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Climate-Integrated Contingency Funding Plans for Indonesia's Big-Four Banks

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Abstract

Climate change is a systemic macro-financial risk, yet quantitative frameworks integrating physical and transition climate risks into bank contingency funding planning remain limited, particularly in emerging markets like Indonesia. Methods: This study develops the Climate-Integrated Liquidity Coverage Ratio (CI-LCR) framework and applies it to Indonesia's Big-Four commercial banks (Bank Mandiri, Bank Rakyat Indonesia, Bank Central Asia, Bank Negara Indonesia). The empirical analysis utilizes a balanced panel (2018–2024), three NGFS climate scenarios, and ordinary least squares trend regression computed from a verified banking risk database. Results: In the worst-case scenario (Compound Climate Liquidity Stress), Bank Mandiri (94.00%) and Bank Rakyat Indonesia (92.50%) fall below the 100% regulatory minimum, whereas Bank Central Asia (212.63%) and Bank Negara Indonesia (117.62%) remain compliant. Corrected estimates show pre-2025 liquidity trajectories were statistically weak for all four banks. Furthermore, a disclosure assessment of fifteen banks reveals significant climate-governance weaknesses (average score 2.13 of 6). Conclusion: The proposed framework accordingly puts forward a dedicated climate transition liquidity buffer of 4.20 trillion Rupiah and a climate-based activation mechanism (C-TAT), providing a reproducible approach for integrating climate risk into Indonesian banking liquidity supervision.

Keywords: *Contingency Funding Plan, Climate Risk, Liquidity Coverage Ratio (CI-LCR), Big-Four Indonesian Banks, OJK CRMS*

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1. Introduction

The intersection of climate change and financial stability has become one of the defining policy challenges of the 2020s. The Network for Greening the Financial System (NGFS, 2023) estimates that unmanaged physical climate risks could cause permanent GDP losses of 10–23% by 2100 under high-warming pathways, disproportionately affecting climate-vulnerable emerging economies. Indonesia, the world's largest archipelagic state, is a salient case: its banking system is exposed to physical climate risks through agriculture, plantation, and coastal-infrastructure lending, and to transition risks from its carbon-intensive energy and commodity sectors.

Despite growing regulatory momentum — including OJK Regulation No. 51/POJK.03/2017 on Sustainable Finance and CRMS Buku 5 (OJK, 2024) — Indonesian banks have not yet quantitatively integrated climate scenarios into their Contingency Funding Plans (CFPs), the mandatory supervisory instrument under BCBS (2008) and OJK SEOJK No. 42/SEOJK.03/2016. Existing CFP frameworks remain designed around market-driven or idiosyncratic stress scenarios, not climate-driven liquidity shocks.

This omission is theoretically unjustified: climate risks are systemic, generating correlated cash outflows and collateral impairment that overwhelm liquidity buffers designed for idiosyncratic shocks (Battiston et al., 2017), which is why supervisors have been repeatedly urged to integrate climate risk into their analytical toolkits (Campiglio et al., 2018; Dikau & Volz, 2021; D'Orazio & Popoyan, 2019). Section 2.1 reviews this literature in depth; empirically, natural disasters impair bank lending in flood-affected regions (Faiella & Natoli, 2018) and raise non-performing loans (Koetter et al., 2020), establishing the climate–liquidity transmission mechanism explored here.

In Indonesia, the empirical stakes are high. Five provinces — Aceh, North Sumatra, Riau, South Sumatra, and West Kalimantan — receive the maximum IRBI flood risk score of 36/36 (OJK, 2024), hosting the dominant agricultural and plantation portfolios of BRI and Bank Mandiri. As Section 4.3 shows, this concentrated physical exposure coincides with a pre-2025 liquidity trajectory that is statistically weak or absent for all four banks, so the sharp 2025 contraction documented here is better read as a continuation of an already-fragile dynamic than as a sudden reversal.

This study is positioned at the confluence of three literatures reviewed in Section 2: the systemic climate-finance literature establishing physical and transition risks as sources of correlated, network-amplified instability (Battiston et al., 2017; Roncoroni et al., 2021); the climate stress-testing literature operationalising NGFS scenarios within prudential frameworks (BCBS, 2013; ECB, 2021; Vermeulen et al., 2021); and the still-nascent, largely conceptual literature on integrating climate risk into Contingency Funding Plans (Bolton et al., 2020; Dikau & Volz, 2021; D'Orazio & Popoyan, 2019). While the first two are comparatively well developed, no existing study operationalises climate scenarios within the specific architecture of a bank's CFP — the instrument that converts a stress-test result into a liquidity buffer and activation protocol. This paper addresses that gap.

The two studies closest in spirit are the ECB's (2021) economy-wide climate stress test and Vermeulen et al.'s (2021) financial-stress framework for De Nederlandsche Bank, both differing from the present study in scope, metric, and institutional target. The ECB (2021) models the joint solvency and credit-risk impact of climate scenarios on the euro-area banking system over a multi-decade horizon but does not translate its results into a

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short-term liquidity-coverage metric or CFP activation thresholds. Vermeulen et al. (2021) similarly measure system-wide financial stress — asset devaluation, funding costs, and probability of default — under disruptive transition scenarios for the Dutch financial sector, but likewise stop short of a bank-level, LCR-consistent metric or an operational trigger mechanism. Both studies, moreover, are calibrated to advanced-economy, temperate-climate contexts that under-weight physical relative to transition risk compared with an archipelagic, high-flood-risk emerging market such as Indonesia. This paper's added value is therefore threefold: (i) it embeds NGFS-calibrated physical and transition parameters directly into the Basel III LCR formula (Eq. 1–8), producing a bank-level, regulatorily comparable CI-LCR metric rather than an aggregate solvency or stress index; (ii) it operationalises that metric into a five-tier Climate-Triggered Activation Threshold (C-TAT) linking CI-LCR bands to concrete CFP actions; and (iii) it calibrates the framework to Indonesia's IRBI flood-risk data and Big-Four disclosures, extending climate-liquidity stress testing to an emerging-market, high-physical-risk setting for which no equivalent CFP framework currently exists.

Building on this positioning, the paper makes four contributions: it derives the CI-LCR formula system embedding physical and transition climate parameters into the Basel III LCR structure (Section 3.1); applies the CI-LCR to Big-Four panel data (2018–2025) to identify which banks breach the regulatory floor under a Compound Climate Liquidity Stress scenario (Section 4); constructs a CFP-Climate Disclosure Scoring Matrix across 15 banks (Section 4.5); and proposes the Climate-Triggered Activation Threshold and Climate Transition Liquidity Buffer models for Bank Indonesia and OJK supervisory use (Sections 4.6–4.7).

The remainder of this paper is organised as follows: Section 2 reviews the relevant theoretical and empirical literature. Section 3 presents the CI-LCR theoretical framework, data sources, and research methods. Section 4 presents the empirical results and discussion. Section 5 concludes with policy recommendations and suggestions for future research.

2. Literature Review

2.1 Climate Risk as a Systemic Financial Threat

The conceptualisation of climate risk as a source of systemic financial instability has gained substantial academic and regulatory momentum since Carney's (2015) “tragedy of the horizon” speech. Battiston et al. (2017) demonstrate that climate risks propagate through financial networks in ways that amplify rather than diversify, undermining the standard assumption that portfolio diversification eliminates aggregate risk — a mechanism directly relevant to the CFP design problem addressed in this paper. Lamperti et al. (2019) quantify the macroeconomic costs of climate-induced financial instability, finding cumulative GDP losses of 1.4–11.5% by 2080 under an unmanaged transition. Roncoroni et al. (2021) confirm that interconnections between banks and investment funds amplify physical climate shocks, with contagion largest in countries with concentrated banking sectors — a characteristic of Indonesia's Big-Four-dominated financial system.

The macroeconomic transmission of climate risk to banking outcomes is well-documented. Kahn et al. (2021), in a 174-country panel study, find that climate change reduces per capita output growth, with particularly severe effects in low-income, high-

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temperature economies. Dafermos et al. (2018) demonstrate using a stock-flow-fund ecological macroeconomic model that temperature increases reduce bank credit and raise NPL ratios, establishing a theoretical basis for the climate-NPL linkage embedded in this paper's inflow impairment factor (β_s).

2.2 Liquidity Regulation and Climate Stress Testing

The Basel III Liquidity Coverage Ratio (LCR), formalised by the Basel Committee on Banking Supervision (BCBS, 2013), requires banks to hold sufficient High-Quality Liquid Assets (HQLA) to cover 30-day net cash outflows under a combined idiosyncratic and market-wide stress scenario. As Drehmann and Nikolaou (2013) note, the LCR is calibrated to market-driven stress and does not account for correlated, slow-moving climate stressors that impair both sides of the balance sheet simultaneously. Brunnermeier and Pedersen (2009) provide the theoretical foundation for how funding and market liquidity spirals interact — precisely the dynamic triggered by a climate shock that depresses HQLA values, triggers deposit outflows from climate-vulnerable regions, and reduces loan repayments from disaster-affected borrowers. Acharya and Mora (2015) provide empirical evidence that banks serving as liquidity providers are particularly vulnerable to correlated funding shocks, reinforcing the case for a dedicated climate liquidity buffer such as the CTLB proposed in this study.

Vermeulen et al. (2021) develop a framework for measuring financial stress under disruptive energy transition scenarios for De Nederlandsche Bank, directly informing the HQLA impairment parameter (δ_s) used here. Semieniuk et al. (2022) quantify stranded-asset losses of up to USD1.4 trillion under disorderly transition, with implications for banks with large carbon-sector exposures such as Bank Mandiri and BRI. Bolton and Kacperczyk (2021) show that equity markets already price a carbon premium, implying that climate-adjusted collateral values will diverge increasingly from regulatory book values — the basis of this paper's HQLA impairment formula.

2.3 Contingency Funding Plans and Climate Integration

The CFP literature has evolved since the BCBS (2008) Principles for Sound Liquidity Risk Management. Adrian and Shin (2014) show that procyclical leverage amplification creates liquidity crises even for well-capitalised banks, arguing for counter-cyclical liquidity buffers — the theoretical antecedent of the Climate Transition Liquidity Buffer (CTLB) proposed here. However, the integration of climate scenarios into CFP design remains almost entirely absent from the academic literature. The BIS Green Swan Report (Bolton et al., 2020) is among the first institutional documents to argue that climate change requires "reverse stress testing" — an approach embedded in this paper's CCLS scenario design. The European Central Bank's (2021) climate stress test pioneered the application of NGFS scenarios to banking supervision; this study applies analogous methodology to the Indonesian institutional and data context. Dikau and Volz (2021) identify a critical gap between regulatory ambition and supervisory operationalisation in developing economies, while D'Orazio and Popoyan (2019) propose a taxonomy of green macroprudential instruments — including climate-differentiated liquidity buffers — that underpins the C-TAT framework proposed in Section 4.

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2.4 Indonesian Banking Context and Climate Vulnerability

Indonesia's banking sector exhibits structural characteristics that magnify climate vulnerability. It is highly concentrated: the Big-Four banks — Bank Mandiri, BRI, BCA, and BNI — collectively held Rp7,914.0 trillion in assets as of December 2025, verified directly from the author's BRDID dataset (Prudential_2025 worksheet). Second, BRI and Bank Mandiri's loan portfolios are disproportionately exposed to climate-sensitive sectors — agriculture, plantations, coal, and petroleum — concentrated in the high-flood-risk provinces of Sumatra and Kalimantan. Third, Indonesia's financial system is still in the early stages of integrating climate risk into supervisory practice, with OJK's CRMS Buku 5 (2024) representing the most advanced instrument to date. Campiglio et al. (2018) emphasise that emerging-market central banks face an acute version of the climate-finance nexus: greater physical vulnerability, less-diversified financial systems, and more constrained supervisory capacity. As demonstrated in Section 4 through the CFP-Climate Disclosure Scoring Matrix, the gap between regulatory aspiration and bank-level implementation remains wide.

3. Research Methods

This study employs a quantitative, formula-based research design to develop and empirically validate the Climate-Integrated Contingency Funding Plan (CI-CFP) framework for Indonesia's Big-Four banks. The methodological framework integrates Basel III liquidity regulation, climate-risk scenario analysis, and empirical banking data into a transparent and fully reproducible analytical system.

The empirical analysis is based on the author's integrated Excel workbook, *CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx*, which serves as the primary computational platform for all statistical analyses, climate-scenario simulations, parameter calibrations, and policy evaluations presented in this paper. The workbook contains the complete BRDID panel dataset, prudential banking indicators, descriptive statistics, Jarque-Bera normality tests, Pearson correlation analysis, OLS trend regression, IRBI flood-risk data, CI-LCR scenario simulations, calibration parameters, Climate Transition Liquidity Buffer (CTLB) calculations, Climate-Triggered Activation Threshold (C-TAT) modelling, and sensitivity analyses.

Every table, numerical result, equation, and empirical finding reported in this manuscript is generated directly from, and is traceable to, the corresponding worksheets of the workbook. This integrated research design ensures full computational transparency, methodological consistency, and reproducibility, allowing independent verification of all reported results from the underlying source data. The following sections describe the CI-LCR formula system, scenario architecture, calibration procedures, data sources, and analytical methods that collectively form the proposed CI-CFP framework.

3.1 The CI-LCR Formula System

The Climate-Integrated Liquidity Coverage Ratio (CI-LCR) is derived through a sequential modification of the Basel III LCR framework (BCBS, 2013). Consistent with Brunnermeier and Pedersen (2009), a climate shock simultaneously impairs three components of the standard LCR: (i) the market value of HQLA through climate-induced collateral deterioration; (ii) net cash outflows through deposit flight and counterparty risk amplification; and (iii) net cash inflows through borrower default in climate-exposed sectors.

$$LCR = HQLA\_net / Net\ Cash\ Outflows \geq 100\% \quad (Eq.\ 1)$$

$$Net\ Cash\ Outflows = Cash\ Outflows - \min(Cash\ Inflows,\ 0.75 \times Cash\ Outflows) \quad (Eq.\ 2)$$

$$HQLA^* = HQLA\_net \times (1 - \delta_s) \quad (Eq.\ 3)$$

$$\delta_s = (IRBI / 36) \times \rho_s \times \omega \quad (Eq.\ 4)$$

$$CF\_out\_climate = CF\_out \times (1 + \alpha_s) \quad (Eq.\ 5)$$

$$CF\_in\_climate = CF\_in \times (1 - \beta_s) \quad (Eq.\ 6)$$

$$CI\text{-}LCR = HQLA^* / [CF\_out\_climate - 0.75 \times CF\_in\_climate] \quad (Eq.\ 7)$$

$$CI\text{-}LCR\_simplified = LCR\_baseline \times (1 - \delta_s) / (1 + \alpha_s) \quad (Eq.\ 8)$$

Equation 8 is applied for Scenarios A and B, where CF_in is conservatively set to zero, yielding the lower bound of climate liquidity adequacy. The full Equation 7 is applied for Scenario C (CCLS), where inflow impairment is non-trivial ($\beta_s \approx 0.400$). This dual-formula approach is consistent with the ECB (2021) climate stress test methodology, which uses simplified scenarios for orderly pathways and full dynamic models for acute and compound scenarios. The Pearson correlation matrix in Section 4.2 and the OLS trend regression in Section 4.3 are presented as exploratory, aggregate, system-wide analyses; causal inference regarding the marginal impact of climate shocks on liquidity is operationalised exclusively through the deterministic CI-LCR simulation (Equations 1–9).

3.2 NGFS Scenario Architecture and Parameter Calibration

Three NGFS Phase IV (2023) scenarios are operationalised: Scenario A (Orderly Transition) — a rapid, well-coordinated transition to net-zero with moderate physical risk; Scenario B (Physical Risk) — a delayed transition with elevated physical impacts concentrated in Sumatra and Kalimantan; and Scenario C (CCLS, Compound Climate Liquidity Stress) — a simultaneous major flood event and an abrupt transition shock, consistent with the Green Swan framework (Bolton et al., 2020). Table 1 presents the parameter calibration, sourced directly from the CI_LCR_Parameters worksheet of the author's Excel workbook.

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Table 1. CI-LCR Parameter Calibration by NGFS Scenario

Parameter	Symbol	Scenario A (Orderly)	Scenario B (Physical Risk)	Scenario C (CCLS)	Calibration Basis
HQLA Impairment Factor	δ_s	0.031	0.083	0.145	Eq.10 + OJK IRBI Buku 5 + NGFS ρ
Outflow Stress Multiplier	α_s	0.06	0.40	0.70	BNPB DIBI + Koetter et al. (2020); Chen et al. (2025)
Inflow Impairment Factor	β_s	0.025	0.25	0.400	OJK NPL data + Zhang et al. (2023); Dafermos et al. (2018)
NGFS Severity Factor	ρ_s	0.15	0.40	0.70	NGFS Phase IV (2023)
CI-LCR Factor $[(1-\delta)/(1+\alpha)]$	factor	0.914	0.655	0.684	Eq.14 (A,B) / Eq.13 (C: full CCLS formula)

Note: Collateral weight ω = 0.343 (calibrated). Source: CI_LCR_Parameters worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. (Panjaitan, 2026).

3.3 Disaster Flood Index (DFI) and IRBI Integration

The Disaster Flood Index (DFI) proxy is constructed from the OJK CRMS Buku 5 IRBI (Indonesia Risk and Banking Index) provincial flood scores, normalised to a 0–36 scale, where DFI = IRBI/36. Table 2 presents the ten provinces most relevant to Big-Four credit exposure.

Table 2. IRBI Flood Risk Index — Key Provinces for Big-Four Bank Credit Exposure

Province	IRBI Score (0–36)	Risk Level	Primary Bank Exposure	DFI Proxy (%)
Aceh	36.0	Very High	BRI (agriculture), BNI (trade)	100.0
North Sumatra	36.0	Very High	BRI (palm oil), Mandiri (corporate)	100.0
Riau	36.0	Very High	BRI (plantation), Mandiri (energy)	100.0
South Sumatra	36.0	Very High	Mandiri (coal/CPO), BRI (agriculture)	100.0
West Kalimantan	36.0	Very High	BRI (mining), BNI (plantation)	100.0

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DKI Jakarta (Central)	21.0	Medium-High	All Big-4 (HQ/property/trade)	58.3
DKI Jakarta (West)	22.5	Medium-High	BCA (CASA), BNI (property)	62.5
DKI Jakarta (North)	21.1	Medium-High	Mandiri (port/industry)	58.6
East Java	24.0	Medium-High	BNI (property), BCA (retail)	66.7
West Java	22.0	Medium-High	BCA (Jabodetabek CASA), BNI	61.1

Note: Source: IRBI_Data worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx, per OJK CRMS Buku 5 (2024).

3.4 Climate Transition Liquidity Buffer (CTLB)

The CTLB provides a forward-looking, sector-level liquidity buffer requirement against transition risk, calibrated using exposure-at-default (EAD), loss-given-default (LGD), a five-year transition probability of default (PD_trans), and a bank-specific discount rate (DR):

$$CTLB_i = \Sigma_j \in S\ [EAD_{i,j} \times LGD_j \times PD\_trans_j, t+5 \times DR_i] \quad (Eq.\ 9)$$

PD_trans is calibrated using carbon-sector transition risk intensities documented by Semieniuk et al. (2022) and Bolton and Kacperczyk (2021), adjusted to the Indonesian regulatory context, consistent with D'Orazio and Popoyan's (2019) call for sector-differentiated liquidity buffers.

3.5 CFP-Climate Disclosure Scoring

A three-dimensional content-analysis scoring matrix is applied to the 2023–2025 sustainability reports and CFP disclosures of 15 banks (6 Indonesian, 9 international), evaluating: (1) Climate Scenario Analysis (0–2), (2) LCR/HQLA Climate Stress (0–2), and (3) CFP-Climate Linkage (0–2), for a maximum score of 6. This follows the qualitative content-analysis approach of Berg et al. (2022), adapted to climate-liquidity integration.

3.6 Data Sources and Panel Structure

The primary dataset — the Bank Risk Dataset Indonesia (BRDID) — comprises annual prudential indicators for the Big-Four banks over 2018–2025: Capital Adequacy Ratio (CAR), Non-Performing Loan ratio (NPL), Liquidity Coverage Ratio (LCR), total assets, loans, deposits, Return on Assets (ROA), Return on Equity (ROE), and Loan-to-Deposit Ratio (LDR), sourced from bank annual reports and OJK banking statistics. HQLA and net cash outflow figures for CI-LCR calibration are derived from 2025 Annual Reports. IRBI flood risk data are sourced from OJK CRMS Buku 5 (2024). The balanced estimation panel covers 2018–2024 (N=28 bank-year observations); 2025 observations (N=4) are reserved exclusively for CI-LCR scenario calibration, for a total raw dataset of N=32. All descriptive statistics, normality tests, correlation coefficients, and OLS trend regressions reported in Section 4 were re-computed directly from the BRDID_Panel, Desc_Stats, JB_Normality, Pearson_Corr, and OLS_Trend worksheets of the author's Excel workbook (), and every reported statistic in this manuscript is traceable to a specific worksheet cell.

4. Results

4.1 Big-Four Prudential Position, December 2025

Table 3 presents the key prudential indicators for all four banks as at December 2025, sourced from the Prudential_2025 worksheet, which is itself derived from the BRDID_Panel 2025 observations.

Table 3. Big-Four Bank Prudential Indicators — December 2025

Indicator	Mandiri	BRI	BCA	BNI	Big-4 System
Total Assets (Rp T)	2,830.0	2,135.0	1,587.0	1,362.0	7,914.0
Total Credit (Rp T)	1,895.0	1,521.0	993.0	900.0	5,309.0
Third-Party Funds (Rp T)	2,106.0	1,467.0	1,249.0	1,041.0	5,863.0
LCR — Bank Only (%)	137.40	135.21	310.80	171.93	—
LCR — Consolidated (%)	140.19	136.92	310.93	176.49	—
NSFR — Bank Only (%)	109.95	117.71	158.80	141.87	—
CAR (%)	19.36	21.06	29.80	20.70	—
NPL Gross (%)	0.96	3.29	1.70	1.90	—
Loan at Risk / LAR (%)	6.05	8.50	4.80	8.50	—

Note: Source: Prudential_2025 worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx; cross-verified against BRDID_Panel 2025 observations. Figures in Rp Trillion. NSFR = Net Stable Funding Ratio; LAR = Loan at Risk.

Table 4 presents selected BRDID panel observations for 2018, 2021, and 2025, illustrating the full historical trajectory used in the descriptive, normality, correlation, and trend analyses of Sections 4.2–4.3.

Table 4. Bank Risk Dataset Indonesia (BRDID) — Selected Observations, 2018–2025

Bank / Year	CAR (%)	NPL (%)	LCR (%)	Assets (Rp T)	Loans (Rp T)	Deposits (Rp T)	ROA (%)	ROE (%)	LDR (%)
BCA – 2018	23.40	1.40	278.20	825	538	630	4.00	18.80	81.60
BCA – 2021	25.70	2.20	396.30	1,228	637	976	2.80	18.30	62.00
BCA – 2025	29.80	1.70	310.80	1,587	993	1,249	3.90	23.30	76.80
BRI – 2018	21.21	2.14	186.00	1,297	838	944	3.68	20.49	89.57
BRI – 2021	25.28	3.08	201.00	1,678	1,043	1,139	2.72	14.09	83.67

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BRI – 2025	21.06	3.29	135.21	2,135	1,521	1,467	3.26	16.84	91.96
Mandiri – 2018	20.96	2.79	190.00	1,202	768	841	3.17	16.23	96.74
Mandiri – 2021	19.60	2.81	200.56	1,726	1,050	1,291	2.53	16.24	80.04
Mandiri – 2025	19.36	0.96	137.40	2,830	1,895	2,106	3.19	23.15	88.92
BNI – 2018	18.50	1.90	170.00	809	498	552	2.80	16.10	88.80
BNI – 2021	19.70	3.70	205.00	965	582	729	1.40	9.40	79.70
BNI – 2025	20.70	1.90	171.93	1,362	900	1,041	2.10	12.70	86.40

Note: Source: BRDID_Panel worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. Full panel (N=32, 2018–2025) available in the source workbook. All figures independently verified against the worksheet's raw data rows.

4.2 Descriptive Statistics, Normality, and Correlation

Table 5 presents descriptive statistics for the 2018–2024 estimation panel (N=7 per bank). BCA exhibits by far the highest mean and most volatile LCR (mean 316.97%, SD 69.82), reflecting a sharp 2020–2021 build-up followed by gradual normalisation; it also records the lowest mean NPL (1.76%) and, notably, the widest CAR range of the four banks (23.40–29.40%, range 6.00pp), reflecting a sustained capital build-up over 2018–2024. BRI shows the highest mean NPL (2.81%) and the lowest mean LCR (184.43%), consistent with its concentrated exposure to agricultural and micro-enterprise lending in high-IRBI provinces. Bank Mandiri's NPL range (0.97%–3.29%) indicates high sensitivity to macroeconomic and sector-specific cycles. BNI recorded the single lowest CAR observation in the entire panel (16.80% in 2020) and a CAR range of 5.20pp, reflecting acute capital volatility during the 2020 stress year.

Table 5. Descriptive Statistics — Big-Four Banks Panel (N=7 per bank, 2018–2024)

Bank	Variable	N	Mean	SD	Min	Max	Median	Range
BCA	CAR (%)	7	26.44	2.30	23.40	29.40	25.80	6.00
BCA	NPL (%)	7	1.76	0.31	1.30	2.20	1.80	0.90
BCA	LCR (%)	7	316.97	69.82	220.00	396.30	323.00	176.30
BRI	CAR (%)	7	23.23	1.87	20.61	25.28	23.30	4.67
BRI	NPL (%)	7	2.81	0.34	2.14	3.12	2.94	0.98
BRI	LCR (%)	7	184.43	22.20	145.00	209.00	190.00	64.00
Mandiri	CAR (%)	7	20.41	0.85	19.46	21.48	20.10	2.02
Mandiri	NPL (%)	7	2.16	0.91	0.97	3.29	2.39	2.32
Mandiri	LCR (%)	7	188.15	25.36	139.21	220.00	191.02	80.79
BNI	CAR (%)	7	19.63	1.74	16.80	22.00	19.70	5.20
BNI	NPL (%)	7	2.73	0.93	1.90	4.30	2.30	2.40
BNI	LCR (%)	7	187.64	23.80	147.95	219.00	191.50	71.05

Note: Mean = $(1/N)\cdot\Sigma X_i$; SD = $\sqrt{[(1/(N-1))\cdot\Sigma(X_i-\bar{X})^2]}$. Source: Desc_Stats worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. These figures supersede any previously circulated draft values; all are recomputed directly from the BRDID_Panel raw data.

Table 6 presents Jarque-Bera (JB) normality tests on the pooled panel (N=28). Contrary to earlier draft findings, the corrected computation shows that LCR itself is non-normally distributed (JB = 15.25, $p < 0.001$), driven by pronounced right-skewness (S = 1.57) from BCA's 2021–2023 LCR spike. NPL and CAR are normally distributed at the 5% level, while ROA remains non-normal (JB = 6.66, $p = 0.036$), consistent with the asymmetric shock distribution documented in bank profitability literature (Kahn et al., 2021) and driven by the extreme left-tail 2020 pandemic-provisioning observation (BNI ROA = 0.5%).

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Table 6. Jarque-Bera Normality Test — Pooled Big-Four Panel (N=28, 2018–2024)

Variable	N	Skewness	Excess Kurt.	JB Statistic	p-value	$\chi^2(2)$ Crit.	Decision
LCR (%)	28	1.573	1.782	15.247	<0.001	5.991	Reject H_0 — Non-normal
NPL (%)	28	0.319	0.130	0.495	0.781	5.991	Fail to reject — Normal
CAR (%)	28	0.614	-0.165	1.790	0.409	5.991	Fail to reject — Normal
ROA (%)	28	-1.061	1.100	6.665	0.036	5.991	Reject H_0 — Non-normal

Note: JB = $(N/6)\times[S^2+(K-3)^2/4]$; $\chi^2(2)$ critical = 5.991 at α=0.05. Source: JB_Normality worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. Because LCR is non-normal, the Pearson correlation results below are interpreted as an exploratory, descriptive characterisation of linear association rather than a fully parametric inferential test.

Table 7 presents the Pearson correlation matrix and significance tests for the pooled panel. LCR is very strongly and negatively correlated with LDR ($r = -0.809$, $t = -7.03$, $p < 0.001$), confirming that credit expansion is the primary structural driver of liquidity buffer erosion across the Indonesian Big-Four — consistent with Adrian and Shin's (2014) procyclical leverage framework. LCR is also significantly positively correlated with CAR ($r = 0.620$, $p < 0.001$). However, contrary to an earlier draft's reported results, LCR shows no statistically significant association with either ROA ($r = 0.092$, $p = 0.641$) or ROE ($r = 0.236$, $p = 0.227$) in the corrected data, indicating that liquidity strength and profitability move largely independently across the Big-Four sample. NPL is significantly negatively correlated with both ROA ($r = -0.696$, $p < 0.001$) and ROE ($r = -0.832$, $p < 0.001$), corroborating standard bank-performance transmission channels.

Table 7. Pearson Correlation Matrix — Pooled Big-Four Panel (N=28, 2018–2024)

Variable	CAR	NPL	LCR	ROA	ROE	LDR
CAR	1.000	-0.319†	0.620***	0.587**	0.534**	-0.604***
NPL	-0.319†	1.000	-0.186 n.s.	-0.696***	-0.832***	0.133 n.s.
LCR	0.620***	-0.186 n.s.	1.000	0.092 n.s.	0.236 n.s.	-0.809***
ROA	0.587**	-0.696***	0.092 n.s.	1.000	0.889***	-0.159 n.s.
ROE	0.534**	-0.832***	0.236 n.s.	0.889***	1.000	-0.267 n.s.
LDR	-0.604***	0.133 n.s.	-0.809***	-0.159 n.s.	-0.267 n.s.	1.000

*Note: $t = r\times\sqrt{(N-2)}/\sqrt{(1-r^2)}$, df=26. ***p<0.001; **p<0.05; †p<0.10; n.s. = not significant. Source: Pearson_Corr worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. This matrix is an exploratory, system-wide descriptive analysis and does not establish causal relationships; causal inference for climate-shock transmission is operationalised exclusively through the deterministic CI-LCR simulation (Eq. 7).*

4.3 OLS Trend Regression: A Corrected Finding

To characterise the pre-2025 LCR trajectory, OLS linear trend regressions are estimated for each bank using calendar year as the trend variable (2018=t_1, 2024=t_7). This recomputation, performed directly and formula-verifiably from the BRDID_Panel data in the OLS_Trend worksheet, yields results that differ materially from earlier drafts of this study and therefore warrant explicit emphasis. Table 8 presents the corrected results.

Table 8. OLS Linear Trend Regression — LCR and NPL (2018–2024)

Bank	Variable	Intercept (α_0)	Slope β_1 (pp/yr)	R^2	p-value	Interpretation
BCA	LCR (%)	-39,633.87	+19.77	0.374	0.144	Positive but not significant
BCA	NPL (%)	-164.25	+0.082	0.327	0.180	No significant trend
BRI	LCR (%)	14,764.50	-7.21	0.493	0.079†	Negative, marginal (10%)
BRI	NPL (%)	-233.94	+0.117	0.559	0.053†	Rising, marginal (10%)
Mandiri	LCR (%)	16,707.66	-8.17	0.485	0.082†	Negative, marginal (10%)
Mandiri	NPL (%)	695.80	-0.343	0.667	0.025*	Declining, significant (5%)
BNI	LCR (%)	1,930.75	-0.86	0.006	0.867	No significant trend
BNI	NPL (%)	118.21	-0.057	0.018	0.777	No significant trend

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*Note: Model: $Y_{i,t} = \alpha_0 + \beta_1 \times TREND\_t + \varepsilon_{i,t}$; TREND = calendar year. Source: OLS_Trend worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx, independently re-verified by the author via manual OLS computation (confirmed exact match, e.g., BCA slope = $\Sigma(t-\bar{t})(y-\bar{y})/\Sigma(t-\bar{t})^2 = 553.5/28 = 19.77$). *p<0.05; †p<0.10 (marginal).*

These corrected results overturn the previously circulated narrative that all four banks exhibited strong, statistically significant LCR improvement over 2018–2024. In fact, only BCA shows a positive slope, and it is not statistically significant (R^2=0.374, p=0.144); BRI and Bank Mandiri show marginally significant negative LCR trends (p≈0.08); and BNI shows an essentially flat, non-significant trend (R^2=0.006). The only statistically significant trend in the entire panel is Bank Mandiri's declining NPL trajectory (β=−0.343 pp/year, p=0.025), indicating steadily improving asset quality even as its LCR trend was flat-to-negative.

Extending each bank's fitted 2024 trend value by one additional year (using the verified OLS_Trend slope and intercept) yields the following trend-projected 2025 LCR values: BCA 396.04%, BRI 155.57%, Mandiri 155.45%, and BNI 184.19%. Comparing these to the actual 2025 Annual Report LCR figures (BCA 310.80%, BRI 135.21%, Mandiri 137.40%, BNI 171.93%) shows that all four banks recorded 2025 outcomes below their own trend projections — by 85.2, 20.4, 18.1, and 12.3 percentage points respectively. This is a substantively different and, arguably, more consequential finding than a simple 'trend reversal' narrative: because the underlying 2018–2024 trend was already weak, flat, or mildly negative for three of the four banks, the 2025 liquidity contraction documented in this paper represents the continuation and acceleration of a pre-existing, largely undetected liquidity fragility — not a sudden departure from a previously robust buffer build-up. This finding strengthens, rather than weakens, the case for climate-integrated liquidity supervision: standard historical trend monitoring alone would not have flagged the underlying fragility now being tested against climate scenarios in Section 4.4.

4.4 CI-LCR Under NGFS Climate Scenarios

Table 9 presents the central empirical results: CI-LCR values for all four Big-Four banks under the three NGFS scenarios, computed from 2025 Annual Report LCR baselines. Under Scenario A (Orderly Transition), all banks remain comfortably above the 100% regulatory floor. Under Scenario B (Physical Risk), both Bank Mandiri (90.01%) and BRI (88.58%) breach the floor, while BNI (112.63%) and BCA (203.61%) remain compliant.

Table 9. CI-LCR Results — Big-Four Banks Under Three NGFS Climate Scenarios

Bank	Baseline LCR (%)	Sc. A Orderly (%)	Sc. B Physical (%)	Sc. C CCLS — Full Eq.13 (%)	CCLS Δ (pp)	Reg. Floor Status (Sc. C)
Bank Mandiri	137.40	125.60	90.01	94.00	-43.40	BREACH ✗
BRI	135.21	123.59	88.58	92.50	-42.71	BREACH ✗
BCA	310.80	284.10	203.61	212.63	-98.17	PASS ✓
BNI	171.93	157.16	112.63	117.62	-54.31	PASS ✓

Note: CI-LCR Full (Eq.7): $LCR \times (1-\delta)/[(1+\alpha)-0.75\times(1-\beta)]$. Eq.14 simplified used for Scenarios A and B. Source: CI_LCR_Scenarios worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. Baseline LCR per Table 3 (2025 Annual Reports, Bank Only).

Under Scenario C (CCLS) — the most severe compound scenario — Bank Mandiri records a CI-LCR of 94.00% and BRI 92.50%, both below the 100% floor, placing them in the CRISIS tier of the C-TAT framework (Section 4.7). BNI, at 117.62%, remains above the regulatory floor but falls within the RED tier (100–120%), one level above CRISIS. Only BCA, with its superior baseline liquidity position, maintains a robust CI-LCR of 212.63% under CCLS, remaining in the GREEN tier. These findings are consistent with Battiston et al.'s (2017) prediction that concentrated sectoral exposures amplify climate-financial contagion, and with Roncoroni et al.'s (2021) finding that network concentration increases system-level vulnerability.

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4.5 CFP-Climate Disclosure Gap Analysis

Table 10 presents the CFP-Climate Disclosure Scoring Matrix for 15 banks. No institution scores above 3 out of 6 points, and the system average is 2.13/6. Most strikingly, the CFP-Climate Linkage dimension scores 0.00 for every bank in the sample, confirming that explicit integration of climate scenarios into CFP activation protocols is entirely absent from current banking practice, both in Indonesia and internationally.

Table 10. CFP-Climate Disclosure Scoring Matrix — 15 Banks (2023–2025 Reports)

Bank	Type	Climate Scenario Analysis (0–2)	LCR/HQLA Climate Stress (0–2)	CFP-Climate Linkage (0–2)	Total /6	Category
Bank Mandiri	Indonesian	2	1	0	3	Developing
BNI	Indonesian	2	1	0	3	Developing
BRI	Indonesian	1	0	0	1	Nascent/Absent
BCA	Indonesian	1	0	0	1	Nascent/Absent
Bank BTN	Indonesian	0	0	0	0	Nascent/Absent
CIMB Niaga	Indonesian	1	0	0	1	Nascent/Absent
HSBC	International	2	1	0	3	Developing
Barclays	International	2	1	0	3	Developing
Standard Chartered	International	2	1	0	3	Developing
DBS	International	2	1	0	3	Developing
UOB	International	1	0	0	1	Nascent/Absent
BNP Paribas	International	2	1	0	3	Developing
Deutsche Bank	International	2	1	0	3	Developing
JP Morgan	International	2	1	0	3	Developing
Citibank	International	1	0	0	1	Nascent/Absent
System Average	All Banks	1.53	0.60	0.00	2.13	—

Note: Scoring: 0=Absent, 1=Partial, 2=Explicit; Max=6. Source: CFP_Disclosure worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. Indonesian banks: BRI, BNI, Bank Mandiri, BCA, Bank BTN, CIMB Niaga. International: HSBC, Barclays, Standard Chartered, DBS, UOB, BNP Paribas, Deutsche Bank, JP Morgan, Citibank.

Notably, even leading international banks (HSBC, DBS, JP Morgan) score identically to the best Indonesian banks, suggesting the governance gap identified by Dikau and Volz (2021) is a global rather than an emerging-market-specific phenomenon.

4.6 Climate Transition Liquidity Buffer (CTLB) Decomposition

Table 11 presents the sector-level CTLB decomposition under Equation 9. The system-level CTLB requirement is Rp4.1982 trillion, concentrated in agricultural flood-prone portfolios (Rp1.2750T, BRI), palm oil plantation (Rp0.7854T, BRI), and petroleum/gas (Rp0.6080T, Bank Mandiri).

Table 11. Climate Transition Liquidity Buffer (CTLB) — Sector Decomposition (Eq. 9)

Carbon Sector	EAD (Rp T)	LGD (%)	PD_trans 5yr (%)	DR (%)	CTLB (Rp T)	Primary Bank
Coal (Kalimantan/Sumatra)	85	45	18	8.0	0.5508	Bank Mandiri
Palm Oil Plantation	120	35	22	8.5	0.7854	BRI
Crude Petroleum & Gas	95	40	20	8.0	0.6080	Bank Mandiri
Heavy Industry (cement/steel)	60	30	15	8.0	0.2160	Bank Mandiri
Agricultural (flood-prone)	200	30	25	8.5	1.2750	BRI
Property (DKI Jakarta)	150	25	12	7.0	0.3150	BCA
Plantation (West Kalimantan)	80	35	20	8.0	0.4480	BNI
TOTAL CTLB (System)	790	—	—	—	4.1982	Big-4 Aggregate

Note: $CTLB_i=\Sigma_j[EAD_{i,j} \times LGD_j \times PD\_trans_{j,t+5} \times DR_i]$. Source: CTLB_Model worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. Relative to bank-level HQLA positions, the Rp4.20T system requirement represents under 1% of system HQLA, but targets the most climate-vulnerable portions of the loan book.

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4.7 Climate-Triggered Activation Thresholds (C-TAT)

Table 12 presents the five-tier C-TAT framework, linking CI-LCR ranges to meteorological (BMKG), disaster (BNPB), and regulatory (OJK) triggers, operationalising the ECB's (2021) recommendation for pre-defined supervisory escalation protocols.

Table 12. Climate-Triggered Activation Thresholds (C-TAT) — CI-CFP Framework

Level	CI-LCR Range	Climate Trigger	CFP Actions
GREEN	>200%	Normal; no BMKG/BNPB alert	Routine CRMS monitoring; quarterly IRBI update
YELLOW	150–200%	BMKG >75mm/day; BNPB Siaga 2; IRBI >30	Pre-position HQLA; alert Treasury
ORANGE	120–150%	BNPB Darurat; IRBI ≥36	Execute contingency lines; restrict disbursement
RED	100–120%	Sustained CCLS; deposit outflow >10%	Full CFP activation; BI repo; halt disbursement
CRISIS	<100%	System-wide CCLS realised	BI Emergency Liquidity Assistance; KSSK activation

Note: Source: C_TAT worksheet, CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. Under the 2025 baseline, Mandiri (137.4%) and BRI (135.21%) sit in the ORANGE zone before any climate shock; BNI (171.93%) is in the lower YELLOW zone; only BCA (310.80%) is GREEN. Under Scenario C, Mandiri and BRI would trigger CRISIS-zone responses.

4.8 Sensitivity Analysis of CI-LCR

Table 13 presents a one-way sensitivity analysis of CI-LCR to the HQLA impairment factor (δ_s), with α_s and β_s held at their Scenario C calibrated values.

Table 13. Sensitivity Analysis: CI-LCR vs. δ_s (HQLA Impairment) — CCLS Base

δ_s Value	Stress Level	Mandiri (%)	BRI (%)	BCA (%)	BNI (%)
0.05	Low	104.44 PASS	102.78 PASS	236.25 PASS	130.69 PASS
0.10	Moderate	98.95 BREACH	97.37 BREACH	223.82 PASS	123.81 PASS
0.145*	Calibrated CCLS	94.00 BREACH	92.50 BREACH	212.63 PASS	117.62 PASS
0.20	Elevated	87.95 BREACH	86.55 BREACH	198.95 PASS	110.06 PASS
0.30	Severe	76.96 BREACH	75.73 BREACH	174.08 PASS	96.30 BREACH
0.40	Extreme	65.96 BREACH	64.91 BREACH	149.21 PASS	82.54 BREACH

*Note: *Calibrated CCLS value (α_s=0.70, β_s=0.400 fixed). Source: Analysis_Sensitivity (Section C), CFP_Climate_Risk_BigFour_Leonard_14052026_HQLA.xlsx. A parallel sensitivity to α_s (outflow stress, Section D of the same worksheet) confirms that α_s is an even more dominant transmission channel than δ_s: at α_s=1.00 (all other parameters at Scenario C values), Mandiri, BRI, and BNI all breach the floor (75.80%, 74.59%, and 94.85% respectively), while only BCA remains above the floor (171.47%).*

The sensitivity results confirm substantial heterogeneity in climate-liquidity fragility. At the calibrated CCLS level, Mandiri and BRI already breach the floor; when δ_s rises to 0.30, BNI also breaches (96.30%); BCA remains above the threshold even at δ_s=0.40 (149.21%), confirming its structurally superior liquidity resilience.

4.9 Policy Implications

The corrected empirical results generate four specific policy implications for Bank Indonesia and OJK. First, the CRMS Buku 5 framework should be extended to require CI-LCR calculation in annual CFP submissions, using the formula system derived in Section 3.1. Second, the C-TAT framework should be incorporated into OJK's liquidity risk management regulation, creating an explicit regulatory mandate for climate-triggered CFP activation. Third, the CTLB should be recognised as a voluntary — and eventually mandatory — macroprudential buffer. Fourth, and most urgently given the corrected trend findings of Section 4.3, Bank Indonesia and OJK supervisory monitoring should not rely on simple historical LCR trend extrapolation to gauge liquidity resilience: because Mandiri and BRI's pre-2025 LCR trends were already flat-to-negative, a trend-based early-warning system would have failed to flag the fragility that the CI-LCR framework reveals under climate stress. Climate-scenario-based stress testing, rather than trend monitoring alone, is therefore the more reliable supervisory tool for these two institutions specifically.

4.10 Discussion

Sections 4.1–4.9 report the study's empirical results; this subsection separates that reporting from interpretation, comparing each key finding against the literature reviewed in Section 2 and, in particular, against the two studies closest in design to this paper — the ECB's (2021) economy-wide climate stress test and Vermeulen et al.'s (2021) financial-stress framework.

4.10.1 CI-LCR Breaches Under Compound Climate Stress

The finding that Bank Mandiri and BRI breach the 100% floor under the CCLS scenario (Table 9) is consistent with Battiston et al.'s (2017) argument that climate risk propagates through concentrated sectoral exposures rather than diversifying away, and with Roncoroni et al.'s (2021) finding that contagion is largest in banking systems with concentrated, network-dense structures — a close description of Indonesia's Big-Four-dominated system. It also aligns directionally with the ECB (2021) stress test, which likewise finds that banks with concentrated carbon-intensive and physically-exposed loan books absorb disproportionately larger losses under adverse NGFS scenarios. The two exercises are not numerically comparable, however, because the ECB reports solvency and credit-loss impacts over a multi-decade horizon, whereas the CI-LCR is a 30-day liquidity-coverage metric: a bank can be solvency-resilient in the ECB sense while still breaching a short-horizon liquidity floor if a shock is sudden and correlated, which is precisely the compound (CCLS) mechanism modelled here. Vermeulen et al. (2021) similarly find that disruptive transition scenarios generate system-wide financial stress for Dutch banks and insurers, but their stress index aggregates asset devaluation and funding-cost effects rather than isolating a regulatory pass/fail liquidity threshold; the present study's CI-LCR breach finding is therefore a more operationally direct — and, for supervisory purposes, more actionable — result than either comparator produces, which is consistent with the added-value claim set out in Section 1.

4.10.2 The Corrected Pre-2025 Liquidity Trend

The weak-to-negative pre-2025 LCR trend for three of the four banks (Table 8) is broadly consistent with Dafermos et al.'s (2018) stock-flow-fund prediction that climate-related pressures erode bank balance sheets gradually and cumulatively rather than only through discrete shock events, and with Kahn et al.'s (2021) cross-country finding that climate effects on financial and macroeconomic outcomes are often slow-moving and easily missed by conventional trend monitoring. The finding diverges, however, from Koetter et al.'s (2020) result that extreme weather events raise non-performing loans: Bank Mandiri's NPL trend over the same 2018–2024 window is significantly declining ($\beta=-0.343$, $p=0.025$) even as its LCR trend is flat-to-negative. This divergence is best read not as a contradiction of Koetter et al. but as a scope difference — their result is identified from discrete disaster events, whereas the panel used here captures aggregate portfolio quality, which can improve through provisioning and underwriting discipline even while liquidity resilience deteriorates for climate-unrelated structural reasons (for example, loan growth outpacing deposit growth). Neither the ECB (2021) nor Vermeulen et al. (2021) report a comparable pre-shock trend correction, since both studies are calibrated stress simulations rather than historical trend re-estimations; this is accordingly a methodological contribution specific to this paper rather than a point of direct comparison.

4.10.3 The Disclosure and CFP-Linkage Gap

The zero CFP-Climate Linkage score recorded for all fifteen banks, including leading international institutions, confirms and extends Dikau and Volz's (2021) argument that a gap exists between regulatory ambition and supervisory operationalisation of climate risk. Dikau and Volz frame this gap primarily as an emerging-market phenomenon linked to constrained supervisory capacity; the present result — that HSBC, DBS, and JP Morgan score no better on CFP-Climate Linkage than Indonesia's leading domestic banks — suggests the gap is better characterised as a global, instrument-specific phenomenon: institutions have advanced further in climate scenario analysis (a disclosure exercise) than in linking those scenarios to the operational CFP activation protocols that actually govern a liquidity crisis response. This is also consistent with D'Orazio and Popoyan's (2019) observation that green macroprudential instruments, including differentiated liquidity buffers, remain largely at the design stage rather than the implementation stage internationally, not only in Indonesia.

4.10.4 Sensitivity: Outflow Stress as the Dominant Channel

The sensitivity results in Section 4.8, which show the outflow stress multiplier (α_s) to be a more dominant driver of CI-LCR deterioration than the HQLA impairment factor (δ_s), align closely with Brunnermeier and Pedersen's (2009) theoretical account of funding-liquidity spirals, in which deposit and counterparty outflows — rather than collateral markdowns alone — tend to dominate acute liquidity episodes. This is also consistent with Acharya and Mora's (2015) empirical finding that banks acting as liquidity providers are disproportionately exposed to correlated funding shocks. The result gives an Indonesia-specific empirical grounding to a mechanism that the ECB (2021) and Vermeulen et al. (2021) treat primarily at a theoretical or system-wide level, rather than decomposing it into bank-level, parameter-specific sensitivities as done here.

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5. Conclusion and Suggestion

1. This study develops a novel, empirically validated, and formula-based Climate-Integrated Contingency Funding Plan (CI-CFP) framework for Indonesia's banking system. Its core contribution is the Climate-Integrated Liquidity Coverage Ratio (CI-LCR) formula system (Equations 1–9), which integrates physical climate risk through the OJK Indonesia Disaster Risk Index and transition climate risk through the Network for Greening the Financial System Phase IV scenarios into the Basel III Liquidity Coverage Ratio framework.
2. Application of the framework to Indonesia's Big-Four banks using 2025 Annual Report data demonstrates that Bank Mandiri and Bank Rakyat Indonesia fall below the 100% regulatory Liquidity Coverage Ratio requirement under both the Physical Risk Scenario (90.01% and 88.58%) and the Compound Climate Liquidity Stress Scenario (94.00% and 92.50%), whereas Bank Central Asia (212.63%) and Bank Negara Indonesia (117.62%) remain compliant even under the most severe climate stress scenario.
3. The independently verified re-estimation of the 2018–2024 trend regression overturns the earlier draft's conclusion of strong liquidity improvement. The corrected results indicate that only Bank Central Asia exhibits a positive but statistically insignificant trend, Bank Mandiri and Bank Rakyat Indonesia display marginally significant declining trends, and Bank Negara Indonesia shows an essentially flat trend. Since all four banks reported 2025 Liquidity Coverage Ratios below their own projected trends, the observed liquidity contraction represents a continuation of structurally fragile liquidity conditions rather than a sudden deterioration from previously strong liquidity positions.
4. The Climate Disclosure Scoring Matrix identifies a significant governance gap because none of the fifteen evaluated domestic and international banks explicitly integrates climate scenario analysis into its Contingency Funding Plan. In addition, the Climate Transition Liquidity Buffer model estimates a system-wide transition liquidity requirement of Rp4.1982 trillion across seven carbon-intensive sectors, while the Climate-Triggered Activation Threshold framework converts Climate-Integrated Liquidity Coverage Ratio outcomes into operational supervisory response levels. Sensitivity analysis further demonstrates that High-Quality Liquid Asset impairment and stressed cash outflow assumptions are the dominant drivers of climate-related liquidity vulnerability.
5. Although the proposed framework is fully transparent and reproducible, several limitations remain. The correlation and trend analyses are exploratory rather than causal, annual report disclosures are used in place of supervisory granular data, the disaster risk index reflects historical rather than forward-looking climate conditions, and the transition liquidity model applies static loss-given-default assumptions that may underestimate risks under severe transition scenarios.
6. Despite these limitations, the proposed Climate-Integrated Contingency Funding Plan provides a robust, transparent, and policy-oriented framework for integrating climate risk into liquidity supervision. Its consistency with Basel III principles, together with its calibration using publicly available Bank Indonesia, OJK, and Network for Greening the Financial System data, enhances its regulatory relevance, transparency, reproducibility, and practical applicability for climate-related banking supervision in Indonesia.
7. Future research should extend the observation period as additional post-2025 data become available and move beyond the exploratory correlation and trend analyses used

here toward more rigorous causal designs. Specifically, a bank fixed-effects panel regression — with annual LCR or CI-LCR as the dependent variable and IRBI flood scores, sectoral carbon exposure, and NGFS transition indicators as explanatory variables — would allow the climate–liquidity relationship to be estimated while controlling for unobserved, time-invariant bank characteristics. A Structural Equation Modeling (SEM) approach could complement this by simultaneously estimating the latent, multi-stage transmission pathway from physical and transition climate exposure, through asset-quality and funding-cost channels, to liquidity outcomes, thereby testing rather than assuming the mediation structure implicit in Equations 1–9. Beyond these two methods, future work should develop forward-looking disaster risk and loss-given-default indicators, and expand the framework by incorporating banking network contagion and fire-sale transmission mechanisms under evolving international climate scenarios.

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