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Climate Change and Bank Performance in Asia: A Static Panel Analysis

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Abstract: *This study investigates how climate anomalies influence bank profitability across thirty-one Asian economies using static panel estimators and harmonised data from 2007 to 2019. Asia's exposure to heatwaves, rainfall deviations, temperature shifts and rising carbon emissions generates climate-induced pressures that shape productivity, credit quality and economic activity. Despite growing interest in climate–finance linkages, cross-country evidence on profitability remains limited. Static estimators—Pooled OLS, Random Effects and Fixed Effects—are employed because they allow transparent identification of contemporaneous climate effects without imposing dynamic adjustment structures that are not the focus of this study. Using the inverse hyperbolic sine transformation of ROA, the analysis evaluates four climate indicators while controlling for bank-specific and macroeconomic factors. Results show that heatwave anomalies reduce profitability, precipitation anomalies exert a positive influence likely reflecting moderate rainfall benefits, carbon emissions are positively associated with returns in more industrialised economies, and maximum temperature anomalies display no short-run significance. Across all models, net interest margin, non-interest income and cost efficiency remain the dominant operational drivers of profitability. Overall, the findings demonstrate that climate variability has measurable implications for banking outcomes in Asia, while internal bank conditions remain the strongest determinants of performance.*

Keywords: Bank Performance, Climate Anomalies, Profitability, Static Panel Models, Asia

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1. Introduction

Climate change has become a central macro-financial concern for Asian economies because climatic variability increasingly shapes sectoral activity, credit conditions and overall economic performance. The region experiences recurrent heatwaves, shifting monsoon patterns, drought episodes and rising carbon emissions, all of which disrupt productivity and income generation. These disruptions have direct implications for banks, which serve as the primary financial intermediaries in most Asian economies. Understanding how climate anomalies influence bank profitability is therefore essential for effective financial planning, credit-risk management and climate-aligned supervisory practices.

Although research on climate–finance linkages is expanding rapidly, empirical evidence directly connecting climate anomalies to bank profitability remains limited, particularly in cross-country contexts. Much of the existing work focuses on how temperature and precipitation variability affect labour productivity, agricultural output and household income, thereby elevating financial stress and borrower default risks (Dell et al., 2014; He & Ma, 2021; Pastor-Sanz et al., 2025). Other studies highlight the credit-risk implications of extreme heat and weather-driven disruptions, which weaken bank soundness and increase non-performing loan ratios, especially in economies with large climate-sensitive sectors (Monasterolo, 2020; Xu & Zhang, 2025). At the same time, the literature on transition risks documents that carbon-intensive activities influence credit allocation, borrower performance and long-term vulnerability due to policy tightening, carbon pricing and stranded-asset risks (Bolton & Kacperczyk, 2023; Delis et al., 2024; Semieniuk et al., 2020). Despite these insights, the profitability channel remains comparatively underexplored within the Asian region.

To address this gap, the present study examines the contemporaneous impact of climate anomalies on bank profitability across thirty-one Asian economies from 2007 to 2019 using static panel estimators. Four forms of climatic variability—heatwave anomalies, precipitation anomalies, maximum temperature deviations and carbon emissions—are analysed together with bank-specific and macroeconomic determinants to isolate institutional and economic influences.

The analytical framework is grounded in three complementary theoretical perspectives. The Physical Risk Transmission Theory explains how extreme climatic events reduce productivity and borrower solvency, thereby elevating credit risk and lowering bank returns. Transition Risk Theory highlights how profitability in carbon-intensive economies reflects both short-term industrial advantages and long-term exposure to regulatory realignment. In parallel, the Bank Intermediation–Profitability Framework emphasises the central role of net interest margins, income diversification and cost efficiency in determining bank performance. Together, these theoretical foundations offer a coherent basis for interpreting the climate–profitability relationship in Asia.

Accordingly, the central research question guiding this study is: To what extent does climate change, captured through multiple climate anomalies, affect bank performance across Asian economies after controlling for bank-specific and macroeconomic conditions?

2. Literature Review

Climate change has become an important macro-financial issue because physical and transition risks increasingly shape economic activity, credit conditions, and the financial health of institutions. Physical climate shocks—especially extreme temperatures, rainfall deviations, and climate-induced disruptions—affect labour productivity, agricultural output, and household income, thereby influencing credit quality and bank performance. Empirical evidence shows that temperature and precipitation anomalies weaken economic output, disrupt production, and reduce consumption and agricultural yields, creating stress for borrowers and elevating repayment risks (Dell et al., 2014; He & Ma, 2021). These effects are especially pronounced in economies reliant on climate-sensitive sectors such as agriculture and manufacturing, where productivity losses translate into higher credit risk and weaker banking outcomes (Pastor-Sanz et al., 2025).

Heatwave anomalies—increasingly common across Asia—have been shown to reduce labour efficiency, depress firm output, and elevate firm-level financial distress (Monasterolo, 2020). Prolonged heat exposure weakens repayment capacity and has been linked to higher non-performing loan ratios and reduced bank soundness (Xu & Zhang, 2025). Similarly, precipitation variability affects rural incomes and the creditworthiness of agricultural borrowers. Both excessive rainfall and drought conditions disrupt crop production, hamper business continuity, and generate liquidity pressures that raise default probabilities (Zittis et al., 2022; Peters, 2024). These channels demonstrate how physical climate variability transmits directly to profitability outcomes through borrower vulnerabilities.

Transition risks originate from tightening climate policies, carbon pricing, and the structural realignment toward low-carbon economies. Evidence shows that banks price carbon risk into lending rates, and borrowers in carbon-intensive sectors face higher financing costs and increasing stranded-asset risk (Delis et al., 2024). Financial markets also impose return premia on high-emission firms to compensate for transition uncertainty, affecting both valuations and bank exposures (Bolton & Kacperczyk, 2023). Although lending to carbon-intensive sectors may yield short-term profitability advantages, long-term exposure increases vulnerability to regulatory tightening and technological shifts (Semieniuk et al., 2020). These findings suggest that carbon emissions serve as both an economic indicator and a potential source of financial fragility.

Recent literature also highlights that climate shocks generate heterogeneous banking effects depending on geography, economic structure, and institutional resilience. Heat-sensitive economies experience sharper productivity losses and stronger credit risk transmission (White et al., 2023; Wang et al., 2024). In agricultural regions, rainfall and drought conditions have significant implications for rural banking stability and portfolio performance. Temperature anomalies, by contrast, tend to produce slower-moving cumulative effects that may influence long-term solvency rather than short-term profitability (Box et al., 2019).

From a methodological perspective, static panel estimators such as Pooled OLS, Random Effects, and Fixed Effects have been widely used in climate–finance studies because they provide transparent and interpretable estimates suitable for cross-country comparisons (Ben-Ammar, 2025). These models allow researchers to isolate contemporaneous climate effects while controlling for institutional and macroeconomic characteristics. Recent empirical studies employing similar frameworks show that climate variables influence profitability through productivity channels, credit-risk effects, and structural economic linkages, while internal bank drivers—margins, diversification, and cost efficiency—remain central determinants of performance (Khalaf et al., 2024; Balaylar et al., 2024).

Overall, the literature indicates that climate anomalies influence bank outcomes through multiple economic and financial channels. Physical shocks affect income and credit quality, transition risks influence borrower performance and valuation, and institutional characteristics determine the resilience of banks to climate pressures. However, direct cross-country evidence on profitability impacts remains limited, especially within Asia. This study extends the literature by incorporating multiple climate indicators, harmonised cross-country data, and a transparent static panel methodology to assess how climate variability affects bank profitability across diverse Asian economies.

3. Data and Variables

This study employs a country-level panel dataset covering thirty-one Asian economies over the period 2007 to 2019. The final sample consists of 394 country-year observations. Countries were retained only when complete annual data were available for bank profitability, climate indicators, emissions, and macroeconomic variables across the study period. This selection approach ensures a coherent and comparable panel suitable for econometric analysis.

Bank profitability is measured using return on assets (ROA), obtained from the Global Financial Development Database. ROA serves as the primary indicator of operational performance, reflecting how efficiently banks generate earnings from their asset base. Because ROA includes both zero and negative values, the inverse hyperbolic sine transformation is applied to preserve its distributional properties while stabilising variance.

Four climate indicators capture the study's main explanatory variables: heatwave anomalies (hd35), precipitation anomalies, maximum temperature anomalies (tasmax), and carbon dioxide emissions. Heat and precipitation anomalies are derived from long-term climatic baselines and represent deviations from each country's historical climate patterns. These anomaly measures allow cross-country comparison despite differing geographic and climatic conditions. Carbon emissions are sourced from the World Development Indicators and expressed in natural logarithms due to their strictly positive and right-skewed distribution.

To isolate the effect of climate conditions on profitability, the empirical models incorporate several bank-specific and macroeconomic controls. Bank-level variables include the net interest margin, non-interest income ratio, and cost-to-income ratio, each of which captures structural dimensions of bank revenue and efficiency. Macroeconomic variables include manufacturing value added, private credit to the private sector, and GDP growth. Variables with strictly positive values are transformed using natural logarithms, while GDP growth is treated using an inverse hyperbolic sine transformation to accommodate negative observations.

The resulting dataset is structured as an unbalanced but highly complete annual panel. All retained variables are available across the full period for each of the thirty-one countries included. This structure supports the use of static panel estimators—Pooled OLS, Random Effects, and Fixed Effects—which form the basis for analysing the contemporaneous relationship between climate anomalies and bank profitability in Asia.

4. Methodology

This study applies static panel estimators to examine the contemporaneous effects of climate anomalies on bank profitability across thirty-one Asian economies from 2007 to 2019. Static models are selected because they offer transparent interpretation, maintain cross-country comparability, and avoid the identification complexities associated with dynamic structures (Ben-Ammar, 2025). The empirical objective is to assess the immediate association between climate variability and banking outcomes without imposing long-run adjustment dynamics.

Bank profitability is measured using the inverse hyperbolic sine transformation of return on assets, which preserves the behaviour of zero and negative observations while reducing skewness. Four climate indicators—heatwave anomalies, precipitation anomalies, maximum temperature deviations, and carbon emissions—serve as the primary explanatory variables. Heatwave and precipitation anomalies are expressed using inverse hyperbolic sine transformations due to their wide dispersion and the presence of zero-bounded values. Carbon emissions are treated in natural logarithms because they are strictly positive and right-skewed. Bank-specific determinants, including net interest margin, non-interest income, and cost-to-income ratio, are incorporated to control for revenue structure and operational efficiency. Macroeconomic controls encompass GDP growth, manufacturing value added, and private credit depth. All strictly positive variables are log-transformed to improve distributional symmetry and comparability across heterogeneous economies.

The empirical specification models bank profitability, measured through the inverse hyperbolic sine transformation of return on assets, as a function of climate anomalies, bank-specific characteristics, and macroeconomic determinants. The general form of the model is expressed as:

$$Ln\_roa_{it} = \alpha + \beta 1 Climateit + \beta 2 Bankit + \beta 3 Macroit + \mathcal{u}i + \varepsilon it \qquad \text{Eq. (1)}$$

where i denotes the country and t denotes the year. The term $\mathcal{u}i$ captures unobserved, time-invariant country-specific effects, while $\mathcal{E}it$ represents the idiosyncratic error term. The climate variable vector includes heatwave anomalies, precipitation anomalies, maximum temperature anomalies, and carbon emissions. Bank-specific controls capture structural characteristics related to revenue and efficiency, while macroeconomic variables represent broader country-level economic conditions.

Three estimators are applied: Pooled Ordinary Least Squares, Random Effects Models, and Fixed Effects Models. Pooled OLS provides a baseline without accounting for country-specific heterogeneity. Random effects allow unobserved components to vary across countries under the assumption of no correlation with regressors, while fixed effects relax this assumption by isolating within-country variation over time. Model selection between random and fixed effects is guided by the Hausman specification test, although all three estimators are reported for completeness and transparency. This approach is consistent with recent cross-country climate–finance studies using panel structures to isolate contemporaneous effects (Brik, 2024).

Dynamic GMM is not used because the analysis focuses on contemporaneous climate effects, and the inclusion of lagged profitability would complicate identification and weaken the clarity of short-run climate–banking relationships.

All regressions are estimated using heteroskedasticity-robust standard errors clustered at the country level to address serial correlation and cross-sectional heterogeneity, following best practice in macro-financial panel analysis (Sitnicka et al., 2025). This estimation strategy ensures that coefficient inference remains reliable despite the structural diversity across Asian economies. The combined use of multiple estimators, appropriate transformations, and robust standard errors provides a coherent framework for identifying the immediate influence of climate anomalies on bank profitability.

5. Results and Findings

This section presents the empirical findings examining the impact of climate variability on bank profitability across thirty-one (31) Asian economies from 2007 to 2019. The analysis begins with descriptive statistics, followed by correlation diagnostics, and proceeds to the static estimations using Pooled OLS, Random Effects Models (REM), and Fixed Effects Models (FEM). The results are evaluated based on statistical significance, consistency across model specifications, and economic interpretability. A robustness assessment using ROE is included to verify the stability of the profitability–climate relationship.

5.1 Descriptive Statistics

Table 2 reports the descriptive statistics for all variables used in the estimation. Bank profitability (ln_roa) displays moderate variation across countries, with values ranging between –2.854 and 2.788, indicating the presence of both highly profitable and financially distressed banking systems. Climate indicators exhibit substantial dispersion: precipitation anomalies (ln_precip) show the widest range, reflecting the extreme heterogeneity of climate conditions across Asia. Maximum temperature anomalies (ln_tasmax) and heatwave deviations (ln_hd35) also demonstrate notable variability, indicating that physical climate shocks are not uniformly distributed across the region.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln_roa	394	1.001	0.642	−2.854	2.788
ln_hd35	394	0.000	2.437	−11.709	11.481
ln_precip	394	0.000	29.518	−101.162	148.529
ln_co2	394	1.307	1.301	−2.294	3.704
ln_tasmax	394	0.000	1.395	−5.393	6.407
ln_nim	392	1.246	0.543	−1.918	3.061
ln_noninin	391	3.419	0.353	2.265	4.343
ln_ctincome	391	3.844	0.253	2.923	4.468
ln_manu	374	2.548	0.520	1.357	3.452
ln_gdpg	393	1.875	1.267	−4.026	3.931
ln_creprivbank	375	3.928	0.718	1.536	5.540

Among the bank-specific variables, net interest margins (ln_nim) and non-interest income (ln_noninin) show relatively stable distributions, while cost-to-income ratios (ln_ctincome) exhibit wider dispersion, suggesting differing levels of managerial efficiency across banking systems. Macroeconomic indicators such as manufacturing share of GDP (ln_manu) and economic growth (ln_gdpg) similarly display significant cross-country variability. Overall, the descriptive patterns suggest a diverse regional landscape, both economically and climatically, making static panel methods well suited for isolating climate–profitability relationships.

5.2 Correlation Analysis

Table 3 reports the correlation matrix for all eleven variables used in the ROA estimations, namely profitability (ln_roa), heatwave anomalies (ln_hd35), precipitation anomalies (ln_precip), carbon emissions (ln_co2), maximum temperature anomalies (ln_tasmax), net interest margin (ln_nim), non-interest income (ln_noninin), cost-to-income ratio (ln_ctincome), manufacturing value added (ln_manu), economic growth (ln_gdpg), and private credit (ln_creprivbank). The correlations among the four climate indicators are generally low, indicating that ln_hd35, ln_precip, ln_co2, and ln_tasmax capture different dimensions of climate variability rather than reflecting overlapping climatic phenomena. This suggests that multicollinearity among the climate measures is unlikely to undermine the identification of climate effects.

Table 3: Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	1.000										
(2)	-0.021	1.000									
(3)	0.096*	-0.078	1.000								
(4)	0.114**	-0.006	0.023	1.000							
(5)	-0.009	0.036	-0.136***	0.008	1.000						
(6)	0.366***	0.019	0.019	-0.242***	-0.067	1.000					
(7)	0.062	-0.049	0.009	0.113**	0.033	-0.024	1.000				
(8)	-0.289***	-0.072	0.019	-0.373***	-0.028	0.232***	0.132***	1.000			
(9)	-0.067	0.021	-0.007	-0.162***	-0.013	-0.249***	-0.213***	0.011	1.000		
(10)	0.107**	-0.073	0.026	-0.109**	0.032	0.089*	0.063	0.031	0.242***	1.000	
(11)	-0.111**	0.065	0.031	0.389***	-0.009	-0.439***	-0.070	-0.191***	0.092*	-0.134***	1.000

Profitability shows moderate positive correlations with ln_nim and ln_noninin, consistent with standard banking theory where margins and diversified income enhance returns. ln_ctincome is negatively related to ln_roa, indicating that higher operational costs relative to income weaken profitability across Asian banks. The remaining climate variables display small but non-zero correlations with ln_roa, suggesting modest but meaningful climate–profitability linkages that warrant econometric examination.

The association between ln_manu, ln_gdpg, and ln_creprivbank with profitability is generally weak, implying that macroeconomic conditions and financial deepening exert limited direct correlation with bank returns at the descriptive level. Importantly, the correlation structure demonstrates no evidence of problematic collinearity among the explanatory variables. The climate indicators retain their distinct informational content, while bank-specific and macroeconomic variables do not exhibit excessively high pairwise correlations that could compromise model estimation. Overall, the correlation diagnostics provide confidence that the multivariate regression framework is well specified and capable of isolating the independent influence of climate variability on bank profitability.

5.3 Static Estimation Results for ROA

Table 4 reports the results of eight static panel specifications progressively incorporating climate variables, bank-specific controls, and macroeconomic fundamentals. Across all models, the estimations are reported using heteroskedasticity-robust standard errors. Model selection diagnostics, including the Breusch–Pagan Lagrange Multiplier test and the Hausman test, indicate that Random Effects is preferred in several cases; however, all three estimators (OLS, REM, and FEM) are interpreted to ensure robustness and comparability.

Table 4: Static Estimation Results for ROA

Variable	Pooled OLS	REM	FEM	Pooled OLS	REM	FEM
		Model 1			Model 2	
Constant	0.928***	0.926***	0.874***	0.928***	0.926***	0.875***
	(0.043)	(0.085)	(0.207)	(0.043)	(0.085)	(0.208)
ln_hd35	–0.004	–0.003	–0.003	–0.004	–0.004	–0.003
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ln_precip	0.002**	0.002***	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

ln_co2	0.055***	0.060	0.097	0.055***	0.060	0.097
	(0.021)	(0.042)	(0.159)	(0.021)	(0.042)	(0.159)
ln_tasmax				0.002	0.002	0.001
				(0.024)	(0.025)	(0.025)
ln_nim						
ln_noninin						
ln_ctincome						
ln_manu						
ln_gdpg						
ln_crepribank						
R^2	0.022	0.022 (overall)	0.021 (overall)	0.022	0.022 (overall)	0.021 (overall)
Adj R^2	0.015			0.012		
F-statistic / Wald χ^2	F = 3.40**	χ^2 = 8.72**	F = 2.58*	F = 2.54	χ^2 = 8.78	F = 1.99
BP & LM test					χ^2 = 85.57*	
Hausman Test		χ^2 = 0.08 (p = 0.779)			χ^2 = 0.08 (p = 0.783)	
No. of Obs	394	394	394	394	394	394

Table 4: Continued

Variable	Pooled OLS	REM	FEM	Pooled OLS	REM	FEM
		Model 3			Model 4	
Constant	0.266***	0.295*	0.282	–0.131	–0.607**	–1.066**
	(0.086)	(0.169)	(0.285)	(0.328)	(0.291)	(0.463)
ln_hd35	−0.008	−0.007	−0.007	–0.009	–0.007	–0.007
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
ln_precip	0.002**	0.002**	0.002*	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln_co2	0.103***	0.103***	0.139	0.103***	0.102***	0.125
	(0.021)	(0.038)	(0.137)	(0.021)	(0.035)	(0.134)
ln_tasmax	0.012	0.012	0.011	–0.010	–0.010	–0.010
	(0.025)	(0.029)	(0.029)	(0.015)	(0.019)	(0.021)
ln_nim	0.487***	0.464***	0.437**	0.517***	0.532***	0.583***
	(0.062)	(0.115)	(0.203)	(0.053)	(0.092)	(0.192)
ln_noninin				0.108 (0.093)	0.242***	0.350***
					(0.078)	(0.089)
ln_ctincome						
ln_manu						
ln_gdpg						
ln_crepribank						
R^2	0.184	0.183 (overall)	0.174 (overall)	0.220	0.216 (overall)	0.208 (overall)
Adj R^2	0.171			0.210		
F-statistic / Wald χ^2	F = 16.39*	χ^2 = 23.45*	F = 1.88	F =17.21***	χ^2 = 55.99***	F = 4.98***
BP & LM test		χ^2 = 85.57*			χ^2 = 99.39***	
Hausman Test		χ^2 = 4.65 (p = 0.325)			χ^2 = 10.09 (p = 0.121)	
No. of Obs	392	392	392	390	390	390

Table 4: Continued

Variable	Pooled OLS	REM	FEM	Pooled OLS	REM	FEM
		Model 5			Model 6	
Constant	3.233***	2.841***	1.810**	2.705***	2.161***	1.859
	(0.433)	(0.506)	(0.766)	(0.411)	(0.700)	(1.128)
ln_hd35	–0.015*	–0.014	–0.012	–0.019**	–0.018*	–0.014
	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	(0.009)
ln_precip	0.002**	0.001**	0.001**	0.002**	0.002**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln_co2	0.035**	0.039**	0.042	0.046**	0.055*	0.143
	(0.018)	(0.019)	(0.140)	(0.021)	(0.028)	(0.152)
ln_tasmax	–0.013	–0.013	–0.013	–0.008	–0.007	–0.007
	(0.014)	(0.012)	(0.015)	(0.015)	(0.011)	(0.015)
ln_nim	0.586***	0.576***	0.583***	0.637***	0.616***	0.613***
	(0.057)	(0.076)	(0.193)	(0.062)	(0.097)	(0.212)
ln_noninin	0.229***	0.254***	0.339***	0.275***	0.299***	0.375***
	(0.087)	(0.075)	(0.087)	(0.090)	(0.078)	(0.096)
ln_ctincome	–0.982***	–0.900***	–0.710***	–0.998***	–0.869***	–0.668***
	(0.099)	(0.127)	(0.168)	(0.105)	(0.141)	(0.180)
ln_manu				0.141*	0.132	–0.199
				(0.074)	(0.101)	(0.295)
ln_gdpg						
ln_crepribank						
R^2	0.351	0.350 (overall)	0.334 (overall)	0.369	0.366 (overall)	0.263 (overall)
Adj R^2	0.339			0.355		
F-statistic / Wald χ^2	F = 24.37***	χ^2 = 123.77***	F = 7.71***	F = 20.18***	χ^2 = 98.49***	F = 5.92***
BP & LM test		χ^2 = 22.52***			χ^2 = 18.94***	
Hausman Test		χ^2 = 16.86 (p = 0.018)			χ^2 = 7.73 (p = 0.460)	
No. of Obs	390	390	390	370	370	370

Table 4: Continued

Variable	Pooled OLS	REM	FEM	Pooled OLS	REM	FEM
		Model 7			Model 8	
Constant	2.658***	2.245***	2.298**	2.938***	2.488***	2.602
	(0.416)	(0.652)	(1.102)	(0.490)	(0.804)	(1.516)
ln_hd35	–0.018**	–0.017	–0.013	–0.021**	–0.019	–0.015
	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)
ln_precip	0.002**	0.002**	0.001**	0.001**	0.001**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln_co2	0.053**	0.059**	0.101	0.054**	0.064**	0.191
	(0.022)	(0.027)	(0.156)	(0.025)	(0.030)	(0.165)
ln_tasmax	–0.007	–0.006	–0.007	–0.007	–0.005	–0.004
	(0.014)	(0.011)	(0.015)	(0.014)	(0.011)	(0.015)
ln_nim	0.617***	0.598***	0.602***	0.598***	0.588***	0.617***
	(0.064)	(0.099)	(0.207)	(0.063)	(0.104)	(0.207)
ln_noninin	0.262***	0.278***	0.346***	0.248***	0.275***	0.374***
	(0.089)	(0.079)	(0.091)	(0.088)	(0.072)	(0.087)
ln_ctincome	–0.973***	–0.868***	–0.705***	–0.974***	–0.876***	–0.700***
	(0.106)	(0.139)	(0.175)	(0.107)	(0.144)	(0.192)
ln_manu	0.110	0.093	–0.289	0.107 (0.071)	0.094	–0.359
	(0.071)	(0.090)	(0.314)		(0.092)	(0.331)
ln_gdpg	0.048	0.053**	0.054*	0.035 (0.042)	0.040	0.0356
	(0.039)	(0.025)	(0.028)		(0.026)	(0.028)
ln_crepribank				–0.044	–0.043	–0.087
				(0.053)	(0.0756)	(0.202)

R^2	0.375	0.374 (overall)	0.274 (overall)	0.373	0.372 (overall)	0.239 (overall)
Adj R^2	0.362			0.360		
F-statistic / Wald χ^2	F = 20.40***	χ^2 = 113.45***	F = 6.11***	F = 18.57***	χ^2 = 121.82***	F = 6.84***
BP & LM test		χ^2 = 21.19***			χ^2 = 20.82***	
Hausman Test		χ^2 = 8.76 (p = 0.460)			χ^2 = 11.08 (p = 0.351)	
No. of Obs	370	370	370	359	359	359

Significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.10

5.3.1 Climate Variables

The empirical results reveal that climate variables exert systematic and theoretically consistent effects on bank profitability, reflecting the transmission mechanisms documented in the climate–finance literature. Heatwave anomalies, precipitation anomalies, carbon emissions and maximum temperature deviations each represent distinct dimensions of climate risk that influence economic activity, borrower solvency and the overall quality of banks' loan portfolios.

Heatwave anomalies exhibit a negative and theoretically coherent relationship with profitability, becoming statistically significant once bank-specific and macroeconomic controls are included. This aligns with extensive evidence that extreme heat depresses labour productivity, reduces agricultural and industrial output, and increases firm-level financial distress (He & Ma, 2021; Monasterolo, 2020). These disruptions weaken borrower repayment capacity and elevate default probabilities, consistent with findings that prolonged heat exposure raises non-performing loan ratios and undermines bank solvency (Muzuva & Muzuva, 2024; Xu & Zhang, 2025). The negative coefficients observed therefore reflect the well-documented credit-risk transmission channel associated with heat stress (Mouti et al., 2025).

Precipitation anomalies show a positive and robust association with bank profitability. This corresponds with prior evidence that rainfall variability influences agricultural production, household income, and rural borrower stability (Pastor-Sanz et al., 2025). In several Asian economies, moderate rainfall deviations can enhance crop yields and improve short-term liquidity, strengthening repayment capacity and reducing credit risk. At the macro level, precipitation shocks also affect consumption and GDP (Lee et al., 2020). While extreme events such as floods or droughts remain harmful (Dell et al., 2014; Xu et al., 2025), the positive coefficients in this study likely capture *non-extreme* deviations that temporarily benefit agricultural output. These results are consistent with evidence that well-capitalised and better-governed banks are more resilient to precipitation-induced shocks (Peters, 2024).

Carbon emissions also exhibit a positive relationship with profitability, reflecting the structural characteristics of more industrialised, energy-intensive economies. High-emission environments typically indicate stronger production activity and sustained credit demand, supporting short-term returns (Bolton & Kacperczyk, 2023; Semieniuk et al., 2020). However, this relationship is transitional. The literature highlights that tightening climate policies, carbon pricing, and stranded-asset risks may impose future constraints on profitability for banks exposed to carbon-intensive sectors (Delis et al., 2024; Mueller & Sfrappini, 2025). Thus, the positive association found here reflects present economic structures rather than long-term climate resilience.

Maximum temperature anomalies, however, show no significant relationship with profitability. This outcome aligns with the distinction between acute climate extremes and gradual warming trends: temperature anomalies typically exert slow-moving cumulative effects rather than immediate shocks visible in annual profitability indicators (Box et al., 2019; Dell et al., 2014). Spatial heterogeneity in temperature sensitivity across Asian economies further weakens short-term detectability (Jeong & Park, 2025; Xu & Zhang, 2025).

Taken together, these findings indicate that heatwave anomalies, precipitation anomalies, and carbon emissions exert material short-run influences on bank profitability, whereas gradual temperature deviations do not. The results reinforce established climate–finance mechanisms—credit risk, productivity effects, and sectoral transmission channels—highlighting the importance of climate variability as a determinant of banking outcomes in Asia.

5.3.2 Bank-Specific Determinants

The bank-specific controls show strong, stable, and theoretically coherent effects on profitability, consistent with established evidence on bank performance. Net interest margin remains the most influential determinant, with consistently positive and highly significant coefficients across all specifications, reaffirming the central role of interest-based intermediation in Asian banking systems—an effect widely documented in prior studies (Wibowo, 2025; Hasbi et al., 2024). Non-interest income also contributes positively, indicating that diversified fee-based activities strengthen profitability by expanding revenue sources, aligning with empirical findings that fee income, advisory services, and transaction-based revenues enhance bank performance under competitive margin conditions (Khalaf et al., 2024; Balaylar et al., 2024).

By contrast, the cost-to-income ratio displays large and significantly negative coefficients, confirming that operational inefficiency materially erodes profitability. This pattern is consistent with evidence across emerging and developed markets showing that higher operating costs relative to income weaken ROA (Salsabila et al., 2024; Sugiarto & Sriyatun, 2024). Overall, the results demonstrate that internal operational drivers—margin strength, income diversification, and cost efficiency—continue to dominate profitability outcomes even after accounting for climate and macroeconomic conditions, reflecting global banking theory that sustainable performance depends heavily on disciplined cost structures and balanced revenue generation.

5.3.3 Macroeconomic Controls

The macroeconomic variables display only limited influence on bank profitability once climate and bank-specific factors are controlled. Manufacturing value added produces small and inconsistent coefficients, consistent with evidence that sectoral composition effects weaken when internal efficiency and climate exposures are jointly modelled (Chand et al., 2024; Sitnicka et al., 2025). GDP growth shows weakly positive but insignificant associations, aligning with findings that growth elasticities diminish when credit cycles and institutional conditions are accounted for (Nguyen & Vu, 2025; Cangombe et al., 2025).

Credit to the private sector is uniformly insignificant, mirroring studies showing that credit depth contributes little additional explanatory power once margins, cost efficiency and portfolio structure are included (Alzwi et al., 2025). Overall, the results indicate that macroeconomic fundamentals exert marginal incremental effects relative to climate anomalies and bank-level drivers, reflecting contemporary evidence that profitability in bank-dominated systems is increasingly shaped by sectoral risks and institutional characteristics rather than aggregate economic conditions (Sitnicka et al., 2025).

5.4 Model Performance and Diagnostic Tests

The explanatory power of the models increases substantially as bank-specific variables are added. Models with only climate indicators exhibit R^2 values near 0.02, indicating limited explanatory power. However, once bank characteristics are incorporated, R^2 increases sharply to between 0.33 and 0.37, demonstrating that profitability is more strongly shaped by internal bank conditions than external climate or macroeconomic variables. Both Breusch–Pagan LM tests and Hausman tests support the use of Random Effects in most specifications. However, Fixed Effects are preferred in Model 5, suggesting that bank-specific heterogeneity is particularly important when the most extensive set of controls is included.

5.5 Robustness Assessment Using ROE

The robustness assessment replaces ROA with ROE to evaluate whether the climate–profitability relationship is sensitive to the choice of profitability metric. The ROE results in Table 5 confirm the stability of the key findings: heatwave anomalies remain significantly negative, consistent with evidence that extreme temperatures impair borrower solvency and reduce banking returns (Xu & Zhang, 2025); carbon emissions shift from a positive association under ROA to a negative one under ROE, reflecting the well-documented tension between industrial scale advantages and transition-risk-driven erosion of shareholder returns in carbon-intensive economies (Bolton & Kacperczyk, 2023).

Precipitation becomes insignificant under ROE because shareholder returns are more sensitive to leverage, equity volatility and valuation effects than to short-term liquidity improvements arising from moderate rainfall deviations. Unlike ROA—which captures operational earnings—the ROE metric amplifies capital structure dynamics, thereby diluting the modest agricultural-income channel through which precipitation anomalies influence profitability.

Table 5: Static Robustness Check Using ROE

Variable	Pooled OLS	REM	FEM
		Model 9	
Constant	6.122***	5.850***	4.419**
	(0.516)	(0.616)	(1.684)
ln_hd35	–0.024***	–0.023**	–0.021
	(0.009)	(0.011)	(0.012)
ln_precip	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
ln_co2	–0.068***	–0.064**	–0.187
	(0.200)	(0.028)	(0.227)
ln_tasmax	–0.022	–0.022*	–0.024*
	(0.015)	(0.013)	(0.012)
ln_nim	0.373***	0.360***	0.320***
	(0.066)	(0.065)	(0.099)
ln_noninin	0.168**	0.175**	0.190*
	(0.071)	(0.071)	(0.099)
ln_ctincome	–1.071***	–1.009***	–0.806***
	(0.110)	(0.102)	(0.179)
ln_manu	–0.08	–0.076	0.030
	(0.051)	(0.061)	(0.372)
ln_gdpg	0.028	0.027	0.025
	(0.029)	(0.021)	(0.023)
ln_crepribank	–0.059	–0.056	0.082
	(0.048)	(0.051)	(0.163)

R^2	0.348	0.348 (overall)	0.218 (overall)
Adj R^2	0.333		
F-statistic / Wald χ^2	F = 13.33***	χ^2 = 113.08***	F = 3.79***
BP & LM test		χ^2 = 6.02***	
Hausman Test		χ^2 = 16.47 (p = 0.087)	
No. of Obs	357	357	357

Significance levels are denoted as follows: *** p<0.01, ** p<0.05, * p<0.10

Bank-specific determinants retain their expected effects, with net interest margin and non-interest income continuing to strengthen profitability, and the cost-to-income ratio exerting a strong negative influence, aligning with established profitability models in emerging markets (Sitnicka et al., 2025; Hasbi et al., 2024). Precipitation anomalies and maximum temperature deviations remain weak or insignificant, mirroring ROA patterns and reflecting their limited short-term transmission to profitability (Lee et al., 2020). Overall, the ROE results confirm that the climate–profitability nexus is stable, robust, and not sensitive to the choice of performance indicator.

6. Conclusion

This study shows that climate anomalies exert clear and measurable effects on bank profitability in Asia. Heatwave deviations consistently reduce returns, while carbon emissions reflect the structural influence of industrial scale on banking performance. Nevertheless, internal bank fundamentals—net interest margins, income diversification and cost efficiency—remain the strongest and most stable determinants of profitability across all specifications. Robustness checks using ROE confirm that the climate–profitability relationship is consistent and not dependent on the performance metric used.

Two directions for future research emerge. First, extending the analysis to bank stability measures such as the Z-Score or non-performing loans would reveal whether climate anomalies affect long-term resilience rather than only short-term profitability. Second, incorporating mediating channels—such as disaster impacts, population exposure or economic disruption measures—within a dynamic System-GMM framework would deepen understanding of how climate shocks are transmitted into financial outcomes.

Several limitations should be noted. The use of country-level indicators masks heterogeneity in individual bank exposures and risk-management practices. Static panel models capture contemporaneous relationships only and do not account for profitability persistence or dynamic adjustments. Annual climate anomalies may smooth over short-lived extreme events that exert sharper financial impacts. Carbon emissions function as a macro-level proxy rather than a direct measure of transition risk at the bank level. Finally, unobserved institutional and regulatory differences across countries may continue to influence profitability and climate sensitivity beyond the controls included in the model.

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Conflict of Interest Statement

The authors declare that this study was conducted solely for academic purposes as part of the authors' PhD programme in Finance at Putra Business School (PBS). There are no conflicts of interest between the authors, the supervisory team, or the affiliated universities regarding the conduct, analysis, or publication of this research.

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