Dynamic Correlations Between Climate Shocks, Macroeconomic Volatility, and Geopolitical Uncertainty in Emerging Market Portfolios

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1. Introduction and Problem Statement

There is one question that keeps coming up in central bank stress tests, in asset manager risk reports, and increasingly in finance ministry briefings across emerging economies — when a climate shock hits, does it hit alone, or does it arrive together with the other risks that are already stretching portfolios? The honest answer, at least in the empirical literature as it currently stands, is that we do not know well enough. And we especially do not know for emerging markets.

The last few years have handed us enough evidence to take this question seriously. In 2022, the Indian subcontinent experienced its most intense and prolonged heatwave on modern record. That same year, the rupee depreciated sharply, domestic inflation hit an eight-year high, and global financial conditions tightened rapidly as the US Federal Reserve moved into one of its most aggressive rate hike cycles in four decades. Simultaneously, the Russia-Ukraine conflict drove a global commodity price shock and triggered a geopolitical risk episode of a scale not seen in decades. Indian equity markets and sectoral indices moved sharply throughout this period. What we cannot cleanly answer is how much of that movement was driven by the heat and monsoon disruption, how much by macroeconomic tightening, and how much by the fact that all three were compounding each other at the same time.

This is not a minor empirical puzzle. If climate risk is largely uncorrelated with macroeconomic and geopolitical shocks, then it adds to the total risk load on a portfolio but does not fundamentally break diversification strategies. Investors can hedge it, price it separately, and treat it as one more sector-level or country-level exposure. But if climate risk tends to spike precisely when macroeconomic conditions are already deteriorating and geopolitical tensions are running high — that is a very different situation. Under that scenario, climate risk behaves as a systemic factor. It is non-diversifiable. It amplifies tail losses at exactly the moment when portfolio resilience matters most, and the standard Value-at-Risk and Expected Shortfall models currently used by Indian banks, insurance companies, and large pension funds are systematically understating risk. The Reserve Bank of India, the Securities and Exchange Board of India, and

institutional investors managing hundreds of billions in assets need to understand which of these two worlds they are operating in.

The existing literature has not given them an answer for the Indian context. The foundational work by Engle, Giglio, Kelly, Lee, and Stroebel (2020) constructed factor-mimicking portfolios for climate risk using US newspaper data and US equity returns. Bolton and Kacperczyk (2021) examined carbon risk premia in US and European stock markets. European central banks, particularly the ECB and the Bank of England, have conducted extensive climate stress tests using NGFS transition scenarios. These are important contributions, but they were built on institutional contexts — deep capital markets, mature ESG disclosure requirements, and relatively stable macroeconomic environments — that describe the US and Europe, not India or South Asia. In emerging markets, the transmission channels are structurally different. Financial markets are thinner and more susceptible to sudden stops. Monsoon variability can shift food inflation by several percentage points within a single quarter. Geopolitical risk is structurally higher owing to regional tensions. A framework calibrated for Frankfurt or New York does not straightforwardly apply in Mumbai or Jakarta.

This paper is our attempt to fill that gap.

2. Research Objectives and SDG Alignment

This paper pursues three specific objectives. First, we construct a composite, high-frequency climate risk index for India covering the period 2004 to 2024, drawing on textual analysis of major Indian financial newspapers and validated against known climate events and policy milestones. Second, we estimate the time-varying conditional correlations between this climate risk index, macroeconomic volatility measures, and a geopolitical risk index using a DCC-GARCH framework, with the specific goal of identifying whether these correlations rise during crisis episodes relative to tranquil periods. Third, we test whether the co-movement between risks is asymmetric across the return distribution — that is, whether it is stronger in the left tail of portfolio returns, which is the portion of the distribution that matters most for capital adequacy and systemic risk assessment.

These objectives connect directly to three of the United Nations Sustainable Development Goals. The most direct link is to SDG 13 — Climate Action — specifically Target 13.1, which calls for strengthening resilience and adaptive capacity to climate-related hazards, and Target 13.3, which calls for improving education, awareness-raising, and institutional capacity on climate change mitigation, adaptation, and impact reduction. Understanding whether and how climate risk interacts with macroeconomic and geopolitical shocks is a precondition for building genuine climate resilience in financial systems. A risk management framework that treats climate risk as

isolated from other systemic pressures will underperform precisely when resilience is most needed.

The paper also bears on SDG 8 — Decent Work and Economic Growth — particularly Target 8.10, which focuses on strengthening the capacity of domestic financial institutions in developing countries. Inadequate risk measurement in large institutional portfolios — pension funds, insurance companies, public sector banks — can result in capital misallocation and, in stress scenarios, systemic fragility that falls disproportionately on workers and lower-income households. Finally, there is a clear connection to SDG 17 — Partnerships for the Goals — through the paper's engagement with the NGFS framework and its contribution to the international discourse on climate-related financial risk in emerging economies, a conversation in which India's voice and evidence base have so far been underrepresented.

3. Methodology

The empirical strategy of this paper rests on three interconnected components, applied sequentially.

Climate Risk Index Construction. We construct a composite climate risk index for India using two approaches in parallel. The first follows the newspaper-based textual analysis methodology developed by Engle et al. (2020), applied to a corpus of major Indian financial and general newspapers — the Economic Times, Business Standard, and the Hindu — covering January 2004 through December 2024. Articles are searched for the co-occurrence of climate and risk-related keyword sets, and the resulting monthly index captures variation in market-relevant climate news intensity over time. The second draws on the Climate Policy Uncertainty index of Gavriilidis (2021) alongside the India-specific Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016), allowing us to isolate climate policy uncertainty from broader economic policy noise. Both indices are validated against known reference events — the 2009 and 2014 drought episodes, the 2015 Paris Agreement, the 2018 Kerala floods, the 2021 COP26 Glasgow summit, and the 2022 heatwave — to confirm that spikes in the constructed series align with events that carried genuine climate-financial relevance for Indian markets.

Macroeconomic and Geopolitical Risk Variables. The macroeconomic volatility component comprises four variables: the realized monthly volatility of the Nifty 50 index, the realized volatility of the USD/INR exchange rate, the surprise component of India CPI inflation (measured as deviation from the median Bloomberg consensus forecast), and the output gap derived from HP-filtered quarterly GDP data. For geopolitical risk, we use the Caldara and Iacoviello (2022) Geopolitical Risk Index alongside its India-specific country component, supplemented by binary event indicators for the major India-Pakistan tension episodes and the

2020 and 2022 India-China border conflict periods. This granularity is important because generalized global geopolitical risk indices smooth over the specific regional shocks that are most disruptive to South Asian portfolios.

Dynamic Correlation Analysis. The core econometric analysis estimates a DCC-GARCH model in the specification of Engle (2002), applied to bivariate and multivariate combinations of the climate risk index, macroeconomic volatility composite, and geopolitical risk index. The DCC framework is well-suited to this problem because what we need is not the average unconditional correlation between these variables — that is a secondary result — but rather how those correlations evolve through time, and specifically whether they spike during compound stress episodes. A static Pearson correlation between climate risk and exchange rate volatility is close to uninformative for risk management purposes. A time-varying conditional correlation that rises from 0.15 in quiet periods to above 0.60 during the 2022 compound shock is a result that carries direct practical implications for capital buffers and stress test design.

We supplement the DCC analysis with two robustness and extension approaches. The first is a Time-Varying Parameter VAR estimated using the Primiceri (2005) algorithm, which traces how the impulse responses between climate shocks and macroeconomic variables have changed across the full twenty-year sample. This is important for understanding whether the relationship has intensified over time, as the growing salience of climate-related events and the deepening of Indian capital markets would both suggest. The second is a quantile regression framework that examines whether the correlation structure is symmetric across the portfolio return distribution. We expect — and preliminary evidence supports — that the co-movement between climate, macro, and geopolitical risk is significantly stronger in the bottom decile of returns, which is the tail that stress tests and capital adequacy frameworks are designed to protect against.

4. Data and Expected Results

The primary data sources are the CMIE Prowess database for Indian corporate and market data, the RBI Data Warehouse (DBIE) for macroeconomic series, and Bloomberg for high-frequency equity and foreign exchange data. The newspaper corpus is drawn from the ProQuest South Asian Newspapers database and the Economic Times digital archive. The sample runs from January 2004 through December 2024, providing two full decades of monthly observations that span multiple major climate episodes, two global financial crises (2008 and 2020), and several significant geopolitical events in the South Asian context.

We expect the results to show, first, that the time-varying correlations between climate risk and macroeconomic volatility are significantly higher during identified compound shock episodes than during tranquil periods — specifically during the 2009 drought-recession overlap, the 2020

COVID-monsoon disruption, and the 2022 heatwave-inflation-geopolitical risk convergence. Second, we expect that the quantile regression results will confirm asymmetry, with left-tail co-movement substantially stronger than co-movement in the upper and middle portions of the return distribution. Third, the TVP-VAR results are expected to show that the impulse response of macroeconomic volatility to climate shocks has grown in magnitude over the sample period, consistent with rising physical climate exposure and deeper financial market integration. If these results hold, the implication is clear: climate risk in India cannot be treated as a standalone, long-horizon environmental concern. It is a near-term systemic risk factor that compounds with the macroeconomic and geopolitical volatility that emerging market portfolios already face regularly.

5. Policy Implications

The findings of this paper speak directly to three active regulatory and institutional questions in India and in the broader emerging market policy context.

For financial regulators, the results provide empirical grounds for updating climate stress testing methodology. The Reserve Bank of India's 2022 Discussion Paper on Climate Risk and Sustainable Finance acknowledged the need for climate scenario analysis but did not incorporate dynamic inter-risk correlation into its proposed stress testing framework. If climate risk systematically co-moves with macroeconomic downturns, then stress scenarios that treat climate shocks as independent from macroeconomic deterioration will underestimate capital requirements in precisely the tail events that prudential frameworks are meant to capture. The same applies to SEBI's BRSR framework for institutional disclosure — requiring firms to report climate risk in isolation from broader systemic risk context may give investors an incomplete picture of true portfolio vulnerability.

For institutional investors, including the EPFO, LIC, and National Pension System funds that collectively manage assets exceeding $400 billion, the result that climate risk is non-diversifiable during compound shock episodes has direct implications for Strategic Asset Allocation. If the correlation between climate exposure and macroeconomic volatility rises sharply in left-tail scenarios, then holding green assets as a hedge against brown assets may provide less protection than standard correlation-based models suggest. Investors need dynamic, regime-aware hedging frameworks rather than static allocation rules.

More broadly, this paper contributes to an international conversation about how the NGFS framework — built largely on the institutional structures of advanced economies — should be adapted for emerging market application. India is both one of the most climate-vulnerable major economies and one of the fastest-growing financial markets in the world. The risk measurement frameworks being developed now will shape how hundreds of billions in institutional capital is allocated over the next decade. Getting the correlation structure right is not an academic fine

point — it is a practical prerequisite for building a financial system that can absorb the compound shocks that the coming decades will almost certainly deliver.

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