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Assessing Liquidity at Risk in Turkish Banks: A Copula-Driven Monte Carlo Stress Test

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Abstract

This study presents a two-stage liquidity stress testing framework for the Turkish banking sector. In the first stage, independent Monte Carlo simulations are used for each bank to calculate Liquidity Coverage Ratio (LCR) distributions under different stress scenarios (Base, Adverse, Severe Adverse). In the second stage, the t-copula method is used to account for interbank correlations and tail dependence; thus, the potential for a bank's liquidity squeeze to spread system-wide is evaluated holistically.

The analysis covers 27 banks representing 86% of the sector's total assets as of December 2024. Banks are classified into two groups based on systemic importance: 8 domestically systemically important banks (DSIB) and 19 other banks. Differentiated shock parameters are applied to each group to account for their distinct risk profiles.

First-round results show that as scenario severity increases, LCR values tend to decrease and failure rates tend to rise. Under the Severe Adverse scenario, the sector-wide failure rate ranges from 72–77% for Total LCR and 31–45% for FX LCR. The DSIB group shows higher vulnerability in Total LCR under the Severe Adverse scenario, while the Other Banks group carries higher risk in FX LCR.

In the second-round analysis, with tail dependence included, systemic risk appears higher. Second-round failure rates for FX LCR are higher than first-round results, indicating stronger interbank dependence in FX liquidity. Joint breach analysis shows that, on average, 19.5–20.8 banks can simultaneously fall below the LCR threshold under the Severe Adverse scenario.

Banks with both high individual vulnerability and high systemic linkages are identified. These findings support policy recommendations including risk-based supervision, increased HQLA buffers, strengthened FX liquidity management, and accounting for tail dependence in stress tests. The study contributes to the liquidity risk management literature and provides a framework applicable by supervisory authorities and banks.

Keywords: liquidity stress testing; scenario analysis; bank run; contagion; Monte Carlo simulations; copula model

JEL Codes: G01, G17, G21, G28, G32

Note

This article reflects the author's personal views and does not represent the official position of the Banking Regulation and Supervision Agency of Türkiye.

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1. Introduction

Liquidity risk is a structural concept arising from the need to manage maturity mismatches between assets and liabilities. Liquidity risk is multidimensional, and assessing banks' resilience to funding risks requires multifaceted analysis. Stress tests constitute an important part of these analytical methods for supervisory authorities and banks, enabling financial institutions to be prepared in advance for economic fluctuations and market anomalies and to take measures before vulnerabilities turn into crises. Methodology development efforts for stress tests have gained momentum especially after crises, and have been made mandatory in most countries through rule sets developed by international organizations and national supervisory authorities. In practice, stress tests are subject to periodic or ad-hoc tests conducted internally by banks and to applications and assessments by authorities on an individual and consolidated basis.

Liquidity stress tests analyze banks' capacity to meet and withstand withdrawal movements in their liabilities with their short-term liquid assets. This analysis includes dynamics such as the loss of value of liquid assets or constraints on access to additional funding sources. As a result of the applied stress tests, the resilience and potential losses of each bank and the banking sector are revealed, shedding light on measures and policies that can be taken. Whether compliance with liquidity buffers (LCR and NSFR) introduced with Basel III can be maintained even under stressed conditions, and how much liquidity support is needed for banks that fall below regulatory thresholds, is clarified. The feature of liquidity stress tests across the banking sector provides the opportunity to test each bank's liquidity resilience and the system's liquidity adequacy against shocks simulated under different scenarios.

This study is based on a comprehensive literature that analyzes the effects on liquidity and default risk, taking into account macroeconomic shocks, fluctuations in asset prices, and interbank linkages in the banking sector. Brunnermeier and Pedersen (2009) showed that the feedback mechanism between market and funding liquidity can increase financial institutions' vulnerability. Cifuentes et al. (2005), Adrian and Shin (2008), Cipriani et al. (2008), and Aikman et al. (2019) demonstrate how an effect arising from an asset price shock creates disruption through its impact on banks' assets' current value, showing the contagion dimension through interbank linkages. Allen and Gale (2000) and Gai and Kapadia (2010) theoretically and empirically demonstrate how the network structure and linkage density among banks can lead to contagious defaults system-wide. Drehmann and Nikolaou (2013) emphasize that the distribution of banks' liquidity buffers and the probability of liquidity shortfalls are sensitive to changes in market and funding conditions. Acharya and Merrouche (2013) empirically show that the loss of confidence in the interbank market during crisis periods increases liquidity squeezes and systemic risk.

Additionally, van den End (2010) analyzes banks' liquidity risk and the level of liquidity buffers by incorporating the interaction between market and funding liquidity and potential feedback on banks into a framework. Iori et al. (2008), Gorton and Metrick (2012), Battiston et al. (2012), Billio et al. (2012), Huang et al. (2012), Adrian and Brunnermeier (2016), and Glasserman and Young (2016) have developed new metrics in terms of interconnectedness among financial institutions, contagion in financial networks, and contributions to systemic risk. Systemic liquidity analyses have gained considerable importance due to the impact of vulnerabilities such as experiences gained from recent crises and increasing linkages between financial markets. Studies showing the interaction among financial institutions and the spread of liquidity shocks, such as FSB (2023, 2024) on system-wide systemic risk including non-bank financial institutions, MAS (2023) focusing on a stress test on NBFI types that may have the most impact on banks in Singapore, and the Bank of England's (BoE) (2024) System-Wide Exploratory

Scenario (SWES), are becoming widespread. According to ESRB (2025), the scope of institutions and assets monitored within systemic liquidity should be expanded, and the power and tendency of stress propagation should be measured.

FSB (2024) emphasizes that policies and regulations are needed to manage liquidity pressures in NBFIs arising from increases in margin and collateral calls during stress periods. In banks' internal stress tests, expected stress and withdrawal rates may differ on a bank-specific basis rather than general assumptions; during crisis periods, banks may take actions such as selling liquid assets, reducing credit commitments, and shrinking balance sheets (Baudino et al., 2024). These fire sales reduce asset valuations, negatively affecting balance sheets, and can trigger additional sales due to liquidity provision panics and regulatory constraints (Cifuentes et al., 2005; Brunnermeier and Pedersen, 2009).

In this study, the effects of asset price shocks, deposit withdrawals, and funding source contractions on banks' default and risk are addressed in an integrated manner, both through direct shocks and a t-copula-based contagion mechanism. Thus, interactions between liquidity risk, market risk, and banks' default risk are analyzed comprehensively from a systemic risk perspective. This approach implements advanced stress testing frameworks proposed in the literature (Cont et al., 2013; Cont et al., 2020; Upper, 2011) and holistically evaluates the impact of differentiated shocks by bank groups and balance sheet items on systemic risk. The methods and assumptions used in the study are developed based on scenarios widely used in the International Monetary Fund (IMF)'s Financial Sector Assessment Program (FSAP) country assessment reports, by regulatory authorities, and in related academic studies.

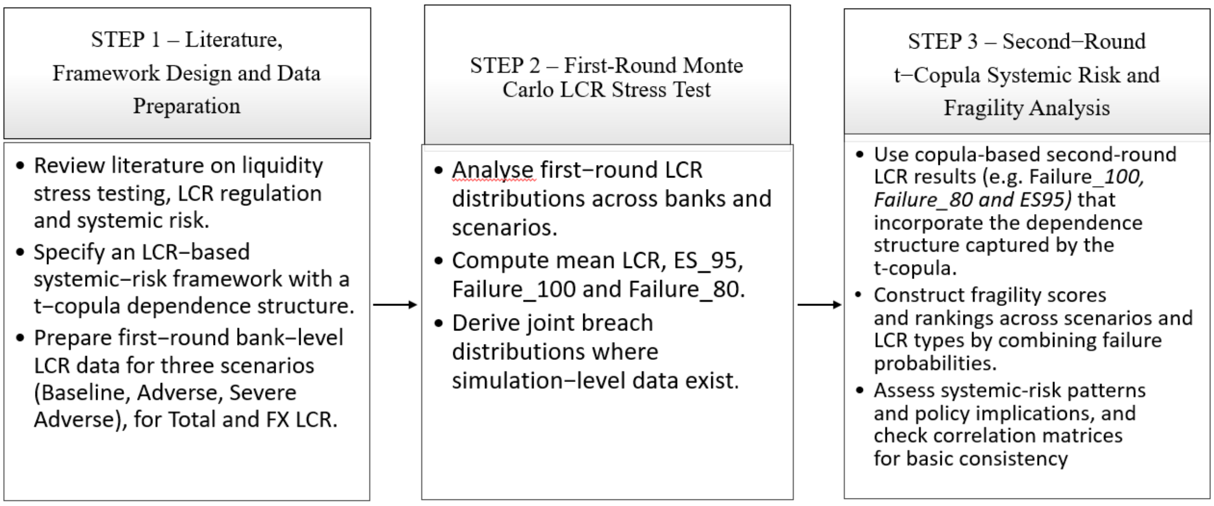
In Türkiye, 64 banks were operating at the end of 2024, and their asset sizes constitute 77.3% of the total financial sector (BRSA, 2024). In this respect, the banking sector still has the highest potential both in terms of its weight and the propagation of shocks, and is of primary importance as a channel for financial crisis formation and shock propagation. Given the prominent weight and critical role of the banking sector within the financial sector in Türkiye, focusing liquidity stress testing applications on the banking sector, also taking into account data constraints, will be effective in measuring the financial system's resilience and managing potential risks in the best way.

The scope of the study includes 27 banks representing 86% of the sector's asset size as of December 2024. Eight of these banks are in the domestically systemically important bank group. The analysis was conducted on an LCR basis using publicly available data published by the Banks Association of Türkiye (BAT). Development and investment banks, some banks with missing data or anomalies detected and with a sector share below 1%, and participation/Islamic banks (representing 7.5% of the sector's asset size as of end-2024) were not included in the analysis due to time series data access constraints.

Regarding the study's contribution to the literature, there are very few studies in the literature on Turkish financial markets in terms of liquidity stress testing applications. Studies in this field will contribute to the development and calibration of stress tests conducted internally by banks and periodically and ad-hoc by supervisory authorities.

Banks are divided into two groups based on balance sheet structures, market shares, and potential contagion effects: systemically important banks and other banks. Each bank group has been subjected to stress testing under three defined adverse scenarios with their own specific run-off rates and asset value loss (haircut) parameters. In applying shocks, Monte Carlo simulation was used with rates randomly drawn from intervals determined for each bank group and LCR item; thus, the distribution of banks' liquidity resilience and worst-case results under different macroeconomic and financial conditions were analyzed. Monte Carlo simulation, in addition to applying shocks in scenario generation, also covers the propagation of vulnerabilities system-wide in second-round effects when multiple banks in the banking system fall below the legal LCR threshold or experience liquidity squeezes. At this stage, interbank correlation and tail dependence were taken into account using copula-based methods; the contagious nature of systemic risk was simulated through the propagation of shocks to other banks via tail dependence parameters determined with t-copula. Thus, the potential for a possible liquidity crisis in the banking system to transform from individual bank risks into systemic risk has been holistically evaluated.

Graph 1: Steps of the LCR−Based Liquidity Stress Testing Framework



The remainder of the article is organized as follows: The next section summarizes the relevant literature, lessons from past crises, applications by international institutions and supervisory authorities, and the liquidity risk management framework in Türkiye. Section III discusses the data subject to the study and the characteristics of stress scenarios. Section IV presents the stress testing results for the Turkish Banking Sector and includes the inferences obtained.

2. Past Crises, Stress Testing Framework, and Related Literature

2.1. Empirical Evidence from Past Crises

The purpose of liquidity stress tests and their contributions to liquidity management can be listed as measuring banks' responses, liquidity adequacy, and identifying alternative sources in crisis or specific stress situations, and determining the capacity and time horizon to meet net cash outflows.

Two main approaches generally stand out in stress tests: cash flow mismatch analysis and liquidity buffer-based analysis (Jobst et al., 2017). In these tests, changes in banks' funding conditions are applied to bank balance sheets and liquidity buffers under different scenarios. The aim is to enable banks to achieve a stable funding profile and become resilient to shocks (Nier et al., 2014; Jobst et al., 2017).

Van den End (2010) developed a stress testing model that analyzes market and funding liquidity together using Monte Carlo simulation on the Dutch banking sector, showing that liquidity risks have a nonlinear character and that collective actions have significant effects on market liquidity. Brunnermeier and Pedersen (2009) modeled two "liquidity spiral" effects that intensify funding constraints through increased collateral requirements due to market illiquidity and contribute to market illiquidity due to investors' reduced trading positions as a result of shocks in funding conditions. The RAMSI model developed at the Bank of England by Aikman et al. (2009) analyzes systemic risk that banks may face under stressed market conditions by integrating funding liquidity with default risks. Čihák (2007) presented a model within the FSAP framework that includes bank-run (deposit flight) and contagion effects, measuring liquidity risk with proportional withdrawals in term and demand deposits and scenarios of contagion from weak to strong banks. Anand et al. (2014) conducted a top-down liquidity stress test within the Bank of Canada's macro-financial risk assessment framework, examining pressure on banks' solvency and the effects of relatively weak banks' inability to meet interbank commitments due to potential counterparty risks in scenarios where fund flows completely stop

Jobst (2014) developed an approach in the Systemic Risk-adjusted Liquidity (SRL) model that combines balance sheet data, market data, and option pricing to measure the probability and effects of multiple institutions experiencing simultaneous liquidity squeezes. The IMF (2011) Global Financial Stability Report (GFSR) includes a section analyzing systemic liquidity risk with a Merton-based model, revealing banks' individual liquidity risks and systemic liquidity crisis potential. Schmieder et al. (2012) contributed to existing studies by developing the stress testing framework used in FSAP reports, applying an extended version of Čihák's (2007) method and modeling the solvency stress test linkage. Schmieder et al. (2012) stated that liquidity crises develop in three stages: in the first stage, a rapid decrease in funding sources; in the second stage, increasingly constrained access to liquidity in markets and loss of collateralized funding opportunities; and in the third stage, the spread of the crisis and the occurrence of bank runs and large deposit withdrawals. Additionally, interventions and measures such as banks' fire sales of assets, use of existing funding limits, renewal of long-term funding, parent company and subsidiary funding support, and central bank liquidity provision have been proposed to reduce the individual effects of the crisis.

De Haan and Van den End (2011) similarly emphasized that loss of confidence and cost increases can lead to the drying up of funding sources, closure of markets, and bank panic. Wong and Hui (2009) modeled the link between solvency and deposit withdrawals within the Hong Kong Monetary Authority, showing the effect of market value losses on banks' solvency and their power to trigger deposit withdrawals.

Liquidity stress tests evaluate financial institutions' resilience to adverse scenarios and focus on these institutions' abilities to manage liquidity risks. Hejlová et al. (2020) developed a stress testing framework that measures liquidity and solvency risks among financial institutions through financial networks, testing the resilience of banks operating in the Czech Republic's liquidity positions to shock combinations in the long term. The measurement is based on LCR and NSFR metrics, and the model analyzing banks' one-year survival period includes bank-specific and market-specific variables. In stress test results, some banks' ratios declined below 100%. Zhao et al. (2023) emphasize the importance of stability and contagion effects in financial networks, showing that central banks' strategic hedging and interest rate policies can reduce liquidity default probabilities. Ferrara et al. (2016) examined contagion effects occurring through financial networks when maturing liabilities cannot be paid and funds cannot be renewed, through banks' liquidity buffers and expected cash flows with interbank data.

Čihák (2007) developed two basic tests to measure liquidity stress: In the first, liquidity shocks were simulated by applying proportional withdrawals in banks' term and demand deposits over several days (for example, 15% daily withdrawal in demand deposits, 3% in term deposits). In the second, the spread of liquidity inadequacy in the system through contagion effects starting from the weakest bank was analyzed; here, which bank the shock would start from was determined with a bank safety index.

Traditional stress tests mostly apply scenarios evaluating liquidity and solvency independently. This situation creates the possibility of reaching insufficient and erroneous results in risk assessments. Cont et al. (2020) developed a metric called Liquidity at Risk (LaR) that systematically models solvency and liquidity linkages, analyzes the integrated effect of financial shocks on financial institutions, and includes the economic impact of the Covid-19 pandemic shock. Scenarios including exogenous (endogenous) liquidity shocks can consist of solvency shocks, margin calls, credit rating downgrades, market shocks, and forced asset sales.

In stress tests, elements such as deposit withdrawals and asset sales are generally considered with 5- and 30-day time horizons; realistic shocks such as liquidity disruptions and rapid cash outflows are taken as the basis. Since assets given as repo or used as collateral are not considered liquid, highly collateralized banks may face difficulties in funding access during liquidity shocks (Jobst et al., 2017). In liquidity stress testing scenarios, fundamental assumptions such as depositor behavior, access to market funding, asset liquidity, and collateral status are used. Deposit volatility is measured with "run-off" rates, and asset value losses with "haircut" applications; thus, how much assets will lose value and how much of deposits will be withdrawn in a stress environment can be predicted (Jobst et al., 2020). During crisis periods (BCBS, 2008), it has been emphasized that banks should regularly conduct liquidity stress tests containing scenarios at different maturities and across markets.

Liquidity stress tests are used to evaluate banks' capacity to withstand adverse shocks with their internal resources (liquidity buffer). Cash flow analysis measures resilience in terms of liquidity by behaviorally withdrawing deposits and liability items such as wholesale funding in panic (bank run) at different maturities, and value reductions or disruptions in asset items (Cipriani, 2007; Catalán, 2015; Jobst et al., 2017). In cash flow analysis, renewal restrictions and asset value declines for different maturity buckets, valuation haircuts due to fire sales of assets such as securities and loans in LCR and NSFR metrics (Coval and Stafford, 2007; Shleifer and Vishny, 2010), and deposit withdrawal parameters have been applied (Schmieder et al., 2012). Banks' liquidity adequacy is evaluated according to whether the remaining liquidity in stress-applied liquidity positions is positive or negative and banks' survival periods. In scenario calibration, realistic shocks like sudden liquidity disruptions or rapid cash outflows are considered, and in sensitivity analyses, historical worst events, expert opinions, and statistical methods are used (ESRB, 2012).

The global financial crisis and the March 2023 crisis in the United States provide important examples in terms of banks' solvency and liquidity resilience. In both financial crises, short-term wholesale funding concentration and asset-liability maturity mismatch are observed as two prominent characteristics of failed institutions. Deposit withdrawals, stress duration, and shares in banking stresses experienced in recent years are given in the following table.

Table 1: Historical Bank Run Episodes and Deposit Outflows

Bank	Duration	Outflow (bn)	Outflow Rate (%)
Northern Rock (2007)	a few weeks	13 (GBP)	56
Washington Mutual (2008)	16 days	18.7 (USD)	10.1
Wachovia (2008)	2 weeks	15 (USD)	3.6
ING Direct (2008)	3 months	4.9 (EUR)	3
Dexia (2011)	1 month	7 (EUR)	8.8
Cyprus Popular Bank (2012)	9 months	10 (EUR)	40

Banco Popular (2017)	2 months	18 (EUR)	24
Silicon Valley Bank (2023)	2 days	42 (USD)	24
First Republic Bank (2023)	3 months	101 (USD)	58
Credit Suisse (2023)	3 months	67 (CHF)	29
Signature Bank (2023)	1 day	17.8 (USD)	20

Source: (BCBS, 2023), (Amamou et al., 2020).

Each bank's failure process stems from a combination of its own structural factors and liquidity movements, and while some banks were rescued by public authorities, others were taken over or subjected to resolution processes. The definitions and durations of stress periods vary from bank to bank, and particularly in long stress periods, precisely determining the most intense period becomes difficult. Additionally, definitions created with publicly available data may differ, and a significant portion of the sample was not subject to LCR implementation during the stress period (BCBS, 2023).

Amamou et al. (2020) showed that in rapid and slow deposit withdrawal scenarios, monthly withdrawal rates were 5.1% and 18.9% respectively, and in withdrawals spread over time, total loss reached 24-40%. In contrast, deposit withdrawals at Silicon Valley Bank and Signature Bank in 2023 occurred very quickly, and the banks were resolved within 1-2 days. This situation has led to debates about whether LCR fulfills its intended function during stressed periods. Indeed, pre-2023 LCR stress testing scenarios generally assumed 5% retail deposit withdrawal over 30 days, while in recent crises these rates have been much higher (Wildmann et al., 2023).

LCR is not designed to cover all possible stress scenarios and is a standard that measures minimum liquidity needs. Therefore, banks and regulators apply stress tests to determine additional liquidity requirements and recommend more frequent reporting and development of additional indicators for early detection of tail events (Wildmann et al., 2023). Recent crises have shown that the speed and magnitude of deposit withdrawals may not be manageable with a 30-day time horizon and that indicators such as LCR and NSFR alone are insufficient. Indeed, prior to Credit Suisse's failure, although LCR and NSFR levels were above regulatory thresholds, these indicators were insufficient to detect the bank's structural liquidity mismatch (BCBS, 2023).

An important change observed in banks' balance sheet and funding composition in recent years is the dependence on wholesale funding and short-term liquidity funding. Additionally, the emergence of products such as synthetic and securitized assets and changing macroeconomic conditions have increased investors' risk appetite, creating increasingly more correlation and information asymmetry among assets.

The March 2023 crisis revealed aspects that need to be developed in liquidity stress tests. This crisis showed that depositors' behaviors are changing rapidly due to the impact of technological developments, and that tests need to be updated to cover such dynamics (Baudino et al., 2024). Recent research has highlighted the role of social media in crisis dynamics, finding that banks with high uninsured deposit ratios had a greater tendency to make stability-emphasizing informational statements, and that social media posts shaped public perception and created contagion effects during the 2023 US banking crisis (Jiang et al., 2025; Chen et al., 2024; Cookson et al., 2023; Henninger, 2023). These findings emphasize the importance of regulators developing social media communication policies and banks establishing rapid, clear, and data-based communication.

2.2. Stress Testing Practices by International Institutions and Supervisory Authorities

Following the 2008 global financial crisis (GFC), IMF's FSAP applications initiated significant revisions; particularly in advanced countries, risk and vulnerability analysis, financial safety nets, and supervisory practices have become more prominent. The new approach emphasizes financial stability and systemic risk-focused macroprudential stress tests, and in the global reform agenda, macroprudential policy and regulatory framework, non-bank financial institutions, and international institutional cooperation come to the fore. This transformation makes stress tests a vital tool not only in assessing risks belonging to individual banks but also in examining the propagation channels of systemic risks and their effects on financial stability.

Parallel to post-GFC regulatory developments, liquidity stress tests have become a fundamental element of financial stability analysis within the FSAP framework. In this context, Jobst et al. (2017) have made important contributions in areas such as the assessment of liquidity risk management practices and identification of gaps (IMF, 2010a; 2011a), development of liquidity stress tests (Schmieder et al., 2012; Schmitz, 2015), modeling of systemic liquidity risk (IMF, 2011; Jobst, 2014), and development of models linking liquidity and default risks in stress testing studies (BCBS, 2013b; 2015). Jobst et al. (2020) note that liquidity stress tests are less developed compared to solvency stress tests due to data constraints and complexity among risk factors. The IMF's FSAP has played a critical role in the application of these tests to countries' financial systems.

In FSAP stress testing applications, there is no specific regulation on how to calibrate the relevant coefficients; however, different coefficients based on expert opinion are applied for each item and its characteristics, as in Adrian et al. (2020). Recent FSAP reports (2023-2025) from multiple countries including Maldives, Saudi Arabia, Luxembourg, Slovakia, Spain, Belgium, Japan, and India have included liquidity stress testing applications (IMF; 2025a; 2025b; 2024a; 2024b; 2024c; 2024d; 2024e; 2023a; 2023b).

Liquidity stress tests have become one of the fundamental elements of financial stability assessments within the FSAP framework. Additionally, in many countries, local authorities also integrate this methodology into their internal supervision and risk management processes to assess system-wide liquidity conditions under stress.

Table 2: IMF FSAP Liquidity Stress Testing Approaches Summary

Approach	Country Examples	Key Methodology
Deposit Concentration/ Sensitivity Analyses	Maldives (2024), Saudi Arabia (2024), Luxembourg (2024)	Top depositor withdrawals, LCR sensitivity to deposit outflows
Cash Flow Based	Maldives (2024), Slovakia (2025), Spain (2024)	Cash flow analysis over different maturity horizons (1 week - 1 year)
LCR-NSFR Based	Belgium (2023), Japan (2024), India (2025), Saudi Arabia (2024)	LCR/NSFR stress tests with scenario-based parameter adjustments

Note: Detailed country-specific analyses, parameters, and results are provided in Table A1 in the Appendix

Overall, liquidity stress tests in IMF FSAP reports are becoming increasingly comprehensive and sophisticated. More integrated, advanced scenarios are being used that focus on the liquidity resilience of the entire financial system, not just the banking sector. Furthermore, parameters and assumptions used in stress tests are being updated in a more realistic and prudent manner in light of lessons learned from financial crises experienced in recent years.

Liquidity stress testing approaches applied in IMF FSAP reports are conducted using different methods and scenarios to measure the resilience of countries' banking sectors against liquidity risk. In FSAP reports prepared in recent years, three main approaches stand out: deposit concentration and sensitivity analyses, cash flow-based stress tests, and LCR-NSFR based analyses. Within the framework of deposit concentration and sensitivity analyses, scenarios such as the simultaneous withdrawal of deposits by banks' most important depositors are simulated, revealing the effects of large depositors' behaviors on banks' liquidity positions. Cash flow analysis is one of the most common methods in liquidity stress tests, though the aggregated presentation of balance sheet items in publicly available data limits the scope of this method. In LCR-NSFR based analyses, stress tests are applied at different severity levels based on regulatory ratios, with elements such as deposit outflow rates, asset value losses, and funding shocks taken into account, and scenarios calibrated considering Basel standards and country-specific risks.Particularly in countries such as Japan, India, and Belgium, liquidity risks are analyzed in detail in both local currency and foreign currency terms.

Authorities' approach to stress tests has changed after the GFC. Authorities have integrated the market risk and liquidity stress dimensions into these tests in addition to solvency stress tests. BCBS (2008) stated that banks should regularly conduct liquidity stress tests containing scenarios at different maturities and across markets after the GFC. During the GFC, connections between different markets and risk types emerged unexpectedly, and the European Central Bank (ECB) highlighted the need for improvement in liquidity stress test scenario design (ECB, 2008).

In their study within the ECB, Dees et al. (2017) applied macro-level stress testing with bank-level data, evaluating funding and market liquidity risks together. In their balance sheet-based liquidity stress test, they calibrated using withdrawal rates on the liability side and haircut rates on the asset side. Three scenarios were applied according to different severity levels: the most severe scenario simulates conditions during the collapse of Lehman Brothers, while the other two scenarios simulate shocks at one-quarter and one-half of that severity. Banks were divided into five groups according to their resilience to liquidity stress, and different haircut and rollover rates were applied to each group. According to Dees et al. (2017), a 100 basis point decline in capital ratio leads to approximately a 10 basis point increase in funding costs. The ECB classifies balance sheet items into four groups: contractual items, items with uncertain maturity, central bank and cash-like assets, and contingent liabilities. While contractual cash flows and nominal values are used as the basis in the Base scenario, deposit outflow rates and asset value losses (haircuts) are gradually increased in adverse and severely adverse scenarios (ECB, 2019).

Supervisory authorities widely use liquidity stress tests to assess the magnitude and importance of liquidity risk. In a study within the Bank for International Settlements (BIS) by Baudino et al. (2024), current practices and areas requiring development of liquidity stress tests applied by regulatory authorities in different countries are summarized. Supervisory authorities review and evaluate banks' internal stress tests in terms of scenario design, model development, and data sources. The Australian Prudential Regulation Authority (APRA) requires banks to adapt and apply their own scenarios through cash flow analysis, liquidity survival period, and LCR/NSFR. The Monetary Authority of Singapore (MAS) specifically determines scenarios that domestically systemically important banks (D-SIBs) must use in their stress tests. The Central Bank of Brazil (CBB) conducts system-wide liquidity stress tests. The Swedish Central Bank (SCB) applies stress tests as part of financial stability policies. The European Banking Authority (EBA) measures banks' resilience to liquidity stress (Baudino et al., 2024).

Table 3: Liquidity Stress Testing Practices by Supervisory Authorities

Authority / Approach	**ECB**	**SCB**	**BCB**
Purpose and Scope	Measuring banks' resilience to liquidity stress (generally only significant banks; however, extended to small-scale institutions once a year)	Assessing vulnerability in liquidity crises and estimating liquidity shortfalls (Large banks only)	Measuring and monitoring liquidity risk for all bank groups, complementary to LCR/NSFR
Approach and Data Source	Monthly authority data; survival period under the assumption that cash inflows-outflows stop	Monthly maturity ladder data; how can banks operate under stress without reducing credit volume?	Authority and clearinghouse data; review and action tool as an early warning indicator
Management (Who conducts the test? Are banks involved in the process?)	Top-down exercise conducted by EBA; banks provide cash flow data. Banks' own stress test results are compared	Top-down exercise conducted by SCB; banks are not involved in the process	Top-down exercise by BCB; banks are not involved in the process
Scenario/Assumption/Horizon	Haircuts on assets, rollover disruptions in liabilities, and demand deposit withdrawals. Same scenario for all banks based on historical and hypothetical static balance sheet. 6 months for SREP, standard annual	Value declines (haircuts) on assets, rollover disruptions in liabilities. Same scenario for all banks based on historical and hypothetical. 6-month horizon. Analysis of long-term propagation effects of shocks	Customized scenarios by financial institution; potential market risk losses; covers changes in exchange rates, interest rates, commodity and stock prices; haircut rates according to funding sources and historical deposit volatility; hypothesis-based. 30-day horizon based on LCR
Method and Output	"Survival period" is calculated for each bank under specific assumptions regarding the rollover of maturing assets/liabilities and deposit outflows according to banks' projected cash flows. Second-round effects are not considered and the simultaneous application of all haircuts is considered a sufficient shock. Liquidity survival period and net liquidity position	Cumulative net cash flows are calculated for each bank. Rollover of maturing assets/liabilities and deposit outflows are assumed. Contagion and second-round effects are not considered. Cumulative net liquidity need over 6 months	Based on bank-specific scenarios and potential losses from different funding items, additional outflows calculated at 95% confidence level with a 30-day "VaR model" according to deposit volatility, and withdrawal of deposits by each bank's top 3 corporate customers. Second-round effects are not calculated.

Source: Baudino et al. (2024).

A common point among these authorities' stress tests is that they are generally based on analyses targeting large-scale banks that constitute the sector's weight. However, they can be applied to the entire sector, including small-scale banks when necessary. In the ECB's liquidity stress testing approach, how liquidity positions will change under various stress levels is analyzed using different rates and assumptions according to the severity of shocks applied to banks' balance sheet items (ECB, 2019). The ECB uses two different stress scenarios: "adverse shock" and "severe shock" (ECB, 2019). While the SCB applies a system-wide single scenario with a similar approach, the BCB performs shock selection appropriate to the bank's profile through bank-specific scenario application; all three central banks assume that reserve usage and repo funding can be provided, ignoring extraordinary liquidity support.

In recent years, a significant portion of global financial assets has been concentrated in non-bank financial institutions (FSB, 2023). Therefore, institutions such as ESMA (2019) and BoE (2024) have developed system-wide stress tests that also include non-bank financial institutions. The Bank of England's System-Wide Exploratory Scenario (SWES) program has been one of the first applications measuring the overall resilience of the financial system. The framework developed by ESRB (2025) particularly assesses systemic liquidity risk more comprehensively in an environment where non-bank financial institutions (NBFIs) and interconnected financial networks have increased. Ding et al. (2024) developed a System-Wide Liquidity (SWL) framework with the Mexico example within the scope of identifying potential liquidity stress in the financial system beyond banks. In this direction, testing applications have transformed into a perspective covering banking and even the entire financial system. Although including NBFIs in existing financial networks and modeling where interbank connections are monitored is challenging, it is necessary for a complete assessment of systemic risk (Baudino et al., 2024).

2.3. An Overview of Liquidity Risk and Liquidity Stress Testing Applications in the Turkish Banking Sector

As of end-2024, the total asset size of the financial sector in Türkiye reached 42.2 trillion TL (approximately 1 trillion USD), representing approximately 97% of Gross Domestic Product (GDP). The banking sector, as the largest component of the financial system, has an asset size of 32.6 trillion TL (900 billion USD) and a 77.5% share within the financial sector (BRSA, 2024).

During this period, a total of 64 banks operate in Türkiye. Of these, 34 are deposit banks, 9 are participation (Islamic) banks, 20 are development and investment banks, and 1 bank operates under the Savings Deposit Insurance Fund (SIDF). While development and investment banks do not have the authority to collect deposits, they concentrate their activities mainly in project and investment financing, and their share within the sector is approximately 6%. Participation/Islamic banks operate according to interest-free banking principles, have the authority to collect deposits under the name "participation funds," but their share in the sector's asset size remains limited at 7.5%.

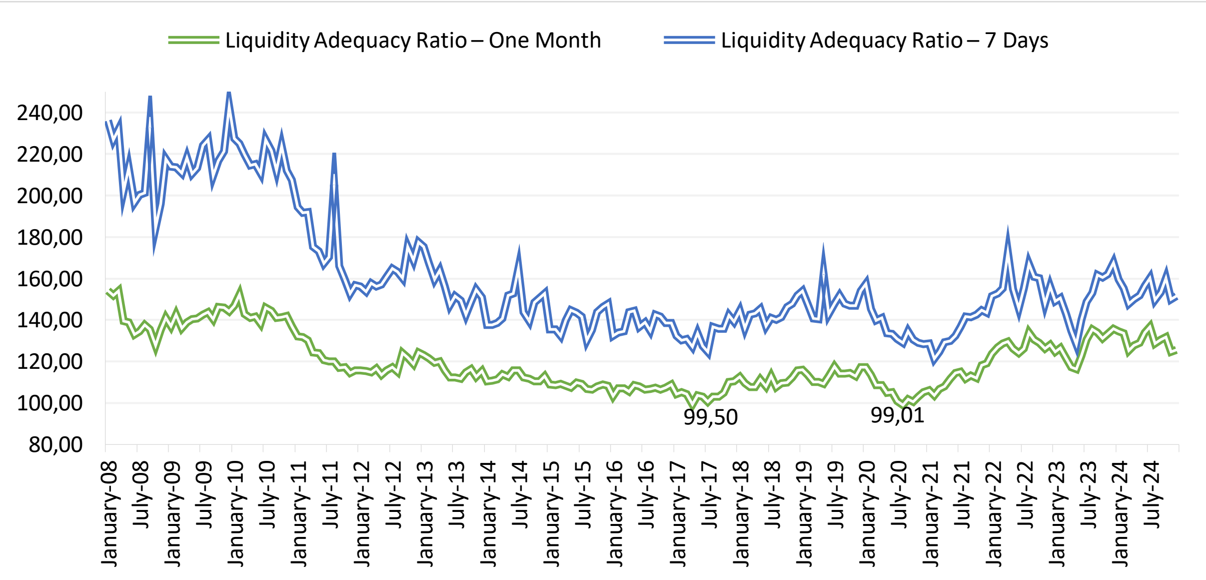
The regulation and supervision of the banking sector in Türkiye is carried out under the authority and responsibility of two main institutions. Banking Regulation and Supervision Agency of Türkiye (BRSA/BDDK) is the main authority responsible for banks' establishment, operations, mergers, transfers, liquidation, and supervision processes, and conducts oversight and regulatory activities to ensure financial stability and confidence in the sector. The Central Bank of the Republic of Türkiye (CBRT/TCMB), in addition to monetary policy practices, undertakes tasks such as liquidity management of the financial system, regulation of payment systems, and supporting financial stability.

BRSA has been actively participating in Basel Committee work as a member since 2009, integrating published standards into banking legislation. Regarding the Basel III accord published by the Basel Committee in 2010, regulations on equity, capital adequacy, liquidity, leverage, and capital buffers have been prepared and put into effect simultaneously with European Union applications. Within the framework of compliance with Basel III regulations, BRSA announced in July 2013 that the "Draft Regulation on Banks' Liquidity Coverage Ratio Calculation" was prepared, with the implementation date planned as January 2014, taking into account European Union regulations and other international developments. The fact that the liquidity adequacy regulation has been in effect since 2006 before the LCR regulation facilitated the compliance process for BRSA and banks regarding the new regulation.

BRSA has planned to increase the place and importance of stress tests within the supervision and oversight structure in parallel with international developments, and in this context, the "Guide on Stress Tests to be Used by Banks in Capital and Liquidity Planning" (Stress Test Guide) was created[2]. The Guide requires banks to prepare their strategic plans and budgets for a three-year forecast period within the framework of stress tests based on scenario analyses, use scenarios to be determined by BRSA in addition to internal assessments, determine their risk appetites and risk limits according to stress test results, and hold capital for adverse conditions. The Guide is similar in nature to the document titled "Principles for sound stress testing practices and supervision" published by BCBS (2009). The purpose of the Stress Test Guide published by BRSA in March 2016 is stated as explaining the good practices expected from banks within the framework of Article 43 titled "Stress Test Program" of the Regulation on Banks' Internal Systems and Internal Capital Adequacy Assessment Process. Within the scope of the Stress Test Guide, stress tests are practices that enable the forward-looking assessment of potential effects of adverse situations and events that are likely to occur on the bank

In the "Regulation on Measurement and Assessment of Banks' Liquidity Adequacy" dated November 2006 issued by BRSA, total and foreign currency liquidity adequacy ratios have been regulated for banks to provide and maintain sufficient liquidity levels. The said ratios are calculated as the ratio of assets to liabilities for Turkish lira and foreign currency. Two separate maturity buckets have been determined in the regulation, with the first maturity bucket being 0 to 7 days and the second maturity bucket being 0 to 31 days. It has been determined that the minimum liquidity adequacy ratio cannot be less than 100% for the total liquidity adequacy ratio and 80% for the foreign currency liquidity adequacy ratio, based on the simple arithmetic averages of both maturity buckets.

Graph 2: Liquidity Adequacy Ratios of the Turkish Banking Sector



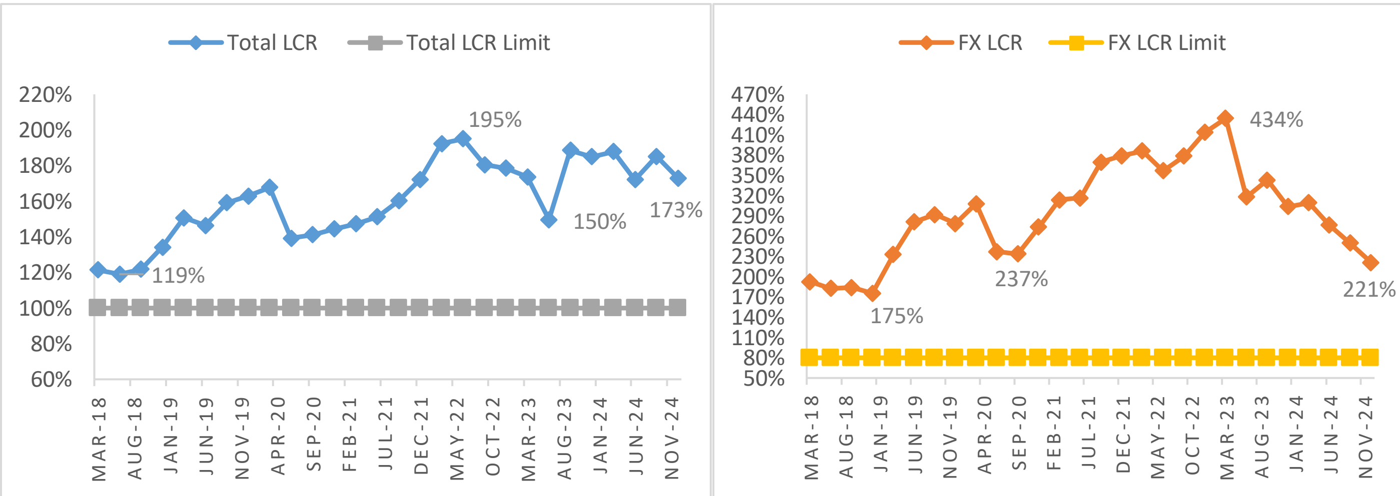
Source: https://www.bddk.org.tr/BultenAylik/

[2] https://www.bddk.org.tr/Duyuru/EkGetir/539?ekId=559

After the GFC, the Turkish banking sector's 7-day and one-month LAR (Liquidity Adequacy Ratio) generally followed a trend parallel to macroeconomic conditions, regulations, and banks' funding structure. The high ratios until 2011 reflect strong capital inflows and abundant liquidity during this period. The decline in the 2011–2013 period was influenced by the European debt crisis, weakening capital flows, and the CBRT's liquidity tightening policies. The fluctuations observed in ratios after 2013 are related to banks' increased use of swaps and short-term external borrowing. The first time LAR fell below 100% in 2017/Q4 coincides with a period when liquidity pressures increased due to rising non-deposit funding and increasing swap liabilities. The decline during the 2020 pandemic period occurred due to accelerated credit growth, increased funding through repos, and rising swap liabilities. In the gradual recovery after 2021, the removal of the asset ratio, reserve requirement regulations, and improvement in liquid asset composition were effective. The marked increase in 2023 and thereafter stems from macroprudential tightening, rising reserve requirement ratios, and banks being encouraged to hold more liquid assets.

LCR is calculated within the framework of the provisions set forth in the "Regulation on Banks' Liquidity Coverage Ratio Calculation" published by BRSA in March 2014, within the scope of compliance with Basel III regulations. According to the regulation, starting from April 2014, banks are required to calculate LCR on both consolidated and non-consolidated bases for total and foreign currency, effective from January 2014, and report to BRSA without any obligation until January 2015. A phased transition for Basel III LCR was envisaged starting from 2015, with a 10 percentage point increase each year, and LCR has been applied at 100% on a total basis and 80% on a foreign currency basis since 2019.

Graph 3: Total and FX Liquidity Coverage Ratios in the Turkish Banking Sector



Source: https://verisistemi.tbb.org.tr/index.php?/tbb/report_mali

In the Turkish banking sector, the legal threshold for total LCR and FX LCR has been applied at 100% and 80%, respectively, since 2019. Throughout the periods shown in the graph, total and FX LCR have remained above the legal threshold. The trajectory of total LCR is largely shaped by economic cycles, liquidity conditions, and credit expansion. During tightening periods, weakening credit demand and accumulation of liquid assets on banks' balance sheets lead to an increase in total LCR, while during growth periods, the ratio sometimes moves downward with increased credit utilization. The strong rise in mid-2022 in the graph can be attributed to the increase in liquid assets due to tight monetary conditions; the decline at the beginning of 2023 can be linked to credit growth and movements on the funding side.

The main determinants of fluctuations in FX LCR are reserve requirement ratios, regulations aimed at reducing FX deposits, maturity rollovers of banks' external borrowing transactions such as eurobond redemptions and syndication/securitization, and changes in collateral ratios for secured borrowings. These elements periodically increase and decrease FX liquidity in banks' hands and lead to the ups and downs seen in the graph. Particularly, the marked rise in 2022 corresponds to a period when FX liquidity strengthened; the gradual decline after 2023 indicates the effect of rising external borrowing costs and steps toward reducing FX liabilities through regulations.

During the 2021-2024 periods, the Turkish banking sector's total and FX LCR levels maintained their trajectory above legal thresholds, showing that liquid assets in total and FX terms are at a level sufficient to meet short-term cash outflows (CBRT, 2023; CBRT, 2024).

In the IMF's stress test and network analysis for Türkiye, the banking system's solvency and liquidity resilience were assessed using end-2021 data. Within the scope of the analysis, in a projection covering the top 10 banks by asset size, it was determined that when temporary regulatory flexibilities are excluded, the CAR (Capital Adequacy Ratio) declined significantly and could fall below the minimum regulatory ratio under the adverse scenario. In the liquidity stress test, it was determined that banks are resilient to low levels of deposit outflows, but show vulnerability in severe outflows, and that fund outflows from retail and corporate deposits are the main risk factor. Additionally, it was emphasized that under aggravated scenarios, some banks' LCR could fall below the legal threshold and that the CBRT's FX liquidity support is of critical importance. Network analyses showed that the banking system is highly interconnected with non-bank financial institutions and households and has the potential for shock propagation in waves (IMF, 2023a).

Looking at studies testing liquidity adequacy and containing stress testing applications on the Turkish banking system, Delikanlı et al. (2013), inspired by van den End (2010)'s stress test methodology, applied a stress test with an exponential distribution and a 0.1% tail risk assumption added to LaR coefficients, concluding that LAR remained above 100% on average over four periods, excluding the worst buckets. Akdoğan and Yıldırım (2014) tested adverse and severely adverse scenarios with metrics such as LCR and NSFR for the 7 largest banks in the Turkish banking system, and also analyzed the effect of the CBRT's three different intervention sets. Öztürker (2021) applied stress tests including severe and extremely severe scenarios and CBRT intervention for Türkiye's 7 largest banks, revealing that the CBRT's interventions such as asset purchases and reserve requirement releases extended banks' survival periods. Overall, these studies emphasize that LCR and NSFR are important for ensuring minimum liquidity, but stress tests should be used as a complementary and early warning tool to regulatory ratios.

3. Liquidity Stress Testing Methodology and Scope

3.1. Data and Scope

Stress tests for measuring liquidity adequacy are generally applied through three separate analyses based on LCR, NSFR, and cash flows. LCR-based stress tests measure banks' ability to meet liquidity shortfalls occurring over a 30-day horizon, NSFR-based stress tests measure banks' capacity to meet their long-term activities with stable funding sources, and cash flow-based tests measure the capacity of cash inflows at different maturities to meet cash outflows.

According to Basel III, LCR is a 30-day forward-looking liquidity metric. Therefore, each LCR_i value obtained from each simulation result represents a snapshot of the bank's 30-day liquidity resilience. LCR has been used in this stress testing application due to NSFR's focus on a 1-year horizon, the fact that it is not legally reported in Türkiye as of the 2023 period, LCR's greater suitability for short-term liquidity stress tests (30-day horizon), and its widespread use in liquidity stress tests in the literature.

As of December 2024, it includes 27 banks representing 86% of the sector's asset size. Eight of these banks are in the domestically systemically important bank group. The analysis has been conducted on an LCR basis using publicly available data published by the Banks Association of Türkiye[3]. Development and investment banks, some banks with missing data or anomalies detected and with a sector share below 1%, and participation/Islamic banks have not been included in the study due to data published by the Participation Banks Association not being suitable for analysis and the inability to ensure time series integrity (they represent 7.5% of the sector's asset size as of end-2024).

Banks have been divided into two separate groups: i) Domestically Systemically Important Banks: 8 banks determined according to BRSA's (1) DSIB and (2) Other Banks: A total of 19 banks including deposit banks outside DSIB for which LCR is calculated and which have reliable data.

This comprehensive study reveals the probabilistic distributions of liquidity risk in the Turkish banking sector and provides a systematic assessment for each bank, period, scenario, and LCR type combination. This approach enables distribution-based risk analysis rather than only point estimates and creates a richer and more informative dataset for decision-makers (regulatory authorities, banks' risk management units, investors). The total number of simulations performed in this study is calculated based on the following parameters:

- Number of Banks: 27 banks
- Number of Periods: 3 periods (2023 Q4, 2024 Q2, 2024 Q4)
- Number of Scenarios: 3 scenarios (Base, Adverse, Severe Adverse)
- LCR Type: 2 types (Total LCR, FX LCR)
- Repetitions per Set: 10,000 simulations
- Total Simulation Sets: 27 × 3 × 3 × 2 = 486 sets
- Total Simulation Repetitions: 486 × 10,000 = 4.860.000 repeated LCR calculations

According to LCR regulations in Türkiye, it is mandatory to achieve and maintain a minimum of 100% for Total LCR and 80% for FX LCR on a weekly basis (BRSA, 2014). These legal requirements have been set by BRSA to ensure that banks manage both their general liquidity positions and FX-based liquidity risks. In this context, analysis has been conducted for both Total LCR and FX LCR for each bank. The list of banks included in the analysis is provided in Table A2 in the Appendix. Simulations work on LCR components obtained after applying Basel III consideration rates to items reported by banks. All LCR items used in the analysis have been taken from components defined in banks' audited financial reports and according to the Basel III framework. Therefore, HQLA, cash outflow, and cash inflow items have been derived from balances in the audited legal reporting set and calculated by applying Basel III consideration

[3] Within the scope of independent audit reports, LCR values are published on a quarterly basis, and in determining systemically important banks, those banks that hold a systemic important bank capital buffer have been taken into account.

rates. For this reason, items used in the stress test are both consistent in terms of regulatory compliance and reliable in terms of data quality.

The stress testing framework consists of two main parts: In the first round, LCR distributions are calculated under different stress scenarios (Base, Adverse, Severe Adverse) by applying independent Monte Carlo simulations for each bank. At this stage, shocks with Uniform distributions are applied to HQLA and cash outflow items, and 10.000 simulation iterations are performed for each bank. This approach reveals banks' individual liquidity risk profiles and changes in LCR values according to scenario severity.

After the shocks applied in the first round, when multiple banks in the banking system fall below the legal LCR threshold or experience liquidity squeezes, the second round examines the system-wide propagation of vulnerabilities. At this stage, interbank correlation and tail dependence are modeled using the t-copula method; the contagious nature of systemic risk is simulated through the propagation of shocks to other banks via tail dependence parameters determined with the copula. Thus, the potential for an extremely adverse development in one bank to spread to other banks and the entire system through the interbank dependency structure is evaluated holistically. Since direct interbank exposure data (interbank exposure matrices) are not available, the contagion mechanism has been modeled through a t-copula-based correlation structure. The hypotheses tested in the study have been defined as follows to test different dimensions of our two-stage LCR stress test.

- H1: Monte Carlo-based stress scenarios applied to Basel III LCR items produce a deterministic deterioration (mean decline, increase in failure rate) in banks' individual LCR distributions as scenario severity increases.
- H2: The t-copula-based second-round analysis significantly increases the probability of joint breach of liquidity thresholds compared to first-round Monte Carlo results; systemic risk is measured higher due to tail dependence.
- H3: Vulnerability scores derived from t-copula-based Failure and ES metrics systematically place banks with high systemic linkages in the upper ranks and reveal a different ranking from traditional single-metric approaches.

The advantages of the method used are as follows: (i) It provides a comprehensive and holistic view of liquidity risk; (ii) The test has been calibrated based on historical realizations and scenarios applied in FSAP reports; (iii) It evaluates banks' liquidity holistically using the LCR.

3.2. First-Round Monte Carlo Simulation Methodology

3.2.1. Scenario Generation and Methodology

The fundamental determinant of the liquidity stress testing framework is scenario design. The scope and severity of scenarios increase the realism of results when considered together with the interaction of exogenous shocks, delayed effects, and financial actor behaviors. Therefore, a reasonable and consistent view should be presented by using both past experiences (historical events) and possible realizations (hypothetical constructs). Scenarios should be able to include multiple stress factors at different severity levels; be applicable at both bank-level and sector-wide; and also cover situations where combined (simultaneous) shocks may occur.

Looking at a hypothetical scenario event, in an environment where the bank's funding capacity decreases, there is a risk of inability to meet liabilities as a result of increased forced asset sales, these sales pulling prices down and weakening collateral values, this creating pressure on credit ratings and accelerating deposit outflows. In this framework, the stress testing methodology should use historical, hypothetical, and reverse stress approaches together; and model the effects of individual, market-wide, and combined shocks that generate margin and collateral demands on cash flows. Shock calibrations should be based on cash outflow rates and cash inflow haircuts observed during crisis periods; and should also be applicable by being adjusted (relaxed or intensified) according to local market conditions.

In the methodology section of the study, inspiration has been drawn from methods used in studies by van den End (2010), Aikman et al. (2009), Nier et al. (2008), Geršl et al. (2016), Jobst et al. (2017), and Hejlová et al. (2020).

Table 4: Liquidity Stress Testing Framework

Risk Type	Definition	Example Scenarios
Market Liquidity Risk	Value loss of assets under stress and decline in collateral/saleability	High-quality asset haircut, market value loss of marketable assets
Funding Liquidity Risk	Inability to roll over liabilities or early withdrawal	Closure of interbank market
Contingent Risks	Triggering of conditional liabilities such as swap agreements	Sudden utilization of credit limits

In this study, copula-based Monte Carlo simulations directly applied to LCR items under three main stress scenarios have been used to assess the short-term liquidity resilience and systemic risk profile of the Turkish banking sector. The analysis has been conducted on HQLA, cash outflows, and cash inflows, avoiding adding additional assumptions to the balance sheet as a whole. Scenarios are not specific to a particular bank's balance sheet; they are based on exogenous assumptions reflecting Türkiye-specific shock dynamics and international crisis experiences. The main risk factors considered are: (i) gradual increase in deposit withdrawals (especially rapid outflows in FX and demand deposits), (ii) defaults in loan repayments and decline in collection rates, (iii) liquidity contraction in interbank and repo markets, (iv) price declines in HQLA and securities (increased haircuts), (v) decline in funding capacity and rising costs, (vi) CDS increases creating margin call/recall pressures in secured borrowing and derivative transactions, and (vii) renewal disruptions in syndication-securitization and bilateral borrowings and haircuts in contract-based liabilities.

In stress scenarios, it is assumed that HQLA's effectiveness will weaken not only due to declining market values but also due to being subject to forced sales, intensive use as repo collateral, and being pledged in derivative transactions. This assumption can deepen liquidity squeezes through the erosion of the LCR buffer, especially under systemic stress. Margin call obligations are also evident in repo and secured borrowing channels in addition to derivative positions; it is anticipated that intra/institutional margin calls with market volatility and CDS increases will increase cash outflow pressure.

In periods when confidence weakens, increased counterparty risk in the interbank market and deterioration in market functionality can strengthen the contagion channel, leading to rapid spread of individual institution shocks to the sector. Additionally, when capital adequacy falls below a certain threshold, mechanisms such as collective recall of conditional funding can trigger large-scale liquidity outflows. Funding cost shocks have been calibrated at different intensities according to source type: risk premium and CDS transition in wholesale funding, competition-based interest increases in deposits, and collateral and repricing effects in repos have been considered.

The analysis horizon is 30 days according to the Basel III definition. Since LCR targets a 30-day forward-looking liquidity window, the impact of shocks has been calibrated to this horizon. To capture tail dependence, Monte Carlo outputs have been combined with t-copula; systemic co-movement and tail risks have been assessed. The study's design produces 30-day stress snapshots at three different calendar points (2023Q4, 2024Q2, 2024Q4) to represent 12-month resilience; thus, the effects of seasonality/policy cycles and different macro regimes have been examined with a limited number but highly representative periods.

Calibration is based on both local and international experiences: 2001 Turkish banking crisis, 2008 global financial crisis, 2018 FX-liquidity shock, 2020 pandemic, 2023 international banking stresses. Schmieder et al. (2012), using the Lehman collapse as a reference, graded shocks as moderate/high/severe/extremely severe and recommended the joint application of individual-combined shocks. The IMF guide (Adrian et al., 2020) emphasizes that basic variables to be used in stress tests should be selected according to the country's vulnerability profile. Sharp depreciation and volatility in exchange rates in countries with high FX-denominated liabilities are the main sources of default and liquidity pressure in banking (Allen and Gale, 2004). The IMF's 2023 Türkiye FSAP report clearly emphasizes the intensity of FX liquidity risk in Türkiye and its potential effects on the system (IMF, 2023a). ECB/SSM and related authorities also show that stress levels in FX positions are generally higher (Baudino et al., 2024). Therefore, run-off and haircut rates applied to FX items have been prudently calibrated to reflect country-specific vulnerabilities.

For systemically important banks (DSIB), literature and practices indicate higher gross outflow pressure and collateral requirements during stress periods. Although they may face higher gross cash outflow pressure and collateral requirements in crises due to larger HQLA buffers, broad customer base, and complex market connections, they generally have the capacity to limit tail risks thanks to diversified funding sources and stronger market access. The ECB envisages higher CBC/haircut levels for systemic institutions in a resolution context; for example, while HQLA haircut is 1–3% in small banks, it can rise to 3–9% in G-SIBs (Amamou et al., 2020). Additionally, stress data covering the 2016–2023 period show that systemic banks experienced higher deposit outflows compared to other banks, especially during crisis times such as COVID-19 (Wildmann et al., 2023).

MAS (2023) applied common scenarios and run-off rates for D-SIBs; validates results by conducting parallel tests with LCR and cash flow data and evaluates supervisory intervention in liquidity shortfalls. Within the scope of IMF (2024a) Spain FSAP, special LCR/NSFR/short-term cash flow tests were applied to systemic banks including a G-SIB; funding and market liquidity risks were covered across multiple currencies; HQLA haircuts were determined according to ECB and market shocks. These observations show that giving higher run-off rates to systemic banks in stress tests can be empirically grounded, not just hypothetical. These foundations, the DSIB/Other banks distinction in our study, and the use of tightened parameters in FX items have been inspired by empirical and regulatory frameworks.

Central bank support (swap lines, etc.) can ease liquidity in crises; however, since it is dependent on preferences and conditions, it has not been taken into account in the Base scenario, consistent with common practice in the literature (Baudino et al., 2024). This choice provides a conservative assessment "without intervention"; the effects of possible interventions would change the results in a positive direction.

Scenarios aim to assess the banking system's resilience to different stress conditions by utilizing both historical experiences and Basel III criteria, and are designed according to increasing severity levels, consistent with stress test methodologies applied by BRSA. Simulations have been applied for three different periods representing Türkiye's recent economic conditions: 2023 Q4, 2024 Q2, and 2024 Q4. The selection of these periods covers critical time intervals to assess the current liquidity risk profile of the Turkish banking sector.

Table 5: Scenario Characteristics

Features	Base Scenario	Adverse Scenario	Severe Adverse Scenario
Historical Reference	2023 Normalization, 2020 Pandemic	2008 Global Financial Crisis, 2023 US banking turmoil, 2018 Turkish FX crisis	2001 Turkish banking crisis, 2008 post-Lehman global shock
Credit Contraction	5–10%	20%	40%
Funding Cost Increase	5–7%	15%+	30%+
Deposit Outflow	0–16%	6–32%	50%+
Contingent / Derivative Liabilities	Swap market functioning, outflow 5–10%	Limited activity, outflow 20–60%	Market frozen, margin calls triggered, outflow 60–100%
Unsecured Funding	Rollover ratio 90–100%	Rollover ratio 50–80%	Rollover ratio 0–30%
Regulatory / Policy Response	Policy rate & reserve requirement adjustments	Higher reserves + swap limits	Interventions ineffective, systemic confidence loss
Confidence Level	Cautious optimism	Fragile market confidence	Confidence erosion, investor flight

In this study, three different calendar periods (2023 Q4, 2024 Q2, 2024 Q4) have been selected to assess the 12-month resilience of the Turkish banking sector. The selection of these periods is based on the following justifications: (i) Capturing different macro-financial regimes: 2023 Q4 normalization, 2024 Q2 mid-year tightening, and 2024 Q4 year-end conditions represent different macro-financial environments; (ii) Observing seasonality and policy cycle effects: Within a 12-month window, it has become possible to assess the sector's resilience under different seasonal and policy cycle conditions; (iii) Statistical power and data availability balance: Three periods provide both statistical power and respect data availability constraints. Thus, by aiming to assess the banking sector's liquidity resilience with 30-day stress snapshots across 12 months and three different periods, it aims to capture dynamics over time rather than a static measurement.

Base Scenario – "Macroeconomic Uncertainties"

It reflects a period when macroeconomic uncertainties have increased; however, there is no panic situation in the financial system yet. Despite deterioration in inflation expectations and interest rate increases, no liquidity contraction is observed in the banking system. Banks are adopting a more cautious approach against maturity mismatch by reassessing credit policies, credit growth rate is decreasing, and financing costs are increasing. Limited outflows are observed in LCR items; particularly, a slight decrease is experienced in derivative transactions and short-term debts. A limited decline in HQLA market values and a partial decline in effectiveness due to repo/collateral usage are expected. Gradual outflows are anticipated in customer deposits, especially for low-stable and non-operational deposits.This design aims to assess 12-month sectoral resilience with three different 30-day stress snapshots; it captures dynamics over time rather than a single static measurement. Detailed run-off and haircut parameters for the Base scenario are provided in Table A3 in the Appendix.

Adverse Scenario – "Credit Flow Constraints and Interbank Market Squeeze"

It indicates a period when a significant stress environment prevails in financial markets and vulnerabilities have increased, such as the 2008 global crisis and 2018 FX and liquidity shocks. As a result of exchange rate shocks, restrictions on swap markets, and narrowing of funding opportunities from external sources, banks are acting more cautiously in lending, and this effect causes a marked contraction in credit volume. Funding costs and customer deposit interest rates increase significantly, and borrowing opportunities from abroad decrease. In addition to medium-high level outflows in LCR items, value loss in HQLA is increasing (10-20%), and margin call pressure in derivative liabilities is anticipated. Outflow rates in customer deposits reach 6-32% levels. Additionally, liquidity contraction in interbank and repo markets, increased counterparty risk, and market dysfunction are anticipated. Detailed run-off and haircut parameters for the Adverse scenario are provided in Table A4 in the Appendix.

Severe Adverse Scenario – "Interbank Market Closure and Confidence Crisis"

It reflects a systemic financial collapse similar to the 2001 crisis and a situation where market functionality is completely lost. As a result of severe exchange rate shocks, capital outflows on a global scale, and shocks in market confidence, banks face high levels of credit contraction; both deposits (over 50%) and funding from external sources are withdrawn from the system. Funding costs climb to extraordinary levels (over 30%), and banks lose access to swap markets completely as they cannot roll over their debts. With a large private bank defaulting, systemic contagion risk rises, and other banks' liquidity positions deteriorate rapidly. High (20-40%) value loss in HQLA and significant outflows including stable deposits are anticipated. In short-term wholesale funding, derivative liabilities, and collateral, outflows close to 100% and total loss risk have been considered. Additionally, liquidity outflows such as capital adequacy falling below a determined level and total recall of all funding provided conditionally (CDS-Z score-rating) have been included. Detailed run-off and haircut parameters for the Severe Adverse scenario are provided in Table A5 in the Appendix.

In studies conducted in recent years, the use of Monte Carlo simulation in liquidity stress tests has become increasingly widespread. Van den End (2010), using weighting factors determined according to Basel III, examined the effects of market and credit shocks on LCR through Monte Carlo simulation. Multi-factor scenarios were created by applying shocks to collateral value losses and outflow rates, banks' liquidity and funding assumptions were tested, and LCR was evaluated dynamically while NSFR was kept constant. Wong and Hui (2009), in their model developed with data from 12 banks in Hong Kong, calculated cash shortfalls and default probabilities through Monte Carlo simulations, also taking into account contagion risk caused by interbank connections.

International regulatory institutions also widely use Monte Carlo simulation in macro and micro-level liquidity stress tests. Institutions such as the IMF and ECB prefer this method to statistically analyze the banking system's resilience to tail risks and the distribution of potential losses under different shock types and scenario combinations (Ding et al., 2024; Amamou et al., 2020). Ding et al. (2024), in their study conducted within the IMF, generated scenario-based shocks and analyzed their system-wide effects through Monte Carlo simulation. Similarly, Amamou et al. (2020) conducted simulations based on the Monte Carlo method to estimate potential liquidity shortfalls under both bank failure and systemic crisis conditions. These studies highlight the flexibility provided by the Monte Carlo approach in analyzing complex systemic interactions, including second-round effects, in liquidity stress tests.

3.2.2. LCR Calculation Method

According to Basel III regulations, LCR is calculated as the ratio of high-quality liquid assets to 30-day net cash outflows to measure banks' resilience against short-term (30-day) liquidity risk, and is maintained at a minimum of 100%. LCR components are obtained by multiplying the balance in each sub-item of HQLA, cash inflows, and outflows by the relevant regulatory weight and summing across all items.

$$HQLA_{b,t_0}=\sum_J w_J^{HQLA} * I_{b,t_0,j} \tag{1}$$

$$Out_{b\ ,t_0}=\sum_J w_J^{Out} * O_{b,t_0,j} \tag{2}$$

$$In_{b\ ,t_0}=\sum_J w_J^{in} * N_{b,t_0,j} \tag{3}$$

The initial LCR is calculated as follows:

$$LCR_{b,t_0} = \frac{HQLA_{b,t_0}}{Out_{b\ ,t_0} - \min\left(In_{b,t_0}, 0.75 * Out_{b\ ,t_0}\right)} \tag{4}$$

Within the scope of the stress test, the lower (a) and upper (b) bounds of shock rates to be applied to each LCR item have been determined by taking into account past crisis data, relevant literature, and institutional practices (e.g., EBA, IMF, ECB stress tests). For each bank group and scenario combination, shock rates to be applied to relevant items have been randomly drawn from a Uniform distribution within these intervals.

The Uniform distribution is based on the assumption that all shock rates within the determined interval ($[a,b]$) can occur with equal probability. This approach enables conducting a stress test consistent with the maximum entropy principle without making a parametric distribution assumption, and also makes it possible to assess banks' resilience to different stress conditions by considering critical scenarios with equal probability.

For each simulation, random shocks have been applied to LCR items in the relevant scenario. $\epsilon_{i,j}$ denotes the shock rate applied to the *j*. item in the *i*. simulation, and $\mathrm{U}(a_{-j,} b_{-j,})$ denotes the Uniform distribution with lower and upper bounds $a_{-j,}$ and $b_{-j,}$ For each simulation i_i and item i_j, the shock rate is drawn from a Uniform distribution:

$$\epsilon_{i,j} \sim \mathrm{U}(a_{j,} b_{j,}) \tag{5}$$

For each simulation, LCR is calculated with the drawn shock rate vector:

$$X_i = (x_{i,1,} x_{i,2,}, \ldots, x_{i,k}) \tag{6}$$

Here, X_i, *i* denotes the parameter vector randomly drawn in the i-th simulation; k denotes the number of parameters in the model (for example, deposit outflow rate, asset value loss, other cash flows). The post-shock value of each item:

$$I_{b,t_0 j}^{(i)} = I_{b,t_0,j} * (1+\epsilon_{i,j}^{HQLA}) \tag{7}$$

$$O_{b,t_0 j}^{(i)} = O_{b,t_0,j} * (1+\epsilon_{i,j}^{out}) \tag{8}$$

$$N_{b,t_0 j}^{(i)} = N_{b,t_0,j} * (1+\epsilon_{i,j}^{in}) \tag{9}$$

Here, I, O, N denote the pre-shock balances of the HQLA item, cash outflow item, and cash inflow item, respectively; the ϵ terms denote the run-off/haircut shocks drawn in the simulation. At each simulation step, these updated balances are multiplied by the weights determined by Basel III to calculate total HQLA, gross outflow, and gross inflow:

$$HQLA_i = \sum_J w_J^{HQLA} * I_{b,t_0,j}^{(i)} \tag{10}$$

$$Out_i = \sum_J w_J^{out} * O_{b,t_0,j}^{(i)} \tag{11}$$

$$In_i = \sum_J w_J^{in} * N_{b,t_0,j}^{(i)} \tag{12}$$

The HQLA, Out, and In items used in this study have been taken as the values reported by banks with Basel III consideration rates applied; therefore, the above formulas represent the general calculation framework. On the other hand, according to Basel III, the portion of cash inflows exceeding 75% of total cash outflows is not considered in the LCR calculation. That is, net cash outflow is calculated as:

$$NetOut_i = Out_i - min\,(In_i, 0.75 * Out_i) \tag{13}$$

$HQLA_i$ ve $NetOut_i$ are the high-quality liquid assets and 30-day net cash outflow updated according to randomly drawn shocks in the simulation. At each simulation step, new values of LCR items are calculated using the drawn shock rates and weights:

$$LCR_i = \frac{HQLA_i}{NetOut_i} \tag{14}$$

When simulations are completed, the expected value of LCR, Variance/Standard Deviation, Value-at-Risk, and Expected Shortfall statistics are calculated as follows:

$$E[LCR] \approx \frac{1}{N} = \sum_{i=1}^{N} LCR_i \tag{15}$$

$$Var[LCR] \approx \frac{1}{N-1} \sum_{i=1}^{N} (LCR_i - \overline{LCR})^2 \tag{16}$$

$$VaR_\alpha(LCR) = quantile(LCR, 1 - \alpha) \tag{17}$$

$$ES_\alpha(LCR) = E[LCR \mid LCR \le VaR_\alpha(LCR)] \tag{18}$$

In this study, the number of simulations N is taken as 10.000. The LCR value obtained from each simulation result is denoted as LCR_i. The arithmetic mean of LCR values obtained from all simulations is denoted by $\overline{LCR}$. The lower bound of LCR at a certain confidence level (for example, 95%), i.e., tail risk, is expressed as VaR_α .

This value represents the maximum value in the worst 5% tail of LCR. Additionally, ES_α denotes the average of LCR values below the VaR value, i.e., worse values, and is also called expected loss.

3.2.3. Simulation Algorithm

Monte Carlo simulation in liquidity stress tests is a numerical method widely used to analyze the distribution of possible outcomes of the banking system under different shock scenarios. This method enables the numerical evaluation of financial models in situations where uncertainty is high and closed-form solutions are not possible. Parameters that are uncertain in the model are repeatedly sampled from appropriate probability distributions, and the model is repeated numerous times (for example, 10,000), with each repetition representing a separate scenario. In Monte Carlo simulation, increasing the number of simulations reduces the error rate ($O(N)^{-1/2}$); this shows that 10,000 repetitions are statistically sufficient, especially for tail risks (VaR, ES) (Glasserman, 2004).

The study conducted by Yamai and Yoshiba (2002) shows that 10.000 simulations significantly reduce the confidence interval of VaR and ES estimates compared to 1,000 simulations. Jorion (2007) states that 5,000 to 10,000 simulations frequently contain sufficient statistical precision for financial risk calculations.In the simulations, shock parameters have been drawn from a Uniform distribution. Different shock intervals have been applied on a scenario basis (Base, Adverse, Severe Adverse), and the LCR formula (LCR = HQLA / Net Outflow) has been calculated in each simulation. In the model, Türkiye-specific shocks (TL credit contraction, FX deposit demand) have been considered at the LCR item level. As a result of each simulation set, 10,000 LCR values have been obtained, and descriptive statistics, quantile values (Q05, Q95), VaR, and ES metrics have been calculated from these values.

3.3. Second-Round Effects Analysis: Copula-Based Approach

3.3.1. Theoretical Rationale and Literature Foundation

In systemic risk modeling, considering contagion effects and second-round effects is very important (Dees et al., 2017). Banks' fire sale responses are modeled as an increase in asset haircuts due to system-wide fire sales of each asset type within the contagion effect framework. Liquidity inadequacy can occur over time or suddenly, and this situation can trigger herd behavior and fire sales. To model contagion effects in stress tests, second-round effects should also be considered by authorities after the propagation of shocks to the financial system (Baudino et al., 2024).

Second-round effects analysis uses a copula-based approach to assess interbank dependence and contagion risk. Copula theory allows separating multivariate distributions as marginal distributions and a dependence structure (Sklar, 1959). Sklar's theorem shows that any multivariate cumulative distribution function (CDF) can be expressed in terms of marginal distributions and a copula function:

$$H(x_1, x_2 \dots, x_\mathrm{d}) = C\,(\mathrm{F}_1(x_1)\,, \dots, \mathrm{F}_\mathrm{d}(x_\mathrm{d})) \tag{19}$$

Here, H is the joint CDF, F_i are the marginal CDFs, and C is the copula function. The copula approach is used to understand tail events as a generalization of dependence beyond linear correlations (Frey & McNeil, 2001; Embrechts et al., 2002). This approach differs from the multivariate extension of extreme value theory used by Poon et al. (2004), which requires observations of joint tail events. The copula approach requires less data to model tail dependence and is more suitable for simulation-based analyses (Embrechts et al., 2002).

The t-copula selection is widely used to model tail dependence in financial data (Embrechts et al., 2002; McNeil et al., 2015). The t-copula can capture tail dependence better compared to the normal copula (Demarta & McNeil, 2005; Joe, 2014). This property is critical for assessing contagion risk among financial institutions under stress conditions (Acharya et al., 2011; Brunnermeier and Pedersen, 2009). The t-copula controls tail dependence through the degrees of freedom parameter (v); low v values correspond to higher tail dependence (Demarta & McNeil, 2005; Joe, 2014).

3.3.2. Probability Integral Transform (PIT) and Data Transformation

The PIT is used to transform marginal distributions to a Uniform distribution. Rosenblatt (1952) showed that transforming a continuous random variable with its own cumulative distribution function results in a Uniform distribution:

$$U_i = F_i(X_i) \sim \text{Uniform}(0,1) \tag{20}$$

In the equation, X_i is the original random variable, F_i is the marginal CDF, and $U_i$is the Uniform transformation result. PIT states that when any continuous random variable is transformed with its own CDF, the result has a Uniform distribution on the [0,1] interval. This transformation is one of the fundamental results of probability theory and plays a critical role in copula modeling (Genest & Rivest, 1993; Cherubini et al., 2004).

In copula modeling, PIT is used to transform marginal distributions to a Uniform distribution. This is because copula functions are defined on the Uniform [0,1] interval. Sklar's theorem shows that the joint distribution can be expressed in terms of a copula function and marginal CDFs. In other words, copula functions cannot be applied directly without PIT; because copula functions assume Uniform marginal distributions (Cherubini et al., 2004; Patton, 2006).

In practice, since the true marginal distributions are unknown, the Empirical Cumulative Distribution Function (ECDF) is used. ECDF is a non-parametric method to estimate the marginal distribution from observed data. ECDF is calculated by counting how many of each observation are below or equal to a certain value:

$$F^{\wedge}_i\ (x) = \frac{1}{n}\sum_{j=1}^{n} 1(X_{ij} \ \leq \ x) \tag{21}$$

Here, n is the number of observations, and 1(·) is the indicator function (1 if value ≤ x, 0 otherwise). ECDF is a method used to estimate the CDF from observed data when the true CDF is unknown. The Glivenko–Cantelli theorem shows that ECDF converges uniformly to the true CDF (Dvoretzky et al., 1956; Massart, 1990). First-round LCR simulations are transformed to Uniform using ECDF:

$$U_{i,t} = \hat{F}_i(LCR_{i,t}) \tag{22}$$

Values obtained from copula simulation are transferred back to the LCR scale using inverse ECDF:

$$LCR^*_{i,t} = \hat{F}_i^{(-1)}(U^*_{i,t}) \tag{23}$$

This step enables modeling the dependence structure through t-copula while preserving bank-specific marginal distributions (Patton, 2006; McNeil et al., 2015).

3.3.3. t-Copula Selection and Parametrization

The t-copula is a copula function based on Student's t distribution and controls tail thickness with the degrees of freedom parameter ν (Demarta & McNeil, 2005). D-dimensional t-copula:

$$C_t(u_1, \ldots, u_d; \mathbf{R}, \nu) = t_{\nu,\mathbf{R}}\ (t_\nu^{-1}(u_1)\ , \ldots, t_\nu^{-1}\ u_d)) \tag{24}$$

where **R**, is a $d \times d$ correlation matrix and t_{ν}^{-1} is the inverse of the univariate t-CDF. Another advantage of the t-copula is that its lower and upper tail dependence coefficients are greater than zero; tail dependence:

$$\lambda_L = \lambda_U = 2t_{\nu+1}(-\sqrt{\nu+1}\,\frac{\sqrt{1-p}}{\sqrt{1+p}}) \quad (25)$$

is expressed as (Cherubini et al., 2004). As ν decreases, tail thickness increases; this is critical in modeling simultaneous declines during stress periods (Joe, 2014). The t-copula's ability to capture dependence in both lower and upper tails provides a critical advantage for modeling co-movements during stress periods (Cherubini et al., 2004; Demarta & McNeil, 2005; Joe, 2014).

In this study, a single t-copula has been calibrated for all banks, and the same copula parameters (**R** ve v) have been used across all scenarios (Base, Adverse, Severe Adverse). This approach is based on the assumption that the dependence structure remains constant independently of scenarios; stress conditions affect marginal distributions, but the interbank dependence structure does not change (Cherubini et al., 2004; McNeil et al., 2015).

3.3.4. Dependence Measurement: Kendall's Tau

Kendall's tau (τ) measures the monotonic relationship between two variables through concordant/discordant pairs (Kendall, 1938). Its definition is:

$$\tau = \mathrm{P}[(X_1 - X_2)(Y_1 - Y_2) > 0] - \mathrm{P}[(X_1 - X_2)(Y_1 - Y_2) < 0] \quad (26)$$

Empirical calculation:

$$\hat{\tau} = \frac{2}{n\,(n-1)} \sum_{i<j} sign\ [(x_i - x_j)(y_i - y_j)] \quad (27)$$

In copula modeling, Kendall's tau is preferred because it is a rank-based dependence measure and is independent of marginal distributions (invariance property) (Nelsen, 2006; Cherubini et al., 2004). For the elliptical copula family (including Gaussian and t-copula), the relationship between Kendall's tau and Pearson correlation is given by Lindskog et al. (2003) and Demarta & McNeil (2005):

$$\rho = \sin\frac{\pi\tau}{2} \quad (28)$$

This transformation is valid for both Gaussian and t-copula and has been used to construct the Pearson correlation matrix **R** from Kendall's tau values. This approach provides a transition from rank-based dependence measure to linear correlation and is widely used in copula parameter estimation (Nelsen, 2006; McNeil et al., 2015).

3.3.5. Correlation Matrix Adjustments

The correlation matrix **R** to be used for copula simulation must be positive definite. If the empirical correlation matrix is not positive definite, it is projected to the nearest positive definite matrix using Higham's (1988) method:

$$\mathbf{R}^* = \arg\min_{\mathbf{R}>\mathbf{0}} \| \mathbf{R} - \widehat{\mathbf{R}} \|_F \quad (29)$$

where $\mathbf{R} - \widehat{\mathbf{R}} \|_F$ denotes the Frobenius norm. Higham's (1988) method calculates the projection of a non-positive definite matrix to the nearest positive definite matrix as a general linear algebra problem; this method is used to project non-positive definite correlation matrices to the nearest positive definite matrix (Borsdorf & Higham, 2010; Qi & Sun, 2006). These methods are applied because the correlation matrix must be positive definite in copula modeling.

Alternatively, it is possible to pull the empirical matrix toward a target matrix (for example, an identity matrix) using the Ledoit & Wolf (2004) shrinkage method:

$$\mathbf{R}^{*}= \alpha\mathbf{T} + (1 - \alpha\ )\ \widehat{\mathbf{R}} \tag{30}$$

where $\alpha \in [0,1]$ is the shrinkage parameter and **T** is the target matrix. This approach makes the correlation matrix stable and positive definite in high-dimensional data (Ledoit & Wolf, 2004). Positive definite matrix projection methods (Higham, 1988; Borsdorf & Higham, 2010; Qi & Sun, 2006) make the correlation matrix positive definite; these methods are applied because the correlation matrix must be positive definite in copula models.

3.3.6. Degrees of Freedom Parameter Estimation

The degrees of freedom ν of the t-copula determines tail thickness; low ν values indicate thicker tails and stronger co-movements during stress periods (Demarta & McNeil, 2005; Joe, 2014). In this study, a single t-copula has been calibrated for all banks, and the ν parameter has been estimated using the Maximum Likelihood Estimation (MLE) method. In the MLE approach, the log-likelihood expression of the t-copula density function is written as:

$$\ell(\nu, \mathbf{R}) = \sum_{t=1}^{T} \log c_t \left(u_{1,t}, \ldots, u_{d,t}; \mathbf{R}, \nu\right) \tag{31}$$

where $c_t\ (\cdot)$ is the density function, **R** is the positive definite correlation matrix, and $u_{i,t}$ is the PIT-transformed value of bank *i* at time *t*. The $\hat{\boldsymbol{\nu}}$ value obtained from the optimization has been used in the same copula simulation across all scenarios (Base, Adverse, Severe Adverse). Thus, the level of tail dependence is controlled consistently with a single parameter and reused in the second-round simulation.

This approach is based on the assumption that the interbank dependence structure remains constant independently of scenarios; stress conditions affect marginal distributions, but the interbank dependence structure does not change (Cherubini et al., 2004; McNeil et al., 2015). The MLE method is a standard approach in copula parameter estimation and provides asymptotically consistent and efficient estimates of parameters (Joe, 2014; Hofert et al., 2018).

3.3.7. Scenario-Conditional Dependence Assumption

In the study, it is assumed that the interbank dependence structure remains constant independently of scenarios. That is, the same t-copula parameters **R** ve ν) have been used across all scenarios (Base, Adverse, Severe Adverse).

This assumption is based on the view that stress conditions affect marginal distributions (each bank's LCR distribution) but do not change the interbank dependence structure. This approach is a common practice in copula modeling, reducing model complexity by limiting the number of parameters and minimizing overfitting risk (Cherubini et al., 2004; McNeil et al., 2015). Additionally, thanks to this assumption, more data can be used for estimating copula parameters, and estimates become more stable (Patton, 2006; Joe, 2014).

In the literature, there are also dynamic copula models that suggest that the dependence structure changes over time or according to conditions (Hafner & Manner, 2012). However, a fixed copula approach has been preferred in this study; this choice is based on model simplicity, limited number of parameters, and the assumption that a fixed dependence structure is sufficient for financial stress tests (Cherubini et al., 2004; McNeil et al., 2015).

3.3.8. Second-Round Simulation Algorithm

In the second-round analysis, to obtain a sufficient number of observations for estimating copula parameters (R matrix and ν), data from 3 periods (2023 Q4, 2024 Q2, 2024 Q4) obtained from first-round simulation results have been pooled. This approach provides approximately 1,111 observations per bank (3 periods × 370 simulations/bank/period), enabling more robust estimation of copula parameters.

The second-round simulation algorithm generates new simulations with t-copula, which better captures tail dependence, while preserving the dependence structure obtained from first-round simulation results. The algorithm consists of the following steps:

Step 1: PIT Transformation

For each bank, ECDF is calculated from first-round simulation results, and LCR values are transformed to the Uniform [0,1] interval:

$$u_i = \hat{F}_i(x_i) \tag{32}$$

where x_i is bank i's first-round LCR value, and , $\hat{F}_i(\cdot)$ *is bank i's ECDF.*

Step 2: Copula Parameter Calibration

From PIT-transformed data, the Kendall's tau matrix is calculated, converted to a Pearson correlation matrix (ρ=sin($\pi\tau$/2)), and made positive definite (Higham, 1988). If necessary, the shrinkage method is applied (Ledoit & Wolf, 2004). The v parameter is estimated using MLE.

Step 3: t-Copula Simulation

Using the calibrated t-copula, N = 10,000 multivariate Uniform vectors $u = (u_1, u_2 \dots, u_d)$ are simulated. The simulation uses the normal variance mixture representation (Demarta & McNeil, 2005):

$$\mathbf{Y} = \frac{\boldsymbol{z}}{\sqrt{W/\nu}} \tag{33}$$

where $\mathbf{Z} \sim \mathrm{N_d}$ (0, $\mathbf{R}$), W $\sim \lambda_\nu^2$ and $\mathbf{Z}$ and W are independent. Then, Uniform values are calculated:

$$u = t_\nu(Y_1), \dots, t_d(Y_1)) \tag{34}$$

where $t_\nu(\cdot)$ is the standard univariate t-distribution function.

Step 4: Inverse PIT

Simulated Uniform values are transformed back to LCR values using the inverse of ECDF (quantile function) for each bank:

$$t_\nu^{new} = \hat{F}_i^{(-1)}(u_i) \tag{35}$$

This step enables modeling the dependence structure through t-copula while preserving bank-specific marginal distributions (Patton, 2006; McNeil et al., 2015).

Step 5: Calculation of Risk Metrics

From second-round simulation results, Mean, Median, VaR, ES, Failure Rate, and other risk metrics are calculated for each bank. These metrics are used to assess interbank dependence and contagion risk. This algorithm generates new simulations with t-copula, which better captures tail dependence, while preserving the dependence structure in first-round results, and enables a more accurate assessment of interbank contagion risk under stress conditions (Cherubini et al., 2004; Demarta & McNeil, 2005; McNeil et al., 2015).

4. Application and Findings

4.1. First-Round Monte Carlo Simulation Results

4.1.1. Descriptive Statistics

The effect of liquidity stress test scenarios for the Turkish Banking Sector on LCR is presented in the following section based on first-round Monte Carlo simulation application, at the sector level and by bank group distribution, with descriptive statistics for DSIB and other bank groups. Within the scope of stress tests, as scenario severity increases, Total LCR and FX LCR levels decline at both sector and group levels. Sector-level results for 2024 Q4 are summarized in Table 6.

Table 6: Sector-Level Summary Statistics – 2024 Q4

LCR	Scenario	N_banks	Min	Max	Mean	Median	SD	Q05	Q95	Failure_100	Failure_080
Total	Base	27	103.6	1012	217	217.6	3.8	211	224	0	-
Total	Adverse	27	77.3	756	153	153.3	5.1	145	162	29	-
Total	Severe Adverse	27	52.9	413	98	98.8	4.5	91.6	106	72.3	-
FX	Base	27	62.5	538	193	193.2	4.2	186	200	-	0
FX	Adverse	27	42.5	367	120	120	4.5	113	128	-	0
FX	Severe Adverse	27	38.1	190	78	77.4	4	71.1	84.1	-	42.5

Note: Complete statistics for 2023 Q4 and 2024 Q2 periods are provided in Table A6 in the Appendix.

While Total average LCR is 217% and FX average LCR is 193% in the Base scenario, they decline to Total 153% and FX 120% in the Adverse scenario, and to Total 98% and FX 78% in the Severe Adverse scenario. Failure rates also increase significantly, reaching 72.3% for Total LCR (below 100% threshold) and 42.5% for FX LCR (below 80% threshold) under the Severe Adverse scenario. This decline confirms the effect of shock parameters. Complete statistics for 2023 Q4 and 2024 Q2 periods are provided in Table A6 in the Appendix.

The mean and median values are close to each other (difference approximately 0.1%), reflecting the central limit theorem effect from 10,000 simulations. Standard deviation ranges from 3-6% for Total and 4-7% for FX LCR, indicating values cluster around the mean. Q05 (5th percentile, VaR at 95% confidence) and ES05 (Expected Shortfall at 5%) values decline as scenario severity increases, indicating rising tail risk. Q05 and ES05 values are close to each other (difference approximately 0.8-1.4 percentage points), showing symmetric distribution. Q05 values in FX LCR are lower than in Total LCR, indicating higher tail risk in FX LCR.

Failure rates (Failure_100 for Total LCR below 100%, Failure_080 for FX LCR below 80%) increase significantly as scenario severity increases. In the Severe Adverse scenario, failure rates reach 72.3% for Total LCR and 42.5% for FX LCR, indicating high non-compliance. The non-compliance rate in Total LCR is higher than in FX LCR.

The DSIB group consists of 8 banks. and descriptive statistics for Total LCR and FX LCR representing this group are presented in Table 7.

Table 7: DSIB Group Summary Statistics – 2024 Q4

LCR	Scenario	N_banks	Min	Max	Mean	Median	SD	Q05	Q95	Failure_100	Failure_080
Total	Base	8	103.6	167.7	132.4	132.3	2.1	128.9	135.9	0	-
Total	Adverse	8	80.3	132.3	101.1	101.0	2.2	97.5	104.7	49.8	-
Total	Severe Adverse	8	52.9	103.7	72.0	71.9	3.2	66.8	77.3	99.8	-
FX	Base	8	80.9	277.8	169.3	169.3	3.5	163.6	175.2	-	0
FX	Adverse	8	66.4	150.5	110.3	110.2	2.7	105.9	114.7	-	12.5
FX	Severe Adverse	8	40.9	110.2	73.5	73.5	4.1	67	80.1	-	63.8

Note: Complete statistics for 2023 Q4 and 2024 Q2 periods are provided in Table A7 in the Appendix.

In the DSIB group, while average Total LCR and FX LCR decline significantly as scenario severity increases, failure rates increase substantially, particularly under the Severe Adverse scenario.

Standard deviation ranges from 2.1-3.5% for Total and 2.7-6.7% for FX LCR, indicating values cluster around the mean. Q05 (5th percentile, VaR at 95% confidence) and ES05 (Expected Shortfall at 5%) values decline as scenario severity increases, indicating rising tail risk. Q05 and ES05 values are close to each other (difference approximately 0.6-1.8 percentage points), showing symmetric distribution. Q05 values in FX LCR are higher than in Total LCR (in Base and Adverse scenarios), but converge in the Severe Adverse scenario, indicating that tail risk in FX may increase under stress conditions.

The Severe Adverse scenario reveals critical vulnerabilities: Total LCR failure rate reaches 99.8%, effectively indicating that nearly all systemically important banks fall below the 100% regulatory threshold. In contrast, FX LCR failure rate reaches 63.8% (below 80% threshold), leaving some banks still compliant. This asymmetry between Total and FX LCR failure rates highlights the differential liquidity risk exposure for systemically important institutions. This decline in maximum values shows that even the strongest banks in the DSIB group have weakened liquidity positions under stress conditions.

Summary statistical data for the 19 banks in the other bank group are presented in Table 8.

Table 8: Other Banks Group Summary Statistics – 2024 Q4

LCR	Scenario	N_banks	Min	Max	Mean	Median	SD	Q05	Q95	Failure_100	Failure_080
Total	Base	19	114.8	1012.8	253.7	253.6	4.6	246.4	261.2	0	-
Total	Adverse	19	77.3	756.4	175.4	175.3	6.3	165.4	186.2	20.2	-
Total	Severe Adverse	19	54.9	413.6	110.2	110.2	5	102	118.5	60.7	-
FX	Base	19	62.5	538.6	203.4	203.3	4.5	196.2	210.9	-	8.7
FX	Adverse	19	42.5	367.5	124.2	124	5.3	115.9	133.2	-	25.2
FX	Severe Adverse	19	38.1	190.6	79.2	79.1	4.0	72.8	85.8	-	73.2

Note: Complete statistics for 2023 Q4 and 2024 Q2 periods are provided in Table A8 in the Appendix.

For the Other Banks group, stress scenarios show results that differ from the sector average, with generally better performance in Total LCR but higher risk in FX LCR.

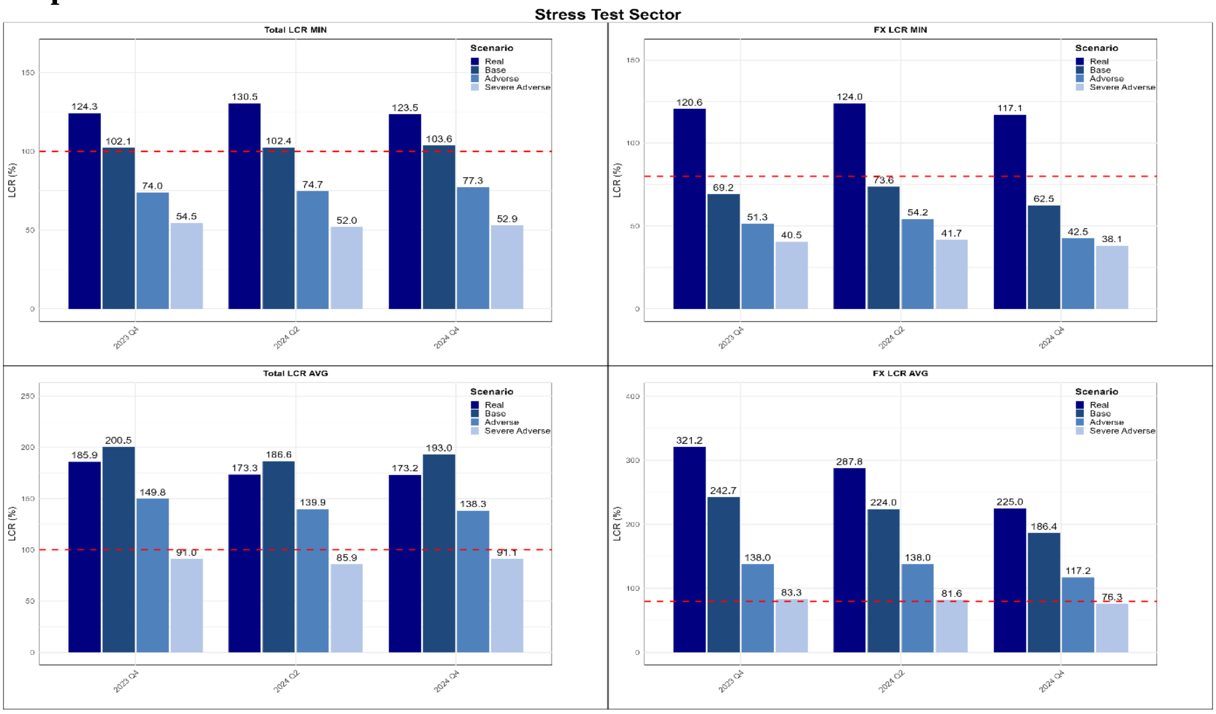
Mean and median values are close to each other (maximum difference 0.3%), reflecting the simulation methodology. Standard deviation ranges from 3.5-6.3% for Total LCR and 4-6.8% for FX LCR. Q05 (5th percentile, VaR at 95% confidence) and ES05 (Expected Shortfall at 5%) values decline as scenario severity increases, indicating rising tail risk. Q05 and ES05 values are close to each other (difference approximately 1-1.5 percentage points), showing symmetric distribution. Overall, Q05 values in FX LCR are lower than in Total LCR (across all scenarios), indicating that tail risk is higher in FX.

The Severe Adverse scenario exposes a contrasting pattern: Total LCR failure rate reaches 60.7%, significantly below the sector average of 72.3%, suggesting relative strength. However, FX LCR failure rate reaches 73.2%, substantially exceeding the sector average of 42.5%. This divergence indicates that while Other Banks maintain better overall liquidity positions, they face disproportionately higher FX-base liquidity risk, warranting focused supervisory attention.

4.1.2. LCR Distributions by Scenario

At the sector level, actual Total LCR and FX LCR between 2023 Q4-2024 Q4 recorded minimum values of 124.3%, 130.5%, and 123.5% respectively for Total LCR, and 120.6%, 124%, and 117.1% for FX LCR. As scenario severity increases, minimum values decline sharply. In the 2023 Q4 period, minimum Total LCR is 102.1% and minimum FX LCR is 69.2% in the Base scenario; while all banks are above the threshold in Total, some banks are below the threshold in FX. In the adverse scenario, minimum Total LCR declines to 74.0% and minimum FX LCR to 51.3%; in the severe adverse scenario, minimum Total LCR declines to 54.5% and FX LCR to 40.5%. In both scenarios and types, most banks fall below the threshold, indicating that liquidity positions weaken under stress conditions.

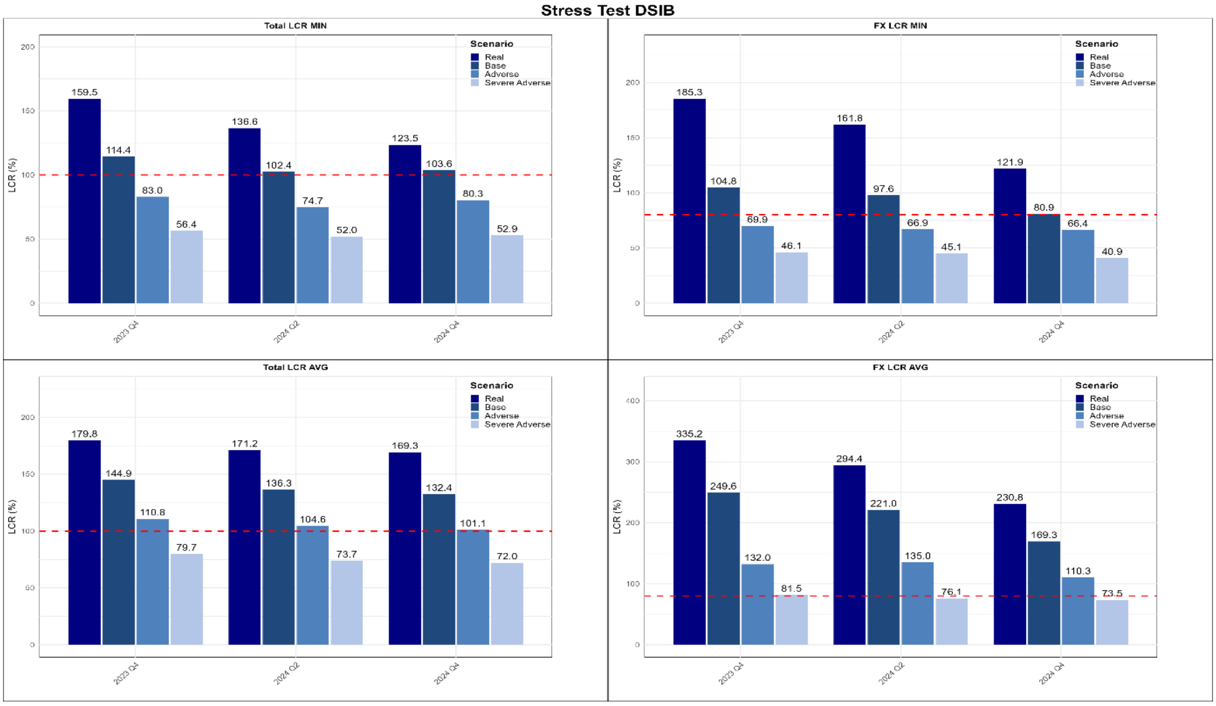
Graph 4: Sector Level LCR Distributions



When examining the periodic trend of average Total LCR and FX LCR values, Base scenario results are generally higher than actual values, particularly in Total LCR. This pattern can be explained through the LCR formula (LCR = HQLA / Net Outflow): in the Base scenario, HQLA values reflect planned and optimized reserve levels, while Net Outflow values are calculated under expected normal conditions. In contrast, actual values reflect realized reserve levels and deposit outflows under current conditions. The higher Base scenario values (reflecting higher planned HQLA and lower projected outflows) compared to actual values indicate that banks' liquidity positions under planned conditions may be better than under current conditions.

Stress test graphs for the DSIB group show a different profile from the sector average.

Graph 5: DSIB Group LCR Distributions



For the DSIB group, actual Total LCR and FX LCR values generally exceed Base scenario values, reflecting higher realized HQLA reserves and lower realized deposit outflows compared to planned conditions.

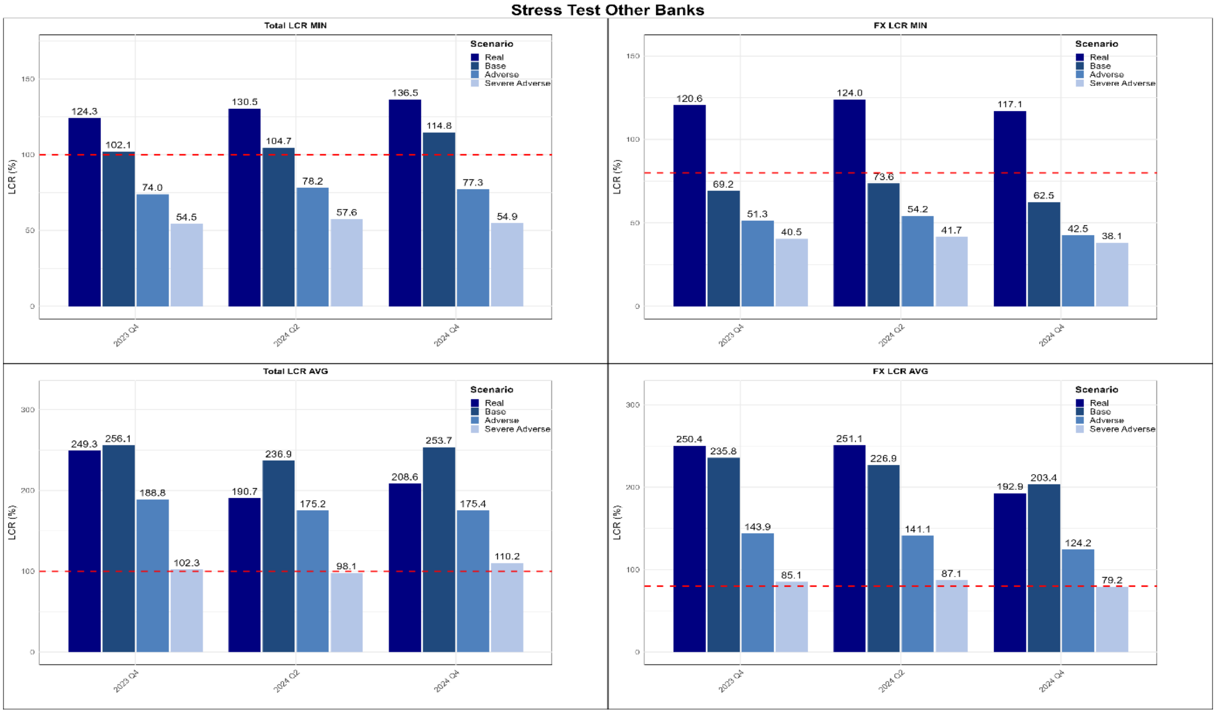
Minimum LCR values exhibit a pronounced downward trajectory as scenario severity intensifies. Under the Base scenario (2023 Q4), minimum Total LCR stands at 114.4% and minimum FX LCR at 104.8%, with all DSIB banks maintaining compliance across both measures. As stress conditions escalate, minimum values deteriorate sharply: in the Adverse scenario, Total LCR drops to 83.0% and FX LCR to 69.9%, resulting in threshold breaches for some institutions. The Severe Adverse scenario reveals the most severe deterioration, with minimum Total LCR declining to 56.4% and FX LCR to 46.1%, pushing most DSIB banks below regulatory thresholds. This progression underscores the DSIB group's heightened vulnerability under stress, with FX liquidity risk manifesting more acutely than Total LCR risk.

The spread between average and minimum values reveals heterogeneous liquidity positions within the DSIB group. Total LCR spreads range from 19.1-27.8% across scenarios, while FX LCR spreads are substantially wider (32.6-62.1%), indicating significant inter-bank variation with some institutions maintaining materially weaker positions.

Under the Severe Adverse scenario, virtually all DSIB banks breach the 100% Total LCR threshold, accompanied by persistent downward trends in FX LCR, collectively signaling elevated systemic liquidity risk. The universal non-compliance in Total LCR under extreme stress, combined with deteriorating FX LCR trajectories, points to the potential for systemic liquidity contagion when financial conditions deteriorate. Given the DSIB group's pivotal role in financial intermediation and systemic importance, these findings underscore the necessity of robust macroprudential frameworks and preemptive liquidity risk management strategies tailored specifically for systemically important institutions.

For the Other Banks group, scenario-based stress test graphs show a different profile from the sector and DSIB group.

Graph 6: Other Banks LCR Distributions



For the Other Banks group (19 banks), actual minimum values show an upward trend from 2023 Q4 to 2024 Q4 (Total LCR: 124.3% to 136.5%; FX LCR: 120.6% to 117.1%). Under stress scenarios, minimum values deteriorate progressively: Base scenario minimums are 102.1% (Total) and 69.2% (FX), declining to 74.0% and 51.3% (Adverse) and further to 54.5% and 40.5% (Severe Adverse), demonstrating substantial sensitivity to stress conditions.

The comparison between Base scenario and actual average Total LCR values reveals a notable asymmetry. In Total LCR, Base scenario assumes planned and optimized HQLA reserve levels that exceed current conditions, combined with lower projected deposit outflows, resulting in Base scenario values exceeding actual values. Conversely, for FX LCR, actual values exceed Base scenario values, reflecting current elevated FX reserve levels (HQLA) that surpass planned conditions and lower realized FX deposit outflows relative to projections. This divergence suggests that while Other Banks demonstrate stronger Total LCR performance under planned conditions, their current FX liquidity positions exceed baseline projections, indicating a favorable shift in FX liquidity management relative to original plans.

4.1.3. Evaluation of Scenario Results

The relationship between scenario severity and LCR decline mathematically demonstrates the effect of shock parameters. As scenario severity increases, LCR decline shows a non-linear relationship and differences emerge between groups. At the sector level, while average Total LCR is 223.2% in the Base scenario (2023 Q4), it declines to 165.7% (25.8% decline) in the adverse scenario and to 95.6% (57.2% decline) in the severe adverse scenario. These decline rates show that LCR decline accelerates as scenario severity increases.

LCR-based liquidity stress tests show different risk profiles between the sector, DSIB, and Other Banks groups with first-round Monte Carlo simulations. In the Base scenario for 2023

Q4, the DSIB group has the lowest average (144.9%) in Total LCR, while Other Banks has the highest (256.1%).

In the adverse scenario, the DSIB group has the highest Failure_100 rate in Total LCR (12.5-49.8%), while the Other Banks group is lower (7.2-20.2%). In the severe adverse scenario, it is observed that almost all of the DSIB group fall below the threshold in Total LCR (Failure_100: 99.8-100%), while the Other Banks group has a lower Failure_100 rate (60.7-67.3%). In FX LCR, the Other Banks group has the highest Failure_80 rate (51.4-73.2%).

From a Monte Carlo simulation methodology perspective, these findings reflect the property of convergence to a normal distribution due to the central limit theorem effect (Glasserman, 2004; Jorion, 2007). The decline in LCR values as scenario severity increases confirms the effect of shock parameters (BCBS, 2013b; Drehmann & Nikolaou, 2013). The increase in failure rates as scenario severity increases shows the importance of tail risk and extreme values (Embrechts et al., 2013). These findings emphasize the importance of stress tests and liquidity risk management for both groups (Borio, 2003; Brunnermeier et al., 2009).

In this context, it shows that the DSIB group shows weaker performance under stress conditions due to its systemic importance and high risk profile, while the Other Banks group shows better performance in Total LCR but carries higher risk in FX LCR. The fact that almost all of the DSIB group fall below the threshold in the Severe Adverse scenario is important from a systemic risk perspective and indicates that additional supervision and oversight measures are necessary. It appears that systemic banks' liquidity management strategies may be insufficient under stress conditions and require attention in terms of supervision-oversight framework and macroprudential policy measures. From a liquidity risk management perspective, additional supervision and oversight measures by regulators are necessary for the DSIB group due to its systemic importance (Acharya et al., 2011; Brunnermeier et al., 2009).

Under FX-denominated liquidity stress, banks' FX funding costs rise, FX deposits are withdrawn, and the value of FX-denominated assets declines (Calvo, 1998; Chang & Velasco, 2001). This affects both the mean and lower tail (adverse scenarios) distribution of FX LCR. The Other Banks group's higher risk in FX LCR shows that FX-specific liquidity risk and exchange rate risk are higher in this group. The fact that FX LCR MIN falls below the threshold even in the Base scenario may indicate a structural vulnerability in FX liquidity for the Other Banks group. Analysis results show that there are different resilience profiles between DSIBs and other banks in the face of FX stress. DSIBs exhibit less extreme FX LCR tail distributions at the same shock bands thanks to larger HQLA stocks and broader wholesale market access. Other Banks, due to smaller HQLA stocks and limited wholesale market access, show higher outflow sensitivity and value loss transition at the same shocks; this produces thicker lower tails and larger expected loss (ES) values.

These findings provide two important implications for policymakers: (i) In FX liquidity stress situations, strengthening FX-denominated stable wholesale backup mechanisms (central bank swap lines, emergency FX credits) especially for non-DSIB banks; (ii) For non-DSIB banks, evaluating tighter collateral/margin management protocols and/or higher FX LCR thresholds. These measures can increase the resilience of the bank group that is more vulnerable, especially in terms of tail risk (VaR and ES), while reducing system-wide FX liquidity risk.

On the other hand, there are limitations to the first-round Monte Carlo simulation methodology. Simulations were conducted with Uniform shock distributions and 10,000 simulation count. Results converge to a normal distribution due to the central limit theorem effect; this causes mean and median values to be close to each other. It should be considered that actual LCR distributions may not be symmetric and tail risks may be higher. Drawing shock parameters from a Uniform distribution and determining scenario severity parameters may differ from actual conditions. These limitations should be considered in interpreting the results.

4.2. Second-Round Effects Analysis Results

4.2.1. Dependence Structure Analysis

In the second-round analysis, the interbank dependence structure obtained from first-round Monte Carlo simulation results has been modeled with t-copula. To obtain a sufficient number of observations for estimating copula parameters (R matrix and ν), data from 3 periods (2023 Q4, 2024 Q2, 2024 Q4) have been pooled. This approach provided approximately 1,111 observations per bank (3 periods × 370 simulations/bank/period), enabling more robust estimation of copula parameters.

The correlation matrix reflects the dependence structure between all pairs of 27 banks. Separate correlation matrices have been calculated for each scenario (Adverse, Severe Adverse) and LCR type (Total, FX). Correlation values have been obtained for a total of 351 bank pairs (27 × 26 / 2). The correlation matrix has been converted from Kendall's tau rank-based dependence measure to Pearson correlation ($\rho = \sin(\pi\tau/2)$). The matrix obtained after transformation has been corrected using Higham's (1988) method to be positive definite and slight shrinkage has been applied. This correlation matrix has been used to determine the dependence structure of the t-copula model.

The summary statistics presented below show the distribution of correlation values among 351 bank pairs for each scenario and LCR type. These statistics are critical for understanding the general characteristics of the interbank dependence structure and how it changes under stress conditions.

Table 9: Summary Statistics of LCR Correlation Matrices

Scenario	LCR Type	N_banks	Mean	Median	Min	Max	SD	Positive
Severe Adverse	Total	27	0.2978	0.3215	-0.7407	0.9407	0.4291	0.7236
Severe Adverse	FX	27	0.3581	0.4356	-0.7804	0.9486	0.3955	0.7977
Adverse	Total	27	0.2491	0.2824	-0.7726	0.9459	0.4734	0.6268
Adverse	FX	27	0.3092	0.4395	-0.7114	0.947	0.4548	0.6923

Correlation matrix analysis shows that the interbank dependence structure changes according to scenarios and LCR type. In the Severe Adverse scenario, average correlation (Total: 0.2978, FX: 0.3581) is higher than in the Adverse scenario (Total: 0.2491, FX: 0.3092). This indicates that interbank dependence increases under stress conditions and co-movements strengthen. From a systemic risk perspective, banks' liquidity positions moving more similarly under stress conditions increases the risk of experiencing common liquidity problems (Acharya et al., 2011; Brunnermeier and Pedersen, 2009).

For FX LCR, average correlation is higher than for Total LCR. This shows that interbank dependence is stronger in FX liquidity and that FX market shocks affect banks more similarly; additionally, the positive correlation rate is also higher in FX LCR, which shows that interbank co-movements are more widespread in FX liquidity.

Median correlation values are generally higher than mean values (especially in FX LCR), which shows that the correlation distribution is right-skewed and that positive correlation exists between most bank pairs. Maximum correlation values (0.94-0.95) show that there is very strong positive dependence between some bank pairs and that these pairs carry the risk of experiencing common liquidity problems under stress conditions. Minimum correlation values (-0.71 to -0.78) show that there is negative dependence between some bank pairs, meaning that while one bank's liquidity position deteriorates, the other may improve.

This dependence structure has been used to capture tail dependence effects in second-round simulation with the t-copula model. The t-copula, which shows high tail dependence with low degrees of freedom (ν), better models interbank joint extreme movements under stress conditions (Demarta & McNeil, 2005; Embrechts et al., 2002).

Bank-level correlation matrix analysis shows that the interbank dependence structure is heterogeneous. While very high positive correlation (0.90-0.95) is observed between some bank pairs, negative correlation (-0.71 to -0.78) is found between some pairs. This heterogeneity is critical from a systemic risk analysis perspective. High-correlation pairs show the pairs with the highest risk of experiencing common liquidity problems under stress conditions, while low or negative correlation pairs are important from a portfolio diversification and risk distribution perspective. Detailed lists of bank pairs with the highest correlation values for each scenario and LCR type are presented in Tables A9 and A10 in the Appendix.

Analysis of high-correlation bank pairs shows that Bank V and Bank W frequently appear in the highest correlation pairs in both Total and FX LCR. Bank V appears in 9 across all scenarios and LCR types, which shows that this bank is in a critical position from a systemic risk perspective. Bank W appears in 9 pairs, especially in Total LCR in the Adverse scenario, and shows strong dependence with other banks as a systemically important bank.

In FX LCR, strong dependence is observed between foreign banks (Bank L, Bank K, Bank M, Bank O) and Bank V, which shows that FX market shocks affect these banks similarly. In Total LCR, stronger dependence is observed among domestic banks.

High-correlation pairs show that when one bank experiences liquidity problems under stress conditions, the probability of the other bank facing similar problems is high. The presence of systemically important banks (DSIB) in these high-correlation pairs is critical from a systemic risk perspective.

Low or negative correlation bank pairs, where one bank's liquidity position may improve while the other deteriorates, are detailed in Tables A11 and A12 in the Appendix. Negative correlation may arise because banks operate in different segments or have different liquidity profiles. Low or negative correlation bank pairs show that the interbank dependence structure is heterogeneous. Bank AB and Bank Z show strong negative correlation with foreign banks (Bank D, Bank O, Bank H, Bank M, Bank F). Negative correlations between foreign banks and domestic banks show that banks operating in different segments may be affected differently under stress conditions. Particularly, the negative correlation between Bank O and Bank L (-0.610) shows that there is also negative dependence among foreign banks. These findings show why tail dependence effects are important in second-round analysis and how contagion risk can spread.

4.2.2. Second-Round LCR Simulation Results

This section presents second-round simulation results and subsequently compares them with first-round results.

Table 10: Second-Round LCR Simulation Results – Sector-Wide Summary

Scenario	LCR Type	N_banks	Mean	ES_95	Failure_100	Failure_80	Min	Max
Severe Adverse	Total	27	0.95	0.94	0.79	0.75	0.39	0.64
Severe Adverse	FX	27	0.82	0.81	0.67	0.85	0.59	0.46
Adverse	Total	27	1.58	1.57	0.21	0.01	0.01	0.90
Adverse	FX	27	1.33	1.29	0.33	0.15	0.15	0.56

Second-round simulation results differ from first-round results with the inclusion of tail dependence effects. In the Severe Adverse scenario, average LCR is calculated as 95% for Total LCR and 82% for FX LCR. In the Adverse scenario, it is calculated as 158% for Total LCR and 133% for FX LCR.

In the Severe Adverse scenario, the Failure_100 rate for Total LCR is 79% and the Failure_80 rate for FX LCR is 85%, which are higher than first-round results. In the Adverse scenario, the Failure_100 rate for Total LCR is calculated as 21% and the Failure_80 rate for FX LCR as 15%. This shows that with the inclusion of tail dependence effects, joint extreme movements are observed more frequently and systemic risk is higher.

Table 11: Second-Round LCR Simulation Results – Group Comparison

Scenario	LCR Type	N_banks	Group	Mean	ES_95	Failure_100	Failure_80
Severe Adverse	Total	8	DSIB	0.76	0.64	0.96	0.65
Severe Adverse	Total	19	Other Banks	1.03	0.85	0.66	0.28
Severe Adverse	FX	8	DSIB	0.76	0.63	0.93	0.58
Severe Adverse	FX	19	Other Banks	0.84	0.68	0.81	0.59
Adverse	Total	8	DSIB	1.07	0.93	0.35	0.01
Adverse	Total	19	Other Banks	1.79	1.44	0.15	0.01
Adverse	FX	8	DSIB	1.26	1	0.29	0.12
Adverse	FX	19	Other Banks	1.36	1.05	0.36	0.16

Group-based second-round simulation results show different risk profiles between DSIB and Other Banks groups. In the Severe Adverse scenario, average LCR for Total LCR is calculated as 76% for the DSIB group and 103% for the Other Banks group. The Failure_100 rate for the DSIB group is 96.2%, and for the Other Banks group it is 66.19%, showing that the DSIB group carries higher risk.

For FX LCR in the Severe Adverse scenario, the DSIB group average is calculated as 76% and the Other Banks group as 84%. The Failure_80 rate for the DSIB group is 58% and for the Other Banks group is 59%, showing high risk for both groups. In the Adverse scenario, for Total LCR, the DSIB group average is calculated as 107% and the Other Banks group as 179%. The Failure_80 rate for the DSIB group is 12% and for the Other Banks group is 16%, showing that the Other Banks group carries higher risk.

4.2.3. First-Round vs. Second-Round Comparison

In the first-round analysis, separate simulations were conducted for 3 periods (2023 Q4, 2024 Q2, 2024 Q4). In the second-round analysis, data from these 3 periods were pooled to estimate t-copula parameters and simulations were conducted. Therefore, second-round results should be compared not with a specific period of the first round, but with the pooled data of all periods.

First-round results show variability across periods. For example, in the Severe Adverse scenario, first-round average LCR for Total LCR is calculated as 95.6% in 2023 Q4, 90.9% in 2024 Q2, and 98.9% in 2024 Q4. Second-round results calculate average LCR as 95%. This value is close to the average of all periods of the first round, but in terms of Failure_100 rate, second-round results (75.08%) are at a similar level to all periods of the first round (2023 Q4: 75.9%, 2024 Q2: 77%, 2024 Q4: 72.3%).

A different situation is observed for FX LCR. In second-round results, the Failure_80 rate for FX LCR (58.75%) is higher than all periods of the first round (2023 Q4: 31.1%, 2024 Q2: 44.5%, 2024 Q4: 42.5%). This shows that tail dependence effects are stronger in FX liquidity and that interbank dependence creates higher systemic risk in FX LCR.

Group-based comparison shows different effects between DSIB and Other Banks groups. In first-round analysis, for the DSIB group in the Severe Adverse scenario, Total LCR Failure_100 rates show variability across periods (2023 Q4: 100%, 2024 Q2: 100%, 2024 Q4: 99.8%). Second-round results calculate the Failure_100 rate for the DSIB group as 96.20%. Although this value appears lower than all periods of the first round, it should not be forgotten that inter-period variability is eliminated in second-round analysis due to data pooling.

For the Other Banks group, first-round Severe Adverse scenario Total LCR Failure_100 rates are calculated as 65.7% in 2023 Q4, 67.3% in 2024 Q2, and 60.7% in 2024 Q4. Second-round results are calculated as 66.19%, which is close to the average of all periods of the first round. However, for FX LCR, the second-round Failure_80 rate (28.30%) is lower than all periods of the first round (2023 Q4: 56.1%, 2024 Q2: 51.4%, 2024 Q4: 73.2%). For the DSIB group, the FX LCR second-round Failure_80 rate (65.28%) is higher than or at a similar level to all periods of the first round (2023 Q4: 43.4%, 2024 Q2: 57.7%, 2024 Q4: 63.8%). This shows that systemically important banks (DSIB) are more affected by tail dependence effects and are more fragile from a systemic risk perspective.

4.2.4. Joint Breach Probabilities

Joint breach probabilities show the probability of multiple banks falling below the legal LCR threshold simultaneously. This metric includes the probability of multiple banks experiencing liquidity problems at the same time, i.e., a systemic crisis perspective.

In the first-round analysis, the number of banks breaching in each simulation iteration was calculated, and statistical summaries (mean, median, percentiles) were derived from these values. Joint Breach numbers were calculated as the mean and 95th percentile values of 10.000 simulations. Mean_Breach shows the average number of banks breaching across all simulations.

Table 12: First-Round Joint Breach Analysis – Severe Adverse Scenario (2024 Q4)

Scenario	LCR Type	Period	Mean_Breach	Median_Breach	Q95_Breach	Breach_Rate_Mean
Severe Adverse	Total	2023 Q4	20.5	27	27	0.76
Severe Adverse	FX	2023 Q4	14.1	15	27	0.52

Note: Mean_Breach shows the average number of banks breaching across all simulations. Complete period-level detailed results for all scenarios and periods are provided in Table A13 in the Appendix.

In the Severe Adverse scenario, average breach numbers (Mean_Breach) range from 19.5-20.8 for Total LCR and 14.1-19 for FX LCR. Variability is observed across periods, and especially in FX LCR, the average breach number rises to 19.0 in 2024 Q4 (2023 Q4: 14.1, 2024 Q2: 14.4).

Median values are 27 for Total LCR across all periods and 15-27 for FX LCR. This shows that in half of the simulations, all banks breach in Total LCR, while in FX LCR it varies across periods. In the worst 5% of simulations (Q95), all 27 banks are in breach status in both LCR types. Breach_Rate_Mean values range from 0.72-0.77 for Total LCR and 0.52-0.70 for FX LCR. This shows that breach probability is high in the Severe Adverse scenario and that all banks may experience liquidity problems simultaneously in extreme events.

In the Adverse scenario, average breach numbers (Mean_Breach) range from 2.4-7.8 for Total LCR and 2.5-5.8 for FX LCR. An increasing trend is observed across periods, rising from 2.4 in 2023 Q4 to 7.8 in 2024 Q4 for Total LCR, and from 2.5 in 2023 Q4 to 5.8 in 2024 Q4 for FX LCR. Median values are 0 across all periods, showing that there is no breach in half of the simulations. However, in the worst 5% of simulations (Q95), 27 banks are in breach status in Total LCR across all periods, while in FX LCR, 22 banks in 2023 Q4 and 27 banks in other periods are in breach status. Breach_Rate_Mean values range from 0.09-0.29 for Total LCR and 0.09-0.21 for FX LCR. These values are significantly lower than in the Severe Adverse scenario (0.52-0.77), which confirms that breach probability increases as scenario severity increases.

First-round analysis shows that in extreme events (worst 5% of simulations), the probability of many banks experiencing liquidity problems simultaneously is high. As scenario severity increases (Adverse → Severe Adverse), breach numbers increase, which emphasizes the importance of stress tests (BCBS, 2013b; Drehmann & Nikolaou, 2013). Inter-period analysis shows that liquidity risk may change over time and the necessity of regular stress tests.

In second-round analysis, the interbank dependence structure has been taken into account using the t-copula model (Cherubini et al., 2004; Nelsen, 2006). In second-round analysis, systemic risk assessment has been conducted using bank-level Failure_100 and Failure_80 values.

In second-round analysis, with the inclusion of tail dependence effects, Failure_100 and Failure_80 rates occur at higher levels compared to first-round results. For example, in the Severe Adverse scenario, the second-round Failure_100 rate for Total LCR is 75.08%, while first-round results range from 72.3-77% across periods. For FX LCR, the second-round Failure_80 rate is 58.75%, while first-round results range from 31.1-44.5%. When comparing joint breach probabilities in first-round analysis (Mean_Breach_Count: 20.3 Severe Adverse Total, 5.7 Adverse Total) with failure rates in second-round analysis, it is seen that systemic risk is higher in second-round analysis with the inclusion of tail dependence effects.

While traditional correlation-based models inadequately estimate the probability of these extreme events occurring together, the t-copula approach captures these risks more accurately thanks to its tail dependence property (Embrechts et al., 2002; McNeil et al., 2015). High joint breach probabilities show that when one bank experiences liquidity problems, the probability of other banks facing similar problems is high and that contagion risk has strong propagation potential. This is especially more critical for systemically important banks (DSIB) because problems in these banks can affect the entire system. The findings obtained show why tail dependence effects are important in second-round analysis and the importance of systemic risk management.

4.2.5. Fragility Ranking

Fragility rankings show the ordering of banks according to bank-level fragility scores derived from second-round t-copula simulation results. These rankings are used to evaluate banks according to their risk of experiencing liquidity problems under stress conditions and to identify critical banks from a systemic risk perspective.

Traditional risk assessment approaches generally focus on a single risk metric (for example, average LCR or VaR) and may inadequately evaluate banks' fragility. In this study, two fundamental risk components have been combined in calculating the fragility score:

(1) Regulatory non-compliance risk (Failure rate)

(2) Extreme loss risk (Expected Shortfall)

This approach, consistent with comprehensive risk assessment principles proposed in the Basel III framework, takes into account both the probability of legal threshold violation and tail risk.

The framework of the methodology essentially takes into account regulatory non-compliance (60%) and extreme loss risk (40%). A bank falling below the legal threshold can lead to both regulatory intervention and market confidence loss. Therefore, a higher weight (60%) has been given to the failure rate. This weight reflects the importance of Basel III LCR requirements and the critical consequences of regulatory non-compliance from a systemic risk perspective (BCBS, 2013b). On the other hand, Expected Shortfall (ES_95) is a risk metric that captures tail risk beyond VaR. Banks with low ES_95 values have the potential to experience higher losses under extreme stress conditions. Therefore, a penalty term derived from ES_95 (40% weight) has been included in the score. This approach focuses not only on average performance but also on resilience in extreme events (Artzner et al., 1999; Acerbi & Tasche, 2002).

According to LCR type, using Failure_80 for FX LCR and Failure_100 for Total LCR, FX LCR takes into account the 80% legal threshold applied in Türkiye; Total LCR takes into account the 100% threshold according to Basel III standards (BCBS, 2013a).

This scoring methodology provides a comprehensive fragility assessment by combining two risk components in a weighted manner. The score being in the 0-1 range ensures comparability across different scenarios and LCR types. Banks with high scores are considered fragile in terms of both regulatory non-compliance risk and extreme loss risk.

Banks with higher score values are considered more fragile. Score values are in the 0-1 range, with a score of 1 meaning the most fragile bank. This methodology provides a comprehensive fragility assessment by taking into account both regulatory non-compliance risk (failure rate) and extreme loss risk (ES_95) (Glasserman, 2004; Jorion, 2007).

Table 13: Second-Round Fragility Rankings – Top 5 Banks (Severe Adverse Scenario)

LCR Type	Rank	Bank	Score	Mean	ES_95	Failure_Rate
Total	1	Bank Q	0.78	0.64	0.56	100%
Total	2	Bank AB	0.78	0.67	0.56	100%
Total	3	Bank C	0.77	0.68	0.58	100%
Total	4	Bank B	0.76	0.68	0.59	100%
Total	5	Bank W	0.76	0.74	0.59	100%
FX	1	Bank C	0.84	0.46	0.41	100%
FX	2	Bank A	0.83	0.51	0.44	100%
FX	3	Bank M	0.81	0.59	0.46	99%
FX	4	Bank J	0.79	0.61	0.52	100%
FX	5	Bank N	0.78	0.64	0.54	100%

Note: Complete rankings for all scenarios (Top 10) are provided in Tables A14 and A15 in the Appendix.

According to fragility rankings (Table 13, detailed rankings in Tables A14 and A15 in the Appendix), the core bank group with high fragility across both Total and FX LCR includes Bank C, Bank A, Bank Q, Bank R, Bank AB, Bank W, Bank Y, and Bank M, which commonly rank in the top positions under both Severe Adverse and Adverse scenarios. In FX LCR, Bank C, Bank A, Bank J, Bank L, and Bank M frequently appear in the top rankings.

When fragility rankings and dependence structure analysis (correlation matrix) are evaluated together, banks that are critical from a systemic risk perspective are those with both high individual fragility and high correlation with other banks. Some banks are of critical importance even if their individual fragilities are relatively low, because they frequently appear in high-correlation pairs (see Tables A14 and A15 in the Appendix). These banks, when experiencing a liquidity shock, increase the risk of other banks with which they are highly correlated also facing similar problems.

Under the Severe Adverse scenario, both banks ranking in the upper positions in fragility rankings and banks appearing in high-correlation pairs become more prominent. This pattern indicates that as stress level increases, risk concentrates in fewer critical banks, highlighting the importance of targeted supervisory focus on these systemically connected institutions.

4.3. Model Validation

Goodness-of-fit tests have been applied to evaluate whether the t-copula model captures the true dependence structure and to validate the reliability of simulation results.

Table 14: Model Validation: Correlation Matrix Properties and Goodness-of-Fit Tests

Scenario	LCR Type	Banks	Correlation Pairs	Mean ρ	Min ρ	Max ρ	Positive Definite	Symmetric
Severe Adverse	Total	27	351	0.298	–0.741	0.941	Yes	Yes
Severe Adverse	FX	27	351	0.358	–0.78	0.949	Yes	Yes
Adverse	Total	27	351	0.249	–0.773	0.946	Yes	Yes
Adverse	FX	27	351	0.309	–0.711	0.947	Yes	Yes

These tests evaluate whether the estimated copula parameters (R matrix and ν) capture the true dependence structure.

The fundamental properties of correlation matrices have been checked to assess the model's mathematical consistency. Correlation matrices calculated for each scenario and LCR type have the mathematical properties necessary for t-copula simulations:

- Positive definiteness: All correlation matrices are positive definite (minimum eigenvalue ≈ 0.05). This property shows that the matrix is usable for t-copula simulations.
- Symmetry: All correlation matrices are symmetric (R = R^T). This property shows the mathematical consistency of the correlation matrix and that the interbank dependence structure is correctly represented.
- Validity: All correlation values are correctly in the [-1, 1] range, showing that all values are valid.
- Heterogeneity: Correlation values are distributed over a wide range (min: -0.78, max: 0.95), and this heterogeneity reflects the diversity of the interbank dependence structure and shows that the model can capture different dependence structures.

The mathematical properties of correlation matrices and the distribution of correlation values show that the t-copula model has been applied consistently. Correlation matrices for all scenarios and LCR types are positive definite, symmetric, and have valid values. These results support that the model is mathematically consistent and that simulation results are reliable (Higham, 1988; Borsdorf & Higham, 2010).

4.4. Robustness Checks

To assess the robustness of our copula-based methodology, a comparative analysis between t-copula and Gaussian copula specifications are conducted. While the t-copula explicitly captures tail dependence, which is crucial for systemic risk assessment, the Gaussian copula assumes no tail dependence. A robustness check comparing these two approaches helps validate our methodological choices and assess the sensitivity of our results to different copula specifications.

The robustness check is conducted using the same first-round Monte Carlo simulation results, applying both t-copula and Gaussian copula to model interbank dependencies in the second-round analysis. For each scenario (Adverse and Severe Adverse) and period (2023 Q4, 2024 Q2, 2024 Q4), we estimate both copula specifications using the same correlation matrix obtained from first-round LCR distributions. The correlation matrix is transformed using Kendall's tau rank correlation and corrected to ensure positive definiteness using Higham's (1988) method.

The key difference between the two copula specifications lies in their treatment of tail dependence:

– Gaussian copula: Assumes no tail dependence; extreme events are treated as independent across banks.
– t-copula (ν = 5): Captures tail dependence; extreme events are more likely to occur simultaneously across banks.

Table 15 presents the mean joint breach counts for both copula specifications. The mean joint breach count represents the average number of banks simultaneously falling below the LCR threshold (100% for Total LCR, 80% for FX LCR) across 10,000 second-round simulations.

Table 15: Mean Joint Breach Counts: t-Copula vs. Gaussian Copula

Period	LCR_Type	t-Copula (Adverse)	Gaussian (Adverse)	t-Copula (Severe Adverse)	Gaussian (Severe Adverse)
2023Q4	Total	2.39	2.39	20.44	20.40
2023Q4	FX	2.52	2.53	14.05	14.03
2024Q2	Total	6.88	6.88	20.88	20.88
2024Q2	FX	3.71	3.71	14.49	14.56
2024Q4	Total	7.83	7.85	19.49	19.47
2024Q4	FX	5.79	5.79	18.93	18.91

Both copulas use the same correlation structure, ensuring that differences in results are solely attributable to tail dependence effects. Results show consistent patterns between t-copula and Gaussian copula across all scenarios and periods. Differences in mean joint breach counts are minimal, ranging from 0.01 to 0.1 banks (less than 0.5% of the sample). This consistency indicates that our findings are not driven by copula choice but reflect genuine patterns in the data. The close agreement also suggests that correlation structure, rather than tail dependence, primarily drives joint breach probabilities, consistent with the literature (Embrechts et al., 2002; McNeil et al., 2015). A limitation is that only two copula specifications are compared; other copula families might yield different results, though they are less commonly used in systemic risk applications.

4.5. Systemic Risk Analysis and Policy Implications

The findings obtained provide important policy implications from a systemic risk management perspective. Especially for systemically important banks, additional liquidity requirements and stress tests are critical to reduce contagion risk. Additionally, since systemic risk is seen to be higher with the inclusion of tail dependence effects, this effect should be taken into account in stress tests.

It would be beneficial to take liquidity-focused supervision and oversight measures for banks that rank in the upper positions in fragility rankings and frequently appear in high-correlation pairs. These banks should be subject to more frequent and detailed stress tests due to both their individual fragilities and systemic connections (BCBS, 2013b).

For banks with both high fragility and high correlation, additional HQLA buffers above legally minimum LCR requirements can be created. This buffer will both provide protection against individual liquidity shocks and reduce contagion risk for banks critical from a systemic risk perspective (Borio et al., 2017; Brunnermeier et al., 2009). For banks that both rank in the upper positions in fragility rankings and appear in high-correlation pairs in FX LCR, FX liquidity management plans should be strengthened. These plans should aim to be prepared against FX market shocks and reduce FX liquidity risk (Eichengreen & Hausmann, 2005; Calvo, 1998). For banks that frequently appear in high-correlation pairs, systemic connections should be regularly monitored and evaluated. This monitoring will help early detection of contagion risk and taking appropriate macroprudential measures. Fragility ranking and correlation analysis results should be used to update stress test scenarios. Especially for banks with both high fragility and high correlation, more severe stress scenarios should be developed and banks' resilience should be tested.

These policy recommendations aim to reduce both individual risks and systemic risk. When fragility rankings, correlation analysis, and tail dependence effects are used together, effective and specific measures that will increase the stability of the financial system can be taken.

5. Conclusion

This study presents a two-stage liquidity stress testing framework for the Turkish banking sector. In the first stage, LCR distributions have been calculated under different stress scenarios (Base, Adverse, Severe Adverse) using independent Monte Carlo simulations for each bank. In the second stage, interbank correlation and tail dependence have been taken into account using the t-copula method; thus, the potential for a bank's liquidity squeeze to spread system-wide has been evaluated holistically. This approach implements advanced stress testing frameworks proposed in the literature (Cont et al., 2013; Cont et al., 2020; Upper, 2011) and holistically evaluates the impact of differentiated shocks by bank groups and balance sheet items on systemic risk.

The study's methodological contribution is that it addresses systemic risk beyond individual bank risks in an integrated manner with a t-copula-based dependence structure. The feedback mechanism between market and funding liquidity emphasized by Brunnermeier and Pedersen (2009) has been modeled through interbank LCR correlations and tail dependence parameters. Contagion effects arising from asset price shocks by Cifuentes et al. (2005), Adrian and Shin (2008), and Aikman et al. (2019) have been addressed as the propagation of liquidity shocks among banks. Theoretical and empirical findings on interbank network structure and connection density by Allen and Gale (2000) and Gai and Kapadia (2010) have been empirically tested through correlation matrices and copula parameters. Findings on the distribution of banks' liquidity buffers and liquidity shortfall probability by Drehmann and Nikolaou (2013) have been extended through LCR distributions and failure rates.

Analysis results show a tendency for LCR values to decline and failure rates to rise as scenario severity increases. In the Severe Adverse scenario, the sector-wide failure rate ranges from 72-77% for Total LCR and 31-45% for FX LCR. The DSIB group shows higher fragility, especially in Total LCR under the Severe Adverse scenario (99-100% failure rate), while the other banks group carries higher risk in FX LCR. These findings are consistent with empirical findings by Acharya and Merrouche (2013) that loss of confidence in the interbank market during crisis periods increases liquidity squeezes and systemic risk. In second-round analysis, with the inclusion of tail dependence effects, systemic risk is seen to be higher. Especially in FX LCR, second-round failure rates are higher than first-round results, which shows that interbank dependence is stronger in FX liquidity. Joint breach analysis reveals that on average 19.5-20.8 banks can simultaneously fall below the LCR threshold under the Severe Adverse scenario. These findings extend metrics on interconnectedness among financial institutions and contributions to systemic risk by Glasserman and Young (2016) and Adrian and Brunnermeier (2016) in the context of liquidity risk.

When fragility rankings and correlation analysis are evaluated together, banks with both high individual fragility and high systemic connections are identified. These findings support policy recommendations such as risk-based supervision and monitoring, increased HQLA buffers, strengthened FX liquidity management plans, and accounting for tail dependence in stress tests. These policy recommendations aim to reduce both individual bank risks and systemic risk. When fragility rankings, correlation analysis, and tail dependence effects are used together, effective and specific measures that will increase the stability of the financial system can be taken. This approach is consistent with FSB (2024)'s emphasis that policies and regulations are needed to manage liquidity pressures in NBFIs during stress periods. Additionally, findings by Baudino et al. (2024) that expected stress and withdrawal rates in banks' internal stress tests may differ on a bank-specific basis have been supported in this study by applying differentiated shock parameters for DSIB and other banks.

The applied framework provides the opportunity to evaluate vulnerabilities revealed by shocks in the banking sector and risks that will occur system-wide as a result of their propagation from a macroprudential perspective in terms of liquidity adequacy and systemic risk, to identify fragile bank groups and banks, and to develop existing policies and practices. The current framework can be used in stress testing applications as a monitoring and preventive tool focused on the banking system and can be applied periodically or ad-hoc by supervisory authorities and banks. This framework extends van den End (2010)'s approach that incorporates the interaction between market and funding liquidity and potential feedback on banks into a framework, with a t-copula-based dependence structure. Additionally, it applies metrics on contagion in financial networks and contributions to systemic risk by Iori et al. (2008), Gorton and Metrick (2012), Battiston et al. (2012), and Huang et al. (2012) in the context of liquidity risk.

Finally, in the analysis conducted, it has been assumed that banks or public authorities will not take additional policy measures (actions) regarding liquidity squeezes. When actions that can be taken by the Central Bank, Supervisory Authority, and banks are considered, it is estimated that the effect of these shocks will be lower, and results should be evaluated in this context. In future studies, modeling these policy actions and integrating them into the stress testing framework will increase the realism of the analysis and enable more comprehensive policy evaluations. Additionally, expanding this framework to include non-bank financial institutions, similar to system-wide stress testing applications by FSB (2023, 2024), MAS (2023), and BoE (2024), will be an important step toward expanding the scope of institutions and assets monitored within systemic liquidity, as suggested by ESRB (2025).

6. References

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Appendix

Table A1: Liquidity Stress Testing Approaches Applied in IMF FSAP Reports

1- Deposit Concentration/Sensitivity Analyses	IMF (2024c) Maldives (2024): The withdrawal of the top 5 depositors of each bank simultaneously was simulated. 7 banks (49.9% of sector assets) experienced liquidity shortfalls in both local currency and foreign exchange positions when large deposits were withdrawn	IMF (2024b) Saudi Arabia (2024): LCR sensitivity and concentration analysis including the withdrawal of the top 10 deposits in each bank was conducted.	IMF (2024d) Luxembourg (2024) In the liquidity stress test, LCR's sensitivity to deposit withdrawal stress was measured, and the decline in LCR was measured against retail deposit withdrawals ranging from 5% to 40%.
2- Cash Flow Based	IMF (2024c) Maldives (2024): According to the IMF's methodology, banks' resilience to cash outflows using their liquid assets was measured.	IMF (2025a) Slovakia (2025): In the cash flow analysis stress testing application, 4 separate stress testing levels were determined for maturity ranges from 1 week to 1 year, and the number of banks exposed to funding gaps was calculated within the framework of increasing discount rates.	IMF (2024a) Spain (2024): In the structural liquidity analysis, the resilience of 10 systemically important banks to stresses was assessed. This approach is based on a more detailed cash flow (CF) analysis that evaluates banks' capacity to meet cash outflows over one week and three months. These were applied as 3 separate scenarios: in the market scenario, loss of value of liquid assets and decrease in liquidity inflows; in the outflow scenario, decrease in deposit renewal; and aggressive combined scenario.
Liabilities	Run-off Rates	Run-off Rates	Run-off Rates
Term deposits	Local currency: 1-7 days 10%; 7-30 days 5%; 1-3 months 1%; over 3 months 0%; undistributed 0% Foreign currency: 1-7 days 20%; 7-30 days 10%; 1-3 months 5%; over 3 months 5%; 6 months and over 0%; undistributed 0%	Scenario weights were set at 10%, 15%, 20%, and 25%..	Weighted sum of Basel outflow scenarios, weights calculated as (1-x)% Basel + x% Outflow. 25% Outflow \50% Outflow \ 75% Outflow \ 100% Outflow. In the aggressive scenario, it was found that 7 banks' LCR declined below 100%.
Demand deposits	Local currency: 1-7 days 40%; 7-30 days 30%; 1-3 months 20%; 3-6 months 10%; 6 months and over 5%; undistributed 5% Foreign currency: 1-7 days 30%; 7-30 days 15%; 1-3 months 15%; over 3 months 10%; 6 months and over 5%; undistributed 5%		
Wholesale funding	All currencies and maturities 100%		
Assets	Rollover Rates		
Loans	Local/Foreign currency: 1-7 days 50%; 7-30 days 50%; 1-3 months 50%; 3-6 months 30%; 6 months and over 30%; 1-3 years 30%; 3 years and over 10%; undistributed 10%		
Other assets	All currencies and maturities 100%		

3- LCR-NSFR Based	IMF (2023b) Belgium (2023): LCR stress test applies 6 stress testing scenarios by modifying the weights of inflow-outflow items for borrowing and credit items. Six different scenarios were simulated and calibrated as Basel, mild, and extreme stress testing scenarios.	IMF (2024e) Japan (2024): Under hypothetical and severe liquidity outflow assumptions, banks' resilience was measured based on cash flows up to 6 months maturity and LCR up to 30 days, on a JPY and foreign currency basis. This stress testing analysis conducted on 23 banks covering 82% of the banking system was calculated under stressed conditions for cash flow-based up to 6 months maturity and for LCR and NSFR.	IMF (2025b) India (2025): In the liquidity stress test, 46 commercial banks representing 94% of the sector share were measured for liquidity adequacy with cash flows over a 12-month time horizon and LCR and NSFR over a 1-month time horizon.	IMF (2024b) Saudi Arabia (2024): In liquidity stress tests, outflow intensity was determined according to deposit characteristics in 4 scenarios with different severity levels through LCR-based regulatory approach.

Level 1 HQLA	Basel 0%; Mild 5-13%; Severe 10-23%	Based on the scenarios, value declines of 5-20% in government bonds and 15-40% in corporate bonds; withdrawal shocks of 5-15% for retail deposits and 20-50% for wholesale deposits; and a 30-60% reduction in FX liquidity have been applied.	Scenarios have been applied as multiples of Basel III outflow rates. The Moderate Adverse LCR scenario applies 125% of retail deposit outflow rates and 115% of unsecured wholesale deposit outflow rates; the Severe Adverse LCR scenario applies 150% of retail deposit outflow rates and 125% of unsecured wholesale deposit outflow rates. Additionally, sensitivity analysis has tested higher outflow rates and value declines.	In the worst-case scenario, a value decline of up to 20% including government bonds is assumed for high-quality liquid assets. Withdrawal rates of up to 15% for insured deposits, up to 20% for uninsured deposits, and up to 50% for non-operational deposits are assumed. In the NSFR-based stress test, stable funding items are differentiated by maturities of up to 6 months and 6-12 months across 4 different scenarios, with stable deposit items considered at 85%, less stable items at 80%, and unsecured funding at 40%. For required stable funding items, value declines of up to 15% are applied to high-quality assets with maturities of less than 6 months, 6-12 months, and over 1 year.
Level 2A HQLA	Basel 15%; Mild 30%; Severe 44%			
Level 2B HQLA	Basel 25-50%; Mild 49-64%; Severe 52-77%			
Cash Outflows				
Term deposits	Basel 0%; Mild 10%; Severe 10% (deposits maturing within 30 days: 100%)			
Demand deposits	Basel 5-10%; Mild 10-18%; Severe 10-18%			
Other deposits	Basel 15-20%; Mild 25-32%; Severe 25-32%			
Unsecured Wholesale Funding				
Term, demand, and operational deposits	Basel 5-25%; Mild 10-38%; Severe 25-32%			
Non-operational deposits	Basel 20-40%; Mild 32-54%; Severe 32-54%			
Secured Wholesale Funding				
Repo and government securities-backed	Basel 0-7%; Mild 5-13%; Severe 10-23%			
Level 2A and other assets-backed	Basel 15-25%; Mild 25-38%; Severe 38-52%			
Level 2B and other assets-backed	Basel 25-100%; Mild 38-100%; Severe 52-100%			
Cash Inflows	**Cash Inflows Cash Inflow Haircuts**			
Retail loans and undrawn commitments	Basel 50%; Mild 36%; Severe 30%			
Other loans	Basel 100%; Mild 85%; Severe 75%			
Assets subject to margin calls	Basel 100%; Mild 90-100%; Severe 82-100%			

Table A2: Banks Included in the Analysis

Bank Name	Group	Bank Name	Group	Bank Name	Group
Akbank	DSIB	Habib Bank	Other	Turkish Bank	Other
Alternatifbank	Other	HSBC	Other	Turkland Bank	Other
Anadolubank	Other	ICBC	Other	TEB-BNP	Other
Bank Of China	Other	ING	Other	Garanti Bank-BBVA	DSIB
Burgan Bank	Other	Intesa Sanpaolo	Other	Halkbank	DSIB
Citibank	Other	MUFG Bank	Other	Isbank	DSIB
Denizbank	Other	Odea Bank	Other	Vakifbank	DSIB
Deutsche Bank	Other	QNB	DSIB	Yapi Kredi Bank	DSIB
Fibabank	Other	Sekerbank	Other	Ziraat Bank	DSIB

Table A3: Base Scenario Run-Off and Haircut Parameters

Scenario	Category	Item	LCR_DSIB	LCR_Other_Banks	FX_LCR_DSIB	FX_LCR_Other_Banks
Base	HQLA	High-quality liquid assets	3-6%	2-5%	4-8%	2.5-6%
Base	Cash_Outflows	Less stable deposits	5-10%	4-8%	7-12%	6-10%
Base	Cash_Outflows	Non-operational deposits	8-14%	7-12%	10-16%	9-15%
Base	Cash_Outflows	Derivative liabilities and collateral top-up	50-70%	40-60%	50-70%	40-60%
Base	Cash_Outflows	Collateral given for debts to financial markets	50-70%	40-60%	50-70%	40-60%

Table A4: Adverse Scenario Run-Off and Haircut Parameters

Scenario	Category	Item	LCR_DSIB	LCR_Other_Banks	FX_LCR_DSIB	FX_LCR_Other_Banks
Adverse	HQLA	High-quality liquid assets	6-12%	4-10%	8-16%	5-12%
Adverse	Cash_Outflows	Less stable deposits	10-20%	8-16%	14-24%	12-20%
Adverse	Cash_Outflows	Operational deposits	12-24%	10-20%	16-30%	13-25%
Adverse	Cash_Outflows	Non-operational deposits	16-28%	14-24%	20-32%	18-30%
Adverse	Cash_Outflows	Other unsecured debts	20-30%	15-25%	25-35%	20-30%
Adverse	Cash_Outflows	Secured debts	15-25%	10-20%	20-30%	15-25%
Adverse	Cash_Outflows	Derivative liabilities and collateral top-up	70-90%	60-80%	70-90%	60-80%
Adverse	Cash_Outflows	Debts from structured financial instruments	70-90%	60-80%	70-90%	60-80%
Adverse	Cash_Outflows	Debts to financial markets and payments made	70-90%	60-80%	70-90%	60-80%
Adverse	Cash_Outflows	Debts callable without any condition	60-80%	50-70%	70-90%	60-80%
Adverse	Cash_Inflows	Unsecured receivables collection reduction	20-30%	15-25%	25-35%	20-30%

Table A5: Severe Adverse Scenario Run-Off and Haircut Parameters

Scenario	Category	Item	LCR_DSIB	LCR_Other_Banks	FX_LCR_DSIB	FX_LCR_Other_Banks
Severe_Adverse	HQLA	High-quality liquid assets	12-24%	8-20%	16-32%	10-24%
Severe_Adverse	Cash_Outflows	Stable deposits	10-20%	8-16%	14-24%	12-20%
Severe_Adverse	Cash_Outflows	Less stable deposits	20-40%	16-32%	28-48%	24-40%
Severe_Adverse	Cash_Outflows	Operational deposits	16-28%	14-24%	20-32%	18-30%
Severe_Adverse	Cash_Outflows	Non-operational deposits	32-56%	28-48%	40-64%	36-60%
Severe_Adverse	Cash_Outflows	Other unsecured debts	40-60%	35-55%	45-65%	40-60%
Severe_Adverse	Cash_Outflows	Secured debts	30-50%	25-45%	40-60%	30-50%
Severe_Adverse	Cash_Outflows	Collateral given for debts to financial markets	100%	100%	100%	100%
Severe_Adverse	Cash_Outflows	Derivative liabilities and collateral top-up	100%	100%	100%	100%
Severe_Adverse	Cash_Outflows	Debts from structured financial instruments	100%	100%	100%	100%
Severe_Adverse	Cash_Outflows	Debts callable without any condition	70-90%	60-80%	75-95%	65-85%
Severe_Adverse	Cash_Outflows	Other non-callable or conditionally callable	50-70%	40-60%	60-80%	50-70%
Severe_Adverse	Cash_Inflows	Secured receivables collection reduction	20-30%	15-25%	25-35%	20-30%
Severe_Adverse	Cash_Inflows	Unsecured receivables collection reduction	40-60%	30-50%	45-65%	35-55%
Severe_Adverse	Cash_Inflows	Other cash inflows reduction	30-50%	25-45%	35-55%	30-50%

Table A6: Sector Level Summary Statistics

TYPE	Period	Scenario	N_banks	Min (%)	Max	Mean	Median	SD	Q05	Q95	Failure_100
Total	2023 Q4	Base	27	102.1	920	223	223	3.3	217	228	0
Total	2024 Q2	Base	27	102.4	1107	207	207	3.2	201	212	0
Total	2024 Q4	Base	27	103.6	1012	217	217.6	3.8	211	224	0
Total	2023 Q4	Adverse	27	74	839	165	165.6	5.2	157	174	8.8
Total	2024 Q2	Adverse	27	74.7	998	154	154.1	5.1	146	163	25.4

Total	2024 Q4	Adverse	27	77.3	756	153	153.3	5.1	145	162	29
Total	2023 Q4	Severe Adverse	27	54.5	245	95	95.5	4.2	88.7	102	75.9
Total	2024 Q2	Severe Adverse	27	52	279	90	90.8	3.9	84.6	97.3	77
Total	2024 Q4	Severe Adverse	27	52.9	413	98	98.8	4.5	91.6	106	72.3
TYPE	**Period**	**Scenario**	**N_banks**	**Min (%)**	**Max**	**Mean**	**Median**	**SD**	**Q05**	**Q95**	**Failure_080**
FX	2023 Q4	Base	27	69.2	735	239	239.6	6.7	229	251	0
FX	2024 Q2	Base	27	73.6	768	225	225.1	5.5	216	234	0
FX	2024 Q4	Base	27	62.5	538	193	193.2	4.2	1867	200	0
FX	2023 Q4	Adverse	27	51.3	383	140	140.2	5.9	131	150	1.2
FX	2024 Q2	Adverse	27	54.2	454	139	139.1	5.6	130	149	0.8
FX	2024 Q4	Adverse	27	42.5	367	120	120	4.5	113	128	0
FX	2023 Q4	Severe Adverse	27	40.5	169	84	84	4.3	77.0	91.2	31.1
FX	2024 Q2	Severe Adverse	27	41.7	231	84	84	4.3	76.9	91.1	44.5
FX	2024 Q4	Severe Adverse	27	38.1	190	78	77.4	4.0	71.1	84.1	42.5

Table A7: D-SIB Group Summary Statistics

TYPE	Period	Scenario	N_banks	Min (%)	Max	Mean	Median	SD	Q05	Q95	Failure_100
Total	2023 Q4	Base	8	114.4	166.7	144.9	144.8	2.3	141.1	148.7	0
Total	2024 Q2	Base	8	102.4	182.8	136.3	136.3	2.3	132.6	140.2	0
Total	2024 Q4	Base	8	103.6	167.7	132.4	132.3	2.1	128.9	135.9	0
Total	2023 Q4	Adverse	8	83	131	110.8	110.7	2.7	106.3	115.3	12.5
Total	2024 Q2	Adverse	8	74.7	143.1	104.6	104.5	2.8	99.9	109.3	41.7
Total	2024 Q4	Adverse	8	80.3	132.3	101.1	101	2.2	97.5	104.7	49.8
Total	2023 Q4	Severe Adverse	8	56.4	98.9	79.7	79.7	3.5	74	85.6	100
Total	2024 Q2	Severe Adverse	8	52	101.5	73.7	73.7	3.3	68.5	79.1	100
Total	2024 Q4	Severe Adverse	8	52.9	103.7	72.0	71.9	3.2	66.8	77.3	99.8
TYPE	**Period**	**Scenario**	**N_banks**	**Min (%)**	**Max**	**Mean**	**Median**	**SD**	**Q05**	**Q95**	**Failure_080**
FX	2023 Q4	Base	8	104.8	502.2	249.6	249.4	6.7	238.8	260.7	0
FX	2024 Q2	Base	8	97.6	457.8	221	221	5.1	212.8	229.5	0
FX	2024 Q4	Base	8	80.9	277.8	169.3	169.3	3.5	163.6	175.2	0
FX	2023 Q4	Adverse	8	69.9	187.9	132	132	3.8	125.9	138.4	10
FX	2024 Q2	Adverse	8	66.9	240.4	135	134.8	5.1	126.8	143.6	12.4
FX	2024 Q4	Adverse	8	66.4	150.5	110.3	110.2	2.7	105.9	114.7	12.5
FX	2023 Q4	Severe Adverse	8	46.1	125.1	81.5	81.4	4.4	74.4	88.8	43.4
FX	2024 Q2	Severe Adverse	8	45.1	105.6	76.1	76.1	4.3	69.2	83.1	57.7
FX	2024 Q4	Severe Adverse	8	40.9	110.2	73.5	73.5	4.1	67	80.1	63.8

Table A8: Other Banks Summary Statistics

TYPE	Period	Scenario	N_banks	Min (%)	Max	Mean	Median	SD	Q05	Q95	Failure_100
Total	2023 Q4	Base	19	102.1	920	256.1	256.1	3.7	250.1	262.3	0
Total	2024 Q2	Base	19	104.7	1107.4	236.9	236.8	3.5	231.1	242.8	0
Total	2024 Q4	Base	19	114.8	1012.8	253.7	253.6	4.6	246.4	261.2	0
Total	2023 Q4	Adverse	19	74	839.7	188.8	188.7	6.3	178.8	199.4	7.2

Total	2024 Q2	Adverse	19	78.2	998.9	175.2	175	6.1	165.5	185.5	18.5
Total	2024 Q4	Adverse	19	77.3	756.4	175.4	175.3	6.3	165.4	186.2	20.2
Total	2023 Q4	Severe Adverse	19	54.5	245.6	102.3	102.2	4.5	94.9	109.9	65.7
Total	2024 Q2	Severe Adverse	19	57.6	279.8	98.1	98.1	4.1	91.4	104.9	67.3
Total	2024 Q4	Severe Adverse	19	54.9	413.6	110.2	110.2	5	102	118.5	60.7
TYPE	**Period**	**Scenario**	**N_banks**	**Min (%)**	**Max**	**Mean**	**Median**	**SD**	**Q05**	**Q95**	**Failure_080**
FX	2023 Q4	Base	19	69.2	735.9	235.8	235.5	6.6	225.3	246.9	5.1
FX	2024 Q2	Base	19	73.6	768.8	226.9	226.8	5.7	217.8	236.4	2.8
FX	2024 Q4	Base	19	62.5	538.6	203.4	203.3	4.5	196.2	210.9	8.7
FX	2023 Q4	Adverse	19	51.3	383.7	143.9	143.7	6.8	133.1	155.5	9
FX	2024 Q2	Adverse	19	54.2	454.5	141.1	140.9	5.8	131.9	151	14.5
FX	2024 Q4	Adverse	19	42.5	367.5	124.2	124	5.3	115.9	133.2	25.2
FX	2023 Q4	Severe Adverse	19	40.5	169.1	85.1	85	4.3	78.2	92.2	56.1
FX	2024 Q2	Severe Adverse	19	41.7	231.7	87.1	87.1	4.4	80.1	94.4	51.4
FX	2024 Q4	Severe Adverse	19	38.1	190.6	79.2	79.1	4	72.8	85.8	73.2

Table A9: Top Correlated Bank Pairs – Total LCR

Line	Bank1	Bank2	Correlation	Scenario	LCR Type
1	Bank V	Bank W	0.941	Severe Adverse	Total
2	Bank L	Bank W	0.939	Severe Adverse	Total
3	Bank F	Bank K	0.938	Severe Adverse	Total
4	Bank B	Bank G	0.937	Severe Adverse	Total
5	Bank E	Bank Q	0.932	Severe Adverse	Total
6	Bank G	Bank R	0.931	Severe Adverse	Total
7	Bank K	Bank Q	0.928	Severe Adverse	Total
8	Bank B	Bank R	0.921	Severe Adverse	Total
9	Bank F	Bank Q	0.917	Severe Adverse	Total
10	Bank L	Bank V	0.917	Severe Adverse	Total
Line	**Bank1**	**Bank2**	**Correlation**	**Scenario**	**LCR Type**
1	Bank L	Bank W	0.946	Adverse	Total
2	Bank B	Bank G	0.946	Adverse	Total
3	Bank E	Bank Q	0.944	Adverse	Total
4	Bank M	Bank Q	0.944	Adverse	Total
5	Bank V	Bank Y	0.943	Adverse	Total
6	Bank A	Bank V	0.941	Adverse	Total
7	Bank P	Bank U	0.939	Adverse	Total
8	Bank E	Bank M	0.939	Adverse	Total
9	Bank A	Bank W	0.937	Adverse	Total
10	Bank V	Bank W	0.936	Adverse	Total

Table A10: Top Correlated Bank Pairs – FX LCR

Line	Bank1	Bank2	Correlation	Scenario	LCR Type
1	Bank L	Bank V	0.949	Severe Adverse	FX
2	Bank K	Bank M	0.949	Severe Adverse	FX
3	Bank K	Bank V	0.947	Severe Adverse	FX
4	Bank M	Bank V	0.945	Severe Adverse	FX
5	Bank K	Bank L	0.943	Severe Adverse	FX
6	Bank L	Bank M	0.941	Severe Adverse	FX
7	Bank I	Bank O	0.937	Severe Adverse	FX
8	Bank G	Bank Q	0.922	Severe Adverse	FX
9	Bank P	Bank W	0.919	Severe Adverse	FX
10	Bank G	Bank Y	0.913	Severe Adverse	FX
Line	**Bank1**	**Bank2**	**Correlation**	**Scenario**	**LCR Type**
1	Bank K	Bank V	0.947	Adverse	FX
2	Bank K	Bank M	0.947	Adverse	FX
3	Bank L	Bank V	0.946	Adverse	FX
4	Bank M	Bank V	0.944	Adverse	FX
5	Bank E	Bank Q	0.942	Adverse	FX

6	Bank K	Bank L	0.941	Adverse	FX
7	Bank I	Bank O	0.938	Adverse	FX
8	Bank L	Bank M	0.937	Adverse	FX
9	Bank P	Bank U	0.936	Adverse	FX
10	Bank L	Bank X	0.934	Adverse	FX

Table A11: Least Correlated Bank Pairs – Total LCR

Line	**Bank1**	**Bank2**	**Correlation**	**Scenario**	**LCR Type**
1	Bank D	Bank AB	- 0.741	Severe Adverse	Total
2	Bank O	Bank AB	- 0.690	Severe Adverse	Total
3	Bank D	Bank Z	- 0.612	Severe Adverse	Total
4	Bank D	Bank L	- 0.558	Severe Adverse	Total
5	Bank H	Bank AB	- 0.552	Severe Adverse	Total
6	Bank E	Bank Z	- 0.538	Severe Adverse	Total
7	Bank I	Bank AB	- 0.538	Severe Adverse	Total
8	Bank Q	Bank Z	- 0.523	Severe Adverse	Total
9	Bank J	Bank AB	- 0.523	Severe Adverse	Total
10	Bank D	Bank W	- 0.521	Severe Adverse	Total
Line	**Bank1**	**Bank2**	**Correlation**	**Scenario**	**LCR Type**
1	Bank O	Bank AB	- 0.773	Adverse	Total
2	Bank M	Bank Z	- 0.713	Adverse	Total
3	Bank X	Bank AB	- 0.686	Adverse	Total
4	Bank Q	Bank Z	- 0.675	Adverse	Total
5	Bank H	Bank AB	- 0.669	Adverse	Total
6	Bank E	Bank Z	- 0.654	Adverse	Total
7	Bank F	Bank Z	- 0.648	Adverse	Total
8	Bank O	Bank W	- 0.620	Adverse	Total
9	Bank L	Bank O	- 0.610	Adverse	Total
10	Bank D	Bank M	- 0.575	Adverse	Total

Table A12: Least Correlated Bank Pairs – FX LCR

Line	**Bank1**	**Bank2**	**Correlation**	**Scenario**	**LCR Type**
1	Bank T	Bank Z	- 0.741	Severe Adverse	FX
2	Bank D	Bank Z	- 0.690	Severe Adverse	FX
3	Bank K	Bank T	- 0.612	Severe Adverse	FX
4	Bank M	Bank T	- 0.558	Severe Adverse	FX
5	Bank N	Bank Z	- 0.552	Severe Adverse	FX
6	Bank L	Bank T	- 0.538	Severe Adverse	FX
7	Bank T	Bank V	- 0.538	Severe Adverse	FX
8	Bank S	Bank AB	- 0.523	Severe Adverse	FX
9	Bank D	Bank M	- 0.523	Severe Adverse	FX
10	Bank D	Bank K	- 0.521	Severe Adverse	FX
Line	**Bank1**	**Bank2**	**Correlation**	**Scenario**	**LCR Type**
1	Bank T	Bank Z	- 0.773	Adverse	FX
2	Bank K	Bank T	- 0.713	Adverse	FX
3	Bank M	Bank T	- 0.686	Adverse	FX
4	Bank D	Bank Z	- 0.675	Adverse	FX
5	Bank T	Bank X	- 0.669	Adverse	FX
6	Bank T	Bank V	- 0.654	Adverse	FX
7	Bank L	Bank T	- 0.648	Adverse	FX
8	Bank N	Bank Z	- 0.620	Adverse	FX
9	Bank D	Bank M	- 0.610	Adverse	FX
10	Bank K	Bank N	- 0.575	Adverse	FX

Table A13: First-Round Joint Breach Probabilities – Period-Level Detailed Results

Scenario	**LCR Type**	**Period**	**Mean_Breach**	**Median_Breach**	**Q95_Breach**	**Breach_Rate_Mean**
Severe Adverse	Total	2023 Q4	20.5	27	27	0.76
Severe Adverse	FX	2023 Q4	14.1	15	27	0.52
Severe Adverse	Total	2024 Q2	20.8	27	27	0.77
Severe Adverse	FX	2024 Q2	14.4	17	27	0.53
Severe Adverse	Total	2024 Q4	19.5	27	27	0.72
Severe Adverse	FX	2024 Q4	19.0	27	27	0.70
Adverse	Total	2023 Q4	2.4	0	27	0.09

Adverse	FX	2023 Q4	2.5	0	22	0.09
Adverse	Total	2024 Q2	6.9	0	27	0.25
Adverse	FX	2024 Q2	3.7	0	27	0.14
Adverse	Total	2024 Q4	7.8	0	27	0.29
Adverse	FX	2024 Q4	5.8	0	27	0.21

Table A14: Second-Round Bank-Level Total LCR Fragility Rankings (Top 10)

Line	Scenario	Bank	Mean	ES_95	Failure_100	Score	Group
1	Severe Adverse	Bank Q	0.64	0.56	1	0.78	DSIB
2	Severe Adverse	Bank AB	0.67	0.56	1	0.78	DSIB
3	Severe Adverse	Bank C	0.68	0.58	1	0.77	Other
4	Severe Adverse	Bank B	0.68	0.59	1	0.76	Other
5	Severe Adverse	Bank W	0.74	0.59	1	0.76	DSIB
6	Severe Adverse	Bank A	0.73	0.60	1	0.76	DSIB
7	Severe Adverse	Bank R	0.70	0.61	1	0.76	Other
8	Severe Adverse	Bank M	0.76	0.61	1	0.76	Other
9	Severe Adverse	Bank Y	0.74	0.62	1	0.75	DSIB
10	Severe Adverse	Bank Z	0.76	0.67	1	0.73	DSIB
Line	**Scenario**	**Bank**	**Mean**	**ES_95**	**Failure_100**	**Score**	**Group**
1	Adverse	Bank C	0.90	0.77	0.96	0.66	Other
2	Adverse	Bank Q	0.91	0.78	0.73	0.52	DSIB
3	Adverse	Bank R	0.95	0.82	0.67	0.47	Other
4	Adverse	Bank W	1.00	0.83	0.66	0.46	DSIB
5	Adverse	Bank AB	0.96	0.84	0.66	0.46	DSIB
6	Adverse	Bank B	1.00	0.85	0.50	0.36	Other
7	Adverse	Bank M	1.12	0.82	0.35	0.28	Other
8	Adverse	Bank A	1.01	0.87	0.36	0.27	DSIB
9	Adverse	Bank L	1.17	0.91	0.31	0.22	Other
10	Adverse	Bank Y	1.08	0.95	0.32	0.21	DSIB

Table A15: Second-Round Bank-Level FX LCR Fragility Rankings (Top 10)

Line	Scenario	Bank	Mean	ES_95	Failure_80	Score	Group
1	Severe Adverse	Bank C	0.46	0.41	1	0.84	Other
2	Severe Adverse	Bank A	0.51	0.44	1	0.83	DSIB
3	Severe Adverse	Bank M	0.59	0.46	0.99	0.81	Other
4	Severe Adverse	Bank J	0.61	0.52	1	0.79	Other
5	Severe Adverse	Bank N	0.64	0.54	1	0.78	Other
6	Severe Adverse	Bank E	0.62	0.56	1	0.78	Other
7	Severe Adverse	Bank L	0.65	0.51	0.93	0.75	Other
8	Severe Adverse	Bank G	0.71	0.64	1	0.74	Other
9	Severe Adverse	Bank Z	0.69	0.53	0.85	0.70	DSIB
10	Severe Adverse	Bank W	0.70	0.59	0.81	0.65	DSIB
Line	**Scenario**	**Bank**	**Mean**	**ES_95**	**Failure_80**	**Score**	**Group**
1	Adverse	Bank C	0.56	0.45	1.00	0.60	Other
2	Adverse	Bank A	0.74	0.69	0.93	0.56	DSIB
3	Adverse	Bank M	0.84	0.60	0.67	0.40	Other
4	Adverse	Bank J	0.80	0.63	0.51	0.31	Other
5	Adverse	Bank L	0.94	0.71	0.34	0.20	Other
6	Adverse	Bank F	1.13	0.73	0.30	0.18	Other
7	Adverse	Bank H	1.30	0.82	0.20	0.12	Other
8	Adverse	Bank N	0.92	0.76	0.17	0.10	Other
9	Adverse	Bank E	0.89	0.78	0.09	0.05	Other
10	Adverse	Bank B	1.22	1.07	0	0	Other