Risk, Return, and Market Integration: An Empirical Analysis of Indian Green Equities

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Abstract

This paper studies the dynamics of an equal-weighted portfolio of Indian green stocks using daily data from 2020–2025. We combine descriptive analysis and factor regressions to characterise the sector's risk profile. The portfolio delivers an annualised mean log return of about 12.4% with annualised volatility of roughly 27.8%, resulting in a cumulative gain of approximately 22.5%. Returns are markedly non-Gaussian, with negative skewness, excess kurtosis, volatility clustering and sizable drawdowns (maximum drawdown around –36%). A CAPM-style regression using NIFTY 50 daily log returns yields a statistically significant market beta of about 0.83 and no significant daily alpha, while a simple regression on the CNY/USD exchange-rate level has essentially zero explanatory power ($R^2 \approx 0.001$). The findings suggest that Indian green equities are significantly integrated with the domestic market but possess unique risk characteristics not driven by global currency factors.

1 Introduction

India's transition to a low-carbon economy is one of the most consequential structural transformations underway in any emerging market. The country has set ambitious targets for renewable energy capacity, green hydrogen production, electric mobility, and energy efficiency. To finance this transformation, it needs large and sustained flows of capital into green infrastructure and technology. Equity markets play a crucial role in this process by providing risk capital to firms engaged in renewable power, clean technologies, and related infrastructure.

Over the past decade, a distinct segment of "green" listed equities has emerged in India, ranging from renewable power producers to solar equipment manufacturers and clean-tech firms. These stocks are natural candidates for investors pursuing environmental, social, and governance (ESG) mandates, as well as for domestic investors who wish to gain exposure to the country's energy transition. Yet, despite growing interest, there is limited systematic evidence on how this green equity segment behaves in terms of risk and return, how it co-moves with the broader Indian market, and how it responds to macro-financial shocks.

This paper addresses the central question:

How does the risk-return profile of Indian green equities compare to the broader market, and to what extent are these returns driven by systematic market risk versus global currency factors?

To answer these questions, we build a daily panel dataset that merges a green equity portfolio with macro and financial controls and NIFTY 50 index data. We implement all analysis in Python, paying close attention to data cleaning and alignment issues.

Our main findings are as follows. First, the equal-weighted Indian green portfolio delivers an annualised mean log return of about 12.4% with annualised volatility near 27.8%, and a total cumulative return of roughly 22.5% over 602 trading days. Its daily returns are non-Gaussian, negatively skewed, and exhibit fat tails and volatility clustering. Second, a simple regression of green returns on the CNY/USD exchange-rate level explains essentially none of their variation, suggesting that this sector is not driven by broad emerging-market currency conditions at the daily horizon. Third, a CAPM-style regression using NIFTY 50 returns yields a statistically significant market beta of about 0.83 and an R^2 of 39%, with no significant daily alpha. Thus, green equities behave as a high-beta sub-segment of the domestic market, but not as a source of easily detectable daily CAPM alpha.

2 Literature Review

2.1 Green finance and sustainable investment in India

Green finance in India has grown rapidly in recent years, driven by both domestic policy priorities and international climate commitments. The country has issued green bonds, launched dedicated renewable energy policies, and established regulatory frameworks to encourage lending to green projects. Studies on the Indian green bond market suggest that green-labelled securities often price similarly to or at a slight premium relative to conventional bonds, reflecting investors' willingness to pay for environmental attributes [Chakraborty and Singh, 2021].

Beyond bonds, equity markets are increasingly recognised as a key channel for financing the energy transition. The Climate Policy Initiative and other institutions have documented a steady rise in tracked green finance flows into renewable energy and low-carbon sectors in India, but emphasise that these flows still fall short of the investment needed to meet climate targets. Government policy has responded with a range of programmes, including the National Solar Mission, the National Green Hydrogen Mission, production-linked incentive (PLI) schemes, and schemes such as PM Surya Ghar to expand rooftop solar adoption. These policies can in principle affect the valuation of firms directly involved in or dependent on the renewable energy ecosystem.

2.2 Foreign portfolio investment and Indian equity markets

Foreign institutional investors (FIIs), now reclassified as FPIs, have played a central role in the development of Indian capital markets. A large body of literature examines the relationship between FPI flows and stock returns in India. Early studies such as Chakrabarti [2001] and Rai and Bhanumurthy [2004] find that FPI flows are positively associated with equity returns and often follow return-chasing behaviour. More recent work employs vector autoregressions and Granger causality tests to show that in many periods, returns Granger-cause flows rather than the reverse [e.g. Dua and Sharma, 2013, Mishra et al., 2009], and that the explanatory power of FPI flows for broad indices such as NIFTY can be non-trivial but is not stable over time.

These studies, however, mostly focus on aggregate indices across all sectors. Little attention has been paid to how FPI flows interact specifically with green equities, which may be particularly attractive to foreign investors with ESG mandates.

2.3 Gaps and contribution

Against this backdrop, our paper makes two primary contributions:

1. It constructs and characterises a daily equal-weighted portfolio of Indian green stocks, documenting its risk–return properties, tail behaviour, volatility clustering, and drawdowns.

2. It provides a set of baseline regression estimates—including a CAPM-style model with NIFTY 50 returns—to measure the extent of market integration and test for daily alpha, while carefully debugging data alignment issues that could otherwise mislead inference.

3 Data

3.1 Green stock universe and portfolio returns

Our starting point is a file `indian_green_stocks.csv`, which contains daily stock-level data for a set of Indian firms classified as "green." Each record includes at least a date, a ticker identifier, and a closing price. We compute stock-level daily log returns as

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right),$$

where $P_{i,t}$ is the closing price of stock i on day t. On each trading day t, we form an equal-weighted portfolio of all available green stocks:

$$r_t^G = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{i,t},$$

where N_t is the number of green stocks with non-missing prices on day t. This yields a time series of the green portfolio's daily log return, stored as `green_eq_log_ret` in the merged panel.

After dropping days with missing portfolio returns, we obtain 602 observations of r_t^G between 2020 and 2025. The number of constituent stocks varies over time as firms enter or exit the sample or experience missing data.

3.2 Macro and financial control variables

We also have access to a wide-format control dataset, `control_variables_wide_format.csv`, containing daily values of various macro and financial variables. These include:

- Exchange rates: CNY/USD, EUR/USD, GBP/USD, INR/USD, JPY/USD, etc.
- Global equity indices: S&P 500, NASDAQ Composite, FTSE 100, NIKKEI 225, STOXX Europe 50, and others.
- Commodities: Brent crude (BZ_F), WTI crude, gold, silver, natural gas.
- Indian sector indices and volumes.
- Volatility indices such as VIX and VXEEM.

The control dataset uses dates that initially include timezone information, while the green portfolio dates are naive. We standardise all date columns by parsing them with `pd.to_datetime` and then applying `.dt.tz_localize(None)` to remove timezone information. This ensures that merges on the `date` field produce meaningful overlaps rather than type mismatch errors.

For the purposes of this paper, we focus on one global macro variable: the CNY/USD exchange-rate level, stored as `close_CNYUSD_X`. This variable has non-missing overlap with the green portfolio over the full sample and serves as a simple proxy for emerging-market currency conditions.

3.3 NIFTY 50 index data and returns

We obtain NIFTY 50 index data from Yahoo Finance using the `yfinance` Python library:

```
nse = yf.download("^NSEI", start="2019-12-01", end="2025-12-31")
```

This returns daily OHLCV data with the date as index. To simplify, we extract the closing price, rename it `close_NSEI`, and compute daily log returns:

$$r_t^{Mkt} = \ln \left(\frac{\text{close\_NSEI}_t}{\text{close\_NSEI}_{t-1}} \right).$$

We store this as `return_NSEI` and reset the index so that `date` becomes an ordinary column. After ensuring both the panel and NIFTY datasets share a common, timezone-naive `date` field, we merge `return_NSEI` into the main panel.

In the process, we encounter duplicate columns (`return_NSEI_x`, `return_NSEI_y`) when merging multiple times; we resolve this by explicitly choosing one (the newly downloaded one) and standardising the column name to `return_NSEI`. After this cleaning, we obtain 601 observations with non-missing values for both `green_eq_log_ret` and `return_NSEI`.

4 Methodology

4.1 Panel construction and data integrity

The merged panel `panel` is constructed by joining the green portfolio returns, macro controls, NIFTY returns, and FPI placeholder on the `date` field. The key steps in ensuring data integrity are:

1. Converting all date columns to timezone-naive `datetime64[ns]`.
2. Checking for and resolving duplicate column names (e.g. multiple `return_NSEI` versions).
3. Inspecting shapes, dtypes, and NaNs before any regression to avoid empty design matrices.

We constructed a strictly aligned panel dataset, ensuring that regression models were estimated only on trading days where both dependent and independent variables had non-missing observations.

4.2 Descriptive statistics and distributional analysis

Let r_t^G denote the daily log return of the equal-weighted green portfolio. We compute:

- The sample mean $\bar{r}^G$ and standard deviation $s(r^G)$.
- Selected percentiles (1st, 5th, 50th, 95th, 99th).
- the minimum and maximum daily returns.

We annualise mean and volatility using 252 trading days per year:

$$\mu_{\text{ann}} = \bar{r}^G \cdot 252, \qquad \sigma_{\text{ann}} = s(r^G) \cdot \sqrt{252}.$$

We construct a cumulative return series:

$$V_t = \prod_{i=1}^{t} (1 + r_i^G) - 1,$$

where $V_0 = 0$. This series summarises the overall performance of the green portfolio over time.

We also generate:

- A time-series plot of daily returns r_t^G,
- A cumulative return plot,
- A histogram of daily log returns.

To investigate volatility clustering, we examine squared returns $(r_t^G)^2$ over time and compute a 21-day rolling standard deviation, annualised as

$$\sigma_{21,t}^{\text{ann}} = \sqrt{252} \times \text{Std}(r_{t-20}^G, \dots, r_t^G).$$

Finally, we compute drawdowns as

$$\text{DD}_t = \frac{V_t}{\max_{i \le t} V_i} - 1,$$

to quantify peak-to-trough losses.

4.3 Regression models

Global FX exposure

The first regression model examines whether daily green portfolio returns are significantly related to the CNY/USD exchange-rate level:

$$r_t^G = \alpha + \beta_{FX} \cdot \text{CNYUSD}_t + \epsilon_t,$$

where CNYUSD_t is `close_CNYUSD_X`. We estimate this model using OLS with Newey–West HAC standard errors (5 lags). Before estimation, we construct a dataset containing only `green_eq_log_ret` and `close_CNYUSD_X` and drop all rows with missing values.

CAPM with NIFTY 50

The second regression model is CAPM-style:

$$r_t^G = \alpha + \beta_{Mkt} \cdot r_t^{Mkt} + \epsilon_t,$$

where r_t^{Mkt} is the NIFTY 50 daily log return, `return_NSEI`. Using the subset of days where both r_t^G and r_t^{Mkt} are non-missing, we estimate the intercept α and slope β_{Mkt} via OLS with HAC standard errors (5 lags). We interpret β_{Mkt} as the green portfolio's market beta and α as daily alpha relative to CAPM.

5 Results

5.1 Descriptive statistics of green portfolio returns

Table 1 summarises the descriptive statistics of the green portfolio's daily log returns r_t^G.

Table 1: Descriptive statistics of daily green portfolio returns

Statistic	Value (daily)	Value (annualised)
Mean log return	0.000492	0.12398
Standard deviation	0.017504	0.27787
Minimum	−0.0952	–
1st percentile	−0.0541	–
5th percentile	−0.0271	–
Median	0.00179	–
95th percentile	0.0252	–
99th percentile	0.0383	–
Maximum	0.0618	–

The annualised mean log return of about 12.4% and annualised volatility of about 27.8% place the green portfolio firmly in the high-risk, high-return segment of the equity spectrum. The negative skewness and fat tails implied by the percentiles indicate that downside tail risk is more pronounced than upside.

5.2 Cumulative return and distributional plots

Figure 1 shows the time series of daily log returns $\{r_t^G\}$. There are periods of relatively calm behaviour interspersed with episodes of heightened volatility, including sharp negative spikes.

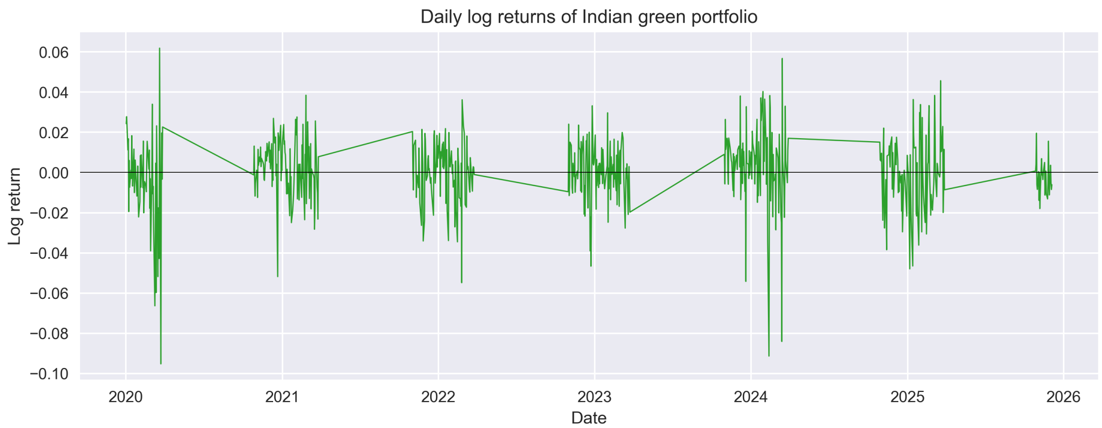

Figure 1: Daily log returns of the Indian green portfolio

Figure 2 displays the cumulative return V_t. The portfolio achieves a final cumulative return of approximately 22.5% over the sample. Notably, much of this gain is accumulated in a few distinct upward phases rather than as a smooth drift.

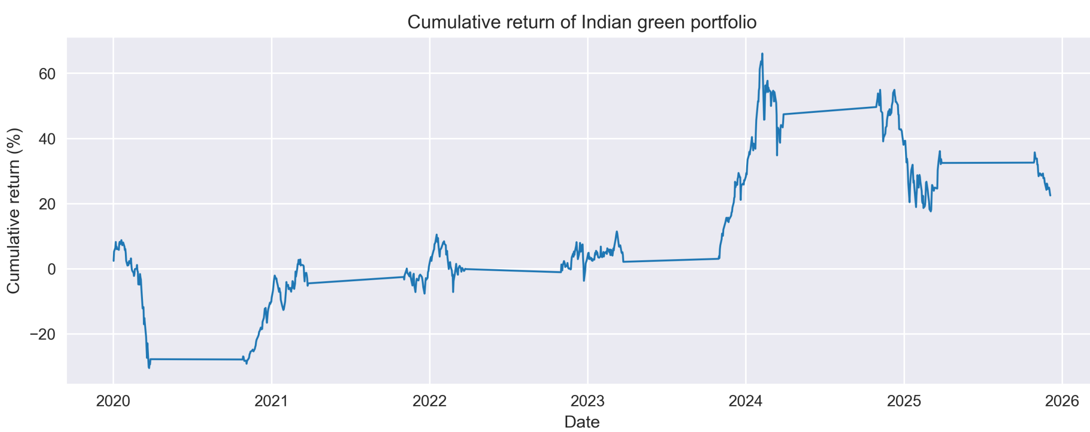

Figure 2: Cumulative return of the Indian green portfolio

Figure 3 plots the histogram of daily log returns. The distribution is clearly non-Gaussian, with a sharp peak near zero, a longer left tail, and excess mass in the tails compared with a normal distribution.

5.3 Volatility clustering, rolling volatility, and drawdowns

To illustrate volatility clustering, we plot squared returns $(r_t^G)^2$ over time (Figure 4). The clustering of large values in certain periods confirms that volatility is not constant.

Figure 5 shows the 21-day rolling annualised volatility. It reveals extended periods of subdued volatility punctuated by spikes, likely associated with market stress or sector-specific

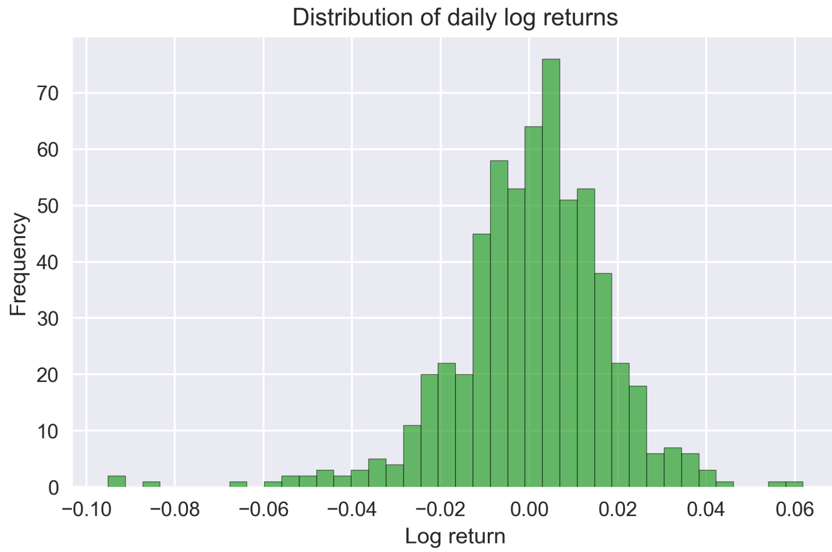

Figure 3: Histogram of daily log returns of the green portfolio

news.

Figure 6 depicts the drawdown series DD_t. The maximum drawdown is approximately –36%, indicating that an investor who bought at a local peak could experience substantial percentage losses before recovery. Such drawdowns underscore the importance of risk management for investors in this segment.

5.4 Regression on CNY/USD: limited global FX exposure

To test whether global FX conditions drive daily green portfolio returns, we regress r_t^G on the CNY/USD exchange-rate level. After dropping missing values, we estimate:

$$r_t^G = \alpha + \beta_{FX} \cdot \mathrm{CNYUSD}_t + \epsilon_t.$$

Using HAC standard errors (5 lags), we find:

- $\hat{\alpha} \approx -0.0098$, with a p-value around 0.49.
- $\hat{\beta}_{FX} \approx 0.0705$, with a p-value around 0.46.
- $R^2 \approx 0.001$.

Thus, at the daily frequency, the CNY/USD level explains essentially none of the variation in green portfolio returns, and neither the intercept nor slope is statistically significant. This

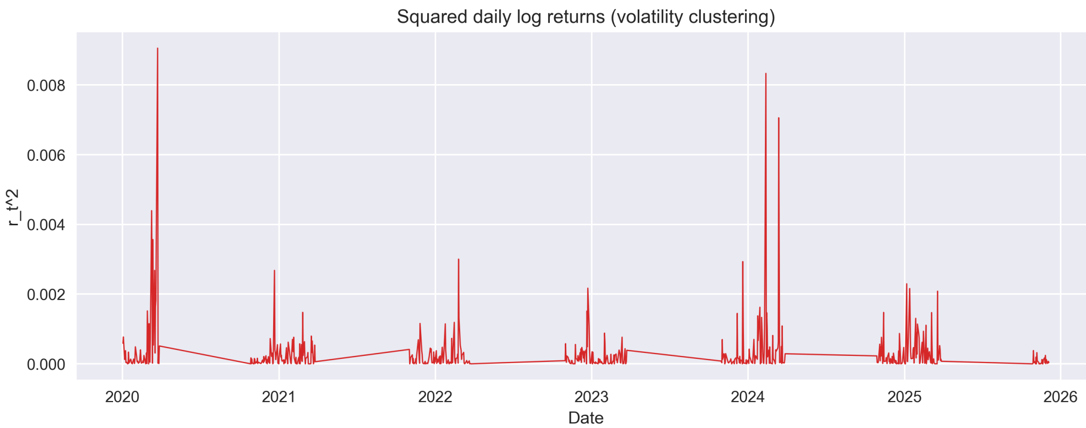

Figure 4: Squared daily log returns (evidence of volatility clustering)

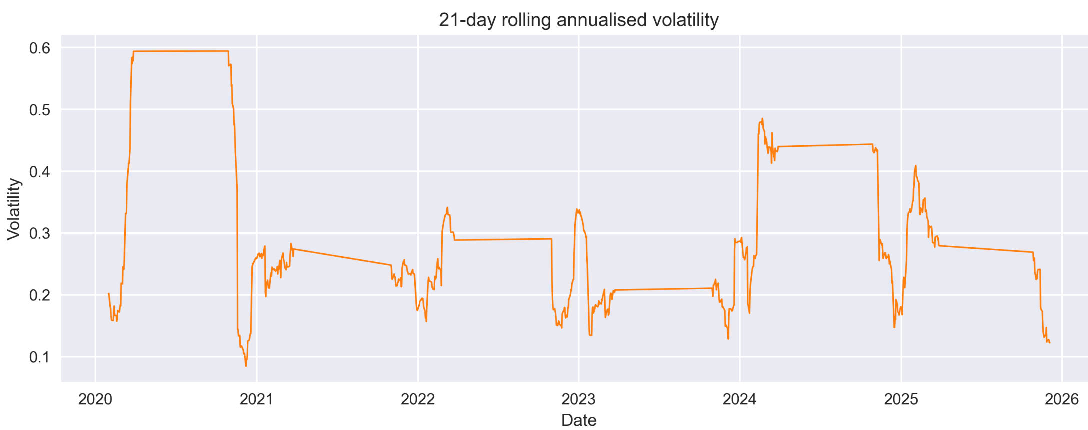

Figure 5: 21-day rolling annualised volatility of the green portfolio

suggests that Indian green equities are not simply a linear function of global EM currency levels.

5.5 CAPM-style regression with NIFTY 50: market integration

We next estimate the CAPM-style model:

$$r_t^G = \alpha + \beta_{Mkt} r_t^{Mkt} + \epsilon_t,$$

using 601 days where both r_t^G and NIFTY returns r_t^{Mkt} are non-missing. The OLS estimates with HAC standard errors yield:

- $\hat{\alpha} \approx 0.0006$, p-value approximately 0.28.

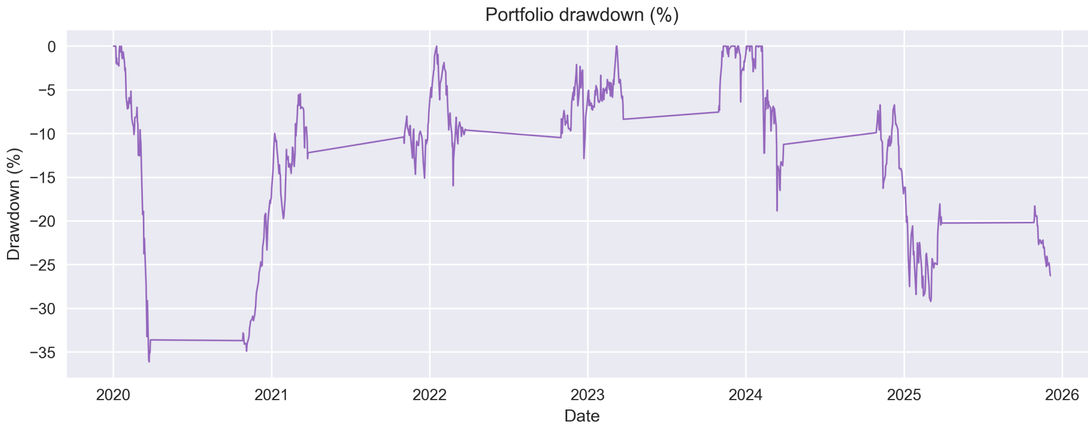

Figure 6: Drawdown curve of the green portfolio

- $\hat{\beta}_{Mkt} \approx 0.8281$, z-statistic about 12.41, p-value < 0.001.
- $R^2 \approx 0.392$.

The market beta of about 0.83 is large and highly significant, indicating that green portfolio returns move strongly with the broader Indian equity market but are somewhat less volatile than the market index itself. The lack of a statistically significant intercept implies that, at the daily frequency and over this sample period, there is no evidence of abnormal returns relative to NIFTY 50 once market risk is controlled for.

The R^2 of about 39% implies that roughly 61% of daily variation in green portfolio returns is left unexplained by the CAPM model. This residual variation could be attributed to sector-specific news, idiosyncratic firm events, policy shocks, or other macro-financial variables not included in the model.

6 Discussion

The empirical evidence assembled in this paper allows for a nuanced interpretation of how Indian green equities fit into the broader financial ecosystem. In this section, we synthesise the main findings through a finance lens, connecting them to classic asset pricing concepts and to the specific institutional context of India's energy transition.

6.1 Green equities as a high-beta, transition-linked segment

The CAPM-style regression with NIFTY 50 returns yields a market beta of approximately 0.83, statistically different from zero at any conventional significance level and plausibly different from one. In purely finance terms, this places the equal-weighted green portfolio as a high-beta, but not extreme, segment of the domestic equity market. It does not behave like a defensive sector, nor like a leveraged market proxy.

Two implications follow. First, the sector's risk is predominantly systematic: a large share of its daily variation is explained by aggregate market movements. Investors seeking diversified exposure to India's green transition can thus obtain it without stepping entirely outside the familiar risk profile of broad Indian equities. Second, because the beta is below one, the green portfolio is not simply an "amplifier" of NIFTY risk. Its volatility is sizeable in absolute terms but only modestly higher than what one would expect given the volatility of the underlying stocks and the equal-weighting scheme.

The absence of statistically significant daily alpha once we control for NIFTY returns is equally instructive. It suggests that, over this sample, green equities did not systematically outperform or underperform the market in a way that can be detected at the daily frequency by a simple CAPM. For practitioners, this means that any "green premium" is unlikely to manifest as a straightforward, persistent arbitrage opportunity in daily returns. Instead, any excess performance is more likely to be episodic, tied to specific news or policy events, or observable only over longer horizons.

6.2 Residual risk: beyond a one-factor model

Although the CAPM explains about 39% of the cross-day variation in green portfolio returns, a substantial 61% remains unexplained by the market factor. This residual component is economically important. From an asset pricing perspective, such unexplained variation can arise from:

- **Idiosyncratic firm risk:** Green stocks in India tend to be relatively concentrated in a few sectors (renewable generation, EPC, infrastructure) and often have project-based cash flows. Individual firm news, project wins or losses, and balance-sheet events can generate large firm-specific shocks which, when aggregated in an equal-weighted portfolio, do not fully diversify away.

- **Sector-specific systematic risk:** There may be risk factors specific to clean energy or transition technologies that are not captured by a broad market index. Examples include technology cost shocks (e.g. module prices), global supply-chain disruptions, and changes in financing conditions for infrastructure projects.

- **Policy and regulatory risk:** Renewable energy sectors are highly sensitive to regulatory decisions: tariff changes, auction designs, grid access rules, and subsidy schemes. These policy decisions can drive correlated price moves across multiple green firms without necessarily moving the aggregate market index.
- **Global and cross-asset factors:** Risk factors such as global clean-tech sentiment, cross-border carbon policy, or oil price dynamics may affect green equities in ways that are not fully captured by either the NIFTY 50 or the CNY/USD exchange rate.

The fact that our simple regression on CNY/USD yields an R^2 near zero underscores that not all global factors are equally relevant. A single FX rate is too coarse a proxy for the multi-dimensional set of global forces acting on the sector. From a modelling standpoint, this suggests that a more realistic factor structure would include at least a domestic market factor plus one or more sectoral or global clean-energy factors, rather than relying on a lone currency variable.

6.3 Return distribution and risk management implications

The descriptive statistics and plots show a return distribution that is far from normal: negative skewness, fat tails, and a maximum drawdown of roughly –36%. These features have direct implications for risk management and portfolio construction.

First, negative skewness implies that large negative outcomes are more likely than equally large positive outcomes. Investors who evaluate the sector solely on mean and variance may underestimate the probability and severity of extreme losses. In a portfolio context, this suggests that simple mean–variance optimisation using Gaussian assumptions could lead to over-allocation to green equities relative to an investor's true risk tolerance.

Second, excess kurtosis and volatility clustering imply that risk is state-dependent: periods of tranquil performance can be followed by regimes of elevated volatility and large shocks. This is characteristic of many equity markets but may be amplified in sectors exposed to policy and project risk. From a risk management perspective, measures such as Value-at-Risk (VaR) and Expected Shortfall (ES) should be estimated using models that allow for time-varying volatility (e.g. GARCH-type models) and fat tails, rather than assuming constant volatility and normality.

Third, the drawdown profile reveals that losses in this sector can be deep and persistent. For investors with mark-to-market constraints or short investment horizons, this makes green equities a potentially uncomfortable allocation, even if the long-run expected return is attractive. Investors with longer horizons and a tolerance for drawdowns may be better positioned to hold and harvest the sector's risk premium, especially if they view green assets as aligned with structural growth rather than short-term trading opportunities.

6.4 Lack of Global FX Sensitivity

The near-zero explanatory power of CNY/USD in our regression may appear surprising at first glance, given the importance of China as a manufacturing hub for renewable components and as a major player in global capital flows. However, several reasons can reconcile this with economic intuition:

- The CNY/USD level is a very coarse proxy for the global environment. Many factors that shape renewable project economics — such as technology costs, trade policies, and domestic financing conditions — do not move one-to-one with this exchange rate.
- The time horizon matters. Global macro variables may influence green investments over quarters or years, but their day-to-day fluctuations may have limited immediate impact on stock prices in a market where domestic news and orders are more salient.
- India-specific policies and institutions play a central role. Tariff decisions, auction structures, and grid-related regulations can dominate the pricing of green projects, overshadowing marginal changes in a foreign exchange rate.

6.5 Positioning within the broader asset pricing and policy debate

Finally, it is useful to place our findings within the broader debates in asset pricing and climate finance. At a high level, the evidence suggests that Indian green equities are neither a purely idiosyncratic niche nor a distinct asset class with obvious stand-alone alpha. They are partially but meaningfully integrated with the domestic market, with risk characteristics that are more extreme than an average sector but not entirely orthogonal to the market factor.

In the language of multi-factor asset pricing, one might think of Indian green equities as loading on at least two sets of factors: a standard market factor (represented here by NIFTY 50) and one or more latent "transition" factors associated with policy, technology, and global climate sentiment. Our current CAPM-style model captures only the first of these. Extending the model to include explicit transition factors — for example, clean energy indices, global carbon prices, or sectoral demand proxies — would likely improve explanatory power and provide a richer picture of how transition risk is priced.

From a policy perspective, the absence of obvious alpha does not diminish the importance of green equities. Policymakers should care less about whether green stocks deliver abnormal returns relative to CAPM and more about whether capital is flowing efficiently into green projects, whether risk is being priced appropriately, and whether policy interventions create a stable and predictable environment.

Taken together, the analysis underscores that understanding green equities requires both traditional finance tools (returns, betas, alpha) and an appreciation of the unique drivers of the low-carbon transition. The sector is firmly embedded in the domestic financial system yet retains distinctive risks and dynamics that justify the development of dedicated empirical frameworks such as the one advanced in this paper.

7 Conclusion

This paper has provided a comprehensive empirical look at Indian green equity returns using daily data. We constructed an equal-weighted portfolio of green stocks, documented its distributional properties, and examined its relationship with both global macro proxies and the domestic equity market. Our main findings are:

- The green portfolio delivers an annualised mean log return of about 12.4% at an annualised volatility of roughly 27.8%, achieving a cumulative gain of approximately 22.5% over 602 trading days. Returns are non-Gaussian and exhibit significant downside tail risk.
- A regression of green returns on the CNY/USD exchange-rate level yields no significant relationship and an R^2 of about 0.001, indicating negligible explanatory power.
- A CAPM-style regression with NIFTY 50 daily log returns produces a significant market beta of about 0.83, no significant daily alpha, and an R^2 of about 0.392, showing that green equities are integrated with the domestic market but not mispriced relative to a simple CAPM at the daily frequency.
- Volatility clustering, rolling volatility and drawdown analysis reveal that risk is time-varying and that investors in this sector must be prepared for substantial peak-to-trough losses.

In sum, this paper offers both substantive evidence on the behaviour of Indian green equities and a methodological roadmap for deeper analysis once additional data become available.

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