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Liquidity Hazard Model for Class I and Class II Banks Pre and Post the Global Financial and Covid-19 Health Crisis: A Pooled OLS Regression Panel Approach

Mubanga Mpundu
University of the Western Cape, Department of Economics,
Robert Sobukwe Road, Bellville, P/Bag X17, Cape Town, South Africa
ORCID: https://orcid.org/0000-0002-4009-9151
E-mail: mmpundu@uwc.ac.za

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ABSTRACT

There have been various debates on how the performance of economies can be analysed and monitored over time. Such attempts aim to drive a conclusion as to what works for economic growth and development. What may work in one region for a given economy might not apply in another. One of the most important factors to consider are external variables which tend to have a huge impact on the way in which an economy reacts to a given shock. Economic shocks can take different forms such as the 2007-2010 financial crisis or the 2019-2022 Covid-19 health pandemic which had huge trickle-down effect on the economies. This article focuses on the liquidity hazard model for class I and II banks before and after the financial crisis. The study used a pooled OLS regression model using panel analysis. The results showed that regression is statistically significant for BDR, LCR and NSFR with F-statistic given as 7.787 and $P < 0.05$. About 21% of the variation in Interest income was explained by the model. The NSFR has a positive impact on II while BDR, LCR, LIBOR OIS and ROA had a negative impact. The liquidity hazard model, particularly the Diamond–Dybvig framework, continues to provide valuable insights into the vulnerabilities of banks. While regulatory measures like Basel III have strengthened liquidity requirements, the evolving nature of banking, influenced by technological advancements and changing depositor behaviours, necessitates continuous adaptation of models and regulations to safeguard financial stability.

1. Introduction

The 2007 to 2009 financial crisis highlighted the importance of bank liquidity hazard models in the optimum performance of banks and the broader financial markets. A turmoil in the financial markets was triggered by the financial crisis in 2007, which demonstrated the important role that effective processes managing liquidity risk play in sustaining the stability of individual banks as well as the soundness of the banking system as a whole in the event of an unpredicted crisis of a systematic nature (Ruozi & Ferrari, 2013). Liquidity Hazard is the inability of banks to meet their expected contractual payments in a timely and cost-effective manner (Ruozi & Ferrari, 2013).

There are several variables that has been studied and their relevance in the banking system with regards to liquidity risk namely liquidity coverage ratio (LCR), net stable funding ratio (NSFR), brokered deposits ratio (BDR), London Inter-Bank offered rate (Libor), overnight index swap (OIS) and return on assets (ROTs).

The Basel Committee on Bank Supervision (BCBS) through the Bank for International Settlements (BIS) introduced the Basel III model in December 2010, to regulate liquidity of banks by means of two new ratios namely LCR and NSFR. LCR addresses liquidity risk and demand banks to maintain adequate high-quality assets stock relative to projective short-term flows (Sidhu et al., 2022). Whereas NSFR addresses funding risk and further long-term bank stability by encouraging banks to adopt safer and more steady funding sources (Sidhu et al., 2022).

Brokered deposits was introduced in the early 1960's which contributed greatly to growth in the housing market and increased the liquidity in banks (Barth et al., 2020). The introduction enabled banks through technological innovation and the introduction of electronic funds exchange (ETFs) to exchange funds across distances at little to no cost (Barth et al., 2020).

The international framework for liquidity risk management was introduced in 2010, which included proposals to introduce the LCR and NSFR. The LCR and NSFR were expected to have a great impact on banking activity and financial markets since it was the first quantitative regulations for liquidity management (Tammenga & Haarman, 2020). The Basel Committee on banking supervision published the final document on the LCR in January 2013 and the NSFR in October 2014 (Tammenga & Haarman, 2020). Tammenga & Haarman (2020) also listed three benefits of the quantitative regulations namely increasing economic welfare, improving soundness of banking sector and preventing excessive loan growth.

Lastly ROA compare income with total liabilities and equity capital (total assets). According to Warrad & Box (2015), ROA measures the ability and efficiency of management in using the firm's assets to generate operating profits and it reports the total return accumulating to all providers of debt and equity, apart from the source of capital. ROAs are thus an important measure to determine the profitability of banks.

The objective of the paper is to determine the liquidity hazard model of 155 Class I and Class II banks during the period 2002q1 to 2023q4 using quarterly bank related data considering the above-mentioned variables. The paper analysis Class I and Class II bank liquidity hazard model pre, pre and post the mortgage financial and Covid-19 health crisis making use of a pooled Regression Panel Approach.

2. Literature Review

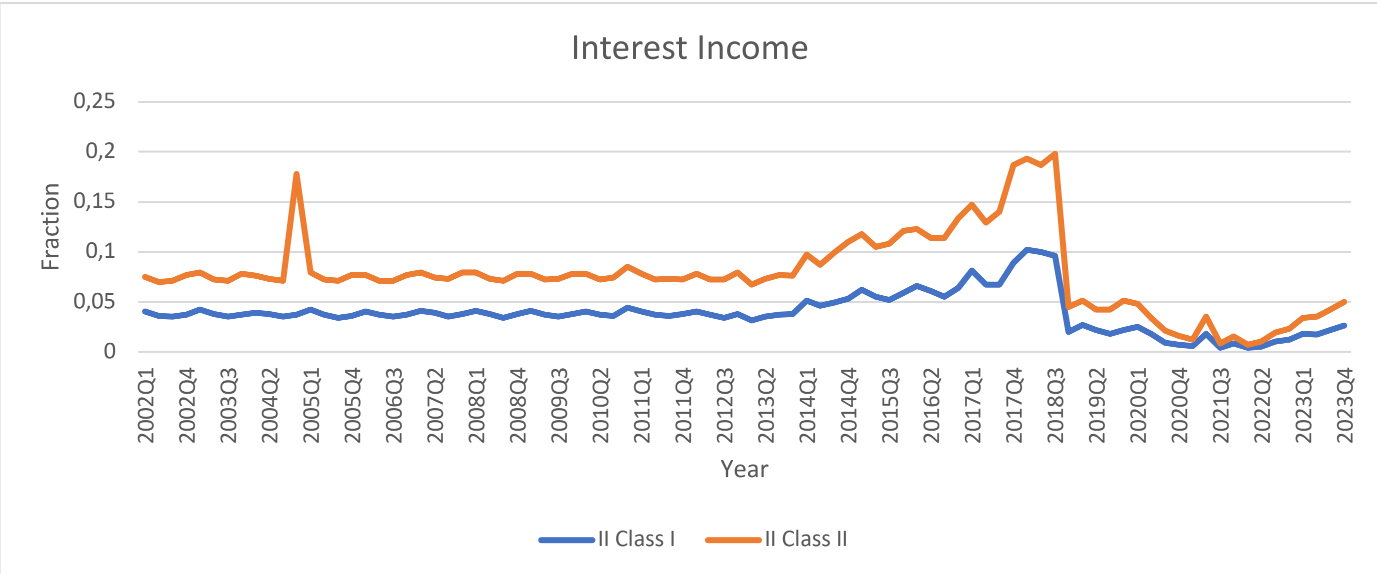
Motivated by the 2007-2009 financial crisis, there exist an ever-growing body of literature on bank liquidity and the factor that influence bank liquidity. Due to the deficiencies identified during the financial crisis the Basel Committee on Banking Supervision (BCBS) imposed different requirements that must be met through the BASEL models. The liquidity framework post financial crisis enhanced banking stability by imposing stricter liquidity requirement (Sidhu et al., 2022). Banks are required to hold liquidity, in view of the fact that if there is an unforeseen rise in customer demand, banks may face liquidity pressure which might lead the way to a crisis in the banking system altogether (Singh & Sharma, 2016).

Liquidity hazard (proxied by Interest Income)

The Basel committee defines liquidity as the ability of banks to fund increases in assets and meet obligations as it becomes due, without sustaining intolerable losses (Tammenga & Haarman, 2020). Whereby, liquidity risk is the potential inability of a bank to punctually and in a cost effective and manner meet its expected contractual payment obligations when they are due (Ruozi & Ferrari, 2013). The central function of banks in any economy is financial intermediation, naturally vulnerable to liquidity risk of both market and institutional-specific nature (Mpundu 2016). Sustaining a balanced level of liquidity is critical from both an economic and individual entity view for banks (Sidhu et al., 2022).

Ruozi & Ferrari (2013), p7 stated that the goals of liquidity management are, *"To ensure at all times an adequate corresponding balance between cash inflows and cash outflows, thus guaranteeing the solvency of the bank; to coordinate the issuing by the bank of short, medium and long term financing instruments; to optimise the costs of refinancing, striking a trade-off balance between liquidity and profitability; to optimise, for banks structured as banking groups, the intra-group management of cash flows, with the aim of reducing dependence on external financial requirements, by means of cash pooling techniques or other optimisation instruments."* In the preceding paragraphs the different requirements introduced to mitigate liquidity risk will be discussed.

Figure 1: Interest Income



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Liquidity coverage ratio (LCR)

One of the liquidity standards known as Liquidity coverage ratio (LCR) was introduced by the Basel III (Sitepu, 2020). LCR was introduced as a regulatory standard to expand bank liquidity (Shahchera & Taheri, 2017). Liquidity risk is addressed by the liquidity coverage ratio (LCR), the LCR demand banks to maintain sufficient high-quality assets stock relative to projected short-term flows (Sidhu et al., 2022). The LCR is calculated as;

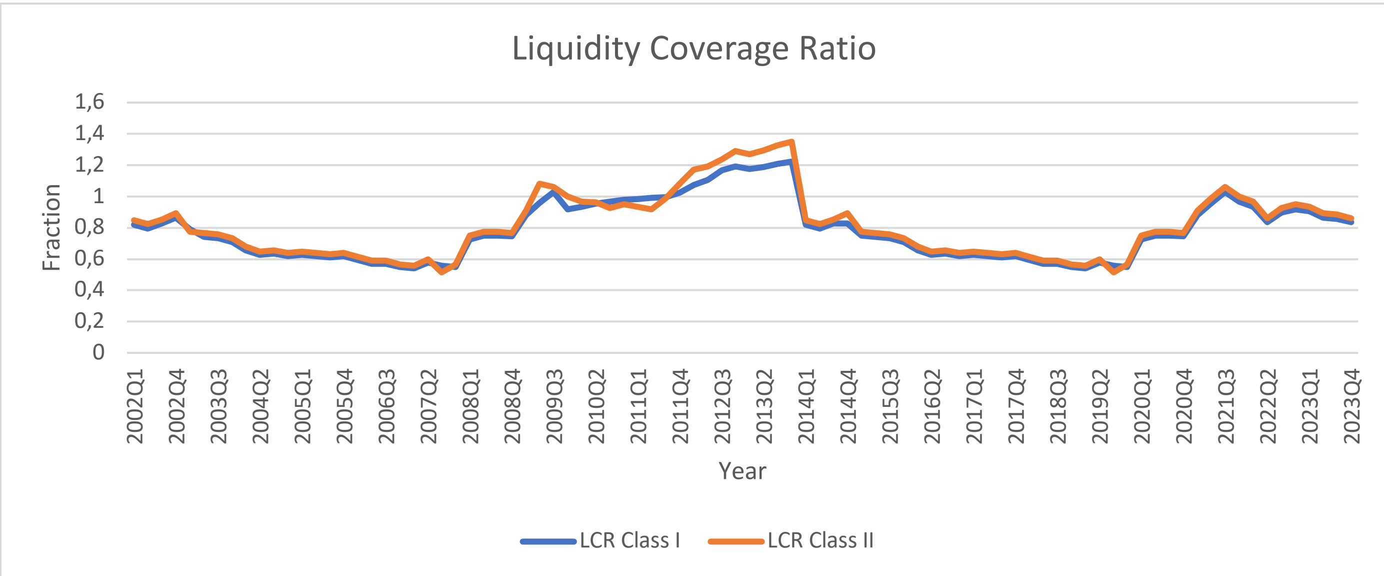
$$LCR = \left(\frac{Value\ of\ High-Quality\ Liquid\ Assets\ (HQLA)}{Total\ Net\ Cash\ Outflows\ Over\ the\ Next\ 30\ Calendar\ Days}\right) \times 100$$

Tammenga and Haarman (2020) investigated whether the introduction of LCR led to better liquidity risk management amongst banks. Based on their findings the argue that the introduction of LCR led to better liquidity risk management for the majority of financial institutions. Further they argue that liquidity risk can be mitigated more when the consistency of the LCR is improved further by refining the regulations.

The study by Sidhu et al., (2022) found that the regulatory pressure that emerged from the liquidity coverage ratio (LCR) improved bank profitability, thereby improving bank performance. Moreover, the study found that higher liquidity levels improved bank profitability, however beyond a certain mark, holding a greater amount of liquid assets leads to a decline in the bank's profitability as liquidity is increased. It was also found that an increase in LCR and its components inflates the funding cost, and this has a damaging effect on the performance of banks. Thus, while liquidity decreases the liquidity risk faced by banks it comes at the cost of profitability.

The study by Shahchera & Taheri (2017), utilised the new liquidity ratio (LCR) introduced by the Basel III to determine the influence of the ratio on banking system stability. The study found that LCR has a notable impact on stability. Whereby it reduces liquidity risk and better the short-term liquidity risk in markets. It was also found that banks with an increased LCR can alter their balance sheets and increase their LCR to agreeing with the BASEL III requirement (LCR=1). The study depicts that a high level of liquidity increases bank stability and therefore concluded a bank with more liquid assets can confront a crisis.

Figure 2: Liquidity Coverage Ratio



Source: Author compilation (2025)

Net stable funding ratio (NSFR)

The net stable funding ratio (NSFR) was introduced to encourage financial stability under the Basel III (Le et al., 2020). The NSFR is a new Basel III liquidity requirement designed to limit funding risk emerging from maturity mismatches between bank assets and liabilities (King, 2013). The NSFR concentrate on funding risk and encourages long-term bank stability by urging more stable and safer funding sources (Mpundu 2017).

$$Required\ amount\ of\ Stable\ Funding = \left(\sum_{i=1}^{n} Carrying\ value\ of\ asset_i \times Factor_i\right) + \left(\sum_{i=1}^{m} off\ balance\ sheet_i \times Factor_i\right)$$

$where\ n = Number\ of\ asset\ accounts$

$m = Number\ of\ balance\ sheet\ accounts$

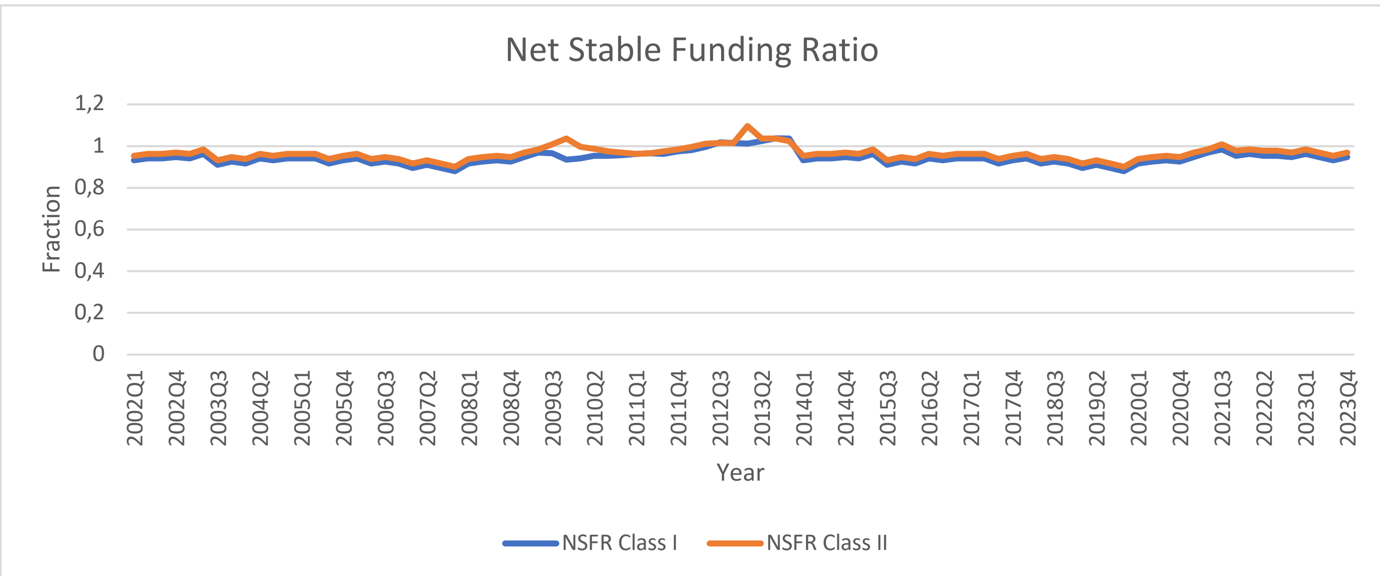
Therefore;

$$NSFR = \left(\frac{Available\ amount\ of\ stable\ funding}{Required\ amount\ of\ stable\ funding}\right) \geq 100\%$$

The studies by Sidhu et al. (2022) and Le et al., (2020) examined the influence of NSFR on the performance and profitability of banks. The two studies concluded that a small increase in the liquidity aid in increasing a banks profit efficiency (thereby reducing profit inefficiency) but increasing liquidity to a greater extent increases inefficiency of banks. However, positively a higher level of NSFR negatively influenced profit inefficiency (Sidhu et al., 2022). When studying the profitability, it was found that though NSFR has no impact on banks return on assets (ROA), it does affect the Net Interest Margins (NIMs) of banks. The results depict an inverse relationship between liquidity/NSFR and NIMS of banks.

King (2013) estimated the NSFR for banks in 15 countries and found that banks exhibited different possible behavioural responses liquidity regulations. Banks may decide to change the composition of their investments, shrink their balance sheets, and change the maturity or composition of their loans. The fore mentioned strategies will have an impact on the broader economy. The study also emphasized that there exists a trade-off between liquidity regulation, bank risk and profitability. Banks may engage in riskier activities or reduce traditional activities such as liquidity creation and market making due to lack of liquidity regulation experience, leading to unintended consequences.

Figure 3: Net Stable Funding Ratio



Source: Author compilation (2025)

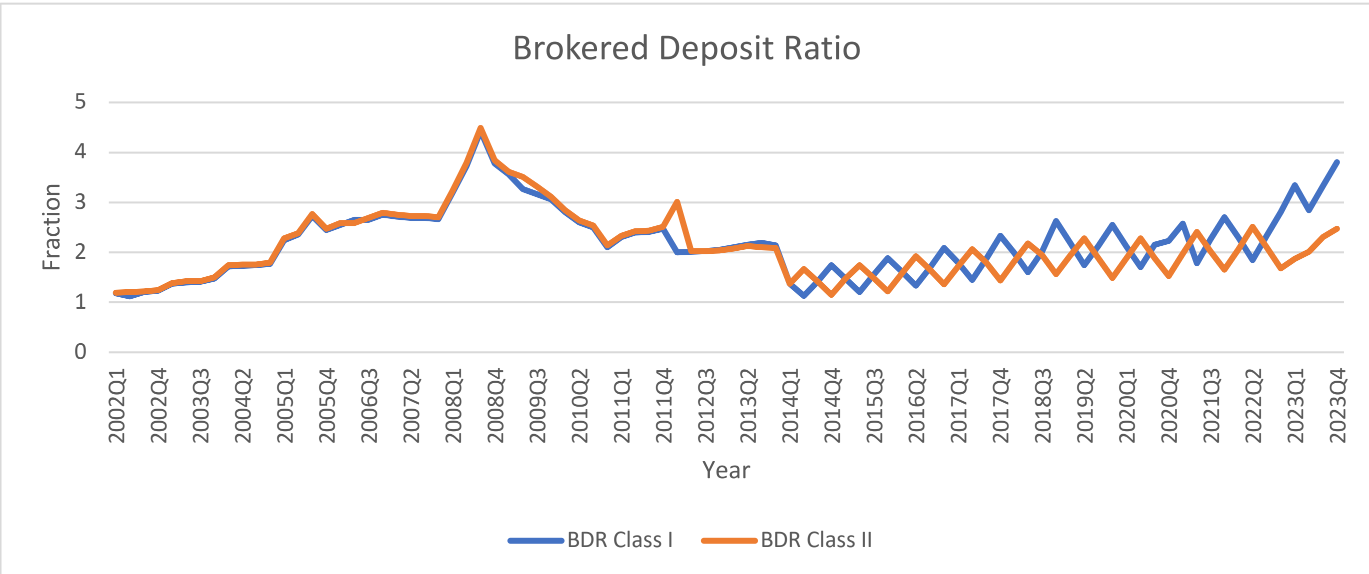
Brokered deposit ratio (BDR)

In the early 1960's brokered deposits made it appearance with the development of electronic fund transfers (EFTs), which made it possible to exchange funds at a high speed across great distances at hardly any cost (Barth et al., 2020).

The study by Rossi (n.d.) and Mpundu *et. al* (2013) found that brokered deposits play an indirect role in explaining bank failure, factors such as asset growth and risk taking that lead to greater losses are some of the primary sources of insolvency. The empirical evidence also found that brokered deposits are not a significant factor to predicts risk.

Lu & Whidbee (2013) examined the impact holding company structure, charter type and measures of bank fragility on the likelihood of bank failure for the financial crisis late 2000's. They found that established banks were more likely to fail if they had relatively low capital rations, they were relatively large institutions, with low liquidity and relied on brokerage deposits.

Figure 4: Brokered Deposit Ratio



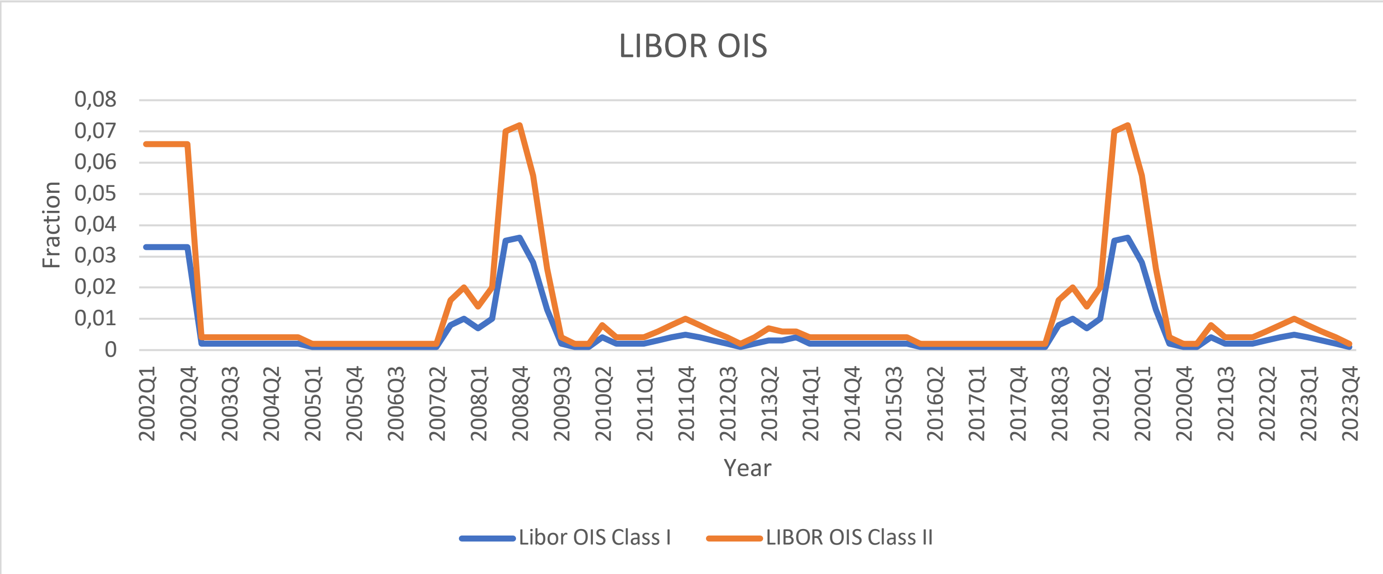
Source: Author compilation (2025)

London Inter-Bank offered rate (Libor) and Overnight Index swap (OIS)

The LIBOR and IOS is closely examined in several studies. The London Inter-Bank offered rate (LIBOR) is defined as the benchmark interest rate widely used, it reflects the average rate at which banks can borrow unsecured funds from other banks (Snider & Youle, 2010). The overnight index swap exchanges the uncollateralized overnight call rate over a specified period and at a fixed interest rate (Ooka et al., 2006). The IOS allows financial institutions to perform more precise risk management compared to other hedging tools.

Gefang et al., (2011) developed a structured dynamic model to study the spreads between Libor and overnight index swap (IOS) rates for a panel of banks and studied the effects of liquidity risk and credit risk on these rates. It was found that surges in the short-term LIBOR-IOS spread was largely driven by liquidity risk during the financial crisis, whereby credit risk had a greater impact over the long term. Eross et al. (2016) studied the liquidity risk contagion within the interbank market by examining the associations of short-term interest spreads. They found that when liquidity shocks affected the short-term interbank market, the leader in moving back to equilibrium level was the Libor-IOS spread followed by the euro-dollar currency swap rate and the US-German bond spreads. The study concluded that liquidity shocks spreading within the interbank market can predict benchmark interest movements.

Figure 5: London Interbank Offered Ratio OIS



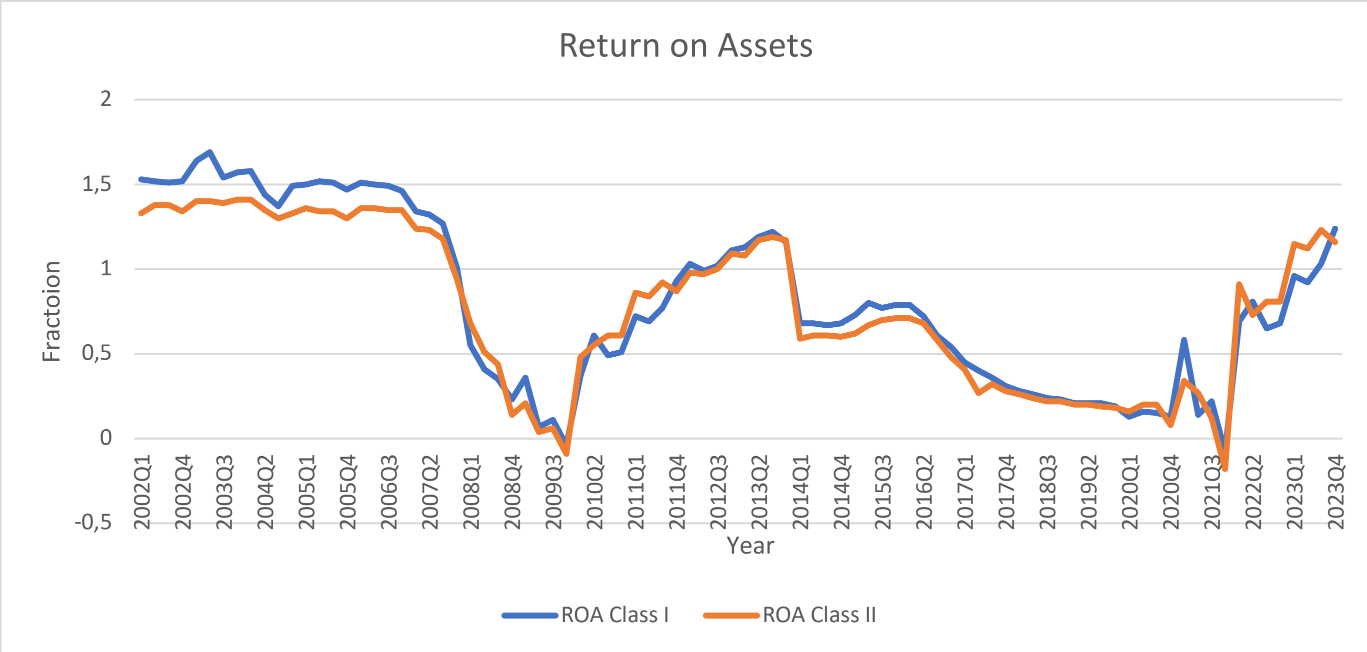
Source: Author compilation (2025)

Return on assets (ROA)

Return on assets (ROA) is a financial ratio that constitute the percentage of profit that banks earn in relation to their total assets (Singh & Sharma, 2016). A high ROA depicts that a bank has adequate ability to manage its assets in achieving profitability (Sitepu, 2020). According to Sitepu (2020) on the grounds of Agency Theory, it can be understood that management will tend to increase profitability by assigning liquidity to productive assets. Furthermore, there will be a reduction in liquidity reserves by transferring it into the productive assets, which displays that ROA is inversely proportional to Liquidity Coverage Ratio.

Warrad & Box (2015) studied whether liquidity through quick ratio has a significant influence on bank profitability of Jordian banks through ROA. The statical results of the study concluded there exist a significant influence of independent variable quick ratio on the dependent variable ROA. In other words, this means that liquidity significantly influences the profitability of Jordanian banks.

Figure 6: Return on Assets



Source: Author compilation (2025)

3. Methodology

Objective

To determine the liquidity hazard model of 155 Class I and Class II banks during the period 2002 to 2023 using quarterly bank related data.

Question/Hypothesis

How can the study determine a liquidity hazard model for 155 Class I and Class II banks during the period 2002Q1 to 2023Q4 using quarterly bank data?

$H_0 = A\ liquidity\ Hazard\ model\ does\ not\ exist\ in\ Class\ I\ and\ II\ Banks\ during\ the\ period\ 2002Q1\ to\ 2023Q4$

$H_1 = A\ liquidity\ Hazard\ model\ exists\ in\ Class\ I\ and\ II\ Banks\ during\ the\ period\ 2002Q1\ to\ 2023Q4$

Data

Liquidity Hazard (proxied by ***Interest Income***), Liquidity coverage ratio (LCR), Net stable funding ratio (NSFR), Brokered deposit ratio (BDR), London Inter-Bank offered rate (Libor), Overnight Index swap (OIS), Return on assets (ROA)

Quarterly data was used ranging from 2002Q1 to 2023Q4 obtained from the Reserve Bank of St. Louis and the Bank for international settlements database. This related into 176 observations combined.

Proposed Method

A pooled OLS regression model was applied using panel analysis.

Model

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots \ldots . \beta_n X_{nit} + \varepsilon_{it} \qquad (1)$$

The pooled OLS estimator is based on the time demeaned variables is fixed effect or within estimator.
Assuming;

1. Regression coefficients are the same for all banks (Class I and II))
2. Regressors are non-stochastic i.e. errors are not correlated with explanatory variables $Cov\ (v_{it}, X_{it}) = 0$
3. Error term, $v_{it} \sim iid(0, \sigma_v^2)$

Hence;

$$II_{it} = \beta_0 + \beta_1 LCR_{it} + \beta_2 NSFR_{it} + \beta_3 BDR_{it} + \beta_4 Libor\ OIS_{it} + \beta_5 ROA_{it} + \varepsilon_{it} \qquad (2)$$

Hazard Rate $\lambda(t)$ = risk of liquidity event

$$\lambda(t) = f(LCR, NSFR, BDR, LIBOR\ OIS, ROA) \qquad (3)$$

Liquidity survival:

$$S(t) = e^{-\int_0^t \lambda(u)du} \qquad (4)$$

The probability that the bank does not face liquidity shortage until time t

Motivation for choosing Pooled OLS panel approach

- Efficiency with homogeneous effects: If the relationship between variables is truly constant across all individuals and time periods, and there is no unobserved heterogeneity, pooled OLS is the most efficient estimator available, producing estimates with the smallest variance.
- Larger dataset: By combining all observations, the pooled approach increases the total sample size, which can be beneficial when working with a limited number of units over a short period. This can increase statistical power, allowing for the detection of smaller effects

Limitations of the Pooled OLS panel approach

- Ignoring unobserved heterogeneity: The primary drawback is that pooled OLS cannot account for unobserved, time-invariant individual characteristics (e.g., managerial skill in a study of firms, or motivation in a study of individuals). This can lead to omitted variable bias if these individual characteristics are correlated with other independent variables.
- Biased estimates: When the unobserved individual-specific effects are correlated with the independent variables, pooled OLS produces biased results. Fixed effects models are specifically designed to address this endogeneity problem.

In choosing the right model, a consideration is made on the research question, if the core research question in the study involves a time-invariant variable (e.g., the effect of gender), the study cannot use a fixed effects model, as the variable will be removed. In this case, a random effects model might be an option if the Hausman test shows it is appropriate. However, since such variables are not considered in this study, the pooled OLS model is the easiest panel model to estimate and interpret. It treats all observations as if they came from one large cross-sectional dataset.

4. Analysis and Interpretation

Table 1: Descriptive Statistics

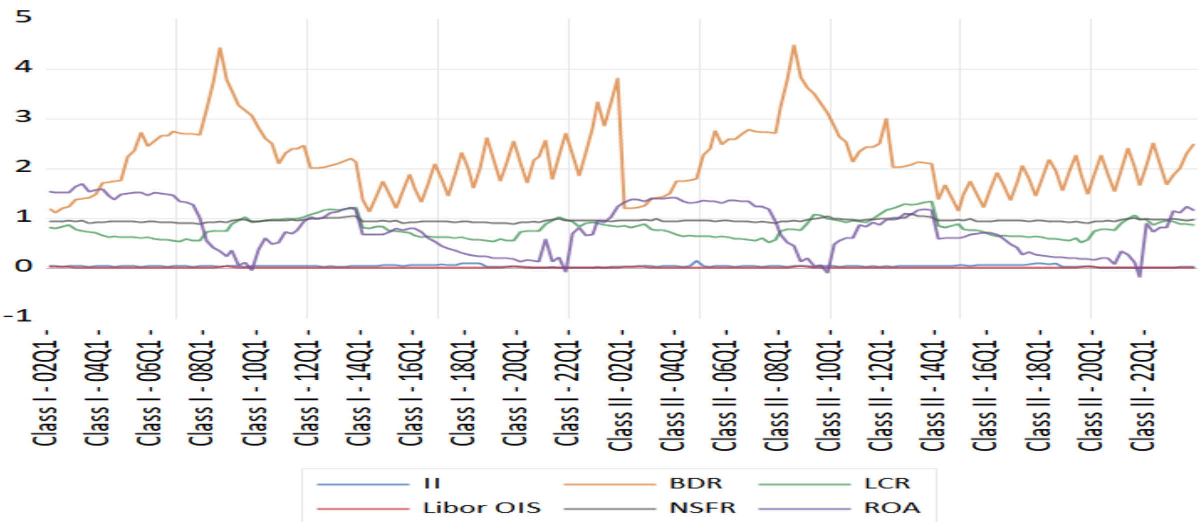
Date: 07/16/25 Time: 12:59
Sample: 2002Q1 2023Q4

	II	LCR	NSFR	LIBOR OIS	BDR	ROA
Mean	0.038875	0.800859	0.953698	0.006381	2.183012	0.791534
Median	0.037000	0.766080	0.947520	0.002000	2.098340	0.725000
Maximum	0.141000	1.350020	1.096430	0.036000	4.491220	1.690000
Minimum	0.003000	0.514560	0.879840	0.001000	1.119600	-0.180000
Std. Dev.	0.020910	0.197217	0.033112	0.009968	0.674324	0.485024
Skewness	1.372816	0.693793	0.867163	2.182387	0.812068	0.032540
Kurtosis	6.866876	2.817203	4.758832	6.243663	3.678007	1.754427
Jarque-Bera	164.9357	14.36462	44.74342	216.8657	22.71507	11.40837
Probability	0.000000	0.000760	0.000000	0.000000	0.000012	0.003332
Sum	6.842000	140.9512	167.8508	1.123000	384.2101	139.3100
Sum Sq.	0.342498	119.6885	160.2707	0.024555	918.3102	151.4371
Sum Sq. Dev.	0.076515	6.806524	0.191867	0.017389	79.57478	41.16849
Observations	176	176	176	176	176	176

All six log-transformed series show moderate dispersion around their means respectively, with standard deviations ranging from 0.0099 (LIBOR OIS) to 0.6743 (BDR). These means closely mirror medians, II (mean 0.0388; median 0.3700), NSFR (0.9536; 0.9475), LIBOR (0.0063; 0.0020), ROA (0.791534; 0.7250), this shows symmetric central tendencies. the skewness values are between 0.0325 (ROA) and 2.1823 (LIBOR OIS), which indicates a bit of asymmetry. Three kurtosis values are below three except for II (6.8668), NSFR (4.7588) and 6.2436 (LIBOR OIS) which points to heavier tails and more extreme observations.

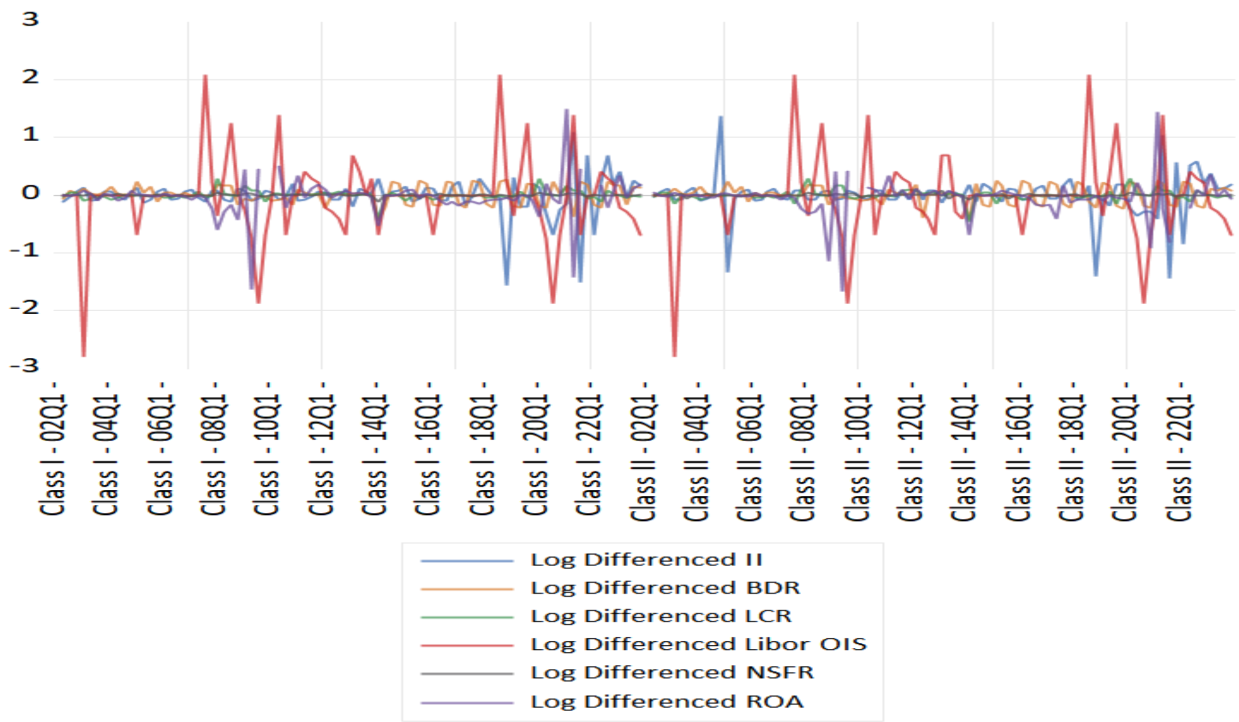
Jarque–Bera tests highlight deviations from normality for LIBOR_OIS (216.8657; p = 0.0000) and II (164.9357; p = 0.0000). The other variables also follow the same trend at 5% level of significance.

Figure 7: Non-Stationary Data at Default



According to Figure 7, the data set was non-stationary at default. Results show the variables reverting away from the zero mean. The variables where then changed for ease of analysis and comparability into logs.

Figure 8: Stationary Data after 1st Difference



The data becomes stationary at 1st difference and after having been converted into logs. The mean reverts along the zero mean.

Figure 8 illustrates how the mean, variance, and correlation become constant over time when the factors are differentiated and become stationary. The white noise method no longer exhibits trending behaviour, and the deviation from the mean remains constant. Without specifying whether variables are stationary at first difference or second difference, the visual assessment in Figures 7 and 8 just indicates that they are stationary when differenced.

The results form Table 2 show regression is statistically significant for BDR, LCR and NSFR with F-statistic given as 7.787 and $P < 0.05$. About 21% of the variation in Interest income is explained by the model. The NSFR has a positive impact on II while BDR, LCR, LIBOR OIS and ROA have negative impact. Three of the independent variables are statistically significant.

The firms having different characteristics may lead to the likelihood of heterogeneity which refers to unobserved firm-specific characteristics. An assumption is made that while these characteristics may vary across the firms, they are time-invariant such as being fixed over time. The fixed effects are hidden by lumping together the firms with different characteristics in one pooled OLS estimation.

Table 2: Panel Least Squares Results

Dependent Variable. Method: Panel Least Squares Sample; 2002Q1 2023Q4 Periods 88 Cross-sections included: 2 Total panel (balanced) observations: 176				
Variable	Coefficient	Std. Error	t-statistic	Prob.
C	-0.215248	0.082540	-2.607809	0.0099
BDR	-0.005394	0.002182	-2.471747	0.0144
LCR	-0.078997	0.015010	-5.262946	0.0000
LIBOR OIS	-0.166753	0.152357	-1.094489	0.2753
NSFR	0.350237	0.096769	3.619307	0.0004
ROA	-0.004792	0.003038	-1.577415	0.1166
Effects Specification				
Cross-section fixed (dummy variables)				
R-squared	0.216585	Mean dependent var	0.038875	
Adjusted R-squared	0.188772	S.D. dependent var	0.020910	
S.E. of regression	0.018833	Akaike info criterion	-5.067420	
Sum squared resid	0.059943	Schwarz criterion	-4.941321	
Log likelihood	452.9330	Hannan-Quinn criter	-5.016275	
F-statistic	7.787054	Durbin-Watson stat	0.748707	
Prob(F-statistic)	0.000000			

Table 3: Wald Test

Test Statistic	Value	df	Probability
t-statistic	0.272203	89	0.7861
F-statistic	0.074094	(1, 89)	0.7861
Chi-square	0.074094	1	0.7855

Null Hypothesis: C(1) = 0

The F-statistic and the Chi-square show that the probability values are insignificant as they are greater than 0.05. Given that the X^2 statistic is insignificant (p-value > 0.05), the H_0 is accepted and a conclusion can be made that the pooled OLS model is more appropriate than the FE-LSDV model. Accounting for heterogeneity is therefore not important in determining how BDR, LCR, LIBOR OIS, NSFR and ROA jointly affect II. The reason could be because of the number of firms considered in this study which is two, the Class I and Class II banks. The firms differ in capital requirements, location, management philosophy, board diversity and corporate structure.

Relevance of using the Wald test in OLS pooled method

The Wald test is a useful tool for evaluating the significance of coefficients and for testing multiple linear restrictions on those coefficients.

- **Single model estimation:** Unlike the likelihood-ratio (LR) test, which requires estimating both a restricted and an unrestricted model, the Wald test only requires the estimation of the unrestricted, or "full," model.
- **Joint significance:** The Wald test can be used to determine if a group of independent variables is jointly significant. The null hypothesis is that all coefficients for a specified group of variables are simultaneously equal to zero. This is valuable for assessing the overall contribution of a set of related predictors (e.g., a set of dummy variables).
- **Variable selection:** If the Wald test indicates that a set of variables is not jointly significant, those variables can potentially be removed from the model without a significant loss of explanatory power. This helps in building a more parsimonious and efficient model.

Limitation of Wald test

- **Comparison to other tests:** In cases where the pooled OLS model is questionable, diagnostic tests like the F-test for fixed effects (which is a form of a Wald test on entity dummy variables) or the Hausman test are necessary to justify the use of pooled OLS over fixed or random effects.

5. Conclusion

A higher brokered deposit ratio may provide banks with increased funding capacity, allowing them to extend more loans or invest in higher-yield assets, thereby potentially boosting interest income. However, this comes with increased risk and cost. For Class I banks, which typically have stronger balance sheets and more stable funding sources, the use of brokered deposits appears to be more strategic and may contribute positively to interest income when managed prudently. In contrast, Class II banks, often smaller or less diversified, may rely more heavily on brokered deposits out of necessity, which can lead to a higher cost of funds and potentially narrower net interest margins. While there is an inherent **inverse relationship** between holding liquidity (to meet LCR requirements) and maximizing interest income, effective asset-liability management can mitigate this tension. The impact varies by bank class, with Class I banks better equipped to manage this balance, whereas Class II banks may face more pronounced trade-offs between profitability and liquidity compliance. The relationship between Interest Income and the LIBOR-OIS spread reveals important insights into the risk sensitivity and funding dynamics of Class I and Class II banks. For **Class I banks**, which typically include globally systemic institutions with diversified operations and robust liquidity buffers, the impact of changes in the LIBOR-OIS spread on Interest Income tends to be more moderate. These banks are often better positioned to absorb market stress, adjust their lending strategies, and benefit from rising spreads through higher lending rates. **Class I banks**, which are generally smaller and less diversified, exhibit a stronger sensitivity to fluctuations in the LIBOR-OIS spread. In periods of widening spreads indicative of heightened interbank credit risk.

Maintaining a healthy NSFR supports sustainable interest income by ensuring that funding mismatches are minimized, thereby allowing banks to focus on core lending and investment activities with reduced risk. The dynamic between funding stability and interest-generating capacity highlights the importance of strategic balance sheet management, especially in differing regulatory and operational contexts of Class I and Class II banks. Class I banks, typically larger with diversified portfolios, tend to exhibit more stable but sometimes lower ROA due to broader risk exposure and conservative lending practices. In contrast, Class II banks, often smaller and more specialized, may show higher ROA driven by niche market focus and agility, albeit with greater variability. A liquidity harzard model does exist in the Class I and II banks pre and post the financial and health crises.

Recommendation

Prior to the 2007 crisis, the Basel II framework was in place, focusing on risk-sensitive capital adequacy requirements. However, it lacked stringent liquidity provisions, which became evident during the crisis when banks faced significant liquidity shortfalls despite adequate capital. During the COVID-19 pandemic, many banks experienced structural excess liquidity, with daily excess reserves averaging significant amounts. However, the volatility of these reserves posed challenges, as sudden shifts could impact liquidity positions. The pooled OLS regression based on the data used in this paper has highlighted three of the independent variables are significant to the probability of banks facing a liquidity shortage. Consumer behavior in bank deposits and safe investments are not usually assured. More regulation and capital requirements should be encouraged through supervision both in complex large banks (Class I) and smaller banks (Class II).

Implications for policy

- **Continued focus on liquidity:** Regulators must continue to strengthen liquidity requirements, going beyond the capital-centric approach of Basel II. The 2007 crisis exposed a fundamental weakness where sufficient capital did not guarantee liquidity during a panic. Post-crisis frameworks like Basel III addressed this with requirements such as the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). The statement implies that policymakers need to remain vigilant and potentially refine these rules as new risks, like those seen during COVID-19, emerge.
- **Tiered regulation:** The call for differentiated supervision between large, complex banks (Class I) and smaller banks (Class II) reflects a practical approach to regulation. It suggests that a one-size-fits-all model is inefficient and potentially ineffective. Larger banks often pose systemic risks and require more stringent oversight, while smaller banks may face disproportionate compliance burdens from overly complex rules.
- **Dynamic liquidity management:** Banks cannot manage liquidity with a static, rules-based approach. The experience of the pandemic, with its excess liquidity and volatility, highlights the need for dynamic, adaptive liquidity management strategies. Banks must be prepared to handle both liquidity shortages, as in 2007, and unexpected surpluses, as in 2020.
- **Enhanced stress testing:** Stress tests should simulate a wider range of scenarios, including both credit and liquidity shocks, but also rapid shifts in consumer behavior. This would better prepare banks for real-world crises that don't fit neatly into traditional risk categories.

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