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

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Abstract

We introduce a novel elasticity - the capital allocation sensitivity to foreign exchange risk ($CASFX_e$) - that maps FX betas to changes in dollar-per-MW investments in renewable infrastructure assets in emerging and developing economies (EMDE). Our baseline specifications show a one standard deviation increase in FX risk is associated with a material reduction in capital intensity, with regime-switching estimators revealing convex, state-dependent pass-throughs. Beveridge–Nelson decompositions assign 70-80 percent of $CASFX_e$ variance to a permanent component, indicating that currency risk in EMDE contexts is predominantly structural. Tightening macro and global risk conditions amplify, but do not fully explain $CASFX_e$. Linking 'unpriced' FX variance to real investment behaviour, the results underscore the need for deep local-currency markets and targeted long-tenor guarantees to crowd in investment in renewable infrastructure under conditions of persistent FX risk.

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1. Introduction

Recent global needs assessments estimate that EMDEs will require between USD 2 and 2.4 trillion in climate-related investment annually by 2030. Renewable energy infrastructure will constitute the largest share of this pipeline (Songwe et al., 2022; UNEP, 2022).[1] Mobilizing capital at this scale, however, necessitates long-tenor investments in financial environments characterized by high exchange-rate volatility and chronically underdeveloped domestic capital markets. Most EMDEs lack sufficiently deep local debt markets to support infrastructure financing of this magnitude, leading to a heavy reliance on international borrowing in hard currencies (Burger and Warnock, 2006). A central—yet under-researched—constraint in this context is the asset-liability mismatch embedded in project finance across EMDEs: while project revenues are typically denominated in volatile local currencies, debt is usually raised in foreign currency. Consequently, episodes of local currency depreciation can significantly erode interest coverage ratios, trigger covenant breaches, and compel sponsors to either pay for costly hedging or reduce capital commitment.

The literature has long established that firms deploy a range of strategies to manage foreign exchange rate (FX) risk, including derivatives and balance sheet adjustments designed to insulate cashflows from currency shocks (Geczy, Minton and Schrand 1997; Allayannis and Weston 2001; Bartram, Brown and Stulz 2011). More recent work emphasizes a direct pricing channel: elevated FX volatility feeds into higher borrowing costs, especially in green debt markets. Moro and Zaghini (2025) show that spikes in EMDE currency volatility largely eliminate the 'greenium' that advanced-economy issuers typically enjoy, and narrows the yield spread between green and conventional bonds. Little, however, is known about how FX risk affects real capital allocation to infrastructure assets – especially in contexts where hedging instruments are often illiquid, expensive or unavailable. Do sponsors merely spend more, or do they build less? These questions are especially salient in infrastructure finance where cashflows are often contractually rigid and financial structuring options limited. Prior work

[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/).

shows that large multinational firms that actively hedge FX exposures tend to trade at higher market valuations (Allayannis and Weston 2001), as derivatives reduce cashflow volatility and ease financing frictions. In financial markets, FX risk has been linked to persistent excess returns in currency carry trades (Lustig, Roussanov, and Verdelhan, 2011), wider sovereign credit spreads (Du and Schreger, 2016), and time-varying risk premia in global bond markets conditioned on macroeconomic factors (Della Corte, Ramadorai, and Sarno, 2016).

Yet these mechanisms often break down in contexts where hedging markets are incomplete. Bartram et al. (2011) show that the hedging premium collapses when derivative markets are illiquid – a condition that closely mirrors the structural features of project finance in EMDEs. Geczy, Minton and Schrand (1997) similarly find that hedging take-up declines sharply where derivative contracts are costly. Compounding this problem, currency markets in these economies exhibit pronounced crash-risk tails (Chernov et al., 2018) – episodic spikes in FX risks can wipe out unhedged revenue streams even when day-to-day variance looks benign. These insights imply significant unhedged FX risk in EMDEs, where project sponsors must either raise hurdle rates or ration capital when FX risk spikes.

We shift the empirical focus from corporate balance sheets to project-level capital allocation decisions. Using a novel dataset on utility-scale solar and wind transactions from 2010 to 2020, we introduce a new empirical construct - the capital allocation sensitivity to FX risk, $CASFX_e$. This elasticity captures the percentage change in capital intensity – defined as investment per megawatt (dollar-per-MW) – induced by a one-standard-deviation increase in FX risk. Project level data offer key advantages over aggregate balance sheet studies. First, it links currency shocks directly to capacity deployment decisions, avoiding confounds such as tax shields, legacy debt maturities or firm level idiosyncrasies. Second, it preserves critical heterogeneity across technologies, sponsor types, and institutional settings that would be averaged out in firm level analyses. Third, project level data allow for precise identification of investment timing via deal-closing dates, rather than quarterly statements and financial reports. Fourth, project finance is where FX risk is least diversifiable, making it well-suited for isolating its real effects on sponsors' decision-making, even if some sponsors may invest in different projects to partly diversify this risk on portfolio level.

Our analysis situates sponsors' investment decision-making within recent asset-pricing literature on FX risk. Chernov et al (2023) shows that only a small fraction of FX variance is compensated in expected returns. We find a parallel at the project level: even after controlling for macro risk factors and global risk sentiment, the residual $CASFX_e$ remains large and negative. This residual maps well onto the 'unpriced' component of FX risk previously identified—risk that commands no compensating premium in diversified currency portfolios, yet is associated with a material tightening of capital budgets for sponsors in thin emerging FX markets. Together with the pricing penalty documented by Moro and Zaghini (2025), this implies a double-hit to EMDEs: heightened FX risk simultaneously inflates borrowing costs and constrains capital deployment. These patterns are consistent with frictions in currency and capital markets—such as limited hedging depth and high transaction costs—but our analysis does not preclude a role for inefficient risk pricing.

This latter point warrants greater emphasis. Our findings suggest that FX volatility may not be sufficient proxy for FX risk, especially in the context of developing economies. FX risk affects capital allocation not only because it is priced by markets, but also because it amplifies perceived financing risks in contexts with incomplete hedging and limited arbitrage (Ameli et al, 2021a; Ameli et al., 2021b; Wright and Nystrom, 2020). Distinguishing between priced risks and perceived, unpriced uncertainty is essential to understanding capital flows in EMDEs.

We document strong state dependence in $CASFX_e$: while moderate increases in FX risk induce sharp contractions in capital intensity, still higher FX risk elicit a convex investment response—consistent with real option value risk management on the part of sponsors once hedging programs and equity buffers are activated. Sponsors' behaviour clearly shifts with the level of FX stress, but is that response driven by transitory shocks or by a deep structural currency backdrop? Decomposing $CASFX_e$ using the Beveridge–Nelson technique, we find that 70–80 percent of the variation in our FX risk metrics is attributable to a structural (rather than transitory) component.[2] This structural persistence distinguishes our setting from canonical asset-pricing literature, where FX risk is usually modeled as a time-varying response to global liquidity or sentiment (Burnside et al., 2011; Hassan, Mertens, and Zhang, 2021). Our findings are more consistent with real options frameworks, where persistent macro risk

[2] We round down on this range. Actual estimates lie between 70 and 82 per cent.

interacts with capital irreversibility to shape both the timing and scale of investment (Dixit and Pindyck, 1994; Bloom, 2009).

$CASFX_e$ transforms each rolling cross-sectional beta into a unit-free elasticity: $\beta \cdot FX_{risk}/Capital\ Int.$ That simple rescaling gives the metric several desirable properties. First, it is inferred from actual dollar-per-megawatt project commitments, thus capturing investors revealed behaviour rather than a model-implied estimate or assumed weighted average cost of capital uplift. Second, because beta embeds all financing channels through which FX risk transmits, the elasticity consolidates pricing frictions without requiring more granular data. Third, our rolling cross-sectional regressions produce a $CASFX_e$ series that can be decomposed along its structural and transitory components, allowing for a more contemporaneous tracking of FX risk through policy changes and macro shocks. Finally, because $CASFX_e$ is conditioned on projects that reach financial close by definition,[3] it isolates intensive margin responses.

These properties come with boundary conditions that yield three main sources of residual uncertainty. First, unobserved policy interventions that simultaneously stabilise FX markets and subsidise renewables could bias elasticity estimates upward or downward.[4] Lagged controls and two-way clustering mitigate but do not eliminate this simultaneity bias. Second, we cannot discern from our data whether sponsors react to volatility by repricing USD debt or by switching into local-currency tranches—both margins are subsumed in the estimated elasticity. However, given the predominance of US dollar-denominated debt in EMDE financing (Rickman et al., 2025), this limitation likely attenuates rather than invalidates our estimates. Third, pooled monthly averages of risk factors suppress some within-group heterogeneity in time series regressions even if we assume countries with similar economic circumstances can be studied together.

By documenting how FX risk shapes real investment behaviour in renewable infrastructure assets in EMDEs, we make three distinct contributions. First, it extends the

[3] In actual fact, 1.34% of the projects in our data sample were abandoned, but these do not affect our results. We discuss this in greater detail in sections 2 and 3 and in robustness tests.

[4] For example, between 2013 – 2015, the Banco Central do Brazil ran a large-scale swap-auction program, selling USD-BRL swaps to cap the Real's depreciation and dampen volatility. At the same time, BNDES, Brazil's federal development bank, expanded its PROINFA/FINEM credit lines which offered below-market local-currency loans and tax breaks for wind-farm developers.

corporate hedging literature by showing that currency shocks influence *real* not just *financial* investment margins. Second, it links asset-pricing evidence on limited compensation for FX risk to corporate investment decisions under uncertainty. Third, it provides the first systematic evidence of FX risk as a material and quantifiable driver of the clean-energy investment gap in EMDEs, with direct implications for policy and capital-market design. Specifically, to address FX risk in renewable infrastructure investments we argue for (i) deeper and more liquid local-currency debt markets, (ii) long-tenor, performance-contingent guarantees that absorb structural FX risk, and (iii) concessional capital or pooled hedging solutions where market-based tools are absent or remain prohibitively costly. Addressing FX risk is not a peripheral development finance issue – it is a necessary pre-condition to unlocking the scale of capital needed for the energy transition in EMDEs.

2. Data

Our primary dataset comprises project level information on renewables infrastructure – solar and wind – obtained from Bloomberg New Energy Finance (BNEF). We select developing country renewable projects (excluding China)[5] 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. Country macro and institutional data are obtained from the World Bank and country level data on climate-related disasters from the EM-DAT International Disaster database. Our final sample comprises 1,497 renewable energy projects from 47 developing countries over the period 2010 – 2020. Projects in our final dataset are either completed (1477) or abandoned (20).[6] Figure 1 presents countries where renewable infrastructure projects are located. Brazil, India, Mexico, South Africa and Vietnam are the five countries with the most projects in our sample.

[5] First, utility-scale renewables in China are financed almost entirely with on-shore RMB at subsidized, policy-bank rates so face limited cross-border, hard-currency project finance exposure in principle. Second, we exclude China for reasons of outlier weight and sample balance. Renewable infrastructure projects from China constitute more than 50% of the raw unprocessed dataset.

[6] Abandonment could theoretically be non-random—if high FX volatility discouraged project sponsors, omitting such cases might bias FX-related estimates. However, abandoned projects represent just 1.3 % of the sample, and mean comparisons of standardized FX-volatility measures between completed and abandoned projects reveal no statistically significant differences. These projects are thus kept in the sample.

Unless otherwise stated, capital intensity is the dependent variable in this analysis. We define capital intensity as investment value per unit of capacity (mUSD/MW) as a measure of cost efficiency in renewable infrastructure capital deployment. Countries exhibit significant heterogeneity in investment levels and project sizes, leading to variations in capital intensity. Some countries may have high total investment values but develop disproportionately small infrastructure projects. Others are more efficient, achieving higher installed capacity with lower investment. By normalizing investment with capacity, we control for scale effects and mitigate distortions arising from size heterogeneity.

Our control variables are the following. *Offtaker Credit Score* measures the creditworthiness of the renewable energy purchasing entity; *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 institutional political stability annually; *IRQ* measures how well laws and regulations support market efficiency and economic activity of a country annually; *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 annually; *Inflation* measures the monthly percentage change in consumer price inflation rate (%) for each country; *Curr. Balance* 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 annual interest rates adjusted for inflation; *CO_2 per capita* is the total annual national carbon emissions divided by the country's population; *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 per year; *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; *Range FX* is the difference between maximum and minimum log FX returns over a 24-month period on country level; *VIX,* also known as the fear gauge, is a measure of financial market volatility reflecting the implied 30-day volatility of out-of-money S&P 500 option prices.

Our primary dataset is a repeated cross-section where each project is observed once. To reduce idiosyncratic noise while retaining economically meaningful variation, projects are grouped by country income status (low-income L, lower middle-income LM and upper middle-income UM) over time.[7] This classification is important for two reasons. First, without loss of generalization, we assume that countries within the same income categories exhibit similar economic dynamics and can be studied together. The second is more data-driven. We aggregate projects within each income group and time to obtain reasonably sized clusters while reducing sparseness. To limit the influence of outliers and ensure comparability, we winsorised control variables within-group at the 5% level.

We report summary statistics on project-related, institutional, macro, climate and currency risk variables in Table 1 and sample country status breakdown in Table A1. The average project in our sample allocates \$1.516 million per MW of capacity, reflecting heterogeneity in investment scale. IPS sits just above the first quartile (μ= 26.3) but at approximate median levels for IRQ (45.095), IRL (47.182), and IVA (51.838), suggesting that while governance varies, most countries have basic institutional frameworks in place. Low institutional stability raises the probability of regime change, unpredictability in regulatory changes, uncertainty about contract enforcement and weak governance structures. Lenders may respond by shortening debt tenors, adding expensive political-risk insurance, or requiring larger debt-service-reserve accounts. Macroeconomic conditions are characterized by high average inflation (7.179%) and a mean current account deficit of 2.403% of GDP, indicating moderate external imbalances. Sovereign debt is reported on average at 60.437% of GDP (σ = 16.704), real interest rates at 10.925% (σ = 14.277), underlying differences in country contexts, elevated financing costs and fiscal pressures. High inflation and real rates erode real returns and raise project hurdle rates, while heavy debt burdens and deficits constrain governments' ability to subsidize renewable ventures or access external financing, all of which are capable of shaping capital allocation decisions in infrastructure projects.

[7] Because the income-status dimension provides only three clusters (L, LM, UM), we report results with both conventional two-way cluster-robust errors and wild-cluster bootstrap standard errors in robustness tests, following MacKinnon and Webb (2017).

Proxy variables for climate risk are CO_2 per capita, share of renewable capacity, and disaster intensity. CO_2 emissions average 2.566 $MtCO_2e$ per person. Renewable capacity forms 42% of total installed generation on average with substantial variation ($\sigma = 26.871\%$), indicating that some countries have already reached high penetration levels while others remain early in their transition. Disaster intensity measures economic damages per affected capita ($\mu = 63.348\, mUSD/person$), underscoring sporadic but large financial shocks from climate-related events. Countries have heterogeneous transition incentives and climate-shock exposures: jurisdictions with high CO_2 emissions may demand and yet resist renewable infrastructure investments because (i) path-dependent rents tie investors and workers to the incumbent sector (Acemoglu et al., 2012), (ii) high renewable shares signal policy maturity and lower incremental gains (Polzin et al., 2019; Eyraud et al., 2013), and (iii) extreme but infrequent disaster losses can abruptly alter project risk capital, resilience and insurance requirements (Dell et al., 2014; Burke and Emerick, 2016). Kahn et al. (2021) show that extreme weather events influence capital allocation in the energy sector as sponsors demand higher returns in disaster-prone regions. Climate vulnerability, then, may accelerate policy support for renewable infrastructure, particularly if disasters highlight the risks associated with fossil-fuel-dependent energy systems (Hsiang and Jina, 2014).

Longrun FX volatility ($\mu = 0.035,\ \sigma = 0.019$) captures long-term exchange rate volatility. Shortrun FX volatility ($\mu = 0.034,\ \sigma = 0.031$) reflects fluctuations in exchange rates over a shorter window, more reflective of temporary and speculative activity in FX markets. Unlike longrun volatility, shortrun FX volatility may affect working capital and short-term project cashflows (Forbes et al., 2018). With Range FX ($\mu = 0.142;\ \sigma = 0.123$), we capture medium term exchange rate uncertainty and the range of movements over a two-year period. Range FX captures another dimension of FX risk other than volatility. Wide FX ranges signal greater ambiguity on future currency paths and have been shown to curb corporate investment by balance-sheet–constrained firms (Carranza et al., 2003), effectively forcing sponsors to apply higher implicit hurdle rates.

We include the VIX to capture broad shifts in global risk sentiment. This way, we isolate the unique effects of domestic FX risk in EMDE renewable infrastructure investments, rather than capturing general global risk sentiment.

3. Empirical Approach

Exploratory analysis of drivers of capital intensity in renewable investments

To capture nonlinear interactions among macroeconomic, institutional, climate, and financial factors, we build a random forest (RF) model - an ensemble of decision trees that mitigates overfitting while uncovering hierarchical dependencies (Breiman, 2001). We train separate RF models for pre-2016, post-2016, and the full sample (2010 – 2020) to capture any time-specific heterogeneity. We conduct a within-group standardisation of all variables before the RF estimation to equalize feature scales and prevent high-variance variables from dominating split selection. To reduce dimensionality, we run three sets of principal component analyses (PCA) to create the following composite variables from the first principal components. Macro risks: Inflation, Debt-to-GDP, Real IR; Institutional risks : IPS, IRQ, IRL, IVA; and Climate risks: CO2 per capita, Share of Ren. Capacity, Disaster Intensity. LCOE, Offtaker Credit Score and the FX risk metrics complete the risk factor list. The RF model is an ensemble of decision trees 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: the predictor vector for the ith observation and Y_i: the dependent variable (Capital Int). Each tree is trained on a randomized subset of observations and features and recursively partitions the feature space into regions R_m with an 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 $|R_m|$ is the number of observations in the region R_m. The final ensemble prediction is 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 optimize model performance via an exhaustive grid search cross-validation (three folds for each subsample and five for the full sample) that preserves temporal ordering of the data with time-series splits and avoids leakage of future information into training periods. We select the best models proxied by ones that produce the least mean square errors (MSE).

Capital allocation sensitivity to currency risk in renewable energy investments

How does FX risk affect the amount of capital (USD/MW) that sponsors commit to renewable infrastructure projects in EMDEs? Specifically, we estimate:

$$CI_{s,t} = \alpha + \beta_1 FX\ Risk_{s,t} + \beta_2 Controls_{s,t-1} + \mu_s + \lambda_t + \varepsilon_{s,t} \qquad (4)$$

where $FX\ Risk_{s,t}$ is a vector comprising Longrun FX volatility, Shortrun FX volatility and Range FX; $Controls_{s,t-1}$ a vector of lagged project-related controls; μ_s: country status fixed effects; λ_t: fixed effects for year-month periods. Standard errors are double-clustered on country income status and time (year-month).

Next, we explore whether capital-intensity responses to FX risk exhibit regime-switching effects by developing threshold and spline-based regressions. Our priori is that beyond certain tipping points, investment behavior may change markedly — e.g. lenders tighten credit, or sponsors demand higher returns when currency fluctuations exceed a critical level. Splines, in contrast, allow for multiple kinks in the FX–capital-intensity relationship, accommodating nonlinear adjustments without imposing a single break (Dahlquist et al. 2009). For s index country-status groups and t year-months, we estimate the model:

$$CI_{s,t} = \alpha + \beta_1 FXRisk_{s,t} + \beta_2\left(X_{s,t} 1\{FXRisk_{s,t} > \tau\}\right) + \gamma Controls_{s,t-1} + \mu_s + \lambda_t + \varepsilon_{s,t} \quad (5)$$

where the variables have their usual meanings. More specifically, we grid-search over quantiles from the 10th to the 90th percentile of the FX-risk metric (in 2-pp increments) and, for each τ, compute the out-of-sample mean-squared error in a rolling three-fold time-series cross-validation. We choose a τ that minimizes the average out-of-sample mean square error. β_2 then, measures the discrete change in FX sensitivity once volatility crosses τ. To capture richer nonlinearities, we augment the FX variables with piecewise-linear spline terms at knots $\{\kappa_1, \kappa_2, \kappa_3\}$. Specifically:

$$CI_{s,t} = \alpha + \sum_{k=0}^{3} \delta_k max\{FXRisk_{s,t} - \kappa_k, 0\} + \gamma Controls_{s,t-1} + \mu_s + \lambda_t + \varepsilon_{s,t} \quad (6)$$

where κ_0 by convention and $\kappa_{1:3}$ are first chosen manually based on domain-informed breakpoints, then re-estimated via the time series cross-validation routine described above to minimize the out-of-sample MSE.[8]

To translate estimated sensitivities into economically interpretable metrics, we compute an elasticity metric – the capital allocation sensitivity to FX risk ($CASFX_e$) - defined as a proportional change in capital intensity per one-unit change in FX risk pooled across income groups. Using 18-month rolling window cross-sectional regressions akin to (4), we extract β_t and compute the monthly CAS elasticity as:

$$CASFX_{e_t} = \hat{\beta}_t FX\ Risk_t / CI_t \qquad (7)$$

To assess whether $CASFX_e$ is related to macro and global risk factors, we regress $CASFX_e$ on income group aggregated monthly contemporaneous macroeconomic factors, and the VIX to capture systemic and global risk sentiment. Formally, we fit:

$$CASFX_{e_t} = \alpha + \delta' Z_t + \varepsilon_t \qquad (8)$$

All variables have their usual meanings. Z is a vector that includes Inflation, Real Interest Rates, Debt-to-GDP, Current Balance, and VIX.

We note some limitations that occur as a result of our experimental design. First, we cannot rule out endogeneity concerns fully: unobserved contemporaneous shocks (e.g. policy shifts) may simultaneously affect FX risk and capital intensity, and although we lag controls in the pooled regression frameworks, this simultaneity bias is not fully mitigated. It is also indeterminable from the data whether investors *decide* to originate in local or foreign currency. Second, aggregating project-level data and country-specific macro information into status-pooled monthly averages dampens idiosyncratic noise but may conceal meaningful within-group heterogeneity. Third, our rolling cross-sectional regressions and out-of-sample cross-validations guard against overfitting and look-ahead bias.

[8] In addition to domain-informed breakpoints, $\kappa_{1:3}$ is in line with standard practice and for parsimony (Steyerberg, 2016) which recommends 3-5 knots for data of this scale.

Empirical framework for currency risk decomposition

We decompose $CASFX_e$ into structural and transitory components using an ARIMA-based Beveridge–Nelson (BN) algorithm. This identification is especially relevant for policy and investment strategies in developing countries, where higher and more volatile currency regimes may deter long-term climate finance and infrastructure investment. In the first step, we conduct unit root tests via the Augmented Dickey–Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests; only series integrated of order one (I(1)) enter the BN procedure (Beveridge and Nelson, 1981; Proietti, 2016). For all I(1) series, we estimate an $ARIMA(p, 1, q)$ model:

$$\left(1 - \sum_{i=1}^{p} \emptyset_i L^i\right)(1 - L)CASFX_{e_t} = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_t \qquad (9)$$

where L is the lag operator, $\emptyset_i$ and θ_j are autoregressive and moving average parameters respectively, and ε_t white noise. The lag orders (p, q) are selected based on minimizing the Akaike Information Criterion (AIC). The structural trend component of $CASFX_e$ is the long-run forecast of the $ARIMA(p, 1, q)$ model:

$$S_t = CASFX_{e_0} + \sum_{s=1}^{t} \hat{\psi}(L)\varepsilon_s \qquad (10)$$

where $S_0 = CASFX_{e_0}$ and $\hat{\psi}(L)$ captures the cumulative impact of shocks. The transitory component T_t follows:

$$T_t = CASFX_{e_t} - P_t \qquad (11)$$

To understand the relative importance of these components, we compute the signal to noise ratio – the ratio of the structural trend variance to transitory variance - and the variance share of the structural trend component respectively.

4. Results

Is currency risk the principal thing?

Figure 2 presents results on feature importance ranking of risk factors that predict capital intensity, using three datasets: pre-2016, post-2016, and the full sample. Across all pre-2016 specifications, LCOE—followed by institutional and macro risks—emerge as the most important predictors of capital intensity. This underscores the fundamental role of cost competitiveness in renewable infrastructure investment decisions and project bankability (Baldwin et al., 2020). Post-Paris, macro risks become the highest-ranked predictors, while climate and institutional risks rank second and third in two of the three specifications. Climate risks are especially important in emerging markets, where vulnerabilities to physical climate shocks are high and adaptive capacity limited (Buchner et al., 2021). Emerging countries now account for over half of global emissions, with extreme events occurring more frequently than expected under standard probabilistic models (Masson-Delmotte et al., 2021). The post-Paris result suggests greater recognition of climate risks by institutional investors and sponsors and rising incentives to decarbonize, along with a growing integration of climate factors in disclosure and investment frameworks. Of the FX risk metrics, Longrun FX volatility ranks highest, reaching 19.3% in feature importance score post-Paris, just behind climate risks. Model diagnostics are presented in Table 2, where Ljung-Box statistics confirm the absence of residual autocorrelation at 1, 6 and 12 month lags. The drop in R-square values (from 65% pre-Paris to 26% post-Paris) reflects the difficulty of predicting capital intensity in this period - reflects a surge in unmodeled shocks to EMDEs not fully accounted for in macro, institutional and FX controls (see Table A1).

In the full-sample analysis, R-square climbs to 55%. LCOE and macro risks remain most important, while Longrun FX volatility remains the most important of the FX risk metrics. Longrun FX volatility scores reflect the extended duration exposure to FX volatility embedded in renewable infrastructure projects and the increased volatility of emerging market currencies, especially post-Paris (Nelson, Shrimali, 2022).[9] Range FX—the 24-month high–low spread—registers the lowest feature importance among FX metrics. Unlike volatility measures, high–low ranges do not capture frequency or clustering of shocks, and may thus register less in sponsor decision-making. Shortrun FX volatility, on the other hand, may be relatively easier to

[9] Appendix Figure A1 presents currency-impacting events for key EMDEs.

hedge or amortize over a longer funding horizon and thus exert a weaker average change in model predictions of capital intensity. Our random forest results demonstrate that the importance of currency risk exhibits temporal dynamics. Overall, while FX risk is not the principal risk factor, it exerts a meaningful importance score that has increased over time.

We present partial dependence plots (PDPs) in Figure 3. These plots show the average change in the model's prediction of capital intensity—as FX risk varies, holding all other inputs at their observed values. In Figure 3, the PDPs show that increases in FX volatility broadly predict lower capital intensity, with steeper average declines post-Paris and threshold dynamics beyond certain tipping points.

Currency risk in renewable energy investments

Building on the exploratory findings from the random forest models, we estimate the sensitivity of capital allocation in renewable infrastructure investments to FX risk in developing economies. These indicate the extent to which currency risk shapes renewable infrastructure investments in developing economies. Results of our baseline model are presented in Table 3.[10] Panel A shows that Longrun FX volatility (-0.080), Shortrun FX volatility (-0.130), and Range FX (-0.148) are statistically significant at the 1% level. A one standard deviation increase in Longrun FX volatility is associated with an 8% reduction in dollar per MW investment. Panel B confirms this pattern when including only time fixed effects: a standard deviation rise in FX risk is associated with a material reduction in capital intensity.

The PDP charts in Figure 3 suggest there may be threshold effects that moderate the relationship between FX risk and capital intensity. Specifically, we are interested in identifying structural breaks or regime-switching thresholds which guide the relationship between capital intensity and FX risk. In Table 4, we allow for changes to the sensitivity of capital intensity to FX risk once an empirically estimated threshold ($\tau \approx$–0.9 Shortrun FX volatility; $\tau \approx 0.9$; Longrun FX volatility; $\tau \approx 1.05$ Range FX) is breached. Below these thresholds, higher FX risk

[10] While we apply PCA to reduce dimensionality and explore joint patterns across related risks in the random forest analysis, we revert to individual observed variables in the regression framework to preserve interpretability and policy relevance.

is associated with significantly lower levels of capital intensity (coefficients: –0.402, –0.366 and –0.271). Once volatility exceeds estimated thresholds, however, the negative impact is significantly attenuated. $FX \cdot 1(FX > \tau)$ terms are positive and - for the Shortrun FX volatility (0.254) and Longrun FX volatility (0.266) - significant.

While a single threshold uncovers a two-regime response, the underlying decision process is unlikely to flip abruptly between low and high FX risk and may rather reflect a richer set of regime-switching incentives (Ang and Timmermann, 2012). Table 5 reports cubic spline estimates that capture distinct marginal effects in low-, mid-, and high-volatility regimes instead of a single abrupt break. In Panel A, visual knots based on PDP plots in Figure 3 reveal an inverse U-shaped relationship between capital intensity and FX risk. Initial jumps in FX risk are significant and negatively associated with capital intensity. Shortrun FX volatility (-1.061), Longrun FX volatility (-1.445) and Range FX (-0.600) yield significantly negative responses at the lowest breakpoint for FX risk. Sensitivities rebound positively at intermediate levels of FX risk for Shortrun FX volatility (1.791) and Longrun FX volatility (2.133); and turn significantly negative at further elevated FX risk levels at knot 3. Panel B's cross-validated knots confirm the existence of significant regime-switching effects.[11] We note that Range FX shows an initial drop that remains flat in knots 2 and 3, reflecting the fact that it is driven by episodic extremes and not day-to-day drifts by definition. The absence of well-defined knots in Range FX is apparent from Figure 3.

These results provide important insights into the relationship between FX risk and capital allocation on project level. When currency swings are low, project sponsors absorb small shocks through hedges or covenant waivers - and USD/MW allocations remain robust. As volatility breaches a moderate threshold, however, lenders may tighten covenants, hedging costs rise, and investors pull back, scaling down capital intensity. From our results, marginal increases in FX risk generally deliver steep declines in capital intensity. Yet if volatility climbs

[11] While Panel B confirms the same kink pattern for Shortrun FX volatility and FX Range in Panel A, we observe that the shape of the spline is sensitive to the optimal selection process for Longrun FX volatility. The key outcome, however, remains. Both specifications report significant regime-switching effects, and that high FX risk is associated with lower levels of capital intensity.

even higher, two forces are likely: real option timing value[12] may encourage sponsors to re-enter or accelerate spending, for example once new hedging structures and equity buffers are in place, momentarily boosting capex; before at very extreme levels of FX risk, the cost of collateral, tighter policy interventions, or the sheer expense of implementing the hedging program negatively impacts capital intensity. This multiple regime-switching behavior reflects convex risk-pricing, the availability (and eventual exhaustion) of local-FX hedges, real-option dynamics in capex timing and risk-management thresholds, and policy regime shifts. Altogether, these patterns align with theories of investment under uncertainty (Dixit and Pindyck, 1994), highlighting investor considerations embedded in long-lived, capital-intensive assets.

We call the capital allocation sensitivity to FX risk, $CASFX_{\mathrm{e}}$ - the proportional change in capital intensity per one standard deviation change in FX volatility. $CASFX_e$ has several desirable properties. First, it is inferred from actual project 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). It captures the structural sensitivity of capital allocation to FX risk as a product of our experimental design. Second, $CASFX_e$ reflects a behavioural risk adjustment of project sponsors to FX risk - especially relevant for long-term renewable infrastructure assets - in relatively illiquid markets. Third, without needing full observability of underlying financial contracts, $CASFX_e$ backs out risk perceptions mainly from observed capital intensity, rather than through unavailable granular financing data, where disclosure standards may vary.[13] Fourth, it is conceptually time-varying and allows us to study FX sensitivity elasticities with shifting macro conditions, policy regimes, or investor sentiment, in contrast with static hurdle and weighted average cost of capital approaches. Fifth, it is agnostic to the source of capital (debt vs. equity) and thus captures the

[12] Real-option timing value refers to the idea that when uncertainty becomes very large, investors treat the option to delay or stage projects as more valuable. In our context, when FX volatility breaches a critical threshold, sponsors gain flexibility by deferring drawdowns until new hedging instruments, covenant amendments or equity infusions become available—effectively treating each financing decision as a sequential *option* whose exercise threshold shifts with volatility.

[13] $CASFX_e$ may be described as a project-implied FX risk discount – an actual reduction in capital intensity attributable to FX volatility - which would require an increase in hurdle rates to make projects viable. This definition, however, is less elegant in an asset pricing sense as this would require CAS FX to be priced in equilibrium models.

aggregate investment response, regardless of whether FX risk is priced more heavily by lenders or equity sponsors in renewable projects. This is particularly relevant in EMDEs where capital structures are often opaque or non-standard.

Figure 4 shows rolling $CASFX_e$ constructed from 18-month cross-sectional regressions.[14] Between 2011 and 2020, the evolution of $CASFX_e$ tracks major currency- and commodity-market shocks in emerging economies. $CASFX_e$ ranged between –0.2 to –1.0 during the 2011–2013 taper tantrum and Euro-area tensions and intensified to near -1.28 as the 2014–2015 commodity collapse and EM sell-off deepened currency volatility.[15] The most pronounced drop in $CASFX_e$ occurs in late 2015–early 2016—coinciding with China's surprise currency devaluation and the global 'flash crash' and the beginning of US Federal Reserve tightening cycle.[16] As commodity prices and central-bank interventions stabilized currencies post-2016, elasticities reverted to a 0 to –0.6 range.

Macroeconomic drivers of the capital allocation sensitivity to FX risk

To assess whether $CASFX_e$ is explained by systemic macro variables, we regress monthly $CASFX_e$, estimated from the rolling cross-sectional regressions, on inflation, real interest rates, debt-to-GDP, current balance, and VIX. The constant term α is the quantity of interest. It is the baseline $CASFX_e$ that remains after accounting for macroeconomic drivers. The results are presented in Table 6. For each $CASFX_e$ metric derived from the three underlying FX-risk measures—Shortrun CAS Elasticity (-0.287), Longrun CAS Elasticity (-0.494), and Range CAS Elasticity (-0.340)—the α is negative and significant at the 1 % level. This implies that even after controlling for macro and global risk factors, significantly less capital is allocated for a sustained level of FX risk in EMDEs. This persistence in $CASFX_e$ reflects structural barriers in financial systems—such as limited hedging markets and market

[14] We adopt an 18-month rolling window for the baseline $CASFX_e$ because it minimizes the bias–variance trade-off: 12-month windows are more responsive but are more sensitive to idiosyncratic deal noise, whereas 24-month windows offer slightly smoother estimates but add no improved predictive power in cross-validation.

[15] Oil prices peaked around $115/barrel in June 2014 and then fell by roughly 50 percent over the next year. That collapse, together with a U.S. rate-rise scare, triggered an EM equity sell-off and capital outflows that forced currencies like the Brazilian Real, South African Rand and Indian Rupee sharply lower.

[16] As EMDE currencies plunged and FX volatility spiked in 2014–16, the cost and availability of currency hedges dried up: local banks demanded ever larger margins, cross-currency swaps became prohibitively expensive, and many bilateral hedges simply couldn't be rolled over. $CASFX_e$ in this period reflects this risk sentiment.

frictions—that cannot be mitigated by macroeconomic improvements alone. The unexplained α mirrors the "unpriced" component of currency variance documented by Chernov et al. (2023), who show that most FX risk is not rewarded in expected returns yet loads on the stochastic-discount factor. Alternatively, in a risk-reward paradigm, FX volatility does not fully equate to risk. We argue that this is especially valid in EMDEs where market hedging and market frictions persist. In our EMDE setting, we interpret residual $CASFX_e$ as an unpriced risk component that acts as a drag on capital intensity. Moreover, this residual $CASFX_e$ constitutes a business-model risk—a de facto cost of doing business in EMDEs. Sponsors who continue to invest under these conditions must internalize currency shocks at the portfolio level, either by forgoing higher explicit returns or by deploying superior risk-management capacity (e.g. diversified project pipelines, internal hedging) to absorb losses that cannot be offset by market compensation.

In Table 6, higher levels of inflation, real interest rates and debt-to-GDP are associated with larger negative impacts on $CASFX_e$, confirming that tighter macro conditions diminish renewable energy projects' capacity to absorb FX risk. VIX also has a significant negative effect on $CASFX_e$, consistent with flight-to-safety behavior among emerging market investors (Egli et al., 2022). Similarly, higher debt-to-GDP ratios are associated with higher levels of $CASFX_e$ in a result that likely reflects the partially offsetting role of MDB guarantees, particularly for countries with moderate to severe sovereign risk positions.[17] These results show that while macroeconomic factors and external global risk sentiment are material drivers of $CASFX_e$, a residual component of capital allocation sensitivity remains that is persistent and a part of the risk complex in EMDEs.

Structural and transitory currency risk dynamics

[17] 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. In emerging economies, project finance often relies on public and or multilateral development bank guarantees. As a result, even when a country has large debt, projects can benefit from MDB facilities that insulate investment decisions from swings in sovereign debt levels.

The results of the previous section compel an investigation on the structural and transitory elements of $CASFX_e$ and how much of the elasticity is driven by either component.[18] We begin with unit root tests to establish the stochastic properties of CAS elasticities in Table 7. Longrun CAS Elasticity, Shortrun CAS Elasticity and Range CAS Elasticity – $CASFX_e$ defined for the three FX risk metrics – are all integrated of order one (I(1)). This suggests the existence of a structural component to $CASFX_e$ that accumulates over time. Given these properties, we present the BN decompositions of CAS elasticity for the three FX metrics in Figure 5. In Figure 5, structural components represent FX risk that sponsors must incorporate ex-ante, while transitory components capture short-lived deviations.

Figure 5 underscores that sponsors' sensitivity to FX risk is driven far more by structural than by short-lived transitory shocks. In all three panels, the dashed transitory lines remain clustered around zero. In contrast, the solid structural trends show pronounced troughs during the 2014–16 commodity-price collapse and emerging-market sell-off—especially for Longrun CAS Elasticity. This suggests a 'long memory' feature in sponsors capital allocation behavior, where past episodes of FX volatility continue to weigh on investor decisions even after short-term conditions stabilize. In Table 7, we assess this dominance by computing the signal-to-noise ratio (SNR) and the variance share of the structural trend component. SNR ranges between 2.4 and 4.2 while the variance share of the permanent component ranges between 70 and 82 per cent of total $CASFX_e$ variance. Both metrics demonstrate that structural elements dominate transitory volatility in our FX risk metrics.

Robustness tests

Across a battery of alternative specifications in Table 9, our core finding—that higher FX risk is associated with reductions in capital intensity—is robust. To verify that the negative association between FX risk and capital intensity is not an artefact of model choice or small-cluster inference, we re-estimate baseline specifications with wild-cluster bootstrap standard errors on country income group clusters following MacKinnon and Webb (2017).

[18] We considered other forms of decomposition. Unlike HP Filter decompositions, state-space models or Loess decompositions, the BN decomposition is fully data-driven, based on the forecasting behaviour of the underlying process. This is desirable in our application as we do not have to optimize trend-cycle balance.

The baseline pooled regressions as well as time series splits before and after the Paris Conference confirm our results. While Longrun FX volatility misses conventional significance in the pre-Paris period, it confirms results obtained in the random forest analysis on the subdued influence of FX risk in capital allocation in the period, but the increased importance thereafter.

Excluding renewable infrastructure projects from low-income countries, our primary results remain robust. Our findings are not driven by the smallest, riskiest economies.

Allowing for an interaction between FX risk and institutional strength (IPS) likewise yields a consistently negative main effect of FX risk, suggesting that even stronger institutional provisions do not fully insulate sponsors against currency swings.

Next, we apply permutation-based feature importance to random forest regressions to fit the same controls and FX inputs. Across repeated draws, all FX variables consistently rank among the top predictors of capital intensity, aligning with the TWFE-based results. Longrun FX volatility is still the most influential FX risk metric (Feature importance score = 17.3%)

The spline-based wild-bootstrap results strongly corroborate our core patterns. For both Longrun and Shortrun FX volatility, the three-segment splines reveal the same convex, regime-switching response—sharp reductions in capital intensity at low–moderate volatility, a partial rebound in the middle regime, and renewed declines at the highest volatility. Range FX exhibits a significant initial negative effect that then levels off at higher spreads, mirroring the flat segments seen in our original spline estimates.

Similarly, our regime-switching threshold models—selected via rolling three-fold cross-validation—capture discrete breaks in FX risk pricing but prove fragile: the bootstrapped 95 % confidence intervals for these breakpoints span more than one standard deviation of the τ. This volatility in estimated thresholds highlights their sensitivity to sample variation, reinforcing that while threshold approaches reveal potential regime shifts, spline-based specifications offer more reliable marginal effects for policy and risk management.

Broader economic implications and applications

Developing countries vary in their exposure and responsiveness to macro-financial shocks (Bekaert, Harvey and Lundblad, 2005) and consequently to $CASFX_e$. Sponsors in more mature UM economies may more dynamically recalibrate CAS elasticities in response to macro

volatility, reflecting deeper financial intermediation and more accessible hedging. LM sponsors may be more constrained and show relatively less incremental elasticity adjustment. A number of factors may account for this when considering inflation and real-rate shocks, for example. First, when inflation or real-rate shocks hit, UM sponsors can adjust their hedges and project structures more dynamically, so that changes in macro conditions translate into measurable shifts in $CASFX_e$. LM economies often lack liquid FX hedging markets and so large inflation moves may already be baked into project contracts. New inflation surprises therefore have little incremental effect on how much FX risk ultimately feeds into $CASFX_e$. Second, UM governments often have stronger institutions for monetary and fiscal stabilization. Increases in inflation or real rates are therefore seen as signals of changing macro-policy stances—investors update expectations about future exchange-rate paths and financing conditions, altering capital allocation (higher elasticity). In LM countries, inflation volatility may stem more from structural supply shocks or political instability. Investors learn over time that a 1-point inflation move is not necessarily predictive of long-term policy changes, so it does not shift their ex-ante capital-intensity responses. Sponsors in more mature UM economies may more actively recalibrate CAS elasticities in response to macro volatility, reflecting deeper financial intermediation and more accessible hedging (Maggiori et al., 2020). LM sponsors may be more constrained and show relatively less incremental elasticity adjustment. Differentiated policy solutions are vital.

Our findings underscore the catalytic role that multilateral development banks and development finance institutions can play, especially in contexts where structural buffers are weaker. Rather than broad public-finance interventions, a more efficient strategy would be to deploy partial guarantees or hedging facilities calibrated to the structural component of FX risk. By isolating the structural component that drives $CASFX_e$, such a facility can underwrite sticky FX risk—leaving transient shocks to market hedges or short-term liquidity lines. This sharp focus ensures public capital is catalytic, covering the most costly, enduring FX exposures, and thereby maximizes the impact of blended-finance de-risking.

Our findings suggest that residual FX risk – after controlling for macro factors – is a substantial barrier to scaling climate investments. Our regime-switching results justify embedding empirically validated volatility cut-offs into project-approval and covenant

frameworks, ensuring that capital adequacy rules and covenant waivers automatically adjust as FX risk crosses critical thresholds.

For climate investment policy, these insights highlight that while macro-stabilizing reforms (e.g., inflation targeting, fiscal prudence) can improve near-term bankability, they may not fully overcome the embedded investor caution reflected in the persistent component of CAS elasticities—particularly in LM countries. This points to a need for differentiated structural interventions and direct support for developing domestic debt markets alongside blended finance mechanisms to lower the cost of capital for renewable energy.

Yet, the most natural solution to FX risk in renewable infrastructure investments in developing countries lies not necessarily in developing hedging solutions and instruments; but rather in expanding local currency financing.

5. Conclusion

Meeting the annual USD 2 trillion climate investment need in developing economies will require investors deploy long-tenor capital in volatile exchange-rate environments. This paper introduces $CASFX_{\mathrm{e}}$, a time-varying elasticity that maps project-level FX betas into percentage changes in capital intensity. Leveraging granular project-finance data, we show that FX risk operates as a latent tax on renewable infrastructure deployment. Using state-contingent estimators, we identify a convex pass-through mechanism: as FX volatility rises from low to moderate levels, capital intensity falls sharply; it then rebounds partially—reflecting sponsors' hedging and equity-buffer adjustments, and real option value timing—only to decline again once FX risk reaches extreme highs.

Importantly, about 70–80 percent of the estimated $CASFX_{\mathrm{e}}$ variance is structural rather than transitory, indicating that FX risk functions as a structural barrier to investment rather than a cyclical shock. Macro risk factors and global risk sentiment do not fully explain $CASFX_{\mathrm{e}}$: higher inflation, real interest rates, and VIX all have negative impacts on sponsors sensitivity to FX risk, yet a significant residual remains, reflecting the persistent baseline FX risk EMDE investors are faced with.

These results carry two central implications. First, conventional hedging solutions are insufficient to fully mitigate capital rationing induced by structural FX risk, particularly given

the fragmented nature of EMDE derivative markets. We argue that policy differentiation is vital, given heterogeneities in country contexts. Second, blended-finance instruments can achieve greater leverage when they target the structural component of FX risk—through local-currency denominated instruments and layered guarantees that ease collateral constraints.

These findings extend the corporate-hedging literature by showing that unpriced FX risk constrains real investments capacity, not merely financial valuations. They also reconcile asset-pricing evidence on limited FX compensation with capital-budgeting behaviour: investors reduce exposure in the face of heightened uncertainty precisely because the associated risks are largely uncompensated. While the data does not allow us to isolate local-currency origination, the evidence suggests that without targeted interventions to transform structural FX risk into a diversifiable cost, global ambitions on renewable infrastructure investment will fall short of the Paris-aligned trajectory. Deepening local-currency debt markets, extending guarantee maturities and scaling pooled hedging mechanisms directly address the structural component of risk that remains beyond the reach of risk diversification.

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Data availability

The proprietary project level dataset underlying this paper cannot be shared publicly.

Figure 1. Renewable energy 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.

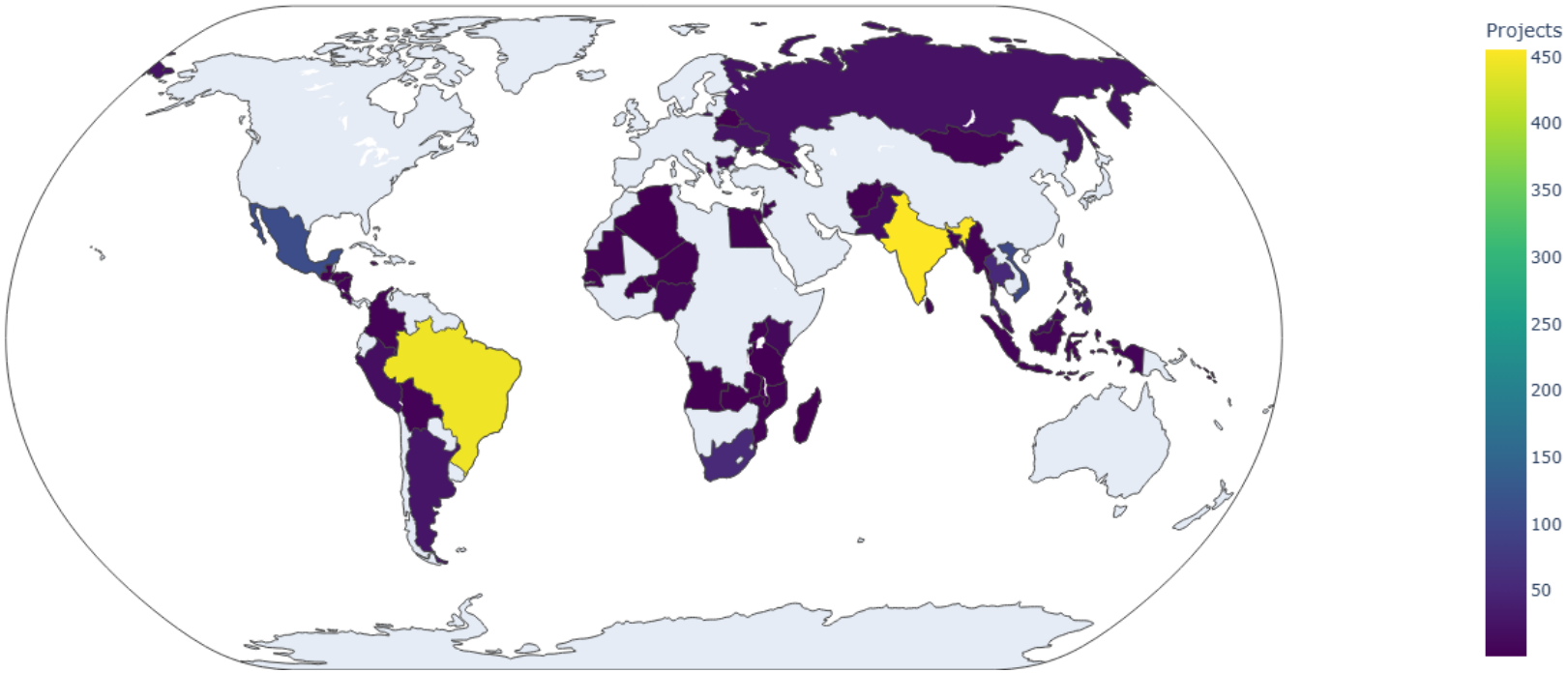
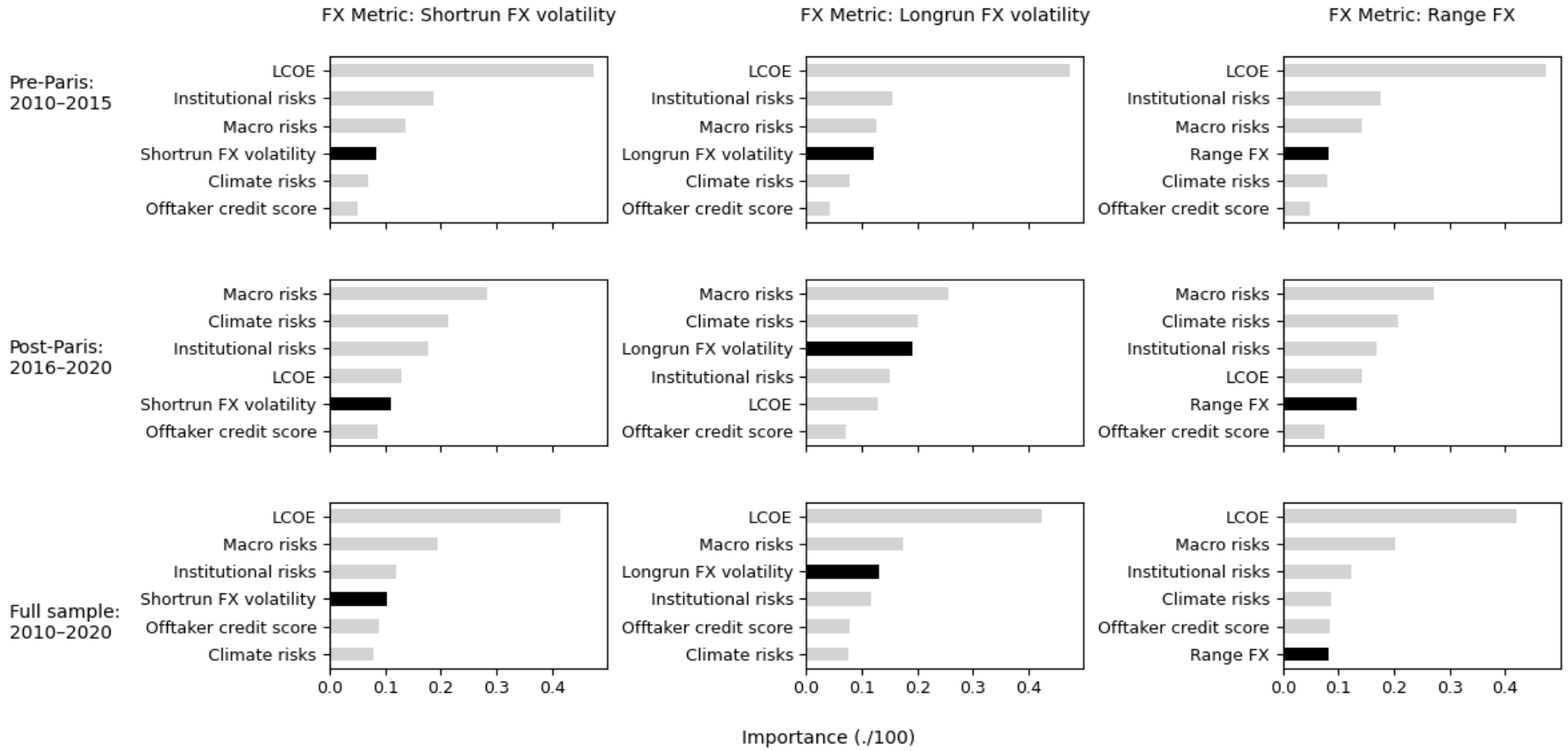
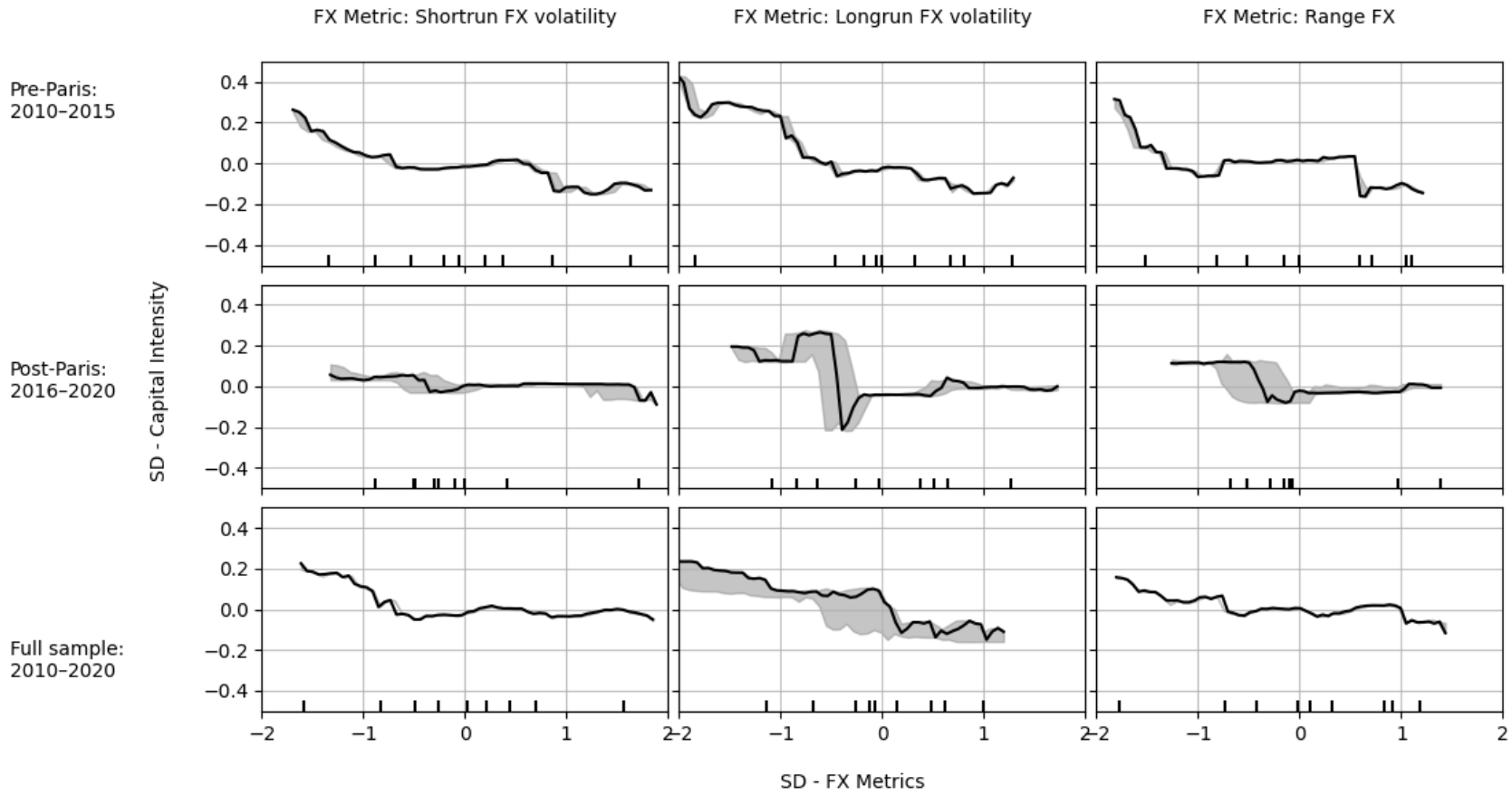


Figure 2. Feature Importance Scores from Random Forest Models across Configurations (2010–2020).



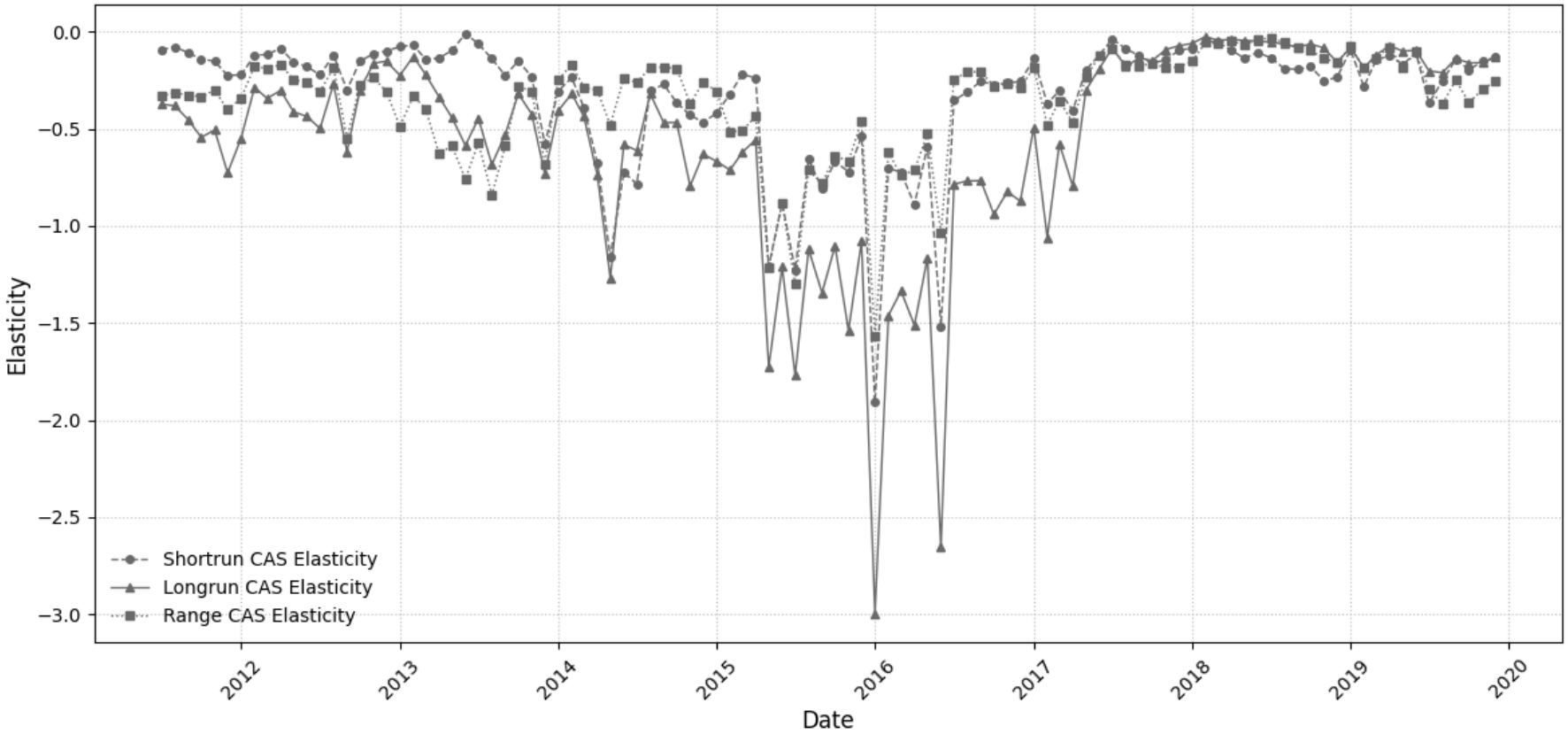
Notes: Figure 2 presents feature importance rankings (./100) from Random Forest models for three configurations. All variables are defined in Table A1. *Pre* models use project and risk data before Paris. *Post* models use data from 2016 – 2020 while the f*ull sample* uses data from 2010 – 2020. The 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 *Range FX.* 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. Model diagnostics are presented in Table 3.

Figure 3. Partial dependence plots from Random Forest model for FX risk metrics.



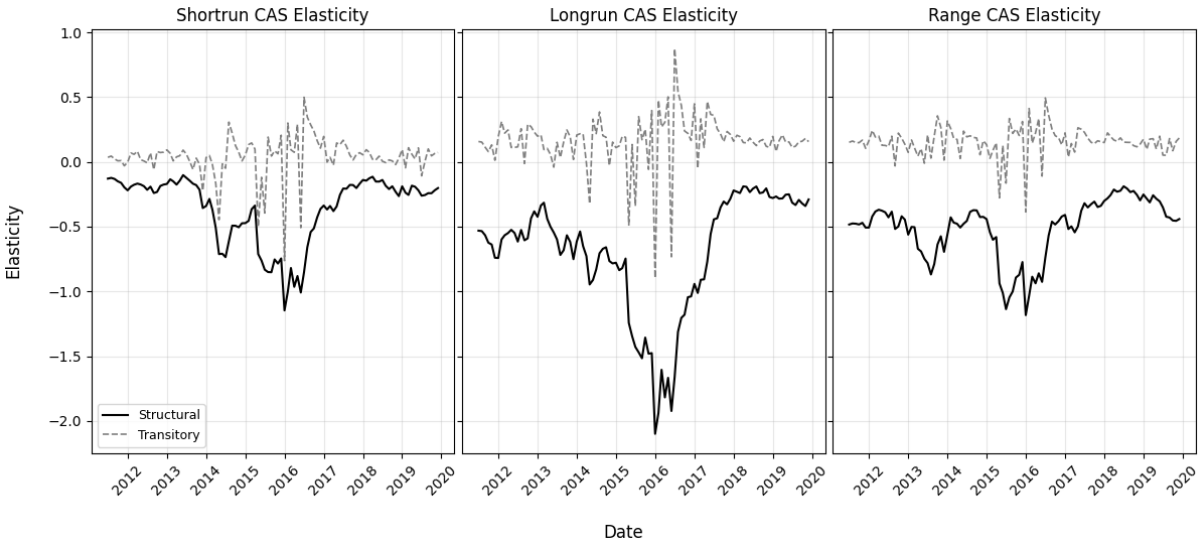
Notes: Figure 3 presents partial dependence plots with 95% bootstrapped confidence bands for FX risk metrics within +/- 2 SDs based on results in Figure 2. The horizontal and vertical axes show standard deviation (SD) moves in FX volatility metrics and capital intensity. All underlying variables and data stratification are defined in Table A1 and Figure 2 respectively.

Figure 4. 18-month rolling capital allocation sensitivity to FX risk ($CASFX_e$).



Notes: Figure 4 plots the elasticity of capital intensity to FX risk derived as follows. For each month, we estimate a cross-sectional regression of project-level capital intensity on FX risk measures and control covariates over a 18-month rolling windows. The estimated beta coefficients are then scaled by monthly averages of the ratio of FX risk to capital intensity to yield elasticities.

Figure 5. Decomposition of $CASFX_e$ into structural and transitory components.



Notes: Figure 5 presents the decomposition of the elasticity of capital intensity to FX ($CASFX_e$) —captured by the Shortrun CAS Elasticity, Longrun CAS Elasticity and Range CAS Elasticity—into structural and transitory components using the Beveridge-Nelson (BN) decomposition. Each series is first tested for unit roots. For I(1) series, we estimate an ARIMA(p,1,q) model, where the lag structure (p,q) is selected based on the Akaike Information Criterion (AIC). The BN structural trend is derived as the long-run forecast of the I(1) process, while the transitory component represents the short-run deviation from the structural trend.

Table 1. Summary statistics.

Variable	N	μ	σ	Median
Panel A: Project-related variables				
Capital Int.	1497	1.516	1.330	1.220
Offtaker Credit Score	1497	57.217	21.627	58.667
LCOE ($/kWh)	1497	-2.297	0.439	-2.289
Panel B: Institutional Risk variables				
IPS	1497	26.252	15.413	23.223
IRL	1497	47.182	11.020	52.582
IRQ	1497	45.095	11.985	43.333
IVA	1497	51.838	16.744	60.190
Panel C: Macro Risk variables				
Inflation (%)	1497	7.179	6.059	5.805
Curr. Balance (%)	1497	-2.403	3.002	-2.857
Debt-to-GDP (%)	1497	60.437	16.704	67.102
Real IR (%)	1497	10.925	14.277	4.216
Panel D: Climate Risk variables				
CO2 per Capita (MtCO2e/p)	1497	2.566	1.864	2.161
Share Ren. Capacity (%)	1497	41.985	26.871	26.330
Disaster Int. (mUSD/p)	1497	63.348	328.553	0.003
Panel E: Currency Risk variables				
Longrun FX volatility	1497	0.035	0.019	0.030
Shortrun FX volatility	1497	0.034	0.031	0.027
Range FX	1497	0.142	0.123	0.130
Panel F: Global risk factor				
VIX	1297	16.870	5.665	15.520

Notes: Detailed variable definitions are provided in Table A1, and summary statistics by status in Table A2. Table 1: count (N), mean (μ), standard deviation (σ) and median for all variables. Panel A: the natural logarithm of USD million invested per MW (Capital Int.), Offtaker credit score, the natural log of levelized cost of electricity (LCOE in USD/kWh). Panel B: annual indices for political stability (IPS), regulatory quality (IRQ), regulations and laws (IRL), and voice and accountability (IVA). Panel C: percentage change in monthly inflation, real interest rate, annual debt-to-GDP and annual percentage change in current account balance. Panel D: per-capita CO_2 emissions, share of renewable capacity, and disaster damages per affected person (USD). Panel E: 60-month (Longrun FX volatility) and 12-month rolling FX log-return volatilities (Shortrun FX volatility), and the 24-month high-low FX (Range FX) log-return spread. Panel F reports the volatility index (VIX).

Table 2. Random Forest model diagnostics.

	(1)	(2)	(3)
Pre Paris: 2010 - 2015			
MSE	0.367	0.357	0.360
R-square	0.649	0.659	0.655
Ljung-Box (No. lags)			
1	0.749	1.428	1.207
6	3.776	5.614	4.243
12	12.856	14.127	13.016
Post Paris: 2016 – 2020			
MSE	0.694	0.702	0.703
R-square	0.265	0.257	0.255
Ljung-Box (No. lags)			
1	0.605	0.609	0.556
6	5.015	5.501	5.117
12	8.235	9.709	8.774
All : 2010 - 2020			
MSE	0.445	0.443	0.450
R-square	0.555	0.557	0.551
Ljung-Box (No. lags)			
1	0.067	0.205	0.028
6	0.950	1.099	1.163
12	12.412	13.171	12.314

Notes: Table 3 presents summary diagnostics for the random forest models in Figure 2. For each configuration — pre-Paris (2010–2015), post-Paris (2016–2020), and the full sample (2010–2020)—we report the mean squared error (MSE), R-square, and the Ljung-Box Q-statistics (lags: 1, 6, and 12) to assess residual autocorrelation. Columns (1)–(3) correspond to models that respectively include Shortrun FX volatility, Longrun FX volatility and Range FX. Statistical significance for the Ljung-Box test is indicated by * for 10%, ** for 5%, and *** for 1% significance levels. Lower MSE and higher R-squared indicate better model performance, while insignificant Ljung-Box statistics suggest residuals are not serially correlated.

Table 3. Currency risk in renewable infrastructure investments.

Panel A: With country status and year-month FE			
Variable	(1)	(2)	(3)
Longrun FX volatility	-0.080***		
	(0.013)		
Shortrun FX volatility		-0.130***	
		(0.016)	
Range FX			-0.148***
			(0.003)
IPS	0.011	-0.004	-0.007
	(0.026)	(0.026)	(0.026)
Share Ren. Capacity	-0.034	-0.031	-0.023
	(0.025)	(0.026)	(0.027)
LCOE	0.563***	0.542***	0.538***
	(0.050)	(0.051)	(0.054)
CO2 per capita	0.007	-0.003	0.003
	(0.022)	(0.023)	(0.023)
Year-month FE	Yes	Yes	Yes
Country Status FE	Yes	Yes	Yes
Adj. R-Sq.	0.213	0.241	0.244
N	1,494	1,494	1,494
Panel B: With year-month FE			
Longrun FX volatility	-0.081***		
	(0.013)		
Shortrun FX volatility		-0.129***	
		(0.014)	
Range FX			-0.146***
			(0.004)
IPS	0.009	-0.006	-0.010
	(0.025)	(0.025)	(0.025)
Share Ren. Capacity	-0.035	-0.033	-0.025
	(0.025)	(0.026)	(0.028)
LCOE	0.556***	0.547***	0.544***
	(0.046)	(0.043)	(0.049)
CO2 per capita	0.025	-0.008	-0.005
	(0.023)	(0.024)	(0.024)
Year-month FE	Yes	Yes	Yes
Country Status FE	No	No	No
Adj. R-Sq.	0.212	0.234	0.243
N	1,494	1,494	1,494

Notes: The sample period is 2010 – 2020. The dependent variable is Capital Int. Standard errors are double-clustered on entity and time. ***1% significance; **5% significance; *10% significance. All variables are defined in Table A1.

Table 4. Threshold regressions: currency risk effects in renewable investments.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
CV Threshold (τ)	-0.895	-0.895	0.989	0.989	1.052	1.052
Shortrun FX volatility	-0.402***	-0.395**				
	(0.142)	(0.154)				
Longrun FX volatility			-0.366***	-0.347***		
			(0.135)	(0.131)		
Range FX					-0.271*	-0.251*
					(0.151)	(0.142)
FX.1(FX> τ)	0.254***	0.266***	0.509*	0.429*	0.076	0.031
	(0.025)	(0.092)	(0.301)	(0.259)	(0.419)	(0.389)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country Status FE	Yes	No	Yes	No	Yes	No
Adj. R-Sq.	0.259	0.251	0.250	0.235	0.255	0.250
N	1497	1497	1497	1497	1497	1497

Notes: Table 4 presents two-way fixed effects regression results estimating threshold effects of FX volatility on capital intensity in renewable investments. For each FX metric (Shortrun FX volatility, Longrun FX volatility, and Range FX), the threshold value (γ) is selected via cross-validation (CV). Each FX metric is interacted with an indicator for values above τ (FX.1). (1), (3) and (5) include country status and year-month fixed effects, (2), (4) and (6) include only time fixed effects. Standard errors are double-clustered by country status and time. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Spline regressions: currency risk effects in renewable investments.

FX Metric	Knots	β_1	β_2	β_3	Adj. R^2
Panel A: Visual Knots					
Shortrun FX volatility	-1.120, –0.400, 0.300	–1.061**	1.791***	-1.291***	0.281
		(0.412)	(0.479)	(0.121)	
Longrun FX volatility	–1.000, 0.000, 0.800	-1.445***	2.133***	-1.293***	0.237
		(0.392)	(0.762)	(0.254)	
Range FX	–0.600, 0.100, 0.700	-0.600***	0.498	-0.127	0.239
		(0.230)	(0.513)	(1.889)	
Panel B: Cross-validation Knots					
Shortrun FX volatility	–1.587, –0.262, 0.447	–0.523**	0.862***	-0.814***	0.278
		(0.254)	(0.319)	(0.121)	
Longrun FX volatility	-1.146, –0.672, 0.260	0.705	-3.255**	2.718**	0.260
		(0.607)	(1.656)	(1.146)	
Range FX	–1.767, –0.728, -0.021	-0.299***	0.060	-0.001	0.257
		(0.037)	(0.410)	(0.642)	

Notes: All specs include two-way FE, include controls and standard errors are double-clustered by country status and time. *Knots* gives the three breakpoint values from visually inspecting partial dependence plots from the random forest model (Panel A). Panel B uses the knot set with the lowest average mean square error based on computing the out-of-sample MSE of the two-way FE spline regression for each candidate set of knots in cross-validation tests. β_i is the coefficient on $max(FXRisk_i - Knot_i, 0)$. *p < 0.10; **p < 0.05; ***p < 0.01. Adj. R^2 adjusted R-square.

Table 6. Macroeconomic drivers of $CASFX_e$.

Variable	Shortrun CAS Elasticity	Longrun CAS Elasticity	Range CAS Elasticity
Constant	-0.273***	-0.476***	-0.331***
	(0.038)	(0.080)	(0.045)
Inflation	-0.042**	-0.041	-0.053***
	(0.019)	(0.041)	(0.021)
Real IR	-0.284***	-0.434***	-0.206***
	(0.056)	(0.096)	(0.055)
Debt-to-GDP	0.057*	0.089	0.062***
	(0.030)	(0.056)	(0.022)
Curr. Balance	-0.003	0.042	0.012
	(0.022)	(0.046)	(0.026)
VIX	-0.056*	-0.146***	-0.061**
	(0.030)	(0.047)	(0.027)
Adj. R-Sq.	0.471	0.421	0.330
N	102	102	102

Notes: Time-series regressions of monthly $CASFX_e$ – estimated from rolling past 18-month cross-sectional regressions - on key macro variables. Dependent variables are the Shortrun CAS Elasticity (col. 1), Longrun CAS Elasticity (col. 2), and Range CAS Elasticity (col. 3) Control variables are defined in Tabe A1. We present coefficients and Newey–West (HAC) standard errors (max lags = 12) to correct for serial correlation. Adjusted R-squared and sample size (N) are reported. Significance: *** p<0.01; ** p<0.05; * p<0.10.

Table 7. Beveridge-Nelson Decomposition of CAS Elasticity.

Test	Shortrun CAS Elasticity	Range CAS Elasticity	Longrun CAS Elasticity
Panel A: Stationarity tests for original CAS Elasticity series			
ADF Test p-value	0.399	0.067	0.317
KPSS p-value	0.100	0.087	0.096
Panel B: BN-decomposition stationarity of permanent component			
ADF Test p-value	0.428	0.327	0.638
KPSS p-value	0.100	0.080	0.010
Panel C: BN-decomposition stationarity test of transitory component			
ADF Test p-value	0.003	0.000	0.113
KPSS p-value	0.100	0.100	0.100
Panel D: Post BN-decomposition diagnostics			
SNR	2.427	3.749	4.428
Variance share of trend	0.708	0.789	0.816

Notes: Table 7 combines unit-root tests and Beveridge–Nelson (BN) decomposition diagnostics for the three $CASFX_e$ series (Shortrun, Range, Longrun). Panel A reports p-values from Augmented Dickey–Fuller (ADF) and KPSS tests on the original series; ADF tests the null of a unit root, while KPSS tests the null of stationarity both at the 95% level. Panel B applies the same tests to the permanent component extracted from ARIMA (p, 1, q)-based BN decomposition (optimal order chosen by AIC). Panel C reports stationarity tests for the transitory component. Panel D summarizes BN post-decomposition diagnostics: the signal-to-noise ratio (variance of the trend relative to variance of the cycle) and the variance share of the trend.

Table 8. Model definitions for robustness tests.

No.	Model	Definition
1	baseline	Two-way fixed effects (FE) model on 2010–2020 data with wild-cluster bootstrap standard errors (SEs).
2	pre2016 twfe	Two-way fixed effects (FE) model on 2010–2015 data with wild-cluster bootstrap standard errors (SEs).
3	post2016 twfe	Two-way FE model on 2016–2020 data with wild-cluster bootstrap SEs.
4	interaction twfe	Full-sample two-way FE including FX × IPS interaction, with wild-cluster bootstrap SEs
5	noL_wild	Re-estimates the pooled regression on the full sample excluding all projects from low-income countries with wild-cluster bootstrap errors.
6	rf_perm	A random-forest permutation-importance check that computes the average drop in the Random Forest's predictive R^2 when the FX feature is randomly permuted, quantifying its importance.
7	spline_wild	Two-way FE with three spline segments on FX (CV-selected knots), using wild-cluster bootstrap SEs
8	threshold	Single "optimal-breakpoint" threshold (τ) estimate: the value of FX_t at which you split the sample to minimize total SSR in two separate OLS regressions (low vs. high FX)
9	threshold_boot	A bootstrap of that threshold estimator: you resample the data many times and record the distribution of the estimated breakpoint

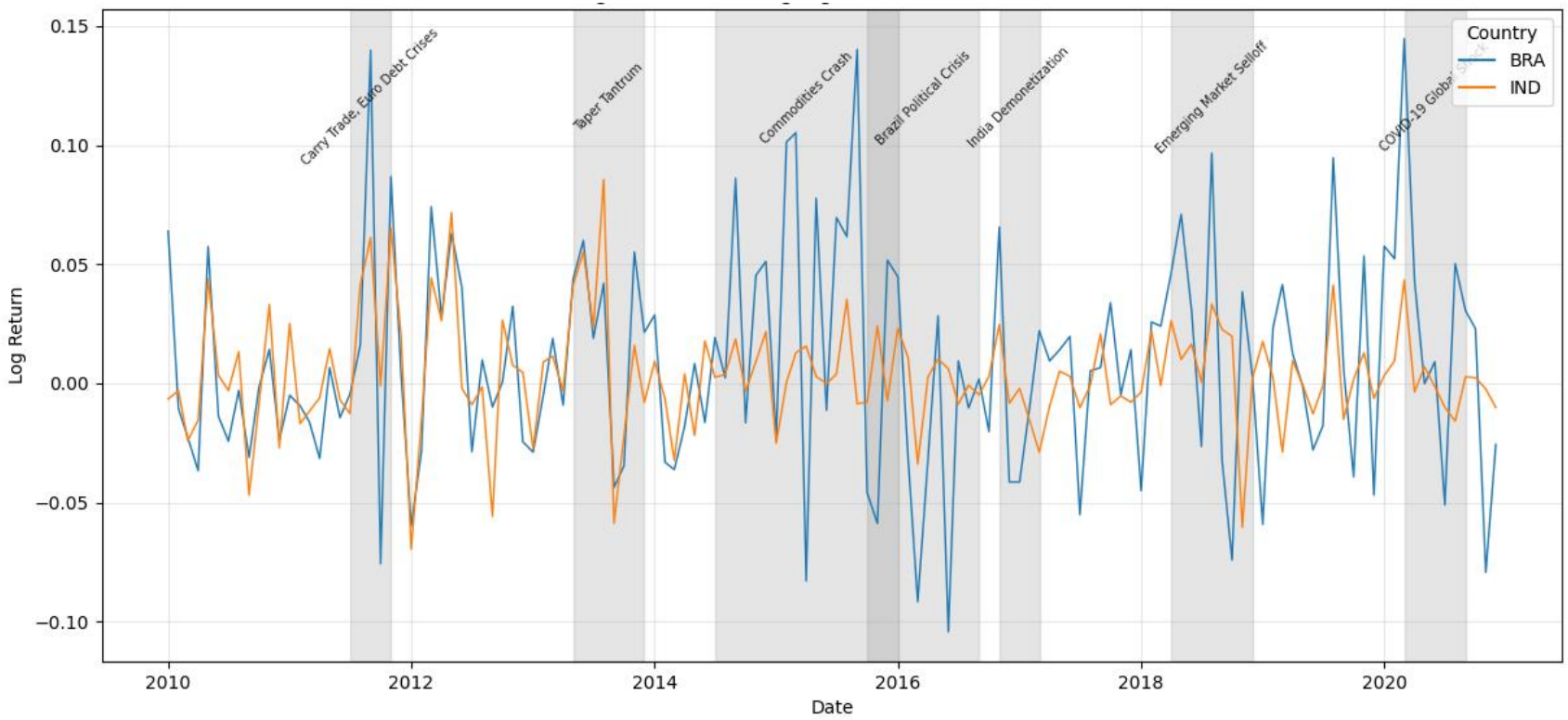
Table 9. Robustness tests.

Model	FX Metric	β	SE	Feature Imp.	Spline (β_1)	Spline (β_2)	Spline (β_3)	mean(τ)	CI (τ)	Robust (y/n)
baseline	Longrun FX volatility	-0.146***	0.021							y
pre2016 twfe	✓	-0.168	0.101							y
post2016 twfe	✓	-0.144***	0.039							y
interaction twfe	✓	-0.161***	0.007							y
noL_wild	✓	-0.149***	0.021							y
rf_perm	✓			0.173						y
spline_wild	✓				-0.549***	0.589***	0.027			y
threshold_boot	✓							0.474	[-0.555, 1.134]	n
baseline	Shortrun FX volatility	-0.195***	0.034							y
pre2016 twfe	✓	-0.169***	0.022							y
post2016 twfe	✓	-0.178***	0.017							y
interaction twfe	✓	-0.186***	0.022							y
noL_wild	✓	-0.197***	0.034							y
rf_perm	✓			0.138						y
spline_wild	✓				-0.906***	1.582***	-1.129***			y
threshold_boot	✓							0.050	[-0.328, 0.221]	n
baseline	Range FX	-0.198***	0.007							y
pre2016 twfe	✓	-0.169**	0.066							y
post2016 twfe	✓	-0.174***	0.037							y
interaction twfe	✓	-0.195***	0.010							y
noL_wild	✓	-0.200***	0.007							y
rf_perm	✓			0.077						y
spline_wild	✓				-0.125***	-0.118	-0.220			y
threshold_boot	✓							-0.235	[-0.428, 0.984]	n

Notes: Table 9 provides results of robustness tests run. FX Metric is defined in Table A1. β - estimated coefficient on the FX metric; SE its standard error; "Feature Imp." the Random-Forest importance; "Spline (β)." the spline coefficients; "mean (τ)" the cross-validated threshold and "CI (τ)" its 95 % bootstrap confidence interval for τ and for β in noL_wild. Threshold (knots) parameters maximize out-of-sample within-R-square (MSE) through cross-validation. *** p<0.01; ** p<0.05; * p<0.10

Appendix

Figure A1. Currency Returns (vs USD) from 2010 – 2020 for Brazil and India.



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

Table A1. Variable definitions

Variable	Definition
Capital Int.	Natural logarithm of the ratio of nominal investments (mUSD) per unit of capacity (MW)
CO_2 per capita	Amount of sovereign carbon emissions divided by country population
Curr. Balance (% GDP)	Measures a country's net trade and financial flows annually (as % GDP)
Debt-to-GDP (%)	Debt-to-GDP measures gross sovereign debt as a percentage of annual GDP
Disaster Int (mUSD/p)	Measures economic damages from natural disasters, adjusted by number of people affected
Inflation (%)	Percentage monthly change in consumer price inflation rate for each country
IPS	Measures likelihood of political instability and/or politically motivated violence, including terrorism.
IRL	Measures perceptions of the extent to which agents have confidence in and abide by the rules of society, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence
IRQ	Measures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development
IVA	Measures perceptions of the extent to which a country's citizens are able to participate in selecting their government, freedom of expression, association, and free media.
LCOE	Measures the average lifetime cost of producing energy in USD/kWh
Longrun FX Volatility	The 60-month rolling standard deviation of the natural logarithm of FX returns
Offtaker Credit Score	Offtaker Credit Score measures the creditworthiness of the entity purchasing renewable energy
Range FX	The difference between maximum and minimum log FX returns over a 24-month period
Real IR (%)	Measures inflation-adjusted borrowing costs (%)
Share of Ren. Capacity (%)	Measures the percentage of total installed electricity generation capacity derived from renewables
Shortrun FX Volatility	The 12-month rolling standard deviation of the natural logarithm of FX returns
VIX	Measures agents' expectation of 30-day forward-looking volatility based on S&P 500 options prices

Table A2. Summary statistics by country status.

Variable	Status	μ	σ	Median
Project-related variables				
Capital Int. (mUSD/MW)	L	3.200	3.052	2.395
	LM	1.473	1.035	1.236
	UM	1.513	1.480	1.165
Offtaker Credit Score	L	25.251	24.079	19.968
	LM	64.376	16.558	58.667
	UM	51.060	23.241	52.948
Institutional Risk variables				
IPS	L	18.310	11.471	16.307
	LM	18.618	15.421	11.374
	UM	33.946	11.069	34.286
IRL	L	25.317	14.762	22.143
	LM	47.909	11.146	53.521
	UM	47.055	10.158	48.826
IRQ	L	29.593	11.593	25.476
	LM	37.056	7.356	36.842
	UM	53.389	9.656	55.450
IVA	L	33.380	10.811	34.975
	LM	47.881	19.234	60.190
	UM	56.211	12.404	61.786
Macro Risk variables				
Inflation (%)	L	6.397	6.158	5.033
	LM	8.279	5.856	8.610
	UM	6.122	6.069	4.978
Curr. Balance (% change)	L	-10.967	12.975	-7.839
	LM	-2.301	2.462	-2.857
	UM	-2.273	2.423	-2.858
Debt-to-GDP (%)	L	46.250	36.214	36.214
	LM	62.303	13.482	67.702
	UM	58.989	18.541	60.634
Real IR (%)	L	11.084	10.487	8.230
	LM	2.154	4.170	2.474
	UM	19.515	15.496	22.404
Climate Risk variables				
CO2 per Capita (MtCO2e/p)	L	0.234	0.165	0.202
	LM	1.730	0.843	1.397
	UM	3.449	2.161	2.413
Share Ren. Capacity (%)	L	51.650	32.309	62.020
	LM	27.201	10.238	25.170

	UM	56.213	30.015	78.930
Disaster Int. (mUSD/p)	L	0.001	0.000	0.000
	LM	129.703	461.086	0.002
	UM	0.026	0.085	0.004
FX Risk variables				
Longrun FX volatility	L	0.031	0.015	0.025
	LM	0.027	0.022	0.024
	UM	0.042	0.013	0.048
Shortrun FX volatility	L	0.030	0.032	0.019
	LM	0.026	0.038	0.021
	UM	0.041	0.019	0.039
Range FX	L	0.144	0.087	0.136
	LM	0.118	0.158	0.098
	UM	0.167	0.067	0.170

Notes: n(UM)= 746; n(LM)= 731; n(L)=20; n=1497. L – Low-income; LM – lower middle-income; UM – Upper middle- income countries. Definitions shown in Table A1.