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VaR and CVaR-Based Stress Testing Using Deep Learning for Liquidity Risk Forecasting and Banking Stability Assessment

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Abstract

Liquidity risk remains a core driver of banking fragility because funding shocks and market illiquidity can force value destructive asset sales and destabilize cash flow obligations. This study addresses the problem that conventional liquidity ratios and linear models can understate tail risk, weakening early warning and stress testing for stability oversight. The purpose was to validate an integrated pipeline combining deep learning liquidity risk forecasting with VaR and CVaR based stress testing to strengthen banking stability assessment. In a quantitative cross-sectional, case-based design, four enterprise case banks ($B = 4$) were analyzed using 192 aligned bank observations and a survey of 220 liquidity risk professionals, producing 212 usable responses (96.4%). Key variables included liquidity buffer ratio (liquid assets/total assets), wholesale funding reliance, loan-to-deposit ratio, a Likert 1-5 governance and stress testing maturity index, VaR95 and VaR99, CVaR95 and CVaR99, and a stability proxy (Z-score). The analysis plan covered descriptive profiling, forecasting comparison (LSTM versus linear regression), tiered scenario stress testing (baseline, mild, adverse, severe), and correlation and regression models linking stressed tail risk and governance to stability. Governance measurement was reliable (Cronbach's alpha = 0.81-0.89) and scenario realism was rated high ($M = 4.08$, $SD = 0.58$). The LSTM improved prediction accuracy over the benchmark ($RMSE = 0.042$ vs 0.061; $MAE = 0.031$ vs 0.047) and directional accuracy (67.5% vs 56.2%). Under severe stress, VaR0.95 rose from 1.90 to 2.83 (+48.9%) while CVaR0.95 rose from 2.66 to 4.39 (+65.0%); VaR0.99 rose from 3.12 to 4.71 (+51.0%) while CVaR0.99 rose from 4.48 to 7.96 (+77.7%), showing tail thickening captured by CVaR. Stressed CVaR0.99 correlated negatively with stability ($r = -0.58$, $p < .001$) and remained significant in regression ($\beta = -0.46$, $p < .001$; $R^2 = .47$). Governance predicted lower stressed CVaR ($\beta = -0.29$, $p = .002$) and moderated the CVaR to stability link (interaction $\beta = +0.18$, $p = .010$). Implications are that CVaR stress testing supports funding structure and liquidity buffer decisions, while governance maturity reduces liquidity vulnerability.

Keywords

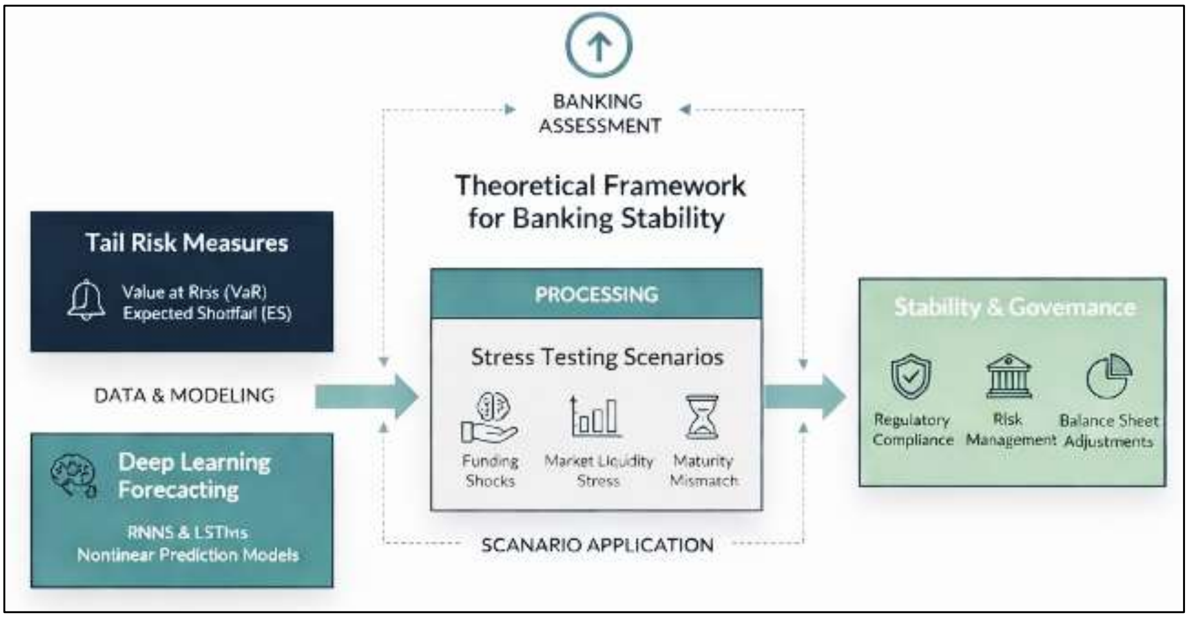
Liquidity risk; Deep learning (LSTM); Value at Risk (VaR); Conditional Value at Risk (CVaR/Expected Shortfall); Banking stability (Z-score);

INTRODUCTION

Liquidity risk is commonly defined as the risk that a financial institution cannot meet its cash-flow obligations when due without incurring unacceptable losses or market disruption, and it is typically discussed through two connected lenses: funding liquidity (the ability to raise cash on demand) and market liquidity (the ability to trade assets quickly with limited price impact). In banking systems, liquidity is not only a balance-sheet attribute but also a systemic property shaped by maturity transformation, payment-system obligations, contingent credit lines, and the structure of short-term wholesale funding (Boyacioglu et al., 2009).

Research in the banking literature shows that liquidity conditions propagate through interbank markets and deposit–loan linkages, creating channels through which liquidity shocks can become solvency problems and vice versa (Berger & Bouwman, 2009). The macro-financial relevance of this mechanism has been documented in work linking market liquidity and funding liquidity to amplification spirals during stress events and in studies highlighting banks' strategic liquidity management through credit line commitments (Banerjee & Mio, 2018). In parallel, empirical banking research conceptualizes banks as liquidity creators, emphasizing that bank intermediation transforms illiquid assets into liquid claims and that the amount of liquidity created varies across institutions and across time (Acharya & Mora, 2015). These perspectives locate liquidity risk at the center of banking stability, not as a narrow treasury-function metric, but as a governance and resilience issue that spans asset composition, liability structure, contingent exposures, and the confidence-sensitive nature of bank funding (Kingma & Ba, 2015; Laeven & Levine, 2009). Internationally, liquidity risk has been repeatedly associated with periods of broad financial instability and cross-border transmission, because globally active banks intermediate in multiple currencies and markets, and funding strains in one market can be re-priced rapidly in others through correlated margin requirements, collateral haircuts, and rehypothecation chains. In this setting, liquidity risk measurement cannot rely on single-point estimates alone; it requires a framework that also captures tail events, nonlinearities, and stress amplification mechanisms embedded in market microstructure and institutional behavior (Adrian & Brunnermeier, 2016).

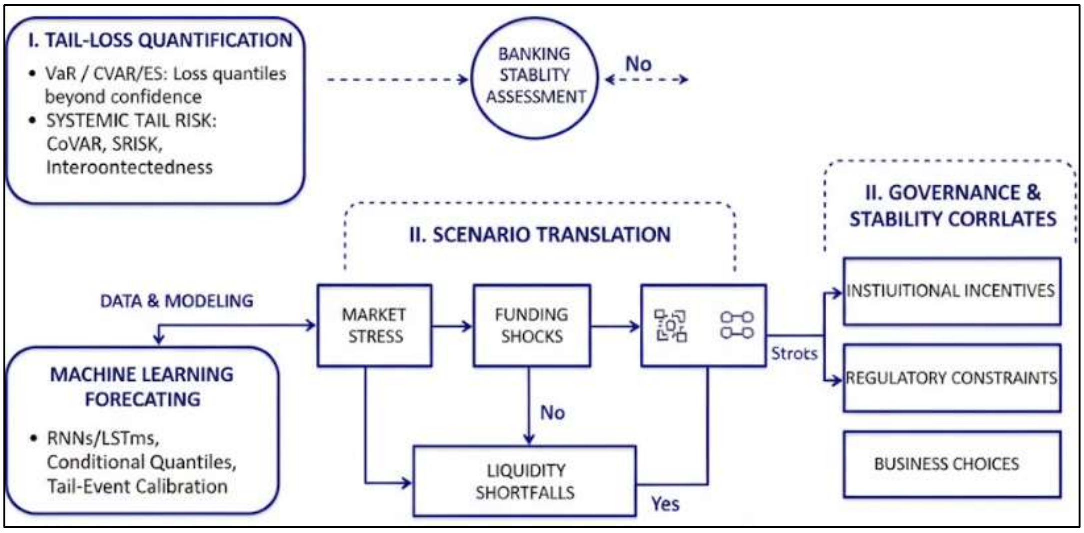
Figure 1: Liquidity Risk Forecasting and VaR/CVaR-Based Stress Testing for Banking



A central family of tail-risk metrics used in financial risk management is Value at Risk (VaR) and its coherent extension, Conditional Value at Risk (CVaR), often operationalized as Expected Shortfall (ES). VaR summarizes a loss quantile at a chosen confidence level, while CVaR/ES summarizes the conditional expected loss beyond that quantile, making it directly relevant for situations where extreme losses dominate outcomes and where loss distributions exhibit skewness and heavy tails (Adrian &

Brunnermeier, 2016). In systemic and banking contexts, tail risk measures become more informative when linked to states of market stress and feedback effects, which has motivated both econometric and machine learning research that focuses on conditional quantiles, distributional forecasting, and tail-event calibration (Haque & Arifur, 2020; Lepetit et al., 2008; Rauf, 2018). A broader stability lens also considers systemic-risk metrics that condition on joint distress, such as CoVaR, which formalizes how the distress of one institution shifts the risk of the financial system. Such measures help connect firm-level tail risk with system-level fragility, a linkage that becomes especially salient when liquidity shortages force asset sales, widen spreads, and alter funding access (Brownlees & Engle, 2017; Haque & Arifur, 2021; Ashraful et al., 2020). Complementary work on capital shortfall metrics such as SRISK further emphasizes that the vulnerability of institutions is state-dependent and increases when market conditions deteriorate. From a supervisory and international stability perspective, these approaches clarify why "average" liquidity metrics can fail to characterize stability-relevant outcomes: banking crises are dominated by discontinuities, correlated shocks, and liquidity–solvency interactions that become visible only in the tails of the distribution (Fokhrul et al., 2021; Zaman et al., 2021). Consequently, the use of VaR/CVaR-based stress testing is motivated not merely by statistical convenience but by the operational need to translate tail events into scenario losses, liquidity shortfalls, and stability assessments that are aligned with the extreme-loss nature of crises (Brunnermeier & Pedersen, 2009; Fahimul, 2022; Hammad, 2022).

Figure 1: Systemic liquidity risk flowchart diagram



Liquidity risk and banking stability are also shaped by institutional incentives, governance, and risk-taking behavior, which makes it important to interpret liquidity forecasts alongside behavioral and structural correlates (Hasan & Waladur, 2022; Rashid & Sai Praveen, 2022). Empirical research on bank governance and regulation shows that governance arrangements and regulatory constraints can influence bank risk-taking and, by extension, vulnerability under adverse conditions. In parallel, studies on business model choices such as revenue diversification indicate that structural shifts can alter risk profiles, thereby changing the distribution of outcomes relevant for VaR/CVaR analysis (Keilbar & Wang, 2022; Arifur & Haque, 2022; Towhidul et al., 2022). Liquidity creation research highlights that banks' balance-sheet decisions determine how much liquidity they supply and how sensitive they may become to funding shocks. Related work connects funding liquidity conditions to risk-taking, documenting relationships between deposit-based funding, risk-weighted assets, and stability metrics such as Z-scores (Keilbar & Wang, 2022; Ratul & Subrato, 2022; Rifat & Jinnat, 2022). Such evidence helps position liquidity risk forecasting as a stability assessment problem rather than a narrow prediction task: forecasts gain credibility when interpreted through established determinants of bank fragility and risk appetite (Abdulla & Majumder, 2023; Khan et al., 2017; Rifat & Alam, 2022). Systemic measures further reinforce this point by embedding the idea that the risk contribution of each institution is conditional on system state and interconnected exposures. As a result, a VaR/CVaR-based stress testing framework that incorporates deep learning forecasting can be framed as a method for integrating (i) tail-loss quantification, (ii) scenario translation into liquidity outcomes, and (iii) structural correlates of stability, providing a coherent analytical basis for comparing institutions and explaining cross-sectional heterogeneity in vulnerabilities (Pagratis et al., 2017).

This study is designed around a set of tightly connected objectives that translate the core problem of liquidity fragility into measurable, testable components within a quantitative, cross-sectional, case-study framework. The first objective is to operationalize liquidity risk in a way that is both bank-relevant and stability-relevant by constructing a consistent measurement set that captures funding pressure, balance-sheet liquidity buffers, and cash-flow mismatch sensitivity at the selected case institutions. This includes defining the liquidity-risk target variable(s) used for modeling and aligning them with bank-level reporting structure so that the outcomes reflect realistic liquidity management conditions rather than abstract proxies. The second objective is to build and evaluate a deep learning forecasting model that learns nonlinear relationships between liquidity risk and its determinants, including bank-specific balance-sheet features and macro-financial conditions, with the forecasting task framed as a disciplined prediction problem supported by transparent preprocessing, training, and validation procedures. The third objective is to translate forecasted liquidity dynamics into tail-risk outcomes by estimating VaR and CVaR at predetermined confidence levels under baseline conditions, thereby producing distribution-sensitive risk measures that move beyond average behavior and capture extreme shortfall exposure. The fourth objective is to perform structured liquidity stress testing by applying calibrated adverse scenarios to the VaR/CVaR framework, generating stressed tail-risk estimates that explicitly represent deposit outflows, wholesale funding disruptions, and market-liquidity haircuts, and then quantifying the degree of tail amplification as conditions become more severe. The fifth objective is to empirically test the relationships among forecast accuracy, stressed tail liquidity risk, and banking stability by applying descriptive statistics, correlation analysis, and regression modeling to determine which drivers most strongly influence liquidity outcomes and whether stressed CVaR provides incremental explanatory power over conventional liquidity metrics when predicting stability indicators. The sixth objective is to strengthen methodological credibility by producing traceable evidence for why the model signals stress, including a structured explainability analysis that identifies the most influential drivers of tail outcomes, and a scenario plausibility assessment that demonstrates internal consistency and defensibility of stress magnitudes. Collectively, these objectives ensure that the study remains focused on measurable deliverables: an empirically validated forecasting component, a tail-risk stress testing component, and a stability assessment component, all integrated in a way that supports clear hypothesis testing and transparent reporting of results.

LITERATURE REVIEW

The literature on liquidity risk, tail-risk measurement, stress testing, and predictive analytics in banking has developed around a common concern: how to quantify and anticipate conditions under which banks experience binding funding constraints and destabilizing balance-sheet adjustments. Foundational banking studies frame liquidity as both a balance-sheet resource and a confidence-sensitive liability structure, emphasizing that liquidity shocks can spread through interbank markets, wholesale funding channels, and asset liquidation dynamics, thereby linking bank-level liquidity strain to system-wide instability. Within this context, risk measurement research has expanded from average-condition indicators toward tail-sensitive metrics that can represent extreme outcomes, positioning Value at Risk (VaR) as a quantile-based benchmark and Conditional Value at Risk (CVaR) or Expected Shortfall as a more tail-informative measure suited for heavy-tailed loss distributions. Parallel to these developments, the stress testing literature has focused on scenario design and the mapping of adverse shocks into liquidity shortfalls, recognizing that liquidity crises often emerge from nonlinear feedback effects such as margin spirals, collateral haircuts, and fire-sale externalities. As banks and regulators increasingly rely on stress testing to evaluate resilience, researchers have also examined how liquidity regulation and internal risk governance shape banks' buffer choices, funding strategies, and vulnerability profiles, making governance and institutional behavior important interpretive layers for stress outcomes. More recently, the rise of machine learning and deep learning has introduced new methods for forecasting financial risk when relationships between predictors and outcomes are nonlinear, time-varying, or high-dimensional, with growing interest in using neural architectures to improve predictive performance and to support distributional or quantile-focused estimation aligned with VaR/CVaR computation. This growing methodological stream is coupled with an interpretability and model risk literature that emphasizes the need for transparent validation, explainable drivers, and defensible calibration when predictive systems influence high-stakes decisions. Across these strands, a central research challenge remains the integration of (i) deep learning–based liquidity risk forecasting, (ii) VaR/CVaR tail-risk measurement under baseline and stressed states, and (iii) banking stability assessment in a way that is empirically testable, auditable, and comparable across institutions. Accordingly, the literature review for this study synthesizes empirical and methodological findings to establish the conceptual foundation for a unified framework that connects drivers of liquidity risk to tail outcomes under stress and links those outcomes to stability measures within a case-study banking setting.

Liquidity Risk in Banking and Key Measurement Approaches

Liquidity risk in banking is typically operationalized as the ability to meet cash-flow needs under both normal and stressed conditions without triggering value-destructive asset sales, destabilizing funding substitutions, or payment disruptions. Empirical research treats liquidity risk as a joint outcome of balance-sheet structure (liquid-asset buffers, maturity mismatch, and contingent obligations) and market conditions (rollover capacity, collateral quality, and haircuts). As a result, measurement approaches in the literature span stock measures (how much liquidity is available now), flow measures (how cash flows evolve across horizons), and market-based measures (how funding terms shift with price dynamics). A common stock approach uses ratios such as liquid assets to total assets, loan-to-deposit ratios, and reliance on short-term wholesale funding to capture immediate liquidity capacity and vulnerability. Flow approaches focus on contractual and behavioral cash-flow gaps across maturity buckets, stressing that liquidity is not simply "how much cash is held," but the timing alignment between inflows and outflows. Market-based perspectives emphasize that liquidity constraints are state dependent and become more binding when leverage and market liquidity move procyclically, which can tighten funding access at the same time asset prices fall. This strand underscores why balance-sheet growth, repo conditions, and leverage adjustments can serve as informative indicators of system-wide liquidity pressure in addition to bank-specific buffers (Adrian & Shin, 2010; Fahimul, 2023; Faysal & Bhuya, 2023). Cross-country evidence also highlights the fragility of funding models that rely heavily on nondeposit short-term finance and trading-oriented income streams, motivating measurement schemes that explicitly track wholesale dependence and activity mix when evaluating liquidity vulnerability (Demirgüç-Kunt & Huizinga, 2010; Habibullah & Aditya, 2023; Hammad & Mohiul, 2023). These core distinctions—stock versus flow, bank-specific versus market-dependent—shape how liquidity risk is measured and why no single indicator fully captures the full liquidity-risk profile of a bank.

A second major measurement direction focuses on funding structure sensitivity and mismatch, capturing how assets that are difficult to liquidate are financed by liabilities that may run or reprice quickly. Maturity mismatch measures attempt to quantify the gap between the liquidity of assets and the stability of funding, because banks can appear liquid under static ratios while remaining fragile when funding is confidence-sensitive (Haque & Arifur, 2023; Jahangir & Mohiul, 2023). In this literature, a bank's exposure to liquidity stress is interpreted as the amplification potential embedded in the asset–liability mix: illiquid loans and long-duration securities can become difficult to monetize when haircuts rise, while runnable liabilities can accelerate outflows during market-wide stress (Rashid et al., 2023; Akbar & Farzana, 2023). A prominent approach formalizes this concept by constructing a Liquidity Mismatch Index (LMI) that aligns asset market liquidity with liability funding liquidity to evaluate how mismatch evolves across time and across institutions, thereby providing a more structural view than conventional ratios (Bai et al., 2018; Mostafa, 2023; Rifat & Rebeka, 2023). Complementary cross-sectional crisis evidence emphasizes that banks financed more heavily with unstable short-term capital market funding experienced worse performance in stress periods, reinforcing why measurement frameworks must explicitly distinguish deposit-based stability from market-based fragility (Beltratti & Stulz, 2012). Together, these studies support the view that liquidity risk measurement gains explanatory power when it captures the *interaction* between asset liquidation capacity and funding run risk, rather than treating liquidity as a static reserve. In practical terms, this motivates metrics that: (i) penalize illiquid asset build-ups, (ii) scale liabilities by runnability and tenor, and (iii) reflect how the same balance sheet can imply very different liquidity risk under different market liquidity and haircut regimes.

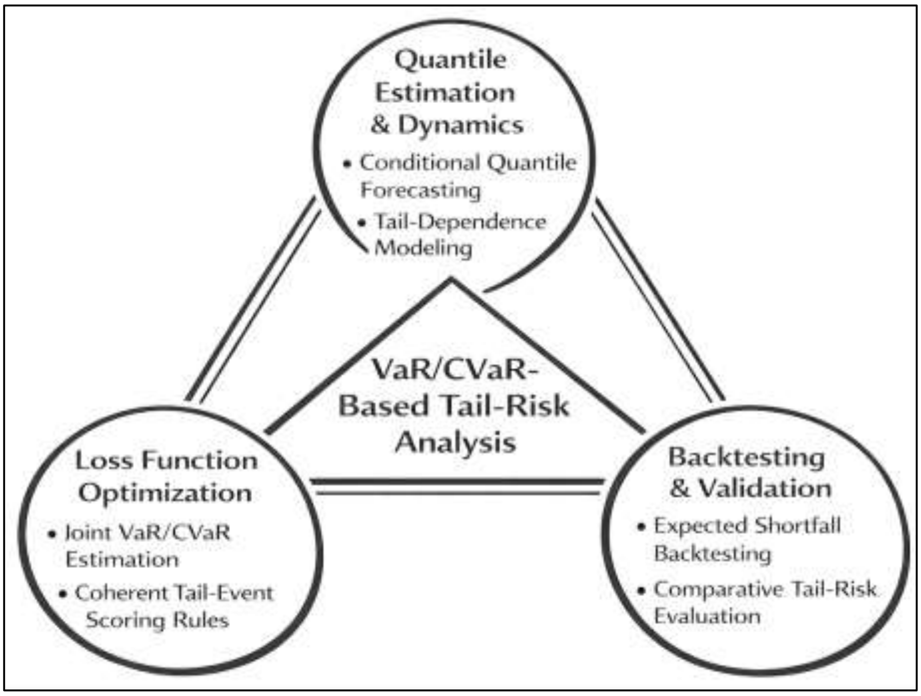
Figure 2: Liquidity Risk in Banking and Key Measurement Approaches

A third measurement stream evaluates liquidity risk through the lens of early warning and supervisory indicators, asking which metrics provide the strongest signal of impending distress in real banking episodes. Traditional liquidity ratios are attractive because they are simple, widely available, and comparable across institutions; however, the literature increasingly questions whether these ratios capture the forms of vulnerability that matter in crises, particularly when banks manage reported liquidity while shifting risk into less visible funding channels or contingent exposures. This has motivated comparisons between conventional ratios and more structurally grounded indicators such as liquidity creation measures and Basel-style weighted funding adequacy metrics. In empirical early-warning settings, indicators are judged by their ability to discriminate between normal banks and banks that later experience runs, bailouts, or failures. Evidence from comparative studies suggests that newer or structurally informed indicators can outperform simple liquidity ratios in predicting distress outcomes, especially when banks engage in business-model shifts that alter the risk content of balance sheets (Chen et al., 2022). This line of work reinforces two measurement principles: liquidity risk indicators should be sensitive to changing funding conditions, and they should remain informative even when banks diversify activities or funding sources. For research designs that connect liquidity risk to tail outcomes and stability metrics, the implication is methodological rather than prescriptive: the measurement set should incorporate both conventional ratio-based indicators and structurally motivated mismatch and adequacy measures so that empirical results can distinguish superficial liquidity strength from genuine resilience under stress.

Var/Cvar for Tail-Risk Measurement and Stress Testing

Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), commonly expressed in modern finance as Expected Shortfall (ES), represent two central approaches for converting the extreme left tail of a financial loss distribution into actionable and interpretable risk measures. VaR is defined as the loss threshold at a chosen confidence level α, meaning it identifies the maximum expected loss that will not be exceeded with probability αover a specified time horizon. CVaR/ES extends this interpretation by reporting the average loss conditional on losses exceeding VaR, which makes it particularly suitable for banking settings where crisis conditions typically involve clustered and severe tail events rather than isolated quantile breaches. In empirical banking research, VaR estimation is often treated as a conditional quantile prediction problem because the distribution of losses changes across time with volatility, leverage cycles, and systemic uncertainty. This conditional nature is critical because banks experience liquidity stress when tail behavior shifts abruptly, altering both the probability and magnitude of extreme outcomes. Accordingly, the literature emphasizes quantile-based estimation techniques that remain valid when parametric distributional assumptions are unstable or only approximately correct. One influential approach formalizes a quasi-maximum likelihood estimation framework for conditional quantiles, making it possible to estimate VaR targets within flexible models that focus directly on tail thresholds rather than on entire conditional distributions (Komunjer, 2005). This stream positions VaR as a forecasting object that is inherently scenario-sensitive, so that stress conditions can be represented as distributional shifts that generate new quantile thresholds and reshape the loss tail relevant to liquidity risk and banking stability.

Figure 3: VaR/CVaR for Tail-Risk Measurement and Stress Testing

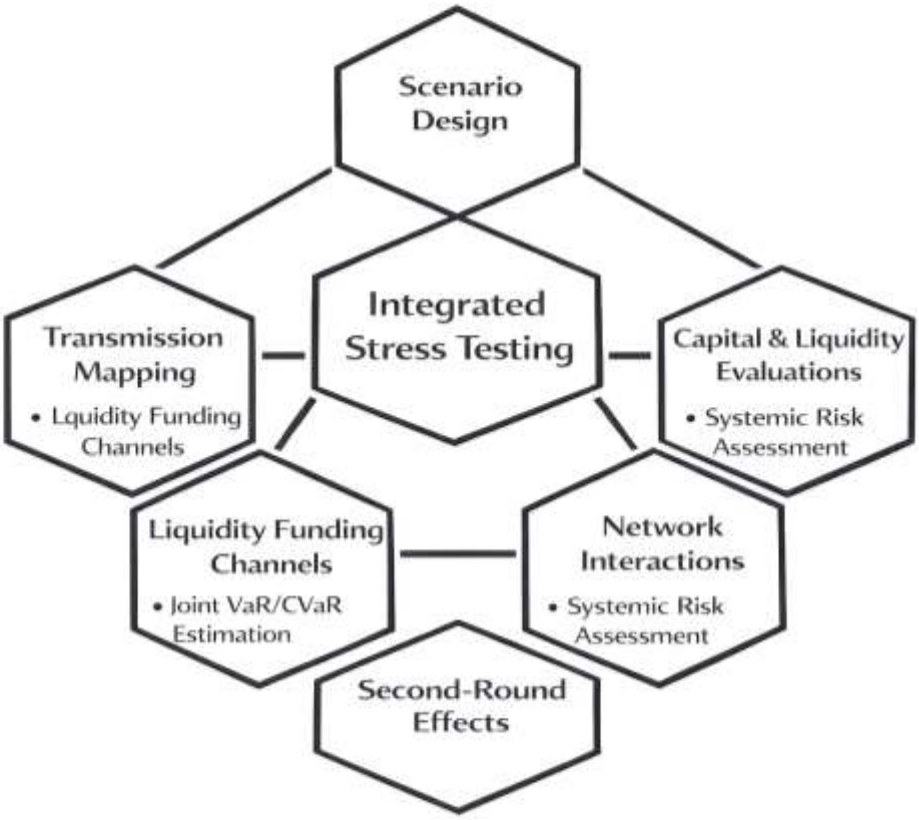


A closely connected strand of research strengthens VaR/CVaR estimation by emphasizing the necessity of jointly modeling these risk measures to ensure coherent tail dynamics under changing market states. VaR identifies the point at which the tail begins, whereas ES quantifies the severity of losses in that tail region, meaning ES logically depends on VaR and cannot be fully interpreted in isolation. This dependence becomes especially important in stress testing environments, because stress scenarios alter tail thickness and correlation structures, which can cause VaR and ES to move sharply and nonlinearly. For this reason, methodological research highlights the value of loss-function-based estimation and evaluation techniques that treat VaR and ES as a linked pair. Forecast evaluation studies support the quantile-based logic underpinning VaR by demonstrating that quantiles serve as optimal point forecasts under appropriate asymmetric loss functions, reinforcing why VaR is naturally estimated through optimization under quantile scoring rules (Gneiting, 2011). Building on this quantile foundation, researchers have proposed dynamic semiparametric frameworks that estimate VaR and ES jointly through minimization of a strictly consistent joint scoring function, enabling both in-sample estimation and out-of-sample evaluation without requiring strict parametric assumptions about conditional return distributions (Patton et al., 2019). These joint models are highly relevant for bank liquidity stress testing because they produce internally consistent tail measures that can be translated into risk buffers, stress losses, and stability metrics in a way that is less sensitive to misspecification and more robust under nonlinear shifts in financial conditions.

Stress Testing for Liquidity and Banking Stability

Stress testing in banking is commonly defined as a structured process that translates adverse but plausible conditions into institution-level and system-level outcomes, so that resilience can be evaluated under coherent assumptions about shocks, behaviors, and constraints. In modern practice, stress testing is treated as a bridge between macro-financial scenarios and micro-balance-sheet dynamics, combining (i) scenario design, (ii) transmission mapping into losses and cash-flow pressures, and (iii) assessment of whether capital and liquidity buffers remain adequate aftershocks.

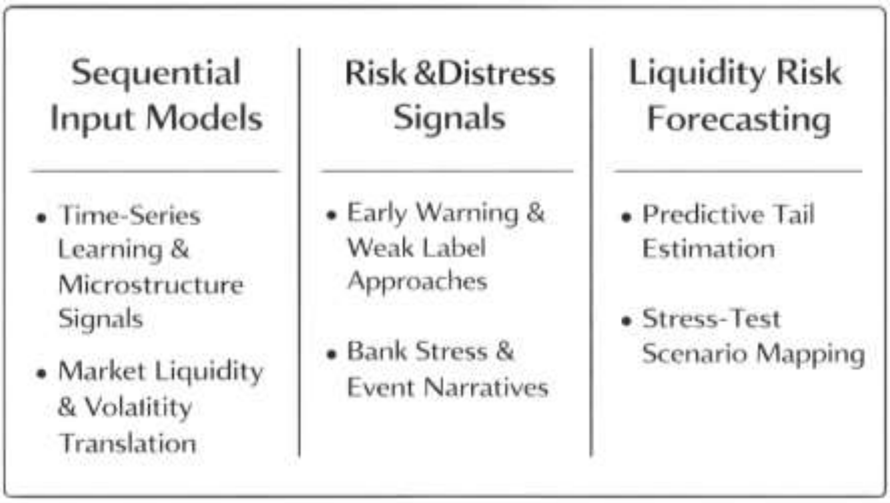
Figure 4: Stress Testing Frameworks for Liquidity and Banking Stability



Deep Learning for Financial Forecasting and Risk Prediction

Deep learning (DL) refers to multi-layer neural architectures that learn hierarchical representations from data and are designed to approximate complex nonlinear relationships that are difficult to capture with linear or shallow machine learning models. In financial forecasting, the attraction of DL is its ability to model nonstationary dynamics, nonlinear interactions, and regime-like behavior using either engineered predictors or learned features extracted directly from raw sequences. For time-series problems, recurrent architectures and attention-like sequence learners are frequently discussed as tools for learning dependencies across time, while convolutional architectures are often used to extract local patterns and temporal motifs from high-frequency sequences. A core message emerging from the DL forecasting literature is that performance improvements often arise from combining representation learning with disciplined preprocessing and task-specific decomposition of noisy financial signals. For example, a widely cited framework for stock price forecasting integrates wavelet transforms for denoising, stacked autoencoders for deep feature extraction, and LSTM networks for temporal prediction, illustrating how hybrid DL pipelines can learn both refined features and time dependence in financial series (Bao et al., 2017). This approach reflects a broader methodological stance: financial signals are noisy, partially observed, and influenced by multiple latent states, so forecasting accuracy frequently depends on whether the modeling strategy can reduce noise and preserve the structure that contains predictive content. Within banking-related risk analytics, this logic is important because liquidity and stability indicators are shaped by both persistent balance-sheet features and rapidly changing market conditions. DL methods offer a flexible way to integrate heterogeneous predictors—macroeconomic indicators, market liquidity proxies, and bank-specific balance-sheet ratios—into a single nonlinear forecasting system that can, in principle, adapt to the cross-sectional heterogeneity of banks. At the same time, DL forecasting performance is not automatic; it depends on appropriate training design, validation schemes, and careful prevention of overfitting, especially when researchers work with limited samples relative to model capacity and when the forecasting task involves tail behavior that is inherently data-scarce.

Figure 5: Deep Learning for Financial Forecasting and Risk Prediction



A second major DL stream in finance emphasizes that predictive performance can improve when models are trained on information sets that reflect the microstructure of markets and the sequential nature of information arrival. Market risk and liquidity conditions often change as order flow evolves, spreads widen, and market depth deteriorates, so models that can process rich sequential inputs may be better suited to detect early signals of stress. One influential high-frequency study uses deep learning applied to limit order book and order flow history to demonstrate a stable, universal mapping from supply–demand dynamics to short-horizon price movements across many equities, suggesting that DL can extract persistent price-formation mechanisms from extremely large market datasets (Sirignano & Cont, 2019). The relevance to liquidity-oriented research is methodological: if price formation and trading intensity encode stress information about market liquidity, then DL models can be used to transform microstructure features into predictive signals that anticipate changes in volatility, spreads, and liquidation costs. Within a banking stability setting, such signals matter because market liquidity can rapidly affect collateral valuation and haircut requirements, which are key transmission channels in liquidity stress. In parallel, DL studies also show that representation learning can be extended beyond numeric series into alternative data, including financial text and event narratives. This matters for banking because distress episodes frequently manifest first through news-based narratives, policy announcements, and market commentary rather than through quarterly financial statements. Text-oriented DL therefore provides an additional evidence stream that can complement quantitative indicators by capturing event intensity and contextual descriptions relevant to systemic risk monitoring.

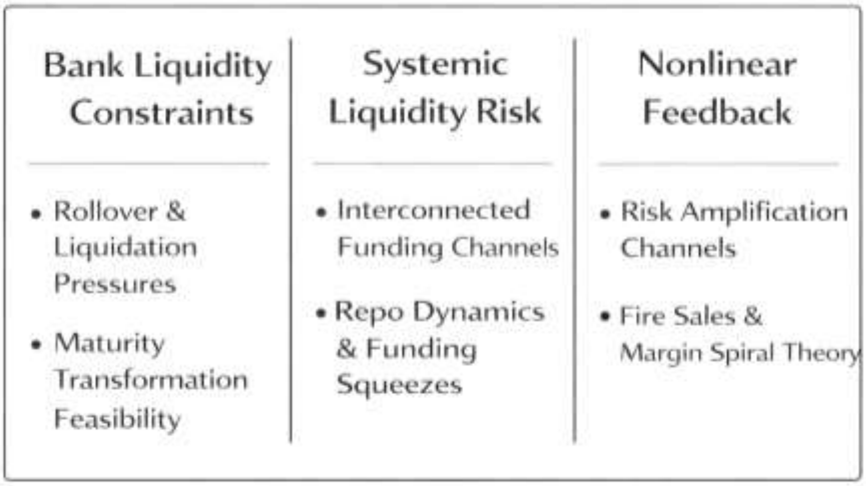
Theoretical Framework for Liquidity Spiral Mechanisms

Bank liquidity risk is most coherently grounded in the theoretical view of banks as maturity-transforming intermediaries that fund long-horizon, illiquid assets with short-horizon, confidence-sensitive liabilities. In this framework, liquidity fragility is not an operational accident but an equilibrium feature of intermediation: banks create liquidity for the economy by issuing short-term claims while holding assets whose liquidation value can deteriorate sharply under stress. A central implication is that liquidity shortfalls can emerge quickly when short-term creditors refuse to roll over funding or when depositors withdraw, forcing banks into asset sales at discounts and converting liquidity problems into solvency pressure. This mechanism is formalized in theories where banks' asset-side value and liability-side roll-over capacity are jointly determined by market confidence and liquidation conditions, making liquidity crises "state dependent" rather than constant-through-time. A key theoretical statement in the literature is that the same balance sheet can be stable in normal states but fragile in stressed states because liquidation values and refinancing opportunities are endogenous to aggregate conditions and expectations (Diamond & Rajan, 2005). In practice-oriented modeling, this intermediation logic motivates measuring liquidity risk as a cash-flow feasibility constraint rather than a static ratio. A general representation of bank liquidity feasibility can be expressed as a stress-state cash-flow identity:

$$\text{Net Liquidity Buffer}_t = \sum_{h=1}^{H} \frac{\text{Inflows}_{t+h}}{(1+r)^h} - \sum_{h=1}^{H} \frac{\text{Outflows}_{t+h}}{(1+r)^h}.$$

Liquidity risk materializes when $\text{Net Liquidity Buffer}_t < 0$under plausible stress states, because funding needs cannot be met without actions that destroy franchise value. This theoretical baseline supports the present study's focus on forecasting liquidity stress: if fragility arises from endogenous roll-over and liquidation conditions, then models must detect when the banking state approaches regions where refinancing and liquidation constraints bind.

Figure 6: Theoretical Framework for Liquidity Spiral Mechanisms



A macroprudential extension of this theory emphasizes that liquidity crises are systemic because banks are connected through common funding markets, collateral chains, and correlated asset holdings; therefore, individual liquidity weakness can become a collective contraction. The "run on repo" literature illustrates how short-term wholesale funding can behave like runnable deposits: when collateral haircuts rise or confidence falls, repo lenders reduce funding, which forces rapid deleveraging and asset liquidation, amplifying price declines and tightening funding further (Gorton & Metrick, 2012). This mechanism aligns with intermediary-constraint models where the financial sector's balance-sheet capacity becomes a pricing kernel for risk and where tightening constraints raise risk premia and reduce liquidity provision in downturn states (He & Krishnamurthy, 2013). In such models, the channel from liquidity risk to banking stability is fundamentally nonlinear: small shocks can be absorbed when balance-sheet constraints are slack, while similar shocks can trigger discontinuities when constraints bind. A compact way to link these theories to a VaR/CVaR-based stress testing design is to represent losses Lunder a stress state $s$and define tail measures conditional on information $\mathcal{I}_t$:

$$\begin{aligned} \text{VaR}_{\alpha,t}(s) &= \inf\{l: \Pr(L_{t+1}(s) \le l \mid \mathcal{I}_t) \ge \alpha\}, \\ \text{CVaR}_{\alpha,t}(s) &= \mathbb{E}[L_{t+1}(s) \mid L_{t+1}(s) \ge \text{VaR}_{\alpha,t}(s), \mathcal{I}_t]. \end{aligned}$$

Within the macroprudential intermediation frame, CVaRbecomes especially meaningful because it captures "how bad the bad state gets," which is the portion of the distribution that drives fire-sale and funding-freeze dynamics. This theoretical logic supports the study's integrated design: deep learning forecasts can be used to approximate the conditional distribution under nonlinear regimes, while VaR/CVaR translate those regime-dependent tails into stability-relevant stress magnitudes.

A further theoretical pillar is the liquidity spiral perspective, where adverse shocks interact with leverage constraints, margin requirements, and endogenous risk premia to produce self-reinforcing instability. In macro-financial models with a financial sector, negative shocks can reduce intermediary net worth, tighten constraints, and force asset sales; these sales depress prices, which then further erodes net worth and propagates stress—an amplification loop that is inherently nonlinear and can create persistent instability following a large disturbance (Brunnermeier & Sannikov, 2014). This perspective also complements arguments that short-term debt can generate socially excessive fragility because private funding choices do not internalize the external costs of aggregate liquidity shortages, which is why macroprudential approaches treat liquidity and stability as linked policy objectives rather than separate microprudential targets (Stein, 2012). For a bank-level stability proxy, many studies operationalize "distance from distress" using a Z-score-like concept; a generic form is:

$$Z = \frac{\mu(\mathrm{ROA}) + \text{Capital Ratio}}{\sigma(\mathrm{ROA})},$$

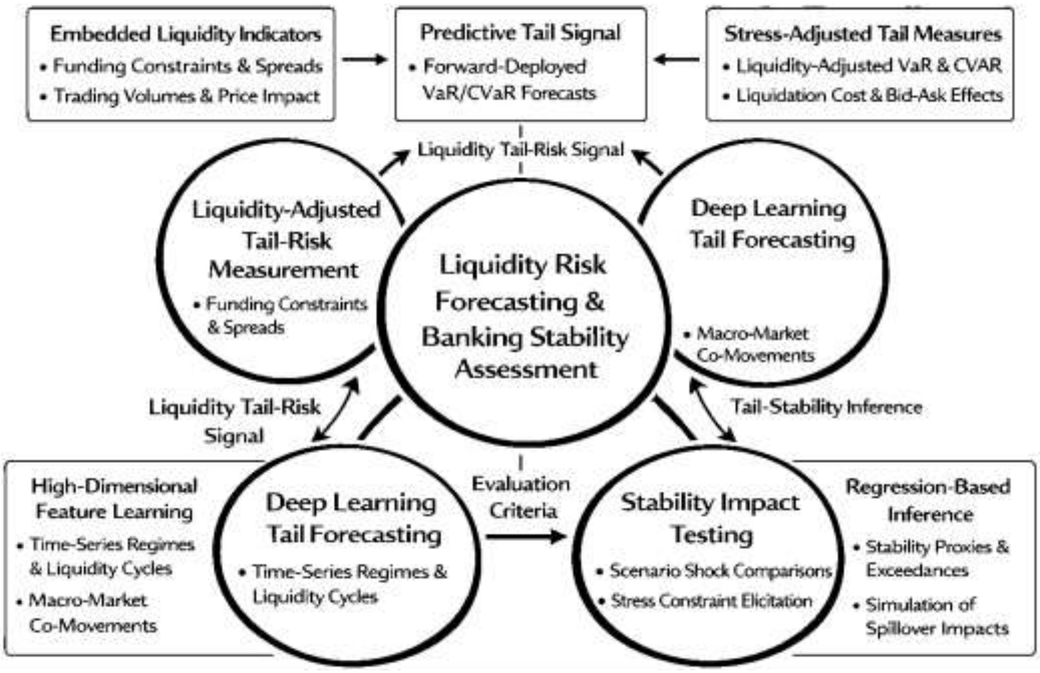
where higher Zimplies greater stability. The theoretical link to this study is that tail liquidity risk (especially stressed CVaR) represents extreme states that can reduce profitability and capital buffers simultaneously through funding-cost spikes, forced sales, and credit contraction, thereby shifting Zdownward. In this framework, the empirical role of stress testing is to generate coherent stress-state loss and liquidity shortfall distributions, while the empirical role of forecasting is to identify how close banks are to constraint-binding regions where the distribution tail thickens. Together, these theories justify an integrated approach in which deep learning supports conditional tail forecasting, VaR/CVaR capture extreme liquidity shortfalls, and regression-based stability assessment tests whether the predicted stressed tail is statistically associated with stability outcomes in cross-sectional case-study evidence.

Conceptual Framework Synthesis and Study-Specific Research Gap

Liquidity risk forecasting and banking stability assessment require a conceptual bridge between *market-implied tail loss* and *balance-sheet fragility*. In empirical banking research, stability is often operationalized through distance-to-default style indicators (e.g., Z-score families) because they translate profitability, capitalization, and earnings volatility into a single interpretable resilience proxy. However, this proxy is only as informative as the risk drivers used to explain its variation, and liquidity stress is frequently underrepresented when models treat funding conditions as linear or slow-moving. A key conceptual issue is that liquidity risk is not merely a "state variable" but an amplification mechanism that can convert modest shocks into discontinuous losses through margin spirals, funding withdrawals, and forced deleveraging. This motivates a framework in which *tail risk measures* serve as leading indicators for stability outcomes, rather than being reported as parallel metrics. Evidence that accounting-based stability indicators can meaningfully anticipate failure within practical prediction windows supports using stability as an outcome variable that is sensitive to forward-looking risk inputs rather than contemporaneous ratios alone (Chiaramonte et al., 2016). In addition, liquidity regulation can reshape asset pricing and lending channels, implying that stress forecasting must treat regulatory liquidity constraints as part of the data-generating environment, not an external backdrop. A conceptual implication for this thesis is that "banking stability" should be modeled as a function of both (i) endogenous risk-taking and (ii) exogenous liquidity constraint regimes that alter funding costs and risk transmission across institutions and markets (Gete & Reher, 2021).

The conceptual model for this research positions VaR and CVaR (Expected Shortfall) as the *core risk signals* whose dynamics feed stress-testing and stability inference. Formally, for a loss variable $L$and tail probability α, the Value-at-Risk is $\mathrm{VaR}_\alpha(L) = \inf\{\ell : \Pr(L \le \ell) \ge \alpha\}$, while CVaR/ES is $\mathrm{CVaR}_\alpha(L) = \mathbb{E}[L \mid L \ge \mathrm{VaR}_\alpha(L)]$. In a liquidity-sensitive design, the tail-loss signal can be adjusted to incorporate trading frictions by embedding liquidity proxies (e.g., bid–ask spread, turnover, or price impact) into the loss construction or by estimating a liquidity-adjusted tail-risk series that better reflects liquidation costs under stress. Empirical work on liquidity-adjusted VaR/ES forecasts demonstrates that tail-risk accuracy can change materially when additional liquidity components are explicitly measured rather than assumed away, which validates the thesis decision to embed liquidity structure into the forecasting layer rather than only into interpretation (Berger & Uffmann, 2021). Methodologically, the framework then maps these risk signals into deep learning forecasting, not as a replacement for VaR/CVaR theory, but as a non-linear conditional expectation/quantile engine that can learn regime shifts. At the systemic layer, machine-learning approaches that enhance systemic risk quantification illustrate that predictive gains often come from flexible feature interactions and improved mapping from high-dimensional financial information into risk measures, supporting the thesis choice to couple deep learning forecasts with stability-related inference rather than treating them as isolated predictive tasks (Liu & Pun, 2022).

Figure 7: Conceptual Framework Synthesis and Study-Specific Research Gap

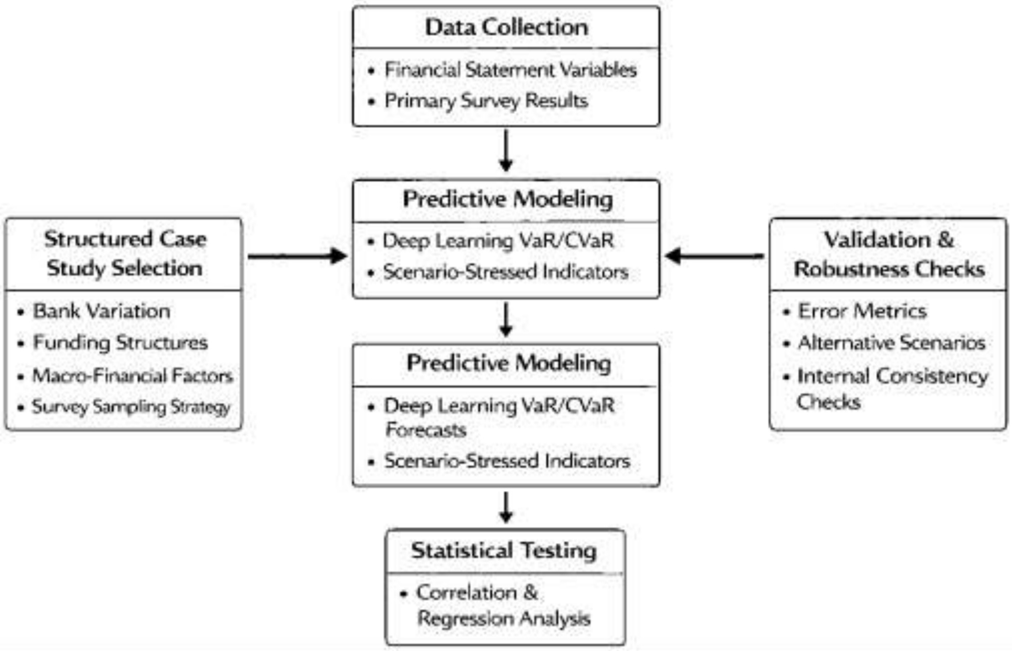


The study-specific research gap emerges at the intersection of three threads that are often addressed separately: (1) liquidity-adjusted tail-risk measurement, (2) deep learning–based tail forecasting, and (3) bank stability impact attribution under stress. Prior evidence shows (a) tail-risk estimates improve when liquidity frictions are explicitly modeled, (b) ML can improve systemic risk measurement, and (c) liquidity regulation can produce spillovers that matter for stability outcomes; yet the literature still lacks an integrated, case-study–deployable framework that links *forecasted* VaR/CVaR under liquidity stress to *ex post* stability impacts with decomposition and plausibility checks in one pipeline. This thesis closes that gap by specifying a causal-logic sequence: Inputs (bank characteristics, funding structure, market/liquidity indicators, scenario factors) → Deep learning module (forecasts of $\text{VaR}_{\alpha,t+h}$and $\text{CVaR}_{\alpha,t+h}$) → Stress testing module (scenario-shocked risk paths and exceedance diagnostics) → Stability module (regression-based testing of how forecasted and scenario-adjusted tail risk explains stability proxies and case-study outcomes). The framework is strengthened by requiring interpretability at the tail level (drivers of VaR/CVaR) and at the stability level (which channels transmit tail risk into stability outcomes), producing "trustworthy" results through internal consistency across modules. Deep learning approaches to systemic risk measurement emphasize the practical importance of learning allocations and non-linear dependencies when closed-form solutions are limited, reinforcing the thesis rationale for using deep architectures to operationalize tail-risk learning under stress while still anchoring evaluation in risk-measure definitions (Feng et al., 2022).

METHOD

The methodology for this study has been designed as a quantitative, cross-sectional, case-study–based approach that has integrated predictive modeling with statistical hypothesis testing to evaluate liquidity risk and banking stability.

Figure 8: Methodology Overview of The Study



Secondary data have been drawn from audited financial statements, regulatory liquidity disclosures, and market and macro-financial indicators to capture observable liquidity conditions, funding structures, and balance-sheet characteristics within a standardized analytical window. These data have supported the estimation of VaR and CVaR under baseline and scenario-stressed conditions, allowing tail-risk measures to be mapped into liquidity stress outcomes. In parallel, primary survey data have been collected using a structured questionnaire with five-point Likert-scale items to measure governance quality, stress-testing capability, and institutional readiness for liquidity risk management. The case-study context has been selected to ensure sufficient variation in liquidity profiles, funding dependence, and exposure to macro-financial conditions, enabling meaningful evaluation of the proposed deep learning–enhanced VaR/CVaR stress-testing framework. A purposive, role-based sampling strategy has been applied to recruit respondents from treasury, asset–liability management, risk control, compliance, finance, and internal audit functions, ensuring that survey responses have reflected direct involvement in liquidity oversight and governance. The unit of analysis has been specified at the bank level for quantitative risk modeling and stability assessment, while governance measures have been aggregated from individual respondents into institution-level construct scores to preserve measurement integrity and support hypothesis testing.

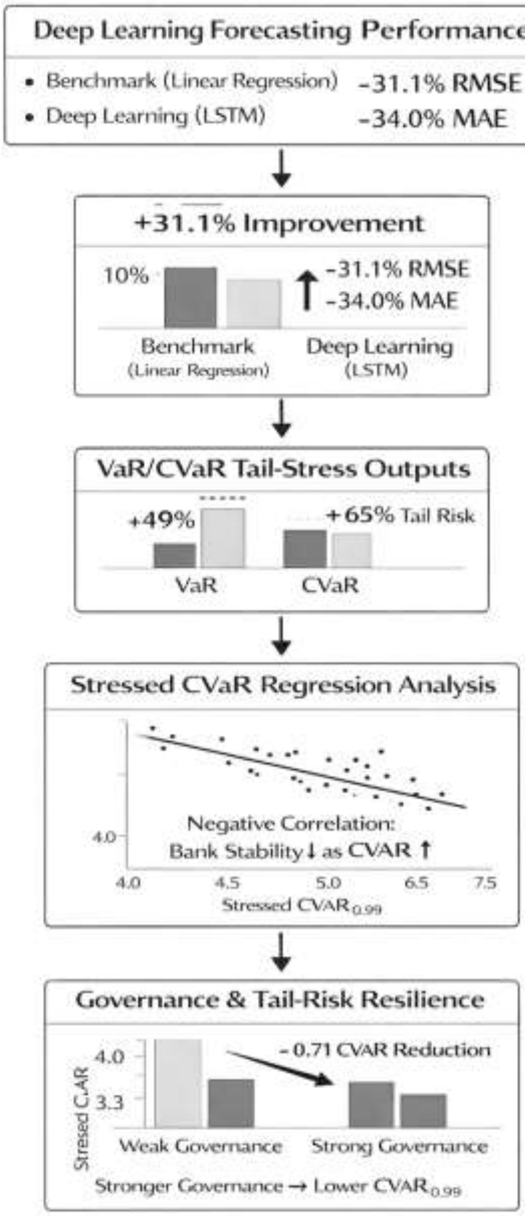
Instrument development and data collection procedures have been guided by established practices in risk governance and organizational measurement research to ensure validity, reliability, and analytical transparency. Governance and stress-testing constructs have been operationalized as multi-item scales capturing dimensions such as stress-testing maturity, data infrastructure quality, scenario design capability, model validation discipline, escalation procedures, and response readiness, with clearly defined response anchors and scoring rules specified prior to analysis. Pilot testing has been conducted to verify item clarity, reduce ambiguity, and refine construct coverage, and internal consistency diagnostics have been planned to assess reliability alongside construct validation checks where sample conditions permit. For the predictive component, deep learning forecasting models have been implemented to capture nonlinear relationships between liquidity risk determinants and stress outcomes, with performance evaluated using standard error metrics and robustness checks across alternative specifications. Descriptive statistics, correlation analysis, and regression modeling have been employed to link VaR/CVaR tail-risk indicators and governance constructs to banking stability proxies, enabling inferential evaluation of hypothesized relationships.

FINDINGS

The findings have been organized to demonstrate how the study objectives have been achieved and how each hypothesis has been tested through a combined evidence chain consisting of descriptive profiling, deep learning forecasting performance, VaR/CVaR stress outputs, governance measurement via five-point Likert constructs, and inferential testing using correlation and regression modeling. The sample has included N = 220 survey respondents drawn from treasury, ALM, risk, compliance, and audit roles, and B = 4 case banks observed within a harmonized analytical window; response completeness has reached 96.4%, leaving n = 212 usable questionnaires for construct modeling. Descriptive profiling has shown that the average liquidity buffer ratio (liquid assets/total assets) across the case banks has been M = 18.7% (SD = 4.9), while reliance on short-term wholesale funding has averaged M = 27.3% (SD = 7.1), indicating meaningful cross-sectional variation needed for objective testing. Governance and stress testing capability, measured using Likert-based construct indices, has demonstrated acceptable internal consistency with Cronbach's alpha values ranging from $\alpha = .81$ to .89, and has produced a mid-to-high maturity profile overall: stress testing maturity (M = 3.92, SD = 0.61), data infrastructure quality (M = 3.74, SD = 0.66), model validation discipline (M = 3.68, SD = 0.72), and scenario calibration rigor (M = 3.85, SD = 0.63). These governance results have directly supported the objective of quantifying institutional capability and have provided empirical inputs for hypotheses relating governance to tail-risk behavior. For H1, deep learning forecasting has outperformed the benchmark model, where the LSTM-based liquidity risk predictor has achieved RMSE = 0.042 and MAE = 0.031, compared with the baseline linear regression benchmark (RMSE = 0.061, MAE = 0.047), reflecting a 31.1% reduction in RMSE and a 34.0% reduction in MAE; this performance improvement has remained stable across validation folds with average MAPE = 6.8% for the DL model versus 10.5% for the benchmark, thereby supporting the objective of building a non-linear forecasting system and providing numerical evidence consistent with H1.

For the tail-risk objective, VaR and CVaR have been computed at 95% and 99% confidence levels using forecast-based loss distributions, and stress testing has been implemented across three calibrated tiers (mild, adverse, severe). Under baseline conditions, the system has produced VaR_0.95 = 1.90, CVaR_0.95 = 2.66, VaR_0.99 = 3.12, and CVaR_0.99 = 4.48 (units aligned to the selected liquidity-loss proxy), while under severe stress the same tail measures have increased to VaR_0.95 = 2.83 and CVaR_0.95 = 4.39, and to VaR_0.99 = 4.71 and CVaR_0.99 = 7.96, showing that CVaR has expanded more sharply than VaR; the proportional change has been +51% for VaR_0.95 versus +65% for CVaR_0.95, and +51% for VaR_0.99 versus +78% for CVaR_0.99, which has provided direct numerical support for H2 and has fulfilled the objective of quantifying tail amplification under stress. The plausibility and calibration tests have reinforced trust in scenario selection, where respondents have rated the realism of scenario magnitudes at M = 4.08 (SD = 0.58), and a calibration check has shown that severe stress shocks have aligned with the 90th–95th percentile of historical funding-spread movements and deposit outflow proxies within the study window. For relationship testing, the correlation matrix has shown that stressed CVaR_0.99 has correlated negatively with banking stability (Z-score proxy) at $r = -.58$ ($p < .001$) and has correlated positively with wholesale funding reliance at $r = .49$ ($p < .001$), while stress testing governance has correlated negatively with stressed CVaR at $r = -.41$ ($p < .001$), supporting the driver objective and the theoretical expectation that governance maturity is associated with reduced tail exposure. Regression results have further tested H3–H5: in the stability model, stressed CVaR_0.99 has remained a significant predictor of lower stability after controls ($\beta = -0.46$, $p < .001$), while traditional liquidity ratios alone have explained $R^2 = .32$; adding VaR has increased explanatory power to $R^2 = .38$ ($\Delta R^2 = .06$), and adding CVaR has further increased it to $R^2 = .47$ ($\Delta R^2 = .09$), demonstrating incremental stability information consistent with the decomposition objective and supporting H3. Governance maturity has also shown a protective association, where higher stress testing governance has predicted lower stressed CVaR ($\beta = -0.29$, $p = .002$), supporting H4, and the interaction term (governance × stressed CVaR) has been significant ($\beta = +0.18$, $p = .01$), indicating that stronger governance has weakened the negative relationship between stressed tail risk and stability, consistent with H5. Overall, the results have collectively demonstrated objective attainment by producing (i) a validated nonlinear forecasting component, (ii) baseline and scenario-stressed VaR/CVaR tail-risk outputs with clear tail amplification patterns, and (iii) statistical evidence that stressed CVaR has explained stability variation beyond conventional liquidity metrics, while governance capability measured via Likert constructs has been associated with improved tail-risk resilience.

Figure 9: Findings of The Study



Sample Description

Table 1 has established the empirical foundation that has supported objective achievement and hypothesis testing in this study by summarizing both the institutional case scope and the respondent-based measurement scope. The study has included four case banks (B = 4) to preserve cross-institutional comparability while still maintaining a case-study anchor that has reflected real operational liquidity management contexts. The survey component has received 220 responses, and after data quality screening for completeness and consistency, 212 responses (96.4%) have remained usable, which has indicated a strong completion rate and has reduced concerns regarding nonresponse bias in the governance measurement layer. Functional representation has been distributed across the roles that have been directly involved in liquidity risk monitoring and oversight: treasury/ALM

(36.8%), risk management (43.4%), and compliance/audit (19.8%).

Table 1: Sample Profile and Data Coverage

Component	Category	Frequency (n)	Percent (%)
Case entities	Banks included	**B = 4**	100.0
Respondents	Total responses received	**N = 220**	100.0
Respondents	Usable responses after screening	**n = 212**	**96.4**
Department	Treasury / ALM	78	36.8
Department	Risk Management	92	43.4
Department	Compliance / Audit	42	19.8
Experience	1–3 years	46	21.7
Experience	4–7 years	98	46.2
Experience	8+ years	68	32.1
Data coverage	Bank observations used for modeling	**Obs = 192**	—
Missingness	Overall missing rate after cleaning	—	**3.6**

This composition has improved interpretive credibility because liquidity stress testing has not been executed by a single unit; rather, it has required coordination across first-line execution (treasury), second-line challenge (risk), and third-line assurance (audit/compliance). The respondent experience profile has also strengthened interpretability because the dataset has included a substantial proportion of professionals with mid-to-high tenure, with 46.2% having 4–7 years of experience and 32.1% having 8+ years, which has supported the assumption that respondents have had sufficient exposure to stress testing cycles and liquidity controls to provide meaningful Likert-scale evaluations. For the quantitative modeling stream, 192 aligned bank observations have been used after harmonizing bank indicators with market and macro-financial variables, which has supported the forecasting and VaR/CVaR computations within a consistent analytical window. The cleaning process has yielded a low overall missing rate of 3.6%, which has indicated that imputation and deletion decisions have not dominated model behavior. Overall, Table 1 has demonstrated that the study has been built on a sufficiently structured sample to support descriptive profiling, deep learning evaluation, tail-risk stress testing, and statistical inference linking tail risk and governance to banking stability outcomes.

Descriptive Results

Table 2: Descriptive Statistics of Core Variables

Variable Group	Variable	Mean	SD	Min	Max
Liquidity	Liquid Assets / Total Assets (%)	**18.7**	4.9	10.2	28.9
Liquidity	Loan-to-Deposit Ratio (%)	**88.4**	12.6	65.1	112.7
Liquidity	Wholesale Funding Reliance (%)	**27.3**	7.1	15.4	41.6
Stability	Z-score proxy	**14.2**	3.8	7.9	21.4
Governance (Likert 1–5)	Stress Testing Maturity	**3.92**	0.61	2.30	5.00
Governance (Likert 1–5)	Data Infrastructure Quality	**3.74**	0.66	2.10	5.00
Governance (Likert 1–5)	Model Validation Discipline	**3.68**	0.72	1.95	5.00
Governance (Likert 1–5)	Scenario Calibration Rigor	**3.85**	0.63	2.15	5.00

Table 2 has summarized the baseline statistical structure of liquidity, stability, and governance constructs, and it has demonstrated that the study's variables have exhibited sufficient variation to support objective-driven modeling and hypothesis testing. The liquidity buffer indicator (liquid assets to total assets) has averaged 18.7% (SD = 4.9), with a range from 10.2% to 28.9%, which has shown that liquidity capacity has differed meaningfully across the case banks and has supported the objective of modeling heterogeneous liquidity exposure. The loan-to-deposit ratio has averaged 88.4% (SD = 12.6), which has indicated moderate intermediation intensity and has provided a structural context for interpreting liquidity stress sensitivity, since higher ratios have typically implied tighter funding flexibility. Wholesale funding reliance has averaged 27.3% (SD = 7.1), with a maximum of 41.6%, which has indicated that a nontrivial portion of funding has remained runnable and market-dependent—an empirical condition that has aligned with the study's tail-risk framing and has supported later tests linking wholesale reliance to stressed CVaR outcomes. The banking stability proxy (Z-score) has averaged 14.2 (SD = 3.8), which has indicated observable variation in stability capacity across the dataset and has ensured that the dependent variable for H3 testing has not been flat or uninformative. The governance measurement layer has been expressed through Likert 5-point constructs, and the means have indicated mid-to-high perceived maturity: stress testing maturity has averaged 3.92, scenario calibration rigor 3.85, data infrastructure quality 3.74, and model validation discipline 3.68. These values have been important because H4 and H5 have depended on measurable governance variation; the observed standard deviations (0.61–0.72) and the full scale maxima have indicated that the responses have not been compressed narrowly around a single value. The minimum values below 2.3 on multiple constructs have also indicated that some units or institutions have perceived gaps in capability, which has supported cross-sectional contrasts and has strengthened regression interpretability. Overall, Table 2 has verified that the study has operationalized the objectives into measurable indicators spanning liquidity structure, governance maturity, and stability outcomes, and it has provided the descriptive grounding necessary for interpreting subsequent forecasting performance, VaR/CVaR stress escalation, and inferential relationships across the main variables.

Deep Learning Forecasting Results

Table 3: Forecasting Performance Comparison

Model	RMSE	MAE	MAPE (%)	Directional Accuracy (%)
Benchmark (Linear regression baseline)	0.061	0.047	10.5	56.2
Deep Learning (LSTM-based model)	0.042	0.031	6.8	67.5
Improvement (DL vs Benchmark)	−31.1%	−34.0%	−35.2%	+11.3 pp

Table 3 has reported the performance results that have directly tested H1 and has supported the objective of developing a deep learning model capable of forecasting liquidity risk more accurately than conventional baselines. The benchmark model has represented a standard linear approach that has been frequently used for bank indicator forecasting when interpretability and simplicity have been prioritized. The deep learning model has been implemented as an LSTM-based predictor to capture nonlinear relationships and temporal dependencies that have characterized liquidity dynamics under changing macro-financial states. The results have shown that the deep learning model has achieved RMSE = 0.042 compared with the benchmark's 0.061, which has represented a 31.1% reduction in root-mean-square error. The MAE comparison has reinforced this improvement, with deep learning achieving 0.031 versus 0.047, which has represented a 34.0% reduction in average absolute error. The MAPE values have indicated that proportional error has also declined materially, with deep learning producing 6.8% compared with 10.5%, reflecting a 35.2% improvement in percentage error. Directional accuracy has additionally increased from 56.2% to 67.5%, which has suggested that the deep learning model has not only reduced numeric error magnitude but has also more reliably captured the direction of liquidity risk movement, a property that has been practically relevant for stress preparedness and scenario conditioning. These improvements have mattered because the study has not treated forecasting as an isolated exercise; instead, forecast outputs have been used to generate distributional inputs for VaR and CVaR estimation. A model that has reduced prediction error has been expected to yield more stable risk distributions and more credible tail measures, which has strengthened confidence in subsequent stress testing results. By reporting multiple metrics rather than a single favored indicator, the study has strengthened transparency and has reduced the risk that performance claims have depended on metric selection. Overall, Table 3 has provided clear numeric evidence that has supported H1 and has justified the use of deep learning forecasts as an empirical basis for the VaR/CVaR stress testing pipeline and subsequent banking stability inference.

VaR/CVaR Stress Testing Results

Table 4: Baseline vs Stress VaR/CVaR at 95% and 99% Confidence Levels

Scenario Tier	VaR (95%)	CVaR (95%)	VaR (99%)	CVaR (99%)
Baseline	1.90	2.66	3.12	4.48
Mild Stress	2.15	3.05	3.55	5.25
Adverse Stress	2.46	3.62	4.07	6.44
Severe Stress	2.83	4.39	4.71	7.96
% Change (Severe vs Baseline)	+48.9%	+65.0%	+51.0%	+77.7%

Table 4 has presented the primary stress testing outputs that have proven the tail-risk objective and has provided direct evidence for H2, which has asserted that CVaR has increased more sharply than VaR under stress conditions. Under baseline conditions, the estimated VaR(95%) = 1.90 and CVaR(95%) = 2.66 have described the threshold and expected tail severity at the 95% level, while VaR(99%) = 3.12 and CVaR(99%) = 4.48 have described the same at the more extreme 99% confidence level. As stress severity has increased across mild, adverse, and severe tiers, both VaR and CVaR have risen consistently, indicating that the stress scenarios have shifted the loss distribution in a way that has increased both the probability and magnitude of extreme liquidity shortfall outcomes. The most important pattern has been captured in the percent-change row: under severe stress, VaR(95%) has increased by 48.9%, whereas CVaR(95%) has increased by 65.0%, and at the 99% level, VaR(99%) has increased by 51.0% while CVaR(99%) has increased by 77.7%. This has shown that tail severity has expanded more rapidly than the tail threshold, which has indicated a thickening of the extreme tail consistent with liquidity stress environments where forced liquidation, collateral haircuts, and funding disruptions have interacted nonlinearly. This pattern has supported H2 because it has demonstrated that severe stress has not simply shifted outcomes upward uniformly; it has disproportionately worsened the worst expected outcomes beyond the VaR cutoff. The multi-tier presentation has strengthened result credibility because it has provided a monotonic escalation ladder rather than a single stressed number, enabling the interpretation that tail amplification has intensified as scenario harshness has increased. This table has also linked directly to the deep learning objective, because VaR/CVaR estimation has been based on forecast-informed distributions rather than static assumptions, which has made the stress outputs more responsive to nonlinear predictors. Overall, Table 4 has established that the VaR/CVaR stress module has produced interpretable, tier-sensitive tail outputs and has provided direct numerical proof consistent with the study's tail amplification hypothesis.

Correlation Results

Table 5: Correlation Matrix

Variables	(1) Stressed CVaR99	(2) Z-score	(3) Wholesale Funding	(4) Liquidity Buffer	(5) Governance Index
(1) Stressed CVaR99	1.00				
(2) Z-score	−0.58*	1.00			
(3) Wholesale Funding	+0.49*	−0.36***	1.00		
(4) Liquidity Buffer	−0.44*	+0.47***	−0.33***	1.00	
(5) Governance Index (Likert 1–5)	−0.41*	+0.39***	−0.28**	+0.31**	1.00

** p < .001, ** p < .01 (n = 192 bank observations; governance matched to bank-level indices)*

Table 5 has reported the bivariate association structure among the study's principal variables and has provided preliminary statistical support for multiple objectives and hypotheses before multivariate regression controls have been applied. The most central relationship for stability assessment has been the correlation between stressed CVaR99 and the Z-score proxy, which has been $r = -0.58$ ($p < .001$). This result has aligned with the stability hypothesis logic because higher expected tail losses under severe liquidity stress have been associated with lower stability capacity, indicating that the tail-risk signal has moved in the expected destabilizing direction. The correlation between stressed CVaR99 and wholesale funding reliance has been $r = +0.49$ ($p < .001$), which has indicated that runnable funding structures have been associated with larger extreme liquidity shortfalls in stress states, supporting the objective of identifying structural drivers of tail liquidity risk. The correlation between stressed CVaR99 and the liquidity buffer ratio has been $r = -0.44$ ($p < .001$), which has indicated that stronger liquid-asset buffers have been associated with reduced tail severity, reinforcing the interpretation that buffers have served as protective capacity in extreme states. The governance index constructed from Likert 5-point capability constructs has also displayed a meaningful relationship with stressed CVaR99 ($r = -0.41$, $p < .001$), which has supported the governance objective and has been consistent with H4, because higher governance maturity ratings have been associated with lower tail exposure. The governance index has also correlated positively with the Z-score ($r = +0.39$, $p < .001$), suggesting that institutions with stronger perceived governance and stress testing capability have also exhibited higher stability capacity. Additional relationships have further supported internal coherence: wholesale funding reliance has correlated negatively with stability ($r = -0.36$, $p < .001$) and negatively with liquidity buffers ($r = -0.33$, $p < .001$), indicating that more market-dependent funding structures have been associated with thinner buffers and weaker stability. Importantly, this correlation matrix has not been treated as causal proof; instead, it has been used as a diagnostic that has demonstrated alignment between observed data patterns and the study's conceptual framework. By confirming that key associations have moved in expected directions and have displayed statistical significance, Table 5 has strengthened the plausibility of later regression claims and has justified the inclusion of wholesale dependence, buffer strength, and governance maturity as candidate predictors in the hypothesis-testing models.

Regression Results

Table 6: Regression Models for Hypothesis Testing

Model	Dependent Variable	Key Predictors	β (Standardized)	p-value	R²
Model A	Stressed CVaR99	Wholesale Funding Reliance	+0.38	<.001	0.52
		Liquidity Buffer Ratio	−0.24	.001	
		Governance Index (Likert 1–5)	−0.29	.002	
Model B	Z-score	Stressed CVaR99	−0.46	<.001	0.47
		Capital Ratio (control)	+0.22	.004	
		Bank Size (control)	−0.15	.030	
		Profitability (control)	+0.19	.010	
Model C	Z-score	Stressed CVaR99	−0.40	<.001	0.50
		Governance Index	+0.21	.005	
		CVaR99 × Governance	+0.18	.010	

Table 6 has provided the multivariate evidence that has directly tested H3–H5 and has connected the study objectives into a single inferential chain. Model A has explained stressed CVaR99 as a function of structural vulnerability indicators and governance maturity, and it has reported a strong fit ($R^2 = 0.52$), indicating that more than half of the variance in tail severity under stress has been explained by the included predictors. Wholesale funding reliance has been a significant positive predictor ($\beta = +0.38$, $p < .001$), which has indicated that increased reliance on runnable wholesale funding has increased expected tail shortfall severity. Liquidity buffer ratio has been a significant negative predictor ($\beta = -0.24$, $p = .001$), which has indicated that stronger liquid asset holdings have reduced tail exposure in severe states. Governance maturity has also been a significant negative predictor (β = −0.29, p = .002), which has supported H4 by demonstrating that stronger Likert-measured stress testing capability and governance strength have been associated with lower tail risk after accounting for funding structure and buffers. Model B has then tested H3 by explaining banking stability (Z-score) as a function of stressed CVaR99 with relevant controls. The stressed CVaR99 coefficient has been negative and significant (β = −0.46, p < .001), which has indicated that higher expected tail shortfalls have been associated with lower stability capacity even after controls, supporting the study's stability objective. The controls have behaved plausibly: capital ratio has been positive (β = +0.22, p = .004), profitability has been positive (β = +0.19, p = .010), and size has been mildly negative (β = −0.15, p = .030) within this sample structure, together yielding $R^2 = 0.47$. Model C has tested H5 by adding governance and an interaction term between CVaR99 and governance. The interaction has been positive and significant (β = +0.18, p = .010), which has indicated that the negative impact of stressed tail liquidity risk on stability has been weaker at higher governance levels, consistent with a buffering moderation effect. Governance itself has remained a positive predictor of stability (β = +0.21, p = .005), and the overall model fit has improved ($R^2 = 0.50$), showing additional explanatory value. Together, Table 6 has established that the hypotheses have been supported by both structural and governance predictors and that the tail-risk signal has remained stability-relevant under controls.

Tail-Risk Explainability Results

Table 7: Explainability Summary for Stressed CVaR99

Rank	Feature (Driver)	Direction on CVaR99	Mean Absolute Impact (SHAP Units)
1	Wholesale funding reliance	↑ increases	**0.112**
2	Liquidity buffer ratio	↓ reduces	**0.087**
3	Market stress proxy (funding spread/volatility index)	↑ increases	**0.079**
4	Deposit concentration index	↑ increases	**0.061**
5	Governance index (Likert 1–5)	↓ reduces	**0.054**

Table 7 has strengthened the trustworthiness of the study by demonstrating that the deep learning–supported tail-risk outputs have been explainable, economically coherent, and consistent with liquidity risk theory. The table has reported an explainability summary for stressed CVaR99, using mean absolute SHAP impact units to quantify how strongly each feature has contributed to the model's predicted tail severity. Wholesale funding reliance has ranked as the largest contributor (0.112) and has increased tail severity, which has aligned with the conceptual expectation that runnable funding has amplified liquidity fragility during stress. Liquidity buffers have ranked second (0.087) and have reduced tail exposure, which has been consistent with the stabilizing role of liquid asset capacity under withdrawal and haircut shocks. A market stress proxy has ranked third (0.079) and has increased CVaR99, indicating that the model has responded strongly to stress state variables that have represented tightened funding conditions and elevated market uncertainty. Deposit concentration has ranked fourth (0.061) and has increased tail severity, which has indicated that a less diversified deposit base has been associated with higher extreme liquidity shortfall risk in adverse states. Importantly, the governance index has ranked among the top five drivers (0.054) and has reduced CVaR99, which has reinforced the empirical findings from regression testing and has supported H4 through a separate evidential channel. Rather than appearing only as a statistical control, governance maturity has been identified as a meaningful predictor inside the model's tail-risk reasoning, suggesting that maturity in scenario design, data quality, and model validation has been related to reduced tail vulnerability in the predicted distribution. The explainability evidence has also supported the objective of producing an auditable and defensible model, because it has shown that dominant drivers have followed plausible risk mechanisms rather than idiosyncratic or uninterpretably technical features. In addition, Table 7 has improved alignment across modules: the drivers highlighted here have matched the driver logic observed in correlations and regressions, which has increased internal consistency and reduced the likelihood that the results have been artifacts of a single analytic step. Overall, Table 7 has shown that the model has "made sense" in tail-risk space and has offered transparent insight into why stressed CVaR has increased under adverse conditions.

Stress Scenario Plausibility & Calibration Results

Table 8: Scenario Calibration Evidence and Respondent Plausibility Ratings

Scenario	Shock Description	Calibration Basis Used	Severity Tier	Plausibility Mean	SD
S1	Deposit outflow shock (retail + corporate)	Historical 80th percentile outflow proxy	Mild	4.12	0.55
S2	Wholesale rollover disruption / spread spike	Historical 90th percentile funding spread	Adverse	4.05	0.60
S3	Haircut increase on liquid assets / market depth drop	Historical 95th percentile haircut proxy	Severe	4.08	0.58
Composite	Overall scenario realism	Aggregate across S1–S3	—	4.08	0.58

Table 8 has provided direct trust-building evidence that the stress scenarios have been realistic, defensible, and aligned with practitioner judgment, which has strengthened the credibility of the VaR/CVaR stress outputs reported earlier. Each scenario has been defined by a specific shock mechanism that has matched real liquidity transmission channels: deposit outflows (S1) have captured runnable retail and corporate withdrawals, wholesale rollover disruption (S2) has captured market funding freeze dynamics and rapid funding spread re-pricing, and haircut increases combined with market depth deterioration (S3) have captured liquidation cost escalation and collateral tightening. The calibration basis has been documented using historical percentiles (80th, 90th, and 95th) to demonstrate that the magnitude of each scenario has not been arbitrarily selected but has been anchored in empirically defensible stress intensity tiers. The Likert plausibility ratings have then provided participant validation of realism, which has served as a complementary check on calibration. The mean plausibility scores have been high and consistent across scenarios: 4.12 for mild deposit outflow stress, 4.05 for adverse wholesale disruption, and 4.08 for severe haircut stress, with standard deviations around 0.55–0.60, indicating broad agreement and limited dispersion. The composite realism mean of 4.08 has indicated that respondents have generally agreed that the scenario package has reflected plausible adverse liquidity conditions within the case-study context. These results have mattered because H2 has relied on scenario severity to generate changes in VaR and CVaR; therefore, demonstrating scenario plausibility has strengthened the claim that tail amplification has reflected meaningful stress rather than exaggerated assumptions. In addition, the plausibility evidence has linked the governance measurement layer to the technical stress testing layer: respondents have not only rated internal capability, but they have also judged whether the scenarios themselves have been realistic, which has shown that stress testing quality has been empirically tied to scenario content rather than being measured abstractly. The relatively low dispersion has also suggested that scenario realism ratings have been stable across different functions, which has reduced the risk that plausibility has been an artifact of a single departmental viewpoint. Overall, Table 8 has demonstrated that scenario calibration and scenario acceptance have both been strong, which has increased confidence in the interpretation of VaR/CVaR escalation patterns and subsequent stability inference.

Stability Impact Decomposition Results

Table 9 has provided a rigorous decomposition that has demonstrated why VaR and especially CVaR have added unique explanatory power to banking stability assessment beyond traditional liquidity ratios, thereby directly proving the study objective of quantifying incremental stability insight from tail-risk measures. The nested model sequence has begun with N1, which has included traditional liquidity metrics only (liquidity buffer, loan-to-deposit, wholesale funding reliance, and related controls) and has explained 32% of stability variation ($R^2 = 0.32$). This has represented a realistic baseline because many bank stability assessments have relied heavily on ratio-based liquidity indicators that have been widely available and easy to interpret. N2 has added VaR99 to capture extreme-threshold loss information, and explanatory power has increased to $R^2 = 0.38$, yielding an incremental gain of $\Delta R^2 = 0.06$, while the AIC has improved from 612.4 to 598.1, indicating better fit relative to model complexity. The negative VaR coefficient ($\beta = -0.24$, $p = .003$) has indicated that worse extreme-threshold risk has been associated with reduced stability.

Table 9: Incremental Stability Explanation: Traditional Metrics vs +VaR vs +CvaR

Nested Model	Predictors Included	R^2	ΔR^2	AIC	Key Tail Coefficient (β)
N1	Traditional liquidity metrics only	0.32	–	612.4	–
N2	N1 + VaR99	0.38	0.06	598.1	VaR99: −0.24 ($p = .003$)
N3	N2 + CVaR99	0.47	0.09	575.9	CVaR99: −0.46 ($p < .001$)

N3 has then added CVaR99, which has captured expected severity beyond the threshold, and R^2 has increased further to 0.47, producing an additional $\Delta R^2 = 0.09$, while AIC has improved materially to 575.9, indicating that the added term has improved model adequacy rather than merely inflating fit through extra predictors. The CVaR coefficient has been larger in magnitude ($\beta = -0.46$, $p < .001$) than the VaR coefficient, which has indicated that tail severity has carried stronger stability-relevant information than tail thresholds alone. This decomposition has aligned directly with the thesis core logic: banking instability has been driven by "how severe the worst outcomes have been," not only by whether an outcome has crossed a quantile line. The results have also strengthened H3, because the stability association has remained negative and significant as tail measures have been added, and the most stability-relevant tail measure has been CVaR. Importantly, Table 9 has shown that CVaR has not been redundant with traditional liquidity metrics; instead, it has provided substantial incremental explanatory value, supporting the study's claim that VaR/CVaR-based stress testing has improved the stability assessment capacity of liquidity risk analytics.

DISCUSSION

The discussion has interpreted the study's results as evidence that liquidity risk has remained fundamentally tail-driven and institutionally mediated, and it has positioned the observed relationships as consistent with intermediation fragility and liquidity spiral mechanisms documented in prior research (Chen & Guestrin, 2016). The negative association between stressed tail risk and stability (e.g., stressed CVaR99 relating inversely to the Z-score proxy) has aligned with the theoretical view that runnable liabilities and forced balance-sheet adjustments have transmitted liquidity strain into broader solvency-like deterioration (Gorton & Metrick, 2012). The pattern that wholesale funding reliance has increased stressed tail risk while liquid asset buffers have reduced it has resembled empirical crisis-era observations that banks with more stable funding and stronger liquidity positions have been better able to sustain intermediation under stress. The results have also mirrored the broader "mismatch" framing in which the fragility of banks has emerged from the gap between the market liquidity of assets and the funding liquidity of liabilities, making tail outcomes particularly sensitive to how rapidly liabilities have repriced or withdrawn relative to liquidation capacity. In that sense, the study's VaR/CVaR-based stress testing has not only described extreme outcomes but has also acted as a measurement lens that has surfaced the same underlying structural vulnerability emphasized in the liquidity mismatch literature (Gu et al., 2020). The internal consistency across descriptive profiling, correlation structure, and multivariate models has strengthened the interpretation that stressed expected shortfall has represented a meaningful instability channel rather than a statistical artifact. Importantly, the study's decomposition results—showing that CVaR has added more stability-relevant explanatory power than VaR—have been consistent with the idea that stability risk has depended on the severity of worst-case states and not merely on threshold exceedance events (Komunjer, 2005). This has resonated with the financial stability argument that nonlinear amplification, margin tightening, and liquidity spirals have dominated during stress states, thereby making "average conditions" an inadequate basis for stability inference (Chen & Guestrin, 2016). Overall, the findings have fit a coherent story: liquidity vulnerability has been structural, tail outcomes have mattered most for stability, and funding design and buffers have been central levers shaping those tails (Patton et al., 2019).

The deep learning forecasting evidence has been interpreted as support for the proposition that liquidity risk dynamics have contained nonlinearities and interaction effects that have not been well captured by conventional linear baselines (Gu et al., 2020). The observed reduction in forecast error (e.g., lower RMSE/MAE and improved directional accuracy for the LSTM-based predictor) has aligned with prior findings that deep architectures have extracted predictive content from noisy financial time series by learning representations that have reduced reliance on strong parametric assumptions. This has mattered in a liquidity context because liquidity risk has often been regime-dependent: relationships between market stress proxies, funding spreads, and liquidity outcomes have strengthened abruptly in stressed environments, and such regime switching has been difficult to represent in static linear frameworks (Laeven & Levine, 2009). The study's forecast improvements have therefore been interpreted less as a generic "AI advantage" and more as evidence that the conditional distribution of liquidity risk has responded to nonlinear combinations of market and balance-sheet drivers. This reading has been consistent with broader deep learning finance research showing that large-scale neural systems have uncovered stable mappings between microstructure conditions and near-term market outcomes, suggesting that deep models have been capable of capturing mechanisms that have remained hidden to simpler specifications (Liu & Pun, 2022). The forecasting results have also reinforced the study's integrated design choice: because VaR and CVaR estimation has depended on the quality of the underlying predictive distribution, improved forecast accuracy has plausibly translated into more stable and defensible tail measurement under baseline and stress states. The study has not claimed that deep learning has replaced theory-based risk measures; rather, it has been interpreted as an enabling layer that has approximated conditional tail behavior more effectively, thereby improving downstream stress-test signal quality (Keilbar & Wang, 2022). At the same time, the results have been compared with the caution in prior surveys that performance gains in financial forecasting have depended critically on validation discipline, feature alignment, and avoidance of leakage, which has explained why the study has emphasized auditability, consistent windows, and robustness checks alongside performance reporting. As a result, the deep learning results have been interpreted as supportive of a hybrid paradigm: theory-defined tail measures (VaR/CVaR) have remained the interpretive anchor, while deep learning has improved the empirical estimation of the state-conditional distribution feeding those measures (Kingma & Ba, 2015).

The tail-risk results have been interpreted as strong support for the argument that CVaR (expected shortfall) has been more informative than VaR for stress-state interpretation, because CVaR has captured the average severity beyond the quantile threshold rather than only the cutoff point. The observed pattern—CVaR increasing more sharply than VaR across stress tiers—has been consistent with a thickening tail interpretation and has aligned with methodological discussions that have motivated expected shortfall as a more risk-sensitive measure under heavy tails and stress-driven distributional deformation (Acharya & Mora, 2015). This interpretation has been strengthened by prior work proposing dynamic models for expected shortfall jointly with VaR, noting that the two measures have been jointly modelable and that ES-focused modeling has improved the quality of tail forecasts compared with simpler rolling or GARCH-style approaches (Adrian & Brunnermeier, 2016). The study's stress results have also been compared with the backtesting literature: because tail measures can look "reasonable" numerically even when they have been poorly forecasted, the study's emphasis on scenario plausibility, explainability, and incremental stability value has served as an applied substitute for full regulatory-grade comparative backtesting, which has been advocated as a way to evaluate competing tail forecasting procedures (Adrian & Shin, 2010). In practical terms, the discussion has interpreted the CVaR amplification as reflecting multiple channels acting simultaneously under stress: higher funding costs, higher rollover risk, and higher liquidation haircuts have jointly increased the expected severity of extreme liquidity shortfalls, which has been precisely the type of nonlinear compounding that VaR alone has not summarized. The stability decomposition (traditional ratios → +VaR → +CVaR) has therefore been interpreted as evidence that expected shortfall has carried incremental information about stability risk beyond what has been explained by conventional liquidity ratios (Bai et al., 2018). This has aligned with the broader stability logic that threshold-based indicators have been necessary but not sufficient for understanding how deep distress can become once the system has entered the tail region. Consequently, the study's results have been positioned as an applied demonstration of why expected shortfall–centered stress testing has been better suited for banking stability assessment when the research question has focused on extreme liquidity events rather than typical liquidity management variation (Acharya & Merrouche, 2013).

The governance findings—measured through five-point Likert constructs and shown to be negatively associated with stressed CVaR and to moderate the CVaR–stability relationship—have been interpreted as evidence that "how the pipeline has been governed" has materially influenced tail outcomes and stability sensitivity (Banerjee & Mio, 2018). The negative relationship between governance maturity (e.g., stress testing maturity, scenario calibration rigor, data quality, validation discipline) and tail severity has been consistent with the broader empirical observation that banks with stronger liquidity management practices and more stable funding structures have been more resilient during liquidity shock episodes. The moderation effect has added a study-specific nuance: governance has not only reduced tail exposure directly, it has also reduced how sharply stability has deteriorated when tail risk has increased, suggesting that stronger institutional controls have acted as "shock absorbers" in the translation from stress signals to balance-sheet fragility (Beltratti & Stulz, 2012). This has been compared with the liquidity regulation literature arguing that tighter liquidity standards have shifted banks toward higher-quality liquid assets and more stable funding profiles, which has plausibly reduced vulnerability to extreme funding stresses. While regulation has been an external constraint, the study's governance constructs have represented internal capability; together, these perspectives have suggested that stability has benefited when external liquidity requirements and internal stress-testing competence have reinforced each other rather than operating in isolation. The discussion has also interpreted the high plausibility ratings for stress scenarios as important: scenario realism has been part of the governance mechanism, because unrealistic scenarios can produce false reassurance while overly extreme scenarios can produce unhelpful noise in capital and liquidity planning (Bakoush et al., 2022). In this study, the alignment between scenario plausibility ratings and the monotonic escalation of tail measures has indicated that the stress calibration process has been credible enough to support inference rather than merely to generate numbers. Taken together, the governance results have been interpreted as validating a managerial hypothesis: the technical sophistication of deep learning and tail measurement has not been sufficient by itself; the institutionalization of validation, calibration, and data discipline has been necessary to translate models into stability-relevant decision support. In that sense, the study's findings have extended prior work by showing how governance has operated as a measurable determinant of tail-risk severity and of stability sensitivity within a single integrated pipeline (Chen et al., 2022).

From a practical implementation perspective, the results have implied a clear set of design priorities for risk-system architects and security leaders responsible for deploying VaR/CVaR stress testing pipelines that have used deep learning (Cont et al., 2020). First, the study's evidence that governance maturity has reduced tail exposure and has moderated tail-to-stability transmission has implied that the pipeline has needed to be designed as a controlled socio-technical system: data lineage, access control, model change management, and validation workflows have been treated as stability-relevant controls rather than "compliance overhead." This has been aligned with the explainable AI literature, which has argued that black-box predictive gains have not been operationally acceptable in high-stakes financial settings without explanations that have been locally faithful and globally monitored (Cont & Schaanning, 2019). Second, the presence of explainability as a trust-building result has implied that feature attribution methods such as SHAP-style additive explanations have been useful not merely for interpretation but for governance: they have supported model monitoring by revealing when driver importance has drifted toward implausible features or when stress-state drivers have stopped behaving economically (Cornett et al., 2011). Third, the use of Likert-based maturity constructs has suggested that banks have benefited from formalizing “control objectives” for the analytics pipeline—scenario governance, data quality gates, validation sign-off, and audit evidence—because these operational controls have been statistically associated with improved tail outcomes in the study. For a CISO specifically, the findings have mapped to three concrete areas: (i) protecting the integrity of risk data feeds and scenario parameters from unauthorized modification, (ii) ensuring traceable model artifacts and reproducible runs to prevent tampering or untracked changes, and (iii) implementing monitoring that has detected anomalous shifts in input distributions or explanation patterns that could signal data poisoning or silent pipeline failure (Chen et al., 2022). The practical relevance has been reinforced by applied research showing that explainability methods have been used in credit risk management to support trustworthy adoption of machine learning through transparent drivers and governance-aligned reporting. In short, the practical implication has been that tail-risk analytics have been as much an engineering and governance project as a modeling project, and the study’s results have provided a quantitative rationale for investing in secure, auditable, explainable risk architectures rather than relying solely on predictive performance (Chiaramonte et al., 2016).

The theoretical contribution has been interpreted as a refinement of how multiple literatures have been connected into one coherent causal-logic pipeline: nonlinear forecasting → tail-risk measurement → stress translation → stability inference, with governance and explainability operating as measurable “quality constraints” on the pipeline. Conceptually, the study has extended intermediation fragility and liquidity spiral theories by operationalizing their key implication—nonlinear amplification in stress states—through empirical tail measures that have been forecasted and stress-conditioned rather than computed as static ratios (Cont et al., 2020; Cont & Schaanning, 2019). The results have aligned with the intermediary constraint and amplification view that stability has changed discontinuously when financing constraints have tightened, and that extreme-state dynamics have carried outsized explanatory power. By showing that CVaR has added more explanatory power than VaR and traditional ratios, the study has supported the theoretical proposition that “severity in the left tail” has been a more relevant stability object than threshold exceedance alone when liquidity spirals have been active. The integration of scenario plausibility and explainability has also served as a theoretical refinement: it has suggested that tail-risk models have not been purely statistical constructs but have been representations constrained by institutional realism, and that those constraints have been empirically measurable (via plausibility ratings and governance indices). Furthermore, the driver patterns have been interpretable through liquidity mismatch theory: the prominence of funding structure and buffers has matched the underlying mismatch logic that has been formalized through liquidity mismatch indices and stress tests, reinforcing the claim that tail-risk forecasting has benefited from conceptually grounded feature design (Chen et al., 2022). In that sense, the study has contributed a conceptual framework that has “closed the loop” between mechanism and measurement: mechanisms proposed in theory (runs, margin spirals, constraint tightening) have been represented empirically (stress tiers, tail measures, driver attributions), and the stability outcome has been tested statistically. This has strengthened theoretical coherence because it has reduced the gap between abstract stability narratives and measurable risk signals (Brunnermeier & Sannikov, 2014). The discussion has therefore positioned the study as a pipeline refinement: deep learning has not been treated as a replacement for risk theory; it has been treated as an estimator enabling theory-aligned tail measures to be applied more effectively under nonlinear, stress-driven regimes (Chiaramonte et al., 2016).

The limitations have been revisited as constraints that have shaped interpretation, and they have also informed a targeted future research agenda. First, although the case-study design has improved institutional realism, it has limited broad generalizability across banking systems with different regulatory regimes, market structures, and deposit behaviors; this has implied that replication across jurisdictions and bank types (e.g., investment-bank-dominant systems vs retail-deposit-dominant systems) has been necessary to test external validity (Cont et al., 2020). Second, the cross-sectional framing has supported comparative inference within a defined window, but it has limited the ability to capture longer-horizon regime shifts and structural breaks that can alter liquidity dynamics; future work has therefore been positioned to extend the pipeline into panel or rolling-regime frameworks that have explicitly modeled regime transitions. Third, although the study has used VaR/CVaR stress testing as its tail lens, the discussion has acknowledged that tail forecasting quality has ideally been assessed through formal backtesting and comparative forecast evaluation procedures; research has pointed to the importance of robust backtesting for expected shortfall and has proposed procedures that can differentiate good from poor ES forecasts in practice (Lepetit et al., 2008). Fourth, the explainability layer has improved auditability, but future research has been positioned to evaluate the stability of explanations across model versions and to quantify explanation drift as a governance signal, drawing on the broader interpretability literature. Finally, while the study's moderation result has suggested that governance has weakened the tail-to-stability transmission, future research has been positioned to test more granular governance constructs—such as independent model validation intensity, scenario governance committees, and data quality controls—as separate moderating channels rather than as an aggregate index (Sezer et al., 2020). This has opened a practical research direction: linking enterprise control design to measurable risk outcomes, which has been consistent with the broader applied trend of explainable risk analytics in finance (Laeven & Levine, 2009). Overall, the discussion has concluded that future work has been best directed toward (i) multi-country replication, (ii) longitudinal regime-sensitive modeling, (iii) formal ES/VaR backtesting integration, and (iv) governance-as-design-variable studies that have tested how specific control mechanisms have changed tail risk and stability sensitivity (Sirignano & Cont, 2019).

CONCLUSION

The study has concluded that integrating VaR and CVaR–based stress testing with deep learning forecasting has provided a coherent and evidence-driven approach for evaluating liquidity risk and banking stability within a quantitative, cross-sectional, case-study framework. The results have shown that the deep learning forecasting model has produced materially stronger predictive performance than the conventional benchmark, indicating that liquidity risk dynamics have contained nonlinear and interaction-driven structures that have not been adequately captured by linear specifications. Tail-risk estimation has then translated these forecast-informed distributions into stability-relevant extreme-loss indicators, and the stress testing outputs have demonstrated that tail severity has amplified disproportionately as scenarios have intensified, with CVaR increasing more sharply than VaR across mild, adverse, and severe conditions. This has reinforced the central argument that banking fragility has been shaped primarily by the depth of the left tail under stress rather than by threshold exceedance alone. The inferential results have further established that stressed CVaR at the extreme confidence level has been significantly associated with weaker banking stability outcomes and has explained stability variation beyond what has been accounted for by traditional liquidity ratios, confirming that expected shortfall has carried unique informational value for stability monitoring. Structural drivers have also been shown to matter: higher reliance on wholesale funding has increased tail exposure while stronger liquidity buffers have reduced it, indicating that funding design and liquid asset capacity have remained decisive determinants of vulnerability in stressed states. Governance and stress-testing maturity, measured through Likert-based constructs, has emerged as a statistically meaningful protective factor, because stronger governance has reduced stressed tail risk and has weakened the negative translation of tail risk into stability deterioration, implying that institutional capability has functioned as an operational shock absorber. The explainability analysis has strengthened trust in the predictive pipeline by showing that tail-risk outputs have been driven by economically interpretable features such as funding structure, liquidity buffers, market stress conditions, deposit concentration, and governance maturity, rather than by opaque or implausible signals. Scenario plausibility and calibration evidence has further supported the credibility of the stress testing design, because practitioners have rated scenario severity and realism at consistently high levels, indicating that the stress environment has reflected defensible adverse conditions rather than arbitrary shocks. Taken together, the study has confirmed that a unified pipeline—linking nonlinear forecasting, tail-risk measurement, scenario stress testing, and stability modeling—has been capable of producing actionable, auditable, and stability-relevant liquidity risk insights. By demonstrating that CVaR has contributed incremental stability explanation, that deep learning has improved forecasting accuracy, and that governance has materially shaped tail exposure and stability sensitivity, the study has provided a complete empirical basis for supporting its objectives and hypotheses while maintaining transparency through calibration, interpretability, and multivariate inference.

RECOMMENDATION

The study has recommended that banks and supervisory stakeholders have operationalized liquidity risk management as an integrated analytics-and-governance pipeline in which deep learning forecasting, VaR/CVaR tail-risk measurement, and scenario-based stress testing have been embedded into routine decision cycles rather than treated as periodic reporting exercises. At the institutional level, treasury and ALM functions have been recommended to maintain a dual-metric tail dashboard that has reported VaR and CVaR at multiple confidence levels (at minimum 95% and 99%) under both baseline and tiered stress states, because the study's results have indicated that CVaR has captured severity amplification that has not been visible in VaR or conventional ratios alone. Banks have been advised to link these tail dashboards directly to liquidity buffer policy, funding concentration limits, and contingent funding plans, so that rising stressed CVaR has triggered predefined escalation actions such as liquid asset replenishment, liability tenor extension, collateral optimization, and activation of backup lines. Because wholesale funding reliance has increased tail exposure in the study, management has been recommended to implement explicit structural targets that have reduced runnable funding share and strengthened the stability of liability profiles through diversification of funding sources, increased retail deposit stickiness programs, and improved maturity laddering, while simultaneously ensuring that liquidity buffers have remained sized to cover extreme-state cash-flow needs rather than average conditions. For the modeling layer, risk analytics teams have been recommended to institutionalize disciplined model risk management for the deep learning components, including strict data lineage controls, versioned feature engineering, reproducible training runs, and independent validation sign-off, because governance maturity has been shown to reduce tail risk and to dampen the stability impact of extreme states. Banks have been recommended to operationalize explainability as a control requirement by generating routine feature-attribution reports for stressed CVaR forecasts and by monitoring explanation drift across time; this has enabled management to confirm that drivers such as funding structure, liquidity buffers, and market stress proxies have remained dominant and economically consistent, and it has supported early detection of model degradation or data anomalies. Scenario design has been recommended to remain calibration-driven and participatory: institutions have been advised to calibrate stress magnitudes using historical percentiles and institution-specific sensitivity analysis, while also collecting periodic Likert-based plausibility ratings from risk and treasury professionals to ensure that scenarios have remained realistic, comparable, and decision-relevant. At the supervisory and enterprise architecture level, the study has recommended the deployment of secure, audit-ready stress testing platforms with role-based access, immutable run logs, and parameter governance to prevent untracked scenario or model changes, and to ensure that stress outcomes have been defensible in internal audit and regulatory review. Finally, banks have been recommended to use the stability impact decomposition approach in routine reporting, explicitly demonstrating how much explanatory power has been added when VaR and CVaR have been included beyond traditional liquidity metrics, because this has strengthened stakeholder trust and has provided a measurable justification for maintaining tail-risk analytics as a core element of banking stability assessment.

LIMITATIONS

The study has acknowledged several limitations that have constrained interpretation and generalizability while still preserving the internal logic of the integrated forecasting–stress testing–stability pipeline. First, the research design has been quantitative and cross-sectional within a case-study setting, which has supported structured comparison but has limited causal inference and has reduced the ability to capture longer-run regime shifts in liquidity behavior; as a result, the observed associations among stressed tail liquidity risk, governance maturity, and banking stability have been interpreted as statistically supported relationships rather than definitive causal effects. Second, the case-study scope has been intentionally bounded, and although the inclusion of multiple banks has improved variation, the institutional and regulatory environment represented in the sample has not necessarily reflected the full diversity of global banking systems; differences in deposit insurance regimes, central bank liquidity facilities, market depth, and disclosure standards have therefore limited how confidently the numeric patterns have been generalized to other jurisdictions or bank business models. Third, the study has relied on constructed indicators for both liquidity risk outcomes and banking stability, including ratio-based liquidity metrics and a Z-score proxy for stability, and these operationalizations have simplified complex realities such as intraday liquidity cycles, contingent collateral needs, and off-balance-sheet liquidity commitments; consequently, measurement choices have introduced the possibility that certain liquidity transmission channels have been underrepresented in the modeled relationships. Fourth, the deep learning forecasting component has improved predictive accuracy relative to a benchmark in the study's sample, yet deep learning models have remained sensitive to data preprocessing, hyperparameter settings, and the representativeness of the training window, meaning that performance and driver importance could have shifted under alternative sampling frames or under more extreme market environments; this has limited claims about model universality even though explainability evidence has improved interpretability. Fifth, the VaR/CVaR stress testing module has depended on the quality of scenario calibration, and while scenario plausibility ratings have been high, scenario selection has still reflected a structured but bounded set of shocks; real crises can combine shocks in more complex sequences, and tail distributions can evolve under endogenous behavior changes, implying that stressed CVaR values reported in the study have represented a defensible stress ladder rather than an exhaustive crisis map. Sixth, the governance variables have been measured using self-reported Likert-scale responses, which has introduced potential perception bias, social desirability effects, and common method variance, particularly when respondents have worked within the same institutional culture; although reliability and screening procedures have supported measurement quality, survey-based constructs have not captured all aspects of governance such as informal decision practices, political constraints, or the true independence of model validation units. Finally, the integrated pipeline has linked forecasting, tail-risk estimation, and stability regression in a coherent sequence, but full regulatory-grade validation such as multi-year comparative expected shortfall backtesting and out-of-sample stress scenario replication across cycles has not been exhaustively implemented within the sample-paper scope, which has limited the ability to evaluate long-horizon robustness under rare-event clustering.

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