Unpacking Currency Risk in Climate Investments: A Decomposition Framework for Emerging Markets.

Papa Orgen[1,2]
University College London

Sumit Kothari[1]
University College London

Nadia Ameli[1]
University College London

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Abstract

We assess the dynamic effects of foreign exchange risk in renewable energy investments using machine learning, Bayesian Model Averaging, and structural vector autoregression techniques. Currency risk exerts a significant downward effect on capital intensity, with over half of the currency risk discount on climate investments driven by persistent macroeconomic factors - inflation, real interest rates, political stability, and business cycle risk. These effects exhibit heterogeneity across countries and time, underscoring the importance of stable macro-financial environments. Policy implications emphasize targeting the stable component of currency risk with structural hedging mechanisms to unlock investment and reduce the cost of capital in developing countries.

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[1] Institute of Sustainable Resources, Bartlett School of Environment, Energy and Resources, University College London (UCL), United Kingdom.
[2] Corresponding Author Email: p.orgen@ucl.ac.uk.

1. Introduction

Transitioning from fossil fuels to renewable energy is a critical part of the global strategy for addressing climate change. The scale of investment required to finance this transition, particularly in emerging markets and developing economies (EMDEs), is substantial.[1] While renewable energy costs continue to fall[2], capital deployment remains constrained by high financing costs, policy uncertainty and notably, currency risk (Ameli et al., 2021). Unlike in developed markets, where renewable energy projects benefit from stable macroeconomic environments and mature financial systems, projects in EMDEs frequently rely on foreign currency-denominated financing, exposing project companies to substantial currency risk (Rickman et al., 2025). The ensuing cashflow mismatches at settlement are in part exacerbated by foreign exchange rate volatility, which ultimately increase financing costs. Currency depreciation, volatility, and liquidity constraints raise the cost of capital and limit the ability of developing economies to attract private capital at scale (Egli et al., 2022).

EMDEs face significant macroeconomic volatility, which directly impacts capital flows and investment decisions. Exchange rate fluctuations, inflationary pressures, and sovereign risk premiums contribute to higher financing costs, particularly for long-term infrastructure and energy projects (Servén, 2003; Aguiar and Gopinath, 2007). These risks are amplified in underdeveloped domestic capital markets, where in part, the lack of liquidity and hedging instruments in domestic markets make foreign currency financing both necessary and costly. Eichengreen and Hausmann (1999) characterize this as the "original sin"—the inability of EMDEs to borrow abroad in their own currencies due to macroeconomic and institutional weaknesses.

A growing body of work in sovereign and corporate debt markets shows that exchange rate risk is systematically priced by investors (Du and Schreger, 2016; Engel and Park, 2018). More recent evidence indicates that currency risk shapes the issuance patterns of sustainability-linked debt, with EMDEs

[1] EMDE countries (Other than China) require the largest increase in investment: these regions currently have low investment levels, significant development needs, and are projected to contribute over 50% of global emissions by 2030. (https://www.lse.ac.uk/granthaminstitute/publication/raising-ambition-and-accelerating-delivery-of-climate-finance/).

[2] In 2023, the global weighted average LCOE of new onshore wind and solar PV projects were respectively 67% and 56% cheaper than the least-cost weighted average fossil fuel-fired solution.

increasingly reliant on foreign currency instruments to attract global capital (Rickman et al., 2025). However, this strategy raises exposure to adverse exchange rate movements, which can affect the value of project cash flows and elevate the cost of capital (Burnside et al., 2001; Dailami and Hauswald, 2007).

These dynamics have pronounced implications for capital-intensive sectors. While technology costs for renewables have declined sharply, the cost of capital remains a major constraint in EMDEs, often exceeding 12%, compared to 3–6% in developed markets (Wright and Nystrom, 2020; Egli et al., 2022). Macroeconomic risks—particularly inflation, real interest rates, and currency volatility—are consistently identified as key drivers of elevated capital costs (Polzin et al., 2019; Steffen, 2021). Ameli et al. (2021) empirically demonstrate that macro fundamentals are directly linked to project bankability, while Buchner et al. (2021) emphasize the role of institutional credibility and monetary stability in attracting climate finance.

In response, recent policy literature advocates for the use of de-risking instruments and foreign exchange guarantee mechanisms to mobilize private capital. Persaud (2023, 2024) propose that multilateral development banks (MDBs) absorb currency risk via structured guarantees to lower risk premia. Melekh et al. (2024) similarly argue for international risk-sharing tools to catalyse renewable energy investments in lower-income economies. Despite growing policy interest, there remains a critical empirical gap: we find a lack of studies on the systematic, quantitative assessment of how currency risk is priced into investment decisions, its importance among the constellation of risks project developers face, and its dynamic interaction with other macroeconomic risk factors.

We fill this gap by introducing a novel framework that estimates and decomposes the currency risk discount embedded in nominal renewable energy investments. Using project-level data across 1,502 renewable energy transactions in EMDEs, we investigate to what extent currency risk influences investment in renewable energy projects. First, is currency risk the principal risk determinant for renewable energy investments? Second, can the influence of currency risk on renewable energy investments be explained by broader macroeconomic conditions, or is it a unique risk factor? Third, if a measurable currency risk effect exists – independent of it being unique or not - what are its time-series characteristics? We assess the

dynamic structure of the estimated currency risk discounts on whether stable risk components dominate transitory fluctuations, and the policy implications thereof for the design of risk mitigation instruments aimed at hedging currency risk in renewable energy investments.

Using three metrics - the rolling 60-month foreign exchange (FX) volatility, rolling 12-month FX volatility and the rolling 12-month range of FX movements - as proxies for currency risk in the presence of appropriate controls, our findings reveal that while currency risk is not the principal determinant of investments in renewable energy projects, it exerts a meaningful influence on the level of investments. The coefficient on currency risk is significantly negative - implying a discount on capital intensity - across all FX volatility measures[3]. Consistent with our priori, on a standalone basis, the currency risk discount is not unique, but largely explained by broader macroeconomic conditions. Decomposing the currency risk discount shows that stable risk components dominate transitory fluctuations. Dynamic variance decomposition analysis further highlights the evolving macroeconomic determinants of the stable component of the currency risk discount.

In the first step, we develop and tune a Random Forest model - a machine learning algorithm - to rank the relative importance of risk factors - including macro, institutional, climate, and FX volatility variables – in explaining capital intensity – the amount of investment in US dollar terms per megawatt (MW) of energy produced.[4] Drawing on data from 1,502 renewable energy projects between 2010 and 2020, our analysis reveals that while the levelized cost of electricity remains the primary determinant of renewable energy investment, the relative influence of various risk factors - including macroeconomic, climate, currency, and institutional risks - has evolved over time, particularly in the period before and after the adoption of the Paris Agreement[5].

[3] The negative coefficients on currency risk metrics in the capital intensity analysis reflect a 'currency risk discount'—a reduction in investment per megawatt (MW) due to perceived currency risk. This discount implies that, under a risk-return framework, investors demand a higher expected return (hurdle rate) to compensate for exposure to currency fluctuations. While the premium itself is not directly observed in investment figures, its effect is inferred through the reduced willingness to invest at given cost levels, necessitating higher expected returns to attract capital. We use project level investment and size data in this analysis, given cross-sectional cost of capital data is largely unavailable.

[4] We normalize the dollar value of renewable energy project investments by capacity (MW) to account for time-invariant heterogeneity in renewable energy investment dynamics

[5] We situate the Random Forest analysis around the adoption of the Paris Agreement to explore whether the relative importance of risk factors influencing renewable energy investment shifted in response to the globally coordinated climate policy framework.

This result raises the question of whether currency risk significantly influences capital intensity within these broad range of risk factors as an embedded discount. In the absence of granular project-level data, we develop a Bayesian Modelling Average (BMA) framework to address model uncertainty in estimating currency risk discounts. To enhance robustness, we employ Huber and Quantile regression methods alongside bootstrap resampling, generating distributions of model estimates and computing the frequentist average of coefficient estimates to mitigate sensitivity to outliers. The results show that all currency risk measures are significantly and negatively associated with capital intensity.

Is the currency risk discount unique? That is, is the residual discount still significant in the presence of systemic macro risk factors? To address this, we conduct a second BMA analysis, regressing the estimated currency risk discount on systemic macro factors. We find that macroeconomic conditions largely subsume currency risk discounts. The findings suggest that once inflation, interest rates, and current balances are considered, there is no additional currency risk discount, suggesting that currency risk is not an independent factor. Intuitively, when currency risk increases, capital is allocated less intensively, meaning that currency risk manifests through risk-averse investment behavioural channel.

To uncover the time-series structure of the currency risk discount, we estimate a Structural VAR model that decomposes macroeconomic contributions to stable and volatile components of FX risk. Next, we use a Cholesky decomposition with economic priors as an identification strategy to quantify the dynamic interactions of macroeconomic risks to stable currency risk discounts. This allows us to decompose the relative contributions of inflation, real interest rates, institutional political stability, and business cycle risk over time to stable currency risk. We find that short-term FX risk is primarily driven by business cycle shocks, while long-run FX risk is associated with persistent monetary conditions. The heterogeneous effects of macroeconomic drivers across different currency risk metrics highlight the need for tailored policy responses that address the temporal dynamics of currency risk. Given the long-term nature of renewable energy investments, these findings emphasize the importance of structural hedging mechanisms designed to mitigate persistent macroeconomic risks.

Our results contribute to the empirical literature on climate finance in a number of ways. First, our diagnosis of the currency risk discount as a function of systemic risk factors yields important policy implications. As the stable component of the currency risk discount dominates transitory fluctuations, policymakers should prioritize structural hedging mechanisms that target the stable components of currency risk over short-term hedging instruments for renewable energy investments. Such an approach may be cost effective, given the entire risk premium is not hedged, and may unlock significant investment capital. Second, our study advances empirical research and policy discussions on the role of currency risk in renewable energy investments in developing countries, bridging a gap between finance theory and investment behaviour in sustainability. By introducing a currency risk discount estimation and decomposition framework – given the lack of cross-sectional cost of capital data - we offer a novel empirical approach for measuring currency risk in renewable energy investments, providing valuable insights for both academic research and policy formulation. The rest of this article is structured as follows. Section 2 introduces Data and the variables underlying this analysis. Section 3 presents empirical methods used. We discuss methodology-based results in Section 4. Section 5 concludes.

2. Data

Our primary data sample comprises project level information on renewable energy – solar and wind – projects obtained from Bloomberg New Energy Finance (BNEF). We select developing country renewable projects (excluding China) with non-empty fields for deal value (in millions USD) and capacity (in megawatt, MW). Next, we merge project-level information with macro, institutional, climate and other project-specific risk factors to obtain the dataset for this analysis. Country macro and institutional data are obtained from the World Bank databank and country level data on climate-related disasters from the EM-DAT International Disaster database. We merge project and risk factor data on country and time to obtain a data sample comprising 1,502 renewable energy projects from 49 developing countries over the period 2010 – 2020. The distribution of project counts is shown in Figure 1. India, Brazil, Mexico, Vietnam and South Africa account for the top five countries with the most projects in our sample.

Our empirical analysis of currency risk dynamics in renewable energy investments employs capital intensity as the dependent variable. We define capital intensity as project investment value (mUSD) divided by capacity (MW). Countries exhibit significant heterogeneity in investment levels and project sizes, leading to variations in capital allocation efficiency. Some countries may have high total investment values but also build disproportionately large energy projects, while others may achieve relatively higher installed capacity with lower investment amounts. By normalizing investment by installed capacity, we control for scale effects and mitigate distortions arising from heterogeneity in project size. This transformation facilitates cross-country and income-group comparability and ensures that variations in capital intensity reflect differences in investment efficiency rather than absolute funding levels. We take the square root of capital intensity as a variance stabilization measure to reduce skewness while maintaining relative differences between observations.

Our control variables are the following. Offtaker Credit Score measures the creditworthiness of the entity purchasing renewable energy; LCOE is the natural logarithm of global levelized cost of electricity values. LCOE accounts for global cost variations in solar and wind energy production; IPS measures the overall stability and effectiveness of political institutions of a country on an annual basis; IRQ measures how well laws and regulations support market efficiency and economic activity of a country on an annual basis; IRL provides contract enforcement and rule of law scores, measured on an annual basis; IVA – institutional voice and accountability - measures the degree of political freedoms, democratic participation, and transparency in governance on an annual basis; Inflation measures the monthly percentage change in consumer price inflation rate (%) for each country; Current Balance (% GDP) measures a country's net trade and financial flows annually; Debt-to-GDP measures gross sovereign debt as a percentage of GDP annually; Real IR is interest rates adjusted for inflation; CO_2 per capita measures the individualized carbon emissions on country level annualized; Share of Ren. Capacity measures the percentage of total installed electricity generation capacity derived from renewable sources; Disaster Int measures economic damages from natural disasters (mUSD), adjusted by the number of people affected; Longrun FX Volatility is the 60-month rolling standard deviation of the natural logarithm of FX returns on country level; Shortrun FX

Volatility is the 12-month rolling standard deviation of the natural logarithm of FX returns on country level; FX Spread (12M) is the difference between maximum and minimum log FX returns over a 12-month period on country level.[6] We winsorise control variables at the 2.5% level to reduce the influence of outlier observations. We address structural heterogeneity in control variables across income groups by applying within-group standardization, ensuring that variations in capital intensity and its determinants capture relative deviations within each group rather than cross-group disparities. Standardization is performed at the income group level—low-income (L), lower-middle-income (LM), and upper-middle-income (UM) countries—to control for differences in economic structure, financial conditions, and investment constraints. This transformation mitigates scale-induced biases and enhances comparability while preserving meaningful within-group variation for statistical inference. We report summary statistics on the macro, micro and project-specific variables in Table 1. The mean Capital Int. for projects in our data sample is 1.16 with a standard deviation of 0.455. By implication, projects in our sample invest $1.360 million per MW of installed capacity. On average, countries represented in our sample have relatively low political stability (IPS) just above the first quartile (26.088) but around median levels of rule of law in terms of voice and accountability (IVA) at 52.164. On a macro level, the average monthly change in Inflation is 6.383% while Real IR is reported as 12.153%. Countries in our sample have debt profiles that are around 60.606% of GDP.

Inflation, real interest rates, and debt-to-GDP are critical macroeconomic factors as they directly influence investment decisions, financing costs, and sovereign risk, all of which impact capital intensity in renewable energy projects. High inflation erodes the real value of money, increasing the cost of capital for long-term renewable energy investments. Inflation volatility can affect exchange rates and attract monetary policy response, impacting the cost of capital. Real interest rates determine the cost of borrowing and the required rate of return for infrastructure investments. Higher real interest rates make capital-intensive projects less attractive by increasing financing costs. When real rates are high enough, government and corporate bonds become more attractive relative to infrastructure projects, fuel perceptive and sentiment

[6] Figure 2 visualizes the three currency risk metrics in the case of Brazil and India.

risks, and ultimately cross-border capital flows into emerging markets. High debt-to-GDP, on the other hand, signals potential fiscal distress, increasing sovereign credit risk. Countries with high debt burdens may have reduced fiscal room to support renewable energy investment through subsidies, tax incentives, or public-private partnerships.

Proxy variables for climate risk include CO2 per capita, share of renewable capacity and disaster intensity. Higher CO_2 emissions per capita are often associated with economies reliant on fossil fuels and hence a transition risk measure. Investors in high emissions jurisdictions may have a stronger regulatory inventive to transition toward cleaner energy sources, influencing capital allocation. Empirical research suggests that carbon pricing mechanisms and emissions reduction policies, such as carbon taxes and cap-and-trade systems, increase investment in renewables by altering the relative cost of energy production (Newell et al., 2021; Aldy and Stavins, 2012). However, in some cases, high polluting economies may also face entrenched fossil-fuel interests, leading to higher capital costs for renewable projects due to political and financial barriers (Acemoglu et al., 2012).

The share of renewable energy in a country's total energy mix can influence capital intensity through economies of scale and technological maturity. Countries with a higher existing share of renewable capacity may experience lower capital costs due to more developed infrastructure, supply chains, and regulatory frameworks that support renewable investment (Polzin et al., 2019). Conversely, nations with a low share of renewable energy may require higher initial capital outlays to develop foundational infrastructure, leading to higher capital intensity (Eyraud et al., 2013). Empirical studies highlight that renewable energy diffusion follows an S-curve, where early investments tend to have higher costs before cost reductions from learning effects and economies of scale set in (Nemet, 2009; IEA, 2022).

Climate-induced natural disasters (e.g., hurricanes, floods, wildfires) pose both physical and financial risks to energy infrastructure. High disaster intensity can lead to increased capital intensity due to the need for resilient infrastructure, higher insurance costs, and risk premiums demanded by investors (Dell et al., 2014; Burke and Emerick, 2016). Kahn et al. (2021) present evidence showing that extreme weather events influence capital allocation in energy markets, with investors requiring higher returns in disaster-

prone regions. At the same time, climate vulnerabilities may accelerate policy support for renewables, particularly if disasters highlight the risks associated with fossil-fuel-dependent energy systems (Hsiang and Jina, 2014).

Longrun FX Volatility captures structural exchange rate uncertainty and increases the cost of foreign-denominated financing, as lenders demand higher risk premiums to compensate for potential depreciation risks (Servén, 2003; Aguiar and Gopinath, 2007). Shortrun FX Volatility reflects fluctuations in exchange rates over a shorter window, capturing temporary shocks and speculative movements in currency markets. Unlike long-run volatility, short-run fluctuations are transitory, affect working capital and short-term project cash flows (Forbes et al., 2018) and reduce the efficiency of hedging mechanisms (Burnside et al., 2001). With FX spread (12M), we capture short-term exchange rate uncertainty and the associated range of potential movements. Wide ranges indicate increasing uncertainty about future currency movements, leading to risk-averse investment behaviour (Carranza et al., 2003). A wider range of FX movements may discourage renewable energy investments by increasing financial uncertainty, thereby raising the threshold for risk capital required to compensate for currency fluctuations. Panel E of Table 1 presents FX Spread (12M) (0.101) as the most volatile on average, followed by Shortrun FX volatility (0.033) and Longrun FX volatility (0.030).

3. Empirical Approach

Key Predictors of Capital Intensity in Renewable Investments

Traditional parametric regression models often impose restrictive assumptions which may not adequately capture the intricate interactions among financial and economic risk factors. The flexibility and robustness of random forest (RF) models make them well-suited for assessing non-linear relationships, hierarchical interactions among predictors, and mitigate overfitting through ensemble learning (Breiman, 2001). We train a RF model to address the complexity of relationships between macroeconomic risks, institutional factors, climate risks, financial constraints, and their effects on Capital Int. To reduce dimensionality in our dataset, we run three sets of principal component analysis (PCA) to create the following aggregate variables

from the first principal component of the respective analyses. Macro risks (from: Inflation, Debt-to-GDP, Real IR), Institutional risks (from: IPS, IRQ, IRL, IVA) and Climate risks (from: CO2 per capita, Share of Ren. Capacity, Disaster Int.). LCOE, Offtaker Credit Score and the FX risk metrics complete the risk factor list. The RF model is built as an ensemble of decision trees where each tree is trained on a randomly bootstrapped sample of the dataset. Given a training dataset of observations:

$$\{(X_i, Y_i)\}_{i=1}^{N} \qquad (1)$$

where X_i represents the predictor vector for the ith observation and Y_i is the dependent variable (Capital Int). The RF model constructs multiple decision trees, with each trained on a randomized subset of observations and features. Each decision tree recursively partitions the feature space into regions R_m with the objective to minimize impurity. The output for each region is the mean of the dependent variable within that region:

$$\hat{Y}_m(X) = \frac{1}{|R_m|}\sum_{\forall X_i \epsilon R_m} Y_i \qquad (2)$$

where $|R_m|$ represents the number of observations in the region R_m. The final ensemble prediction is computed as the average of all trees:

$$\hat{Y}_{RF}(X) = \frac{1}{B}\sum_{b=1}^{B} \hat{Y}_b(X) \qquad (3)$$

where B is total number of decision trees. We optimise performance through hyperparameter tuning and by selecting the best models proxied by ones that produce the least mean square error (MSE) using grid search cross-validation.

Estimating Currency Risk Discounts in Renewable Energy Investments

Economic and financial models are often subject to model uncertainty due to competing theories and variable selection ambiguities. Single-model estimation approaches assume that a single model specification adequately captures the underlying data-generating process. However, in the presence of model uncertainty, such an assumption may lead to biased inferences and omitted variable bias (Koop, 2003). Bayesian Model Averaging (BMA) addresses this issue by integrating across multiple models, weighting each model by its posterior probability given the data. This approach has been widely applied in

finance and macroeconomics to improve inference reliability, including applications in stock return predictability (Avramov, 2002), sovereign risk modelling (Eklund & Karlsson, 2007), and monetary policy uncertainty (Koop, 2003). We apply BMA in two sequential estimation steps. In the first BMA, we estimate the impact of currency risk on capital intensity in regressions of the form:

$$Y_{i(c,t)} = \beta_0 + \beta_{FX} FX_{c,t} + \beta_1 Controls_{c,t-1} + \varepsilon_i \qquad (4)$$

where Y_i represents capital intensity for project i located in country c in year t; $Controls_{c,t-1}$ are country-level lagged values of risk factors project i is exposed to at $t-1$. $Controls$ include IPS, Share of Ren. Capacity, LCOE and CO2 per capita; $FX_{i,t}$ is one of Longrun FX volatility, Shortrun FX volatility or FX spread (12M) project i is exposed to at t. β_{FX} is the variable of interest. Conditioned on results obtained in Equation (4), we investigate whether systemic macroeconomic variables such as Inflation, Real IR, Debt-to-GDP and Business cycle risks explain the variation in RP_i. The second stage BMA regression is of the form:

$$RD_{FX,ct} = \beta_0 + \beta_1 Systemic_{c,t} + \varepsilon_{c,t} \qquad (5)$$

$RD_{FX,ct}$ is the country level project currency risk discount estimated in (4). We model the project-driven country currency risk discount $RD_{FX,ct}$ as a function of systemic risk factors: inflation, real interest rates, debt-to-gdp and current balance.

The described modelling framework is implemented for Huber and Quantile regressions. Huber Regression minimizes a loss function that behaves quadratically for small residuals but linearly for large residuals, thereby reducing sensitivity to outliers. Quantile regressions estimate $Q_\tau(Y|X) = X\beta_\tau$ for $\tau\epsilon\{0.25, 0.50, 0.75\}$ to capture heterogenous effects across different investment levels.[7] To achieve robust model estimates and inference, we employ bootstrap resampling (1000 replications):

$$X^* \sim F(X), Y^* \sim F(Y) \qquad (6)$$

[7] While BMA provides a probabilistic framework to account for model uncertainty, combining it with robust regression estimators and bootstrap resampling ensures that our estimates are not only model-agnostic, but also resilient to distributional assumptions—an important consideration given that investment-level data often exhibit heavy tails or skewed distributions. Although our implementation embeds these estimators within a BMA framework, we are not the first to apply Fama-MacBeth style regressions in such context. Recent empirical studies, including Bolton and Kacperczyk (2021) and Sautner et al. (2023), have used similar two-step estimation strategies to examine the pricing of environmental and transition risk factors in asset returns.

where X^* and Y^* are randomly sampled from the empirical distribution. This way, we generate bootstrap distributions of model coefficients. The final BMA estimates are averages across models from the distribution of model coefficients in a frequentist manner[8]. The bootstrapped standard errors are obtained as the sum of within model and between model variance:

$$\sigma^2_{BMA} = E[Var(\beta_k|M_k, Y)] + Var[E(\beta_k|M_k, Y)] \quad (7)$$

where $[Var(\beta_k|M_k, Y)]$ captures within-model variance, representing the expected variance of β_k across different models M_k and $Var[E(\beta_k|M_k, Y)]$ the between-model variance. This two-stage framework allows us to isolate the influence of currency risk on investment outcomes and examine the extent to which systemic macro conditions explain its variation.

Empirical Framework for Currency Risk Decomposition

The estimated currency risk impacts form the basis for a time-series decomposition aimed at isolating stable and transitory components of the currency risk discount. Of interest is developing a framework for understanding the dynamic components of the currency risk impact on renewable energy investments. Does the stable component of currency risk dominate its more transitory or volatile elements? If systemic macro factors account for most of the variation in currency risk, to what extent do these macroeconomic factors drive the variance of its stable component? Let

$$RP_t = \mu + \sum_{i=1}^{p} \phi_i RP_{t-i} + \epsilon_t \quad (8)$$

$$\epsilon_t = \sigma_t z_t, \qquad z_t \sim N(0,1)$$

where RP_t is the FX risk premium at time t, σ_t the conditional variance and z_t an i.i.d. normal innovation. Then the conditional variance follows a GARCH(p,q) process:

$$\sigma_t{}^2 = \omega + \underbrace{\sum_{i=1}^{p} \alpha_i \epsilon^2_{t-i} + \sum_{j=1}^{q} \beta_j \sigma^2_{t-j}}_{\text{short-term volatility component}} \quad (9)$$

[8] While BMA is traditionally implemented using Bayesian posterior model probabilities, our approach adopts a frequentist analogue by averaging across bootstrapped estimates from alternative model specifications. This empirical BMA strategy allows us to retain the flexibility of robust estimators and simplifies computational challenges associated with high-dimensional Bayesian integration.

where ω is the long-term volatility component, α_i measures the sensitivity to past shocks and β_j captures volatility persistence. The resulting residual ϵ_t can be decomposed into a predictable (stable) and stochastic (volatile) component. The stable component serves as the basis for structural analysis.

To model the dynamic relationships between macroeconomic shocks and stable FX risk premium, we estimate a Structural Vector Autoregressive (SVAR) model of the form:

$$BY_t = C_1 Y_{t-1} + C_2 Y_{t-2} + \cdots + C_p Y_{t-p} + \epsilon_t \quad (10)$$

where B is the contemporaneous coefficient matrix, Y_t is the stable component of the FX risk premium, Inflation, Real IR, IPS and Business cycle risk. ϵ_t represents orthogonal structural shocks. To uniquely identify B, we impose a recursive ordering Cholesky decomposition:

$$\Sigma_u = PP'$$

where P is a lower triangular matrix. This decomposition assumes that shocks affect some variables contemporaneously, while others respond with a lag. The identification strategy is as follows. Inflation is assumed to be the most exogenous factor, responding only to its own shocks within the same period. Real IR is affected contemporaneously by inflation but does not influence inflation in the same period. Institutional Political Stability is influenced by macroeconomic shocks but responds with delay. Business cycle risk is assumed to be affected by all macroeconomic shocks but does not contemporaneously influence them. The time-varying currency risk impact on capital intensity from Equation (4) is the most endogenous variable, reacting to all shocks but not affecting them contemporaneously. This recursive ordering ensures a structural identification where macroeconomic shocks (inflation, real rates) propagate through the system, influencing institutional risks, business cycle fluctuations, and stable currency risk premia. To quantify the relative contributions of shocks over time we compute 250-period dynamic forecast error variance decompositions[9] (FEVD) (Diebold, Yilmaz, 2012) as:

$$\theta_{i,j}(h) = \frac{\sum_{k=0}^{h-1}(e_i' B^{-1} C_k e_i)^2}{\sum_{k=0}^{h-1}(e_i' B^{-1} C_k B^{-1} e_i)^2} \quad (11)$$

[9] We use 250-day horizons as they seem reasonable amount of time to estimate time-varying betas. Cosemans et al. (2016) use semi-annual data in estimating time-dependent security beta using prior firm fundamentals. Lewellen and Nagel (2006) estimate CAPM alphas and betas using varied rolling windows in the form of monthly, quarterly, semi-annual and annual estimates noting that as long as betas are relatively stable within a month, simple CAPM regressions estimated over a short window - using no conditioning variables - provide direct estimates of assets' conditional alphas and betas.

where $\theta_{i,j}(h)$ is the proportion of variance in Y_i explained by ε_j over h periods[10].

4. Results

Investment contexts in EMDEs

Foreign investment plays a critical role in financing renewable energy and climate-related infrastructure in EMDEs primarily due to the long-dated and capital-intensive nature of renewable energy projects, and the limited depth of domestic financial markets. Unlike domestic investors who operate in local currency and are largely insulated from exchange rate fluctuations, international investors face significant currency risk when financing assets in EMDEs. This risk—amplified by macroeconomic volatility, inflationary pressures, and limited hedging instruments—can deter capital inflows or attract higher risk premia (Ameli et al, 2021). Yet, despite these challenges, international capital continues to flow into EMDE renewables. This paradox is often explained by the search for yield, diversification motives, strategic long-term positioning, and increasingly, the rise of sustainability-linked investment mandates that prioritize climate goals over short-term returns. Against this backdrop, the Paris Agreement of 2016 established clearer long-term policy signals and redefined the risk-reward calculus for investors on the energy transition.

Is currency risk the principal thing?

We present results on feature importance ranking of risk factors that may affect capital intensity. We structure the data into three sets: Pre – 2016, Post 2016 and All and run a RF model to identify temporal and structural patterns in predictive contributions from the risk factors before and after the Paris Agreement. The Paris Agreement marked a significant shift in global climate policy, setting ambitious goals for decarbonization and sustainable investment. Given this institutional shift, we examine temporal dynamics in climate investment predictors pre- and post-Paris. Results are presented in Figure 3.

[10] Given the absence of repeated temporal observations and the cross-sectional nature of our sample, we abstract from calendar time and instead treat the FX risk discount as a structured series of observations matched to macroeconomic fundamentals. Our GARCH decomposition thus captures inherent volatility versus persistent components in the discount series, and our FEVD analysis attributes variance in the stable component to macro factors across the sample.

Across all configurations, LCOE emerges as the most important determinant of capital intensity, reflecting its continued dominance in renewable energy investment decisions, ahead of macro, climate and FX risks. A notable shift emerges in the full period model (compared to pre and post periods): the importance of institutional risks declines slightly relative to Longrun FX Volatility even while the two other currency risk proxies, Shortrun FX Volatility and FX spread (12M) remain the least important predictors of capital intensity in their respective configurations. This result likely reflects the extended duration of exposure to currency risk embedded in renewable energy projects. The increasing importance of Longrun FX Volatility can be explained by several factors. First, many climate-related investments in emerging markets are financed using foreign currency-denominated debt, which exposes investors to exchange rate fluctuations over time (Egli et al., 2022). A depreciating local currency can significantly increase debt servicing costs, negatively impacting the financial viability of projects. Second, the post-Paris period has coincided with increased volatility in emerging market currencies, in part due to global economic disruptions, trade uncertainties, and monetary policy shifts in major economies (Nelson, Shrimali, 2022). This is reflected in the improved feature importance scores of all FX risk metrics in the post-Paris period.

The fact that Longrun FX Volatility only surpasses Institutional risks in the full-period analysis—but not in the pre- or post-Paris windows—suggests that its importance may be conditional on longer time horizons rather than specific policy shifts. On the other hand, transitory currency risk volatility may be more easily hedged away using market-based instruments in emerging markets, and less so if persistent in the long-run. Overall, while Longrun FX Volatility gains importance over time, it is not the principal risk factor affecting investment decisions.

In *Pre-2016* model configurations, a clear trend emerges: Levelized Cost of Electricity (LCOE) remains the dominant factor influencing investment decisions. As renewable energy technology has advanced, LCOE has continued to decline, making investments in wind and solar energy increasingly attractive (Baldwin et al., 2020). The cost competitiveness of renewable energy projects determines their bankability, as lower LCOE enhances expected cash flows and improves the internal rate of return for investors (Steffen, 2021).

While LCOE retains its primacy, a nuanced shift is observed in its relative importance in the *post-Paris* configurations. Macro, climate and institutional risks appear to play a more pronounced role compared to the pre-Paris era. Macro contributions could be attributed to the emphasis placed on climate finance mobilization post-2015, as global and regional climate finance mechanisms gained prominence in facilitating investments (Buchner et al., 2021). In the post-Paris period, climate risks remain a consistently relevant predictor, reflecting heightened investor awareness and integration of climate vulnerability metrics into due diligence processes. Our climate risk factor aggregates CO2 per capita, Disaster Intensity and the share of installed renewable capacity. The impact of climate risks on investment is particularly relevant for emerging markets, where the physical consequences of climate change are more pronounced, and adaptive capacity is often lower (Buchner et al., 2021). Emerging markets now account for more than half of global carbon emissions[11] even as the incidence of extreme physical events continue to occur more frequently than conventional probability distributions would suggest (IPCC, 2021). The post-Paris period likely reflects an increased awareness of these risks and country incentives to decarbonise, even as financial institutions integrate climate-related risks into their investment models. Institutional risks also emerge as an important predictor of renewable investments, especially in the post-Paris period. Strong institutions—defined by regulatory stability, contract enforceability, and financial transparency—reduce project uncertainty and facilitate investor confidence (Fankhauser et al., 2017). The heightened importance of institutional risks post-2016 suggests that investors have placed greater emphasis on governance frameworks and the overall political environment in their decision-making. This aligns with findings from De Haas and Popov (2019), who show that renewable energy investments thrive in jurisdictions with clear regulatory policies and credible enforcement mechanisms.

To better understand the marginal effects of currency volatility across time, we present partial dependence plots (Figure 4). The PDP plots help isolate the marginal effect of each currency risk metric on the dependent variable, capital intensity, while holding all other predictors constant. Across all three currency risk metrics, a general downward trend in the partial dependence plots suggests that as FX

[11] https://edgar.jrc.ec.europa.eu/report_2024

volatility increases, capital intensity declines. Higher FX volatility translates into higher risk-adjusted discount rates, making project financing costlier, especially for investments denominated in foreign currency. Longrun FX Volatility consistently exhibits a more pronounced negative impact on investment than Shortrun FX volatility. This distinction likely reflects the structure of project finance: long-term FX volatility affects debt servicing profiles and discount rates over extended horizons, whereas short-term volatility may be more easily hedged or absorbed through pricing mechanisms. In summary, pre-Paris, partial dependence slopes decline gradually. Post-Paris, steeper drops in Longrun FX Volatility and FX spread (12M) align with rising geopolitical risks, debt crises, and tighter financial conditions which amplify currency volatility.

Currency risk in renewable energy investments

Results of the previous section raise the question of to what extent currency risk is embedded in investment decisions, and whether it manifests as a distinct risk discount that investors account for at the project level? We estimate currency risk discounts to assess the role of FX factors in pricing mechanisms and determine whether they function as standalone risk drivers or are primarily embedded within broader macroeconomic risks. This allows us to link predictive importance (from Random Forests) to actual pricing behavior through FX risk discounts.

We present results from the two-step BMA analysis in Table 2. We report BMA coefficients and bootstrapped standard errors from Huber and Quantile (25%, 50%, 75%) regressions discussed above. Panel A estimates the effect of currency risk on capital intensity project-specific risk factors as controls. For the avoidance of doubt, capital intensity is the dependent variable and Longrun FX Volatility, Shortrun FX Volatility and FX spread (12M) are the variables of interest. All coefficients on FX risk factors - Longrun FX volatility (-0.048), Shortrun FX volatility (-0.066) and FX spread (12M) (-0.064) - are all statistically significant and negative. Higher levels of currency risk volatility are associated with lower levels of capital intensity in renewable energy investments. Shortrun FX Volatility and FX spread (12M) report larger marginal responses in capital intensity than Longrun FX Volatility, reflecting smoothening

effects embedded in Longrun FX Volatility. Investor risk aversion offers another explanation for the larger Shortrun FX Volatility impacts on capital intensity. Higher currency volatility may lead investors to adopt a "wait-and-see" approach, postponing investment decisions until currency fluctuations stabilize. Alternatively, capital may be reallocated to smaller-scale projects with lower exposure to currency fluctuations, effectively reducing the per-MW capital allocation. This behavioural adjustment is especially relevant for renewable energy projects, where investors have flexibility in structuring projects in response to economic conditions. Another important consideration is the availability of risk mitigation instruments, such as hedging. However, if hedging is expensive or unavailable, investment allocations are likely to be reduced (Della Corte et al., 2016).

Consistent with results obtained in the random forest models, LCOE has a statistically and economically significant positive effect (0.201), confirming that higher generation costs per kWh require greater capital intensity. Similarly, CO_2 per capita (0.082) is positively correlated with capital intensity, indicating that in economies with higher carbon footprints, investors allocate more capital per unit of capacity. This could either reflect policy incentives to speed up decarbonisation goals or the necessity of additional capital expenditures to meet environmental goals. Institutional political stability (IPS, 0.038) positively impacts capital intensity. Conversely, the share of renewable capacity (-0.054) is negative but statistically insignificant, implying the level of market penetration of renewables does not significantly affect capital intensity at the project level.

The estimated currency risk discount has unique properties. First, it is inferred from actual investment behaviour and not assumed discount rates as in traditional approaches that rely on cost of capital models, credit spreads, or risk-adjusted return expectations (Harvey et al., 2002; Ang et al., 2006). Second, it captures risks as priced by emerging market investors based on capital allocation in relatively illiquid, long-term renewable energy assets. This highlights the importance of understanding how long-run macro volatility is capitalized ex-ante into project-level investment behaviour, especially in illiquid markets (Dixit & Pindyck, 1994). This means that the discount reflects embedded currency risk in actual capital commitments rather than speculative considerations. Third, we bypass data limitations on the cost of capital

and financial structuring. A major challenge in studying climate finance in developing markets is the lack of granular data on project financing terms such as the exact cost of debt, equity risk premiums, and weighted average cost of capital (WACC). Given renewable energy investments often involve a mix of private capital, public subsidies, and development finance institutions (DFIs), estimating market-equivalent cost of capital directly is difficult. The project-implied currency risk discount - the reduction in capital intensity attributable to FX volatility - sidesteps this issue by backing out risk perceptions from capital intensity rather than granular financing data.

Can the currency risk discount be explained by systemic macroeconomic variables? To answer this question, we regress currency risk discounts on systemic macro risk factors – Inflation, Real IR, Debt-to-GDP and Current Balance. β_0 is the outcome of interest. If the estimated discount is unique, we expect the residual risk discount (β_0) to be statistically significant. The results of this exercise are shown in Panel B of Table 2. Controlling for the above macroeconomic variables, the residual discount is statistically indifferent from zero across all model specifications. This suggests that much of what appears to be an currency risk discount in Panel A is driven by systemic macroeconomic conditions.

Among macroeconomic factors, inflation (-0.030) and real interest rates (-0.026) are both negative and highly significant, implying that macroeconomic instability is associated with larger currency risk discounts as investment per MW shrinks.[12] Current Balance (0.013) has a positive and significant effect on the currency risk discount (discount gets smaller), meaning stronger external positions are associated with larger capital investments, in that current account surpluses reduce external financing constraints, making investments more viable even in volatile FX environments. In contrast, Debt-to-GDP (-0.002) is statistically insignificant, indicating that sovereign debt levels do not directly affect the level of the currency risk discount. The insignificance of debt-to-GDP likely reflects endogeneity in sovereign debt issuance across developing economies. Most countries in the sample operate within shallow domestic capital markets and rely heavily on external borrowing, constraining cross-sectional variation in issuance profiles. In this context, debt levels are endogenous to macroeconomic fundamentals—rising inflation, real interest rates,

[12] In a risk-return paradigm, investors would charge a higher risk premium to compensate for macro instability.

and current account imbalances—which are already accounted for by other covariates. Moreover, investors may heavily discount headline debt ratios when multilateral development banks (MDBs) or concessional finance structures offer guarantees or credit enhancements that assuage sovereign risk concerns in undercapitalized markets. Accordingly, debt-to-GDP exhibits limited marginal explanatory power in the pricing of currency risk premia in capital-intensive investments.

These results underscore that currency risk in EMDE climate investments is not simply an exogenous hazard but is tightly linked to systemic macro stability, highlighting the potential for policy interventions that improve macro fundamentals to indirectly reduce perceived FX risk.

Broader economic implications for currency risk hedging and climate investment policy

Given that the currency risk discount is largely explained by systemic macroeconomic conditions, we next examine its temporal structure. Specifically, we ask whether the discount is primarily driven by a persistent component or by transitory fluctuations. This distinction is policy-relevant: if currency risk is embedded in stable dynamics, then long-term de-risking instruments may be more appropriate than short-term hedging solutions and even more incentivising for long-dated renewable energy investments. To investigate this, we decompose the estimated currency risk discounts for the Longrun currency discount, Shortrun currency discount, and Currency spread discount using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework. The GARCH model captures the time-varying volatility of the risk premium and allows us to separate short-term volatility from more persistent structural variation. The stable component is defined as the difference between the observed discount and the conditional volatility, while the volatile component is proxied by the GARCH-estimated conditional variance.

Figure 5 presents the results of this decomposition. The upper row plots the level of each currency risk discount alongside its volatile component, while the bottom row shows the share of the total premium attributable to the stable component. Across all three metrics, the stable component accounts for over half of the observed risk discount: 54.5 percent in the Longrun currency discount, 53.3 percent in the Shortrun discount, and 53.3 percent in the FX spread discount. This suggests that structural factors—including

macroeconomic fundamentals, monetary policy credibility, and institutional stability—play a central role in shaping investor perceptions of currency risk in EMDEs.

Figures 6 and 7 provide additional country-level decomposition results for Brazil and India, respectively, offering deeper insight into how currency risk structures may interact with renewable energy investment. In Brazil (Figure 6), the stable component of the Longrun currency discount dominates persistently across the entire time series, with values remaining near or above 0.8. This high degree of persistence suggests that long-horizon currency risks in Brazil are closely anchored to macroeconomic fundamentals rather than transitory events. For investors in renewable energy, this is a favourable signal: long-term hedging strategies based on stable, structural indicators are more likely to align with underlying FX risk dynamics. It creates a more predictable environment for foreign capital to engage in infrastructure investments, particularly in assets with long amortization profiles such as solar and wind energy projects.

In contrast, our India results in Figure 7 present a more dynamic and fragmented pattern. Although the longrun component remains largely stable over time, the Shortrun and Currency spread discounts exhibit considerable volatility, especially in the earlier segments of the series. These fluctuations point to a larger role for transient shocks and potential policy interventions in the pricing of short-term FX risk. For renewable energy investors, this implies a more complex risk management landscape. While long-term investments may still benefit from structural predictability, short-term exposure—such as during early-stage project financing or construction—could face greater FX uncertainty. This underscores the need for more responsive, possibly layered hedging strategies that can accommodate both structural trends and episodic volatility in the Indian context.

Given that stable components of the currency risk discount dominate the volatile parts, we next address how macro factors dynamically combine to drive the stable currency risk discounts. Dynamic FEVDs quantify macroeconomic shocks' contributions to the stable currency risk discounts variance over 250-period horizons. Using a Structural Vector Autoregression (SVAR) model with Cholesky decomposition for identification, we estimate the forecast error variance attributable to each systemic factor

and dynamically visualize how the explanatory power of these variables evolves with changing economic conditions (Diebold & Yilmaz, 2012).

Based on macroeconomic theory and the results of the BMA analysis, we select inflation, real interest rates, and institutional and political stability for the FEVD decomposition. We introduce business cycle risk as a fourth factor in this analysis. Business cycle risk captures fluctuations in economic activity and growth cycles that affect investor confidence and capital flows. During economic downturns, currency risks typically rise due to deteriorating sentiment, increased capital flight, and tighter credit conditions. Conversely, in expansionary phases, currency risk discounts may decline as levels of investment improve. This mechanism is particularly important in emerging and developing economies, where investment and capital inflows are closely tied to global financing cycles.

Figure 8 shows the proportion of variance in the stable component that can be attributed to the different macro risk factors over time. First, across all currency risk discount metrics, we observe strong cyclical contributions of business cycle risk (blue). This pattern suggests that currency risk discounts spike when investors anticipate weaker economic performance, underscoring the pro-cyclicality of FX risk. Second, there is considerable heterogeneity in the factor contributions across risk discount types. Inflation (red) and real interest rates (green) play more prominent roles in shaping the longrun currency discount, consistent with monetary policy fundamentals driving long-term exchange rate expectations. In contrast, short-run and currency spread discounts are more sensitive to business cycle fluctuations and political stability, pointing to the influence of macro-financial sentiment and institutional credibility over shorter horizons.

Figures 9 and 10 provide country-specific decompositions of the stable component of the currency risk discount for Brazil and India, respectively. In Brazil (Figure 9), inflation and real interest rates contribute most significantly to the longrun currency discount, consistent with a macro-financial environment in which monetary conditions play a central role in shaping investor expectations around FX stability. Meanwhile, the shortrun and currency spread discounts exhibit heightened sensitivity to business-cycle dynamics and institutional-political conditions, underscoring the influence of domestic macro-

financial cycles and governance perceptions in short-horizon currency risk pricing. For India (Figure 10), the decomposition reveals a more inflation-centric risk profile across all three currency discount measures. Inflation emerges as the dominant contributor, particularly for the short-run and spread components, aligning with India's well-established inflation targeting framework and the anchoring role it plays in monetary transmission. The comparatively modest influence of business cycle risk points to a more policy-driven macro environment, where FX risks are more closely tethered to nominal stability than cyclical growth fluctuations. Together, these results highlight the heterogeneity in macro risk transmission mechanisms across EMDEs and the importance of tailoring FX risk management to country-specific macro-financial structures—an essential consideration for investors in long-horizon renewable energy infrastructure.

For policymakers seeking to address currency risk in climate investments, our findings underscore the value of tailoring risk mitigation tools to the structural nature of currency risk. First, given that stable currency risk discounts dominate volatile components, hedging strategies should prioritize structural and persistent macro-financial drivers over short-term volatility, given renewable energy projects—often financed through long-term, foreign-denominated debt while generating local currency cash flows— are exposed to duration-sensitive FX risk. Rather than deploying generalized public finance support, targeted de-risking instruments—such as partial credit guarantees or risk-sharing facilities—can reduce risk premia and crowd in private capital. However, conventional approaches that hedge the full distribution of FX risk may be cost-inefficient, particularly during periods of global risk aversion when hedging premia spike. A more capital-efficient strategy involves hedging the stable component of FX risk, which not only aligns with investors' long-term return requirements but also optimizes the catalytic use of concessional finance in blended structures.

In economies where currency risk is closely tied to business cycle fluctuations, counter-cyclical fiscal policies and robust foreign exchange reserve buffers may help smooth currency risk exposure. Conversely, in markets where inflation and interest rates exert the most influence on currency risk, the implementation of credible monetary policies and inflation-targeting frameworks can enhance FX stability

and reduce risk perceptions among investors. Moreover, in jurisdictions where institutional and political stability plays a significant role, structural reforms that strengthen regulatory transparency and governance could help reduce currency risk impacts on the level of renewable energy investments.

5. Conclusion

By all accounts, weaning the world off fossil fuels requires a substantial increase in renewable energy investment. Renewable energy projects are often financed with foreign-denominated debt, while revenues are earned in local currency, exposing investors to exchange rate fluctuations that increases capital costs and affect project viability. Despite the widespread recognition of this issue, empirical evidence on currency risk dynamics in climate investments remain scarce and mostly anecdotal. This study provides robust empirical evidence on how currency risk interacts with renewable energy investments in emerging and developing economies. Our multi-method analysis demonstrates that while foreign exchange volatility is not the principal driver of capital allocation—technology cost metrics, notably the levelized cost of electricity, exert the dominant influence, alongside other structural determinants—currency risk nonetheless exerts a statistically and economically significant dampening effect on investment intensity.

However, this currency risk discount in levels of climate investment is not orthogonal to broader economic conditions. Our findings show it is largely explained by systemic macroeconomic fundamentals, particularly inflation, real interest rates, and current account dynamics. When these variables are accounted for, the standalone explanatory power of FX volatility disappears. Importantly, more than half of the currency risk discount is attributable to persistent, stable components rather than transitory shocks. Through GARCH and SVAR decompositions, we show that these stable components are shaped over time by structural drivers—most prominently business cycle fluctuations and monetary fundamentals. The dynamic variance decomposition further highlights a time-varying macroeconomic foundation of currency risk, with business cycles dominating short-horizon FX discounts and monetary stability shaping long-run risk premia.

These insights carry direct policy relevance. First, hedging solutions should be structurally aligned: risk mitigation tools such as currency stabilization facilities or guarantee mechanisms backed by multilateral development banks (MDBs) should focus on hedging the stable component of FX risk. This avoids the inefficiency of fully hedging short-term fluctuations, which are often prohibitively expensive and less relevant for long-duration infrastructure assets. Second, improving monetary and fiscal fundamentals is not only prudent macroeconomic policy - it is also climate finance policy. Credible inflation-targeting regimes and macro-prudential buffers reduce the risk premium embedded in FX volatility, thereby lowering the cost of capital for renewable energy investments. Finally, institutional and political stability, particularly in jurisdictions with volatile short-horizon risk metrics, should be prioritized in de-risking strategies to attract foreign capital.

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Figure 1

Number of projects by country.

The data sample spans the period 2010 – 2020. The figure shows the number of unique projects per country in the final dataset. Projects must be from developing countries, report size of investment (mUSD) and capacity (MW). China is excluded. The resulting project data is matched against macro, project-specific and climate risk variable proxies on country and year-month.

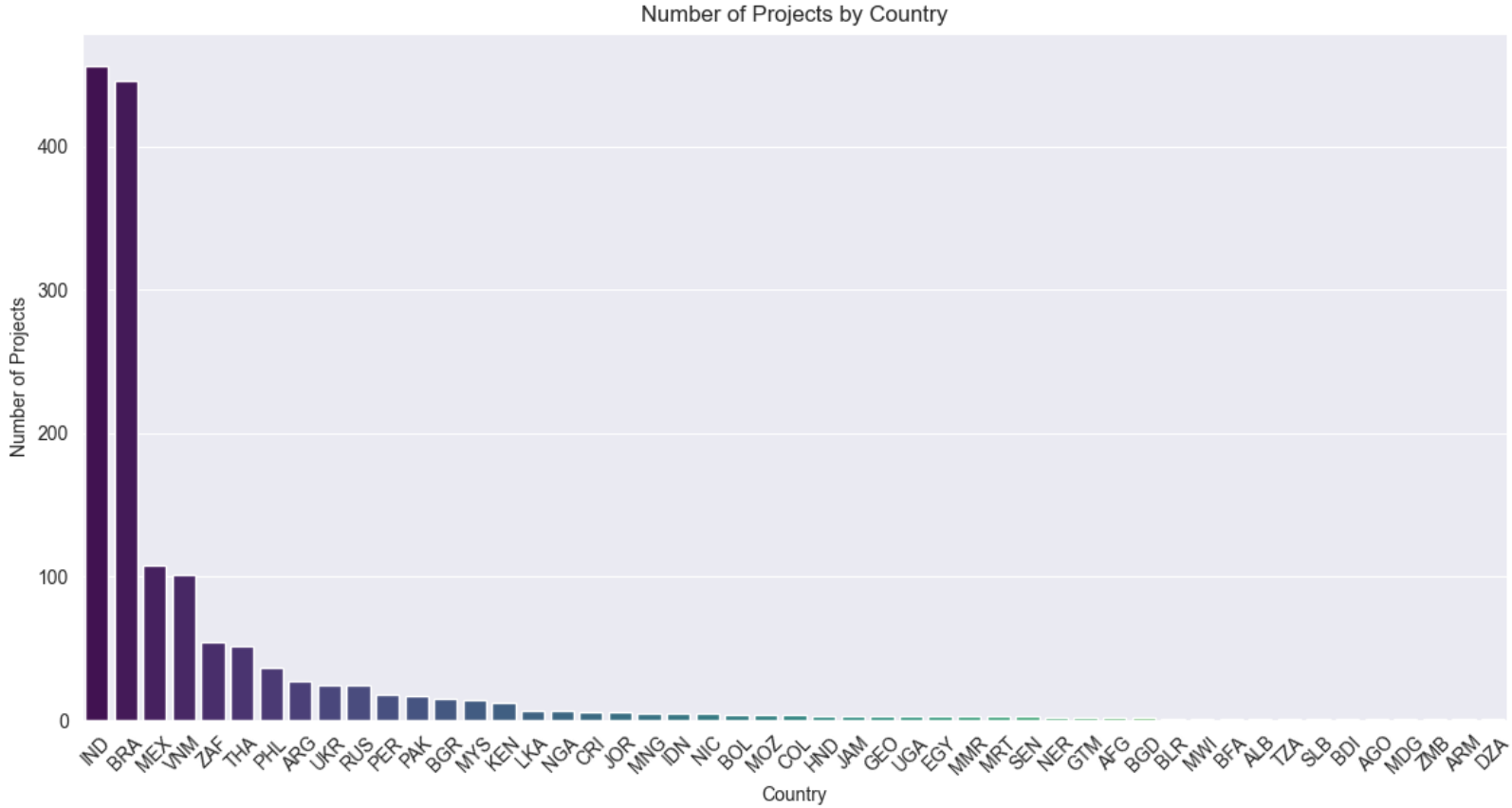


Figure 2

Currency risk proxies – India (IND) and Brazil (BRA) - from 2010 to 2020.

Figure 2 presents the currency risk proxies used, plotted for the India (IND-USD) and Brazil (Real – USD) from 2010 – 2020. The currency risk metrics are defined in Table 1.

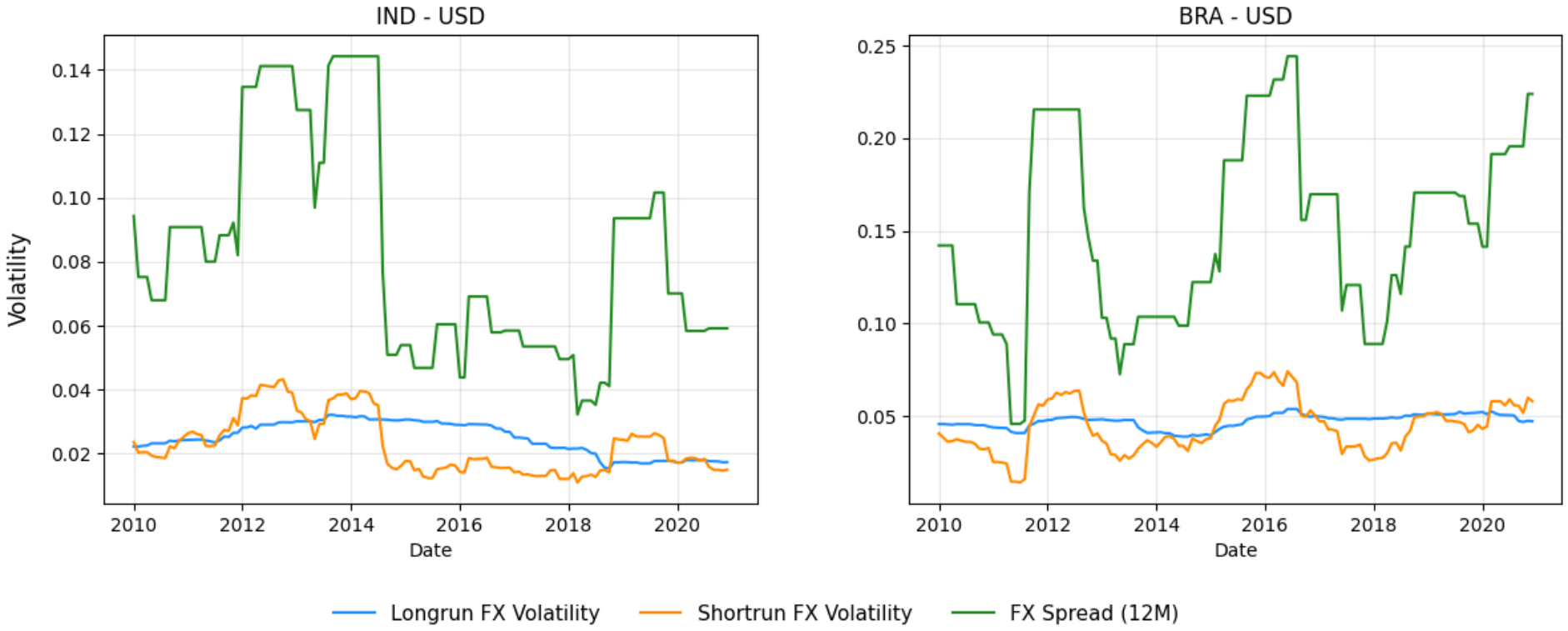


Figure 3

Feature Importance Scores from Random Forest Models across Configurations (2010–2020).

Figure 3 presents feature importance rankings (./100) from Random Forest models for three configurations. All variables are defined in Table 1. *Pre* models use project and risk data before Paris, while *Post* models use data from 2016 – 2020. *All* models use data from 2010 – 2020. The dataset is further split into training (70%) and testing (30%) sets. The dependent variable is *Capital Int.* Independent variables are *Macro risks*, *Institutional risks*, *Climate risks*, *LCOE* and one of either *Shortrun FX volatility*, *Longrun FX volatility* or *FX Spread 12M*. Macro. Macro risk represents the first principal component obtained from running Principal Component Analysis (PCA) on *Inflation*, *Debt-to-GDP*, *Current Balance* and *Real interest rates*. Institutional risks aggregates *IPS*, *IRQ*, *IRL* and *IVA* in a PCA. Climate risks aggregates *Disaster Int.*, *CO2 per capita*, and *Share of Ren. Capacity* in a PCA. A Random Forest Regressor is trained for each configuration to optimize hyperparameters. We report the Durbin-Watson statistic, the R-square and the mean square error (MSE).

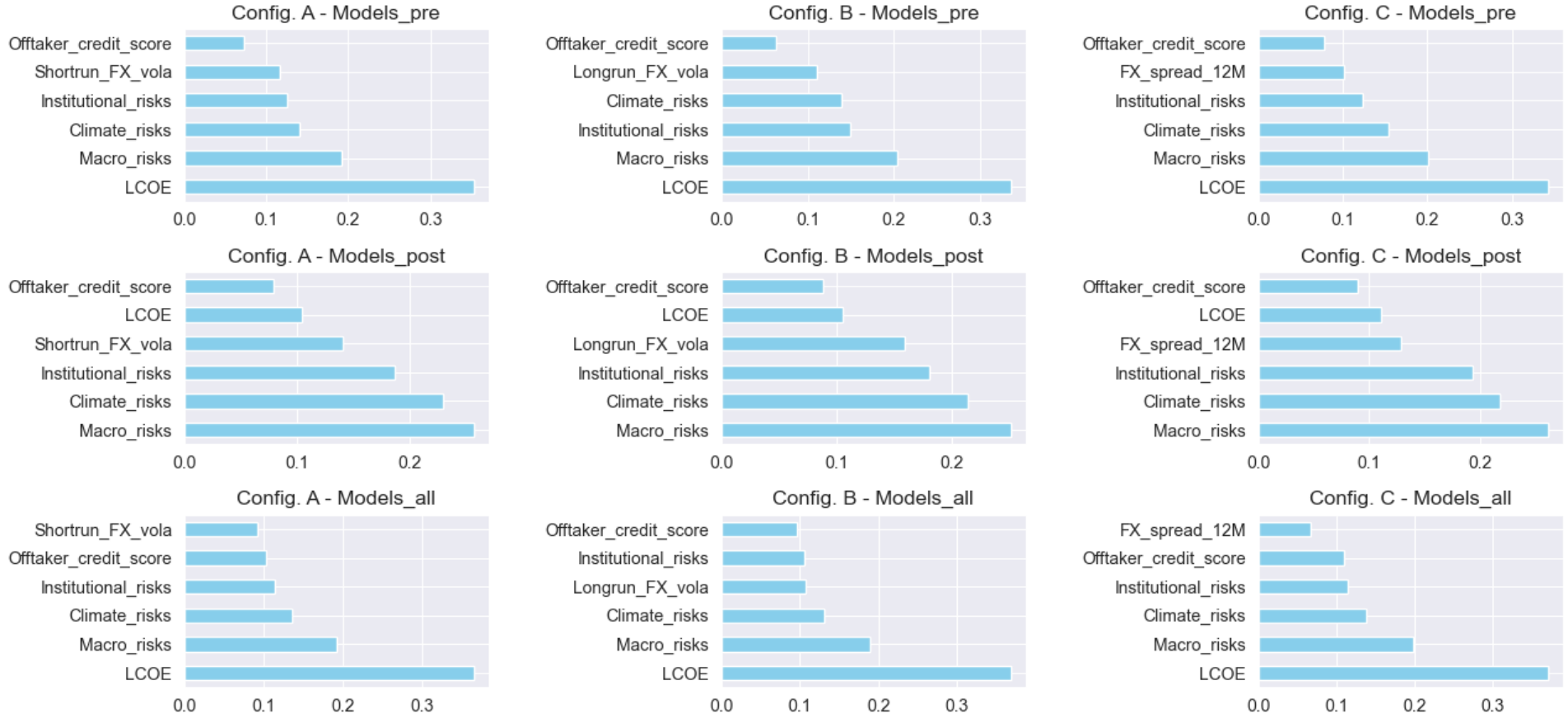


Figure 4

Figure 4 presents partial dependence plots for currency risk metrics based on results in Figure 3. The horizontal and vertical axes show standard deviation moves and capital intensity (in mUSD) respectively. All underlying variables and data stratification are defined in Table 1 and Figure 2 respectively.

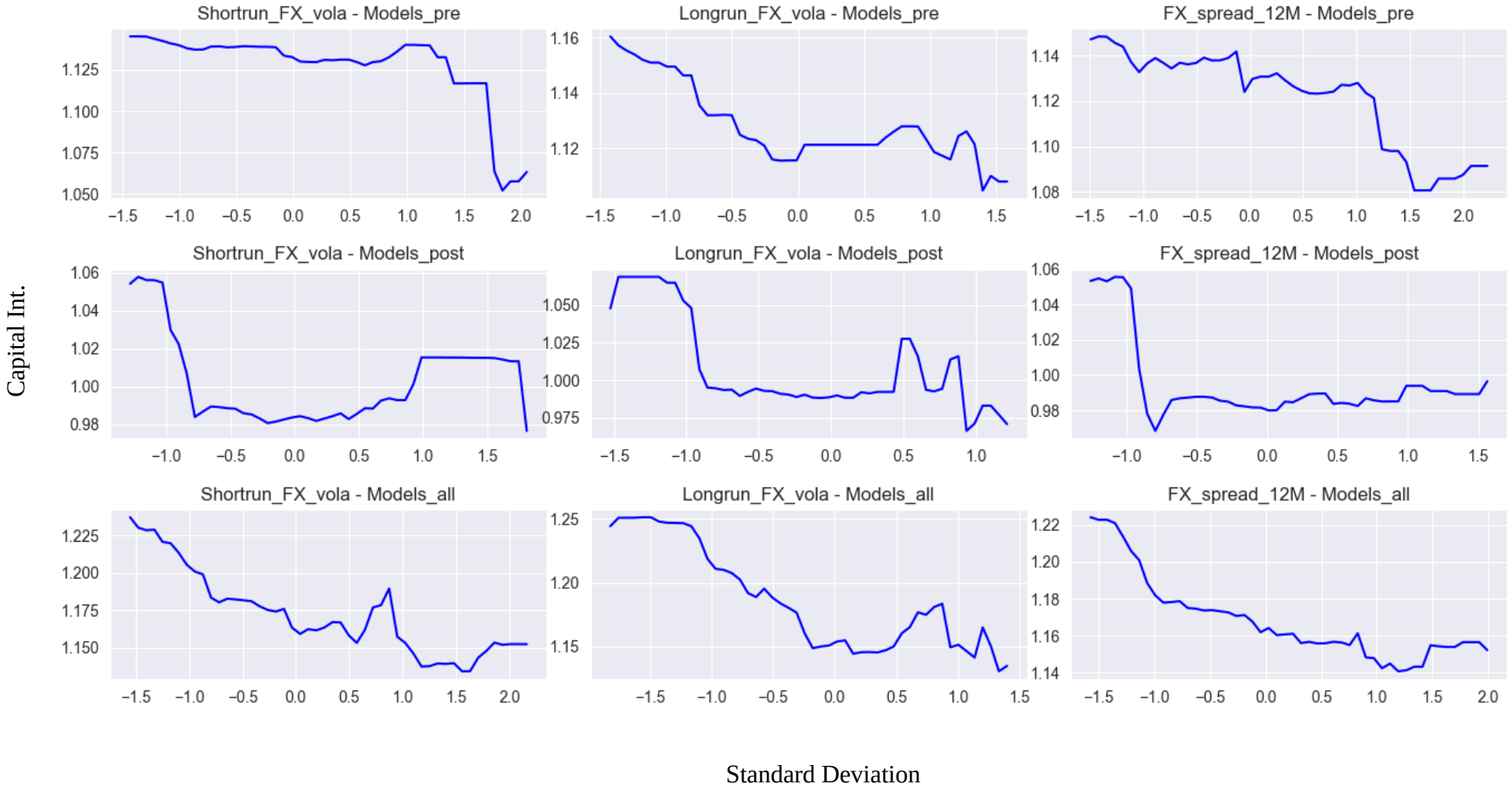


Figure 5

Decomposition of currency risk discounts into stable and volatile components.

Figure 5 presents the decomposition of Long-run (LR_RP), Short-run (SR_RP), and FX Spread (12M) (MM_RP) FX risk premiums into their structural - stable (black) and transitory - volatile (orange) components in the upper row. The bottom row presents the stable proportions of the total FX risk premium. The underlying methodology employs a Generalized Autoregressive Conditional Heteroskedasticity (GARCH (p,q)) model. Optimal parameters of (p,q), are estimated using Akaike Information Criterion to best capture the dynamic properties of FX risk. FX risk premiums are the implied FX risk premium estimated from the Bayesian Model Averaging regressions in Table 3.

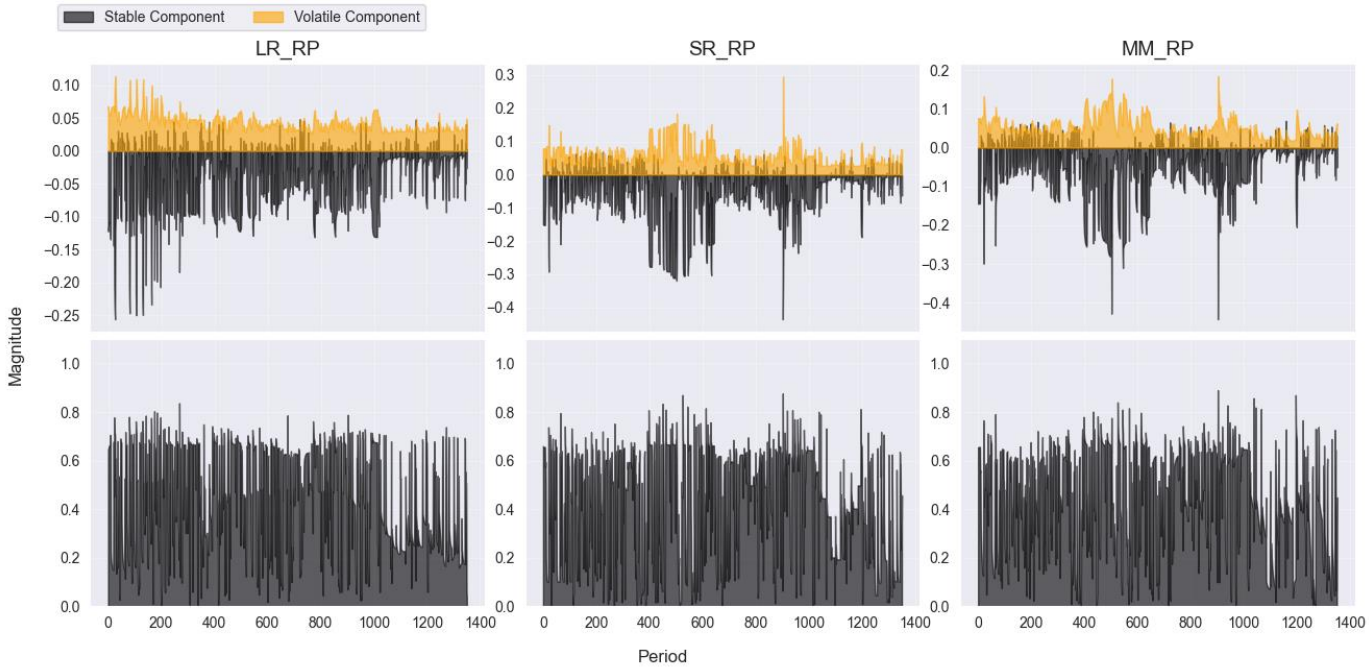


Figure 6

Decomposition of currency risk discounts into stable and volatile components – Brazil.

Figure 6 replicates the currency risk decomposition in Figure 5 for Brazil.

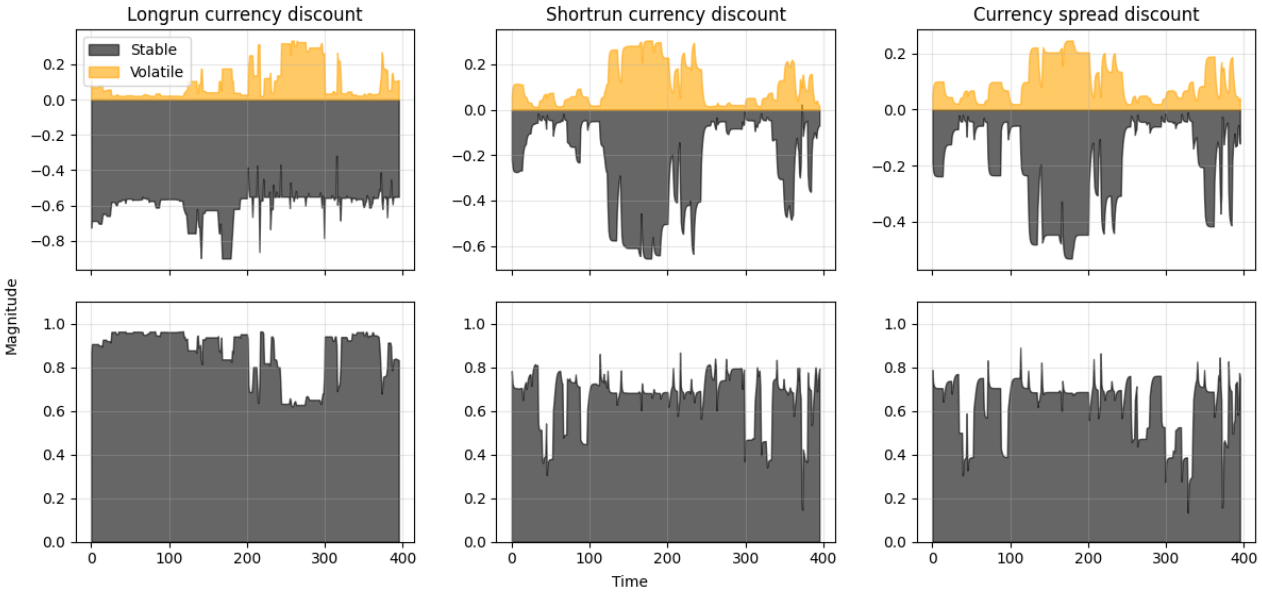


Figure 7

Decomposition of currency risk discounts into stable and volatile components – India.

Figure 7 replicates the currency risk decomposition in Figure 5 for India.

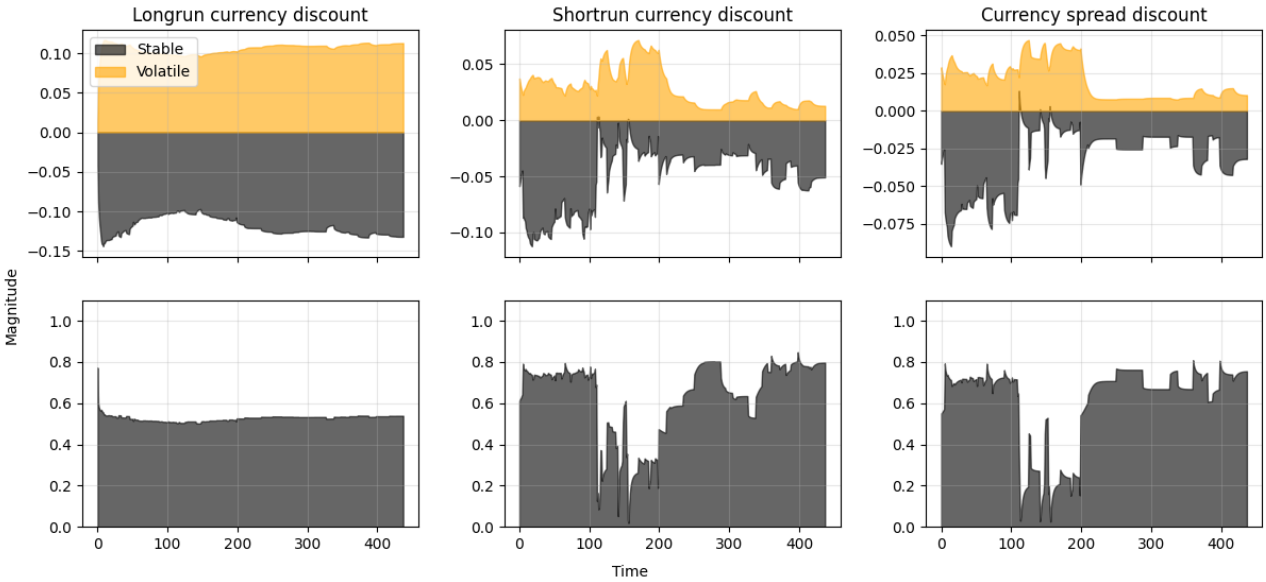


Figure 8

Dynamic Forecast Error Variance Decomposition (FEVD) of the stable component of the currency risk.

Figure 8 presents the dynamic forecast error variance decomposition (FEVD) of the stable components of three FX risk discounts over 250-period rolling windows for: *Longrun currency discount*, *Shortrun currency discount*, and *Currency spread discount*. Discounts are extracted from the Fama MacBeth regressions in Table 2. The decomposition quantifies how different economic shocks contribute to variations in the currency risk discount over time. The dynamic FEVDs are built on a Structural Vector Autoregression (SVAR) model which traces how shocks to fundamental macroeconomic variables influence FX risk discounts over time. Four key macroeconomic factors are included in the SVAR system. Business Cycle Risk (Blue) – Represents fluctuations in economic activity, often linked to GDP growth, trade cycles, and financial stability. Institutional and Political Stability (IPS) (Green) – captures sovereign risk elements such as governance, regulatory stability, and policy consistency. Real Interest Rates (Orange) – reflects monetary policy impacts and the relative attractiveness of domestic assets versus foreign alternatives. Inflation (Red) – measures macroeconomic price stability, which influences exchange rate expectations and investor confidence. The decomposition is computed as:$\Omega_{i,t}(h) = \frac{\sum_{j=1}^{h}(B_{i,j}\varepsilon_j)^2}{\sum_{j=1}^{h}(B\varepsilon_j)^2}$ where $\Omega_{i,t}(h)$ represents the contribution of shock i at time t to the variance forecast over horizon h, and B denotes the Cholesky decomposition matrix of the SVAR residuals. The vertical axis shows the proportion of forecast error variance explained by each factor.

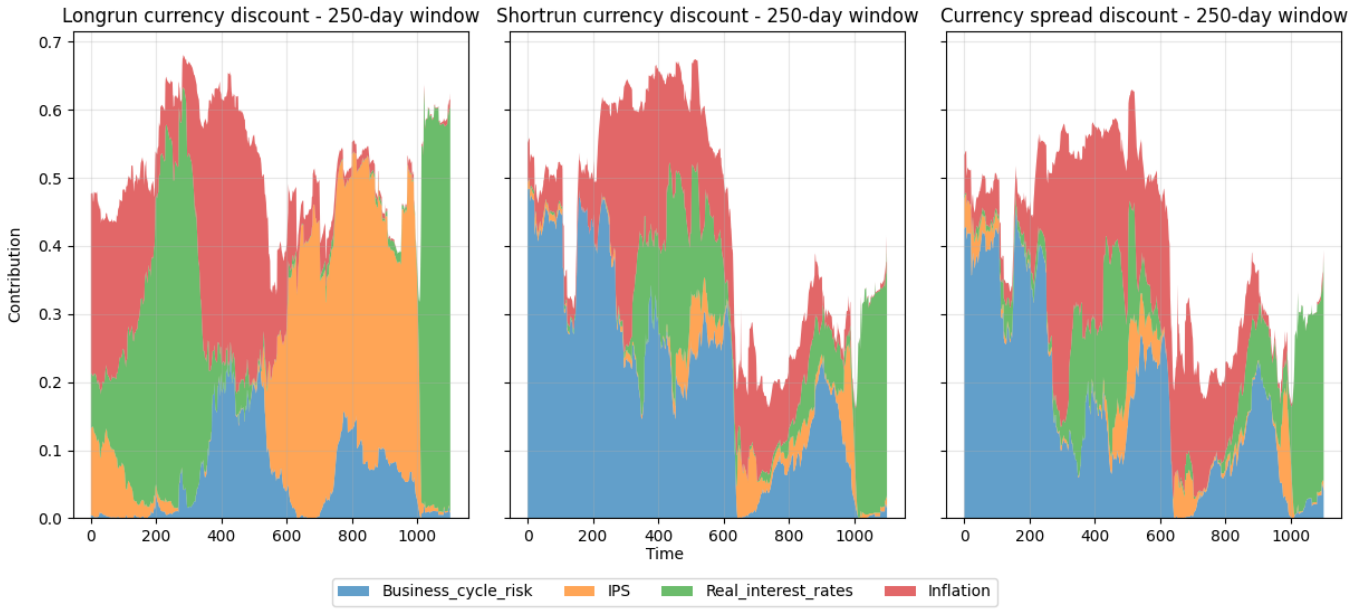


Figure 9

Dynamic Forecast Error Variance Decomposition (FEVD) stable currency risk – Brazil.

Figure 9 replicates the dynamic forecast error variance decomposition (FEVD) shown in Figure 8 for Brazil.

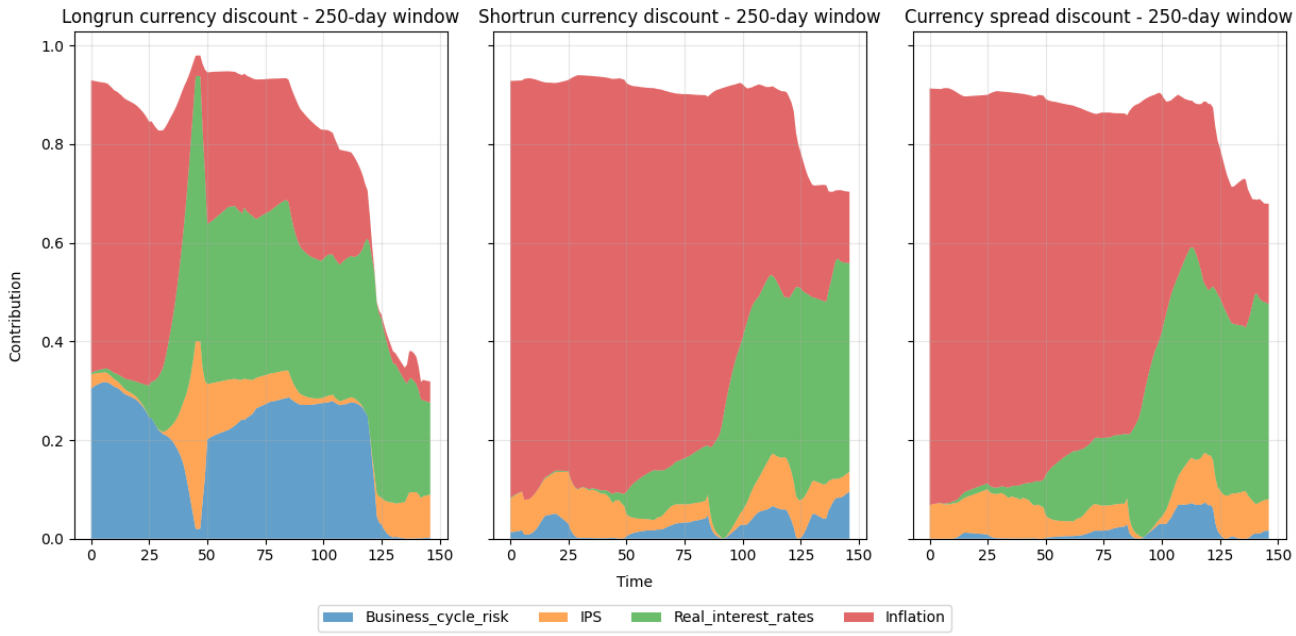


Figure 10

Dynamic Forecast Error Variance Decomposition (FEVD) stable currency risk – India.

Figure 10 replicates the dynamic forecast error variance decomposition (FEVD) shown in Figure 8 for India.

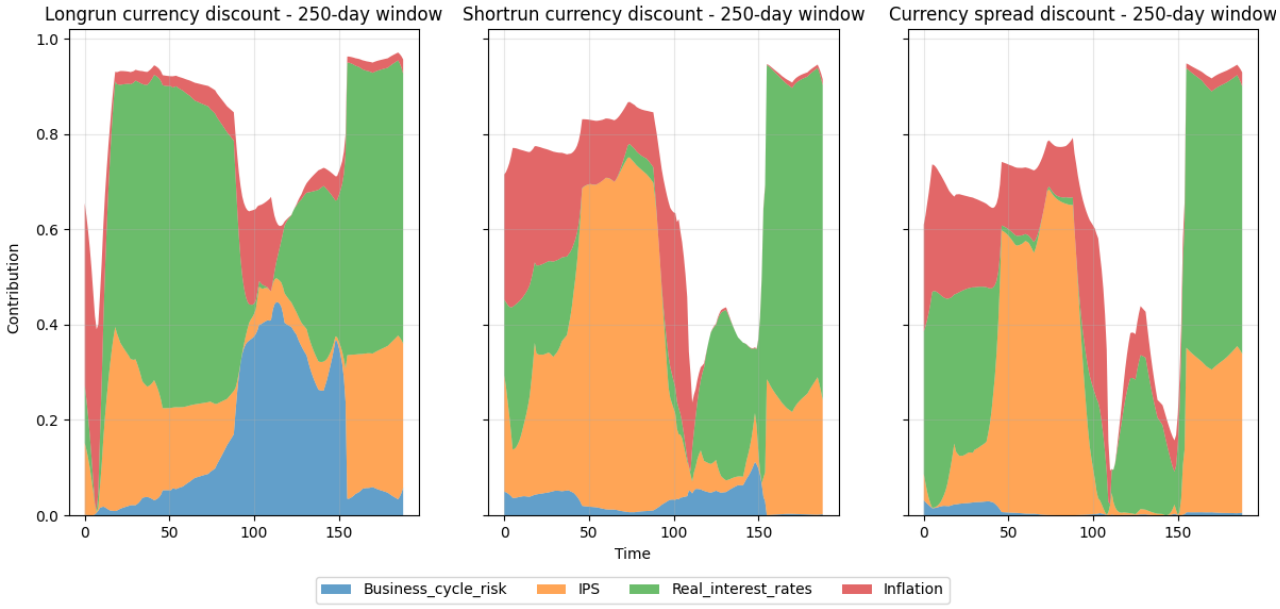


Table 1

Summary statistics.

Table 1 presents summary statistics (the number of observations, mean, median and standard deviation) for the variables used in this analysis. **Panel A** reports on Project-Specific Variables. *Capital Int.* is the square-root of the ratio of nominal investments (mUSD) per unit of capacity (MW); *Off. Credit Sc.* measures the creditworthiness of the entity purchasing renewable energy; *LCOE* measures the average lifetime cost of producing energy in USD/kWh. **Panel B** reports on Institutional Risk Variables annually: *IPS* measures the overall stability and effectiveness of political institutions per country; *IRQ* measures how well laws and regulations support market efficiency and economic activity; *IRL* measures contract enforcement and the rule of law; *IVA* measures the degree of political freedoms, democratic participation, and transparency in governance. **Panel C** reports on Macro Risk Variables: *Inflation* measures the monthly percentage change in consumer price inflation rate (%) for each country; *Curr. Balance* (% GDP) measures a country's net trade and financial flows annually; *Debt-to-GDP* measures gross sovereign debt as a percentage of GDP annually; Real IR measures inflation-adjusted borrowing costs (%). **Panel D** reports on Climate Risk Variables. *CO_2 per capita* measures the individualised carbon emissions on country level; *Share of Ren. Capacity* measures the percentage of total installed electricity generation capacity derived from renewable sources; *Disaster Int*: measures economic damages from natural disasters (in mUSD), adjusted by number of people affected. **Panel E** reports on Currency Risk Variables. *Long-run FX Volatility* is the 60-month rolling standard deviation of the natural logarithm of FX returns; *Short-run FX Volatility* is the 12-month rolling standard deviation of the natural logarithm of FX returns; FX Spread (12M) is the difference between maximum and minimum log FX returns over a 12-month period.

Variable	N	μ	Median	σ
Panel A: Project-specific Variables				
Capital Int.	1502	1.166	1.116	0.455
Offtaker Credit Score	1502	60.036	62.500	20.991
LCOE	1502	-2.340	-2.291	0.418
Panel B: Institutional Risk Variables				
IPS	1502	26.088	22.642	14.258
IRQ	1502	45.976	46.667	10.757
IRL	1502	46.991	52.113	10.292
IVA	1502	52.164	60.190	15.954
Panel C: Macro Risk Variables				
Inflation	1502	6.383	5.571	3.513
Curr. Balance	1502	-2.175	-2.857	2.845
Debt-to-GDP	1502	60.606	67.702	17.282
Real IR	1502	12.153	5.159	14.165
Panel D: Climate Risk Variables				
CO2_per_capita	1502	2.607	2.161	1.873
Share of Ren. Capacity	1502	43.048	28.130	26.657
Disaster Int.	1502	805.850	3.212	4813.525
Panel E: Currency Risk Variables				
Longrun FX volatility	1502	0.030	0.027	0.018
Shortrun FX volatility	1502	0.033	0.030	0.016
FX Range_12M	1502	0.101	0.091	0.061

Table 2

Currency risk in renewable energy project investments.

The sample period is 2010 – 2020. In Panel A, the dependent variable is Capital Int. In Panel B, the dependent variable is the implied current risk discount derived from Panel A results. The dependent variables are lagged and standardised within group (Low income, Low middle income and Upper middle income) to account for country income status heterogeneity. We report Bayesian Model Average (BMA) coefficients and standard deviations (in parenthesis). The estimation framework incorporates Huber and Quantile (25% , 50%, 75%) regressions to reduce the impacts of extreme observations in the data sample and to avoid making distributional assumptions about the data. BMA coefficients and standard errors in both panels are conducted using 2500 bootstrap replications. ***1% significance; **5% significance; *10% significance.

Panel A: Project-specific variables			
Variable	(1)	(2)	(3)
Longrun FX volatility	-0.048**		
	(0.023)		
Shortrun FX volatility		-0.066***	
		(0.015)	
FX Spread (12M)			-0.064***
			(0.015)
IPS	0.038**	0.039**	0.038**
	(0.018)	(0.020)	(0.019)
Share Ren. Capacity	-0.054	-0.048	-0.051
	(0.039)	(0.050)	(0.048)
LCOE	0.201***	0.209***	0.208***
	(0.027)	(0.031)	(0.031)
CO2 per capita	0.082***	0.077***	0.075***
	(0.015)	(0.014)	(0.013)
Adj. R-Square	0.340	0.350	0.349
Panel B: Systemic Macro Variables			
Constant	0.004	0.003	0.001
	(0.015)	(0.026)	(0.028)
Inflation	-0.030***	-0.020***	-0.010***
	(0.004)	(0.007)	(0.008)
Real interest rates	-0.026***	-0.032***	-0.030***
	(0.004)	(0.005)	(0.005)
Debt-to-GDP	-0.002	-0.004	-0.008
	(0.006)	(0.013)	(0.014)
Current Balance	0.013***	0.023***	0.021***
	(0.004)	(0.006)	(0.007)
Adj. R-Square	0.437	0.429	0.412

Appendix

Figure A1

Currency Returns (vs USD) from 2010 – 2020 for Brazil and India

Figure 2 shows monthly log returns for the Indian Rupee – USD and Brazilian Real – USD from 2010 – 2020.

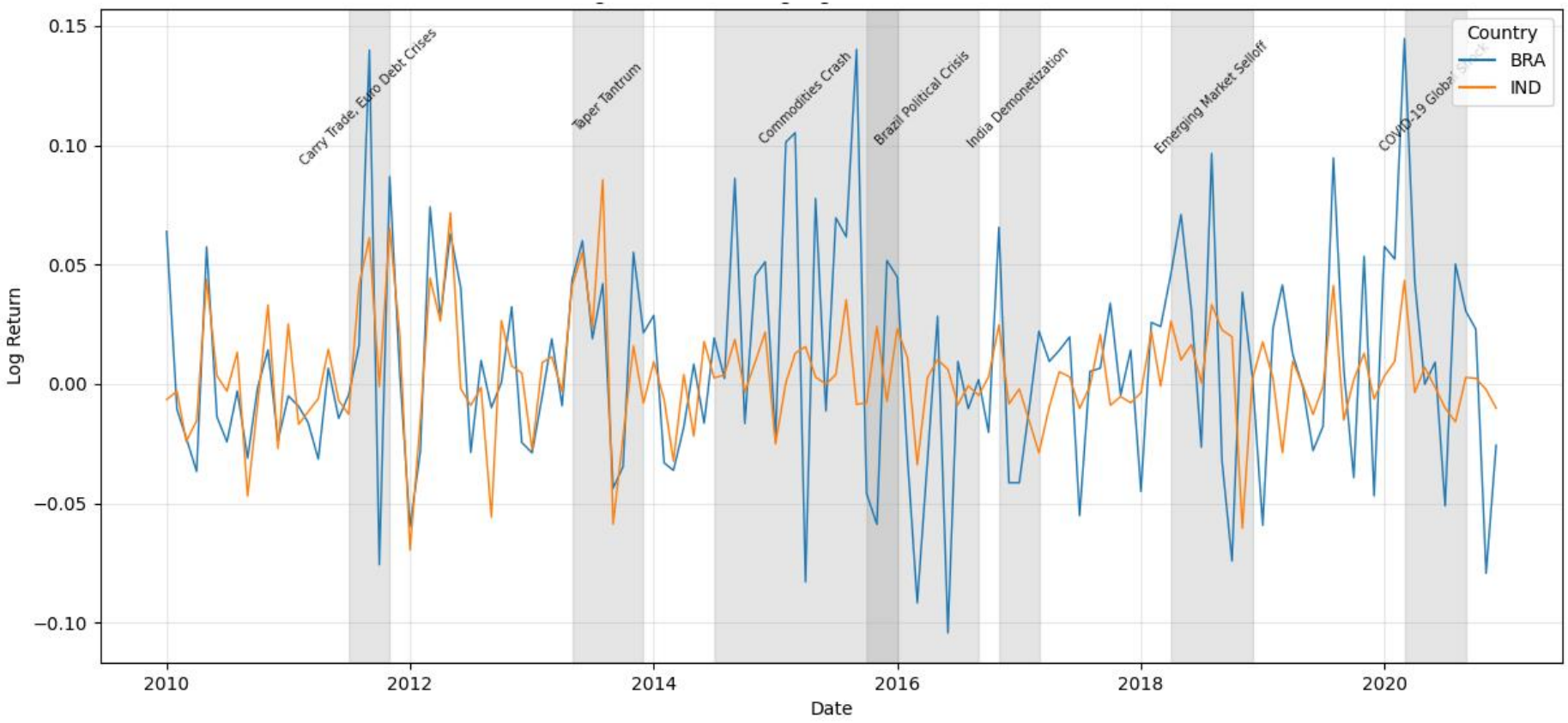


Figure A2

Dynamic Forecast Error Variance Decomposition (FEVD) of the stable component of currency risk.

Figure A2 presents the dynamic forecast error variance decomposition (FEVD) of the stable components of three FX risk discounts over 120-period rolling windows for the three FX risk discount measures: Long-run Risk (LR_RP), Short-run Risk (SR_RP), and FX Spread (12M) (MM_RP). The metrics are extracted from regressions that show the impact of currency instability on capital intensity. The decomposition quantifies how different economic shocks contribute to variations in the currency risk discount over time. The dynamic FEVDs are built on a Structural Vector Autoregression (SVAR) model which traces how shocks to fundamental macroeconomic variables influence FX risk discounts over time. Four key macroeconomic factors are included in the SVAR system. Business Cycle Risk (Blue) – Represents fluctuations in economic activity, often linked to GDP growth, trade cycles, and financial stability. Institutional and Political Stability (IPS) (Green) – captures sovereign risk elements such as governance, regulatory stability, and policy consistency. Real Interest Rates (Orange) – reflects monetary policy impacts and the relative attractiveness of domestic assets versus foreign alternatives. Inflation (Red) – measures macroeconomic price stability, which influences exchange rate expectations and investor confidence. The decomposition is computed as:$\Omega_{i,t}(h) = \frac{\sum_{j=1}^{h}(B_{i,j}\varepsilon_j)^2}{\sum_{j=1}^{h}(B\varepsilon_j)^2}$ where $\Omega_{i,t}(h)$ represents the contribution of shock i at time t to the variance forecast over horizon h, and B denotes the Cholesky decomposition matrix of the SVAR residuals. The vertical axis shows the proportion of forecast error variance explained by each factor.

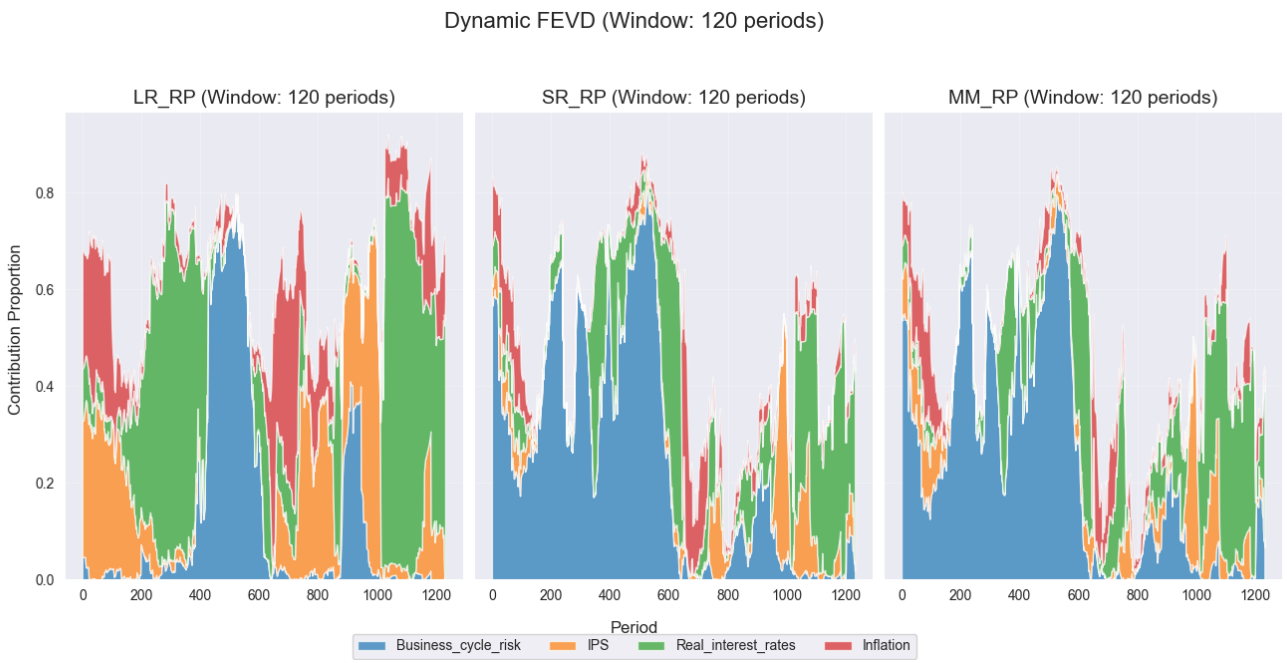


Figure A3

Business cycle risk interpolation - Example output for India

Figure A3 shows business cycle risk in monthly granularity (in blue), interpolated from original quarterly data (red). Business cycle risk data are obtained from the World Bank databank.

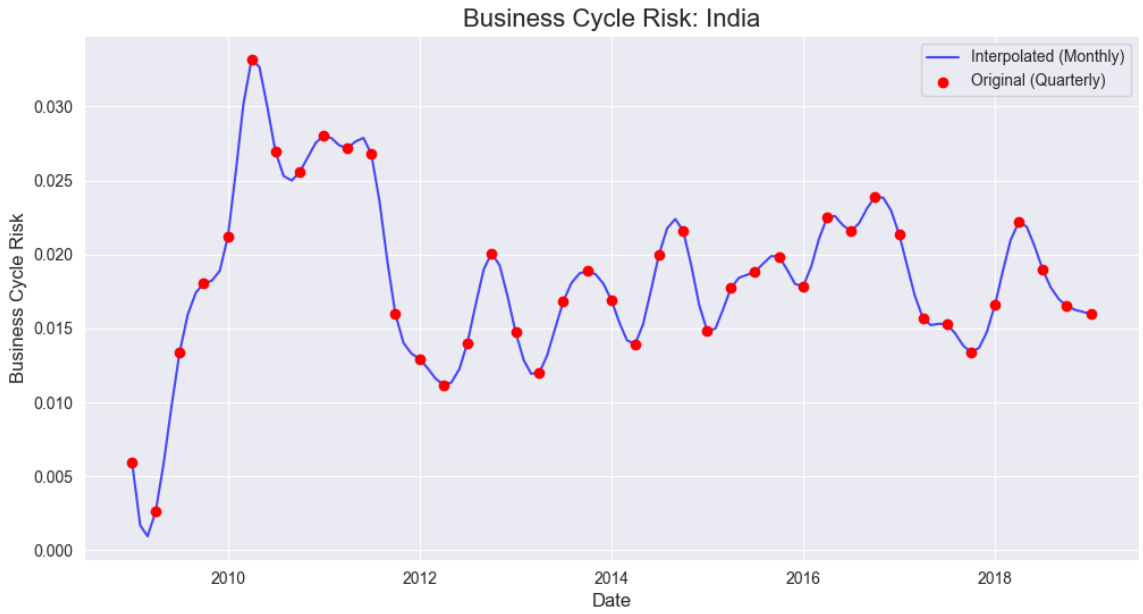


Figure A4

Residual Distribution: Config A – Models_all

Figure A4 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related risks.

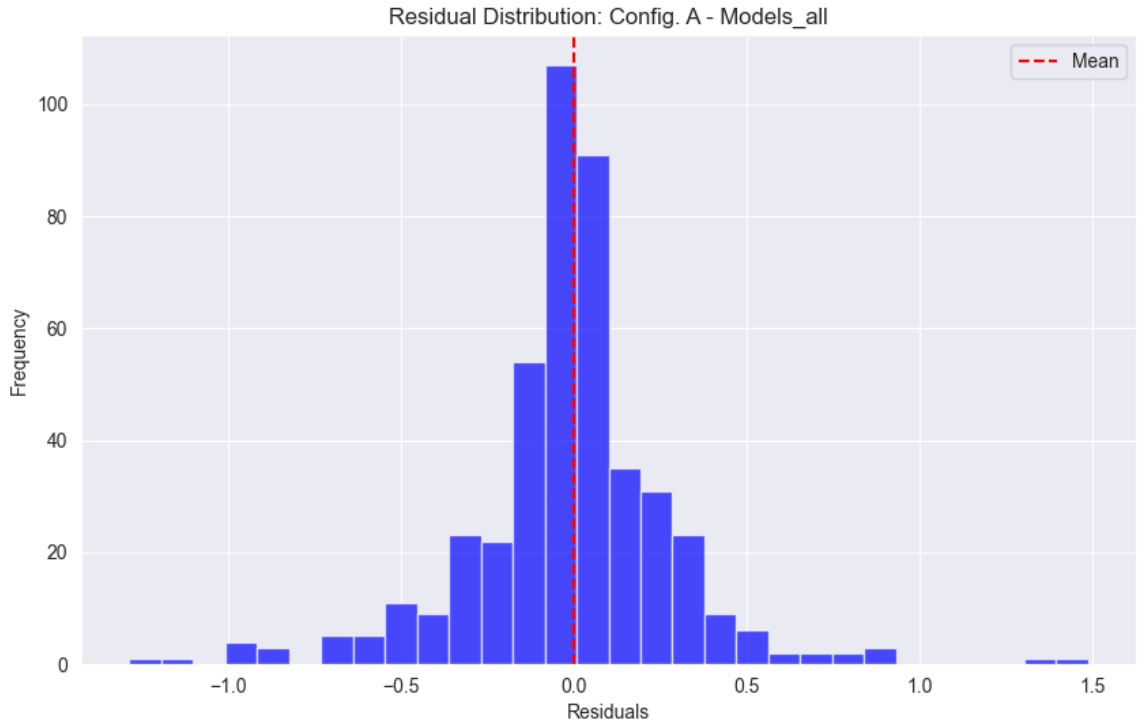


Figure A5

Residual Distribution: Config B – Models_all

Figure A5 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related risks. Longrun FX volatility represents longterm FX risk.

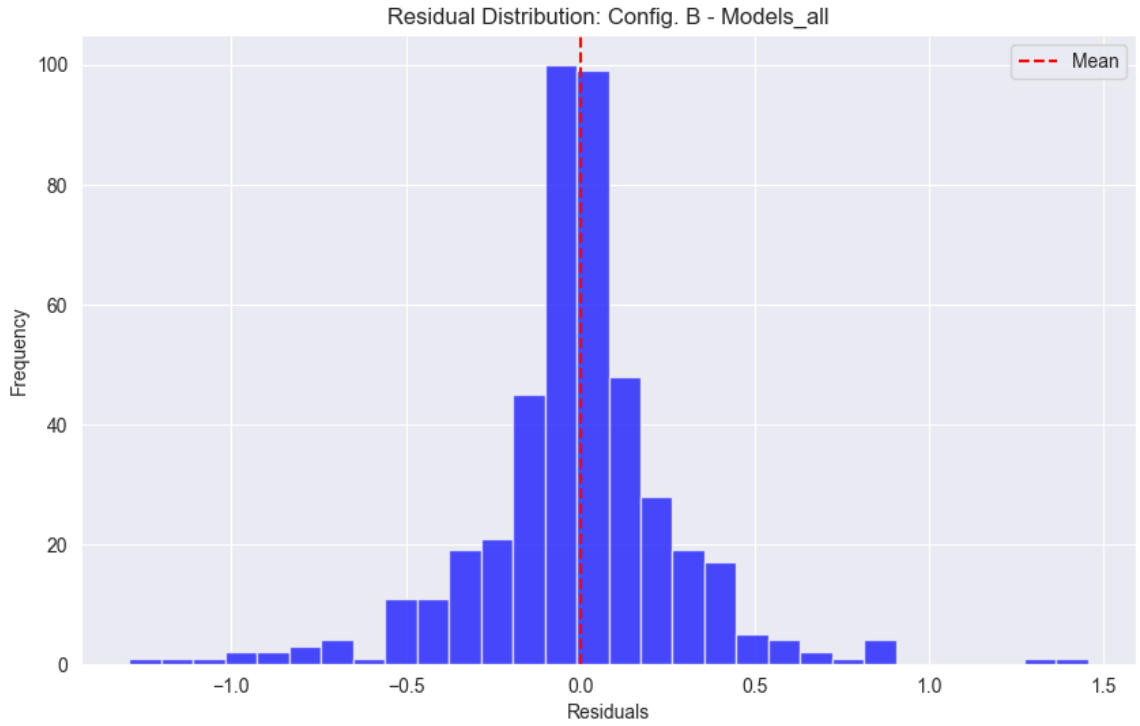


Figure A6

Residual Distribution: Config C – Models_all

Figure A6 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related risks.

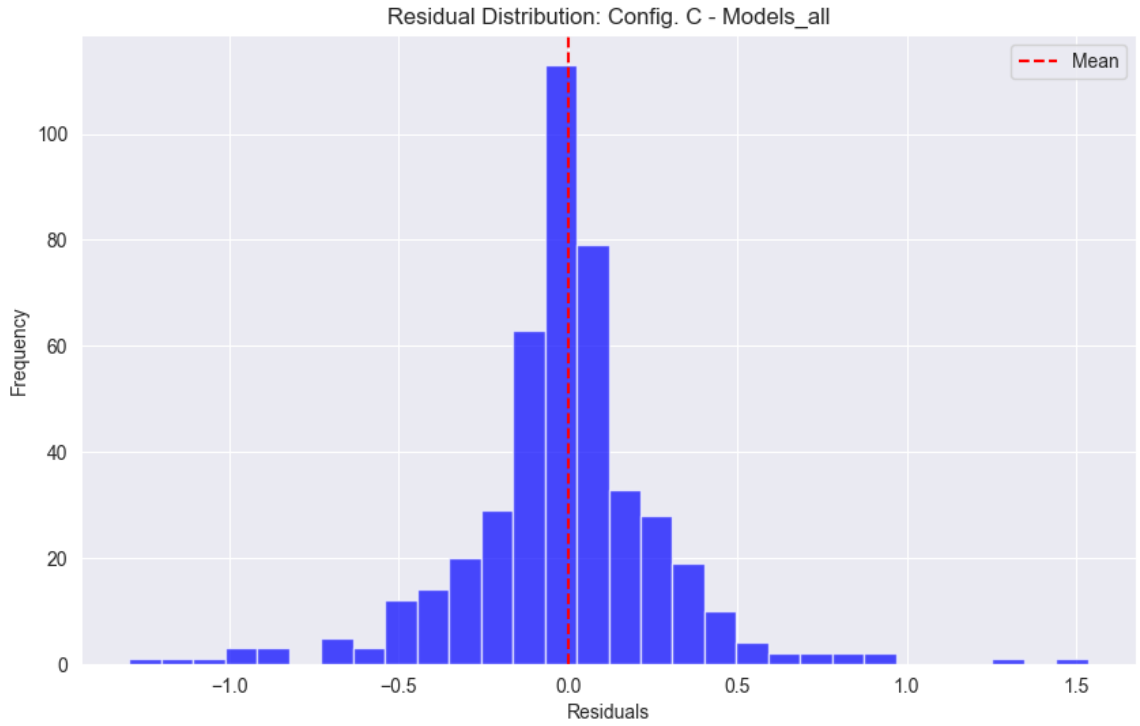


Figure A7

Residual Distribution: Config A – Models_post

Figure A7 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related data from 2016 – 2020.

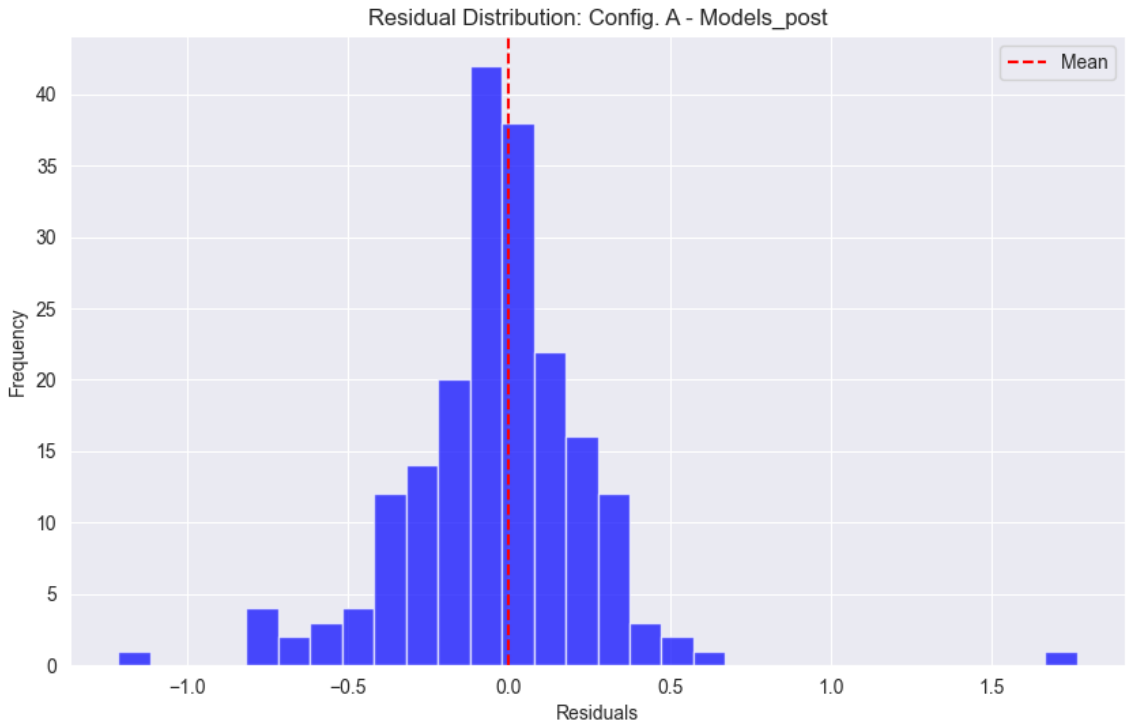


Figure A8

Residual Distribution: Config B – Models_post

Figure A8 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related risks.

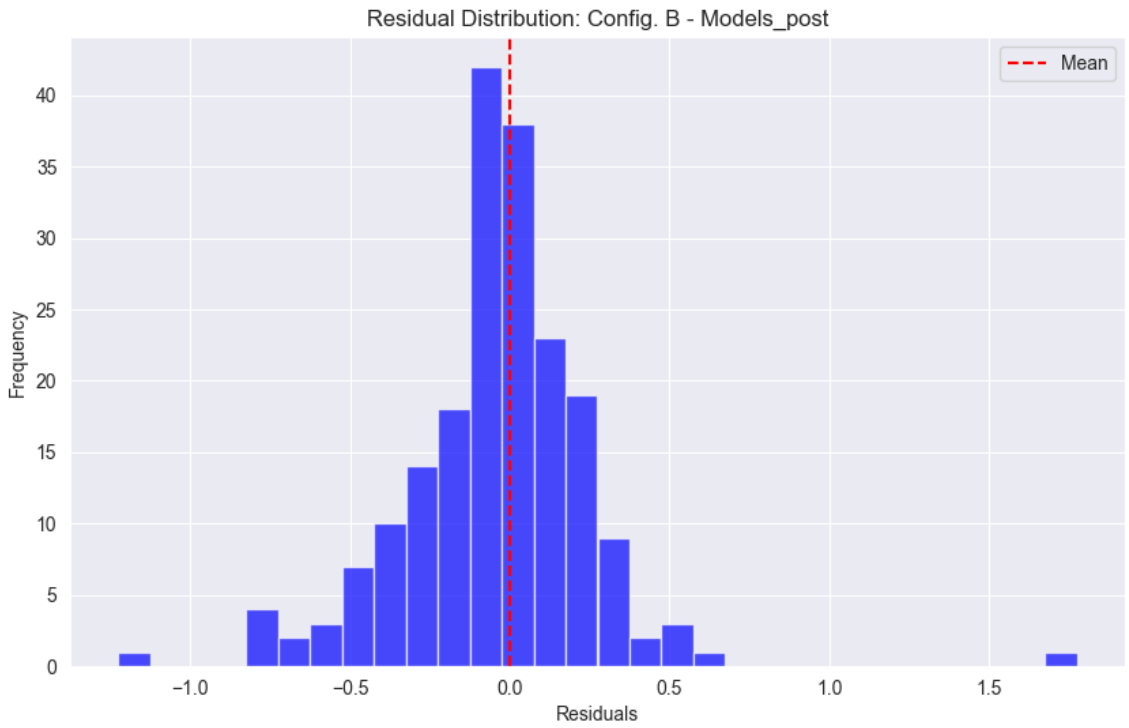


Figure A9

Residual Distribution: Config C – Models_post

Figure A9 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related data from 2016 – 2020.

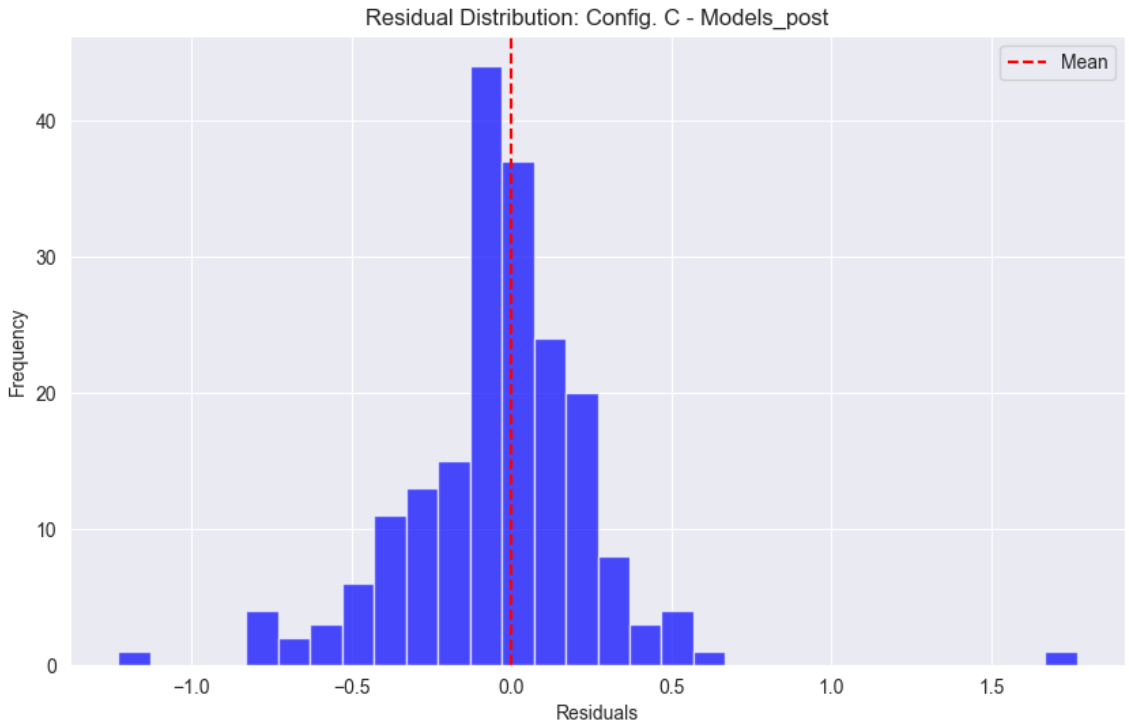


Figure A10

Residual Distribution: Config A – Models_pre

Figure A10 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related data from 2010 – 2015.

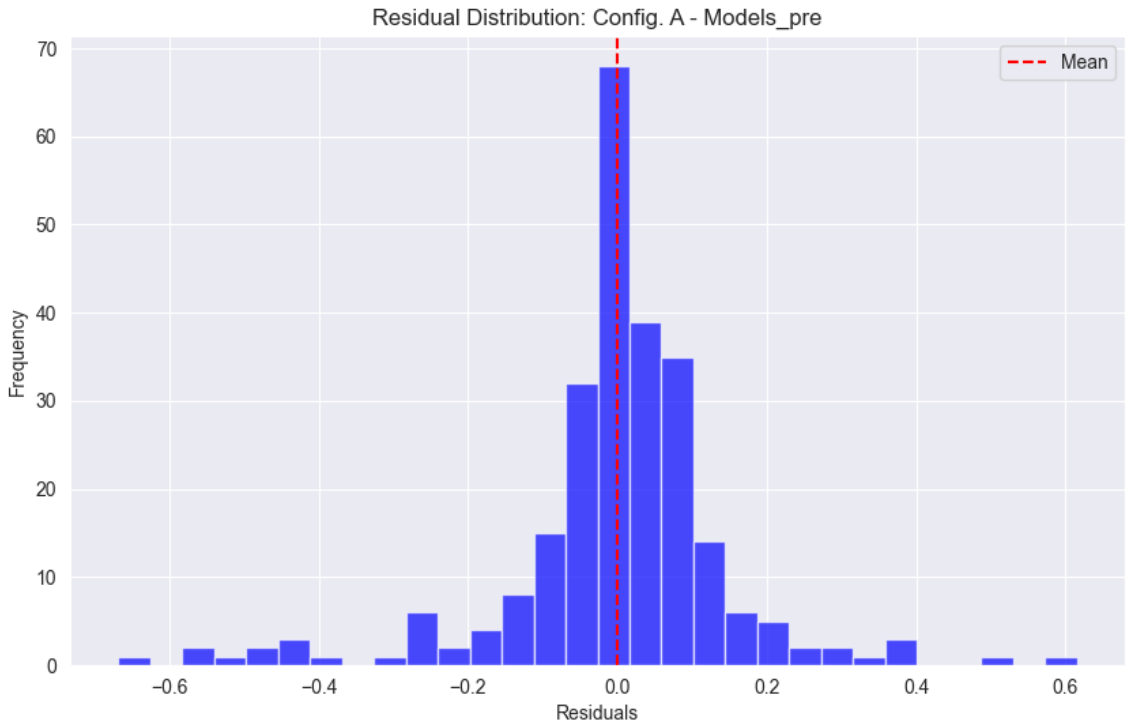


Figure A11

Residual Distribution: Config B – Models_pre

Figure A11 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related data from 2010 – 2015.

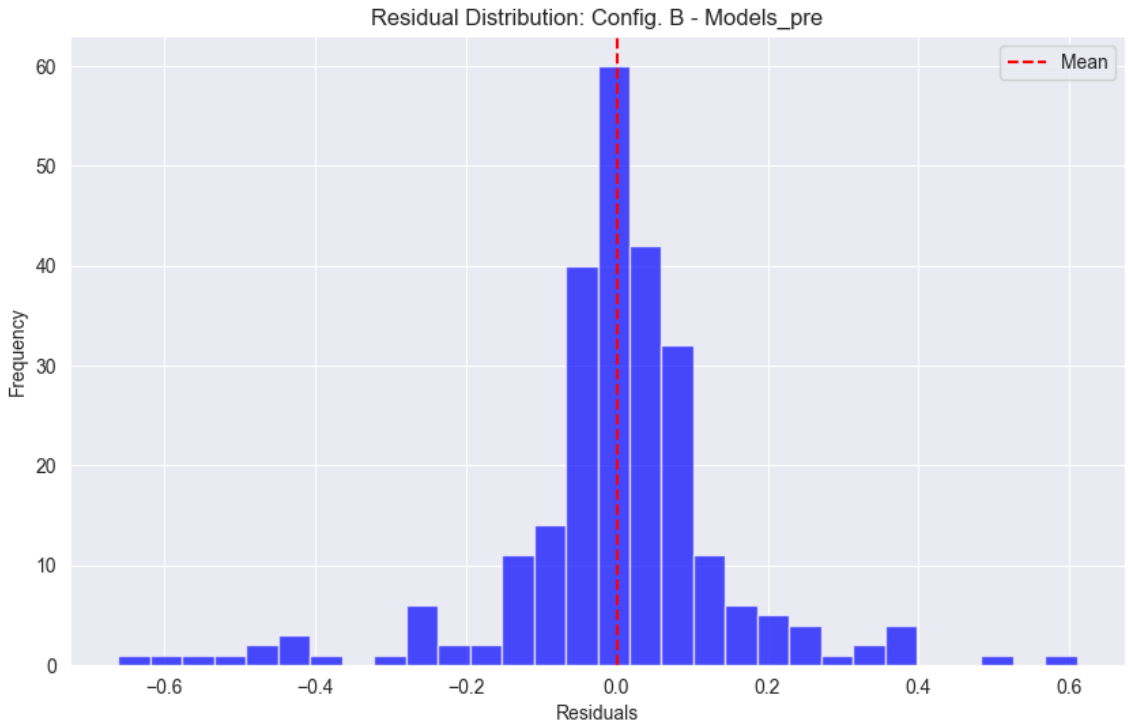


Figure A12

Residual Distribution: Config C – Models_pre

Figure A12 presents the residual distribution from the random forest model using project, macro, project-specific and climate-related data from 2010 – 2015.

