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# Does Directed Lending Affect Climate-Induced Bank Risk? Evidence From India

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## Abstract

This study examines how climate change affects bank risk and investigates the roles of Priority Sector Lending (PSL) and diversification in shaping banks' vulnerability and resilience in an emerging economy using an unbalanced panel of 80 Indian commercial banks over the period 2005–2020. We construct a composite climate change index based on temperature and precipitation anomalies to capture persistent climate stress. Bank risk is measured using ΔCoVaR, which reflects banks' contribution to systemic downside risk, and the Z-score, which captures financial stability and distance-to-default. The analysis employs bank- and year-fixed-effects regressions to evaluate the direct and moderating effects of climate change and PSL on bank risk, respectively, as well as the moderating role of diversification. The results show that climate change significantly increases bank risk by raising ΔCoVaR and reducing Z-scores. PSL independently elevates bank risk and further amplifies the adverse impact of climate change, suggesting that directed lending to climate-sensitive sectors intensifies financial vulnerability. Heterogeneity analysis reveals that public sector banks are the most vulnerable to the combined effects of climate stress and PSL exposure, although similar amplification effects are observed among private and foreign banks. In contrast, both income and asset diversification reduce bank risk and weaken the transmission of climate shocks by lowering tail-risk exposure and strengthening financial stability. The findings identify directed lending as an amplifier of climate-related risks within the banking system and highlight diversification as an effective mechanism for enhancing banking sector resilience.

**Keywords:** Climate Change, Priority Sector Lending, Emerging Economies, Bank Risks, Diversification

## 1. Introduction

Climate change has emerged as a significant source of financial risk, attracting growing attention from both scholars and policymakers (Giglio et al., 2021). Extreme weather events such as floods, cyclones, and droughts disrupt economic activity, weaken borrower repayment capacity, and generate financial stress across institutions. Beyond these acute events, persistent changes in temperature and precipitation also affect economic productivity and financial stability through more gradual channels (Battiston et al., 2021). Recognizing these threats, the Network for Greening the Financial System (NGFS, 2019) identifies climate change as a key driver of systemic financial risk.

The issue is particularly relevant in India, one of the countries most vulnerable to climate-related disruptions, as documented by Germanwatch's Climate Risk Index (CRI) 2026. In recent years, the country has also experienced a growing frequency and intensity of climate-related disasters, including floods, cyclones, droughts, and heatwaves, with significant consequences for economic activity and financial stability. India's banking system plays a central role in financing economic activity and is characterized by a substantial presence of state-owned banks. While regulatory reforms have strengthened financial stability, the Reserve Bank of India (RBI) has increasingly recognized climate-related financial risk (CRFR) as a potential threat to the safety, soundness, and stability of the financial system (RBI, 2021, 2022). In line with the recommendations of the Network for Greening the Financial System (NGFS), the RBI has initiated climate-risk disclosure and supervisory frameworks, while emphasizing the need to integrate sustainability objectives into financial regulation without compromising its core policy mandates (Rao, 2022, 2023). These developments underscore the need to understand how climate change affects bank risk in the Indian context.

A distinctive feature of Indian banking is Priority Sector Lending (PSL), which requires banks to allocate a fixed share of credit to socially important sectors such as agriculture, Micro, Small and Medium Enterprises (MSMEs), housing, and renewable energy. Although PSL supports developmental objectives, many of these sectors are highly vulnerable to climate shocks and often lack adequate risk-buffering capacity. Consequently, PSL may serve as an important channel through which climate-related risks are transmitted to bank balance sheets.

At the same time, diversification offers a potential mechanism for enhancing resilience. Banks can diversify their income sources by increasing reliance on non-interest income, such as fees, commissions, trading, and insurance (Allen & Santomero, 2001), and reduce concentration risk by diversifying asset portfolios across sectors and borrowers (Hsieh et al., 2013). Such strategies may lessen dependence on climate-sensitive lending activities and strengthen banks' ability to absorb climate-induced shocks. Despite growing interest in climate-related financial risks, limited evidence exists on whether diversification can mitigate these risks, particularly in emerging economies.

This study examines how climate change affects bank risk and investigates the roles of PSL and diversification in shaping banks' vulnerability and resilience in India using a panel of 80 commercial banks over the period 2005-2020. We construct a composite climate anomaly index based on temperature and precipitation deviations. Bank risk is measured using ΔCoVaR and Z-score, capturing systemic downside risk and financial stability, respectively. The results show that climate change significantly increases bank risk by raising ΔCoVaR and reducing Z-scores. PSL not only increases bank risk directly but also amplifies the adverse impact of climate change, suggesting that directed lending to climate-sensitive sectors intensifies financial vulnerability. The effect is particularly pronounced among public sector banks. In contrast, both income and asset diversification mitigate climate-induced risk by reducing tail-risk exposure and strengthening financial stability. This study contributes to the literature by examining the climate change-bank risk nexus in an emerging economy, identifying PSL as a channel that amplifies climate-related financial vulnerability, and highlighting diversification as a mechanism that enhances banking sector resilience. The findings provide important policy implications for balancing developmental mandates with financial stability under climate change.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework and hypotheses. Section 3 describes the data and methodology. Section 4 presents the empirical results, including interaction visualizations, endogeneity analysis, and robustness tests, and Section 5 concludes the study.

## 2. Theoretical Framework

### 2.1 Climate Change and Bank Risk

Climate-related events influence energy prices, agricultural productivity, national income, and public health, thereby weakening aggregate economic performance. Since banks intermediate economic activity, such widespread disruptions directly impair their balance sheets.

Climate shocks reduce borrower cash flows, damage collateral values, and increase income volatility, leading to a deterioration in loan quality and higher default probabilities. Empirical evidence shows that natural disasters and temperature anomalies increase non-performing loans, weaken financial stability, and heighten risk spillovers in banking systems (Wu et al., 2023).

Beyond their impact on individual borrowers, climate shocks may also generate systemic vulnerabilities within the banking sector. Banks often exhibit similar credit exposures to climate-sensitive sectors, increasing the likelihood of correlated losses under adverse climate conditions (Jarrow & Lamichhane, 2021). Financial interconnectedness further amplifies the transmission of shocks across institutions (Verma et al., 2019). Given the systemic importance of large banks within the financial system (Rahman et al., 2022), climate-induced stress in individual banks may intensify overall banking sector vulnerability. As climate-related losses become correlated across borrowers and sectors, banks' systemic risk contribution may increase, making climate change a source of both idiosyncratic and systemic banking risk. Accordingly, we hypothesize:

Hypothesis 1: Climate change increases bank risk

### 2.2 Priority Sector Lending, Climate Change and Bank Risk

Priority Sector Lending (PSL) mandates banks to allocate credit to sectors that are socially important but often financially vulnerable. Prior evidence suggests that PSL has been associated with elevated non-performing loans. Chalam (2017) argues that directed lending weakens asset quality by compelling banks to lend to less profitable and riskier segments, while Rajeev & Mahesh (2010) show that priority sector advances contribute disproportionately to bad loans relative to non-priority lending. Because PSL targets sectors characterized by limited collateral, weaker repayment capacity, and higher income volatility, banks with greater PSL exposure are likely to face higher loan defaults and lower financial stability. We thus propose that:

Hypothesis 2: PSL increases bank risk

Climate change is likely to intensify these vulnerabilities. Physical climate risks, such as extreme temperature and precipitation anomalies, can damage assets, disrupt production, and reduce household and business incomes (Hong et al., 2019), thereby weakening borrowers' repayment capacity and increasing default probabilities (Huang et al., 2021). Importantly, many PSL-targeted sectors, including agriculture and micro-enterprises, are particularly vulnerable to such disruptions due to their dependence on climatic conditions and limited adaptive capacity. Consequently, banks with greater PSL exposure may face disproportionately larger credit losses when climate shocks occur. Moreover, the mandatory nature of PSL constrains banks' ability to reallocate credit away from increasingly risky sectors, potentially magnifying the transmission of climate-related stress to bank balance sheets. Accordingly, we hypothesize:

Hypothesis 3: PSL amplifies the positive relationship between climate change and bank risk

## 3. Data and Methodology

The study uses an unbalanced panel of 1,162 bank-year observations from 80 Indian commercial banks, including public, private, and foreign banks, over the period 2005–2020. Banks with insufficient financial information are excluded, and all continuous variables are winsorized at the 0.5th and 99.5th percentiles. Variable definitions and data sources are reported in Table 1. Bank-level financial data are obtained from the Statistical Tables Relating to Banks in India (STRBI), climate data from the India Meteorological Department (IMD) and the Ministry of Statistics and Programme Implementation (MoSPI), and macroeconomic indicators from the World Development Indicators (WDI) and the Database on Indian Economy (DBIE).

*Table 1. Variable description*

| Variables | Definition |
|---|---|
| **Dependent Variables:** | |
| ΔCoVaR | Absolute Delta Conditional Value at Risk |
| Z-score ($Z_{i,t}$) | $Z_{i,t} = \frac{ROA_{i,t} + \frac{Equity}{Assets}_{i,t}}{\sigma(ROA_{i,t})}$ |
| **Variables of Interest:** | |
| CC | Climate Change ($CC_t$) = $\omega_1 TEMP_t + \omega_2 PCPT_t$ |
| PSL | Priority Sector Lending Ratio = Priority Sector Advances to Total Advances |
| **Control Variables:** | |
| GDP_growth | GDP growth rate (%) = $(GDP_t - GDP_{t-1}) / GDP_{t-1}$ |
| Inflation | Growth in Consumer Price Index (%) = $(CPI_t - CPI_{t-1}) / CPI_{t-1}$ |
| M2_growth | M2 money growth rate (%) = $(M2_t - M2_{t-1}) / M2_{t-1}$ |
| Crisis | A dummy variable that takes a value of 1 for the year of the financial crisis (2008 and 2009) |
| lnSize | Size of the bank = Natural log of total assets |
| CRAR | Total capital adequacy ratio (%) = (Tier-1 + Tier-2 Capital) / Risk-Weighted Assets |
| OC | Overhead Cost (%) = Total non-interest operating expenses/total assets |
| CR3 | Industry Concentration = Total assets of the three largest banks over the total assets of the total banking industry (%) |

*Source: Bank-level variables are obtained from STRBI, climate data from IMD and MoSPI, and macroeconomic variables from WDI and DBIE*

### 3.1 Bank Risk and Priority Sector Lending Variables

First, bank risk is measured using the Delta Conditional Value at Risk (△CoVaR), following Adrian & Brunnermeier (2016). While Value at Risk (VaR) captures the potential loss of an individual institution at a given confidence level,

$$\Pr(X^i \leq VaR_q^i) = q\% \tag{1}$$

CoVaR extends this concept by measuring the system's Value at Risk conditional on the distress of bank *i*:

$$\Pr(X^s \leq CoVaR_q^{sys|i} \mid X^i = VaR_q^i) = q\% \tag{2}$$

CoVaR is estimated using quantile regressions of individual bank returns and system returns on lagged macro-financial state variables, including stock market volatility, liquidity spread, and term spread. Finally, ΔCoVaR is computed as:

$$\triangle CoVaR_{0.05,t}^{sys|i} = CoVaR_{0.05,t}^{sys|i} - CoVaR_{0.5,t}^{sys|i} \tag{3}$$

where $CoVaR_{0.05,t}^{sys|i}$ and $CoVaR_{0.5,t}^{sys|i}$ denote the system's conditional Value at Risk when bank *i* is in distress (5th percentile) and in its median state (50th percentile), respectively. A larger absolute value of ΔCoVaR indicates a greater contribution to systemic risk.

To complement this market-based measure, we employ the Z-score as an accounting-based indicator of bank stability and distance-to-default (Laeven & Levine, 2007):

$$Z_{i,t} = \frac{ROA_{i,t} + \frac{Equity}{Assets}_{i,t}}{\sigma(ROA_{i,t})} \tag{4}$$

where ROA is return on assets, Equity/Assets measures capitalization, and σ(ROA) denotes the three-year rolling standard deviation of ROA. A higher Z-score implies greater stability and lower insolvency risk.

Lastly, Priority Sector Lending is measured as the ratio of priority sector advances to total advances, as reported by the RBI.

### 3.2 Climate Change variable

Climate change is measured using deviations in temperature and precipitation from their long-run historical averages, following Khan et al. (2019). Unlike extreme weather events, which capture discrete climate shocks, temperature and precipitation anomalies reflect persistent climate stress and are therefore more suitable for assessing long-term financial vulnerability. Given that Indian banks operate nationwide and report consolidated financial statements, national-level climate anomalies provide a more consistent measure of climate exposure than region-specific events (Mukharjee & Barai, 2025).

Annual temperature and precipitation anomalies for 2005–2020 are computed as squared deviations from their long-run averages (1901–2020). Squaring captures the magnitude of deviations regardless of direction (Wu et al., 2023). The anomaly series are subsequently normalized using min-max standardization to ensure comparability across indicators.

The climate change index is constructed as:

$$CC_t = \omega_1 TEMP_t^* + \omega_2 PCPT_t^* \tag{5}$$

Where ω1 and ω2 denote the weights assigned to standardized temperature and precipitation anomalies, respectively. The weights are proportional to the absolute correlation between each anomaly and the annual growth rate of financial-sector gross value added (GVA), obtained from the Ministry of Statistics and Programme Implementation (MoSPI), thereby assigning greater weight to the climate indicator most closely associated with financial-sector activity.

### 3.3 Models

Following the recent literature (Nguyen et al., 2024), we first estimate the contemporaneous effects of climate change and PSL on bank risks using a fixed-effects estimator, justified by the Hausman test. Equations (6) and (7) test their individual effects, while Equation (8) evaluates the moderating role of PSL:

$$Bank\ Risk_{i,t} = \beta_0 + \beta_1(CC_t) + \beta_2(Control_{i,t}) + \delta_i + \theta_t + \varepsilon_{i,t} \quad (6)$$

$$Bank\ Risk_{i,t} = \beta_0 + \beta_1(PSL_{i,t}) + \beta_2(Control_{i,t}) + \delta_i + \theta_t + \varepsilon_{i,t} \quad (7)$$

$$Bank\ Risk_{i,t} = \beta_0 + \beta_1(CC_t) + \beta_2(PSL_{i,t}) + \beta_3(CC_t{*}PSL_{i,t}) + \beta_4(Control_{i,t}) + \delta_i + \theta_t + \varepsilon_{i,t} \quad (8)$$

Here, $Bank\ Risk_{i,t}$ is the measured by $\Delta CoVaR_{i,t}$ and $Z_{i,t}$. $CC_t$ represents climate change index, $PSL_{i,t}$ denotes the Priority Sector Lending, and $Control_{i,t}$ is a vector of bank and macro-level controls. $\delta_i$ and $\theta_t$ capture bank and year fixed effects, respectively.

### 3.4 Descriptive Statistics

Table 2 presents the descriptive statistics for the key variables used in the analysis. The sample exhibits sufficient variation in bank risk, climate change, Priority Sector Lending, and diversification measures, supporting the subsequent empirical analysis.

*Table 2. Summary Statistics*

| Variable | Observations | Mean | Median | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| ΔCoVaR | 1160 | 0.024 | 0.009 | 0.053 | 0.000 | 0.293 |
| Z-score | 1160 | 1.485 | 0.992 | 2.223 | -3.184 | 10.782 |
| CC | 1160 | 0.442 | 0.301 | 0.253 | 0.259 | 0.859 |
| PSL | 824 | 0.340 | 0.339 | 0.089 | 0.003 | 0.421 |
| Income_Div | 1160 | 0.407 | 0.415 | 0.059 | 0.212 | 0.500 |
| Asset_Div | 1160 | 0.754 | 0.746 | 0.105 | 0.457 | 0.999 |

## 4. Empirical Results and Discussion

### 4.1 Climate Change and Priority Sector Lending (PSL) on Bank Risk

Table 3 reports the regression results for Models (6), (7), and (8), using ΔCoVaR and Z-score as alternative measures of bank risk. Columns (1) and (4) show that climate change significantly increases bank risk. The positive coefficient of CC in the ΔCoVaR specification indicates that climate stress increases banks' systemic risk contribution, implying that distress in an individual bank is more likely to transmit stress to the broader financial system. The estimated effects are also economically meaningful. A one-standard-deviation increase in climate change (0.253) increases ΔCoVaR by approximately 0.04 units, equivalent to about 164% of its sample mean, and reduces the Z-score by approximately 0.17 units (11.2% of its sample mean). These findings are consistent with the view that climate-related shocks disrupt economic activity, weaken borrower repayment capacity, and increase the likelihood of loan defaults. As banks experience a deterioration in asset quality and profitability, their resilience to financial distress declines, increasing both risk spillovers to the financial system and insolvency risk.

Columns (2) and (5) indicate that PSL independently increases bank risk. Economically, a one-standard-deviation increase in PSL (0.089) increases ΔCoVaR by approximately 0.006 units

(23.4% of its sample mean) and reduces the Z-score by approximately 0.03 units (1.9% of its sample mean). Banks with higher exposure to priority sectors exhibit greater contagion risk and lower financial stability. This result is unsurprising given that several priority sectors, particularly agriculture and MSMEs, are highly sensitive to adverse economic conditions and often possess limited risk-absorbing capacity. Consequently, banks with larger PSL portfolios face greater credit risk exposure.

More importantly, Columns (3) and (6) reveal a significant interaction between climate change and PSL. The positive coefficient of CC*PSL in the ΔCoVaR model and the negative coefficient in the Z-score specification suggest that PSL amplifies the adverse effects of climate change on bank risk. Because PSL mandates maintain lending exposure to climate-sensitive sectors irrespective of changing risk conditions, banks have limited flexibility to adjust their portfolios when climate risks intensify. As a result, climate-induced shocks are more readily transmitted to bank balance sheets, leading to a stronger increase in systemic risk and a sharper deterioration in financial stability among banks with greater PSL exposure.

*Table 3. Effect of Climate Change and PSL on Bank Risk*

| | Dependent variable: ΔCoVaR | | | Dependent variable: Z-score | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| CC | .156** (2.41) | | .112** (2.10) | -.662* (-1.92) | | -.173* (-1.77) |
| PSL | | .063*** (6.24) | .028*** (6.22) | | -.311*** (-4.10) | -.412*** (-4.53) |
| CC*PSL | | | .316* (1.85) | | | -1.358** (-2.15) |
| Controls | YES | YES | YES | YES | YES | YES |
| Bank-fixed effects | YES | YES | YES | YES | YES | YES |
| Year- fixed effects | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.529 | 0.491 | 0.116 | .364 | .089 | 0.093 |
| F | 67.39*** | 57.80*** | 7.28*** | 34.38*** | 7.14*** | 7.30*** |
| N | 1064 | 824 | 809 | 1073 | 1034 | 1022 |

*Note: Robust t-statistics based on bank-level clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

### 4.2 Visualization of Priority Sector Lending (PSL)-Climate Change Interaction Effects

Figures 1 and 2 visualize the interaction effects between climate change and PSL on bank risk, complementing the regression results reported in Table 3. Figure 1 shows that the positive relationship between climate change and ΔCoVaR becomes progressively stronger as banks' exposure to PSL increases, indicating that banks with larger priority sector portfolios contribute more to systemic risk under climate stress. Likewise, Figure 2 shows that the adverse effect of climate change on the Z-score becomes more pronounced at higher PSL levels, implying a greater deterioration in financial stability. Overall, the figures reinforce the regression evidence that directed lending amplifies the transmission of climate-related shocks to the banking sector, with banks having greater PSL exposure exhibiting higher systemic risk contribution and lower financial stability under worsening climate conditions.

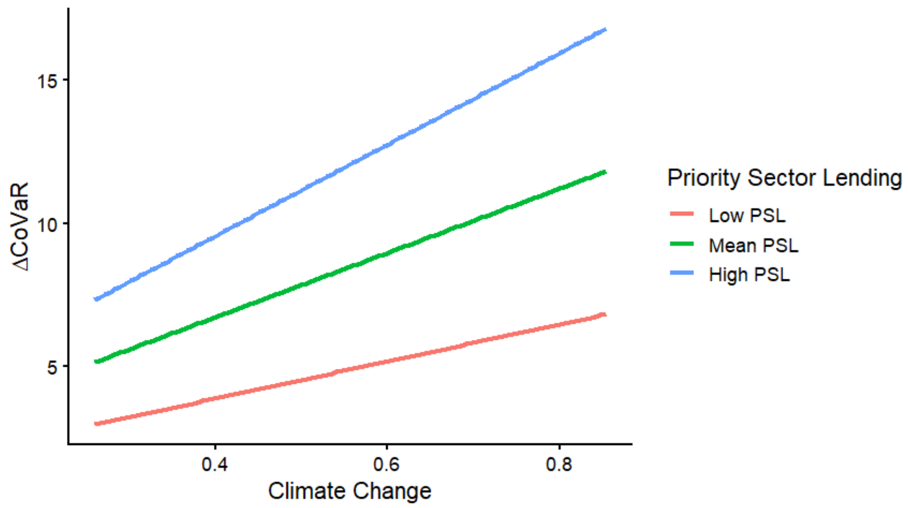


*Figure 1. Interaction effect of climate change and Priority Sector Lending on ΔCoVaR.*

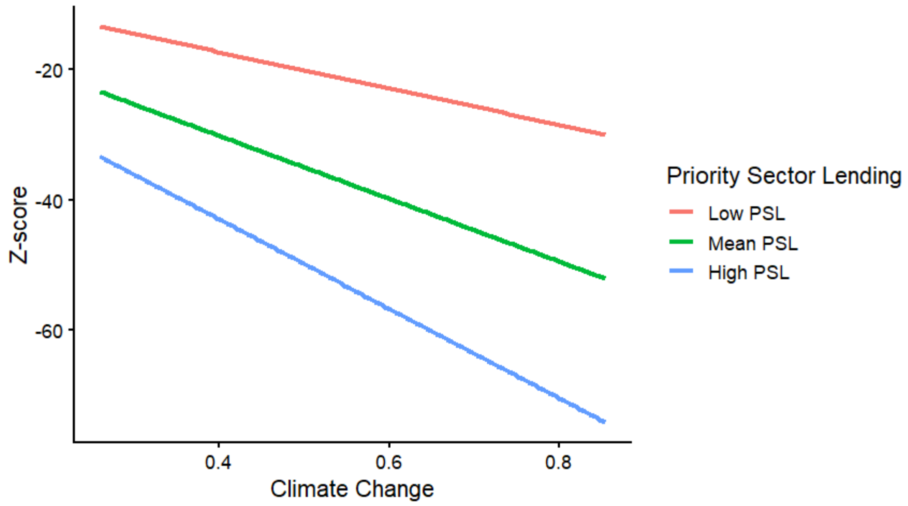


*Figure 2. Interaction effect of climate change and Priority Sector Lending on Z-score.*

### 4.3 Heterogeneity Analysis

Indian banks differ in ownership structure, business objectives, and exposure to priority sector lending. To examine whether climate-related risks vary across bank types, we divide the sample into public sector (PSBs), private, and foreign banks and estimate the impact of climate change and PSL separately for each group, as presented in Table 4.

For PSBs (Panel A), climate change significantly increases bank risk. The positive coefficient of CC in the ΔCoVaR specifications and the negative coefficient in the Z-score models indicate that climate stress raises PSBs' systemic risk contribution while weakening financial stability. This heightened sensitivity is consistent with the dominant role of PSBs in financing priority sectors, particularly agriculture and MSMEs, which are highly exposed to climatic fluctuations. Moreover, PSBs operate under stronger developmental mandates and possess limited flexibility to reallocate credit away from vulnerable sectors when climate risks intensify. Consequently, climate shocks are more readily transmitted to their balance sheets, increasing both risk spillovers and insolvency risk. PSL further aggravates these vulnerabilities, and the significant interaction term suggests that PSBs face the strongest amplification of climate-related risks among all ownership groups, under joint climate and PSL stress.

For private banks (Panel B), climate change alone does not consistently affect ΔCoVaR but significantly reduces Z-scores, indicating a deterioration in financial stability rather than an immediate increase in tail spillover risk. This relatively weaker response may reflect private banks' stronger risk-management practices and more diversified lending portfolios. PSL independently raises ΔCoVaR and lowers Z-scores, confirming that directed lending increases risk exposure even among privately owned institutions. Importantly, the interaction term (CC*PSL) is positive and significant for ΔCoVaR and negative and significant for Z-score, suggesting that PSL amplifies the adverse impact of climate shocks on private banks' risk profiles. This indicates that while private banks may prudently manage climate exposure on a standalone basis, mandated lending to vulnerable sectors weakens their resilience to climate stress.

For foreign banks (Panel C), the direct effect of climate change on risk is generally weaker and less consistent. This may reflect their relatively diversified portfolios and lower exposure to climate-sensitive domestic sectors. However, PSL significantly increases both ΔCoVaR and lowers Z-scores. Notably, the interaction between climate change and PSL remains positive and significant for ΔCoVaR and negative and significant for Z-score, suggesting that even foreign banks are not insulated from climate-related financial vulnerability when exposed to priority sector lending. These findings underscore the role of PSL as an important amplifier through which climate-related risks are transmitted across different ownership structures.

Overall, the heterogeneity results indicate that public sector banks are the most vulnerable to climate-related shocks, while private and foreign banks exhibit comparatively lower standalone exposure. However, the risk-enhancing effect of PSL is prevalent across all ownership categories. The consistently significant interaction between climate change and PSL suggests that directed lending not only increases bank risk directly but also amplifies the transmission of climate-related stress to the banking system.

*Table 4. Heterogeneity analysis based on bank ownership*

| | **Dependent variable: ΔCoVaR** | | **Dependent variable:Z-score** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Panel A: Public Sector Banks (PSBs)*** | | | | |
| CC | .361**<br>(2.43) | .282**<br>(2.09) | -.256*<br>(1.75) | -.572*<br>(-1.80) |
| PSL | .418**<br>(2.58) | .146***<br>(5.14) | -.686***<br>(8.93) | -.280<br>(-0.98) |
| CC*PSL | | 1.456***<br>(3.62) | | -.886***<br>(-4.51) |
| Controls | YES | YES | YES | YES |
| Bank-fixed effects | YES | YES | YES | YES |
| Year- fixed effects | YES | YES | YES | YES |
| $R^2$ | 0.848 | 0.829 | 0.608 | 0.302 |
| F | 119.34*** | 96.13*** | 33.34*** | 9.30*** |
| N | 313 | 313 | 313 | 313 |
| ***Panel B: Private Banks*** | | | | |

| | **Dependent variable: ΔCoVaR** | | **Dependent variable:Z-score** | |
|---|---|---|---|---|
| CC | .131<br>(1.00) | .230<br>(0.04) | -.032<br>(-1.08) | -.458***<br>(-2.63) |
| PSL | .310**<br>(2.56) | .214***<br>(3.34) | -.370***<br>(-3.72) | -.003**<br>(-2.40) |
| CC*PSL | | 1.146***<br>(3.18) | | -.136**<br>(-2.46) |
| Controls | YES | YES | YES | YES |
| Bank-fixed effects | YES | YES | YES | YES |
| Year- fixed effects | YES | YES | YES | YES |
| $R^2$ | 0.412 | 0.439 | 0.365 | 0.551 |
| F | 14.29*** | 14.73*** | 10.83*** | 23.05*** |
| N | 278 | 278 | 278 | 278 |
| ***Panel C: Foreign Banks*** | | | | |
| CC | .128<br>(0.35) | .350*<br>(1.79) | .310<br>(0.58) | -.127<br>(-0.35) |
| PSL | .274***<br>(7.00) | .146***<br>(3.80) | -.205***<br>(-4.97) | -.076***<br>(-3.52) |
| CC*PSL | | .985**<br>(2.08) | | -.367**<br>(-2.08) |
| Controls | YES | YES | YES | YES |
| Bank-fixed effects | YES | YES | YES | YES |
| Year- fixed effects | YES | YES | YES | YES |
| $R^2$ | 0.216 | 0.184 | 0.182 | 0.135 |
| F | 8.29*** | 2.879*** | 12.35*** | 14.54*** |
| N | 443 | 218 | 443 | 431 |

*Note: Robust t-statistics based on bank-level clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

### 4.4 Further Analysis: Role of Diversification

Climate change can increase bank risk by exposing borrowers, industries, and regions to correlated shocks, thereby weakening repayment capacity and increasing the likelihood of loan defaults. In such an environment, diversification may serve as an important risk-management mechanism. By spreading exposures across income sources and asset classes, banks can reduce concentration risk and enhance their ability to absorb adverse shocks. While some studies argue that diversification may increase complexity and monitoring costs (Stiroh, 2004), the prevailing view suggests that a broader income and asset base improves resilience, profitability, and stability, particularly during periods of economic stress (Laeven & Levine, 2007).

In the context of climate change, diversification is expected to mitigate risk by reducing dependence on climate-sensitive sectors and limiting the transmission of localized shocks to bank balance sheets. Income diversification can stabilize cash flows through greater reliance on non-interest income (Albertazzi & Gambacorta, 2009), while asset diversification can reduce vulnerability arising from concentrated lending exposures (Acharya et al., 2006). Accordingly, we examine whether income and asset diversification weaken the adverse impact of climate change on bank risk.

Following previous studies (Abuzayed et al., 2018), income diversification (Income_Div) is measured using the Adjusted Herfindahl-Hirschman Index:

$$Income\_Div = 1- [(\frac{NII}{NOI})^2 + (\frac{NON}{NOI})^2] \tag{9}$$

Where NOI = NII + NON, and NOI, NII and NON denote Net Operating Income, Net Interest Income, and Non-Interest Income, respectively.

Asset diversification (Asset_Div) is measured following Laeven and Levine (2007):

$$Asset\_Div = 1- [\frac{Net\ loans - Other\ Earning\ Assets}{Total\ Earning\ Assets}] \tag{10}$$

Where Other Earning Assets include securities and investments, and Total Earning Assets is the sum of net loans and other earning assets. Both Income_Div and Asset_Div range between 0 and 1, with higher values indicating greater diversification.

Table 5 reports the role of diversification in the context of climate change on bank risk. Panels A and B report the moderating role of income and asset diversification on the relationship between climate change and bank risk, measured by ΔCoVaR and Z-score.

*Table 5. Role of Diversification on the relationship between climate change and bank risks*

| | **(1) ΔCoVaR** | **(2) ΔCoVaR** | **(3) Z-score** | **(4) Z-score** |
|---|---|---|---|---|
| ***Panel A: Effect of Income Diversification*** | | | | |
| CC | .067*** (2.60) | 1.478* (1.84) | -.052*** (-3.20) | .345 (1.05) |
| Income_Div | -5.87** (-1.96) | -7.580*** (-2.62) | 3.689*** (4.89) | 1.774*** (3.28) |
| CC*Income_Div | | -3.368* (-1.74) | | 2.592* (1.92) |
| Controls | YES | YES | YES | YES |
| Bank-fixed effects | YES | YES | YES | YES |
| Year- fixed effects | YES | YES | YES | YES |
| $R^2$ | 0.545 | 0.677 | 0.512 | 0.568 |
| F | 64.73*** | 86.54*** | 56.63*** | 54.20*** |
| N | 1064 | 1064 | 824 | 824 |
| ***Panel B: Effect of Asset Diversification*** | | | | |
| CC | .114*** (2.76) | .641*** (6.93) | -.289*** (-4.66) | -.193*** (-6.02) |
| Asset_Div | -9.428*** (-10.59) | -8.805*** (-2.58) | 7.278*** (6.02) | 7.393*** (4.59) |
| CC*Asset_Div | | -.675*** (8.17) | | .421* (1.65) |

| | (1)<br>**ΔCoVaR** | (2)<br>**ΔCoVaR** | (3)<br>**Z-score** | (4)<br>**Z-score** |
|---|---|---|---|---|
| Controls | YES | YES | YES | YES |
| Bank-fixed effects | YES | YES | YES | YES |
| Year- fixed effects | YES | YES | YES | YES |
| $R^2$ | 0.610 | 0.677 | 0.529 | 0.621 |
| F | 84.36*** | 86.54*** | 60.64*** | 67.59*** |
| N | 1034 | 1034 | 809 | 809 |

*Note: Robust t-statistics computed using bank-level clustered standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

In Panel A, Column (1) shows that climate change increases banks' systemic risk contribution (ΔCoVaR), while Column (3) indicates that it reduces Z-scores, reflecting weakened financial stability. Income diversification itself significantly lowers ΔCoVaR and raises Z-scores, suggesting that a broader mix of interest and non-interest income reduces risk concentration and enhances banks' shock-absorbing capacity. Importantly, the interaction term (CC*Income_Div) is negative and significant in the ΔCoVaR specification and positive and significant in the Z-score model. This implies that income diversification mitigates the adverse impact of climate change by reducing banks' reliance on climate-sensitive lending activities and providing alternative revenue streams during periods of climate-related stress.

Panel B reports results for asset diversification. Columns (1) and (3) confirm that climate change raises risk (higher ΔCoVaR and lower Z-score), while asset diversification independently reduces ΔCoVaR and increases Z-scores. The interaction term (CC*Asset_Div) is negative and significant for ΔCoVaR and positive and significant for Z-score, indicating that asset diversification cushions banks against climate-induced instability. By spreading exposures across sectors and asset classes, diversified portfolios reduce concentration in climate-sensitive borrowers and limit the extent to which climate shocks are transmitted to bank balance sheets. As a result, asset-diversified banks are better positioned to absorb losses arising from climate-related disruptions.

Overall, the results consistently show that diversification, whether through income sources or asset composition, not only reduces bank risk directly but also weakens the transmission of climate-related stress to the banking system. These findings suggest that diversification serves as an effective resilience mechanism, enhancing banks' capacity to withstand the financial consequences of climate change.

### 4.5 Endogeneity Checks

To address potential endogeneity arising from reverse causality between climate change and bank risk, we use the two-step least squares method, following Song et al. (2024), and employ the one-period lag of climate change (CC) as an instrumental variable. As reported in Table 6, the first-stage results (Column 1) show that lagged CC is a strong predictor of current climate change at the 1% significance level. The second-stage estimates (Columns 2–7), based on the instrumented climate change variable ($\widehat{CC}$), remain consistent with the baseline findings. Climate change and PSL continue to increase bank risk, while their interaction further amplifies climate-related financial vulnerability. Likewise, the interaction terms involving income and asset diversification remain significant, confirming their mitigating role against climate-induced bank risk. Furthermore, the first-stage F-statistics exceed the conventional threshold of 10, indicating that the instrument is sufficiently strong and alleviating concerns regarding weak instruments. Overall, the results confirm that the main findings are robust after addressing potential endogeneity.

*Table 6. Endogeneity- Instrumental Variable Approach*

| | **First Stage** | **Second Stage** | | | | | |
|---|---|---|---|---|---|---|---|
| | | PSL as Moderator | | Income Diversification as Moderator | | Asset Diversification as Moderator | |
| | (1)<br>CC | (2)<br>ΔCoVaR | (3)<br>Z-score | (4)<br>ΔCoVaR | (5)<br>Z-score | (6)<br>ΔCoVaR | (7)<br>Z-score |
| *Instrumental Variable: $CC_{t-1}$* | | | | | | | |
| $CC_{t-1}$ | .414***<br>(7.63) | | | | | | |
| Predicted CC ($\widehat{CC}$) | | .349***<br>(8.81) | -.675***<br>(-2.85) | .398**<br>(2.53) | -.126***<br>(-8.58) | .229***<br>(10.82) | -.031***<br>(-2.71) |
| PSL | | .206*<br>(1.69) | -.043***<br>(-3.46) | | | | |
| CC*PSL | | .239***<br>(3.06) | -.079***<br>(-6.74) | | | | |
| Income_Div | | | | -.176***<br>(-4.59) | .026*<br>(1.94) | | |
| CC*Income_Div | | | | -1.127***<br>(-2.95) | .108***<br>(6.23) | | |
| Asset_Div | | | | | | -.209***<br>(-2.78) | .003***<br>(7.08) |
| CC*Asset_Div | | | | | | -.293***<br>(-10.94) | .088***<br>(8.96) |
| Controls | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES |
| Bank FE | YES | YES | YES | YES | YES | YES | YES |
| R-squared | 0.393 | 0.209 | 0.273 | 0.451 | 0.488 | 0.520 | 0.497 |
| F-statistics | 129.36*** | 62.21*** | 88.21*** | 55.61*** | 64.41*** | 73.39*** | 66.89*** |
| Observations | 1081 | 1034 | 806 | 1034 | 806 | 1034 | 806 |

*Note: Robust t-statistics computed using bank-level clustered standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

### 4.6 Robustness Tests

We first examined multicollinearity using Variance Inflation Factors (VIFs). All VIF values were below the conventional threshold of 10, indicating that multicollinearity is unlikely to affect the estimation results. We then assessed the robustness of our findings using an alternative measure of climate risk and an alternative estimation technique. Specifically, we replace the baseline climate change index with the ND-GAIN Index, incorporating its two widely used components—readiness and vulnerability—as alternative climate risk proxies. Since the ND-GAIN indices are reported annually at the national level, each bank-year observation is matched to the corresponding year's values. Table 7 reports the results, which remain qualitatively consistent with the baseline estimates, indicating that our findings are robust to alternative measures of climate risk. We use the two-step System GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998) to conduct this analysis, which effectively addresses potential endogeneity arising from unobserved heterogeneity, simultaneity, and the dynamic nature of bank risk. The results continue to support the main findings, while the Sargan test fails to reject the null hypothesis of instrument validity, confirming that the instruments are exogenous. Overall, these robustness checks strengthen the reliability of our findings.

*Table 7. Robustness Test using System GMM*

| | **(1) ΔCoVaR** | **(2) ΔCoVaR** | **(3) Z-score** | **(4) Z-score** |
|---|---|---|---|---|
| *Replacing CC by Vulnerability* | | | | |
| Vulnerability | 4.728*** (9.60) | 7.325*** (4.36) | 2.829*** (15.90) | 2.740*** (3.29) |
| PSL | .002*** (4.49) | .005** (2.22) | .001*** (4.14) | .022*** (3.50) |
| Vulnerability*PSL | | .099** (2.00) | | .042*** (3.41) |
| Lagged Dependent Variable | YES | YES | YES | YES |
| Controls | YES | YES | YES | YES |
| Sargan Test | 25.33 | 26.40 | 25.43 | 30.47 |
| AR (1) Test | 0.35 | -0.28 | -0.36* | -1.34 |
| AR (2) Test | 1.23 | 0.58 | -2.08 | -0.90 |
| Wald Test | 206.58*** | 112.39*** | 188.40*** | 153.22*** |
| N | 1064 | 1034 | 824 | 809 |
| *Replacing CC by Readiness* | | | | |
| Readiness | -.146*** (-4.53) | -.081** (-2.30) | -.083*** (-5.25) | .082 (1.37) |
| PSL | .002*** (5.22) | .009*** (3.36) | .001*** (4.84) | .005*** (4.21) |
| Readiness*PSL | | -.016** (-2.46) | | -.011*** (-3.45) |
| Lagged Dependent Variable | YES | YES | YES | YES |
| Controls | YES | YES | YES | YES |
| Sargan Test | 25.18 | 28.27 | 23.23 | 32.10 |
| AR (1) Test | -3.00* | -1.29 | -2.16** | -2.20** |
| AR (2) Test | 1.53 | -1.03 | -0.72 | 2.63 |
| Wald Test | 296.83*** | 478.43*** | 387.06*** | 521.53*** |
| N | 1064 | 1034 | 824 | 809 |

*Note: Robust z-statistics computed using bank-level clustered standard errors are reported in parentheses. All models include bank and year fixed effects. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

## 5. Conclusion

This study examines the impact of climate change on bank risk in India and investigates the roles of Priority Sector Lending (PSL) and diversification in shaping banks' vulnerability and resilience. Using a panel of 80 Indian commercial banks over the period 2005-2020, the findings show that climate change significantly increases bank risk by raising banks' systemic risk contribution and weakening financial stability. PSL independently increases bank risk and further amplifies the adverse effects of climate change, indicating that directed lending to climate-sensitive sectors intensifies the climate-related financial risks within banks. The heterogeneity analysis reveals that public sector banks are the most vulnerable to the combined effects of climate stress and PSL exposure, although similar amplification effects are observed among private and foreign banks. In contrast, both income and asset diversification reduce bank risk and weaken the transmission of climate-related shocks.

These findings carry important policy implications. As climate change becomes increasingly material for financial institutions, regulators should incorporate climate considerations into supervisory and risk-management frameworks. While PSL remains crucial for achieving developmental objectives, its implementation should be accompanied by stronger climate-risk assessment, monitoring, and mitigation mechanisms, particularly in climate-sensitive sectors. The results also highlight the importance of encouraging diversification strategies that reduce concentration risk and strengthen banks' resilience to climate-related disruptions. Overall, balancing developmental lending mandates with financial stability considerations will be critical for enhancing the resilience of banking systems in climate-vulnerable emerging economies.

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