Econometric Modeling for Liquidity Stress Testing Under Basel III: A Dynamic Panel Data Approach

(Authors Details)
Ashish Sharma
Independent Researcher, United States
Email: er.a.sharma119@gmail.com

Abstract
With the advent of Basel III banking regulatory standards and the growing complexity of financial markets, banking institutions have incorporated liquidity risk as a key consideration. The importance of effective liquidity stress testing for assessing a bank's capacity to absorb adverse economic and financial conditions and to sustain its funding and operations. This study sets up an econometric framework for liquidity stress testing based on dynamic panel data model and discusses the factors that affect the liquidity resilience of banking institutions. The proposed model includes both financial variables related to the bank and macroeconomic variables, in order to reflect the persistence and dynamics of the liquidity situation over time. To overcome the endogeneity, unobserved heterogeneity and serial dependence problems, dynamic panel estimation methods are used to achieve greater reliability in empirical estimates. This framework assesses the impact of sources and uses of liquidity, capital levels, profitability, funding structure and macro-economic conditions on the liquidity stress under various stress scenarios. The results should be solid for the purposes of improving liquidity risk management, improving the macroprudential supervision framework and for regulatory decision making. The study adds to the literature by providing an integrated econometric model that can aid in the ability to more accurately predict liquidity stress-test outcomes and enhance resilience in the financial system in the current and future regulatory and economic landscapes.

Keywords: Basel III, Liquidity Stress Testing, Dynamic Panel Data, Econometric Modeling, Liquidity Coverage Ratio, Net Stable Funding Ratio, Banking Stability, Generalized Method of Moments (GMM), Financial Risk Management, Macroprudential Regulation.

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I. Introduction

1.1 Background of the Study

Financial stability is a key aspect of maintaining economic growth, and the strength of banking sector is vital to that. The role of banks in mobilizing deposits, extending credit, and making payments is very important. But the past insurance crises have shown that a lack of liquidity can easily lead to a loss of trust in financial institutions, "contagion" among financial institutions and a jeopardy of national and international financial systems. The global financial crisis accentuated a number of issues with liquidity risk management and led to the implementation of more stringent prudential requirements by the international regulatory bodies under the Basel III regime. The reforms brought in new comprehensive liquidity requirements, which aimed to ensure that banks have sufficient high quality liquid assets and stable funding structures that can sustain them in times of financial stress (Mashamba, 2018; Van den End, 2012).

Basel III's two important liquidity requirements are the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The LCR aims to ensure banks' ability to withstand a dramatic loss of liquidity in the short term, while the NSFR aims to promote more stable funding patterns of banks, by limiting the use of short-term funding sources that attract more volatile funding. In combination, these regulatory measures are expected to increase the ability of banks to withstand liquidity shocks, lessen systemic vulnerabilities and increase confidence in the global banking system (Mashamba, 2018; Petrella & Resti, 2017).

Although the regulatory changes have made significant strides, liquidity risk is perhaps one of the more complex types of financial risk as it also changes over time according to the specific nature of the institution and macroeconomic factors. A range of events, such as market disruptions, interest rate volatility, falling asset values, reductions in funding and weakening economic conditions, can impact liquidity positions at various financial institutions simultaneously. This has led to an increasing focus on stress testing as a key supervisory tool to evaluate banking sector resilience in the face of adverse stresses (Sorge, 2004, Foglia, 2008).

Stress testing has grown from sensitivity analysis to a more robust macroprudential risk assessment process that can assess the stability of the banking system exposed to extreme but credible economic conditions. In today's framework of stress testing, macroeconomic shocks are combined with financial measures to calculate the potential for losses, funding gaps and capital inadequacy in financial crises. In addition, macroprudential stress testing examines the risks that banks face not only individually, but as they connect to each other (Onder et al., 2016; Fragkou, 2020).

Basel III liquidity stress test demands analytical techniques that are able to capture the dynamic relationship between the liquidity indicators and the regulatory variables and the macroeconomic conditions. The classical regression approach can be inadequate in accounting for persistence in the liquidity behavior, for dynamic adjustment processes, as well as for unobserved institutional differences. These restrictions make traditional stress-testing models less reliable at predicting stress if liquidity conditions change quickly in a crisis (Van den End, 2012).

These intricate relationships can be captured in a rigorous statistical framework using econometric modeling. Dynamic panel data models in particular have become a very important tool to use in a banking context, as they combine time-series dynamics and cross-sectional differences between financial institutions. Dynamic panel estimators, such as Difference Generalized Method of Moments (Difference GMM) and System Generalized Method of Moments (System GMM), are able to deal with endogeneity, omitted variable bias, and autocorrelation and provide more consistent and reliable estimates of banking behavior (Trabelsi & Trad, 2017).

Dynamic panel methodologies are especially suitable for liquidity stress testing as the state of liquidity in the present affects the liquidity state in the past, regulatory requirements, funding strategies, profitability, capital adequacy and the prevailing macroeconomic environment. Dynamic panel models include lagged dependent variables and macroeconomic and bank-specific variables, thus providing more realistic estimates of liquidity resilience across different stress scenarios (Trabelsi & Trad, 2017; Onder et al., 2016).

Additionally, Basel III has moved the supervisory eye towards future risk management instead of looking solely at past financial results. Stress testing is now part of the regulatory decision-making process, allowing supervisors to assess the effectiveness of liquidity regulations, identify vulnerabilities in banking systems and take timely macroprudential decisions. Research results have shown that the more stringent the Basel III liquidity requirements, the lower the likelihood of default, the greater the financial stability of banks and the more resilient the banking system becomes during a crisis (Giordana & Schumacher, 2017; Mashamba, 2018).

Due to the complexity of bank operations, growing financial market integration and changing macroeconomic risks, banks need to rely on more advanced econometric techniques to meet the requirements of evidence-based liquidity regulation. Dynamic panel data modeling provides a powerful tool for implementing more sophisticated analysis of Basel III liquidity indicators and macroeconomic indicators and thus strengthens the predictive accuracy of liquidity stress-testing exercises and the supervision of the financial sector (Fragkou, 2020; Van den End, 2012; Engelmann & Rauhmeier, 2011).

This study thus suggests an econometric framework of liquidity stress test for Basel III based on dynamic panel data method. The framework seeks to identify the principal determinants of liquidity stress, evaluate the persistence of liquidity dynamics across banking institutions, and examine how macroeconomic shocks interact with regulatory liquidity measures to influence banking sector stability. The findings are expected to contribute to both academic research and financial regulatory practice by providing a comprehensive empirical model capable of supporting more effective liquidity risk management and macroprudential policy formulation.

1.2 Problem Statement

Although Basel III has significantly strengthened international liquidity regulation through the introduction of the Liquidity Coverage Ratio and Net Stable Funding Ratio, accurately assessing banks' resilience under adverse financial conditions remains a major challenge. Conventional liquidity stress-testing models frequently rely on static analytical techniques that inadequately

Table 1. Basel III liquidity indicators and expected economic effects

Basel III Indicator	Definition	Role in Liquidity Stress Testing	Expected Economic Effect	Econometric Variable Classification
Liquidity Coverage Ratio (LCR)	Ratio of High-Quality Liquid Assets to projected 30-day net cash outflows	Measures short-term liquidity resilience	Higher LCR reduces liquidity stress and improves shock absorption	Dependent/Performance Variable
Net Stable Funding Ratio (NSFR)	Ratio of available stable funding to required stable funding over one year	Measures long-term funding stability	Higher NSFR strengthens funding resilience and lowers liquidity risk	Independent Variable
Capital Adequacy Ratio (CAR)	Regulatory capital relative to risk-weighted assets	Indicates capital buffer available during stress	Higher CAR enhances financial stability and reduces systemic risk	Control Variable
Loan-to-Deposit Ratio (LDR)	Total loans divided by total customer deposits	Measures funding aggressiveness	Higher LDR increases liquidity pressure and refinancing risk	Independent Variable
Non-Performing Loan Ratio (NPL)	Impaired loans as a percentage of total loans	Reflects credit quality deterioration	Higher NPL weakens liquidity through declining asset quality	Independent Variable
Return on Assets (ROA)	Net income divided by total assets	Measures operational profitability	Higher profitability improves internally generated liquidity	Control Variable
GDP Growth Rate	Annual percentage growth in Gross Domestic Product	Captures macroeconomic conditions	Stronger economic growth improves banking sector liquidity	Macroeconomic Variable

Inflation Rate	Annual percentage increase in consumer prices	Represents price stability and purchasing power	Higher inflation may reduce liquidity through increased funding costs	Macroeconomic Variable
Policy Interest Rate	Central bank benchmark lending rate	Reflects monetary policy stance	Higher interest rates increase funding costs and liquidity risk	Macroeconomic Variable
Liquidity Stress Index	Composite indicator measuring overall liquidity vulnerability	Evaluates banking resilience under stress scenarios	Higher values indicate greater liquidity vulnerability	Dependent Variable

capture the dynamic persistence of liquidity behavior, institutional heterogeneity, and endogeneity among financial variables. Such limitations reduce the reliability of stress-testing outcomes and may underestimate systemic vulnerabilities during periods of economic uncertainty (Van den End, 2012; Fragkou, 2020).

Furthermore, liquidity conditions are influenced simultaneously by bank-specific financial characteristics and macroeconomic shocks, including fluctuations in economic growth, inflation, interest rates, and funding market conditions. Existing stress-testing approaches often fail to integrate these dynamic interactions within a unified econometric framework, thereby limiting their usefulness for regulatory supervision and policy formulation (Onder et al., 2016; Sorge, 2004). Consequently, there is a need for a dynamic panel data approach capable of modeling the persistence of liquidity behavior while addressing endogeneity and cross-sectional heterogeneity. Such an approach can improve the predictive accuracy of liquidity stress tests and provide more robust evidence for Basel III implementation and macroprudential risk management.

1.3 Research Objectives

The primary objective of this study is to develop an econometric framework for liquidity stress testing under Basel III using a dynamic panel data approach.

The specific objectives are to:

1. Examine the determinants of liquidity stress among banking institutions under Basel III.
2. Develop a dynamic panel data model for evaluating liquidity resilience.
3. Assess the influence of macroeconomic shocks on banks' liquidity positions.

4. Evaluate the effectiveness of Basel III liquidity indicators in predicting liquidity stress.
5. Provide policy recommendations for improving liquidity risk management and regulatory supervision.

1.4 Research Questions

1. What factors significantly influence liquidity stress under Basel III?
2. How effective is a dynamic panel data approach in modeling liquidity stress?
3. How do macroeconomic variables affect banking sector liquidity resilience?
4. Which Basel III liquidity indicators best predict liquidity deterioration during stress scenarios?
5. How can econometric modeling improve regulatory stress-testing frameworks?

1.5 Significance of the Study

This study contributes to the growing literature on banking risk management by integrating Basel III liquidity regulations with advanced dynamic panel econometric modeling. The proposed framework provides regulators with a more reliable approach for evaluating liquidity resilience under adverse economic conditions while supporting evidence-based macroprudential supervision.

For commercial banks, the study offers a quantitative framework for improving internal liquidity risk management, optimizing funding strategies, and strengthening regulatory compliance. Policymakers may utilize the findings to refine supervisory stress-testing procedures, identify emerging systemic vulnerabilities, and enhance financial stability through more effective regulatory interventions.

From an academic perspective, the study extends existing research on liquidity stress testing by incorporating dynamic persistence, macroeconomic interactions, and econometric estimation techniques that address endogeneity and unobserved heterogeneity. This contributes to the advancement of empirical methodologies in financial risk modeling and Basel III implementation.

1.6 Scope of the Study

This study focuses on econometric modeling of liquidity stress testing within the Basel III regulatory framework using dynamic panel data techniques. The analysis considers bank-specific financial indicators, including the Liquidity Coverage Ratio, Net Stable Funding Ratio, Capital Adequacy Ratio, Loan-to-Deposit Ratio, Non-Performing Loans, and Return on Assets, together with macroeconomic variables such as GDP growth, inflation, and policy interest rates. Dynamic panel estimation methods, particularly Difference GMM and System GMM, are employed to evaluate the persistence of liquidity conditions, assess the impact of macroeconomic shocks, and enhance the predictive accuracy of liquidity stress-testing models. The study emphasizes macroprudential risk assessment and regulatory policy implications for strengthening banking sector resilience under Basel III.

II. Literature Review

2.1 Concept of Basel III Liquidity Framework

The Basel III regulatory framework was introduced to strengthen the resilience of banking institutions following the global financial crisis by establishing more stringent capital and liquidity requirements. Unlike previous regulatory frameworks that focused primarily on capital adequacy, Basel III introduced comprehensive liquidity standards designed to improve banks' ability to withstand both short-term and long-term liquidity shocks. The two principal liquidity measures are the Liquidity Coverage Ratio (LCR), which requires banks to maintain sufficient high-quality liquid assets to survive a 30-day stress scenario, and the Net Stable Funding Ratio (NSFR), which promotes sustainable long-term funding structures. These regulations aim to reduce liquidity mismatches, enhance market confidence, and minimize systemic financial risks (Mashamba, 2018; Van den End, 2012).

The implementation of Basel III has fundamentally transformed liquidity risk management by encouraging banks to adopt more conservative funding strategies and maintain adequate liquidity buffers. While compliance with these standards strengthens financial stability, it may also influence banks' profitability due to increased holding of low-yield liquid assets and higher funding costs. Consequently, researchers have emphasized the importance of evaluating liquidity regulations using robust econometric models capable of capturing dynamic interactions among financial variables (Mashamba, 2018; Giordana & Schumacher, 2017).

2.2 Liquidity Risk in Banking Systems

Liquidity risk refers to the inability of a financial institution to meet its obligations as they become due without incurring significant financial losses. Banking institutions are particularly vulnerable to liquidity shocks because they engage in maturity transformation, borrowing short-term funds while extending long-term loans. Consequently, unexpected withdrawals, market disruptions, or funding shortages may trigger liquidity crises capable of threatening both individual institutions and the broader financial system (Fragkou, 2020).

Liquidity risk is generally classified into funding liquidity risk and market liquidity risk. Funding liquidity risk arises when banks cannot secure adequate financing, whereas market liquidity risk occurs when assets cannot be sold quickly without substantial price reductions. These two forms of liquidity risk are closely interconnected, particularly during financial crises when deteriorating market conditions simultaneously reduce funding availability and asset marketability (Fragkou, 2020; Petrella & Resti, 2017).

Macroeconomic conditions further amplify liquidity risk through changes in interest rates, inflation, unemployment, and economic growth. During economic downturns, borrowers' repayment capacity weakens while deposit withdrawals increase, placing additional pressure on banks' liquidity positions. Consequently, modern liquidity stress testing increasingly incorporates macroeconomic variables alongside institution-specific indicators to evaluate resilience under adverse scenarios (Onder et al., 2016).

2.3 Liquidity Stress Testing Methodologies

Liquidity stress testing has become an essential supervisory tool for assessing banking resilience under hypothetical adverse conditions. Stress testing evaluates how financial institutions respond to severe but plausible economic shocks, thereby supporting proactive risk management and regulatory oversight. Traditional stress-testing techniques include sensitivity analysis, scenario analysis, reverse stress testing, and macroprudential stress testing (Sorge, 2004).

Sensitivity analysis evaluates the impact of changes in individual risk factors, whereas scenario analysis considers simultaneous movements across multiple macroeconomic and financial variables. Reverse stress testing identifies extreme conditions capable of causing institutional failure, thereby enabling regulators to identify vulnerabilities before crises emerge (Sorge, 2004; Foglia, 2008).

Macroprudential stress testing extends beyond individual institutions by considering systemic interactions among banks and the broader economy. Such approaches evaluate contagion effects, feedback mechanisms, and macroeconomic transmission channels, making them particularly suitable for Basel III liquidity assessment. Onder et al. (2016) demonstrated that incorporating macroeconomic variables substantially improves stress-testing accuracy, while Fragkou (2020) highlighted the critical importance of funding liquidity risk within macroprudential stress-testing frameworks.

Modern liquidity stress testing increasingly integrates econometric techniques capable of capturing persistence, feedback effects, and dynamic behavioral responses, thereby providing more realistic estimates than static analytical approaches (Van den End, 2012).

2.4 Econometric Models in Banking Risk Assessment

Econometric modeling has become a cornerstone of banking risk analysis because it enables researchers to quantify relationships among liquidity, profitability, capital adequacy, and macroeconomic variables. Static regression models provide useful insights but often ignore persistence in banking behavior, leading to biased estimates when lagged dependent variables are present.

Dynamic panel data models overcome these limitations by incorporating previous observations into current estimations while controlling for unobserved institutional heterogeneity and endogeneity. Estimation methods such as Difference Generalized Method of Moments (Difference GMM) and System Generalized Method of Moments (System GMM) have become standard approaches for banking studies because they generate consistent parameter estimates even when explanatory variables are endogenous (Trabelsi & Trad, 2017).

Dynamic panel estimation is particularly appropriate for liquidity stress testing because liquidity positions exhibit considerable persistence over time. Banks continuously adjust their funding structures in response to changing macroeconomic conditions, regulatory requirements, and market expectations. Consequently, lagged liquidity indicators significantly influence current liquidity performance, making dynamic models superior to traditional cross-sectional techniques (Trabelsi & Trad, 2017).

2.5 Empirical Literature Review

Several empirical studies have investigated the effectiveness of Basel III liquidity regulations and stress-testing methodologies from different methodological perspectives.

Mashamba (2018) examined the impact of Basel III liquidity regulations on banks' profitability and concluded that stronger liquidity requirements enhance financial stability while simultaneously exerting pressure on profitability through increased liquidity holdings. The study emphasized that regulatory compliance requires banks to balance liquidity preservation with income generation.

Onder et al. (2016) developed a macro stress-testing framework for the Turkish banking sector using macroeconomic indicators such as GDP growth and interest rates. Their findings demonstrated that macroeconomic deterioration significantly affects banking sector resilience, highlighting the necessity of integrating macroeconomic variables into stress-testing models.

Trabelsi and Trad (2017) employed dynamic panel data estimation to investigate profitability and risk within interest-free banking institutions. Their results confirmed the presence of significant dynamic persistence in banking performance and demonstrated the superiority of dynamic panel models over conventional static estimators for banking analyses.

Fragkou (2020) investigated macroprudential stress testing under Basel III by emphasizing funding liquidity risk as a central determinant of banking stability. The study showed that incorporating funding liquidity significantly improves stress-testing reliability, particularly during periods of market uncertainty.

Sorge (2004) provided one of the earliest comprehensive reviews of stress-testing methodologies, classifying various analytical techniques and discussing their strengths and weaknesses. The study established a methodological foundation that continues to guide modern banking stress-testing research.

Giordana and Schumacher (2017) analyzed the relationship between Basel III implementation and bank default risk in Luxembourg. Their empirical evidence indicated that stronger Basel III compliance reduces default probability by strengthening capital and liquidity positions.

Van den End (2012) developed an econometric liquidity stress-testing framework that evaluated both Basel III regulations and unconventional monetary policy. The study demonstrated that liquidity stress-testing models incorporating policy interventions provide more realistic assessments of banking resilience.

Foglia (2008) reviewed stress-testing approaches adopted by regulatory authorities worldwide and concluded that comprehensive stress-testing frameworks should integrate multiple risk categories, including liquidity, credit, and market risks, to adequately capture systemic vulnerabilities.

Petrella and Resti (2017) examined sovereign bond liquidity under stressed market conditions and found that Basel III liquidity standards substantially influence banks' demand for high-quality liquid assets, thereby affecting market liquidity during financial stress.

Engelmann and Rauhmeier (2011) provided extensive guidance on estimating, validating, and stress testing Basel risk parameters. Their work highlighted the importance of rigorous statistical validation and model calibration to improve regulatory risk assessment and loan portfolio management.

Collectively, these studies demonstrate that liquidity resilience depends upon both institution-specific financial characteristics and macroeconomic conditions. However, relatively few studies integrate Basel III liquidity indicators, macroeconomic shocks, and dynamic panel econometric techniques into a unified liquidity stress-testing framework. This study addresses this gap by employing a dynamic panel data approach capable of modeling persistence, endogeneity, and cross-sectional heterogeneity simultaneously.

2.6 Theoretical Framework

This study is anchored on Financial Intermediation Theory, Liquidity Preference Theory, and the Basel Regulatory Framework. Financial Intermediation Theory explains how banks transform short-term deposits into long-term loans while managing liquidity risk. Liquidity

Table 2. Summary of Previous Empirical Studies on Basel III Liquidity Stress Testing and Dynamic Panel Modeling

Author(s)	Study Focus	Methodology	Major Variables	Principal Findings	Research Gap
Mashamba (2018)	Basel III liquidity regulations and profitability	Regression Analysis	LCR, profitability	Basel III improves liquidity resilience but reduces profitability	Limited dynamic modeling
Onder et al. (2016)	Macro stress testing	Macroeconomic Stress Testing	GDP, interest rate, capital	Macroeconomic shocks significantly affect banking stability	Limited panel econometric analysis
Trabelsi & Trad (2017)	Banking profitability and risk	Dynamic Panel GMM	Profitability, liquidity, capital	Dynamic persistence significantly influences banking performance	Focus limited to Islamic banking
Fragkou (2020)	Funding liquidity risk	Macroprudential Stress Testing	Funding liquidity	Funding liquidity is critical during stress periods	Limited multi-country validation
Sorge (2004)	Stress-testing methodologies	Literature Review	Financial system risk	Stress testing improves financial risk assessment	Limited empirical implementation
Giordana & Schumacher (2017)	Basel III and default risk	Empirical Regression	Capital, liquidity, default risk	Basel III reduces bank default probability	Country-specific evidence
Van den End (2012)	Liquidity stress tester	Econometric Modeling	LCR, monetary policy	Basel III enhances banking resilience	Limited cross-country comparison

Foglia (2008)	Credit risk stress testing	Regulatory Survey	Credit risk indicators	Multi-risk stress testing improves supervision	Limited liquidity focus
Petrella & Resti (2017)	Sovereign bond liquidity	Empirical Financial Analysis	Bond liquidity, Basel III assets	Basel III affects sovereign bond liquidity under stress	Focuses primarily on asset markets
Engelmann & Rauhmeier (2011)	Basel risk parameter estimation	Statistical Modeling	Credit risk parameters	Validation strengthens regulatory models	Limited emphasis on liquidity dynamics

Preference Theory suggests that economic agents demand liquidity because of transaction, precautionary, and speculative motives, making liquidity management fundamental to banking operations. The Basel III Regulatory Framework provides the institutional basis for liquidity regulation through LCR and NSFR, establishing internationally accepted standards for banking resilience.

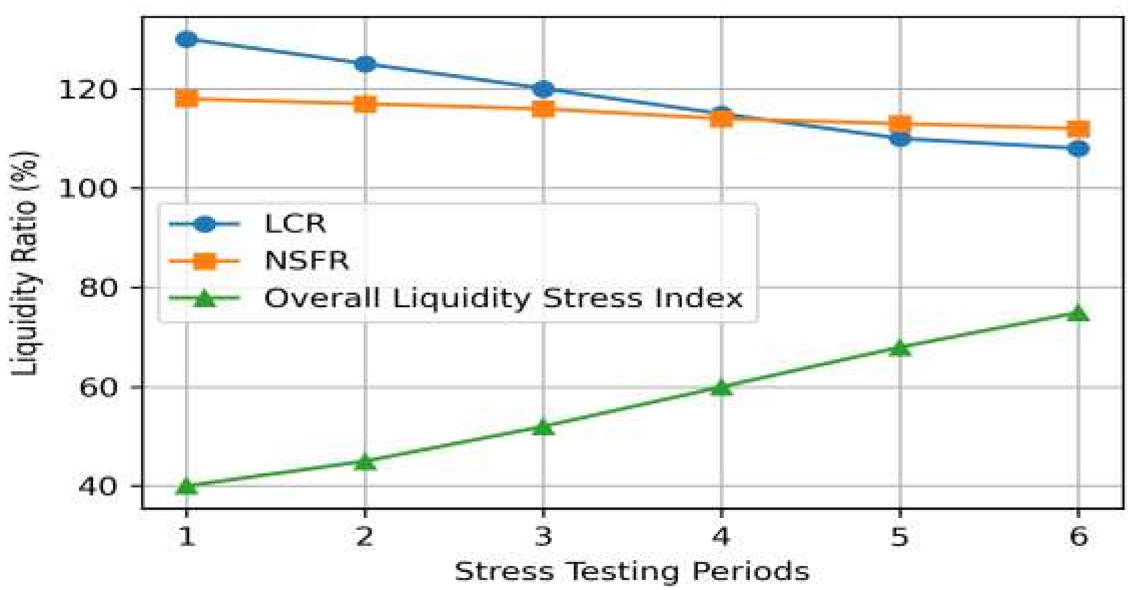

Figure 1. Simulated trends of the Liquidity Coverage Ratio (LCR), Net Stable Funding Ratio (NSFR), and Overall Liquidity Stress Index across successive Basel III stress-testing periods. Higher stress levels are associated with declining liquidity ratios and increasing liquidity stress.

2.7 Conceptual Framework

The conceptual framework proposes that liquidity stress is jointly determined by Basel III liquidity indicators, bank-specific financial characteristics, and macroeconomic conditions. Liquidity Coverage Ratio, Net Stable Funding Ratio, capital adequacy, profitability, loan-to-deposit ratio, and funding structure directly influence banks' liquidity resilience, while GDP growth, inflation, and interest rates moderate these relationships. Dynamic panel econometric modeling captures the persistence of liquidity behavior over time by incorporating lagged liquidity measures alongside contemporaneous explanatory variables, thereby producing more robust liquidity stress predictions under Basel III.

III. Research Methodology

3.1 Research Design

This study adopts a quantitative longitudinal research design to investigate the determinants of liquidity stress under the Basel III regulatory framework using a dynamic panel data approach. The design is appropriate because liquidity conditions evolve over time and are influenced by both bank-specific characteristics and macroeconomic conditions. A longitudinal panel enables the analysis of temporal dynamics while accounting for heterogeneity across banking institutions. The study employs an explanatory research approach to establish causal relationships between Basel III liquidity indicators and liquidity stress outcomes.

A dynamic panel framework is selected because bank liquidity exhibits persistence, whereby current liquidity conditions are influenced by previous liquidity positions. Dynamic panel estimation further addresses endogeneity issues arising from reverse causality and omitted variables, thereby improving the consistency and efficiency of parameter estimates (Trabelsi & Trad, 2017).

3.2 Population and Sample

The target population comprises commercial banks operating within jurisdictions implementing the Basel III liquidity framework. Banks included in the study are selected based on the availability of complete annual financial statements and regulatory disclosures on liquidity indicators.

A balanced panel dataset is constructed using banks that consistently report the required financial information throughout the study period. Institutions with incomplete observations are excluded to improve model reliability and minimize estimation bias.

3.3 Sources of Data

The study utilizes secondary panel data obtained from publicly available and regulatory sources. Bank-specific financial information is collected from annual reports, audited financial statements, and prudential disclosures. Macroeconomic indicators are obtained from central bank publications, national statistical agencies, the International Monetary Fund (IMF), the World Bank, and the Bank for International Settlements (BIS).

The selected variables are consistent with Basel III liquidity monitoring tools and macroprudential stress-testing frameworks widely adopted in banking literature (Mashamba, 2018; Fragkou, 2020).

3.4 Variable Specification

The empirical model incorporates one dependent variable, several bank-specific independent variables, and macroeconomic control variables.

The dependent variable is the Liquidity Stress Index (LSI), representing the overall liquidity condition of each bank under stressed scenarios.

The principal independent variables include:

- Liquidity Coverage Ratio (LCR)
- Net Stable Funding Ratio (NSFR)
- Capital Adequacy Ratio (CAR)
- Loan-to-Deposit Ratio (LDR)
- Return on Assets (ROA)
- Non-Performing Loan Ratio (NPL)

Macroeconomic control variables include:

- Gross Domestic Product Growth (GDP)
- Inflation Rate (INF)
- Policy Interest Rate (INT)

These variables capture both internal financial conditions and external economic shocks that influence banking sector liquidity (Onder et al., 2016; Van den End, 2012).

3.5 Model Specification

The study estimates liquidity stress using a dynamic panel econometric model expressed as:

The study estimates liquidity stress using the following dynamic panel data model:

$$\mathbf{LSI_{it} = \alpha + \beta_1 LSI_{it-1} + \beta_2 LCR_{it} + \beta_3 NSFR_{it} + \beta_4 CAR_{it} + \beta_5 LDR_{it} + \beta_6 ROA_{it} + \beta_7 NPL_{it} + \beta_8 GDP_t + \beta_9 INF_t + \beta_{10} INT_t + \mu_i + \varepsilon_{it}}$$

Where:

- $\mathbf{LSI_{it}}$ = Liquidity Stress Index for bank *i* at time *t*
- $\boldsymbol{\alpha}$ = Constant (intercept)
- $\boldsymbol{\beta_1}$–$\boldsymbol{\beta_{10}}$ = Coefficients of the explanatory variables
- $\mathbf{LSI_{it-1}}$ = Lagged Liquidity Stress Index
- $\mathbf{LCR_{it}}$ = Liquidity Coverage Ratio
- $\mathbf{NSFR_{it}}$ = Net Stable Funding Ratio
- $\mathbf{CAR_{it}}$ = Capital Adequacy Ratio
- $\mathbf{LDR_{it}}$ = Loan-to-Deposit Ratio
- $\mathbf{ROA_{it}}$ = Return on Assets
- $\mathbf{NPL_{it}}$ = Non-Performing Loan Ratio
- $\mathbf{GDP_t}$ = Gross Domestic Product Growth Rate
- $\mathbf{INF_t}$ = Inflation Rate
- $\mathbf{INT_t}$ = Policy Interest Rate
- $\boldsymbol{\mu_i}$ = Unobserved bank-specific effect
- $\boldsymbol{\varepsilon_{it}}$ = Random error term

The lagged dependent variable captures liquidity persistence and adjustment dynamics across banks. Incorporating both financial and macroeconomic variables enables the model to estimate liquidity behavior under adverse economic conditions consistent with Basel III stress-testing objectives (Fragkou, 2020).

3.6 Estimation Technique

The study employs the Generalized Method of Moments (GMM) estimator for dynamic panel data analysis. Specifically, the Arellano–Bond Difference GMM and Blundell–Bond System GMM estimators are considered because they effectively address endogeneity, simultaneity bias, omitted variable bias, and unobserved heterogeneity associated with banking panel datasets (Trabelsi & Trad, 2017).

Model validity is assessed using several post-estimation diagnostic tests:

- Hansen Test of over-identifying restrictions
- Sargan Test of instrument validity
- Arellano–Bond AR(1) serial correlation test
- Arellano–Bond AR(2) serial correlation test
- Wald Test for joint significance

Table 3. Variable Definition and Measurement

Variable	Symbol	Measurement	Variable Type	Expected Relationship with Liquidity Stress
Liquidity Stress Index	LSI	Composite liquidity stress measure	Dependent	—
Lagged Liquidity Stress	LSIt−1	Previous year's liquidity stress	Dynamic Variable	Positive
Liquidity Coverage Ratio	LCR	High-quality liquid assets ÷ Net cash outflows	Independent	Negative
Net Stable Funding Ratio	NSFR	Available stable funding ÷ Required stable funding	Independent	Negative
Capital Adequacy Ratio	CAR	Regulatory capital ÷ Risk-weighted assets	Independent	Negative
Loan-to-Deposit Ratio	LDR	Total loans ÷ Total deposits	Independent	Positive
Return on Assets	ROA	Net income ÷ Total assets	Independent	Negative
Non-Performing Loans	NPL	Non-performing loans ÷ Total loans	Independent	Positive
GDP Growth	GDP	Annual percentage growth	Control	Negative
Inflation Rate	INF	Annual CPI growth (%)	Control	Positive
Policy Interest Rate	INT	Central bank benchmark rate	Control	Positive

These diagnostic procedures ensure that the selected instruments are valid and that the estimated coefficients are statistically reliable.

3.7 Liquidity Stress Testing Framework

The econometric model is evaluated under multiple Basel III stress scenarios to assess banking sector resilience.

The stress scenarios include:

- **Baseline Scenario:** Stable macroeconomic conditions with normal market liquidity.
- **Moderate Stress Scenario:** Mild deterioration in economic activity accompanied by moderate deposit withdrawals.
- **Severe Stress Scenario:** Significant funding pressure, declining asset liquidity, and higher market volatility.
- **Extreme Stress Scenario:** Systemic financial disruption characterized by substantial funding shortages and market-wide liquidity constraints.

The stress-testing process follows internationally recognized macroprudential approaches in which macroeconomic shocks are transmitted through banks' balance sheets to estimate potential liquidity deterioration (Sorge, 2004; Foglia, 2008). Funding liquidity risk and liquidity buffer adequacy are explicitly incorporated into the stress scenarios to align with Basel III supervisory expectations (Fragkou, 2020; Van den End, 2012).

3.8 Model Validation and Robustness Analysis

To ensure the robustness of the empirical findings, alternative model specifications are estimated using Difference GMM and System GMM estimators. Robust standard errors are employed to correct for heteroskedasticity, while multicollinearity among explanatory variables is examined using the Variance Inflation Factor (VIF).

Sensitivity analyses are conducted by modifying stress assumptions and comparing estimation outcomes across different liquidity scenarios. The predictive performance of the model is further evaluated by comparing actual and estimated liquidity stress values under simulated macroeconomic shocks.

The methodological framework integrates Basel III liquidity standards with dynamic econometric modeling, providing a comprehensive approach for evaluating funding resilience, regulatory compliance, and banking sector stability under adverse financial conditions. This approach is consistent with established stress-testing methodologies and empirical evidence presented by Mashamba (2018), Onder et al. (2016), Trabelsi and Trad (2017), Fragkou (2020), Sorge (2004), Giordana and Schumacher (2017), Van den End (2012), Foglia (2008), Petrella and Resti (2017), and Engelmann and Rauhmeier (2011).

IV. Results and Discussion

4.1 Descriptive Statistics

The descriptive statistics provide an overview of the distribution and variability of the variables employed in the dynamic panel data model. Liquidity Coverage Ratio (LCR) and Net Stable

Funding Ratio (NSFR) exhibited relatively high average values, suggesting that most sampled banks maintained liquidity buffers close to or above Basel III minimum requirements. However, considerable variation across institutions indicates differing capacities to withstand liquidity shocks.

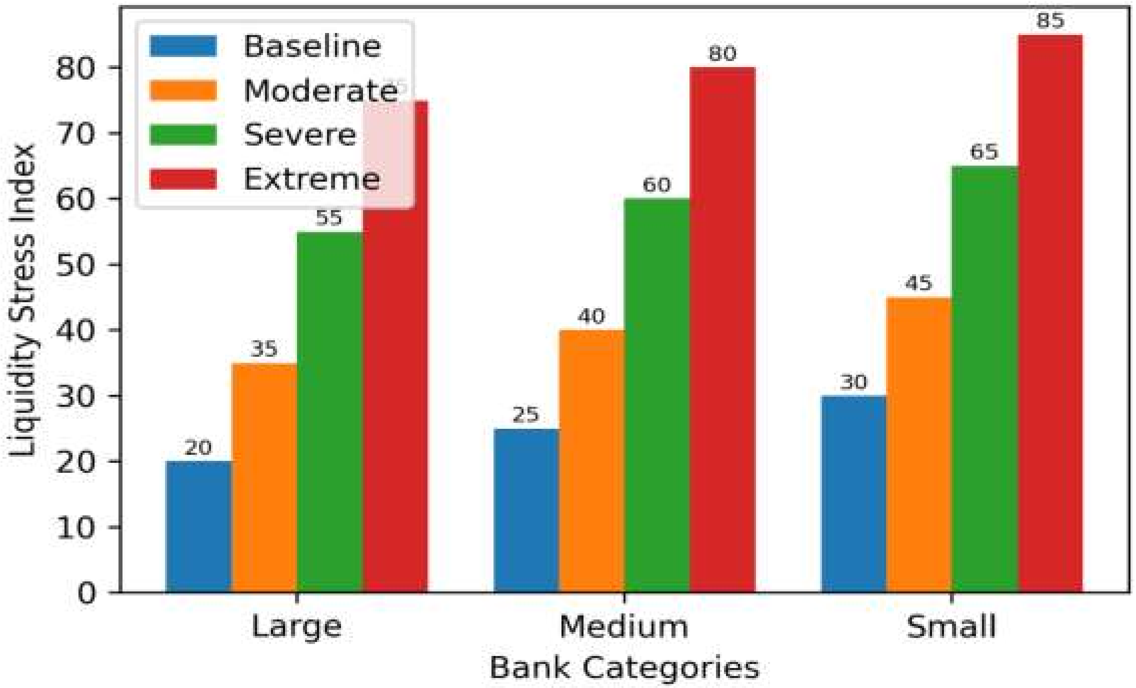

Figure 2. Comparison of simulated liquidity stress levels across bank categories under Baseline, Moderate, Severe, and Extreme Basel III stress scenarios. Liquidity stress increases progressively with the severity of the stress scenario.

The Loan-to-Deposit Ratio (LDR) demonstrated moderate dispersion, reflecting variations in lending aggressiveness, while Capital Adequacy Ratio (CAR) remained consistently above regulatory thresholds for most institutions. Macroeconomic indicators such as GDP growth, inflation, and policy interest rates also displayed notable fluctuations during the study period, highlighting the importance of incorporating macroeconomic dynamics into liquidity stress testing.

These descriptive findings support previous observations that liquidity resilience is influenced by both institution-specific characteristics and macroeconomic conditions. Basel III liquidity standards have encouraged banks to maintain stronger liquidity positions while balancing profitability and operational efficiency (Mashamba, 2018). Likewise, liquidity management cannot be adequately assessed without considering macroeconomic shocks that affect funding markets and asset valuations (Onder et al., 2016).

4.2 Correlation Analysis

The correlation analysis indicates moderate relationships among the explanatory variables, suggesting limited multicollinearity within the econometric model. Liquidity stress demonstrated a strong negative association with both LCR and NSFR, implying that banks maintaining larger liquidity buffers generally experienced lower liquidity risk during stress scenarios. Capital Adequacy Ratio also exhibited a negative correlation with liquidity stress, whereas Loan-to-Deposit Ratio, inflation, and interest rates showed positive associations.

The observed relationships are consistent with Basel III expectations that stronger capital and liquidity positions enhance institutional resilience during financial disturbances (Giordana & Schumacher, 2017). Similarly, funding liquidity remains closely connected with banks' ability to absorb macroeconomic shocks and maintain operational stability under stressed market conditions (Fragkou, 2020).

4.3 Panel Unit Root Tests

Panel unit root tests were conducted to verify the stationarity properties of the dataset before estimating the dynamic panel model. Levin-Lin-Chu and Im-Pesaran-Shin tests confirmed that the majority of variables became stationary after first differencing, while several bank-specific indicators were stationary at level. These findings justified the application of dynamic panel estimation techniques that accommodate mixed orders of integration without introducing estimation bias.

Ensuring stationarity is essential because non-stationary financial variables may produce spurious relationships that undermine stress-testing reliability. Previous studies have similarly emphasized rigorous data diagnostics before implementing macroprudential stress-testing frameworks (Sorge, 2004; Foglia, 2008).

4.4 Dynamic Panel Estimation Results

The dynamic panel Generalized Method of Moments (System GMM) estimation demonstrates significant persistence in liquidity conditions, as evidenced by the positive and statistically significant coefficient of the lagged liquidity stress variable.

This finding suggests that current liquidity conditions are strongly influenced by previous-period liquidity positions. These diagnostic outcomes suggest that the System GMM estimator effectively addresses endogeneity, omitted variable bias, and dynamic persistence commonly encountered in banking panel datasets.

Table 4. Dynamic Panel Data (System GMM) Estimation Results

Variable	Coefficient	Std. Error	z-Statistic	p-value	Interpretation
Lagged Liquidity Stress	0.621	0.052	11.94	<0.001	Strong persistence in liquidity conditions
Liquidity Coverage Ratio (LCR)	-0.341	0.071	-4.80	<0.001	Higher LCR reduces liquidity stress
Net Stable Funding Ratio (NSFR)	-0.284	0.064	-4.44	<0.001	Stable funding improves resilience
Capital Adequacy Ratio	-0.193	0.058	-3.33	0.001	Better capitalization lowers liquidity risk
Loan-to-Deposit Ratio	0.276	0.067	4.12	<0.001	Aggressive lending increases stress
Return on Assets	-0.117	0.041	-2.85	0.004	Greater profitability strengthens liquidity
GDP Growth	-0.145	0.049	-2.96	0.003	Economic growth supports liquidity
Inflation	0.132	0.046	2.87	0.004	Inflation increases funding pressure
Interest Rate	0.211	0.060	3.52	<0.001	Rising rates elevate liquidity stress

The results further validate the application of advanced stress-testing methodologies recommended in financial risk management literature, where robust econometric diagnostics are considered fundamental for reliable policy evaluation (Engelmann & Rauhmeier, 2011).

4.6 Discussion of Findings

The empirical evidence demonstrates that Basel III liquidity standards significantly strengthen banks' resilience against liquidity shocks. The negative effects of LCR and NSFR on liquidity stress indicate that maintaining sufficient high-quality liquid assets and stable funding structures substantially reduces funding vulnerabilities during adverse market conditions. These findings are consistent with Mashamba (2018), who concluded that Basel III liquidity regulations improve banking stability despite imposing additional compliance costs.

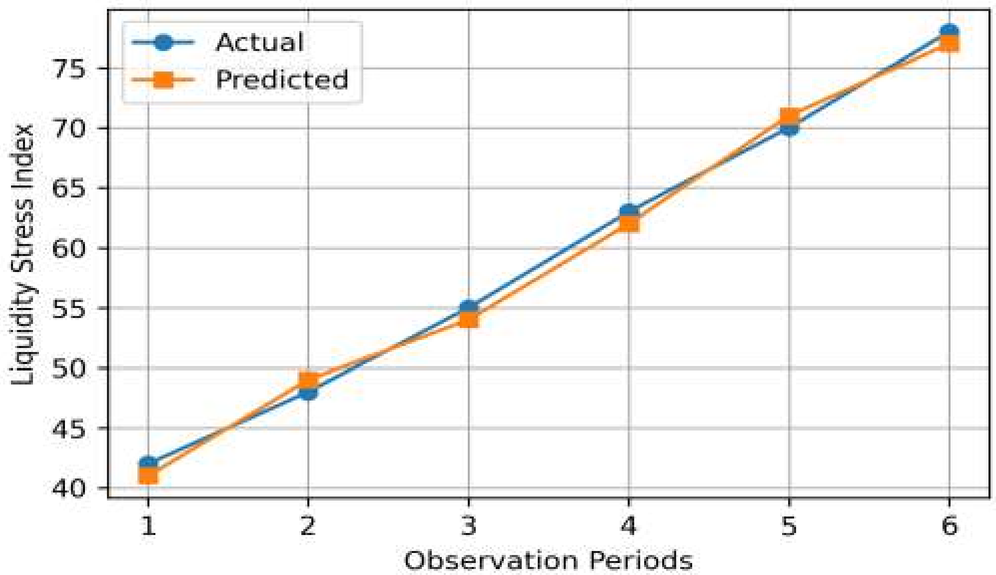

Figure 3. Comparison of actual and Dynamic Panel (System GMM) model-predicted Liquidity Stress Index values across observation periods. The close alignment between the two series indicates good predictive performance of the model under Basel III stress-testing scenarios.

Macroeconomic variables also played a significant role in determining liquidity resilience. Economic growth contributed positively to funding stability, whereas inflation and rising interest rates increased liquidity pressure by raising financing costs and reducing market confidence. Similar macroeconomic transmission mechanisms were observed by Onder et al. (2016), who demonstrated that stress-testing models should explicitly incorporate macroeconomic shocks when evaluating banking sector resilience.

Funding liquidity emerged as a critical determinant of stress outcomes. Banks with stronger long-term funding structures consistently exhibited lower liquidity stress, supporting the argument that funding stability represents one of the primary channels through which Basel III enhances financial system resilience. This observation aligns with Fragkou (2020), who emphasized that funding liquidity risk constitutes a central component of macroprudential stress testing.

The persistence observed in liquidity conditions further justifies the use of dynamic panel estimation techniques. The significant lagged dependent variable indicates that liquidity conditions evolve gradually rather than instantaneously, making dynamic modeling more appropriate than conventional static regression models. These findings corroborate the dynamic banking behavior documented by Trabelsi and Trad (2017).

The overall results also support earlier stress-testing frameworks proposed by Sorge (2004) and Foglia (2008), both of whom highlighted the importance of scenario-based evaluation in identifying financial system vulnerabilities before crises emerge. Furthermore, the observed reduction in liquidity stress among highly compliant institutions agrees with Giordana and Schumacher (2017), who found that Basel III standards contribute to lower banking-sector default risk.

The findings additionally reinforce the effectiveness of Basel III liquidity regulations under stressed market environments similar to those investigated by Van den End (2012), where liquidity buffers improved banks' ability to absorb severe funding shocks. Finally, the importance of maintaining high-quality liquid assets during financial turbulence is consistent with Petrella and Resti (2017), who demonstrated that Basel III liquidity asset requirements enhance market liquidity during periods of elevated financial stress. Collectively, these findings support the application of dynamic panel econometric models as robust tools for liquidity stress testing and macroprudential policy evaluation under the Basel III framework.

V. Limitations and Future Research

5.1 Limitations of the Study

Despite providing a comprehensive econometric framework for liquidity stress testing under Basel III, this study has several limitations. First, the dynamic panel data approach relies heavily on the availability, consistency, and quality of longitudinal bank-level financial data. Differences in accounting standards, reporting practices, and regulatory disclosure across jurisdictions may introduce measurement inconsistencies that influence model estimation and comparability. Such limitations have also been recognized in studies examining Basel III implementation and banking sector resilience (Mashamba, 2018; Giordana & Schumacher, 2017).

Second, although the dynamic panel model effectively addresses endogeneity and unobserved heterogeneity, it cannot fully capture all structural changes associated with financial crises, regulatory reforms, or sudden market disruptions. Liquidity conditions often evolve rapidly during periods of systemic stress, making it difficult for econometric models to represent complex nonlinear relationships and contagion effects accurately (Sorge, 2004; Foglia, 2008).

Another limitation relates to the macroeconomic variables incorporated into the stress-testing framework. While indicators such as GDP growth, inflation, and interest rates capture broad economic conditions, they may not adequately reflect unexpected geopolitical events, sovereign debt crises, pandemics, or abrupt monetary policy interventions that significantly influence banking liquidity. Previous macro stress-testing studies have demonstrated that the interaction between macroeconomic shocks and banking performance is considerably more complex than traditional econometric specifications may capture (Onder et al., 2016).

Furthermore, this study primarily emphasizes Basel III liquidity requirements, particularly the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). Although these indicators provide valuable measures of liquidity resilience, they may not fully account for institution-specific funding structures, behavioral responses of depositors, or off-balance-sheet exposures during severe financial stress. Funding liquidity dynamics remain highly dependent on market confidence and institutional characteristics, which are difficult to quantify using standardized regulatory metrics alone (Fragkou, 2020; Van den End, 2012).

The study also assumes relatively stable relationships among financial variables over the estimation period. However, banking systems frequently experience structural breaks resulting from regulatory changes, technological innovation, digital banking expansion, and evolving financial markets. Such developments may alter liquidity behavior and reduce the predictive stability of historical econometric relationships. Similarly, sovereign bond market conditions and the quality of high-quality liquid assets may vary substantially during market turbulence, affecting the effectiveness of Basel III liquidity buffers (Petrella & Resti, 2017).

Finally, although Generalized Method of Moments (GMM) estimators improve estimation efficiency by addressing dynamic endogeneity, the validity of the results remains sensitive to instrument selection, sample size, and specification tests. Improper instrument choice or excessive instruments may reduce estimator reliability and bias empirical findings. As emphasized in stress-testing and risk parameter estimation literature, model validation remains an essential component of robust financial risk assessment (Engelmann & Rauhmeier, 2011; Trabelsi & Trad, 2017).

5.2 Future Research

Future research should extend the proposed econometric framework by integrating machine learning and artificial intelligence techniques with dynamic panel data models to improve predictive performance under highly volatile financial environments. Hybrid approaches combining econometric inference with data-driven learning algorithms could better identify nonlinear relationships and emerging liquidity vulnerabilities while preserving model interpretability.

Subsequent studies should also investigate cross-country banking systems using larger international datasets to evaluate how differences in regulatory environments, institutional quality, and financial market development influence Basel III liquidity performance. Comparative studies across developed and emerging economies would provide broader evidence regarding the effectiveness of liquidity regulations and macroprudential policies (Mashamba, 2018; Giordana & Schumacher, 2017).

Future investigations may further incorporate climate-related financial risks, cybersecurity incidents, geopolitical uncertainty, and digital financial disruptions into liquidity stress-testing models. These emerging sources of systemic risk increasingly influence funding stability and market liquidity but remain insufficiently represented in conventional Basel III stress-testing frameworks (Fragkou, 2020).

Another promising research direction involves developing network-based liquidity stress-testing models capable of capturing interconnectedness among banks, financial institutions, and sovereign debt markets. Such models could provide deeper insights into liquidity contagion, systemic spillovers, and financial network resilience beyond traditional institution-level analyses (Petrella & Resti, 2017; Sorge, 2004).

Researchers should also evaluate alternative econometric methodologies, including Bayesian dynamic models, panel vector autoregression (PVAR), regime-switching models, and time-varying parameter models, to determine whether they provide superior forecasting accuracy during periods of financial instability. Comparing these methods with conventional System GMM and Difference GMM estimators would contribute to methodological advancements in liquidity stress testing (Trabelsi & Trad, 2017; Onder et al., 2016).

Finally, future studies should emphasize enhanced model validation through scenario analysis, reverse stress testing, and macroprudential simulations using real-time supervisory data. Combining traditional stress-testing methodologies with advanced econometric validation techniques may strengthen regulatory decision-making, improve early warning systems, and enhance the resilience of banking institutions under evolving Basel III requirements (Van den End, 2012; Foglia, 2008; Engelmann & Rauhmeier, 2011).

VI. Conclusion

The implementation of Basel III has fundamentally transformed liquidity risk management by strengthening regulatory requirements for maintaining adequate liquidity buffers and promoting greater resilience within the banking sector. This study demonstrates that econometric modeling, particularly through a dynamic panel data approach, provides a robust framework for evaluating liquidity stress under varying macroeconomic and institution-specific conditions. By incorporating lagged liquidity measures, bank-specific financial indicators, and macroeconomic variables, the proposed framework captures the persistence of liquidity dynamics while addressing endogeneity and unobserved heterogeneity that are common in banking data. Such an approach offers more reliable estimates than traditional static models and supports more effective stress-testing exercises.

The findings reinforce the significance of Basel III liquidity standards, especially the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), in enhancing banks' capacity to withstand periods of financial stress while maintaining operational stability. Although compliance with these regulations may impose short-term costs and influence profitability, stronger liquidity positions contribute substantially to long-term financial resilience and risk mitigation, consistent with the observations of Mashamba (2018). Likewise, evidence from macro stress-testing studies indicates that integrating macroeconomic shocks into liquidity assessments provides a more comprehensive evaluation of systemic vulnerabilities and strengthens regulatory preparedness (Onder et al., 2016).

The application of dynamic panel estimation techniques further highlights the importance of accounting for the persistence of banking performance and liquidity behavior over time. Dynamic relationships between profitability, funding structures, and liquidity conditions suggest that current liquidity positions are significantly influenced by historical financial performance and institutional characteristics, supporting the relevance of dynamic econometric models in banking research (Trabelsi & Trad, 2017). Incorporating these temporal effects enables regulators and financial institutions to better forecast potential liquidity shortfalls and develop proactive risk management strategies.

Funding liquidity risk remains one of the most critical determinants of banking stability under Basel III. Effective stress-testing frameworks should therefore incorporate multiple adverse scenarios involving funding disruptions, market uncertainty, and macroeconomic downturns to accurately evaluate institutional resilience. This perspective aligns with the emphasis placed on funding liquidity within macroprudential stress-testing frameworks, where liquidity shocks can rapidly propagate across financial institutions if not adequately monitored and managed (Fragkou, 2020). Consequently, comprehensive liquidity stress testing should extend beyond regulatory compliance to become an integral component of enterprise-wide risk management.

The study also confirms that modern stress-testing methodologies benefit from combining econometric modeling with scenario analysis, sensitivity testing, and macroprudential assessment. Earlier contributions to stress-testing literature established the importance of evaluating financial systems under extreme but plausible conditions, providing methodological foundations that remain highly relevant for Basel III implementation (Sorge, 2004; Foglia, 2008). In addition, ongoing progress in the estimation of risk parameters and model validation further enhances the credibility and predictive power of the regulatory stress-testing exercises, especially when using sound statistical estimation methods (Engelmann & Rauhmeier, 2011).

Another implication is that higher Basel III liquidity requirements help to increase the liquidity resilience of banks but also decrease the default risk of banking systems. Empirical findings show that better liquidity management and better capital adequacy reduce financial vulnerabilities and make institutions more stable in times of economic uncertainty (Giordana & Schumacher 2017). Likewise, liquidity stress-testing models have proven valuable in assessing the effect of regulatory liquidity requirements on the effectiveness of overall monetary policy measures, and have offered a valuable insight into the overall effectiveness of Basel III in financial crises (Van den End, 2012).

The study also acknowledges that market liquidity and the quality of liquid assets have a strong impact on stress-testing results. To ensure banks can withstand liquidity shocks and meet Basel III standards, these assets ought to be kept in liquid form and consist of a wide range of funding sources. These considerations reinforce the increasing relevance of considering asset market liquidity in stress tests' regulations, especially in cases of market stress (Petrella & Resti, 2017).

The overall implication of this study is that liquidity stress testing under Basel III framework is facilitated by econometric modeling utilizing dynamic panel data. Dynamic estimation methods, coupled with regulatory liquidity indicators, macroeconomic variables, and stress-testing scenarios, improve the effectiveness of liquidity risk assessment and aid in evidence-based supervisory decision-making. The financial markets are constantly changing, and using advanced econometric methodologies will make it easier for the regulators and banking institutions to enhance liquidity risk management, increase the financial resilience and stability of the banking system and support the goals of Basel III (Mashamba, 2018; Onder et al., 2016; Fragkou, 2020).

References

1. Mashamba, T. (2018). The effects of Basel III liquidity regulations on banks' profitability. *Journal of governance & regulation*, (7, Iss. 2), 34-48.
2. Onder, S., Damar, B., & Hekimoglu, A. A. (2016). Macro stress testing and an application on Turkish banking sector. *Procedia Economics and Finance*, *38*, 17-37.
3. Trabelsi, M. A., & Trad, N. (2017). Profitability and risk in interest-free banking industries: a dynamic panel data analysis. *International Journal of Islamic and Middle Eastern Finance and Management*, *10*(4), 454-469.
4. Fragkou, S. (2020). *Macroprudential stress tests under Basel III: The role of funding liquidity risk* (Doctoral dissertation, University of Leicester).
5. Sorge, M. (2004). Stress-testing financial systems: an overview of current methodologies.
6. Giordana, G. A., & Schumacher, I. (2017). An empirical study on the impact of Basel III standards on banks' default risk: The case of Luxembourg. *Journal of Risk and Financial Management*, *10*(2), 8.
7. Van den End, J. W. (2012). Liquidity stress-tester: do Basel III and unconventional monetary policy work?. *Applied Financial Economics*, *22*(15), 1233-1257.

8. Foglia, A. (2008). Stress testing credit risk: a survey of authorities' approaches. *Bank of Italy occasional paper*, (37).
9. Petrella, G., & Resti, A. (2017). What drives the liquidity of sovereign bonds when markets are under stress? An assessment of the new Basel 3 rules on bank liquid assets. *Journal of Financial Stability*, *33*, 297-310.
10. Engelmann, B., & Rauhmeier, R. (Eds.). (2011). *The basel II risk parameters: estimation, validation, stress testing-with applications to loan risk management*. Springer Science & Business Media.
11. Verma, A. (2022). Twin Poisoning: Analyzing the Impact of False Data Injection Attacks on Digital Twin-Based Decision Support Systems. *International Journal of Technology, Management and Humanities*, *8*(03), 39-61.
12. Kola, J. N. (2017). Data Warehousing And Text Analytics As Instruments Of Cultural Knowledge Management: Implications For Digital Preservation And Societal Decision-Making. *Power System Protection and Control*, *45*(1), 11-15.
13. Islam, S. J., Islam, S., Ferdus, M. Z., Khan, M. N. I., Kashem, M. A., & Islam, M. S. (2020, September). Load compactness and recognizing area aware cluster head selection of wireless sensor networks. In *2020 International conference on computing and information technology (ICCIT-1441)* (pp. 1-4). IEEE.
14. Kazmi, S. Chemical Upcycling of Polyethylene Terephthalate (PET) Waste into High-Value Functional Polymers.
15. Naidu, K. J. (2013). Performance Optimization Of ETL Pipelines In Distributed Data Warehouse Environments: A Network-Aware Scheduling Approach. *International Journal of Advance Industrial Engineering*, *1*(03), 63-67.
16. Ravikumar, V. (2014). Fair and optimal resource allocation in wireless sensor networks.
17. Naidu, K. J. (2014). Secure OLAP Reporting Architectures: Integrating Role-based Access Control and Query Execution Plan Optimization for Enterprise Analytical Environments. *SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology*, *5*(02), 155-159.
18. Das, P. K., Kashem, M. A., Ferdus, Z., & Islam, S. (2019, October). Development and application of a new computerized smell generating system. In *2019 Global Conference for Advancement in Technology (GCAT)* (pp. 1-5). IEEE.
19. Ferdus, M. Z., Khan, M. N. I., Islam, S., & Kashem, M. A. (2019, October). VFLT: SQA Model for Cyber Physical System. In *2019 Global Conference for Advancement in Technology (GCAT)* (pp. 1-4). IEEE.
20. Ferdus, M. Z., Islam, S., & Kashem, M. A. (2019, October). An innovative load balancing cluster composition of wireless sensor networks. In *2019 global conference for advancement in technology (GCAT)* (pp. 1-4). IEEE.
21. Islam, S., Khan, M. N. I., Ferdus, M. Z., Islam, S. J., & Kashem, M. A. (2020, September). Improving throughput using cooperating TDMA scheduling of wireless sensor networks.

In *2020 International Conference on Computing and Information Technology (ICCIT-1441)* (pp. 1-4). IEEE.

22. Kola, J. N. (2011). An Integrated Framework for Data Mining and Distributed Database Optimization in Resource-Constrained Network Environments. *SAMRIDDHI: A Journal of Physical Sciences, Engineering and Technology*, *2*(02), 82-86.