Climate-Related Financial Risks and Bank Credit Quality: Empirical Evidence from Indian Scheduled Commercial Banks

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***Abstract*—Climate change increasingly threatens financial stability through physical risks such as extreme weather events and chronic environmental disruptions as well as transition risks arising from decarbonization policies. Despite growing global evidence, empirical studies linking both risk types to bank-level non-performing assets in India remain scarce. This study addresses that gap using panel data from 10 Indian scheduled commercial banks over five fiscal years (FY2020–21 to FY2024–25), yielding 50 bank-year observations. Physical Risk Exposure (PR_EXP) and Transition Risk Exposure (TR_EXP) indices were constructed using an NGFS-aligned weighted sectoral methodology applied to Basel III Pillar 3 disclosures. The Hausman specification test confirmed Random Effects as the appropriate estimator. Moderated panel regression was estimated in R, with climate exposure (CE) as the moderating variable and GDP growth as a macroeconomic control. Robustness was verified using HC3 clustered standard errors. Neither PR_EXP nor TR_EXP exhibited significant direct effects on Gross Non-Performing Assets (GNPA). However, the interaction terms PR_EXP × CE and TR_EXP × CE were positive and highly significant ($\beta = 0.002$, $p < 0.001$), confirming that both climate risk types amplify GNPA through sectoral concentration. GDP growth was negatively and significantly associated with GNPA across all models ($\beta = -0.22$, $p < 0.001$). Model fit improved from $R^2 = 0.29$ to 0.45 after introducing interaction terms. These findings provide empirical support for portfolio diversification mandates and climate-adjusted credit frameworks in Indian banking supervision.**

***Index Terms*—Climate risk; non-performing assets; Physical risk; Transition risk; Panel regression; Indian banking; NGFS; TCFD; Credit risk; Sectoral concentration**

I. INTRODUCTION

India, the fourth largest economy in the world, has reduced its greenhouse gas (GHG) emissions by 7.93% (Press Information Bureau, 2025). Since its accession to the United Nations Framework Convention on Climate Change (UNFCCC) in 1992, India has pursued efforts to reduce GHG emissions and ensure sustainable development through the National Action Plan on Climate Change. Mitigation strategies are essential not only for addressing the effects of climate change but also for sustaining long-run economic growth (Government of India, 2008). In this context, the role of banks is significant; however, their exposure to climate-sensitive sectors threatens financial stability.

The Reserve Bank of India (2022) published a survey on Climate Risk and Sustainable Finance, finding that only a limited number of banks have incorporated climate risk into existing risk management frameworks. The Intergovernmental Panel on Climate Change (IPCC, 2014) projected that India is likely to sustain losses across major economic sectors including energy, transport, agriculture, and tourism. The IPCC Sixth Assessment Report (2023) has since documented realized economic damages across these sectors. As bank exposure to climate-sensitive sectors deepens, vulnerability to climate risk increases correspondingly (Conlon et al., 2024).

Climate change refers to a statistically significant change in the mean and/or variability of the properties of the climate system that persists over an extended period, typically decades or longer, arising from natural internal processes, external forcings, or persistent anthropogenic changes in atmospheric composition or land use (IPCC, 2014). In India, observable consequences include rising temperatures (Krishnan et al., 2020), altered precipitation patterns, increased frequency and intensity of extreme weather events, sea-level rise, and severe drought episodes. Climate risk arises from both the potential physical impacts of climate change (physical risks) and human responses to it through policy and economic transition toward a low-carbon economy (transition risks) (Reisinger et al., 2020).

The increased use of fossil fuels has raised concerns about resource depletion. Human activities contribute approximately 8 billion metric tons of carbon to the atmosphere annually (Chandel & Sharma, 2016). Rapid decarbonization is therefore necessary, entailing large-scale structural change (Semieniuk et al., 2021), which generates transition risks for carbon-intensive sectors and the banks that finance them.

This study is motivated by the observation that despite growing global evidence on climate-financial risk linkages, empirical research connecting both physical and transition risk types to Indian bank credit quality remains sparse. The study advances the literature by constructing NGFS-aligned weighted sectoral exposure indices and applying moderated panel regression to test whether sectoral concentration amplifies the climate risk–GNPA nexus.

II. REVIEW OF LITERATURE

2.1 Theoretical Framework

This study is grounded in two foundational theories. Risk Management Theory (Nieto, 2019) posits that financial institutions are exposed to a range of external and internal risks that must be identified, assessed, and managed effectively. Climate risk is an emerging concern that impairs borrowers' loan-servicing capacity through extreme weather events, regulatory changes, and shifts in market dynamics, potentially elevating GNPA. Financial Intermediation Theory (Scholtens, 2006) explains how banks allocate capital across economic sectors and how their performance depends on borrower repayment capacity. When borrowers operate in climate-sensitive sectors such as agriculture, energy, and coastal infrastructure, climate-related disruptions increase the likelihood of loan default, thereby degrading bank asset quality.

The TCFD (2017) classification of climate-related risks into physical and transition categories provides the conceptual bridge between these theories and the operationalization of climate risk in the present empirical framework. The present study addresses both gaps through a moderated panel regression framework.

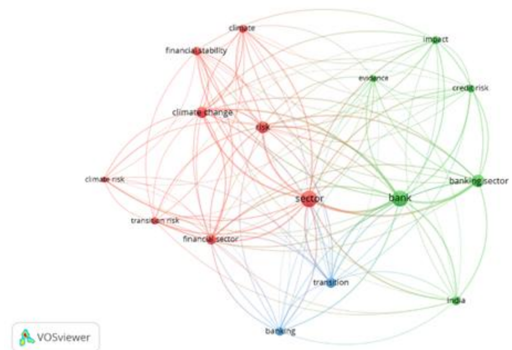

Figure 1: Bibliometric Analysis

2.2 Climate Change, Policy Responses, and Macroeconomic Impacts

Climate change, driven primarily by anthropogenic greenhouse gas emissions, has emerged as a dominant force shaping global economic and financial conditions (Jay et al., 2018; IPCC, 2023). The 2015 Paris Agreement constituted a watershed moment in global climate governance, establishing Nationally Determined Contributions (NDCs) to limit warming to well below 2°C above pre-industrial levels (Dimitrov, 2016; UNFCCC, 2015). India's NDCs emphasize expanding non-fossil electricity capacity and reducing the emissions intensity of GDP, operationalized through the National Solar Mission and the National Hydrogen Mission (Government of India, 2020; Ministry of New and Renewable Energy, 2025). In the absence of adequate mitigation and adaptation, climate change could reduce India's GDP by approximately 2.8% by 2050, driven by agricultural productivity losses, heat-related labor productivity declines, and infrastructure damage (Mani et al., 2018; Kompas et al., 2018).

2.3 Climate-Related Financial Risks and Bank Credit Quality

The TCFD (2017) and the Basel Committee on Banking Supervision (BCBS, 2021) define climate-related financial risks as arising from both the physical impacts of climate change and the transition to a low-carbon economy. These risks are distinct from traditional financial risks in three respects: they operate over extended time horizons, exhibit non-stationarity, and are spatially concentrated, characteristics that complicate conventional risk management (Nieto, 2019; Reisinger et al., 2020).

Physical climate risks generate direct and indirect economic impacts through extreme weather events and long-term climate shifts (IPCC, 2023). Following large-scale natural disasters, bank non-performing loan ratios can rise by 1.0–1.4 percentage points in affected areas, reflecting collateral impairment and disrupted borrower cash flows (Calice et al., 2022; Nie, 2023). In India, Ghosh et al. (2021) estimate that coastal states face potential climate-related losses of up to ₹2.5 lakh crore from cyclones and sea-level rise. High-resolution climatic evidence from China documents that each additional day of extreme rainfall raises NPLs by over ¥710 million (Zhang et al., 2025).

Transition risks arise from policy, regulatory, and technological changes associated with decarbonization (TCFD, 2017; Semieniuk et al., 2021). Fossil-fuel intensive sectors are especially vulnerable to asset stranding and profitability erosion under ambitious mitigation scenarios. Studies estimate that decarbonization-related policy shifts could strand assets worth up to ₹15 lakh crore in Indian bank lending (Vaze et al., 2022; Chava et al., 2023). Lamperti et al. (2019) and Nie (2023) demonstrate that physical and transition risks can jointly affect credit-market channels, elevating NPLs and generating potential capital shortfalls. Banks are exposed to climate risk primarily through their lending portfolios, collateral base, and inter-sectoral linkages with corporates, SMEs, and households (Nieto, 2019). In India, commercial banks provide approximately 70% of corporate credit, making climate-sensitive sectors heavily dependent on bank financing (Vaze et al., 2022). The Reserve Bank of India has begun integrating climate risk into its supervisory framework through NGFS membership and its 2022 Discussion Paper on Climate Risk and Sustainable Finance.

III. RESEARCH GAP

The review of literature identifies three principal gaps after careful analysis. Firstly, limited empirical evidence exists on climate-related financial risks in Indian banks using publicly available regulatory data. Existing studies largely focus on conceptual frameworks or developed-economy contexts (European, Chinese), with limited examination of Indian bank lending portfolios. Second, prior research on Indian banking has primarily identified macroeconomic factors as NPA determinants (Khushpatand & Rahul, 2012; Sanjeev, 2007), without empirically integrating climate risk indices. Third, and most critically, there is inadequate empirical analysis linking sectoral concentration in climate-sensitive industries with bank level Non-Performing Assets in India using a moderated panel regression framework. The present study addresses all these three gaps.

IV. RESEARCH OBJECTIVES

This study pursues the following objectives:

1. To assess the impact of climate-related financial risk exposure on bank credit quality as measured by Gross Non-Performing Assets (GNPA).
2. To identify sectors with high physical and transition climate risk exposure within Indian bank loan portfolios.
3. To measure whether sectoral concentration (CE) moderates the relationship between climate risk indices and GNPA.
4. To examine the role of macroeconomic conditions (GDP growth) as a control variable in the climate risk–GNPA nexus.

V. RESEARCH HYPOTHESES

The following hypotheses are formulated based on the theoretical framework and prior literature:

Table 1. Research Hypotheses

H	Relationship	Expected Direction	Theoretical Basis
H1	Physical risk exposure (PR_EXP) has a significant positive effect on GNPA	Positive	Risk Management Theory
H2	Transition risk exposure (TR_EXP) has a significant positive effect on GNPA	Positive	Financial Intermediation Theory
H3	Climate exposure (CE)	Directional	TCFD Framework

	has a significant direct effect on GNPA		
H4	CE significantly moderates the PR_EXP → GNPA relationship (amplifying)	Amplifying	NGFS Concentration Risk
H5	CE significantly moderates the TR_EXP → GNPA relationship (amplifying)	Amplifying	NGFS Concentration Risk
H6	GDP growth has a significant negative effect on GNPA	Negative	Macroeconomic Theory

Note. H1–H6 tested using Random Effects panel regression with HC3 robust standard errors (R v4.5).

VI. RESEARCH METHODOLOGY

6.1 Research Design

This study adopts a quantitative, explanatory research design to examine the impact of climate risk on bank credit quality. A longitudinal panel data approach is employed across five fiscal years (FY2020–21 to FY2024–25) to capture temporal trends and bank-specific heterogeneity. The explanatory design is appropriate because the study seeks to establish empirical relationships between climate risk exposure and credit quality, rather than merely describing observed patterns.

6.2 Sample and Data

The study covers 10 scheduled commercial banks 5 public sector and 5 private sectors over five fiscal years, yielding a balanced panel of 50 bank-year observations. Banks were selected on the basis of: (1) availability of complete Basel III Pillar 3 sectoral lending disclosures for all five years; (2) representation of both ownership types; and (3) adequate variation in climate-sensitive sector exposure across the sample. Data were obtained from Basel III Pillar 3 disclosures, Reserve Bank of India publications, and the Economic Survey of India. All data sources are publicly available and standardized, ensuring comparability.

Table 2. Sample Banks

No.	Bank Name	Type	Observations
1	State Bank of India (SBI)	Public	5
2	Bank of Baroda (BoB)	Public	5
3	Bank of India (BOI)	Public	5
4	Canara Bank	Public	5
5	Indian Bank	Public	5
6	HDFC Bank	Private	5
7	ICICI Bank	Private	5
8	Bandhan Bank	Private	5
9	Kotak Mahindra Bank	Private	5
10	IDBI Bank	Private	5
	Total	5 Public + 5 Private	50

Note: Period Covered: FY2021-FY2025

6.3 Variable Operationalization

Table 3 defines all study variables. Physical Risk Exposure (PR_EXP) and Transition Risk Exposure (TR_EXP) indices were constructed using NGFS-aligned sector-level weights applied to Basel III Pillar 3 sectoral lending data. $PR\_EXP = \Sigma(W\_i^{PR} \times E\_i)$; $TR\_EXP = \Sigma(W\_i^{TR} \times E\_i)$, where W_i denotes the risk weight (1–3 scale per NGFS sector classification) and E_i denotes the bank's lending share to sector i. Climate Exposure (CE) the proportion of total lending to highly climate-sensitive sectors serves as the moderating variable.

Table 3. Variable Definitions and Sources

Variable	Type	Definition	Scale	Source
GNPA	Dependent	Gross Non-Performing Asset ratio	% of total advances	Basel III Pillar 3
PR_EXP	Independent	Weighted exposure to physically climate-vulnerable sectors	Index (continuous)	Calculated from Basel III + NGFS
TR_EXP	Independent	Weighted exposure to carbon-intensive sectors	Index (continuous)	Calculated from Basel III + TCFD

Variable	Type	Definition	Scale	Source
CE	Moderating	Proportion of lending to highly climate-sensitive sectors	% of total advances	Calculated from Basel III
GDP	Control	Annual GDP growth rate of India	Percentage	Press Information Bureau

6.4 Sector-Level Climate Risk Weights

Table 4. Sector-Level Climate Risk Weights

Sector	PR Weight	TR Weight	Rationale
Agriculture & Allied Activities	3	2	High physical risk (drought, flood, heat stress); moderate transition risk
Power & Energy (Fossil Fuel)	2	3	Moderate physical; high transition risk (carbon pricing, stranded assets)
Infrastructure (Coastal/Urban)	3	2	High physical (sea-level rise, floods); moderate transition
Transportation	2	2	Moderate both fuel transition and extreme weather exposure
Coal & Mining	1	3	Low physical; very high transition risk (phase-out policies)
Manufacturing (Carbon-Intensive)	1	3	Low physical; high transition (regulatory compliance costs)
Real Estate (Coastal)	3	1	High physical (flooding, cyclones); low transition risk
MSMEs (Climate-Sensitive)	2	2	Moderate each limited adaptive capacity amplifies both risks

(NGFS, 2023; TCFD, 2017). Scale: 1 = low risk; 3 = high risk.

6.5 Model Specification

Based on the Hausman specification test, the Random Effects (RE) GLS estimator was selected. The RE estimator exploits both within-bank (time-series) and between-bank (cross-sectional) variation and is appropriate when bank-specific effects are uncorrelated with the regressors. The primary moderated regression equation is:

$GNPA\_it = \alpha + \beta_1(PR\_EXP\_it) + \beta_2(CE\_it) + \beta_3(GDP\_t) + \beta_4(PR\_EXP\_it \times CE\_it) + u\_i + \varepsilon\_it$

A parallel specification is estimated for TR_EXP. Given the near-perfect bivariate correlation between PR_EXP and TR_EXP ($r = 0.952$, VIF > 10 when entered simultaneously), both variables are entered in separate primary models (Models 4 and 5), with a joint model (Model 6) reported for completeness. All analyses were conducted in R v4.5 using the plm, lmtest, sandwich, and car packages.

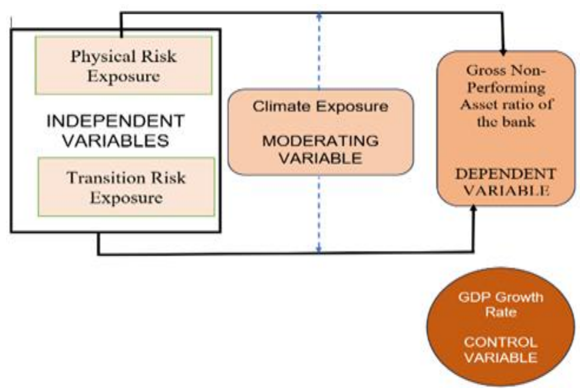

Figure 3.1: Conceptual Framework

VII. DATA ANALYSIS AND INTERPRETATION

7.1 Descriptive Statistics

Table 5. Descriptive Statistics (N = 50)

Variable	N	Mean	SD	Min	Max	Range
PR_EXP (Physical Risk Exposure)	50	111.54	70.81	16.43	262.89	246.46
TR_EXP (Transitio	50	87.83	56.30	13.19	202.68	189.49

Variable	N	Mean	SD	Min	Max	Range
n Risk Exposure)						
CE Climate Exposure (%)	50	21.82	14.54	2.96	73.90	70.94
GDP Growth Rate (%)	50	4.54	6.23	-7.70	8.70	16.40
GNPA Ratio (%)	50	4.53	4.25	1.00	20.56	19.56

PR_EXP exhibits a mean of 111.54 with high standard deviation (70.81), reflecting substantial cross-bank heterogeneity in physical climate risk exposure. The wide range captures the contrast between private sector banks with diversified retail portfolios and public sector banks concentrated in climate-sensitive infrastructure and agriculture. CE averages 21.82%, ranging from 2.96% to 73.90%, indicating that some banks have concentrated nearly three-quarters of lending in climate-sensitive sectors. GDP growth ranged from −7.7% (FY2020–21, COVID-19 contraction) to 8.7%, providing useful temporal variation for causal identification. The mean GNPA ratio of 4.53% is consistent with documented improvements in Indian bank asset quality following the FY2019 NPA peak.

7.2 Pre-Estimation Diagnostic Tests

Shapiro-Wilk tests rejected normality for GNPA ($W = 0.7276$, $p < 0.001$), PR_EXP ($W = 0.9088$, $p = 0.0009$), and TR_EXP ($W = 0.8969$, $p = 0.0004$), confirming that panel methods robust to distributional violations are appropriate. VIF analysis revealed severe multicollinearity for PR_EXP (VIF = 13.544) and TR_EXP (VIF = 11.000) when entered simultaneously, consistent with their near-perfect bivariate correlation ($r = 0.952$). CE (VIF = 2.392) and GDP (VIF = 1.027) remained within acceptable limits. The Panel Effects F-test confirmed significant bank-specific heterogeneity ($F(9,37) = 4.463$, $p = 0.0005$), validating panel over pooled OLS. Hausman specification tests across all three model specifications yielded p-values well above 0.05, confirming Random Effects as the appropriate estimator.

7.3 Correlation Analysis

Table 6. Pearson Correlation Matrix

Variable	PR_EXP	TR_EXP	CE	GDP	GNPA
PR_EXP	1.000	0.952***	0.747***	-0.044	0.251
TR_EXP	0.952***	1.000	0.677***	-0.042	0.216
CE	0.747***	0.677***	1.000	-0.136	0.411**
GDP	-0.044	-0.042	-0.136	1.000	-0.374**
GNPA	0.251	0.216	0.411**	-0.374**	1.000

*** $p < 0.001$; ** $p < 0.01$.

CE exhibits the strongest bivariate correlation with GNPA ($r = 0.411$, $p < 0.01$), suggesting sectoral concentration is the most direct bivariate predictor of credit risk. GDP is negatively correlated with GNPA ($r = -0.374$, $p < 0.01$). The weak and non-significant correlations of PR_EXP and TR_EXP with GNPA ($r = 0.251$ and 0.216, respectively) foreshadow the finding that these variables operate through a conditional moderation mechanism rather than direct effects.

VIII. RESULTS AND DISCUSSION

8.1 Main Effects Panel Regression

Table 7. Main Effects Panel Regression (Dependent Variable: GNPA)

Variable	Model 1 (PR only)	Model 2 (TR only)	Model 3 (Both reference)
PR_EXP	0.011 (0.016)	—	0.029 (0.039)
TR_EXP	—	0.008 (0.018)	-0.019 (0.044)

Variable	Model 1 (PR only)	Model 2 (TR only)	Model 3 (Both reference)
CE	0.065 (0.070)	0.085 (0.060)	0.047 (0.077)
GDP Growth	-0.229*** (0.069)	-0.225** (0.069)	-0.233*** (0.069)
Constant	2.896 (1.630)	3.029 (1.671)	3.026 (1.769)
Observations	50	50	50
R²	0.296	0.291	0.302
Adj. R²	0.250	0.245	0.240

Standard errors in parentheses. *** $p < 0.001$; ** $p < 0.01$.

Across all three main effects models, only GDP Growth achieves consistent statistical significance (β = −0.229 to −0.233, $p < 0.001$), confirming the inverse relationship between economic growth and bank NPAs. Neither PR_EXP, TR_EXP, nor CE is significant in the main effects specifications. The absence of direct climate risk significance is consistent with the theoretical expectation that climate-financial risk transmission is a conditional, sector-specific mechanism rather than a uniform direct effect, motivating the moderation analysis.

8.2 Moderated Panel Regression

Table 8. Moderated Panel Regression (Dependent Variable: GNPA)

Variable	Model 4 (PR+Moderation)	Model 5 (TR+Moderation)	Model 6 (Full reference)
PR_EXP	-0.028 (0.015)	—	-0.121 (0.093)
TR_EXP	—	-0.034 (0.018)	0.110 (0.115)
CE	-0.231* (0.104)	-0.243* (0.111)	-0.197 (0.108)
GDP Growth	-0.218*** (0.066)	-0.217*** (0.065)	-0.213** (0.071)
PR_EXP × CE	0.002*** (0.0005)	—	0.005 (0.003)
TR_EXP × CE	—	0.002*** (0.001)	-0.004 (0.005)
Constant	8.265*** (1.795)	8.229*** (1.969)	8.090*** (1.630)
Observations	50	50	50
R²	0.452	0.435	0.499
Adj. R²	0.404	0.385	0.429

Standard errors in parentheses. *** $p < 0.001$; * $p < 0.05$.

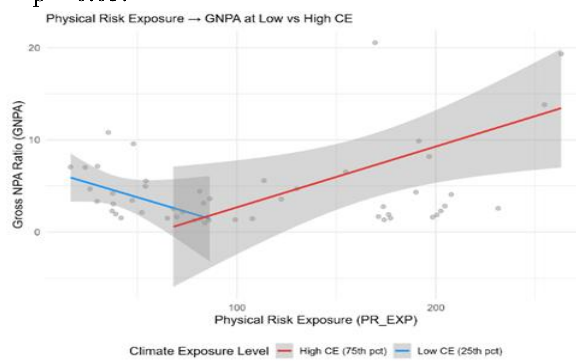

Figure 3: Moderating Effect of CE on PR_EXP → GNPA

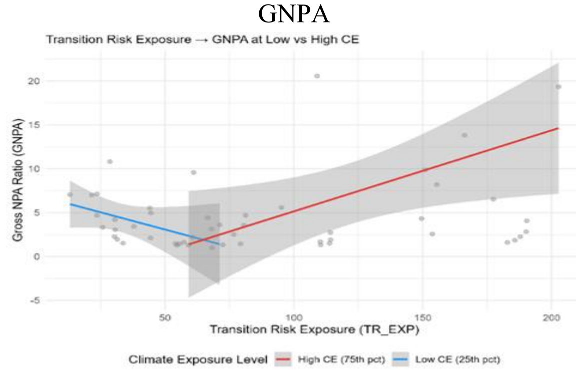

Figure 4: Moderating Effect of CE on TR_EXP → GNPA

The interaction term PR_EXP × CE is positive and highly significant (β = 0.002, $p < 0.001$) in Model 4, indicating that physical climate risk exposure amplifies GNPA when banks have higher sectoral concentration in climate-sensitive industries. R^2 improves substantially from 0.296 (Model 1) to 0.452 (Model 4). Similarly, TR_EXP × CE is positive and highly significant (β = 0.002, $p < 0.001$) in Model 5, confirming that transition risk amplifies GNPA in banks with higher climate-sector concentration. R^2

improves from 0.291 to 0.435. GDP remains negative and significant in both moderated models ($\beta \approx -0.217$, $p < 0.001$). These moderation effects survive HC3 clustered standard error correction, confirming robustness against heteroscedasticity.

8.3 Hypothesis Testing Summary

Table 9. Hypothesis Testing Summary

H	Hypothesis Statement	Result	Interpretation
H1	PR_EXP has a significant positive effect on GNPA	Not Supported	Conditional significant only through CE moderation
H2	TR_EXP has a significant positive effect on GNPA	Not Supported	Conditional significant only through CE moderation
H3	CE directly influences GNPA	Supported* (p<0.05)	Negative conditional main effect in interaction models
H4	CE moderates PR_EXP → GNPA	Supported*** (p<0.001)	Strong amplifying moderation confirmed
H5	CE moderates TR_EXP → GNPA	Supported*** (p<0.001)	Strong amplifying moderation confirmed
H6	GDP has a significant negative effect on GNPA	Supported*** (p<0.001)	Robust across all six model specifications

8.4 Discussion

The finding that PR_EXP and TR_EXP do not directly affect GNPA but do so significantly through the moderating role of CE challenges the assumption of uniform direct climate–credit risk transmission in early climate finance literature. This result is consistent with Conlon et al. (2024), who demonstrated that climate risk effects on bank performance are contingent on portfolio composition. A bank with 70% of lending in climate-sensitive sectors faces compounded credit risk that neither exposure nor concentration alone would predict a non-linear transmission pathway undetectable without interaction terms.

Physical climate risks impair borrower repayment through asset damage (destroying collateral and productive capacity) and income disruption (reducing debt-servicing cash flows). The significance of PR_EXP × CE while PR_EXP alone is not significant confirms that physical climate shocks become financially material at the bank level only under concentrated sectoral exposure, a finding analogous to Battiston et al. (2021) for European banks. The significant TR_EXP × CE interaction directly corroborates Semieniuk et al. (2021) and Vaze et al. (2022) on Indian transition risk, providing the first panel regression evidence that this exposure translates into measurable GNPA amplification.

The consistently negative and significant GDP coefficient ($\beta = -0.22$, $p < 0.001$ across all six models) confirms the dominant role of macroeconomic conditions in determining GNPA. Critically, GDP and climate risk operate as distinct and additive GNPA drivers, neither substitutes for the other. Stress testing frameworks incorporating only macroeconomic scenarios therefore underestimate climate-exposed credit risk.

IX. FINDINGS

Four principal findings emerge from this study:

1. Climate risks operate through conditional moderation, not direct effects. Neither PR_EXP nor TR_EXP directly increases GNPA. However, their interactions with CE are positive and highly significant ($\beta = 0.002$, $p < 0.001$), confirmed robust under HC3 standard errors. This establishes a contingency-based understanding of climate–credit risk linkages in Indian banking.
2. Sectoral concentration (CE) is the critical amplifier. Banks with higher proportions of lending in climate-sensitive sectors face disproportionately elevated NPAs as climate risks intensify. CE as a standalone moderator ($r = 0.411$ with GNPA, $p < 0.01$) is the most direct bivariate predictor among climate variables, providing a quantified empirical basis for supervisory sectoral concentration limits.
3. GDP growth is the dominant macroeconomic determinant of GNPA ($\beta = -0.22$, $p < 0.001$ across all six models), operating additively with the climate risk channel. The COVID-19 contraction year (FY2020–21, GDP = −7.7%) provides a

natural experiment strengthening this identification.

4. Bank-specific heterogeneity is statistically significant ($F = 4.463$, $p < 0.001$), underscoring the importance of bank-level climate risk assessment rather than industry-wide averages. Model fit improved from $R^2 = 0.29$ to 0.45 after introducing interaction terms, confirming the incremental explanatory power of the moderation framework.

X. SUGGESTIONS AND RECOMMENDATIONS

Table 10. Managerial and Policy Recommendations

Area	Recommendation
Portfolio Diversification	Banks with CE above 30% should actively reduce concentration in carbon-intensive and physically vulnerable sectors. Diversification is the most effective lever for reducing climate-driven NPA risk, given the significant CE moderation effect ($p < 0.001$).
Climate Risk Pricing	Loan pricing models should incorporate PR_EXP and TR_EXP scores. Sectors with high physical or transition risk weights should attract higher risk premiums commensurate with their GNPA amplification potential.
Sector-Level Stress Testing	Banks should conduct annual NGFS scenario-based stress tests on sectoral portfolios under Disorderly Transition and Hot-House World scenarios to generate forward-looking GNPA trajectories.
Board-Level Governance	Dedicated Climate Risk Committees at board level (as recommended by RBI, 2022) should be established with explicit authority over sectoral exposure limits, particularly for banks with CE exceeding industry-level thresholds.
Supervisory Framework (RBI)	The significant CE moderation effect provides empirical grounding for incorporating sectoral concentration in climate-sensitive industries into supervisory review processes, ICAAP frameworks, and Pillar 2 capital add-ons.
Green Finance Policy	Priority Sector Lending guidelines could be extended to include green finance targets, with regulatory incentives such as CRR or SLR benefits for banks that reduce TR_EXP-weighted exposures below defined thresholds.

XI. LIMITATIONS OF THE STUDY

Table 11. Limitations and Mitigations

Limitation	Impact on Findings	Mitigation Adopted
Small sample (N = 50)	Limits statistical power for detecting small effects; non-significant direct effects may reflect Type II error	HC3 robust standard errors; panel methods preferred over OLS
No lagged specifications	Climate risks typically manifest with 1–2year lag; contemporaneous specification may understate long-run effects	Noted as limitation; lagged models recommended for future research
Subjective sector weight assignment	NGFS-based weights involve judgment; no sensitivity analysis conducted for alternative weights	Weights assigned a priori and applied uniformly without post-hoc adjustment
Limited bank-level controls	Only GDP controlled for; CAR, ROA, and bank size excluded, risking omitted variable bias	Acknowledged; future models should incorporate bank-level controls
Secondary data constraints	Basel III disclosures may not capture all climate-sensitive sub-sectors	Data standardization ensures cross-bank comparability; acknowledged as boundary condition

XII. SCOPE FOR FUTURE RESEARCH

Future research should extend this framework through the following directions:

1. Lagged panel regression to capture the 1–2year transmission lag between climate shocks and loan default (PR_EXP(t−1), TR_EXP(t−1)).

2. Arellano-Bond GMM dynamic panel models to address potential endogeneity between GNPA and sectoral lending decisions.
3. Threshold regression to identify the critical CE level above which climate risk effects become non-linear.
4. Quantile regression to assess whether climate effects are concentrated in the upper tail of the GNPA distribution.
5. Extending the sample to 20–25 banks, including Regional Rural Banks, expanding the time horizon to 10–15 years, and incorporating forward-looking NGFS scenarios.
6. Cross-country comparative studies with BRICS economies to assess whether the conditional moderation pathway is unique to India or a broader emerging-market feature.

XIII. CONCLUSION

This study examined whether physical and transition climate risks significantly affect Gross Non-Performing Assets of Indian scheduled commercial banks, and whether sectoral concentration moderates these relationships. Using a balanced panel of 50 bank-year observations across 10 Indian scheduled commercial banks (FY2020–21 to FY2024–25) and a Random Effects panel regression framework validated by the Hausman specification test, the study demonstrates that climate-related financial risks do not directly amplify bank credit risk in isolation. They become financially material only when concentrated sectoral exposure provides the transmission pathway. Sectoral concentration is the switch that converts climate exposure into credit risk.

These findings demonstrate that the TCFD physical/transition risk taxonomy is empirically operationalizable from publicly available Basel III disclosures, and that the climate–credit risk relationship in Indian banking is characterised by conditionality rather than direct causation. The study advances Risk Management Theory by demonstrating that climate risk is a conditional amplifier of sectoral concentration risk, and extends Financial Intermediation Theory by specifying the precise transmission mechanism of the interaction between climate risk exposure and sectoral concentration, as the determinant of credit quality deterioration.

As India deepens its Paris Agreement commitments and the Reserve Bank of India advances its climate risk supervisory framework, the integration of sectoral climate risk weights into credit assessment, portfolio concentration limits, and NGFS scenario-based stress testing are financially necessary responses to documented, quantified credit risk amplification mechanisms. Climate risk management in Indian banking is no longer a future agenda item and is a present financial necessity.

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