Indian Institute of Technology Kharagpur

Master's Thesis Project I

Infrastructure Finance:

Risk–Return Analysis and Predictability of Infrastructure Assets in India, the US and Europe

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A thesis submitted in fulfilment of the requirements for the degree of Master of Technology

in

Financial Engineering

VINOD GUPTA SCHOOL OF MANAGEMENT, INDIAN INSTITUTE OF TECHNOLOGY KHARAGPUR,
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CERTIFICATE

This is to certify that the project report entitled "Infrastructure Finance: Risk–Return Analysis and Predictability of Infrastructure Assets in India, the US and Europe" submitted by Aakansh Singh (Roll No. 21CE3FP20) to Indian Institute of Technology Kharagpur towards partial fulfillment of requirements for the award of degree of Master of Technology in Financial Engineering is a record of bona fide work carried out by him under my supervision and guidance during Autumn Semester, 2025-26.

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Declaration

I, Aakansh Singh (Roll No. 21CE3FP20), hereby declare that the report entitled

“Infrastructure Finance: Risk–Return Analysis and Predictability of Infrastructure Assets in India, the US and Europe”

submitted in partial fulfilment of the requirements for the award of the degree of Master of Financial Engineering at Indian Institute of Technology Kharagpur, is an original work carried out by me under the supervision of Dr. Rudra Prakash Pradhan, Vinod Gupta School of Management, IIT Kharagpur.

I further declare that:

1. This dissertation has not been submitted, in part or in full, to any other university or institute for the award of any degree, diploma or any other academic qualification.
2. The work reported here is the result of my own investigation, except where due acknowledgement has been made.
3. All sources of information used in this dissertation have been duly cited and referenced.

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Table of Contents

Abstract

This study examines how listed infrastructure assets behave as investments and how predictable their short-term returns are. The analysis focuses on three types of instruments—InvITs, REITs (or similar vehicles), and infra/utility stocks—across three regions: India, the United States and Europe. Using daily data, the dissertation first compares risk–return profiles, CAPM betas and alphas, and correlation patterns for infra indices and instrument “types” in each region. Indian results show a clear separation: infra stocks deliver very high returns but also very high volatility and beta, while InvITs and REITs offer moderate to high returns with much lower volatility, low beta and more stable drawdowns. US and European infra assets appear more “balanced,” with REITs, MLPs and infra/utility stocks sitting in intermediate risk–return positions and providing a useful benchmark for India.

The second part of the work studies short-horizon predictability of the Indian infra market proxy using AR/ARX models and machine-learning models (MLP and LSTM) at daily and 5-day horizons, with and without global infra inputs. Granger tests show that US and European infra returns carry statistically significant information about future Indian infra returns, and some non-linear models are able to translate part of this into useful signals: five-day MLP and LSTM classifiers achieve direction accuracies in the mid-50% range, improving on simple benchmarks. Although the models do not explain much of the variation in return magnitudes, they provide modest but consistent directional information that can be used as an additional input for portfolio tilts, timing and risk monitoring rather than as standalone trading engines. Overall, the results suggest that listed infra instruments occupy distinct, useful places in the risk–return space, and that carefully designed models can extract limited yet practically relevant predictive content from their short-term dynamics.

Keywords: Infrastructure finance, InvITs, REITs, MLPs, infra stocks, India, United States, Europe, risk–return, CAPM, Granger causality, machine learning, MLP, LSTM, return predictability.

1. Introduction

Infrastructure has moved from being seen purely as a public good to being treated as a distinct financial asset class. Roads, power transmission lines, pipelines, data centres, and other long-lived assets generate relatively stable, contract-backed cash flows over long horizons. At the same time, governments face binding fiscal constraints and large funding gaps, especially in emerging economies. This combination has led policymakers to lean increasingly on capital markets to mobilise long-term capital for infrastructure, rather than relying exclusively on budgetary support or bank lending.

Within this broader shift, listed infrastructure vehicles such as Infrastructure Investment Trusts (InvITs) and Real Estate Investment Trusts (REITs) have become central. These vehicles allow sponsors to "monetise" operating assets, recycle capital into new projects, and offer investors units backed by underlying infrastructure cash flows. In India, InvITs and REITs are relatively young: the regulatory framework has evolved only over the last decade, and the number of listed vehicles is still small compared to global markets. In contrast, the United States and Europe have a longer history with listed infrastructure-like instruments – especially REITs and energy / infrastructure partnerships – and much deeper capital markets.

Despite the policy focus and marketing narrative around InvITs and REITs, there is still limited systematic, data-driven evidence on how these instruments behave as financial assets. They are often pitched as "stable, yield-oriented, quasi-bond" products, but in practice their units trade on stock exchanges and are exposed to market risk, interest-rate cycles, sector-specific shocks, and broader risk sentiment. This raises several questions that are directly relevant for both investors and policymakers:

1. Do InvITs and REITs in India actually deliver return and risk profiles that are distinct from ordinary infrastructure stocks and from the broad equity market?
2. How does the behaviour of Indian InvITs/REITs compare with their counterparts in the US and Europe, where the market is older and more mature?
3. From a portfolio perspective, do these instruments genuinely offer diversification benefits, or do they simply embed equity-like risk with a different label?

In parallel, the time-series behaviour of infrastructure-related indices is also of interest. For regulators, asset managers, and treasury teams, it is useful to know whether short-horizon returns in Indian infrastructure indices are largely random or whether they exhibit some predictability driven by global markets. With the growth of machine learning and deep learning, it has become feasible to move beyond purely linear models and test whether richer models can extract any useful signal from historical data and cross-market linkages.

This Master's Thesis Project sits at the intersection of infrastructure finance, empirical asset pricing, and applied machine learning. Using daily market data, it focuses on three broad regions: India, the United States, and Europe; and analyses:

1. Cross-sectional behaviour of listed infrastructure-related instruments

a. Construction of representative baskets of InvITs, REITs (and analogous vehicles), listed infrastructure companies, and broad market indices in each region.
b. Conversion of raw price data into total-return series wherever possible, so that both price appreciation and cash distributions are captured.
c. Comparison of average returns, volatility, drawdowns, and simple risk-adjusted measures (e.g. Sharpe-type ratios) for different instrument types within each region.
d. Estimation of CAPM-style betas and alphas relative to appropriate market proxies (e.g. infrastructure indices or broad equity indices), to see whether InvITs/REITs behave more like “defensive income” assets or like regular equities.

2. Cross-region comparison
    a. A unified framework that puts India, the US, and Europe on the same footing: common sample windows where feasible, consistent return definitions, and type-wise aggregation (InvIT/REIT/stock/index).
    b. Visual and numerical comparison of cumulative total-return behaviour across regions, including type-wise “average” instruments. For example, comparing Indian InvITs with US REITs and European listed infrastructure firms over the same period.
    c. Analysis of correlation patterns across regions and types, to understand how much global infrastructure behaves as a single asset class versus being segmented by geography.

3. Short-horizon return prediction for Indian infrastructure
    a. Construction of lagged feature sets using daily returns of the Indian infrastructure proxy along with returns of US and European market proxies.
    b. Estimation of benchmark linear models (ordinary least squares regressions, Granger-type causality tests) to quantify whether US or European returns have predictive content for Indian infrastructure returns.
    c. Implementation of machine learning models, including a feedforward Multi-Layer Perceptron (MLP) and a Long Short-Term Memory (LSTM) network, to forecast 5-day-ahead cumulative returns or their sign for the Indian infrastructure index. These models explicitly test whether non-linear patterns and sequence information can improve on simple linear benchmarks.

By combining these pieces, the project aims to provide a coherent, end-to-end picture of listed infrastructure finance across regions. On the one hand, it offers a comparative, type-wise and region-wise view of how InvITs, REITs, infrastructure stocks, and indices have actually behaved over the last several years. On the other hand, it explores in a controlled and transparent way how far one can go in predicting short-horizon movements in Indian infrastructure returns using both traditional econometric techniques and modern machine learning models.

The intended contribution is threefold. First, it creates a clean and reusable dataset of infrastructure-related instruments across India, the US, and Europe with harmonised return definitions. Second, it generates evidence-based insights about risk–return characteristics, beta/alpha behaviour, and diversification potential of InvITs, REITs, and related stocks in different markets. Third, it provides a reality check on the usefulness of predictive models for short-horizon infrastructure returns, highlighting where machine learning adds value and where the data remains effectively noise.

The rest of the report builds on this introduction by detailing the relevant literature, describing the data and methodology, presenting empirical and predictive results, and discussing their implications for investors, regulators, and future research in infrastructure finance.

1.1 Related Research

The first strand of work looks at REITs and InvITs as policy and market innovations in India. The report *India's New Real Estate and Infrastructure Trusts: The Way Forward* provides a practitioner-oriented overview of how REITs and InvITs were introduced by SEBI to deepen India's capital markets and bridge the long-term funding gap in real estate and core infrastructure. It explains the regulatory design (sponsor requirements, leverage limits, minimum public float, distribution rules), outlines potential benefits for sponsors and investors, and highlights early constraints such as sponsor appetite and investor awareness.

Building on this, Shah and Bhagwat's *Critical Assessment of Infrastructure Investment Trust in India* offers a more academic critique. They argue that InvITs can unlock large pools of long-term capital (domestic and foreign) for operational infrastructure assets, but also document issues such as regulatory complexity, concentration in a few sponsors, limited liquidity and the relatively small size of the listed InvIT market so far. In short: the paper says InvITs are a promising vehicle, but the Indian market is still shallow and faces institutional and market-development frictions.

A second strand evaluates the risk–return performance of InvITs and REITs as an asset class. The JIER paper *Performance Analysis of REITs and InvITs in India: A Comparative Study with the Nifty 50* compares listed InvITs and REITs with the Nifty 50 using mean returns, standard deviation, Sharpe ratios, CAPM alpha/beta and non-parametric tests on return distributions. The authors find that Indian REITs and InvITs generally show lower volatility and more stable returns, but their risk-adjusted performance (Sharpe, CAPM alpha) does not consistently beat the broad equity index; instead, they mainly offer diversification benefits rather than pure outperformance. In short: REITs/InvITs behave like "defensive, income-oriented" exposures rather than high-beta growth bets relative to the market.

The third strand focuses on machine-learning models specifically for REIT price/return prediction. Zhang et al. (2023) study the US REIT market and propose a Group Method of Data Handling (GMDH) neural network that uses technical indicators and macro variables to forecast daily REIT returns. They show that the GMDH network delivers lower forecast errors and better trading-strategy performance than traditional econometric models and several baseline ML models, especially because it can capture non-linear relationships in REIT returns. In a related direction, Habbab et al. (in *Improving Real Estate Investment Trusts (REITs) Time-Series Prediction Accuracy Using Machine Learning and Technical Analysis Indicators*) examine how adding a rich set of technical analysis indicators (moving averages, oscillators, trend indicators, etc.) to standard ML models affects predictive accuracy for REIT time series; they report that tree-based ensembles and other non-linear learners with TA features materially improve prediction performance over naïve benchmarks. Taken together, these papers say: (i) REIT returns are predictably related to technical and macro factors, and (ii) flexible ML models can exploit this structure better than simple linear models.

A broader, fourth strand looks at financial time-series forecasting architectures beyond REIT-specific applications. Lazcano et al.'s *Back to Basics: The Power of the Multilayer Perceptron in Financial Time Series Forecasting* systematically compare a simple MLP with recurrent and Transformer-based models on economic and financial series. They show that, for univariate regression tasks of the type considered, a well-tuned MLP often achieves lower forecast errors and shorter training time than more complex RNN/Transformer architectures, and argue that the newest, most complex model is not automatically the best choice. Complementing this, the AAAI-24 paper *StockMixer: A Simple Yet Strong MLP-Based Architecture for Stock Price Forecasting* proposes an all-MLP model that performs indicator mixing, time mixing and stock mixing to capture cross-sectional and temporal correlations in stock data. The authors show that StockMixer outperforms several state-of-the-art RNN, GNN and Transformer baselines on stock benchmarks, while being easier to optimize and more efficient in memory and runtime. In short: recent literature is surprisingly bullish on carefully designed MLP-style architectures for financial forecasting, especially when data are limited or noisy.

Overall, existing research (i) explains why InvITs/REITs were created and what frictions they face in India, (ii) evaluates their risk–return behaviour relative to broad equity indices, and (iii) shows that modern ML – including relatively simple MLP-based models – can significantly improve forecasting of REIT and stock returns. What is still relatively under-explored, and where this MTP positions itself, is a cross-market, instrument-level comparison of InvITs, REITs, infrastructure stocks and broad indices (India vs US vs Europe) combined with systematic ML-based prediction experiments on these infra-oriented assets, to understand both their capital-market behaviour and the practical scope for AI-driven investment strategies in the infrastructure finance space.

Reference	**Study Area**	**Methods Used**	**Key Findings**
India's New Real Estate and Infrastructure Trusts: The Way Forward	Policy and market development of REITs & InvITs in India	Descriptive policy analysis; comparison with global REIT frameworks	Explains why REITs/InvITs were created; shows benefits (capital recycling, transparency) and constraints (low liquidity, regulatory frictions) in India's early-stage trust market.
Shah & Bhagwat — Critical Assessment of Infrastructure	Assessment of InvIT market evolution and challenges	Conceptual review; regulatory evaluation; case-based discussion	InvITs can unlock long-term capital but India's market is still shallow, concentrated, and

Investment Trust in India			constrained by regulation, awareness and liquidity issues.
Performance Analysis of REITs and InvITs in India (JIER)	Risk–return comparison of Indian REITs & InvITs vs Nifty 50	Return metrics, Sharpe ratios, CAPM alpha/beta, non-parametric tests	REITs/InvITs show lower volatility and more stable returns; risk-adjusted performance does not consistently beat Nifty 50; diversification benefits exist but outperformance is not guaranteed.
Zhang et al. (2023) — GMDH model for REIT forecasting	Predicting US REIT returns	Group Method of Data Handling (neural network), technical indicators, macro variables	GMDH network outperforms traditional econometric and baseline ML models; captures non-linear patterns well and improves forecasting accuracy for REIT returns.
Habbab et al. — Improving REIT Time-Series Prediction Accuracy	REIT return forecasting with technical indicators	ML models (tree-based, SVM, neural networks) + rich technical indicators	Adding technical indicators significantly improves prediction accuracy; non-linear models outperform linear ones for REIT time-series forecasting.
Lazcano et al. — Power of the MLP in Financial Time Series	Financial & economic time-series forecasting	Comparative study: MLPs vs RNNs vs Transformers	A well-tuned MLP often beats more complex architectures; simpler models can be more robust and easier to train when data are noisy or limited.
AAAI-24 StockMixer	Cross-asset stock price forecasting	Multilayer perceptron with indicator mixing, time mixing, stock mixing	StockMixer (MLP-based) outperforms RNN/GNN/Transformer models; offers strong prediction accuracy with lower memory and faster training.
A Cross-Country Study of Risk Factors Driving REIT Returns" (2023)	Global REIT return behaviour across different countries	Multifactor regression, cross-country panel analysis; factors include momentum, volatility, skewness, kurtosis, market risk	REIT returns are driven by non-traditional risk factors (volatility, skewness, kurtosis) in addition to market beta. Sensitivity to these factors varies across countries, showing REIT markets are not homogeneous globally.
"Multivariate Modeling of Daily REIT Volatility" — Cotter & Stevenson (2011)	Volatility dynamics of REIT subsectors (equity, mortgage, hybrid REITs)	Multivariate GARCH models (BEKK-GARCH, DCC-GARCH), daily return volatility modelling	REIT subsectors show strong volatility spillovers, meaning shocks in one subsector transmit to others. Mortgage REITs have higher volatility, while equity REITs are more stable. Market-wide volatility strongly influences all REIT segments.

“A Comparative Anatomy of REITs and Residential Real Estate Indexes” — Cotter & Roll (2011)	Comparison between REITs and residential real estate indices	Return distribution analysis, correlation, factor models, tail-risk metrics	REITs behave more like equities (higher volatility, faster price reactions) compared to residential real estate indexes. Real residential prices adjust slowly; REITs incorporate real estate shocks immediately. Shows REITs are financial assets, not pure real-estate proxies.

Table 1

2. Objectives

This report has two broad goals:
(i) to understand how listed infrastructure-related instruments behave as financial assets across India, the United States and Europe, and
(ii) to test whether modern machine-learning models can extract any useful predictive signal from their return dynamics, particularly for the Indian infrastructure segment.
Within this broad aim, the specific objectives are:

1. To construct a consistent cross-country dataset
    a. Compile daily price data for representative sets of InvITs, REITs (and analogous vehicles such as MLP-style instruments), listed infrastructure stocks, and broad market indices in India, the US and Europe.
    b. Clean the data, align trading calendars and build total-return series wherever possible by incorporating both price changes and distributions.

2. To analyse and compare risk–return characteristics across regions and instrument types
    a. Compute key performance measures (mean returns, volatility, drawdowns, Sharpe-type ratios) for InvITs, REITs, infrastructure stocks and market indices in each region.
    b. Compare type-wise “average” instruments (e.g., average InvIT vs average REIT vs average infra stock) within and across regions using cumulative return plots and summary statistics.

3. To study beta, alpha and diversification properties of infrastructure-linked instruments
    a. Estimate CAPM betas and alphas of InvITs, REITs and infrastructure stocks with respect to suitable market benchmarks in each region.
    b. Examine correlations and co-movements within and across regions (India–US–Europe) to assess the extent to which these instruments offer diversification benefits or simply mirror broad equity market risk.
    c. Include focused comparisons such as Indian InvITs vs US MLP-type instruments to see how “infrastructure-like” vehicles differ across markets.

4. To examine short-horizon linkages between Indian infrastructure and global markets
    a. Build linear models (including simple OLS and Granger-style setups) to test whether US and European market returns contain predictive information for 5-day-ahead returns on the Indian infrastructure proxy.
    b. Use these models as a benchmark for more flexible machine-learning approaches.

5. To develop and evaluate machine-learning models for return prediction
    a. Construct feature sets using lagged returns of Indian infrastructure indices and selected global indices, and define 5-day-ahead targets both as continuous returns (regression) and direction/sign (classification).
    b. Train and evaluate a Multi-Layer Perceptron (MLP) and an LSTM-based sequence model, and compare them with linear benchmarks using metrics such as R^{MSE}, R^2 and directional accuracy.
    c. Assess whether these models can deliver not just statistical improvements but also economically meaningful gains, via simple rule-based strategies that go long when the model predicts positive returns and stay flat otherwise.

6. To synthesise implications for investors and policy

    a. Interpret the empirical and predictive results to comment on the role of InvITs/REITs and infra stocks in diversified portfolios.
    b. Discuss what the findings imply for the positioning of Indian InvITs/REITs relative to more mature markets, and for the practical usefulness of AI/ML tools in infrastructure finance.

3. Methodology

3.1 Overall Research Design

The methodology combines a cross-sectional empirical analysis of infrastructure-related instruments across regions with a time-series prediction exercise focused on Indian infrastructure returns. In the first part, the study treats InvITs, REITs, infrastructure stocks and broad market indices in India, the United States and Europe as financial assets with daily returns. Using these return series, it compares risk–return characteristics, CAPM betas and alphas, and correlation patterns within and across regions. In the second part, the study formulates a short-horizon forecasting problem for the Indian infrastructure proxy, builds a set of lagged return features that include both domestic and global information, and trains machine-learning models (MLP and LSTM) to predict 5-day-ahead returns and their sign.

The same underlying data therefore serve two purposes. First, they allow a descriptive, factor-based evaluation of how infrastructure-linked instruments behave in different markets.

Second, they provide a consistent input for testing whether modest predictive structure exists in Indian infra returns and whether non-linear models can exploit it in a meaningful way.

3.2 Data, Sample Construction and Pre-processing

The empirical work is based on daily market data for three regions: India, the United States and Europe. For each region, the sample includes four broad categories of instruments: listed InvITs (or closest infrastructure trust analogues), listed REITs, liquid infrastructure-related stocks (such as construction, utilities, ports or transport companies), and at least one broad equity market index and, where available, a sectoral or infrastructure index. The selection is deliberately representative rather than exhaustive: instruments are chosen so that they are actively traded and have reasonably long and overlapping histories over the study period.

Daily adjusted closing prices are downloaded using Python interfaces to public data providers (such as Yahoo Finance). For each ticker, the raw download includes dates, adjusted close prices and, where available, dividend or distribution series. The overall calendar spans the longest period for which a panel of instruments can be constructed across all three regions. Within this span, two windows are defined: a full-sample window (used for within-region analysis, even if some instruments start or end later) and a stricter common window where all key indices and representative instruments overlap, used for cross-country comparisons.

Because trading calendars differ across countries and exchanges, the data for each region are first aligned to a region-specific daily calendar and then to a global calendar for cross-region work. Non-trading days are kept in the calendar but carry no returns; missing prices around holidays are handled by ensuring that returns are only computed between actual trading days. Instruments with very sparse trading or extended gaps are dropped so that volatility and correlation estimates are not distorted by stale prices.

Adjusted closing prices are used throughout, so that most corporate actions such as splits and bonuses are already reflected in the series. Large level shifts are checked manually to distinguish genuine jumps from data artefacts. For each instrument, daily simple returns are then computed as

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

where P_t is the adjusted close on day t. Log returns $\tilde{r}_t = \ln\left(P_t / P_{t-1}\right)$ are calculated where needed for robustness checks, but simple returns are used for most descriptive statistics and plots because of their more intuitive percentage interpretation.

Conceptually, the preferred object is a total-return series that reinvests cash distributions. If D_t denotes the distribution on day t, a total-return price P_t^{TR} evolves as

$$P_t^{TR} = P_{t-1}^{TR}(1 + r_t^{price}) + D_t$$

Where sufficiently clean distribution data are available, this logic is implemented; where they are not, the study works with price-only returns and notes this limitation explicitly.

3.3 Return Construction and Aggregation

For each instrument, the primary object is the series of daily returns r_t. To study short-horizon dynamics and to define prediction targets, the analysis also considers 5-day cumulative returns. For an instrument with daily returns $r_{t+1}, \dots, r_{t+5}$, the 5-day return from t to $t+5$ is defined multiplicatively as

$$R_{t,t+5} = \prod_{k=1}^{5}(1 + r_{t+k}) - 1$$

This captures compounding over the 5-day window and can be generalised to other horizons if required.

In addition to individual instruments, the study constructs type-level series that represent an "average" InvIT, "average" REIT and "average" infrastructure stock in each region. These are implemented as equal-weighted portfolios. If there are N_{InvIT} InvITs in the sample for a region and $r_{i,t}$ denotes the return on InvIT i on day t, the type-level return is

$$r_t^{(\text{InvIT})} = \frac{1}{N_{\text{InvIT}}} \sum_{i=1}^{N_{\text{InvIT}}} r_{i,t}$$

with an analogous definition for REITs and infrastructure stocks. This aggregation smooths idiosyncratic stock-specific noise and reveals how the segment behaves as a whole.

For each individual series and each type-level portfolio, standard descriptive statistics are computed over the relevant sample window: mean daily return, standard deviation, and higher moments such as skewness and kurtosis. If $r_1, \dots, r_T$ are daily returns, the sample mean is

$$\bar{r} = \frac{1}{T}\sum_{t=1}^{T} r_t$$

and the sample volatility is

$$\sigma = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \bar{r})^2}$$

These quantities are annualised under the usual assumption of 252 trading days per year so that risk–return metrics are comparable to standard asset-class benchmarks.

3.4 Risk–Return and Factor Analysis

The first layer of analysis compares basic performance measures across instruments and regions. For each series, average annualised return and annualised volatility are reported, along with simple Sharpe-type ratios. If $\bar{r}_i$ and σ_i denote the annualised mean and volatility for instrument i and r_f is a constant risk-free rate proxy, the Sharpe measure used is

$$\text{Sharpe}_i = \frac{\bar{r}_i - r_f}{\sigma_i}$$

Maximum drawdown and other downside-risk indicators are also calculated for selected portfolios to capture the magnitude of peak-to-trough losses.

To understand how "equity-like" the instruments are, the study next estimates simple CAPM regressions. For each instrument or type-level portfolio i, excess returns are regressed on the excess return of a suitable market benchmark m:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{m,t} - r_{f,t}) + \varepsilon_{i,t}$$

where $r_{i,t}$ and $r_{m,t}$ are the returns on the instrument and the market index at time t, $r_{f,t}$ is the risk-free rate, β_i is the systematic risk (beta) and α_i is the CAPM alpha. These regressions are estimated separately for each region using appropriate benchmarks (for example, a broad Indian equity index for Indian instruments and a broad US index for US instruments). Comparing the estimated betas and alphas across InvITs, REITs, infrastructure stocks and benchmarks reveals whether these vehicles behave as low-beta, defensive, income-oriented assets or move largely in line with the equity market.

Correlation structures are then examined to study diversification and co-movement. Pairwise correlation coefficients are computed for daily returns of all key series using the standard formula

$$\rho_{ij} = \frac{\text{Cov}(r_i, r_j)}{\sigma_i \sigma_j}$$

and summarised in correlation matrices for each region as well as for selected cross-region combinations. This shows, for example, how strongly Indian InvITs move with Indian infrastructure stocks, how closely Indian infrastructure indices track US or European ones, and whether there are clusters of instruments that offer diversification benefits.

Finally, the results of these exercises are organised in a cross-country comparison. For each main type (InvIT-like vehicle, REIT, infrastructure stock, broad market index), the study contrasts average returns, volatility, Sharpe ratios, betas, alphas and correlations across India, the US and Europe. This allows an assessment of whether Indian InvITs and REITs are converging towards the behaviour observed in more mature markets, or whether they still resemble ordinary equities in terms of risk–return and factor exposure.

3.5 Predictive Modelling Framework for Indian Infrastructure Returns

The second component of the methodology focuses on forecasting short-horizon returns for the Indian infrastructure proxy. The prediction target is the 5-day cumulative return on the chosen Indian infrastructure index. Using the daily returns $r_{t+1}, \dots, r_{t+5}$ of this index, the 5-day return from t to $t+5$ is defined as

$$y_t^{(\mathrm{reg})} = R_{t,t+5} = \prod_{k=1}^{5}(1 + r_{t+k}) - 1$$

This continuous quantity is used in a regression setting. In addition, a binary classification target is defined to capture the direction of movement:

$$y_t^{(\mathrm{cls})} = \begin{cases} 1, & \text{if } R_{t,t+5} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

Thus, the same underlying data support two tasks: predicting the magnitude of the 5-day return and predicting whether it will be positive or non-positive.

Feature vectors are constructed using lagged information from both domestic and global markets. For each prediction time t, the feature set includes recent daily returns of the Indian infrastructure index itself and recent daily returns of selected global benchmarks (for example, a US infrastructure or broad market index and a European index). These returns can be stacked in a fixed-length lag window so that the feature vector x_t summarises the joint behaviour of Indian, US and European markets over the last L days. Additional rolling features such as simple moving averages or rolling volatilities can also be included to give the models some notion of local trend and risk, but the core information comes from lagged returns.

The data are split chronologically into training, validation and test sets to avoid look-ahead bias: an initial segment of the time series is used for training, a subsequent segment for hyperparameter tuning and early stopping, and the most recent segment for out-of-sample evaluation. As a simple benchmark, the study considers naive forecasts such as “the future 5-day return equals the historical mean” or “the future sign is always positive”, against which the machine-learning models must improve.

In the next subsection (not yet written here), the specific architectures of the Multi-Layer Perceptron and LSTM models, their loss functions (MSE for regression, binary cross-entropy for classification), regularisation choices and evaluation metrics (RMSE, R^2, directional accuracy, and simple strategy backtests) are described in detail.

3.6 Machine-Learning Models

The predictive component of this study relies on two families of models that are widely used for financial time-series: a Multi-Layer Perceptron (MLP) that works on fixed-length feature vectors, and a Long Short-Term Memory (LSTM) network that operates directly on sequences. Both are implemented in Python using standard deep-learning libraries, and both are trained separately for the regression and classification versions of the prediction task.

In the MLP set-up, the input at time t is the feature vector $x_t \in \mathbb{R}^d$, which contains lagged returns of the Indian infrastructure index and selected global indices, and optionally some rolling statistics. This vector is passed through a series of fully connected layers with non-linear activation functions. For a network with one hidden layer, the mapping can be written as

$$h_t = \sigma(W^{(1)}x_t + b^{(1)}), \hat{y}_t = W^{(2)}h_t + b^{(2)}$$

where $W^{(1)}, W^{(2)}$ are weight matrices, $b^{(1)}, b^{(2)}$ are bias vectors, $\sigma(\cdot)$ is an element-wise non-linearity (for example, ReLU), h_t is the hidden representation and $\hat{y}_t$ is the model's output. In practice, the architecture may include more than one hidden layer, but the basic idea is the same: the network learns a non-linear transformation of the input features that is useful for predicting the 5-day return or its sign.

The LSTM model treats the problem in explicitly sequential form. Instead of a single feature vector x_t, the model takes as input a window of length K, $(x_{t-K+1}, \dots, x_t)$, representing the recent history of domestic and global returns. This sequence is fed through one or more LSTM layers, which maintain an internal “cell state” designed to capture longer-term dependencies. At each time step s, the LSTM updates a hidden state h_s and cell state c_s according to the usual gated equations (input, forget and output gates). Conceptually, this can be written compactly as

$$(h_s, c_s) = \mathrm{LSTM}(x_s, h_{s-1}, c_{s-1})$$

and after processing the window up to time t, the final hidden state h_t is passed through a dense layer to produce the forecast $\hat{y}_t$. This structure allows the model to weigh which lags and patterns in the recent return history are most relevant for forecasting the next 5-day outcome.

For the regression task, where the target is the continuous 5-day return $y_t^{(\text{reg})}$, both the MLP and LSTM are trained to minimise the Mean Squared Error (MSE) loss over the training set:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{t=1}^{N}(y_t^{(\text{reg})} - \hat{y}_t^{(\text{reg})})^2$$

For the classification task, the models output a probability $\hat{p}_t$ that the 5-day return will be positive. Training then uses the Binary Cross-Entropy (BCE) loss,

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N}\sum_{t=1}^{N}[y_t^{(\text{cls})}\log(\hat{p}_t) + (1 - y_t^{(\text{cls})})\log(1 - \hat{p}_t)]$$

where $y_t^{(\text{cls})} \in \{0,1\}$ is the true direction label. At inference time, a probability threshold (typically 0.5) is applied to convert $\hat{p}_t$ into a predicted class.

Training is done with a stochastic gradient-based optimiser (for example, Adam) with mini-batch updates. Learning rates, the number of hidden units, the depth of the networks, and other hyperparameters are chosen based on validation performance, taking care to avoid overfitting given the relatively limited amount of time-series data. Regularisation techniques such as dropout layers and L_2 weight decay are used where necessary to control model complexity. Early stopping based on validation loss is employed to prevent the models from simply memorising the training set.

3.7 Evaluation and Strategy Backtest

Model performance is evaluated on the held-out test set using both statistical forecasting metrics and simple economic criteria. For the regression task, two standard measures are reported. The first is the Root Mean Squared Error (RMSE), which is simply the square root of the MSE on the test set,

$$\text{RMSE} = \sqrt{\frac{1}{N_{\text{test}}}\sum_{t\in\text{test}}(y_t^{(\text{reg})} - \hat{y}_t^{(\text{reg})})^2}$$

The second is the coefficient of determination R^2,

$$R^2 = 1 - \frac{\sum_{t \in test}(y_t^{(reg)} - \hat{y}_t^{(reg)})^2}{\sum_{t \in test}(y_t^{(reg)} - \bar{y}_{test})^2}$$

where $\bar{y}_{\text{test}}$ is the mean of the true 5-day returns in the test set. The RMSE captures the typical size of the forecast error, while R^2 measures how much of the variance in future 5-day returns is explained by the model relative to a constant-mean benchmark.

For the classification task, the most basic metric is accuracy, i.e. the proportion of correctly predicted up/down moves. In addition, a directional accuracy measure is reported even for regression models by checking whether the predicted return has the same sign as the true return. If $\text{sign}(\hat{y}_t)$ and $\text{sign}(y_t^{(\text{reg})})$ denote the predicted and actual signs, the directional accuracy is

$$\text{DA} = \frac{1}{N_{\text{test}}} \#\{t \in \text{test:sign}(\hat{y}_t) = \text{sign}(y_t^{(\text{reg})})\}.$$

Confusion matrices are also examined to see whether the models are biased towards predicting only one direction (e.g. always “up”) or whether they meaningfully discriminate between positive and non-positive windows.

Because small statistical improvements do not automatically translate into useful trading strategies, the study also considers a very simple rule-based backtest based on the model’s directional predictions. At each decision date t in the test period, the model’s forecast for the next 5-day window is translated into a position indicator s_t :

1. $s_t = 1$ (long) if the model predicts a positive 5-day return (either via $\hat{y}_t^{(\text{reg})} > 0$ or $\hat{p}_t > 0.5$);
2. $s_t = 0$ (cash) otherwise.

The realised strategy return over the window $[t, t+5]$ is then

$$R_{t,t+5}^{\text{strat}} = s_t \cdot R_{t,t+5}$$

where $R_{t,t+5}$ is the actual 5-day return on the Indian infrastructure index. By chaining these window returns, a pseudo time series for the strategy is obtained, from which average return, volatility, Sharpe ratio and maximum drawdown can be calculated in exactly the same way as for any other asset. This simple backtest is not meant to represent a fully realistic trading system (transaction costs, execution lags and leverage constraints are ignored), but it provides a concrete sense of whether the model's forecasts have any economically meaningful content compared to naive benchmarks such as buy-and-hold or "always in cash".

To ensure a fair comparison, all models are evaluated on the same test period and under the same backtest rules. Naive strategies based on unconditional mean or always-long positions are included as reference points. The key question is not whether the models produce spectacular trading profits, but whether they generate consistent, though possibly modest, improvements over these simple benchmarks.

3.8 Implementation Details

All empirical work is carried out in Python using Jupyter notebooks. Data collection, cleaning & descriptive analysis and cross-region comparisons for each region are organised in separate notebooks. The predictive modelling pipeline, including feature construction, train–validation–test splitting and model training, is implemented in a separate notebook. Standard libraries such as pandas and numpy are used for data manipulation, matplotlib or similar tools for plotting, and scikit-learn together with a deep-learning framework (such as PyTorch or Keras) for model implementation.

Random seeds are fixed wherever possible to enhance reproducibility of the results, and care is taken to enforce a strictly forward-looking evaluation (for example, by ensuring that the test set is chronologically after the training and validation sets and that no information from the future leaks into feature construction). The combination of clearly separated notebooks, documented code and a consistent data pipeline makes it possible to replicate the full analysis: from raw price downloads to risk–return tables, CAPM estimates, predictive model training and out-of-sample evaluation on any machine with access to the same data sources.

4. Results and Discussion

4.1 Overview of Results

This chapter presents the empirical findings of the study in four stages. First, it analyses the behaviour of Indian InvITs, REITs, infrastructure stocks and benchmark indices using descriptive statistics, risk–return measures, CAPM regressions and correlation patterns. Second, it summarises corresponding results for the United States and Europe, focusing on how REIT-style and infrastructure-linked instruments behave in more mature markets. Third, it brings these pieces together in a cross-country comparison, contrasting risk–return profiles, betas and co-movement across regions. Finally, it reports the predictive modelling results for the Indian infrastructure proxy, comparing simple benchmarks with MLP and LSTM models and evaluating whether any predictive structure translates into economically meaningful strategies.

4.2 India: Descriptive, Risk–Return and Factor Behaviour

The Indian universe consists of one infra ETF, three InvITs, three REITs and five infrastructure-related stocks (Table 2). The ETF INFRABEES.NS provides an infra-basket benchmark. The three InvITs are IRB InvIT Fund (IRBINVIT.NS) in roads/highways and two power-transmission InvITs, INDIGRID.NS and PGINVIT.NS. The REIT bucket contains Brookfield India REIT (BIRET.NS), Embassy Office Parks REIT (EMBASSY.NS) and Mindspace Business Parks REIT (MINDSPACE.NS). The stock bucket comprises Adani Ports & SEZ (ADANIPORTS.NS), IRB Infrastructure Developers (IRB.NS), Larsen & Toubro (LT.NS), NTPC Limited (NTPC.NS) and Power Grid Corporation (POWERGRID.NS), covering ports/logistics, roads/EPC, engineering & construction and PSU utilities.

Ticker	Name	Type	Sector	Listing_Date	Sponsor	Market_Cap_Crore_INR	Annual_Return	Annual_Volatility	Sharpe_Ratio
INFRABEES.NS	Nippon India ETF Infra BeES	Index/ETF	ETF (Infra basket)	None	—	NaN	20.2600	16.3800	0.8100
IRBINVIT.NS	IRB InvIT Fund	InvIT	Roads / Highways	2017-05	IRB Infrastructure Developers	7,803.7000	5.6300	25.7400	-0.0500
INDIGRID.NS	IndiGrid (India Grid Trust)	InvIT	Power Transmission	2017-06-06	Sterlite Power (orig.) / KKR (IM owner)	14,049.7000	16.1400	10.9800	0.8300
PGINVIT.NS	POWERGRID InvIT	InvIT	Power Transmission	2021-05-14	Power Grid Corporation of India	8,692.3000	8.8500	11.9900	0.1500
BIRET.NS	Brookfield India Real Estate Trust	REIT	Commercial Offices (REIT)	2021-02	Brookfield Asset Management	20,948.3000	13.4200	16.9700	0.3800
EMBASSY.NS	Embassy Office Parks REIT	REIT	Commercial Offices (REIT)	2019-03	Embassy / Blackstone (orig.)	41,007.2000	13.0000	18.8500	0.3200
MINDSPACE.NS	Mindspace Business Parks REIT	REIT	Commercial Offices (REIT)	2020-08	K Raheja Corp	28,442.8000	15.9400	16.5300	0.5400
ADANIPORTS.NS	Adani Ports & SEZ	Stock	Ports / Logistics	2007-11	—	319,680.1000	23.5500	38.8200	0.4300
IRB.NS	IRB Infrastructure Developers	Stock	Roads / BOT / EPC	2008-02-25	—	26,378.7000	47.3800	49.4600	0.8200
LT.NS	Larsen & Toubro	Stock	Engineering & Construction (EPC)	2004-06-23	—	553,657.5000	27.0000	24.2400	0.8300
NTPC.NS	NTPC Limited	Stock	Power Generation (PSU)	2004-11-05	—	316,741.6000	33.7800	26.3100	1.0200
POWERGRID.NS	Power Grid Corporation	Stock	Power Transmission (PSU)	2007-10	—	258,184.8000	28.6100	26.3100	0.8200

Table 2

4.1 Instrument-level risk–return patterns

Table 3 reports annualised return, annualised volatility and Sharpe ratio for each name. On a total-return basis, the infra ETF delivers an annual return of about 20.3% with volatility around 16.4%, giving a Sharpe ratio of roughly 0.81. Among the InvITs, INDIGRID stands out with an annual return of 16.1% and low volatility of 11.0% (Sharpe ≈ 0.83), while PGINVIT has a more modest return of 8.9% at volatility 12.0% (Sharpe ≈ 0.15). IRB InvIT Fund shows a lower annual return of 5.6% and higher volatility (25.7%), resulting in a slightly negative Sharpe ratio.

The three REITs have fairly similar profiles: annual returns in the 13–16% range and volatility between 16.5–18.9%, with Sharpe ratios between 0.32 and 0.54. They cluster around the infra ETF in return–risk space. By contrast, the stocks are clearly more aggressive. IRB.NS has the highest annual return at about 47.4% but also the highest volatility at nearly 49.5% (Sharpe ≈ 0.82). NTPC and POWERGRID deliver annual returns of 33.8% and 28.6% at volatilities around 26%, with Sharpe ratios at or above 0.82–1.02, while L&T returns 27.0% with volatility 24.2%.

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0.82). NTPC and POWERGRID deliver annual returns of 33.8% and 28.6% at volatilities around 26%, with Sharpe ratios at or above 0.82–1.02, while L&T returns 27.0% with volatility 24.2%.

These relationships are visualised in Image 1, which plots annualised return against annualised volatility for all instruments. InvITs (orange circles) and REITs (green squares) sit in a relatively compact region of mid-teens volatility and low-20s returns, close to the infra ETF. The infra stocks (red triangles) fan out towards the top-right, with much higher volatility and, in the case of IRB and NTPC, substantially higher returns. The dashed cross-hairs mark the overall average return and volatility across all instruments; most InvITs and REITs lie close to, or slightly below, this average in return but firmly below it in volatility, while the stocks lie to the right.

Ticker	Name	Type	Sector	Alpha_annual	Beta	t_alpha	t_beta	R2	N_obs
IRBINVIT.NS	IRB InvIT Fund	InvIT	Roads / Highways	-3.6800	0.1700	-0.2700	1.8700	0.0100	1044
INDIGRID.NS	IndiGrid (India Grid Trust)	InvIT	Power Transmission	7.7700	0.1000	1.7000	3.4700	0.0200	1044
PGINVIT.NS	POWERGRID InvIT	InvIT	Power Transmission	0.7300	0.0800	0.1200	2.9000	0.0100	1044
BIRET.NS	Brookfield India Real Estate Trust	REIT	Commercial Offices (REIT)	4.6000	0.1400	0.6500	3.9600	0.0200	1044
EMBASSY.NS	Embassy Office Parks REIT	REIT	Commercial Offices (REIT)	4.9200	0.0800	0.6300	1.6100	0.0000	1044
MINDSPACE.NS	Mindspace Business Parks REIT	REIT	Commercial Offices (REIT)	7.7200	0.0900	1.1600	2.7600	0.0100	1044
ADANIPORTS.NS	Adani Ports & SEZ	Stock	Ports / Logistics	0.2000	1.2300	0.0100	9.9400	0.2700	1044
IRB.NS	IRB Infrastructure Developers	Stock	Roads / BOT / EPC	23.9800	1.2400	1.1200	9.6100	0.1700	1044
LT.NS	Larsen & Toubro	Stock	Engineering & Construction (EPC)	8.3000	0.8800	0.9900	10.3200	0.3600	1044
NTPC.NS	NTPC Limited	Stock	Power Generation (PSU)	15.1800	0.8700	1.5800	11.0900	0.3000	1044
POWERGRID.NS	Power Grid Corporation	Stock	Power Transmission (PSU)	11.7000	0.7500	1.1200	8.3600	0.2200	1044

Table 3

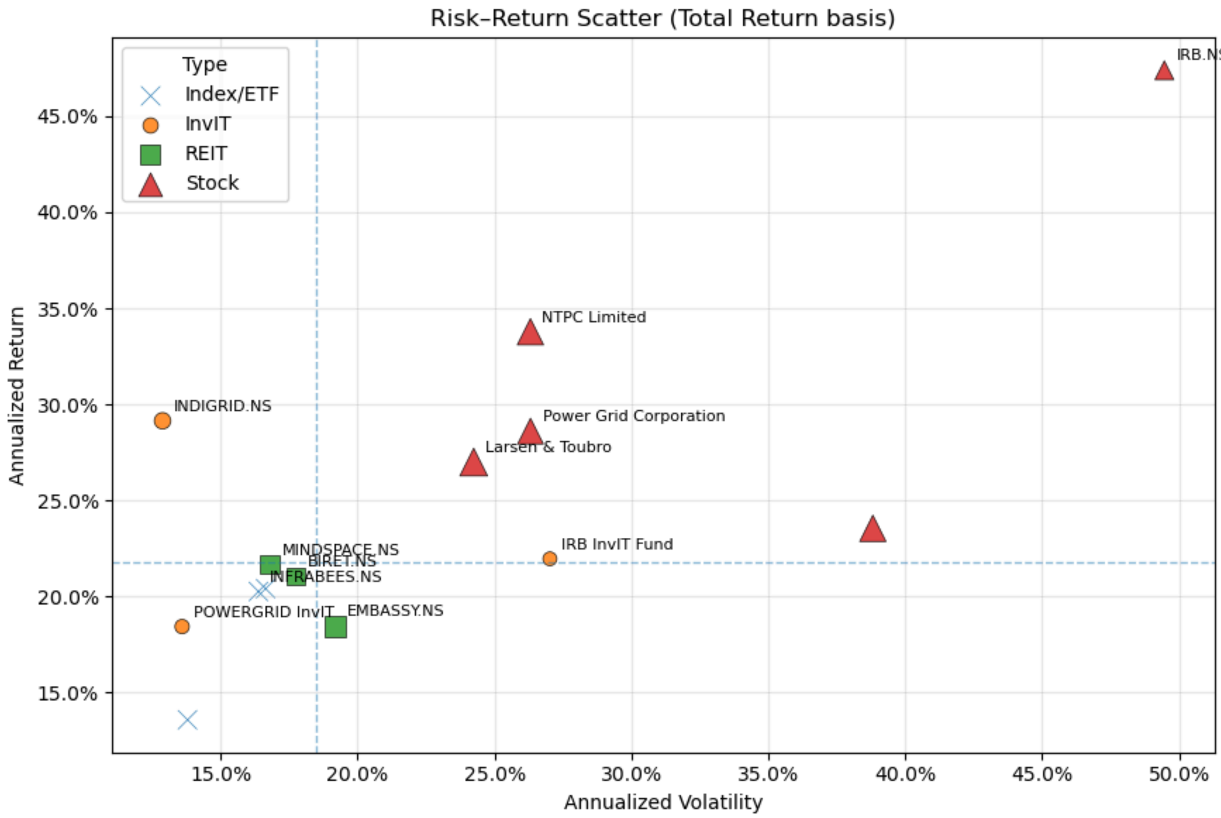

Image 1

4.2.2 Type-level averages: InvIT vs REIT vs Stock

To summarise the segment behaviour, Table 4 reports type-level averages across InvITs, REITs and stocks. On a total-return basis, the InvIT group (three names) has an average annual return of about 23.2% and average annual volatility of 17.8%, giving an average Sharpe ratio of roughly 1.04. The REIT group has an average return of 20.4%, volatility of 17.9% and an average Sharpe of about 0.75. The stock group delivers the highest average annual return at 32.1%, but with much higher volatility of 33.0%, resulting in a Sharpe ratio around 0.78.

These comparisons are shown more clearly in Image 2, which plots bar charts of type-level annualised return, volatility and Sharpe ratio. The left panel shows that stocks have the highest raw return, followed by InvITs and then REITs. The middle panel shows that stocks also have almost double the volatility of InvITs and REITs. The right panel makes the trade-off explicit: on average, InvITs achieve the highest Sharpe ratio, slightly ahead of the stock bucket, while REITs have a somewhat lower Sharpe because of slightly lower returns at similar volatility.

From a domestic investor’s perspective, this means that the InvIT/REIT segment behaves like a lower-volatility equity sleeve. Stocks offer more upside but also substantially higher risk; InvITs, in particular, provide a more favourable balance of return and volatility over the sample, while REITs sit between InvITs and the infra ETF in terms of risk–return.

Type	Count	Ann. Return (avg) %	Ann. Return (median) %	Ann. Vol (avg) %	Sharpe (avg)	Alpha (avg) %	Beta (avg)	R^2 (avg)
InvIT	3	23.1800	21.9600	17.8300	1.0400	14.4900	0.1300	0.0100
REIT	3	20.3900	21.0600	17.9100	0.7500	12.0300	0.1000	0.0100
Stock	5	32.0600	28.6100	33.0300	0.7800	11.8700	0.9900	0.2600

Table 4

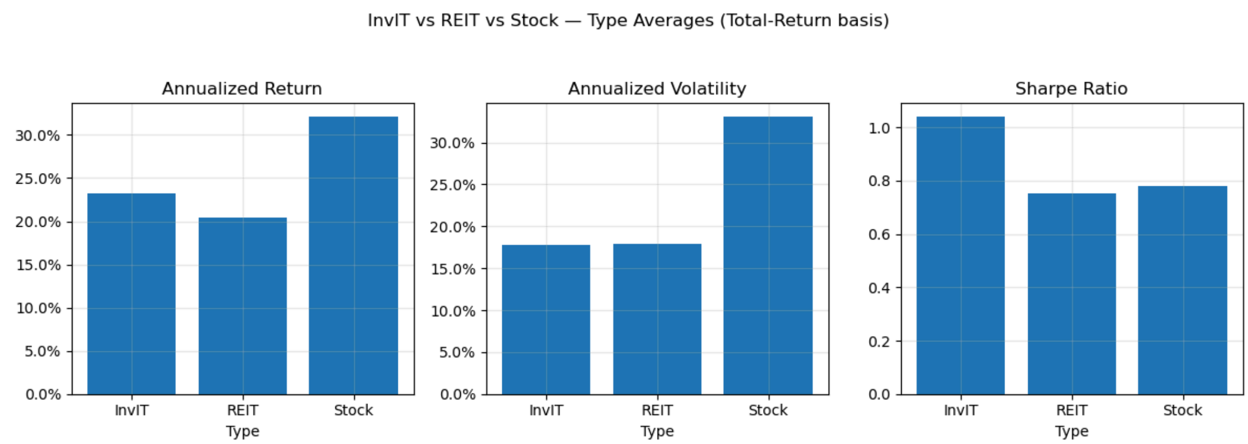

Image 2

4.2.3 CAPM alpha, beta and rolling betas

Table 3 reports CAPM regression results for each instrument with respect to the infra ETF benchmark (INFRABEES.NS). For each ticker, the table shows annualised alpha, beta, their t-statistics and the regression R^2. The three InvITs have betas in a very low range—about 0.17 for IRBINVIT, 0.10 for INDIGRID and 0.08 for PGINVIT—with correspondingly low R^2 values (around 0.01–0.02). Their annual alphas range from approximately −3.7% for IRBINVIT to +7.8% for INDIGRID, but the t-statistics indicate that these alphas are not strongly significant.

The three REITs show a similar pattern: betas between 0.08–0.14, small R^2 around 0.01–0.02, and moderate positive alphas in the 4.6–7.7% range, again with modest t-values. By contrast, infra stocks have betas much closer to—or above—one: ADANIPORTS and IRB both have betas around 1.23–1.24, while L&T, NTPC and POWERGRID have betas between 0.75–0.88. Their R^2 values are much higher (0.17–0.36), indicating that a sizeable fraction of their variance is explained by the infra ETF. Several stocks also show sizeable positive alphas (for example, IRB with about 24% and NTPC with 15% annual alpha), though again the statistical significance is moderate.

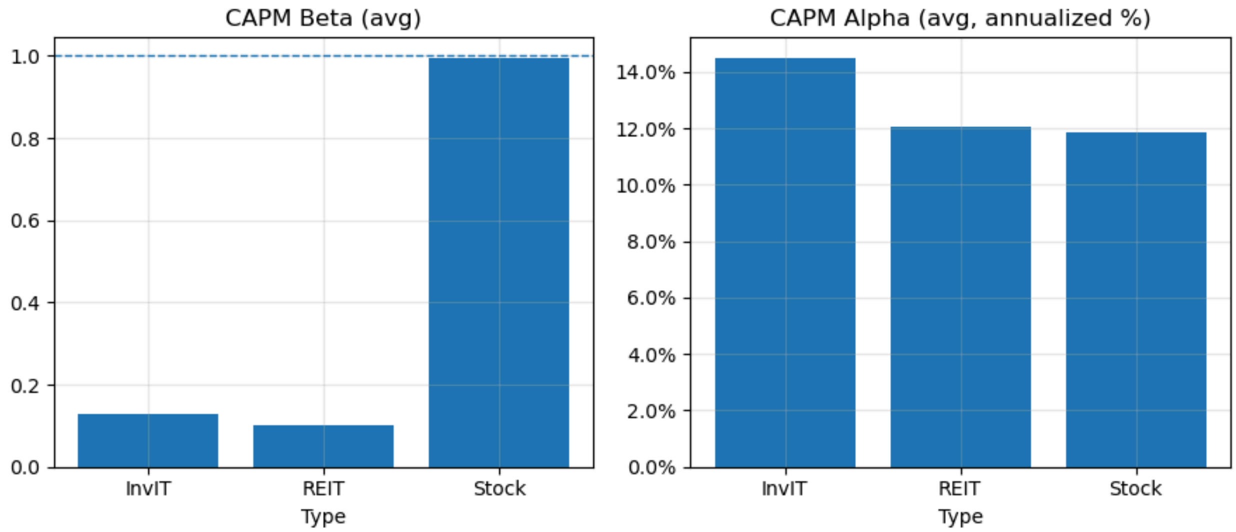

Image 3

Average CAPM metrics by type are summarised in Table 4 and depicted in Image 3. On average, InvITs have beta around 0.13, REITs around 0.10 and stocks essentially 1.0. All three groups show positive average alphas (around 14.5% for InvITs, 12.0% for REITs and 11.9% for stocks), but only the stock bucket has a non-trivial average R^2 (~0.26). The bar plots in Image 3 make the key point visually: beta jumps sharply from the low-teens for InvITs/REITs to almost one for stocks, while average alpha is of similar order across types.

To understand how these risk exposures evolve through time, Image 4 plots rolling 90-day betas of equal-weighted InvIT, REIT and stock groups. Over most of the sample, the stock group's beta fluctuates around or above 1.0, peaking above 1.4 in some periods, while the InvIT and REIT betas oscillate in a much lower band, generally between 0 and 0.4. Towards the end of the sample, the latest rolling betas are roughly 0.26 for InvITs, 0.03 for REITs and 1.06 for stocks, highlighting how insensitive the trust/REIT segment has been to short-term moves in the infra ETF compared with the stock group.

Overall, the CAPM and rolling-beta evidence shows that Indian InvITs and REITs act as low-beta, income-oriented equity exposures. They move with the infra market but with heavily dampened amplitude and relatively low explanatory power from the benchmark. Infra stocks, on the other hand, are high-beta exposures whose returns are much more tightly tied to the infra ETF and the broader market. This difference in beta and volatility is central to the portfolio role that InvITs and REITs can play in India, and it provides a useful reference point for the US and European results in the next section.

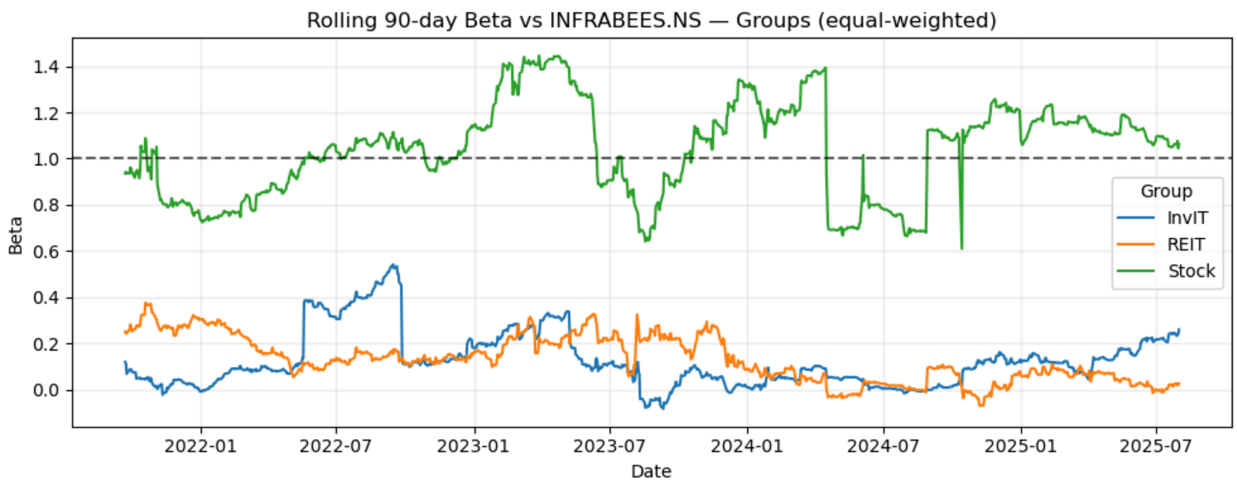

Image 4

4.3 United States: Descriptive, Risk–Return and Factor Behaviour

The US sample combines REITs, MLP-style infra vehicles, listed infra/utility stocks and indices. The REITs are American Tower (AMT), Crown Castle (CCI), Digital Realty (DLR) and Equinix (EQIX), representing tower and data-centre REITs. The infra/utility stocks include Brookfield Infrastructure Partners (BIP), Duke Energy (DUK) and NextEra Energy (NEE). The MLP bucket consists of midstream energy partnerships Enterprise Products Partners (EPD), Energy Transfer (ET) and MPLX LP (MPLX). Two ETFs act as benchmarks: the US infra ETF (PAVE/IFRA in the notebook) and the broad market ETF SPY.

4.3.1 Instrument-level risk–return patterns

Table 5 reports annualised CAPM statistics for each US instrument, while Image 5 plots annualised return against annualised volatility on a total-return basis. The risk–return scatter shows a fairly tight cloud of points between 12–22% annual returns and 20–36% annual volatility.

The infra and utility stocks (DUK, NEE, BIP – red triangles in Image 5) sit towards the lower-return, mid-volatility region. Duke Energy has an annual return of about 12.6% at volatility 22%; NextEra Energy earns roughly 13.8% at 28% volatility; Brookfield Infrastructure Partners returns around 12.1% with volatility close to 31%. Their Sharpe ratios (from the underlying notebook) are positive but modest, reflecting defensive but not spectacular performance.

Ticker	Name	Type	Sector	Alpha_annual	Beta	t_alpha	t_beta	R2	N_obs
AMT	American Tower	REIT	Tower REIT	5.0600	0.6200	0.5600	9.0900	0.2400	1840
BIP	Brookfield Infrastructure Partners	Stock	Listed Infrastructure	-0.2500	0.8800	-0.0300	11.6400	0.4000	1840
CCI	Crown Castle	REIT	Tower REIT	2.9800	0.6200	0.3500	11.7500	0.2400	1840
DLR	Digital Realty Trust	REIT	Data Center REIT	9.6400	0.6200	1.0000	13.0600	0.2100	1840
DUK	Duke Energy	Stock	Electric Utility	3.3800	0.6100	0.5200	9.0800	0.3600	1840
EPD	Enterprise Products Partners	MLPS	Midstream MLP	3.6600	0.7300	0.4700	10.7200	0.3800	1840
EQIX	Equinix	REIT	Data Center REIT	7.5200	0.6200	0.8500	11.9600	0.2200	1840
ET	Energy Transfer	MLPS	Midstream MLP	5.7000	0.9100	0.5000	10.8100	0.3100	1840
MPLX	MPLX LP	MLPS	Midstream MLP	10.9100	0.7200	1.1100	9.6300	0.2300	1840
NEE	NextEra Energy	Stock	Renewables & Utility	3.6300	0.6900	0.4300	12.4900	0.3000	1840
PAVE	Global X U.S. Infrastructure Dev ETF	Index	Infra ETF	3.5500	1.0800	1.0400	48.1000	0.8400	1840
SPY	SPDR S&P 500 ETF	Index	Broad Market	4.8400	0.7300	1.2700	22.0500	0.6500	1840

Table 5

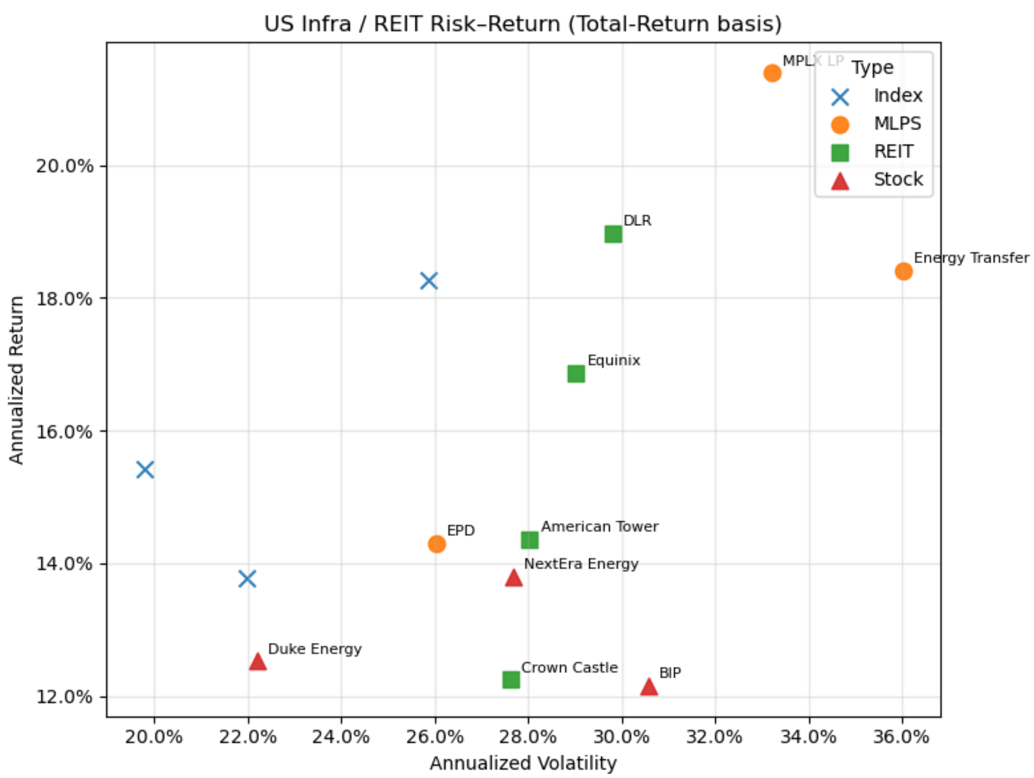

Image 5

The REITs (AMT, CCI, DLR, EQIX – green squares) are clustered in the mid-to-upper part of the scatter. American Tower delivers about 14.3% annual return at 28% volatility; Crown Castle roughly 12.2% at 27–28% volatility. The two data-centre REITs are stronger: Digital Realty earns just over 19% per year at about 30% volatility, while Equinix returns around 16.9% at similar volatility. These names sit clearly above the broad-market ETF SPY, which earns around 15.4% with volatility near 20%.

The MLP-style midstream names (EPD, ET, MPLX – orange circles) are the highest-return, highest-volatility group. Enterprise Products Partners earns about 14.2% per year at 26% volatility; Energy Transfer delivers roughly 18.4% at 36% volatility; MPLX is the standout, with annual returns above 21% and volatility a little above 33%. These observations are reflected in Image 5, where the MLPs sit towards the top-right of the cloud.

The infra ETF and SPY provide useful references: the infra ETF (PAVE) delivers about 18.2% annual return at 26% volatility, roughly in the middle of the REIT/MLP cluster, while SPY lies closer to the lower-volatility, mid-return region. Overall, the US cross-section shows that infra-related vehicles all inhabit a broadly similar risk–return band, with MLPs and data-centre REITs on the more aggressive side, and utilities and tower REITs more defensive.

4.3.2 Type-level averages: MLPS vs REIT vs Stock

Table 6 aggregates these instruments into three groups: MLPS, REIT and Stock. On a total-return basis, the MLP group (EPD, ET, MPLX) has an average annual return of about 18.0% with average volatility of 31.8%, yielding an average Sharpe ratio of roughly 0.50. The REIT group (AMT, CCI, DLR, EQIX) earns an average annual return of 15.6% at volatility 28.6%, with an average Sharpe of around 0.47. The Stock group (BIP, DUK, NEE) is the most conservative: average annual return of about 12.8%, volatility 26.8% and Sharpe ratio roughly 0.41.

Type	Count	Ann. Return (avg) %	Ann. Return (median) %	Ann. Vol (avg) %	Sharpe (avg)	Alpha (avg) %	Beta (avg)	R^2 (avg)
MLPS	3	18.0400	18.4100	31.7600	0.5000	6.7500	0.7900	0.3100
REIT	4	15.6100	15.6100	28.6200	0.4700	6.3000	0.6200	0.2300
Stock	3	12.8300	12.5300	26.8200	0.4100	2.2500	0.7300	0.3600

Table 6

Thus, on average:

1. MLPs offer the highest raw returns but at the highest volatility.
2. REITs sit in the middle: slightly lower returns than MLPs but somewhat lower volatility, with Sharpe ratios very similar to MLPs.
3. Stocks provide the most defensive exposure, with the lowest returns and lowest Sharpe among the three groups.

Compared with India, where stocks had clearly higher Sharpe than REITs on some metrics, the US picture is more balanced: all three types deliver positive but modest risk-adjusted performance, with MLPs and REITs only slightly ahead of infra/utility stocks.

4.3.3 CAPM betas, alphas and rolling betas

Table 5 shows CAPM estimates for each instrument using the US infra ETF (IFRA/PAVE) as the market benchmark. The tower and data-centre REITs (AMT, CCI, DLR, EQIX) all have betas around 0.62 and annualised alphas between roughly 3–10%. Their R^2 values are in the 0.21–0.24 range, indicating that the infra ETF explains a material, but not dominant, fraction of their return variation. The utility and infra stocks (BIP, DUK, NEE) have betas between 0.61 and 0.88, alphas between about −0.25% and 3.6%, and somewhat higher R^2 (0.31–0.40). The MLPs show betas from 0.72 to 0.91 and annual alphas in the 3.7–10.9% range, with R^2 around 0.28–0.33. The infra ETF itself has a beta slightly above one (≈1.08) and alpha around 3.6%, while SPY has beta ≈ 0.73 and alpha ≈ 4.8% relative to IFRA.

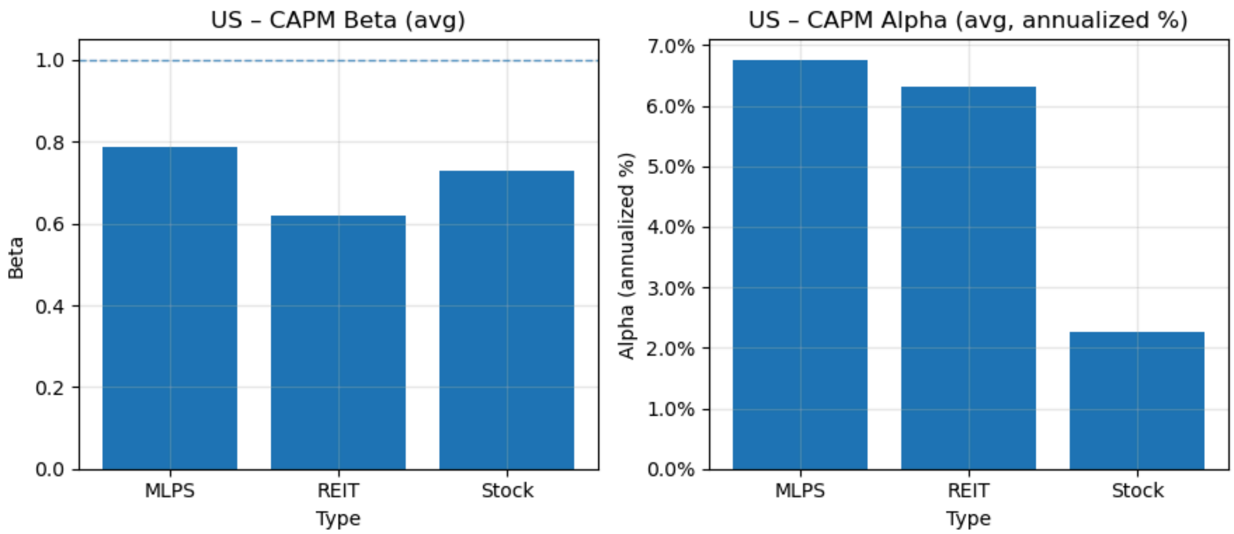

Image 6

Type-level averages of these CAPM metrics are given in Table 6 and visualised in Image 6. On average:

1. MLPs have beta ≈ 0.79 and alpha ≈ 6.75% per year.
2. REITs have lower beta, ≈ 0.62, with alpha ≈ 6.30%.
3. Stocks sit between them in beta (≈ 0.73) but with the lowest alpha, ≈ 2.25%.

Average R^2 is highest for stocks (≈0.36), followed by MLPs (≈0.31) and REITs (≈0.23), suggesting that the infra ETF explains stock returns more tightly than REIT or MLP returns. The bar plots in Image 6 show this clearly: US infra/utility stocks and MLPs are closer to "market-beta" exposures, while REITs deliver similar alpha with lower beta.

Dynamic behaviour is illustrated by the rolling 90-day betas. Image 7 plots rolling betas for representative names (AMT, CCI, EQIX, NEE, DUK, BIP) versus IFRA. Betas vary substantially through time: REIT betas fall towards zero during some periods and rise close to one in others; utility stocks such as DUK and NEE move between roughly 0 and 1, while BIP occasionally spikes well above 1, especially around sharp market moves. Image 8 aggregates this by type, plotting rolling 90-day betas for the infra ETF, MLP group, REIT group and stock group. Over most of the sample:

1. The infra ETF itself fluctuates around beta 1 by definition.
2. Stocks and MLPs generally hover near or slightly below 1.0, with episodes where MLP beta rises above 1.2–1.3.
3. REITs tend to have a lower and more variable beta, sometimes dropping close to zero or even slightly negative, and sometimes rising above 1.0 during risk-on phases.

This time-varying pattern underscores that, in the US market, REITs and MLPs are clearly equity-linked but not simple one-for-one clones of the infra index. They carry meaningful sector-specific risk and react differently across cycles.

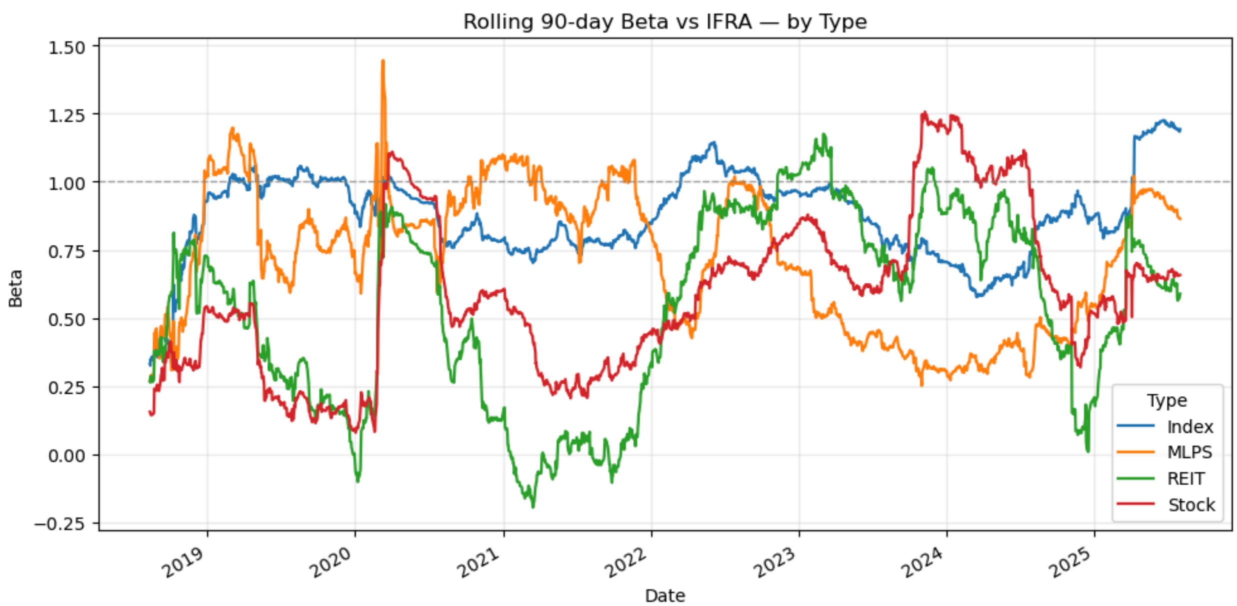

Image 7

4.4 Europe: Infra / Utilities and REIT Behaviour

The European sample focuses on a small set of liquid infra / utility stocks, one REIT-type exposure, and a broad European equity index ETF. The stocks include names such as Iberdrola (ADR), Ferrovial/Enel, National Grid, Engie and RWE. The REIT proxy is Cellnex Telecom, which functions as a tower / telecom-infrastructure vehicle. The broad European ETF (VGK) is treated as the regional market index.

4.4.1 Risk–return profile

The risk–return scatter in Image 8 plots annualised return against annualised volatility on a total-return basis. The index ETF lies at the lower-left corner of the cloud, with an annualised return of roughly 6.3% and volatility around 18.9%. This gives a simple Sharpe ratio of about 0.23 (Table 7) and serves as the benchmark for the region.

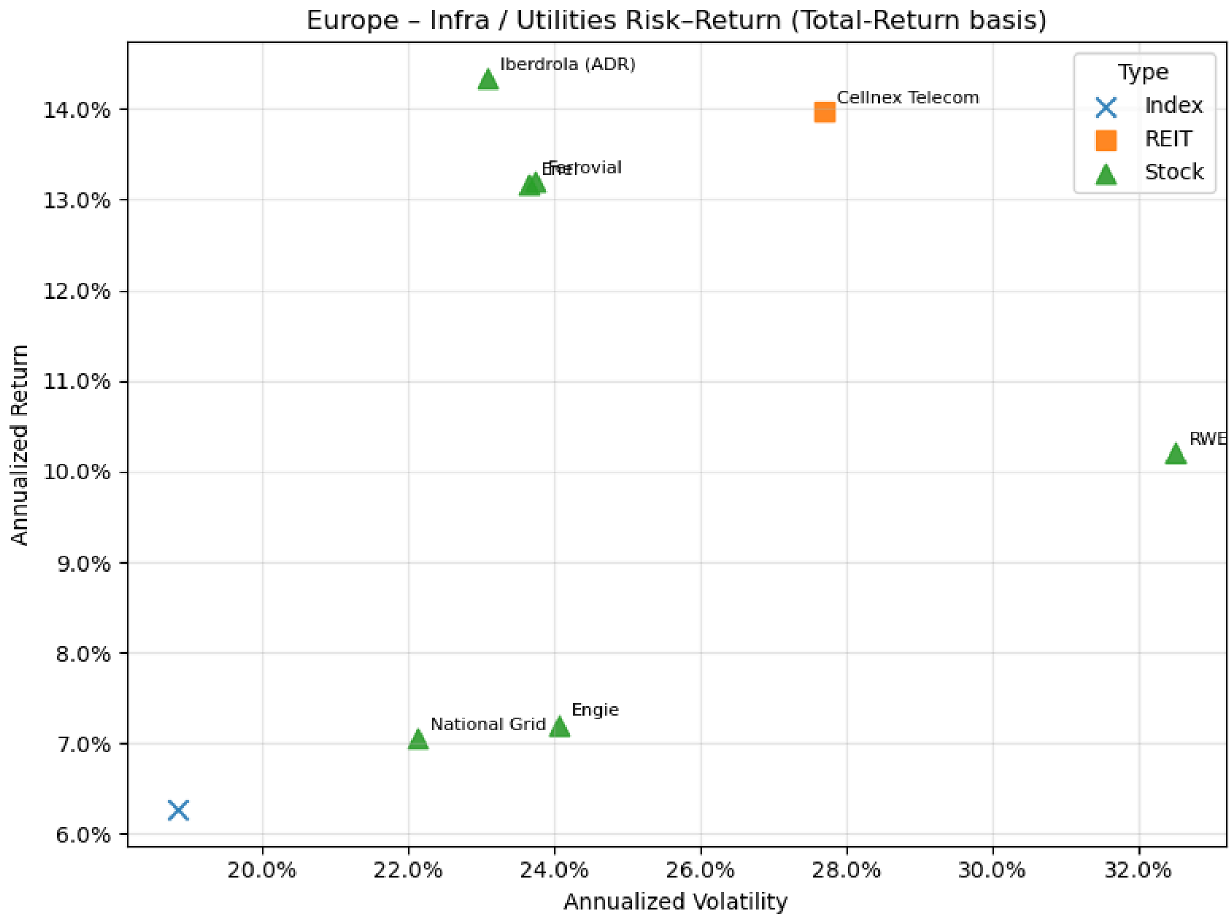

Image 8

Most European infra / utility stocks (green triangles) cluster between 22–25% volatility and 7–13% annual returns. Iberdrola and Ferrovial sit towards the upper part of this cluster, with returns in the low-teens and mid-20s volatility, while National Grid and Engie are more defensive, with returns around 7% at low-20s volatility. RWE is the more aggressive outlier, with volatility above 32% and returns just above 10%, reflecting its more cyclical generation-heavy profile.

The Cellnex Telecom REIT proxy (orange square) lies clearly above the index and most stocks in return space, with an annualised return close to 14% and volatility about 27.7%. Its Sharpe ratio is around 0.43 (Table 7), higher than both the index (0.23) and the average stock bucket (0.36). In other words, the REIT-type exposure delivers roughly double the index return, at higher but still manageable volatility.

Type	Count	Ann. Return (avg) %	Ann. Return (median) %	Ann. Vol (avg) %	Sharpe (avg)	Alpha (avg) %	Beta (avg)	R^2 (avg)
Index	1	6.2800	6.2800	18.8500	0.2300	NaN	NaN	NaN
REIT	1	13.9700	13.9700	27.7100	0.4300	9.8600	0.4900	0.1100
Stock	6	10.8600	11.6800	24.8700	0.3600	5.9500	0.6800	0.2800

Table 7

Overall, Table 7 shows that, on average, the stock bucket earns about 10.9% per year with volatility 24.9%, giving a Sharpe ratio of 0.36, while the REIT earns 13.97% with volatility 27.7% and Sharpe 0.43. All infra-related exposures thus outperform the broad European index on a risk–return basis, with the REIT proxy showing the strongest risk-adjusted performance.

4.4.2 CAPM betas, alphas and rolling betas

Using the European index ETF as the benchmark, the notebook estimates CAPM regressions by type. Table 7 and Image 9 summarise the averages. The REIT proxy has an average beta of about 0.49 and an annualised alpha of roughly 9.9%, with R^2 around 0.11. The stock group has a higher average beta, about 0.68, and a lower (but still positive) annual alpha of 6.0%, with R^2 near 0.28. This indicates that European infra / utility stocks are more tightly tied to the broad market than the REIT proxy, while both earn positive excess returns relative to the benchmark.

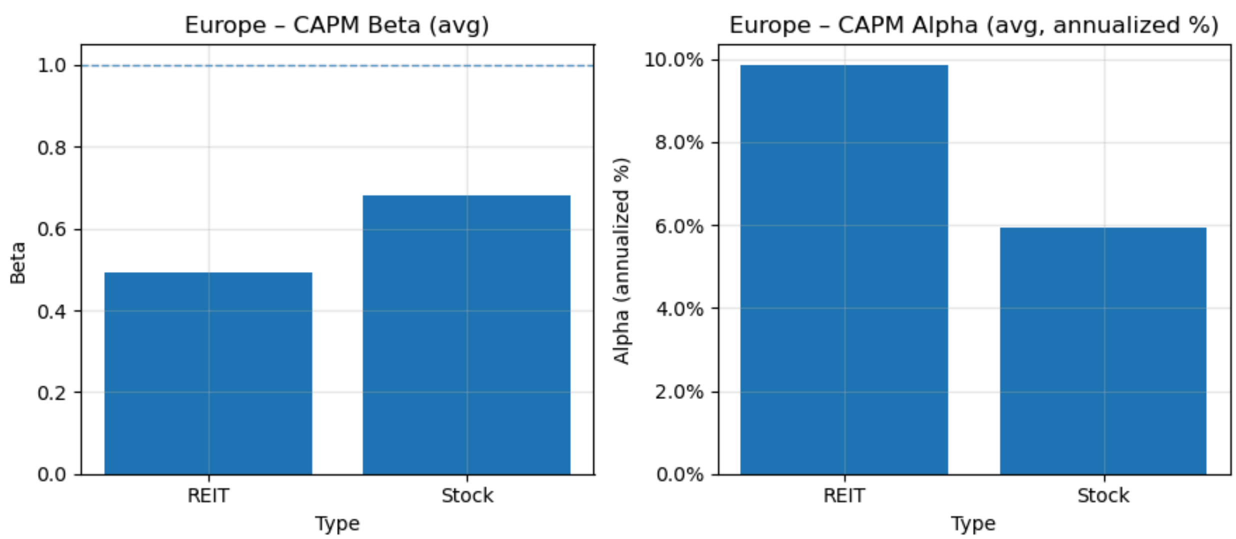

Image 9

Time variation is captured in Image 10, which plots rolling 90-day betas versus VGK by type. The stock-group beta (orange line) mostly fluctuates between 0.5 and 0.8, occasionally approaching 0.9–1.0 in strong risk-on phases. The REIT beta (blue line) is lower and more volatile: it often lies between 0.2 and 0.6, dips close to zero or slightly negative in stress episodes, and spikes above 1.0 during late-cycle rallies. This pattern is consistent with the CAPM averages: the REIT proxy behaves as a lower-beta, more idiosyncratic infra exposure, while the stock bucket is a more conventional moderate-beta play on European utilities and infra.

In summary, the European evidence suggests that infra / utility stocks and REIT-like exposures provide moderate-beta, above-index returns, with the REIT proxy offering the best risk-adjusted performance (higher Sharpe, lower beta, higher alpha). This positions Europe between the very defensive Indian InvIT/REIT market and the more equity-like US infra and MLP segment, and sets the stage for the cross-country comparison in the next section.

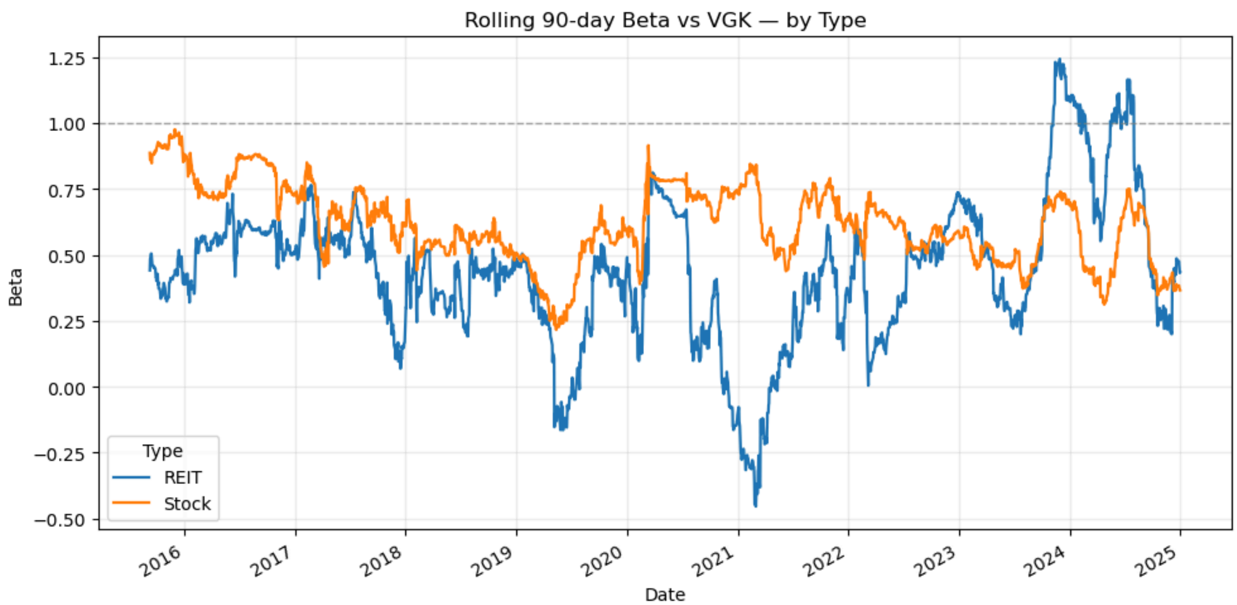

Image 10

4.5 Cross-Country Comparative Analysis

4.5.1 Market indices: India vs US vs Europe

Table 8 reports annualised return, volatility, CAPM beta and alpha, and Sharpe ratio for the infra/equity indices of Europe, India and the US, while Image 11 shows their cumulative total returns, each normalised to 1 at the start of its sample.

On an annualised basis, the Indian infra ETF (INFRABEES.NS) has the highest index-level return at about 22.5%, with volatility around 16.4% and a Sharpe ratio of roughly 0.055. The US infra index (IFRA/PAVE) comes next, with an annualised return of about 14.8%, volatility close to 22.0% and Sharpe around 0.034. The European equity ETF (VGK) has the lowest annualised return, around 10.7%, at volatility 18.8% and Sharpe about 0.031.

Image 11 reflects this: despite starting at different dates, all three indices trend upward, but the Indian infra index climbs more steeply once it enters the sample, while the US and European indices move in longer, more mature cycles. By the end of the period, all three have more than doubled from their starting point, with India achieving the highest annualised growth, followed by the US and then Europe. This already hints that Indian infra equities have been in a particularly strong phase relative to global peers over the sample horizon.

	Region	Type	AnnReturn	AnnVol	Beta	AlphaAnnual	Sharpe
0	Europe	Index	0.1065	0.1875	1.0000	0.0000	0.0306
1	Europe	REIT	0.1805	0.2847	0.4623	0.1138	0.0345
2	Europe	Stock	0.1703	0.2390	0.6177	0.0906	0.0386
3	India	Index	0.2245	0.1638	1.0000	0.0000	0.0549
4	India	InvIT	0.1085	0.1624	0.1207	0.0248	0.0241
5	India	REIT	0.1517	0.1745	0.1034	0.0665	0.0296
6	India	Stock	0.3826	0.3303	0.9946	0.1188	0.0513
7	US	Index	0.1477	0.2197	1.0000	0.0000	0.0338
8	US	MLPS	0.1981	0.3176	0.7876	0.0675	0.0318
9	US	REIT	0.1300	0.2858	0.6220	0.0285	0.0223
10	US	Stock	0.1369	0.2682	0.7282	0.0225	0.0259

Table 8

4.5.2 Type-level risk–return and factor metrics across regions

Table 8 also summarises type-level averages by region – treating InvITs, REITs, infra/utility stocks and US MLPs as separate buckets.

For index-type exposures, India clearly stands out. The Indian infra index delivers a much higher annualised return than the US and European indices, with lower volatility than the US infra index and only slightly higher volatility than the European index. Its beta is, by construction, 1 with zero alpha in the CAPM set-up, but the headline message is that Indian infra has been in a stronger bull phase than its US and European counterparts.

For the trust / REIT-style vehicles, the picture is more nuanced.

1. Europe – REIT: average annual return ≈ 18.1%, volatility ≈ 28.5%, beta ≈ 0.46, alpha ≈ 11.4%, Sharpe ≈ 0.035.
2. India – REIT: annual return ≈ 15.2%, volatility ≈ 17.5%, beta ≈ 0.10, alpha ≈ 6.7%, Sharpe ≈ 0.030.

3. US – REIT: annual return ≈ 13.0%, volatility ≈ 28.6%, beta ≈ 0.62, alpha ≈ 2.9%, Sharpe ≈ 0.022.

European REIT-type exposure offers the highest return and alpha, but at high volatility; US REITs are closer to “ordinary” equities, with moderate betas and more modest risk-adjusted performance. Indian REITs have somewhat lower returns than Europe but much lower beta and volatility, making them the most defensive of the three.

For infra / utility stocks, type-level averages show:

1. India – Stock: annual return ≈ 38.3%, volatility ≈ 33.0%, beta ≈ 0.99, alpha ≈ 11.9%, Sharpe ≈ 0.051.
2. Europe – Stock: annual return ≈ 17.0%, volatility ≈ 23.9%, beta ≈ 0.62, alpha ≈ 9.1%, Sharpe ≈ 0.039.
3. US – Stock: annual return ≈ 13.7%, volatility ≈ 26.8%, beta ≈ 0.73, alpha ≈ 2.3%, Sharpe ≈ 0.026.

Indian infra stocks are clearly the highest-beta, highest-return bucket, with volatility roughly a third higher than European infra stocks and significantly higher than US infra stocks; yet even after accounting for this, their annual alpha is also the largest. European infra stocks sit in the middle: moderate beta and volatility, with solid positive alpha. US infra/utility stocks are the most conservative in terms of performance, with lower returns and alphas and only slightly lower volatility than the European bucket.

The US MLPS sit somewhere between Indian stocks and US REITs. As shown in Table 8, they deliver an average annual return of 19.8% with volatility around 31.8%, beta about 0.79 and alpha roughly 6.8%, with Sharpe around 0.032. This means MLPs have more equity-like risk and return than US REITs, but not as aggressive as Indian infra stocks.

Taken together, the type-level metrics show that:

1. India offers the highest upside (index and stocks) but also the most volatility; InvITs and REITs are very low-beta relative to that backdrop.
2. US infra/utility assets (stocks and REITs) look more like moderate-beta equity sectors, with MLPs providing the higher-return, higher-volatility option.
3. Europe sits in between, with REIT and infra stock exposures earning returns and alphas that are competitive with India on a risk-adjusted basis, but at more moderate absolute levels.

4.5.3 Cumulative paths by type: REITs, stocks and InvIT vs MLP

The cumulative-return plots by type provide a more visual comparison of how these segments evolved over time.

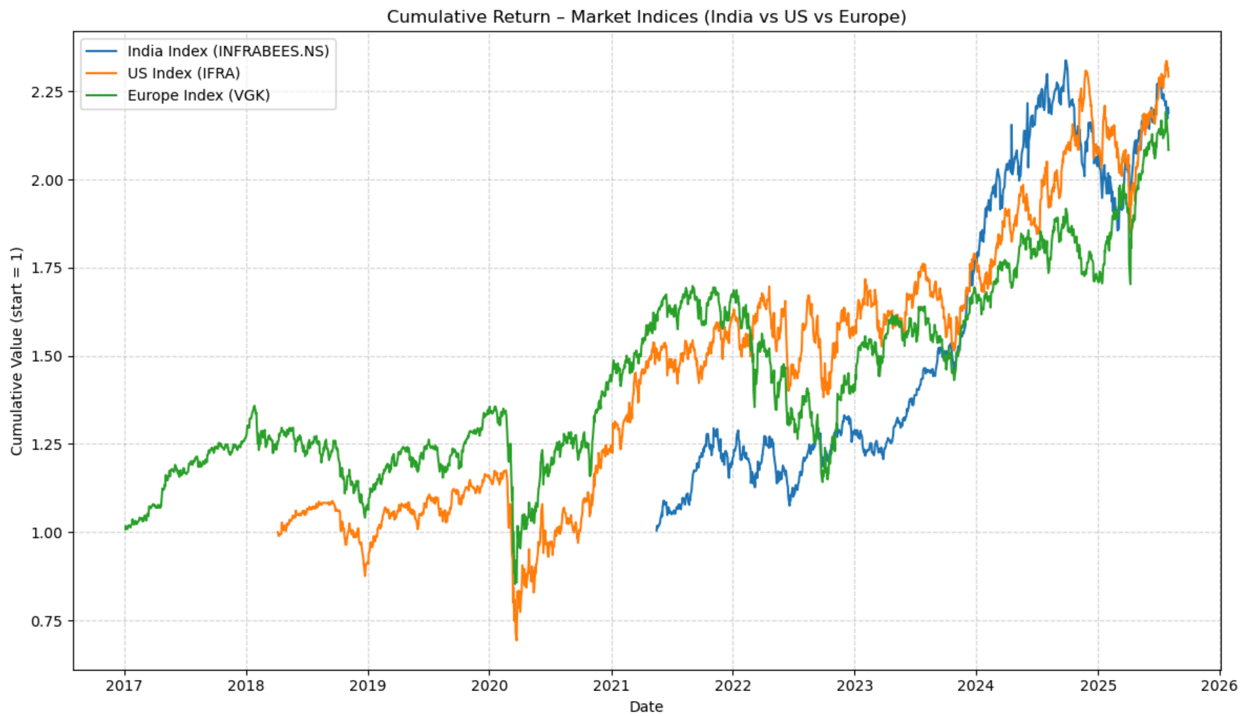

Image 11

Image 12 shows the average cumulative return of REIT-type exposures in Europe, India and the US. Starting from 1 in each region, the European REIT proxy rises very sharply between 2017 and 2021, peaking at almost 6× before correcting and stabilising around 3–3.5×. US REITs show a steadier climb to roughly 2× by the end of the period. Indian REITs start later in the sample and grow more gradually, ending somewhat below US REITs but with a much smoother path and smaller drawdowns. This aligns well with Table 8: Europe delivers the strongest REIT performance in levels, but with high volatility; India delivers defensive, low-beta REIT exposure, while US REITs sit between the two.

Image 13 shows average cumulative returns for infra / utility stocks across the three regions. Here, Indian infra stocks (orange line) dominate: despite only entering the sample around 2021, they rally aggressively to nearly 4× their starting value at the peak, before giving back some gains. European infra stocks (blue) provide a long, steady climb from 2017, reaching around 3.5 times by the end. US infra/utility stocks (green) grow more modestly, ending around 2.1–2.2 times. This is consistent with the annualised numbers in Table 8: Indian infra stocks have been in a strong bull phase, Europeans have delivered solid intermediate performance, and US infra stocks have been the most subdued.

Finally, Image 14 plots Indian InvITs (average) vs US MLPs (average) to directly compare the segments that are closest in spirit: both are infra cash-flow vehicles, but they live in very different markets. The US MLP average (orange) shows a volatile but ultimately strong upward trajectory: despite a sharp Covid drawdown, the cumulative value rises to roughly 2.8–3.0 times by the end of the sample. Indian InvITs (blue) follow a much smoother path with smaller drawdowns, but their cumulative return is lower, finishing around 1.4–1.5 times. This mirrors the type-level metrics: US MLPs are higher-risk, higher-return vehicles, while Indian InvITs are genuinely low-beta, low-volatility exposures whose role is more about stability and yield than capital appreciation.

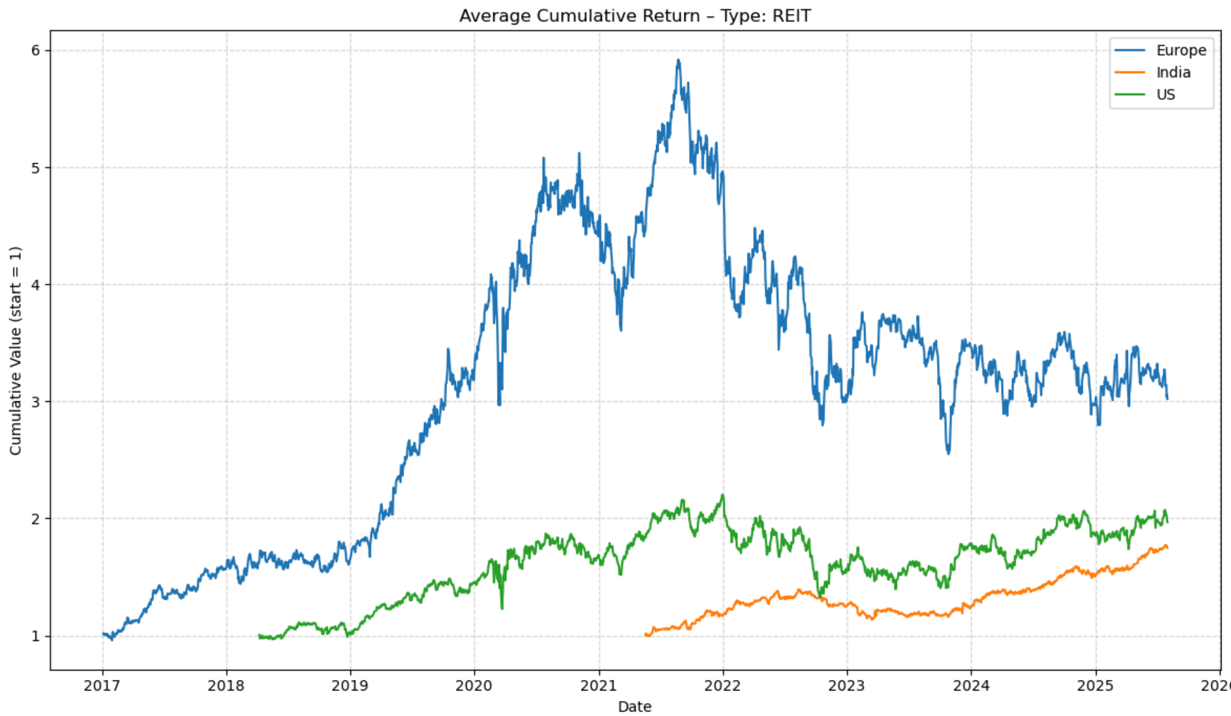

Image 12

Overall, the comparative analysis shows that:

1. India currently offers the highest growth in infra equities, but with substantial risk; its InvITs and REITs are unusually low-beta compared with this backdrop.
2. US infra capital-market instruments (especially MLPs) offer equity-like infra exposure with moderate betas and positive, but not spectacular, alphas.
3. Europe sits between the two, with infra / utility stocks and the REIT proxy delivering respectable returns and alphas at moderate betas, making them a middle-ground between India's aggressive infra stocks and the US's more mature infra sectors.

This cross-country picture is important when the focus shifts from static risk–return characteristics to the dynamic predictability of Indian infrastructure returns using machine-learning models.

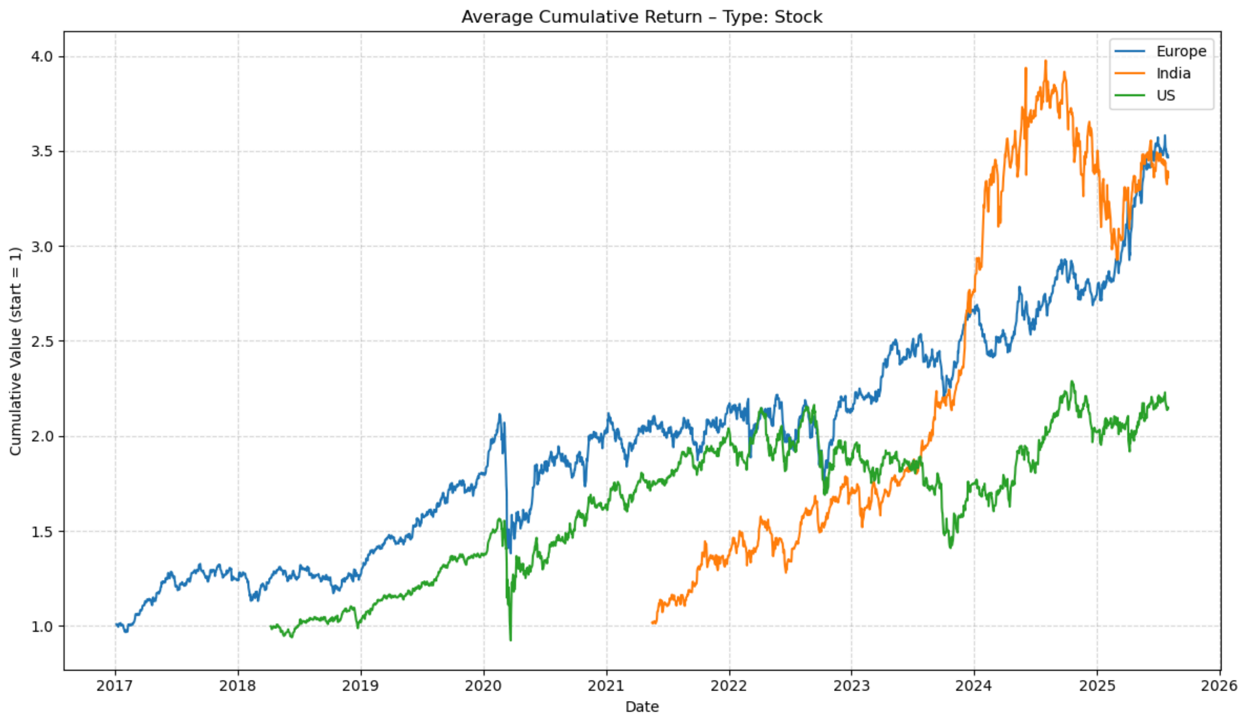

Image 13

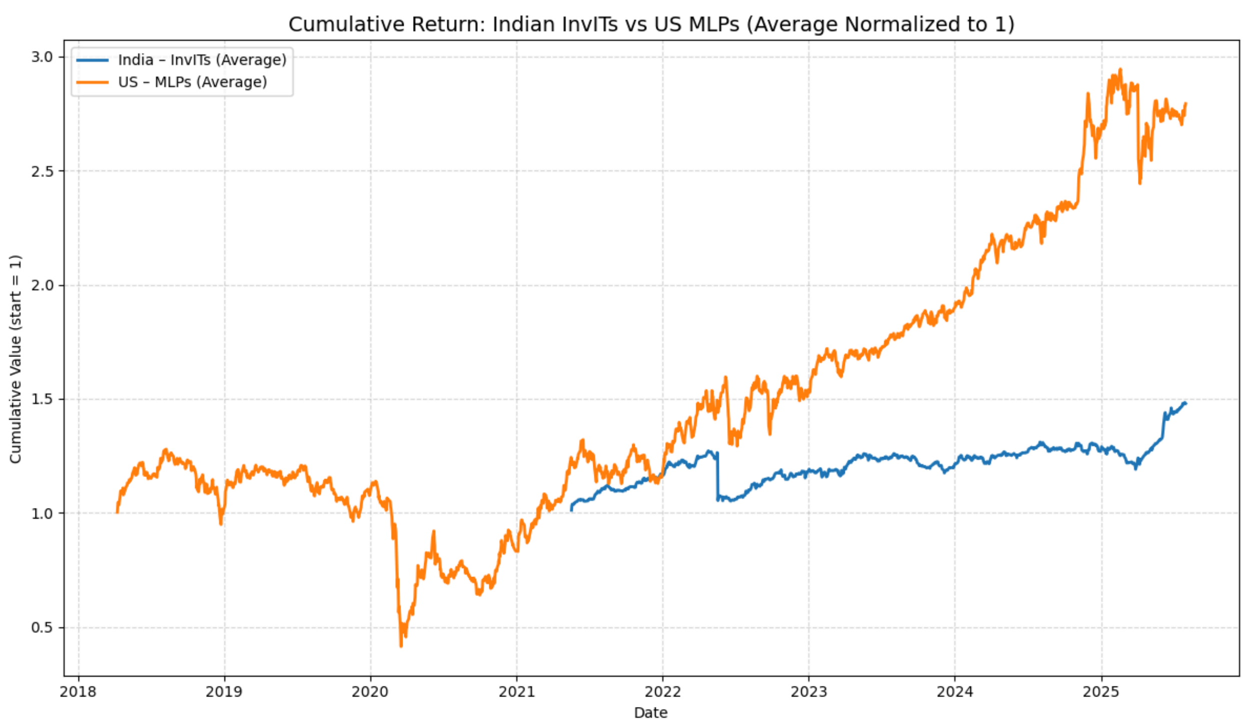

Image 14

4.6 Predictive Modelling of Indian Infrastructure Returns

4.6.1 Granger causality and motivation for global features

Before estimating machine-learning models, simple Granger causality tests were run to check whether daily infra returns in the US and Europe contain information useful for predicting the Indian infra market proxy. For both US → India and Europe → India, and for all lag lengths from 1 to 5 days, the F-statistics are sizeable (for example, around 41–48 at low lags) and the associated p-values are extremely small (well below 0.001).

Across all lags, the null hypothesis that "US (or European) infra returns do not Granger-cause Indian infra returns" is therefore rejected at conventional significance levels. This provides statistical motivation for including global infra returns as explanatory variables in the ARX, MLP and LSTM "global" variants.

4.6.2 Benchmark AR and ARX models (daily horizon)

As a purely time-series benchmark, an AR(1) model was estimated on daily log returns of the Indian infra market proxy, and an ARX(1) model augmented this with lagged US and European infra returns.

For the Indian market proxy, the AR and ARX models perform as follows (validation window):

1. AR (India-only): RMSE ≈ 0.0100, $R^2 \approx -0.02$, directional accuracy ≈ 53.2%.
2. ARX (India + US + EU): RMSE ≈ 0.0103, $R^2 \approx -0.08$; directional accuracy is very similar to the AR model.

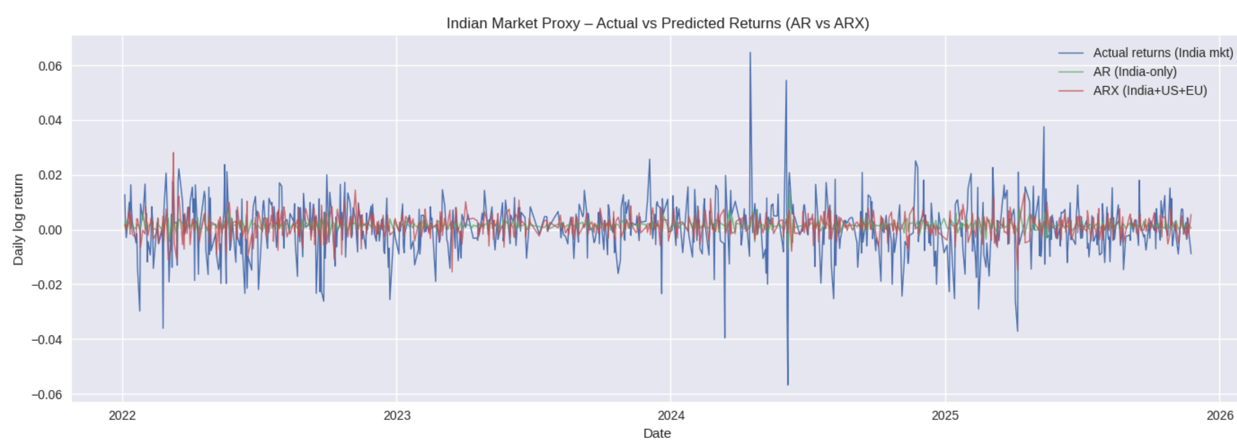

Image 15

The time-series plot in Image 15 (actual vs predicted returns) shows that both AR and ARX predictions are very smooth and stay close to zero, while actual returns display frequent spikes. The scatter plots in Image 16 confirm this: points are tightly clustered around the horizontal axis, with almost no slope, and both models clearly underestimate the magnitude of large positive and negative returns.

A simple sign-based strategy was then constructed which holds the Indian infra ETF only on days when the AR model predicts a positive return, and stays in cash otherwise. Image 17 compares the cumulative log returns of this strategy with buy-and-hold. The AR-based strategy largely tracks the buy-and-hold path but does not deliver a clear improvement; in several sub-periods it slightly underperforms.

Overall, the linear AR/ARX benchmarks offer at best a small edge in directional accuracy over random guessing, but they fail to capture the amplitude of daily infra returns and do not materially improve on buy-and-hold.

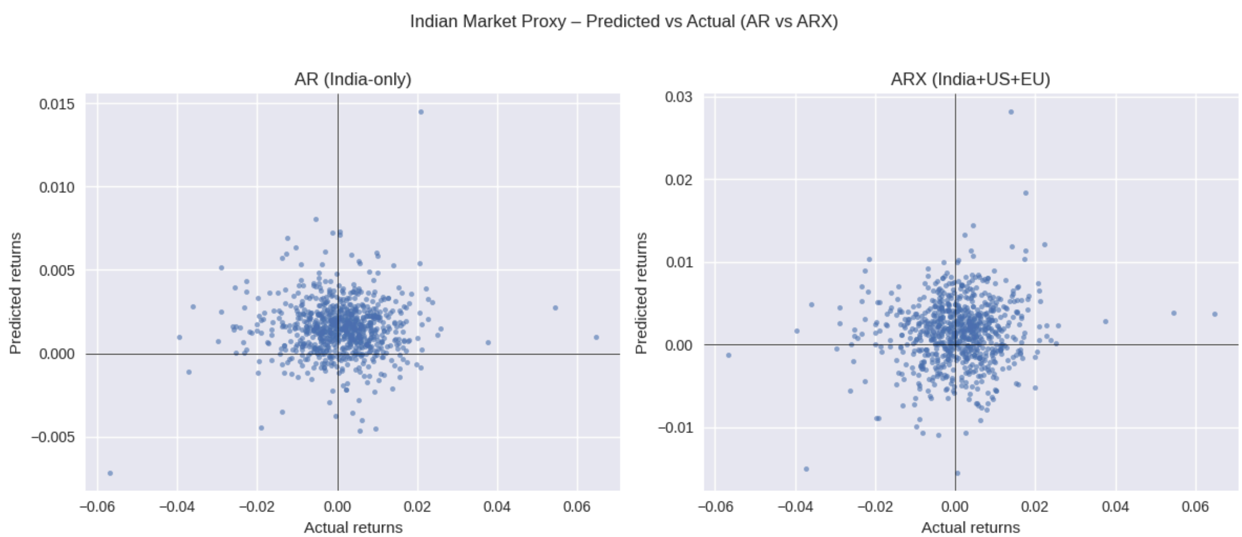

Image 16

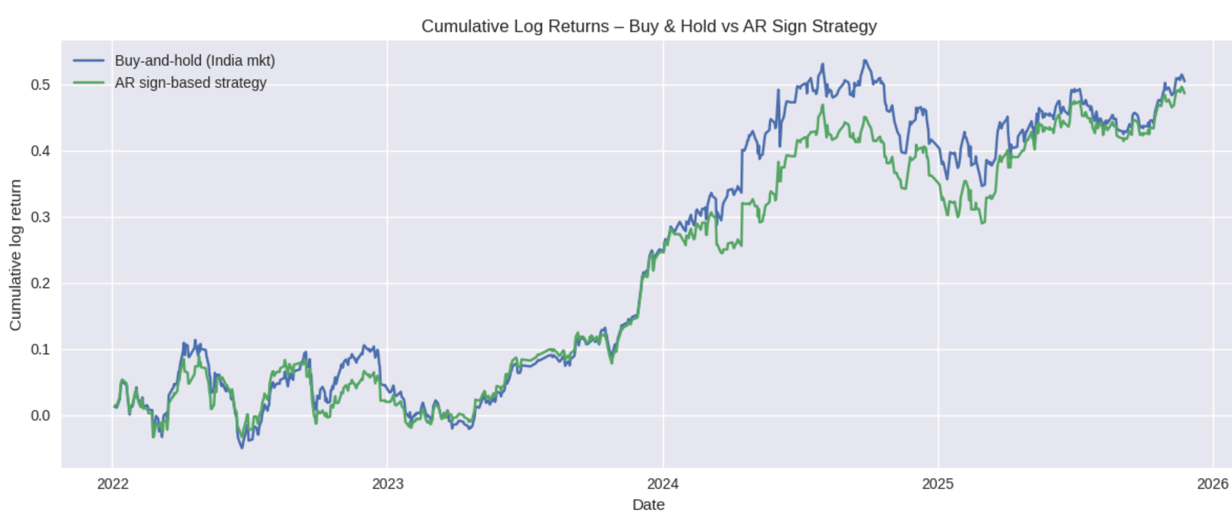

Image 17

4.6.3 MLP models

A multi-layer perceptron (MLP) was then trained using lagged returns as inputs. Two versions were estimated:

1. India-only MLP: uses only lags of the Indian infra index.
2. Global MLP: adds lagged US and European infra returns as additional features.

Daily horizon.
At the daily level, the MLP performs poorly in terms of fit:

1. MLP (India-only): RMSE ≈ 0.0915, $R^2 \approx -0.853$, directional accuracy ≈ 50.3%.
2. MLP (Global): RMSE ≈ 0.1663, $R^2 \approx -0.284$, directional accuracy ≈ 49.7%.

Both models have negative R^2, indicating they are worse than a naïve constant-mean forecast, and their directional accuracies are essentially coin-flip. These daily MLP results therefore do not add much beyond the AR benchmark.

5-day horizon.
When the prediction horizon is extended to 5-day cumulative log returns, the picture improves slightly:

1. 5-day MLP (India-only): RMSE ≈ 0.0253, $R^2 \approx -0.24$, directional accuracy ≈ 55.3%.
2. 5-day MLP (Global): RMSE ≈ 0.0247, $R^2 \approx -0.18$R, directional accuracy ≈ 55.3% (essentially identical to the India-only model).

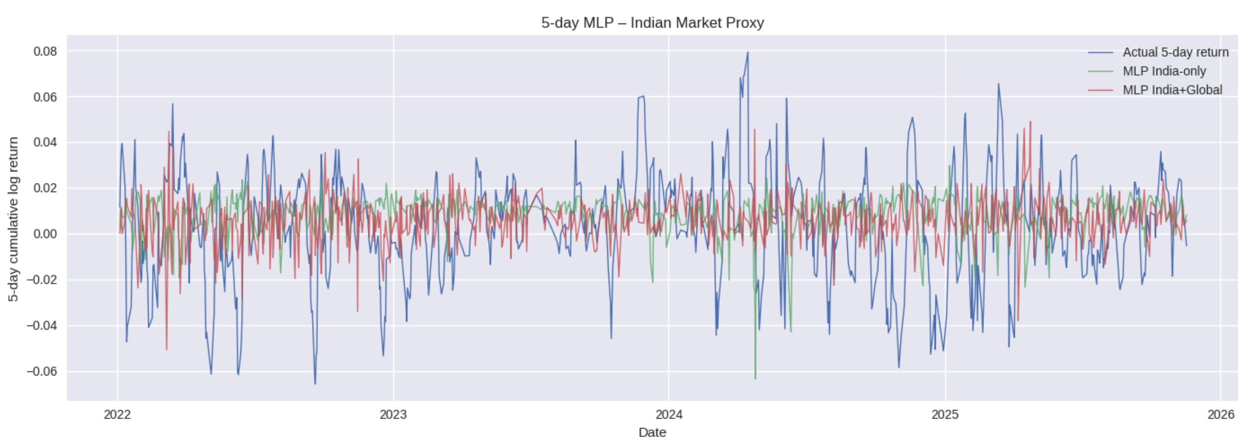

Image 18

The time-series plot in Image 18 shows actual 5-day returns versus both MLP predictions. As with the AR models, the MLP forecasts are much smoother and compressed, but they do manage to get the sign slightly more often than chance. The improvement in RMSE and R^2

when adding global features is modest, and the directional accuracy does not increase; the main gain is that the global variant fits the central part of the distribution a bit better.

4.6.4 LSTM models: regression and classification (5-day horizon)

Given that infra returns may depend on longer histories than a few lags, a recurrent LSTM architecture was estimated on 5-day cumulative returns. Again, two variants were considered:

1. LSTM regression (India-only vs Global): predicts the numeric 5-day return.
2. LSTM classification (India-only vs Global): predicts only the sign (up vs down) of the 5-day return.

Regression results.
For the regression version, the performance summary is:

1. LSTM regression (India-only): RMSE ≈ 0.0296, $R^2 \approx -0.47$, directional accuracy ≈ 53.6%.
2. LSTM regression (Global): RMSE ≈ 0.0269, $R^2 \approx -0.35$, directional accuracy ≈ 53.6%.

So, like the MLP, the LSTM achieves a slight edge in sign prediction but very poor R2R^2R2: the models cannot explain much of the variance in 5-day returns. The time-series plot in Image 19 shows that both LSTM predictions are smoother than the realised series and fail to track large spikes. The scatter plots in Image 20 show a diffuse cloud with almost no slope, especially in the tails, underlining the difficulty of predicting magnitudes.

Classification results.
When the problem is reduced to a binary classification task (predicting only whether the next 5-day return is positive or negative), the LSTM performs somewhat better:

1. LSTM classification (India-only): accuracy ≈ 57.3%.
2. LSTM classification (Global): accuracy ≈ 48.1%.

Thus, the India-only classifier beats the 50% no-skill baseline by about 7 percentage points, while the global version actually underperforms random guessing. Including US and European returns in the LSTM classifier therefore seems to introduce noise rather than useful information for this particular dataset and architecture.

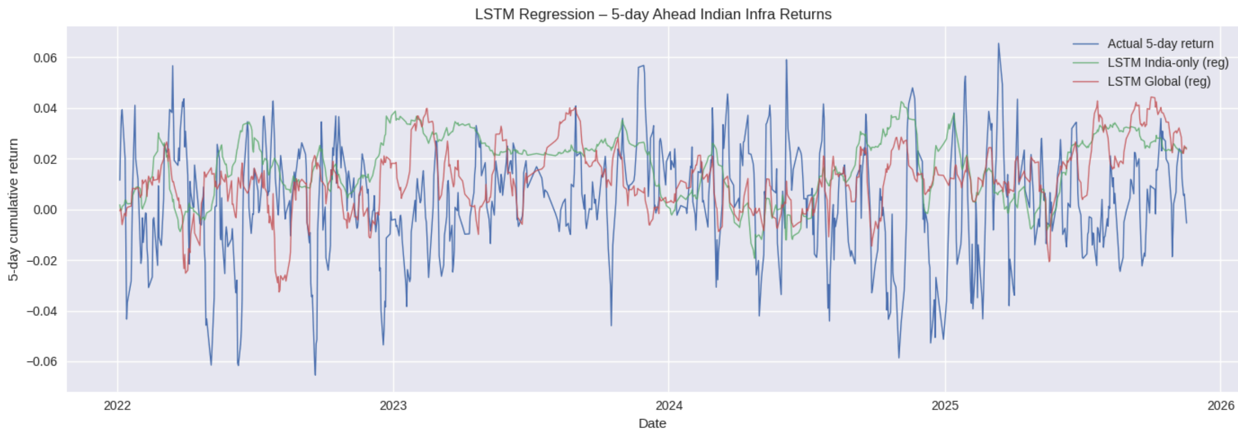

Image 19

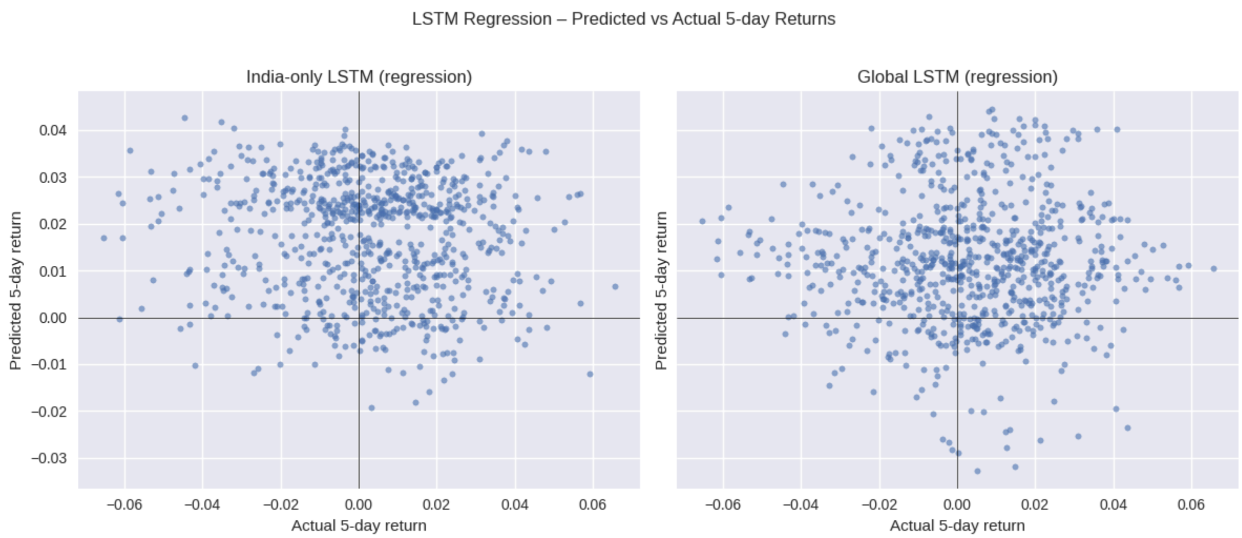

Image 20

5. Managerial Impact

This study has several implications for practitioners who allocate capital to infrastructure, design InvIT/REIT products, manage risk, or shape policy. The empirical results on risk–return characteristics across India, the US and Europe, together with the predictive modelling exercises, offer a reasonably concrete map of where different infra instruments sit on the risk spectrum and how they can be used in practice.

5.1 Portfolio Construction and Asset Allocation

From an asset allocation perspective, the cross-country results suggest that listed infrastructure is not a single homogeneous bucket, but a spectrum. Indian infrastructure stocks behave as high-beta growth exposures: they deliver very strong average returns but at the cost of high volatility, deep drawdowns and betas close to or above one. Indian InvITs and REITs, in contrast, look like lower-volatility, low-beta equity with risk-adjusted performance comparable to or better than the infra ETF. US and European infra and utility names sit somewhere in the middle, with moderate betas and more “mature” return paths.

For a portfolio manager, Indian infra stocks are best treated as a growth sleeve within the equity allocation and sized accordingly, since they can materially increase portfolio risk. Indian InvITs and REITs, by contrast, can be used as stabilising, income-oriented components that still provide exposure to infrastructure but with much smaller swings. US and European infra or utility exposures are well suited for diversifying country-specific risk: their behaviour is close enough to developed-market equities that they can be blended with global equity allocations, but they still bring sectoral diversification. In practice, someone who is building a multi-asset portfolio can combine a relatively small allocation to Indian infra stocks with a more substantial allocation to InvITs/REITs and developed-market infra/utility names to obtain infra exposure that is not overly concentrated in any one risk bucket.

5.2 Product Design and Positioning for InvIT and REIT Sponsors

For InvIT and REIT sponsors, the results help clarify how these vehicles can be positioned to different investor segments. In India, InvITs and REITs have delivered moderate to high returns with markedly lower volatility and beta than infra stocks. This is exactly the profile that long-horizon, liability-driven investors such as pension funds, insurance companies and conservative family offices often seek: equity-linked instruments with relatively stable cash flows and limited drawdowns. The empirical comparison with US MLPs is also useful from a marketing standpoint. While MLPs in the US appear as higher-beta, higher-volatility infra income vehicles, Indian InvITs are closer to “bond-like equity.” Sponsors can use this contrast when speaking to global investors who are familiar with MLPs and REITs, and explain that Indian InvITs sit at a different point on the global infra risk spectrum.

The cross-country comparison of REIT-style vehicles further shows that listed trust structures are already mainstream in developed markets, where they are used as core holdings in income and infra strategies. This gives Indian issuers a data-backed way to argue that InvITs and REITs are not experimental instruments, but part of a globally tested capital-market architecture. The study therefore supports product strategies that emphasise stability, yield and diversification rather than promising aggressive capital gains from InvIT/REIT exposure alone.

5.3 Risk Management and Scenario Analysis

The beta, correlation and rolling-beta results have direct implications for risk managers. In India, InvITs and REITs consistently show lower and more stable betas than infra stocks, while infra stocks themselves have betas around or above one and are tightly correlated with the infra index. This suggests that, in stress testing and capital allocation exercises, shocks to the equity market should be transmitted almost one-for-one to infra stocks, but only partially to InvITs and REITs. Static one-period CAPM estimates are not sufficient, however: the rolling-beta plots reveal that all segments experience periods where their sensitivity to the market changes markedly, especially around major global or domestic events.

Cross-country correlations and the Granger tests indicate that US and European infra returns tend to move ahead of the Indian infra index and contain predictive information at short lags. From a risk-management viewpoint, global infra indices can therefore be treated as leading indicators for Indian infra portfolios, offering an additional lens for monitoring systemic stress. The broader message is that infrastructure assets cannot be treated as automatically defensive; their risk behaviour depends crucially on the specific instrument type and on market regime, and risk systems should reflect this by updating betas and correlation assumptions dynamically rather than relying on static averages.

5.4 Use and Limits of Short-Horizon Prediction Models

The forecasting exercise has more sobering implications for managers hoping to use machine-learning models as stand-alone trading tools in infra markets. Across AR/ARX, MLP and LSTM specifications, the models generally fail to achieve positive R^2 at either daily or five-day horizons, and predicted returns are heavily shrunk toward zero. Some non-linear models do achieve modest improvements in directional accuracy, particularly the five-day MLP and the India-only LSTM classifier, which reach sign prediction rates in the 53–57% range, marginally above both a 50% no-skill benchmark and the AR model. However, these gains are small in absolute terms and do not translate into clear, robust outperformance of buy-and-hold once trading frictions and model uncertainty are taken into account.

For practitioners, this suggests that such models are better used as supplementary signals rather than primary engines for infra trading strategies. For example, an LSTM-based sign indicator could be used as a tilt on top of fundamentally motivated positions, or as one input among several in a broader signal composite, rather than as the sole driver of exposure. The results also highlight the risk of overfitting: performance is highly sensitive to horizon, model specification and feature set, and the global versions do not consistently outperform India-only versions despite strong Granger causality. In practical terms, the real value of these models may lie more in risk-aware timing or regime identification than in precise short-horizon return prediction.

5.5 Policy and Market-Development Implications

Finally, the findings have implications for regulators and policymakers concerned with the evolution of India’s infrastructure financing ecosystem. The evidence that InvITs and REITs in India provide low-beta, income-oriented infra exposure supports efforts to broaden the investor base for these vehicles. Clear and stable tax treatment, supportive listing and disclosure norms, and policies that encourage inclusion of InvITs and REITs in institutional and retail portfolios can help channel long-term capital into infrastructure while offering investors a distinct risk–return profile.

The cross-country comparisons with the US and Europe also underline the role of listed infra vehicles in deep, diversified capital markets. In those regions, REITs, MLPs and infra ETFs are standard tools used by both institutional and retail investors. Continued development and standardisation of the InvIT/REIT regime can help India move in a similar direction and reduce over-reliance on bank-led project finance. At the same time, the weak short-horizon predictability of prices observed in this study is consistent with a reasonably efficient market for listed infra assets. This suggests that policy efforts are likely to be more effective if they focus on transparency, governance, and investor protection rather than trying to engineer predictable price patterns.

Taken together, the managerial impact of the study is to provide a clearer, data-based view of where different infra instruments sit on the risk spectrum across regions, how they can be combined in portfolios, and what can realistically be expected from quantitative models in terms of timing and prediction.

6. Conclusion

This report studied how listed infrastructure assets behave as investments, and how predictable their short-term returns are, across three regions: India, the United States and Europe. The focus was on three main types of instruments—InvITs, REITs (or similar vehicles) and infra/utility stocks—along with their infra or equity indices. On the Indian side, the work combined detailed risk–return analysis of InvITs, REITs and infra stocks with time-series and machine-learning models that tried to predict returns on an Indian infra market proxy. On the global side, similar assets in the US and Europe were used to see how Indian results compare with more mature markets.

For India, the cross-sectional analysis showed a clear separation on the risk spectrum. Infra stocks delivered the highest average returns, but also the highest volatility, large drawdowns and betas close to or above one. They behave like high-beta growth equities. InvITs and REITs, on the other hand, offered moderate to high returns with much lower volatility and very low betas relative to the infra ETF. Their daily returns were less extreme, and their correlation with infra stocks was only moderate. Within a domestic portfolio, they therefore act as lower-risk equity exposure to infrastructure that can reduce overall volatility without completely giving up infra upside.

The US and European results extended this picture. In the US, REITs and infra/utility stocks looked like medium-beta equity sectors, while MLPs were higher-return and higher-volatility, somewhat closer to Indian infra stocks than to Indian InvITs. In Europe, infra/utility stocks and the REIT-type exposure produced returns and alphas above the broad index, with betas and volatility between the Indian and US cases. When all three regions were compared side by side, Indian infra stocks and the Indian infra index were clearly in a strong phase over the sample, with higher absolute returns than US and European peers. On a risk-adjusted basis, however, European infra and the REIT proxy often looked competitive, and US infra assets appeared more conservative. Across regions, trust- and REIT-style vehicles generally had lower beta and smaller drawdowns than infra stocks, but still contributed meaningfully to returns. This makes them useful as a separate building block in infra portfolios.

The second part of the report looked at short-horizon prediction of Indian infra returns. Several models were tried: simple AR and ARX time-series models, and non-linear MLP and LSTM models, at daily and five-day horizons. Both India-only and “global” versions were estimated, where the global version included lagged US and European infra returns as extra inputs. Granger causality tests showed that both US and European infra returns carry statistically significant information about future Indian infra returns at daily lags. But in practice, the forecasting models found it hard to turn this into strong predictive performance. At both daily and five-day horizons, most regression models produced forecasts that were heavily shrunk towards zero and had negative R^2, meaning they did not beat a simple constant-mean benchmark in explaining return sizes.

Some non-linear models did slightly better in predicting the direction of returns. The five-day MLP and the India-only LSTM classifier achieved sign prediction accuracies in the mid-50% range, which is a bit better than both a 50% coin flip and the AR benchmark. However, these gains were small and sensitive to the exact model and horizon, and adding global features did not consistently help. In the LSTM classification case, adding US and European inputs actually made performance worse. Overall, the forecasting results suggest that short-horizon Indian infra returns behave close to an efficient process: there is a small amount of structure that models can pick up, but it is weak and not enough to support aggressive trading strategies by itself.

Putting everything together, the main contribution of this dissertation is to provide a clear, data-based picture of how listed infra assets behave across regions and types, and what realistic limits exist on short-term predictability. InvITs, REITs and infra/utility stocks are not interchangeable; they sit at different points on the risk–return spectrum and play different roles in a portfolio. At the same time, their prices are hard to forecast at short horizons, even with modern machine-learning models. The results are therefore more useful for understanding where these instruments fit in an investor’s toolkit than for promising any “holy grail” trading strategy.

6.1 Future Scope

There are several ways in which this work can be extended and improved in the future.

First, the dataset can be expanded and refined. On the cross-sectional side, future studies could include more InvITs and REITs as the Indian market grows, and add more infra and REIT names from Europe and other regions such as Asia-Pacific. On the time-series side, using longer histories, especially for US and European data would allow a closer look at how these assets behaved across multiple full cycles and crises. It would also be useful to rely more consistently on total-return series that fully account for distributions, so that yield and capital gains can be disentangled more clearly.

Second, the risk–return analysis can move beyond the simple CAPM to richer factor and macro models. This could mean testing multi-factor models that include market, size, value, term-structure and credit-spread factors, or linking infra returns to macro variables such as interest rates, inflation, policy announcements and commodity prices. Such models could help explain why some infra segments or regions deliver higher alphas than others, and would give risk managers better tools for scenario analysis and stress testing.

Third, there is room to explore other prediction horizons, models and objectives. This thesis focused on daily and five-day returns. Future work could examine medium-term horizons, such as one or three months, where fundamentals and macro variables may matter more. Other model families, such as temporal convolutional networks, attention-based models, or hybrids that mix traditional factors with learned features could also be tried, with careful controls to avoid overfitting. It might also be more useful to frame prediction as a decision or portfolio problem from the start, where the model is trained to maximise a risk-adjusted objective under transaction costs, rather than just minimising RMSE.

Finally, there is a natural extension in combining market data with fundamental and text data. This could involve adding firm-level information (such as leverage, credit ratings, asset mix and concession details), regulatory changes, or NLP-based indicators extracted from filings and news. Such a combined dataset would likely improve our understanding of why certain InvITs, REITs or infra stocks behave more defensively or more cyclically, and may add predictive power at longer horizons. As the Indian InvIT and REIT space develops and more data become available, this type of richer, integrated analysis can help investors, issuers and policymakers better understand how infrastructure risk is being priced and how capital markets can support infrastructure development in a more efficient and transparent way.

7. References

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