's failure to fulfil its financial responsibilities (Maulida, Moehaditoyo, & Nugroho, 2018) which causes a financial crisis. A lack of cash flow, low profits, and insufficient liquidity lead to financial distress. In banking, insufficient liquidity can lead to a huge crisis (Isayas, 2021). Financial distress is a major challenge and is depicted by a lack of liquidity, profits, operational efficiency and solvency (Jessie & Tannia, 2024). These are the potential warning signs before leading to bankruptcy (Jessie & Tannia, 2024; Kiros, 2020; Kisman & Krisandi, 2019). Banks, regulators, policymakers, investors, and other concerned stakeholders have their prime focus on lowering the financial distress risk by maintaining the required liquidity levels. Hence, it is essential to understand the relationship between liquidity and financial distress to keep banks stable and robust (Gupta & Kashiramka, 2020). Effective liquidity management of the banks is essential as it helps to meet the short-term financial needs and absorb any financial shocks (Adalsteinsson, 2014). Financial distress implicates the declining financial health of the banks which can lead to insolvency or bankruptcy. Thus, it is important to understand the relationship between liquidity and financial distress. Banks must create effective risk management strategies that guarantee financial stability and protect the depositor's interest.

LCR and NSFR are two important regulatory measures to improve the resilience of banks by guaranteeing sufficient liquidity and stable funding. It is important to understand how LCR and NSFR affect financial distress in the context of Indian banks for several reasons. Firstly, poor asset quality has made Indian banks more susceptible to liquidity shocks. This study examines the impacts of LCR which mandates banks to maintain a sufficient level of high-quality liquid assets to meet short- term obligations. Secondly, the NSFR assists in evaluating banks capacity to continue operating in the face of persistent stress to provide long-term funding stability. In a nation where regulatory frameworks and economic cycles are changing quickly, these ratios offer a standard by which to measure how well a bank manages its liquidity. Thus, this study not only contributes to the academic understanding of risks and liquidity but also offers practical insight into enhancing financial stability in emerging markets like India.

Various research has mentioned the relationship between liquidity and financial distress in the banking sector worldwide (Bu, 2019; Scannella, 2016). Still, there is a lack of studies highlighting detailed analyses specifically for the Indian banking sector. The available studies lack precise insights into how liquidity measures for LCR and NSFR are related to financial distress indicators like Altman's Z-scores in Indian banks. Addressing this gap is critical for improving our knowledge of the liquidity-risk dynamics specific to the Indian banking system. This paper attempts to close the aforementioned gap by examining the complex relationship between liquidity measures and financial distress in Indian banks. Altman's Z-score has been used in this study to measure the financial distress and evaluate the impact of LCR and NSFR in various situations. To address these gaps in this study research question is given below.

RQ1: Does LCR affect the financial health of the Indian banks?

RQ2: Does NSFR affect the financial health of the Indian banks?

The complexity of relationships Quantile Regression Panel Data Method (QRPDM) is used. Thus, an advanced economics model and integrated approach have been adopted in this study to understand the impact of liquidity on financial distress. Furthermore, a complete and representative analysis is presented by methodically gathering data from 23 banks, which covered public and private sector institutions over a decade (2012-2022). The selected sample covers around two-thirds of all scheduled commercial banks in India. According to RBI data, it accounts for 86% of total assets held by banks in the nation. This vast dataset is the foundation for thoroughly investigating liquidity-related issues that influence financial health.

The study is organized as follows: The first section covers the introduction to the study's title. The second section covers the literature study related to the study. The third section evaluates the existing work and establishes the conceptual framework for forming hypotheses. The fourth section mentions the research methodology details. The result of the study is given in the fifth section. Subsequently, the sixth section examines the findings, emphasizing the study's contributions and implications. Finally, section 7 wraps up the paper by offering the conclusions and limitations.

2. LITERATURE REVIEW

The rising occurrence of bankruptcy in Indian banks reflects deep-rooted financial distress within the sector (Branch & Khizer, 2016) highlighting systemic challenges and the need for robust risk management frameworks (Bawa, Goyal, Mitra, & Basu, 2019; Komera & Lukose PJ, 2014). Banking crisis has a direct impact on depositors, investors and economic growth (Bhadury & Pratap, 2018). Banks' interconnection may spread crises, resulting in systemic failures and national or worldwide contagions (Bhattacharya, Boot, & Thakor, 1998). For managers, it is crucial to identify the early warning signs of financial distress in banks. This will help in reducing the impact and necessary steps can be initiated to prevent financial disasters in the banking system. Hence, an effective liquidity management approach is important, particularly for the banking sector due to its financial implications for the nation's economy (Laeven, 2011). The challenges faced by the banks bring out the need for a reliable prediction model that will help in identifying the early signs of financial distress to ensure timely regulatory measures (Benston & Kaufman, 1995). A thorough understanding of liquidity, LCR, NSFR and financial distress is essential for developing this predictive model.

2.1. Financial Distress and Liquidity

The ability to quickly buy or sell an asset with minimal cost and impact on its price is termed liquidity. Since the mid-1980s, this concept of liquidity has been important in stock returns. Some investors may require access to their funds on urgency highlighting the need to maintain the stock liquidity and assets. High liquidity helps banks to tackle or avoid financial distress situations and reduce the chances of bankruptcy. High liquidity acts as a protective buffer for the banks functioning in the highly dynamic market scenario (Shahdadi, Rostamy, Sadeghi Sharif, & Ranjbar, 2020). Liquidity has a substantial impact on financial distress (Susanti & Takarini, 2022; Yuriani, Merry, Jennie, Ikhsan, & Rahmi, 2020). This impact is considerably negative (Azizah & Yunita, 2022). According to Dance and Imade

(2019) liquidity is essential for the financial health, stability, and resilience of the bank. The ability to meet the immediate financial requirements from the available assets requires an extreme liquidity ratio. The lack of financial funds to meet the current bills shows a low liquidity ratio and financial issues (Sutra & Mais, 2019). Understanding the liquidity levels and concerns can help researchers and regulators to predict and prevent financial crises. A study states that liquidity ratios have a significantly and negative influence on financial distress (Lumbantobing, 2020). Another research summarises that liquidity has a minimal negative impact on financial distress (Amanda & Tasman, 2019). Other studies state that liquidity, when judged by the current ratio does not impact financial distress (Antoniawati & Purwohandoko, 2022; Jannah & Dhiba, 2021; Pratiwi & Sudiyatno, 2022; Susilowati, Suwarti, Puspitasari, & Nurmaliani, 2019). These findings bring out the complexity between liquidity and financial distress. Furthermore, it also directs towards a need for detailed analysis between them in different situations.

2.2. Financial Distress and LCR

In 2013, the Basel Committee on Banking Supervision created the LCR. It is the key to ensuring that the banks can sustain the short-term liquidity risk in challenging market situations (Basel Committee on Banking Supervision, 2013). Banks require 30 days of adequate volume of high-quality liquid assets (HQLA) to fulfil the net cash outflows (Hoerova, Mendicino, Nikolov, Schepens, & Van den Heuvel, 2018). The primary objective is to improve the preventive buffer of the banks for challenging market times. The second objective aims for 30 days of sufficient liquid assets to resist liquidity needs in banks. During normal times, the LCR sets a minimum level of 100 per cent. During stressful situations, banks can dip below this level and to ease these issues. HQLA can be used. For effective risk management, banks must regularly monitor the LCR. Understanding the role and impact of LCR is important to manage the liquidity risks in banks, especially in financial distress situations.

H_1: There is a significant relationship between financial distress and LCR in Indian banks.

2.3. Financial Distress and NSFR

NSFR ensures that banks maintain a stable financial profile. It matches the long-term assets with similar liabilities to reduce maturity mismatches (Basel Committee on Banking Supervision, 2013). NSFR aims to prevent the over- reliability of short-term liabilities to support long-term assets. It focuses on the stable financing available over a year compared to the need for stable funding. This lowers the risk of financial distress situations (Mariscal-Cáceres, Cristófol-Rodríguez, & Cerdá-Suárez, 2024). NSFR supports that banks should use stable funding sources, like deposits and extend the maturity of assets. This increases the stability of funding and resists funding shocks. Stable financing is important to maintain financial stability and liquidity risks (Wei, Gong, & Wu, 2017). Hence, it is necessary to explore how financial distress situations impact the NSFR in Indian banks. Understanding this impact will help in evaluating the effectiveness of the liquidity risk management strategies and regulatory frameworks. Figure 1 explains the conceptual model of the study to understand the connectivity of liquidity and financial distress. The following hypothesis is assumed.

H_2: There is a significant relationship between financial distress and NSFR in Indian banks.

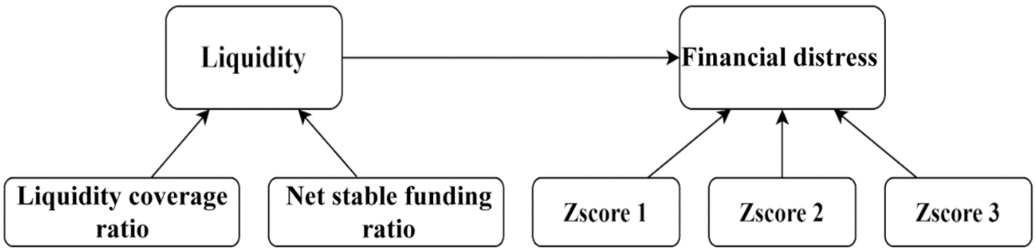

Figure 1. Conceptual framework.

3. DATA COLLECTION AND RESEARCH APPROACH

3.1. Detail of Data Collection

This paper focuses on the Indian banking sector, which involves extensive data collection. A sample of 23 Indian banks was selected to thoroughly analyse the financial factors. Out of 23 banks, 9 banks are public sector banks and 14 are private sector banks. The selection was based on the accessibility of their financial data. The chosen banks show an effective sample for the study as they represent two-thirds of the commercial banks functioning in India covering both the public and private sectors. According to the RBI dataset, this sample accounts for a substantial 86% of the total assets held by banks operating within India, including scheduled banks of the public and private sector banks, small finance banks, foreign banks operating in India, and payment banks. The data collection encompasses an impressive 93% of assets held by all the scheduled private and public commercial banks combined (Reserve Bank of India, 2023). The data collection spanned a decade from 2012 to 2022 and drew from various authoritative sources, including Bloomberg, the Reserve Bank of India (RBI), and annual reports from the respective banks (Duterme, 2023). This extensive and meticulously gathered dataset serves as the cornerstone for a rigorous and comprehensive analysis of the Indian banking sector in the specified timeframe.

3.2. Variables

The variables used to investigate how liquidity affects financial distress are listed below in Table 1.

Table 1. List of variables.

SN	Variables	Type	Code	Definition	Citations
1	Altman's Z-score	DV.	Z-score 1 Z-score 2 Z-score 3	It is a financial metric used to assess the likelihood of financial distress or bankruptcy for a firm. It's calculated using multivariate discriminant analysis and provides a single score that helps evaluate a company's financial health.	Altman (1968)
2	Liquidity coverage ratio	EV.	LCR	It represents the minimum threshold for short-term liquidity in banks. It measures the bank's resilience over thirty days.	Hartlage (2012)
3	Net stable funding ratio	EV.	NSFR	It is a ratio that shows long-term liquidity in banks. It is assessed by dividing the available stable funds with the bank by the required stable fund amount.	Bouzgarrou, Jouida, and Louhichi (2018)
4	Market capitalization	CV.	lmcap	The sum of shares in a bank is multiplied by the share's current list price. The log of market capitalization is used to make the result consistent.	Kanoujiya, Rastogi, and Bhimavarapu (2022)
5	Return on assets	CV.	ROA	It represents the profitability of the bank and is measured as the ratio of net income and total assets.	Shingade, Patil, and Jadhav (2022)

Note: DV, EV, and CV are the dependent variable, exogenous variable, and control variable used in the study.

3.3. Methodology and Models

The research method used in the study is Panel Data Analysis (PDA). It is used in econometrics and various other fields to analyze data that involves the cross-sectional as well as the time series dimensions. Data collection is carried out from multiple entities (banks is the cross-sectional) at various time points (2012- 2022 is the period). This combination makes the result more comprehensive and robust. It increases efficiency, controls the unobserved heterogeneity, and better handles endogeneity. It is used to study complicated relationships that change over time and involve various groups or individuals (Baltagi, 2008; Hsiao, 2007).

The dataset of the study shows non-linear characteristics as confirmed by the Shapiro-Wilk W test for normal data. In such studies, showing non-linear features, non-linear practices need to be pertained to (Kartal, Ali, & Nurgazina, 2022; Kirikkaleli, Kartal, & Adebayo, 2022). These techniques are advantageous in such situations due to their lack of assumptions and requirements that all variables exhibit stationarity in the same order. The quantile regression panel data method (QRPDM) is used to carry out regression. Quantile regression analysis is becoming more popular in research fields because it fixes issues with conventional regression which relies only on the average (mean) as the outcome. It uses the median or other specific values as the outcomes in regression models. Pinto et al. (2024); and Alam, Hussain, and Saqib (2023) assess the liquidity of bank by using static and dynamic model but this study uses QRPDM to understand the relationship between liquidity and financial distress of Indian banks. This approach is supported by various studies (Gowlland, Xiao, & Zeng, 2009; Nguyen, Bakry, & Vuong, 2023; Yeh & Liu, 2023). For example, it can create various regression models for different quantiles like 25/100, 50/100, etc.

There are six quantile models (model 1 - 6) used to evaluate the effect of liquidity on financial distress of Indian banks. Models 7 to 12 represent the quadratic quantile model findings.

$$Z-score1it(\tau) = \theta_1 LCR_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 1)}$$

$$Z-score2it(\tau) = \theta_1 LCR_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 2)}$$

$$Z-score3it(\tau) = \theta_1 LCR_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 3)}$$

$$Z-score1it(\tau) = \theta_1 NSFR_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 4)}$$

$$Z-score2it(\tau) = \theta_1 NSFR_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 5)}$$

$$Z-score3it(\tau) = \theta_1 NSFR_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 6)}$$

$$Z-score1it(\tau) = \theta_1 LCR2_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 7)}$$

$$Z-score2it(\tau) = \theta_1 LCR2_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 8)}$$

$$Z-score3it(\tau) = \theta_1 LCR2_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 9)}$$

$$Z-score1it(\tau) = \theta_1 NSFR2_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 10)}$$

$$Z-score2it(\tau) = \theta_1 NSFR2_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 11)}$$

$$Z-score3it(\tau) = \theta_1 NSFR2_{it} + \theta_2 roa2_{it} + \theta_3 lmcap_{it} + \theta_4 cons_{it} \quad \text{(Eq 12)}$$

In the above equation, the dependent variable of the study is z-score1, z-score2, and z-score3. The exogenous variable is LCR and NSFR. Moreover, lmcap and ROA stand for the log of market capitalization and return on assets, respectively, implemented as control variables for the study. The log is used to reduce the inconsistency that occurs due to intense value concerns (Cepoi, Dragotă, Trifan, & Iordache, 2023). *"it"* is used to symbolize the panel data term where 'i' represents the cross-sectional term, and "t" is the time-series term.

Table 2. Results of descriptive statistics.

Variables	Obv	Mean	St.D	MinV	MaxV
LCR	252	1.256	0.280	0.604	3.715
NSFR	252	1.358	0.155	0.874	2.038
Z-score 1	252	.761	2.59	-0.954	20.880
Z-score 2	252	3.045	11.087	-4.599	93.262
Z-score 3	252	3.932	12.246	-5.366	96.512
Lmcap	252	4.486	0.696	3.001	5.994
ROA	252	.653	0.915	-6.37	2.18

Note: Var, Obv, Mean, St.D, MinV, and MaxV are variables, observations, mean value, standard deviation, minimum value, and maximum value, respectively.

4. DATA ANALYSIS RESULTS

4.1. Descriptive Statistics

Table 2 presents the results of descriptive statistics of various variables used in the study. The variable LCR should be above 1, indicating the fulfillment of the minimum regulatory requirement. The LCR spectrum ranges from 0.604 to 3.715, showing that some Indian banks are not fulfilling the minimum requirement in certain years, whereas others hold liquid assets beyond the minimum requirement in the short run. The mean value stands at 1.256, suggesting that banks have LCR slightly above the minimum regulatory requirement on average. Therefore, the banks' short-term obligations are covered with high-quality liquid assets. The SD stands at 0.28, indicating that the values are clustered around the mean, and banks maintain the LCR requirement consistently over the years. Similarly, banks maintain long-term liquidity requirements consistently over the years without deviation.

The Z-score used to measure financial distress in banks shows that it varies significantly between banks. Some banks show healthy financial conditions with high Z-score values. Some have negative Z-scores, indicating a high risk of financial distress and bankruptcy. Certain variables are kept constant to better understand the relationship between the independent and dependent factors, when accounting for the influence of further factors. This leads to more robust and interpretable conclusions in empirical research. lmcap and ROA stand for the log of market capitalization and return on assets, respectively used as control variables for the study. The value of market capitalization falls in a small range with a relatively small deviation. The average of ROA is positive, showing that the banks are profitable but some firms do have negative ROA indicating losses.

4.2. Multicollinearity and Variance Inflation Factors (VIF)

The liquidity variables LCR and NSFR show a statistically significant and positive correlation. It can imply that firms with an adequate short-term liquidity ratio also tend to have more stable funding in the long period. The LCR and lmcap have a negative statistical correlation whereas the NSFR and lmcap have no significant statistical correlation. The correlation values between the variables are below 0.8, so the data do not face any problem of multicollinearity (Gujarati & Porter, 2009).

Table 3 also presents the VIF of the factors to gauge the multicollinearity concerns between the independent variables. The variables have a VIF lower than 3, so the issue of multicollinearity does not exist. Low correlations between the independent variables will not likely distort the regression analysis results due to multicollinearity. The VIF reconfirms the correlation coefficient results making it more robust.

Table 3. Correlation matrix and variance inflation factor (VIF).

Variables	LCR	NSFR	lmcap	roa	
LCR	1.0000				
NSFR	0.1330** (0.0345)	1.0000			
Lmcap	-0.1607* (0.0105)	-0.0293 (0.6429)	1.0000		
ROA	-0.0940 (0.1359)	-0.1842* (0.0033)	0.0366 (0.5626)	1.0000	
VIF	1.05	1.05	1.03	1.04	1.04

Note: A single star '*' sign over the coefficient presents a 1 % significant level and a double star '**' sign over the coefficient presents a 5 % significant level. The VIF test checks multicollinearity among variables in the model.

Table 4. Shapiro-Wilk W test for normal data.

Variables	Obs.	W	V	z	Prob>z	H0: Normal data	Result
Z-score 1	253	0.348	119.414	11.134	0.000	Reject H0	Not distributed normally.
Z-score 2	253	0.284	131.136	11.352	0.000	Reject H0	Not distributed normally.
Z-score 3	253	0.452	100.384	10.730	0.000	Reject H0	Not distributed normally.

Note: The test is performed for the normality of dependent variables.

4.3. Normality

The above linearity test was conducted to understand the nature of the dependent factors used in the research. Table 4 displays the results of this test. The findings from the Shapiro-Wilk W test for normal data indicate that there is no substantial indication supporting the acceptance of the null hypothesis. In simpler terms, this suggests that the factors do not adhere to the assumptions of normality and linearity. The data is not distributed. When variables exhibit non-linear characteristics, it is advisable to employ a non-linear method. In this context, the quantile panel data regression emerges as a suitable method for understanding the impact of these variables (Kartal et al., 2022; Kirikkaleli et al., 2022).

Table 5. Quantile regression result (Base model).

	Variables	Model 1 (Z-score1)		Model 2 (Z-score2)		Model 3 (Z-score3)	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Q (25)	LCR	0.129	0.365	0.333	0.873	0.195	2.538
	lmcap	-0.469*	0.146	-0.592***	0.350	-4.236*	1.017
	ROA	0.448*	0.110	0.915*	0.264	2.202*	0.767
	Cons	1.696**	0.871	1.704	2.081	16.894*	6.044
Q (50)	LCR	-0.330**	0.157	-1.291***	0.694	-0.190	1.408
	Lmcap	-0.496*	0.063	-1.883*	0.278	-3.906*	0.564
	ROA	0.315*	0.047	0.984*	0.210	2.068*	0.425
	Cons	2.983*	0.375	11.199*	1.654	19.586*	3.353
Q (75)	LCR	-0.714*	0.150	-3.083*	0.767	-3.923*	1.129
	Lmcap	-0.431*	0.060	-1.962*	0.307	-2.573*	0.452
	ROA	0.181*	0.045	0.818*	0.232	0.857*	0.341
	Cons	3.595*	0.357	15.417*	1.827	22.076*	2.689

Note: A single star '*' sign over the coefficient presents a 1 % significant level, a double star '**' sign over the coefficient presents a 5 % significant level, and a triple '***' sign over the coefficient presents a 10 % significant level.

4.4. Regression Results

Table 5 represents base models 1, 2, and 3 at the 25%, 50% and 75% quantile. Base model 1 studies the quantile regression (QR) between the short-run liquidity variable (LCR) and the financial distress variable (z-score1). The relation is negatively significant at 50% and 75% quantiles. This implies that the short-term liquidity represented by LCR negatively impacts financial distress at higher quantiles. The relationship is not significant at the 25% low quantile. A similar result is derived from base model 2 which studies the relation between LCR and z-score2. At 50% and 75% quantiles, the relationship is negatively significant. At 25% low quantiles, the relationship is insignificant between LCR and z-score3 from the base model 3, showing a negative significance relationship only at the 75% quantile.

Table 6. Quantile regression result (Base model).

	Variables	Model 4 (z-score1)		Model 5 (z-score2)		Model 6 (z-score3)	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Q (25)	NSFR	-0.178	0.636	-0.134	1.533	4.532	4.630
	Lmcap	-0.468*	0.140	-0.698**	0.337	-4.250*	1.018
	ROA	0.416*	0.108	0.926*	0.260	2.343*	.787
	Cons	2.126**	1.096	2.850	2.640	11.038	7.972
Q (50)	NSFR	0.061	0.308	1.709	1.299	6.358*	2.507
	Lmcap	-0.432*	0.067	-1.770*	0.285	-3.735*	0.551
	ROA	0.335*	0.052	1.335*	0.221	2.192*	0.426
	Cons	2.155*	0.530	6.479*	2.238	10.108**	4.318
Q (75)	NSFR	0.596**	0.282	3.739*	1.473	5.001**	2.152
	Lmcap	-0.424*	0.062	-1.672*	0.323	-2.647*	0.473
	ROA	0.258*	0.048	1.305*	0.250	1.295*	0.366
	Cons	1.763*	0.486	4.824**	2.537	10.171**	3.705

Note: A single star '*' sign on the coefficient presents a 1 % significant level, a double star '**' sign over the coefficient presents a 5 % significant level.

Table 6 presents the analysis of quantile regression results for base models 4, 5, and 6. The study explores the NSFR influence on financial distress variables (z-score1, z-score2, and z-score3) at different quantiles (25%, 50%, and 75%). At the 75% quantile, a significant and positive relationship between NSFR and financial distress (z-score1, z-score2, z-score3) is noted. This suggests that at higher quantiles, greater long-term liquidity has a positive influence on the z-score. This shows that the financial health of the banks improves, and chances of distress are reduced. This relationship is not statistically significant at the 25% and 50% quantiles in models 4 and 5. At these lower quantiles, other factors can show a substantial part in influencing financial distress. The effect of short-run liquidity and long-run liquidity has the opposite effect on financial distress.

Table 7. Quantile regression result (Quadratic model).

	Variables	Model 7 (z-score1)		Model 8 (z-score2)		Model 9 (z-score3)	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Q (25)	LCR2	0.033	0.097	0.066	0.236	0.043	0.694
	Lmcap	-0.461*	0.143	-0.595***	0.349	-4.230*	1.027
	ROA	0.442*	0.109	0.918*	0.265	2.192*	0.779
	Cons	1.770*	0.693	2.038	1.686	17.062*	4.959
Q (50)	LCR2	-0.098**	0.042	-0.398**	0.181	-0.037	0.380
	Lmcap	-0.492*	0.063	-1.851*	0.269	-3.896*	0.562
	ROA	0.318*	0.047	0.981*	0.204	2.062*	0.427
	Cons	2.691*	0.304	10.065*	1.299	19.365*	2.718
Q (75)	LCR2	-0.172*	0.046	-0.376***	0.230	-0.844*	0.324
	Lmcap	-0.450*	0.068	-1.856*	0.341	-2.552*	0.480
	ROA	0.214*	0.052	0.870*	0.258	1.033*	0.364
	Cons	3.016*	0.332	11.598*	1.646	18.183*	2.318

Note: A single star '*' sign over the coefficient presents a 1 % significant level and a double star '**' sign over the coefficient presents a 5 % significant level, and a triple '***' sign over the coefficient presents a 10 % significant level.

Table 7 represents quadratic quantile models 7, 8, and 9 of Indian banks. In quadratic models 7 and 8 at the 50% and 75% quantiles, the outcome is negatively significant having a p-value less than 0.05. At the 25 % quantile, the result is insignificant. In model 9, the relationship is only significant at a high quantile of 75%. It implies that initially, with the increase in short-term liquidity (LCR), the value of the z-score increases till it reaches a threshold, and after that, the value decreases. Therefore, increased short-term liquidity will initially improve the financial health of the banks. But if this level of LCR crosses the threshold, i.e., there is much more than required liquidity, in such cases, the financial health of the bank will deteriorate shown by the decreasing value of the z-score.

Table 8. Quantile regression result (Quadratic model).

	Variables	Model 10 (z-score1)		Model 11 (z-score2)		Model 12 (z-score3)	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Q (25)	NSFR2	-0.029	0.208	0.152	0.522	1.602	1.567
	Lmcap	-0.471*	0.135	-0.639***	0.338	-4.263*	1.016
	ROA	0.431*	0.104	0.933*	0.262	2.346*	.787
	Cons	1.944*	0.737	2.094	1.844	14.288*	5.533
Q (50)	NSFR2	0.052	0.103	0.637	0.438	2.386*	0.860
	Lmcap	-0.430*	0.067	-1.740*	0.284	-3.772*	0.558
	ROA	0.339*	0.052	1.397*	0.220	2.246*	0.432
	Cons	2.127*	0.366	7.358*	1.546	14.402*	3.039
Q (75)	NSFR2	0.176***	0.098	1.207*	0.511	1.516**	0.740
	Lmcap	-0.420*	0.063	-1.692*	0.331	-2.680*	0.480
	ROA	0.222*	0.049	1.252*	0.256	1.303*	0.372
	Cons	2.258*	0.346	7.701*	1.804	14.208*	2.615

Note: A single star '*' sign over the coefficient presents a 1 % significant level, a double star '**' sign over the coefficient presents a 5 % significant level, and a triple '***' sign over the coefficient presents a 10 % significant level.

Table 8 represents quadratic quantile models 10, 11, and 12 of Indian banks. In quadratic models 10 and 11 at the 75% quantile, the outcome is positively significant having a p-value less than 0.05. At the 25% and 50% quantile, the outcome is insignificant. In model 12, the relationship is significant at 50% and 75% quantiles. It implies that initially, the value of the z-score decreases till it reaches a threshold, and the value increases with the increase in long-term liquidity (NSFR). Therefore, increased long-term liquidity will initially negatively affect the financial health of the banks. But if this level of NSFR crosses the threshold, i.e., there is more than required liquidity. In such cases, the financial health of the bank will improve as shown by the increasing value of the z-score. These insights are valuable for risk management and strategic decision-making within the banking sector.

4.5. Endogeneity and Robustness

The outcomes of the endogeneity test are displayed in Table 9. Two tests were performed to assess the issue of endogeneity: the Durbin Chi2 and Wu Hausman tests, utilizing lag3 values of the variables. Both tests yielded insignificant p-values, which support the null hypothesis that there is no endogeneity. In other words, it suggests that none of the explaining endogenous variables are present. We can conclude that our models are not affected by endogeneity.

Multiple models were investigated in this study to ensure the robustness of our findings. We examined liquidity in banks using both the LCR and NSFR. Additionally, financial distress was assessed using two variations of Altman's Z-scores (Z-score1, Z-score2, and Z-score3). We employed quantile regression and quadratic quantile regression methods to explore the influence of liquidity on financial distress. Consequently, results are robust. Obtained coefficients from quantile regression and quadratic quantile regression methods further validated the significance of the findings.

Table 9. Endogeneity.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Durbin Chi-2	0.348 (0.554)	0.263 (0.607)	0.065 (0.798)	0.078 (0.779)	0.009 (0.924)	0.000 (0.999)
Wu-Hausman test	0.340 (0.560)	0.256 (0.612)	0.063 (0.801)	0.076 (0.782)	0.008 (0.925)	0.000 (0.999)

Note: The value in the parenthesis is the p-value.

5. DISCUSSION

5.1. Hypothesis Testing

The Basel III regulatory framework introduced the liquidity coverage ratio and the net stable funding ratio as critical measures to enhance banking stability. These ratios aim to ensure that financial institutions maintain sufficient liquidity to withstand short-term stress and promote long-term funding stability. This study examines the impact of LCR and NSFR on banks' distress levels and stability. The findings from this study indicate a negative significance of LCR on bank stability. Initially, a higher LCR contributes positively to liquidity management by ensuring that banks are prepared for short-term obligations. However, beyond a certain point, an excessively high LCR can increase banks' distress levels. Therefore, the first hypothesis, that LCR significantly improves bank stability is only partially accepted. This outcome suggests that while maintaining a robust liquidity buffer is essential, an overly conservative approach can result in inefficient capital allocation, reduced profitability, and heightened operational stress. On the other hand, NSFR initially increases stress levels up to a certain threshold. This initial increase in stress can be attributed to the adjustments banks must make to align their funding structures with regulatory requirements. Once this threshold is surpassed, the NSFR significantly improves stability and reduces stress levels. Hence, the second hypothesis state that NSFR significantly reduces bank distress over the long term is accepted. This stabilisation effect underscores the long-term benefits of maintaining a balanced funding structure, enhancing the bank's ability to withstand financial shocks and promoting sustainable growth.

Mariscal-Cáceres et al. (2024); Susanti and Takarini (2022); Yuriani et al. (2020) and Wei et al. (2017) find that liquidity has a positive effect on financial distress. The result of these studies supports the outcome of this study as NSFR positively affect the NSFR at a higher level. Amanda and Tasman (2019) summarises that liquidity has a minimal negative impact on financial distress which supports the finding of this study as LCR affects the distress level of banks. Other studies state that liquidity does not impact financial distress (Antoniawati & Purwohandoko, 2022; Jannah & Dhiba, 2021; Pratiwi & Sudiyatno, 2022; Susilowati et al., 2019) support the finding that NSFR and LCR have no effect on the distress of banks at a low level.

5.2. Implications

This study holds significant implications for various aspects of banking regulation and risk management. It highlights the importance of adjusting the LCR and NSFR requirements to balance short-term liquidity needs with long-term stability goals. When designing and implementing liquidity requirements, regulators and policymakers should take into account the threshold effects shown in this study to prevent unforeseen outcomes. Similarly, banks should aim to build the right balance between keeping appropriate liquidity buffers and efficient capital usage. Bank managers can use the findings of the study to formulate liquidity management strategies. This will help in maintaining the required levels of LCR and NSFR to reduce the financial distress risks. Banks can avoid financial distress situations with regular monitoring of the liquidity balance and following the regulatory norms. Reviews and adjustments of liquidity plans are regularly necessary to ensure the good financial health of the bank in any market scenario. The stakeholders and investors will benefit, helping them towards investment decisions with improved transparency and risk management tools. Investors should consider the liquidity measures LCR and NSFR over the traditional financial measurement factors while evaluating the bank stocks. Banks with a balanced liquidity management approach are likely to remain more stable in varied market scenarios and less prone to financial distress situations. For investors and depositors, banks with a balanced liquidity ratio can be considered as they will be capable of meeting short-term financial needs. Analysts can use the study's findings and methodology to improvise their bank stability and prediction models. Policymakers and regulators can get in-depth insights into effective liquidity management strategies to contribute towards the overall financial system stability. Policymakers should also promote regulations that require accurate disclosure of liquidity conditions and financial health metrics. This can also improve market discipline and investor confidence. The study significantly contributes to inform decision-making, risk mitigation, and regulatory improvements in the banking sector.

6. CONCLUSION

This study aimed to examine the effects of the LCR and NSFR on bank stability. The most important findings reveal that LCR boosts short-term liquidity while excessive levels can increase bank distress. On the other hand, NSFR initially raises stress but enhances stability and reduces distress beyond a certain threshold. These findings support our objectives by highlighting the critical balance required between short-term liquidity and long-term funding stability. In terms of importance, these findings underscore the necessity for banks and regulators not merely to comply with LCR and NSFR requirements but to optimize them. It is important because it provides a detailed understanding of how these ratios function under different conditions. The possible application of these findings extends beyond banking. Non-banking financial companies can also apply these insights to improve their liquidity management practices. Furthermore, these principles can be adapted to other sectors where balancing short-term and long-term financial stability is crucial, thus broadening the scope and relevance of this study.

This paper broadens the understanding of liquidity management and its impact on financial stability within the Indian banking sector. Complex relationships were examined using robust quantitative methods. It provides valuable insights for improving bank risk management strategies and decision-making processes. These insights hold significant relevance for policymakers, regulators, and financial institutions in developing more robust liquidity risk management frameworks, thereby boosting overall financial resilience. This study offers important contributions. It is also important to acknowledge its scope and limitations. The study focuses on an in-depth investigation of liquidity metrics and financial distress. Using an extensive dataset from 23 Indian banks over a decade, it primarily considers variations in Altman's Z-score as proxies.

6.1. Limitations and Future Scope

The study's primary foundation is quantitative data, which may not adequately account for qualitative factors like management styles and market perception which can also have an impact on a bank's funding stability and liquidity. Rigorous statistical techniques were used to minimize biases but it is crucial to recognize the qualitative aspect and unobserved variables may still impact the analysed relationships. Addressing these limitations is essential for framing future research directions in this critical area of financial analysis and risk management. Future research should consider including additional indicators and integrating qualitative data for a more comprehensive analysis within banks by using qualitative analysis to expand on the findings of this study and gain a deeper understanding of the interaction between regulatory compliance, market conditions, and management decisions. Furthermore, the study's concentration on a particular time period and group of banks may limit the finding's applicability to other contexts or categories of NBFC. Researchers may also investigate the long-term effects of these policies, particularly under various regulatory frameworks and economic cycles to provide a more complete picture. Additionally, comparison analyses with banks from other developing nations may provide an essential context for understanding these results' applicability. Future studies could also look into how LCR and NSFR affect non-banking financial institutions since these organizations are essential to the larger financial ecosystem.

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