Evaluating Asset Pricing Models in the Indian Stock Market

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Abstract

This report compares and contrasts the performance of the three most well-established asset pricing models — the Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), and the Fama-French Three-Factor Model — on three of India's largest firms: HDFC Bank, Infosys, and Reliance. All three models are estimated separately based on monthly data available from March 2012 to March 2025. The results suggest that multi-factor models, in particular the Fama-French, are better in terms of explanatory power than CAPM in the Indian market context.

Introduction

Asset pricing models form the backbone of financial economics, helping investors and analysts understand the relationship between risk and expected return. This project aims to examine the practical effectiveness of three major asset pricing models—Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), and the Fama-French Three-Factor (FFF) model—within the Indian stock market. Here three representative stocks (Monthly) from different sectors from March-2012 to March-2025 : Infosys (IT), Reliance Industries (Energy), and HDFC Bank (Banking) are used for comparative analysis.

Background

Asset pricing models are foundational tools in finance, aiming to capture the relationship between expected returns and various risk factors. The Capital Asset Pricing Model (CAPM), introduced in the 1960s by Sharpe, Lintner, and Mossin, links expected returns to a single factor—market risk—represented by the excess market return. Despite its elegance, CAPM often falls short empirically, especially in explaining cross-sectional stock returns.

In response, Ross proposed the Arbitrage Pricing Theory (APT) in 1976. APT allows multiple systematic factors, such as inflation, interest rates, and exchange rates, offering a more flexible framework. However, it lacks explicit guidance on factor selection.

Fama and French (1993) extended CAPM by introducing the Three-Factor Model, adding:

- **SMB (Small Minus Big)**: capturing the size premium.
- **HML (High Minus Low)**: capturing the value premium.

These factors improved model performance in developed markets and showed varying effectiveness in emerging markets like India.

Given India's dynamic financial landscape—marked by policy changes, macroeconomic shifts, and growing participation—this study compares CAPM, APT, and Fama-French models using Indian equities to identify the most explanatory framework for observed returns.

This project attempts a comprehensive empirical analysis of CAPM, APT, and the Fama-French 3-Factor Model on selected Indian stocks — HDFC Bank, Infosys, and Reliance Industries — using data from March 2012 to March 2025. The goal is to assess which model best explains observed returns and to provide insights into the risk factors driving Indian stock performance.

Objectives

The project's objective is to analyze the monthly returns of Infosys, Reliance, and HDFC Bank using CAPM, APT, and Fama-French 3-Factor models. These involves:

- Quantifying their risk exposures (market, macroeconomic, size, value).
- Determining if they generated "Alpha" (returns beyond expected risk compensation) for each stock across all three asset pricing models.
- Comparing which model best explains their returns.
- Providing insights for investors on risk management and performance evaluation.

Literature Review

"Empirical evidence of conditional asset pricing in the Indian stock market" by Das [1](2015) explores the performance of conditional versus unconditional versions of CAPM and the Fama-French three-factor model in the Indian equity market. Using a Kalman filter approach to estimate dynamic betas, the study finds that conditional models — which incorporate macroeconomic information — provide better explanations of return variation than their static counterparts. Size and book-to-market ratios are identified as key firm characteristics influencing returns. The findings suggest that investors actively use prior beliefs and market information to estimate expected returns, and that the conditional Fama-French model effectively captures multiple types of risk, reinforcing its empirical relevance in emerging markets like India.

"Indian Stock Market and the Asset Pricing Models" by Harshita et al.[3](2015) evaluates the performance of the Capital Asset Pricing Model (CAPM), Fama-French three-factor, and five-factor models in the context of the Indian stock market. Using 15 years of data (1999–2014) from companies listed in the CNX 500 index, the authors construct portfolios based on firm characteristics like size, book-to-market ratio, profitability, and investment. Through time-series hierarchical multiple regression, they find that the three-factor model consistently outperforms CAPM in explaining return variations. The five-factor model performs best specifically for portfolios sorted by profitability and investment, while a four-factor version (excluding investment) provides the most parsimonious explanation for other portfolio sorts. The study concludes that extended factor models offer superior explanatory power in emerging markets like India, aligning with global evidence while highlighting unique regional return patterns.

"Comparison of the Applicability of CAPM and Fama-French Model in Different Regions" by Xiao [8](2022) investigates how CAPM and the Fama-French Three-Factor Model perform across global regions with varying market development stages. The study reveals that in developing Asian markets—like China, India, Indonesia, and Sri Lanka—the Fama-French model consistently outperforms CAPM by better capturing size and value effects. In Europe and the U.S., results are mixed: although the Fama-French model generally provides higher explanatory power, in some cases (e.g., during certain periods in the U.S.), CAPM performs comparably. The paper highlights that model effectiveness often depends on market structure, investor behavior, and data period. The author concludes that while both models retain explanatory power, the Fama-French model is preferred in most cases, especially in emerging economies, and recommends selecting pricing models based on regional characteristics rather than one-size-fits-all.

"Model Comparison between CAPM and APT: With focus on application of Factor Models" by Wu [7](2022) systematically compares the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) with a specific focus on their practical application. The paper highlights that while CAPM is simpler and easier to estimate, it is limited by strict assumptions like a positive market premium and the presence of a risk-free asset, which may not always hold in real-world scenarios—especially during crises or negative return periods. In contrast, APT provides greater flexibility by allowing multiple risk factors and does not require a positive market premium, making it more adaptable across time horizons and market conditions. However, APT's implementation demands more effort in selecting relevant macroeconomic factors and accurately estimating sensitivities. The study emphasizes that APT is better suited for markets with sufficient asset variety and when more granular risk decomposition is needed, while CAPM may be effective in stable, efficient markets. Wu concludes that model choice should depend on data availability, market structure, and research objectives, and recommends careful exploratory analysis before empirical application.

"Research on the Financial Model Selection Between Capital Asset Pricing Model, Arbitrage Pricing Model, and Fama-French Model" by Botao Huang et al.[4] (2023) investigates the comparative strengths and applicability of three foundational asset pricing models: CAPM, APT, and the Fama-French three-factor model. The paper emphasizes that while CAPM is conceptually elegant and forms the basis of modern asset pricing, it is built on strong assumptions (like linearity and market equilibrium) that may not hold in real markets. In contrast, APT allows for multiple risk factors and avoids the rigidity of CAPM, but lacks a clear specification of which factors to include. The Fama-French model incorporates size and value factors, offering a more concrete structure that aligns with market observations. Using theoretical discussion, empirical comparisons (including tests on the Chinese SME and ChiNext Boards), and secondary data analysis, the paper finds that no model universally dominates — CAPM performs better in stable, large-cap scenarios, while APT and FFM are preferred in high-risk or multi-factor environments. The study concludes that model selection should depend on investor context, factor relevance, and data availability, rather than relying on a one-size-fits-all solution.

"Risk-Return Analysis of Equity Portfolios: Comparison Between CAPM and Fama-French Three Factor Model" by Ziyan Tang[6] (2024) presents an empirical comparison between CAPM and the Fama-French (F-F) three-factor model using daily return data of 16 major US stocks from 11 industries, covering the period 2012–2021. The study uses OLS regression to estimate model parameters and evaluates performance using R^2, beta coefficients, and residual diagnostics. The CAPM is found to have low explanatory power (low R^2) despite significant beta values, while the F-F model shows higher R^2 and statistically significant SMB and HML factors for many stocks, offering a more accurate fit. The paper also conducts robustness checks across different time periods (5-year and 3-year) and portfolio construction methods (equal-weighted, value-weighted, risk-based), consistently confirming the superior performance of the F-F model. However, the F-F model's complexity and data requirements are noted as practical trade-offs. The study concludes that while F-F provides more reliable risk-return insights, model choice should consider both accuracy and usability.

"Asset Pricing Test Using Alternative Sets of Portfolios: Evidence from India" by Sudipta Das[2] (2019) examines how the choice of test portfolios influences the performance evaluation of asset pricing models in the Indian market. Instead of traditional size and book-to-market sorted portfolios, the study constructs three alternative sets based on firm beta, volatility, and a clustering method. Using both unconditional and conditional models, the paper finds that model performance and risk premium estimates are highly sensitive to the type of sorting criteria used. Notably, the conditional models offer superior explanatory power for average return variations compared to unconditional models. The study concludes that asset pricing tests should consider alternative portfolio construction methods for a more robust evaluation of model validity, especially in emerging markets like India.

"Commodity and Stock Market Interlinkages: Opportunities and Challenges for Investors in Indian Market" by Jhunjhunwala and Suresh[5] (2020) explores the dynamic relationship between the Indian commodity and equity markets, particularly in the context of investment opportunities and risk diversification. Using correlation and co-integration analysis on monthly data from 2005 to 2018, the study finds that commodity and stock markets in India are weakly correlated in the short run, suggesting diversification benefits. However, during periods of economic stress or volatility (e.g., 2008 crisis), the linkage between markets strengthens, reducing diversification advantages. The authors also examine sectoral stock indices and commodity groups (like energy and metals), revealing varying levels of interdependence. The study

concludes that while commodities can enhance portfolio diversification under normal conditions, investors must account for time-varying correlations and macroeconomic events when making asset allocation decisions in India.

Methodology

This study uses a quantitative approach to evaluate CAPM, APT, and Fama-French models on three Indian stocks: Infosys, Reliance, and HDFC Bank, from March 2012 to March 2025.

1. **Stock Selection :** Three diversified, large-cap firms were chosen:
   - Infosys (IT Sector)
   - Reliance Industries (Energy Sector)
   - HDFC Bank (Banking Sector)
2. **Data Collection :**
   - Monthly adjusted stock prices: Yahoo Finance
   - Risk-free rate: 91-day T-Bill yields (RBI)
   - Fama-French factors: Indian dataset from IIM Ahmedabad (https://faculty.iima.ac.in/iffm/Indian-Fama-French-Momentum)
   - APT factors: CPI, interest rate, industrial production, exchange rate (from MoSPI, FRED, DBIE, and Yahoo Finance)
3. **Preprocessing :**
   - Returns: $R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$ Where:
     - $R_{i,t}$: Return of asset i at time t
     - $P_{i,t}$: Price of asset i at time t
     - $P_{i,t-1}$: Price of asset i at time $t-1$
   - Excess returns: $R_{i,t}^{excess} = R_{i,t} - R_{f,t}$ Where:
     - $R_{i,t}^{excess}$: Excess return of asset i over the risk-free rate at time t
     - $R_{f,t}$: Risk-free rate at time t, typically proxied by 91-day Treasury Bill yield
   - Data aligned monthly; missing values interpolated or dropped.
4. **Model Specifications :**
   - **CAPM:**

     $$R_{i,t}^{excess} = \alpha_i + \beta_i R_{m,t}^{excess} + \epsilon_{i,t}$$

     Where:
     - $R_{i,t}^{excess}$: Excess return of stock i at time t
     - $R_{m,t}^{excess}$: Excess market return ($R_m - R_f$)
     - β_i: Sensitivity of stock i to market return (systematic risk)
     - α_i: Abnormal return (unexplained by the model)
     - $\epsilon_{i,t}$: Error term

- **Fama-French 3-Factor Model:**

$$R_{i,t}^{excess} = \alpha_i + \beta_{m,i} R_{m,t}^{excess} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \epsilon_{i,t}$$

  Where:

  - SMB_t: Size factor (Small Minus Big)
  - HML_t: Value factor (High Minus Low)
  - $\beta_{SMB,i}, \beta_{HML,i}$: Sensitivities to size and value factors
  - Other terms same as CAPM

- **Arbitrage Pricing Theory (APT):**

$$R_{i,t}^{excess} = \alpha_i + \sum_{k=1}^{4} \beta_{k,i} F_{k,t} + \epsilon_{i,t}$$

  Where:

  - $F_{k,t}$: Value of k^{th} macroeconomic factor at time t (e.g., inflation, interest rate, IIP, exchange rate)
  - $\beta_{k,i}$: Sensitivity of stock i to factor k
  - α_i: Abnormal return unexplained by macro factors

5. **Evaluation Criteria :**
   - Adjusted R^2, p-values, and t-statistics
   - Residual diagnostics: homoscedasticity, normality
   - Visual fit: actual vs predicted returns
   - Rolling regression (36-month beta trends)

Implementation

All models were implemented in Python (Google Colab) using standard data science tools.

1. **Libraries:**
   - `pandas, numpy, statsmodels, matplotlib, seaborn`.
   - Data validated in Excel before regression analysis.
2. **Data Handling:**
   - Monthly return calculation from adjusted close prices.
   - Merged with Fama-French and macroeconomic datasets on date index.
   - Converted percentage formats to decimals.
3. **Models Execution:**
   - **CAPM:**
     - Linear regression of excess returns on market excess return.
     - Used robust standard errors (HC1) for heteroscedasticity.
     - Diagnostic plots: residual vs fitted, KDE, rolling beta (36-month).

- **Fama-French:**
  - Multivariate regression with excess market, SMB, and HML.
  - Used robust standard errors (HC1) for heteroscedasticity.
  - Diagnostics included residual plots, actual vs predicted, rolling betas (36-month).
- **APT:**
  - Computed monthly shocks: FX, CPI, IIP, Interest rates.
  - Used robust standard errors (HC1) for heteroscedasticity.
  - Multiple regression of excess return on macro factor shocks.
  - Examined residual distribution, time-series plots, rolling betas (36-month).

Results and Analysis

This section presents the empirical results and visual analyses for each asset pricing model—CAPM, Fama-French Three-Factor (FFF), and Arbitrage Pricing Theory (APT)—applied to three Indian stocks: Infosys, Reliance Industries, and HDFC Bank. The analysis is based on monthly data from March 2012 to March 2025.

CAPM Model :

1. **Dataset Snapshot after Preprocessed** :

Date	**INFY.NS**	**INFY_Return**	**Excess_Market**	**Risk-Free Rate**	**Excess_INFY**
2012-03	260.9986	-0.00595	-0.0312	0.00712	-0.0131
2012-04	224.193	-0.14102	-0.0154	0.007103	-0.1481
2012-05	221.211	-0.01330	-0.06366	0.00688	-0.0202
2012-06	229.459	0.0373	0.04897	0.006336	0.03094
2012-07	203.648	-0.1124	-0.01658	0.00695	-0.1194

Table 1: Sample of merged final dataset for INFOSYS Stock

Date	**RELIAN.NS**	**RELI_Return**	**Excess_Market**	**Risk-Free Rate**	**Excess_RELI**
2012-03	166.198	-0.08547	-0.0312	0.00712	-0.0926
2012-04	164.9804	-0.00733	-0.0154	0.007103	-0.0144
2012-05	156.234	-0.0530	-0.06366	0.00688	-0.05989
2012-06	163.375	0.04571	0.04897	0.006336	0.039369
2012-07	164.648	0.00779	-0.01658	0.00695	0.000840

Table 2: Sample of merged final dataset for RELIANCE Stock

Date	**HDFC.NS**	**HDFC_Return**	**Excess_Market**	**Risk-Free Rate**	**Excess_HDFC**
2024-11	1796.050	0.03477	-0.007321	0.004984	0.02979
2024-12	1772.8499	-0.01292	-0.0197055	0.005510	-0.01843
2025-01	1698.75	-0.041797	-0.050489	0.005436	-0.047234
2025-02	1732.40	0.019808	-0.1127084	0.00482	0.014989
2025-03	1828.199	0.055299	0.07017	0.004831	0.050468

Table 3: Sample of merged final dataset for HDFCBANK Stock

2. **Regression Results :**

- **For Infosys:**
  - $\alpha = 0.0049$ (not significant, $p = 0.380$), $\beta = 0.5598$ — less sensitive to market fluctuations.
  - $R^2 = 10.9\%$, F-statistic $= 22.75$ ($p < 0.001$).
  - Residuals fail normality (JB with $p = 5.39 \times 10^{-5}$), Durbin-Watson $= 2.02$ means no autocorrelation.

  The relatively low R^2 and adjusted R^2 score ($= 0.103$) suggests that while the market explains some variation in Infosys' returns, additional factors may be necessary (e.g., size and value factors from the Fama-French model or macroeconomic factors from APT) to improve explanatory power.

- **Graphs and Diagnostics**

Figure 1: Scatter plot of Excess Market Return vs Excess Infosys Return. This plot shows a positive linear trend, indicating that Infosys' excess return is positively related to the market excess return.

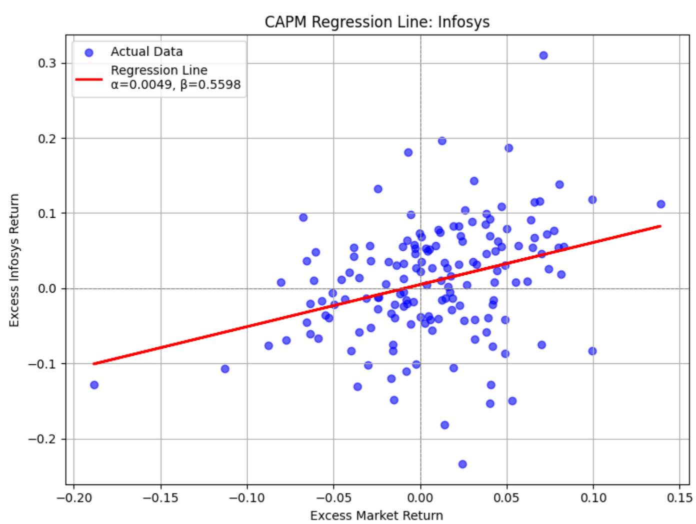

Figure 2: Regression Fit

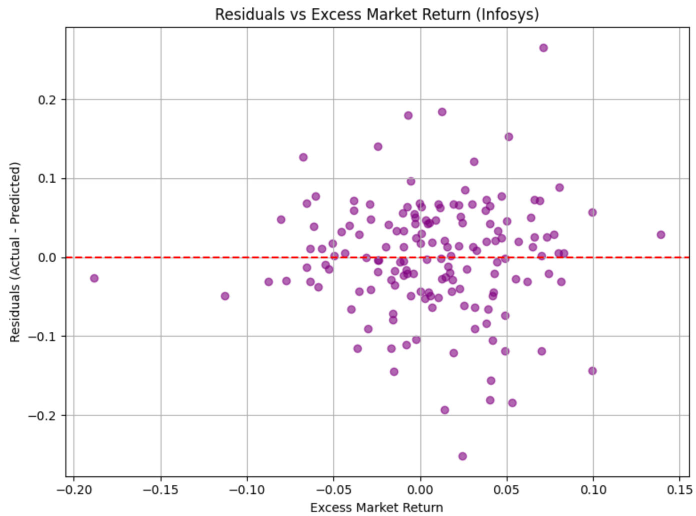

Figure 3: Residuals vs Excess Market Return for Infosys, a random scatter around zero which indicating no clear pattern, thus supporting the linearity assumption.

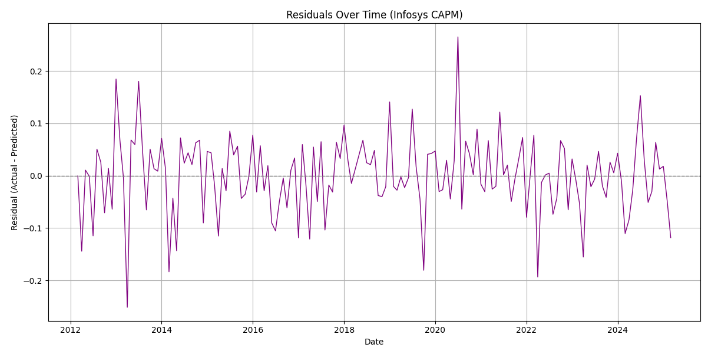

Figure 4: Residuals over time for Infosys under the CAPM model. The randomness around the zero line supports the assumption of no autocorrelation in residuals.

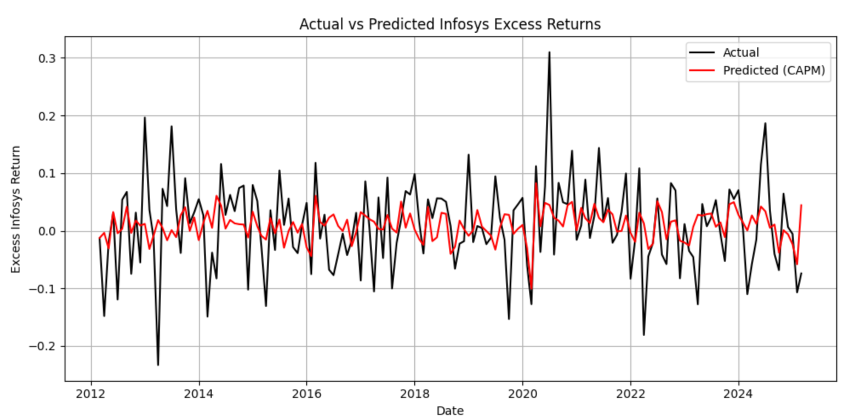

Figure 5: The plot compares actual and predicted excess returns under CAPM, showing that the model captures overall trends but underestimates sharp fluctuations, indicating limited predictive strength.

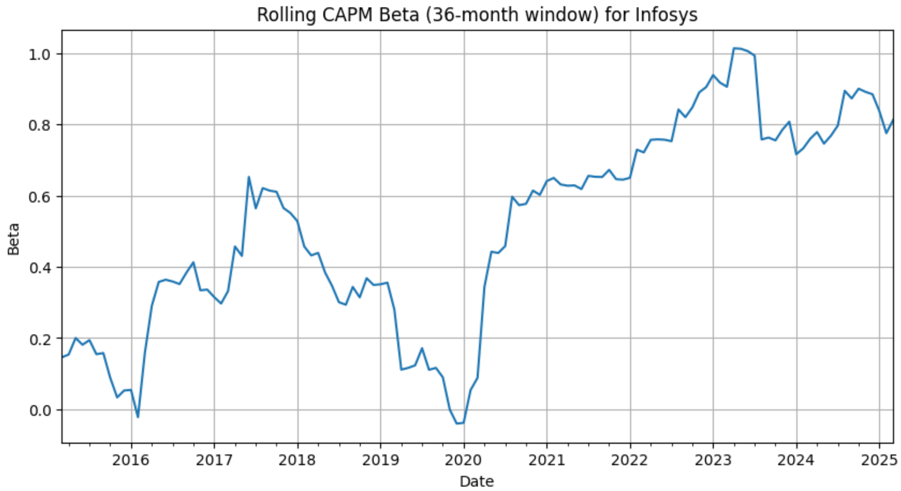

Figure 6: Rolling CAPM Beta (36-month window) for Infosys. The dynamic movement of beta over time suggests changing market sensitivity and evolving risk exposure.

- **For Reliance:**
  - $\alpha = 0.0022$ (not significant), $\beta = 1.0482$ — strong market sensitivity.
  - $R^2 = 39.7\%$, significant regression ($p < 10^{-13}$).
  - Residuals are approximately normal (JB with $p = 0.123$), Durbin-Watson = 1.96.

  Overall, the CAPM shows a strong and statistically significant relationship between Reliance's excess returns and market excess returns, with a relatively high beta, indicating greater sensitivity to market movements.

- **Graphs and Diagnostics**

Figure 7: Scatter plot shows a positive relationship between excess market return and excess Reliance return, indicating that Reliance's performance generally moves in line with the broader market.

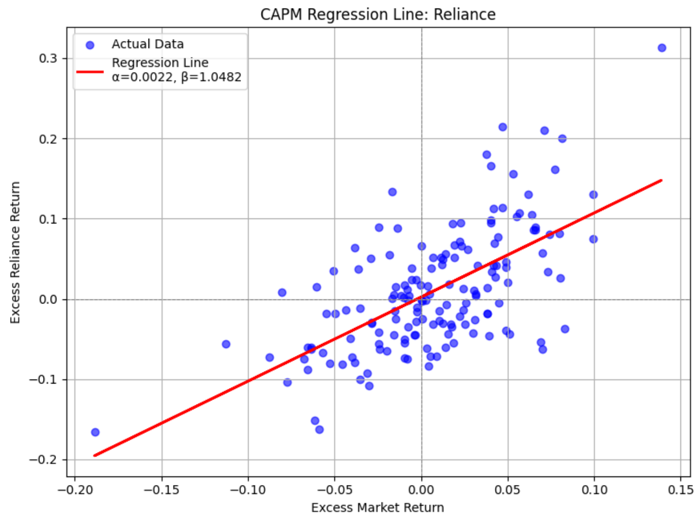

Figure 8: Regression Fit

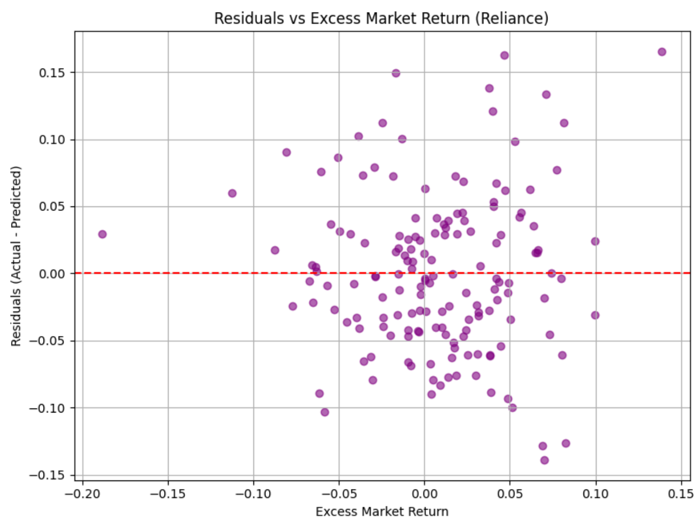

Figure 9: The residuals plot for Reliance shows no clear pattern against excess market return, suggesting that the linear model's assumptions hold reasonably well.

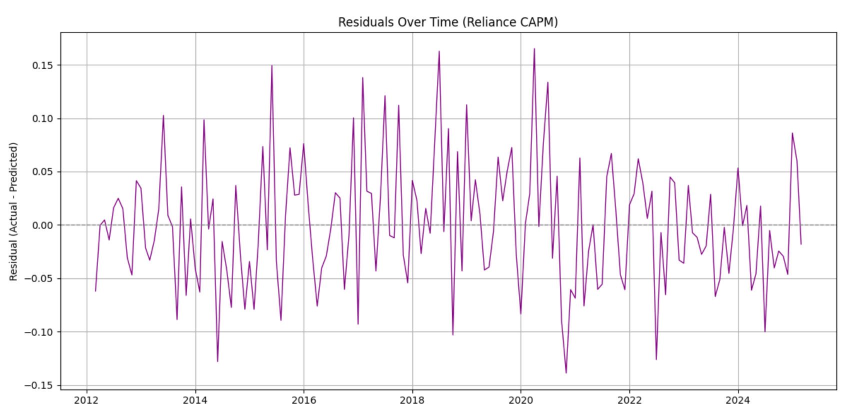

Figure 10: The residuals over time for Reliance under CAPM show random fluctuations around zero, indicating no clear temporal pattern or autocorrelation.

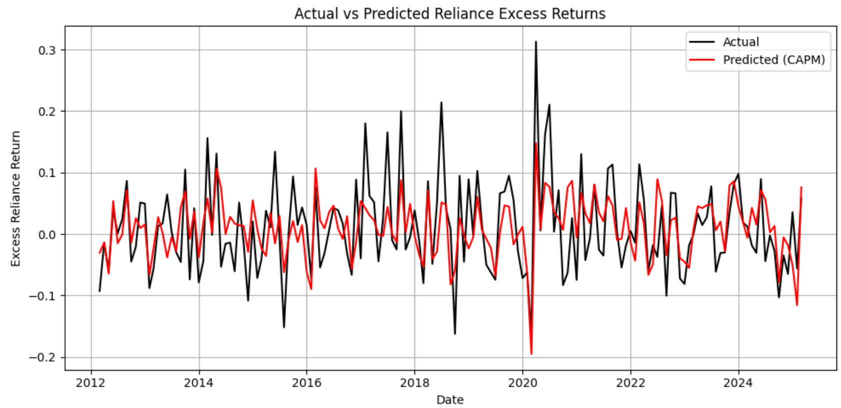

Figure 11: The CAPM model captures the general trend of Reliance's excess returns over time, though some deviations between actual and predicted values are observed.

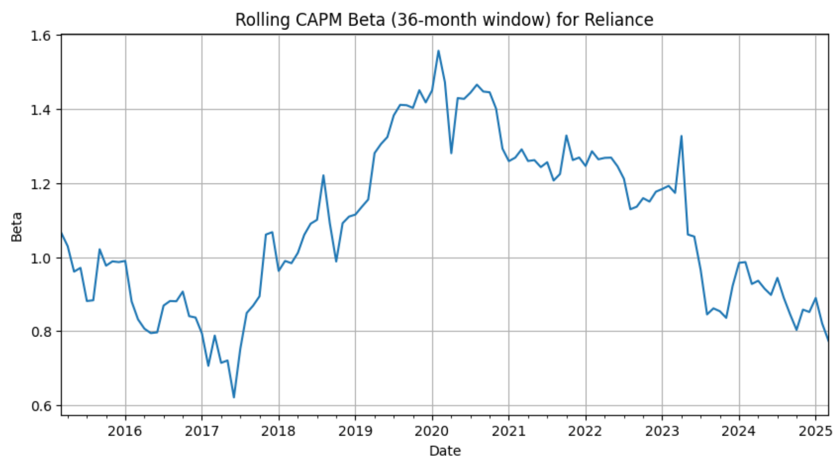

Figure 12: The rolling 36-month CAPM beta for Reliance shows significant variation over time, reflecting changing sensitivity to market movements.

- **For HDFC Bank:**
  - $\alpha = 0.0038$, $\beta = 0.8149$ — moderate market responsiveness.
  - $R^2 = 37\%$, highly significant model.
  - Residuals fail JB normality test, Durbin-Watson = 2.21.

  Overall, the CAPM provides a reasonably good fit for HDFC Bank, capturing a significant portion of its return behavior relative to the market, although some assumptions of the classical linear model are moderately violated.
- **Graphs and Diagnostics**

Figure 13: Scatter plot shows a strong positive relationship between excess market return and excess HDFC return, indicating that HDFC's performance is closely aligned with market movements.

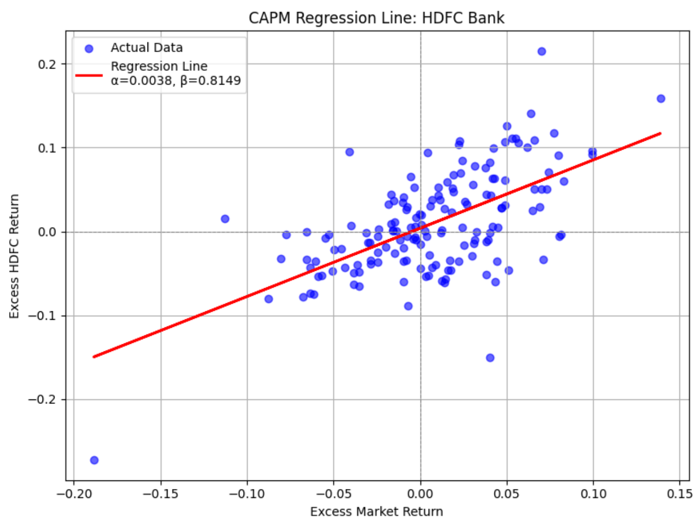

Figure 14: Regression Fit

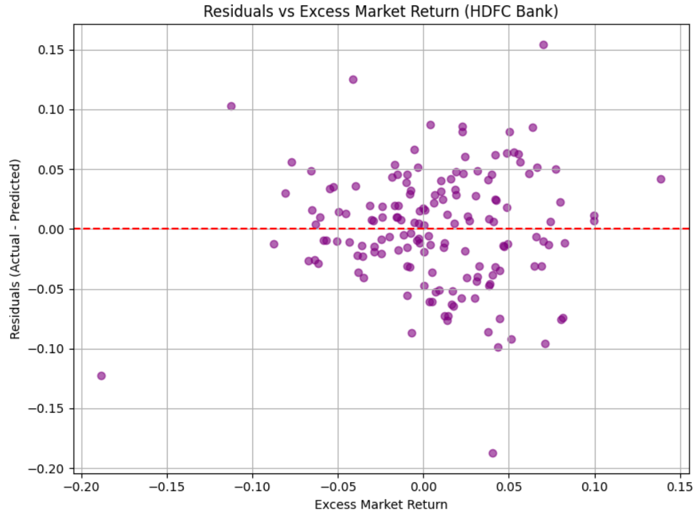

Figure 15: Scatter plot of Residuals vs Excess_Market_Return shows that the residuals are randomly scattered around zero, indicating that the linear model's errors have constant variance and no clear pattern, thus validating the assumption of homoscedasticity.

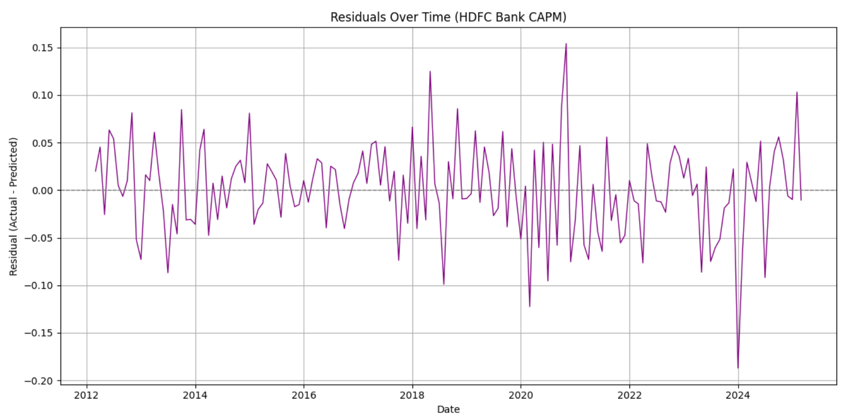

Figure 16: Line plot of residuals for HDFC Bank shows no consistent upward or downward trend over time, supporting the assumption that the residuals are temporally uncorrelated and that the model errors are stable across the years.

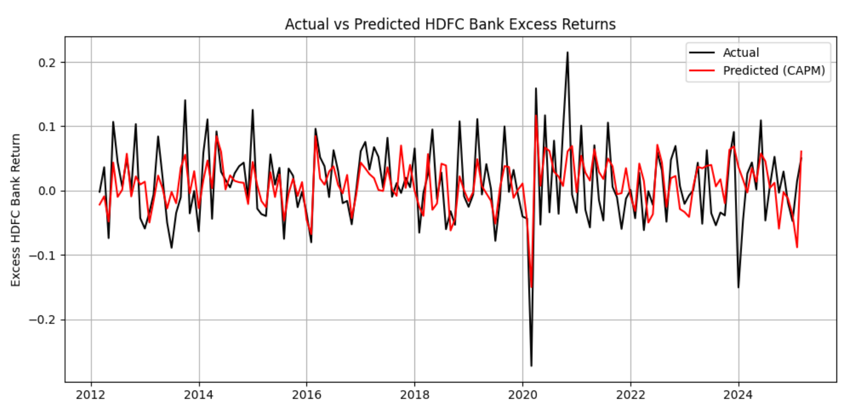

Figure 17: This line plot compares the actual and CAPM-predicted excess returns of HDFC Bank over time, showing that the predicted values closely follow the actual trend, indicating a reasonably good fit of the model.

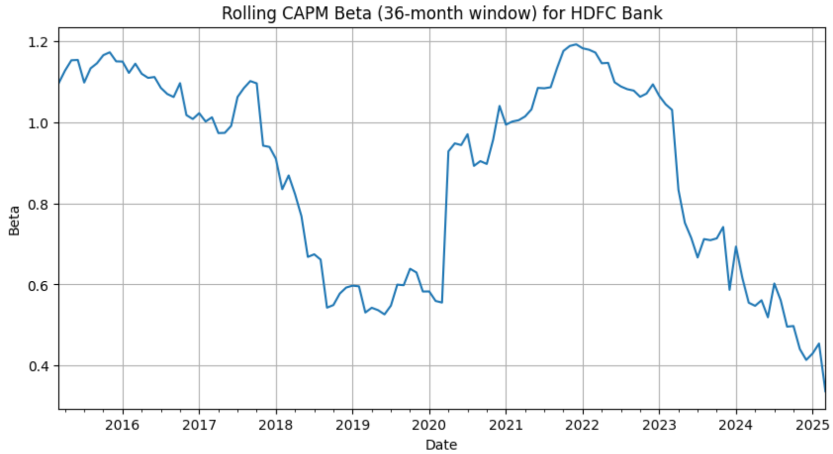

Figure 18: Rolling 36-month CAPM beta shows how HDFC Bank's sensitivity to market movements has evolved over time, with a post-2022 decline indicating reduced systematic risk relative to the market.

Fama French 3-Factor Model :

1. **Dataset Snapshot after Preprocessed**:

Date	SML	HML	Excess_Market	Excess_INFY	Excess_RELI	Excess_HDFC
2012-03	0.01439	-0.0462	-0.0312	-0.01307	-0.0926	-0.001802
2012-04	0.0393	-0.0283	-0.0154	-0.1481	-0.0144	0.036467
2012-05	-0.0027	-0.03758	-0.06366	-0.0202	-0.05989	-0.07379
2012-06	0.000345	-0.01173	0.04897	0.03094	0.039369	0.106958
2012-07	0.02107	-0.04172	-0.01658	-0.1194	0.000840	0.04422

Table 4: Sample of merged final dataset for Infosys, Reliance, and HDFC Bank stocks

2. **Regression Results :**

- **For Infosys:**
  - $\alpha = 0.0062$ (not significant, $p = 0.243$), $\beta_m = 0.8892$ (significant), $\beta_{SMB} = -0.1262$ (NS), $\beta_{HML} = -0.5178$ (significant, $p = 0.001$).
  - $R^2 = 19.8\%$, Adjusted $R^2 = 18.2\%$, F-statistic $= 12.73$ ($p = 1.79 \times 10^{-7}$).
  - Jarque-Bera test = 6.875 ($p = 0.0321$) — residuals deviate from normality.
  - Durbin-Watson = 1.933 — indicates no autocorrelation.

  Overall, the Fama-French 3-Factor model captures some of the systematic behavior of Infosys' returns, with market and value factors playing a notable role. However, the relatively low R^2 and insignificance of the alpha and SMB factor suggest that additional influences may be driving Infosys' return dynamics beyond those included in the FFF framework.

- **Graphs and Diagnostics**

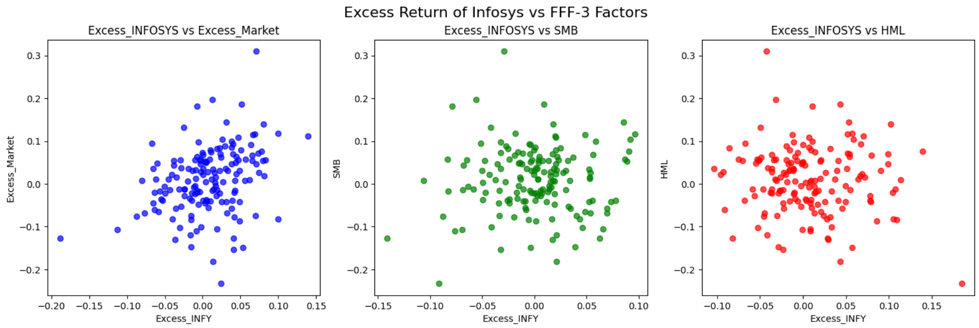

Figure 19: Scatter plots of Infosys excess returns against Fama-French 3 factors. Infosys shows a clear positive relationship with the market excess return, but no strong pattern with size (SMB) or value (HML) factors.

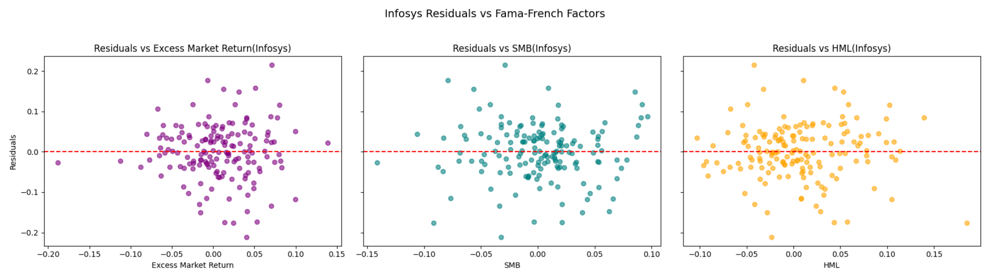

Figure 20: The residual plots for Infosys confirm that the Fama-French 3-factor model does not leave any systematic patterns unexplained. The randomness of residuals across all three factors supports the model's adequacy and indicates that the linear assumptions of the regression hold true.

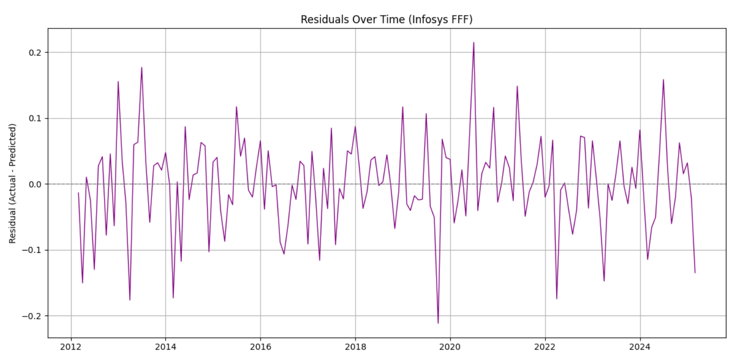

Figure 21: The residuals of the Fama-French model for Infosys fluctuate randomly over time, indicating no clear pattern or autocorrelation.

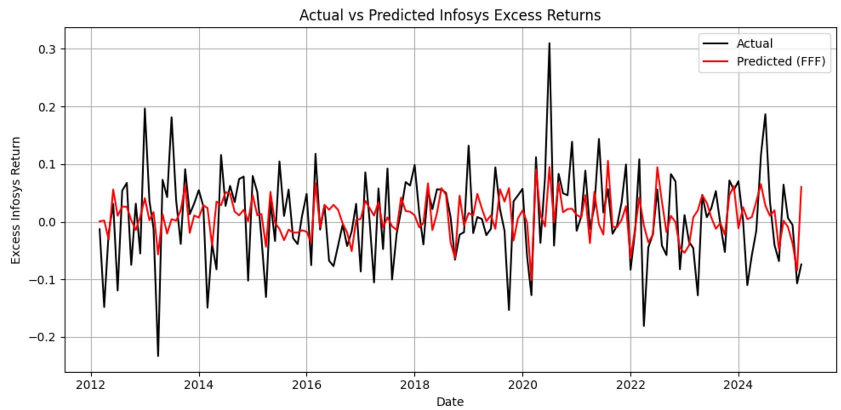

Figure 22: The Fama-French model closely tracks the overall trend of Infosys' excess returns but struggles to capture sharp fluctuations.

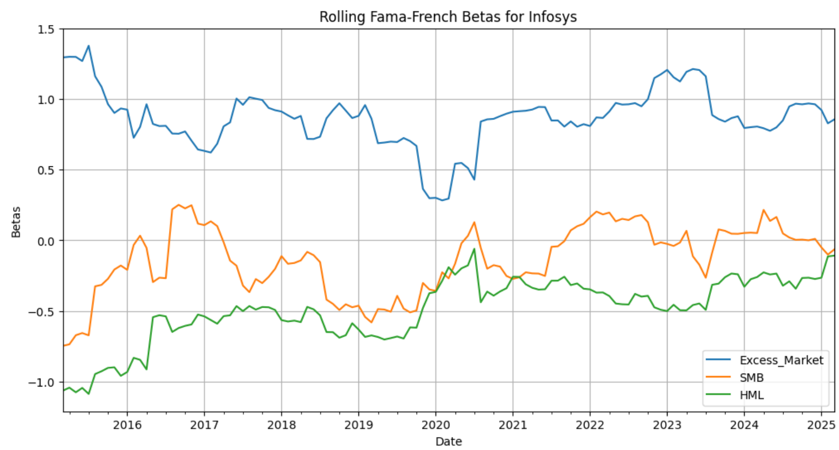

Figure 23: This graph shows the rolling Fama-French factor betas for Infosys over time, where the beta for the market (Excess_Market) remains positive and relatively stable, while the SMB (size) and HML (value) betas fluctuate more, indicating varying sensitivity to small-cap and value/growth factors across the years.

- **For Reliance:**
  - $\alpha = 0.0017$ (not significant, $p = 0.689$), $\beta_m = 1.2065$ (significant), $\beta_{SMB} = -0.4882$ (significant), $\beta_{HML} = -0.0193$ (NS).
  - $R^2 = 46.4\%$, Adjusted $R^2 = 45.3\%$, F-statistic = 30.29 ($p = 1.98 \times 10^{-15}$).
  - Jarque-Bera test = 4.240 ($p = 0.120$) — residuals approximately normal.
  - Durbin-Watson = 2.057 — no significant autocorrelation.

  Overall, the Fama-French model provides a strong fit for Reliance's returns. The stock exhibits high market sensitivity and a significant negative loading on the size factor, while the value factor appears to have negligible influence.

- **Graphs and Diagnostics**

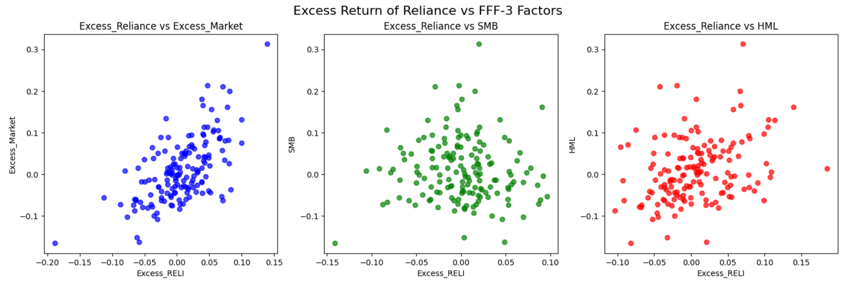

Figure 24: Scatter plots of Reliance's excess returns against the three Fama-French factors—indicating a positive relationship with the market factor, and weaker or noisier relationships with SMB (size) and HML (value) factors.

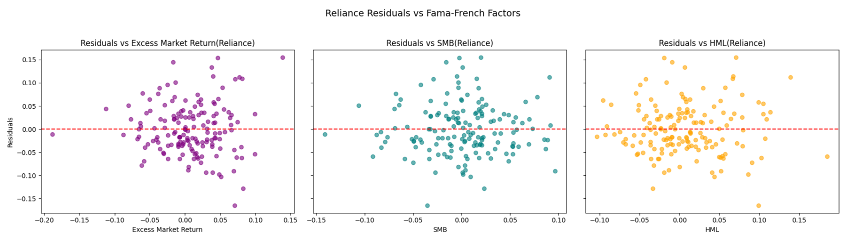

Figure 25: This plot shows the residuals of Reliance's returns plotted against the three Fama-French factors, with no clear pattern—indicating the model captures most of the systematic variation and the residuals appear randomly distributed around zero.

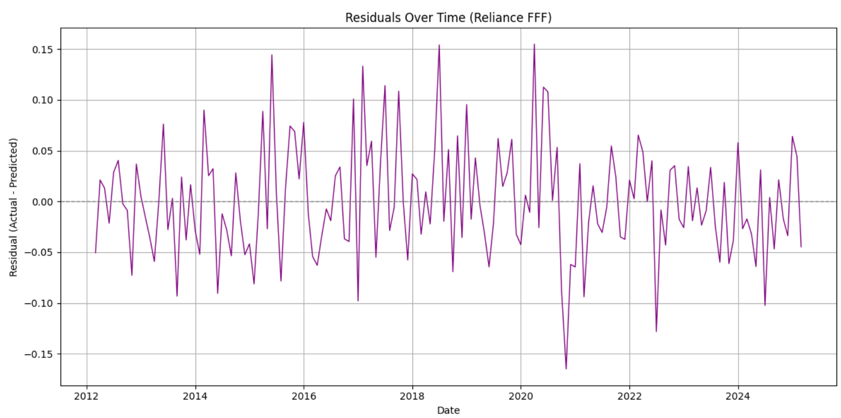

Figure 26: Time series plot of residuals from the Fama-French model for Reliance, showing no clear autocorrelation or persistent trend over time.

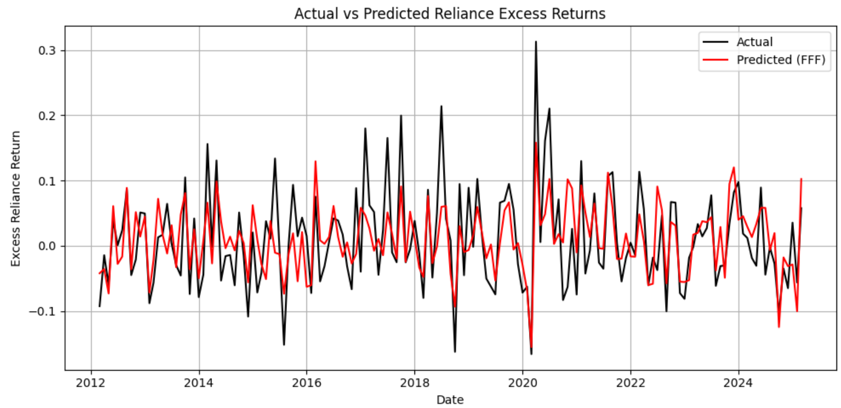

Figure 27: Comparison of actual and Fama-French model-predicted excess returns for Reliance, showing close tracking with occasional deviations.

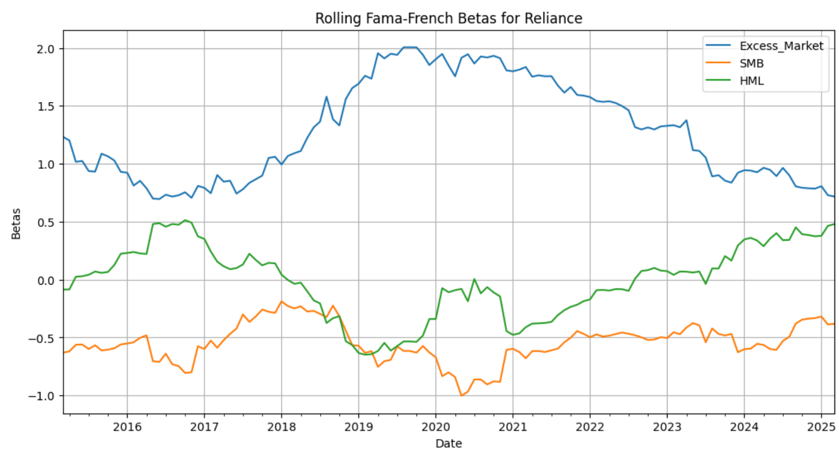

Figure 28: Rolling betas for Reliance with respect to Fama-French factors, highlighting dynamic exposure to market (Excess_Market), size (SMB), and value (HML) over time. **Excess_Market beta**: Generally above 1, meaning Reliance is more volatile than the market, **SMB**: Mostly negative — Reliance behaves more like a large-cap stock (which it is), and **HML**: Switches between positive and negative — showing changing tilt between value and growth orientation.

- **For HDFC Bank:**
  - $\alpha = 0.0037$ (not significant, $p = 0.329$), $\beta_m = 0.8494$ (significant), $\beta_{SMB} = -0.0841$ (NS), $\beta_{HML} = -0.0162$ (NS).
  - $R^2 = 37.3\%$, Adjusted $R^2 = 36.0\%$, F-statistic $= 17.90$ ($p = 5.23 \times 10^{-10}$).
  - Jarque-Bera test $= 11.228$ ($p = 0.00365$) — residuals deviate from normality.
  - Durbin-Watson $= 2.217$ — indicates stable residuals with no autocorrelation.

  Overall, the Fama-French model explains a reasonable portion of HDFC Bank's return variation, with market risk being the dominant factor. The size and value factors appear to have limited explanatory power for HDFC, and although some regression assumptions are slightly violated, the model provides meaningful insights into the stock's market-related behavior.

- **Graphs and Diagnostics**

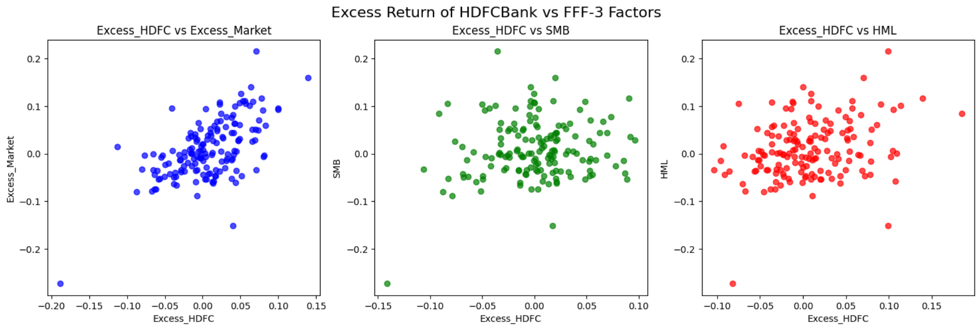

Figure 29: Scatter plots of HDFC Bank's excess return relationship with Fama-French factors illustrate strong market dependence, no clear size effect, and only a weak association with the value factor

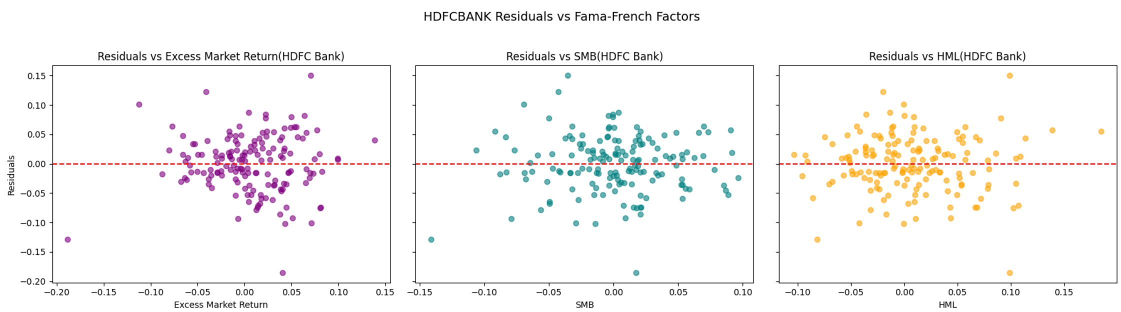

Figure 30: Residual plots for HDFC Bank against Fama-French factors indicate no clear pattern, suggesting that the model has effectively captured the relationship with market, size, and value factors.

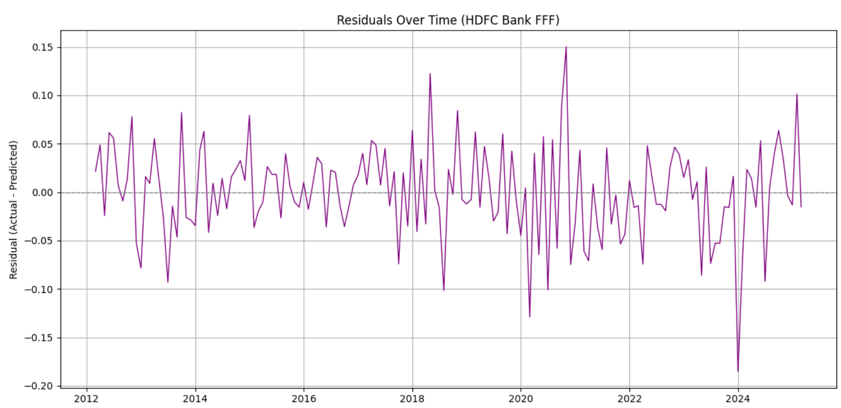

Figure 31: Time series of residuals for HDFC Bank under the Fama-French model, showing no persistent trends or autocorrelation, with errors fluctuating randomly around zero.

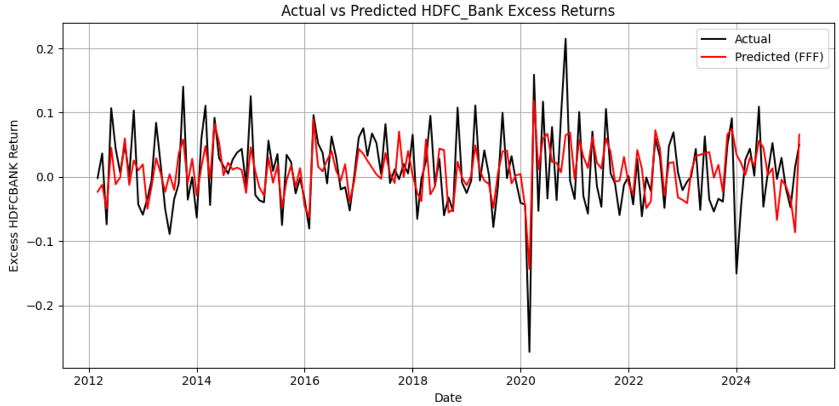

Figure 32: The plot shows actual vs. predicted excess returns of HDFC Bank, where the model (FFF) closely follows the actual return movements over time. The model captures the overall trend and volatility reasonably well, especially during periods of market stability.

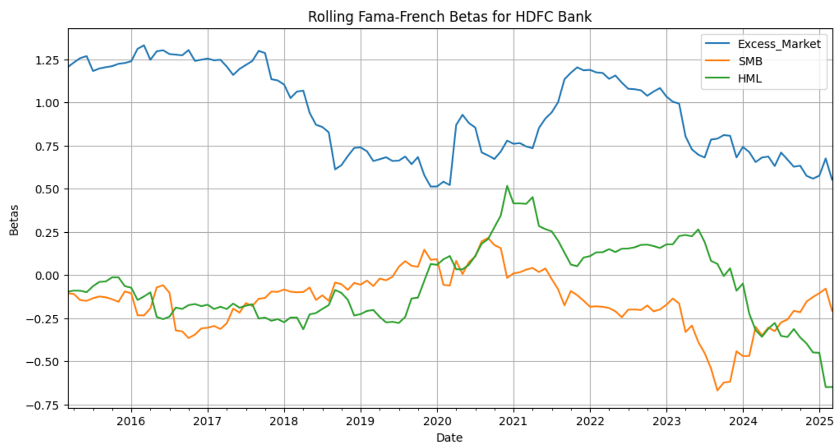

Figure 33: Rolling betas for HDFC Bank with respect to Fama-French factors displays the evolving relationship between HDFC Bank's returns and the three Fama-French factors. The market beta (Blue) starts above 1, indicating high sensitivity to market movements, but steadily declines after 2018, suggesting reduced market exposure over time. The SMB beta (Orange) remains mostly negative, showing that HDFC Bank behaves like a large-cap stock. The HML beta (Green) is generally negative as well, reflecting a tilt toward growth characteristics, with a brief upward movement around 2020–2021, indicating a temporary shift toward value.

APT Model :

1. **Dataset Snapshot after Preprocessed** :

Date	FX_Shock	IIP_Shock	CPI_Shock	Interest_Shock	Excess_INFY
2012-03	0.03668	0	0.0094	0.18	-0.0131
2012-04	0.03283	0.0010	0.01452	0.22	-0.1481
2012-05	0.070235	0.05740	0.00818	-0.03	-0.0202
2012-06	-0.01289	-0.02571	0.01217	-0.36	0.03094
2012-07	-0.001441	-0.00782	0.01303	-0.1	-0.1194

Table 5: Sample of merged final dataset for INFOSYS Stock

Date	FX_Shock	IIP_Shock	CPI_Shock	Interest_Shock	Excess_RELI
2012-03	0.03668	0	0.0094	0.18	-0.0926
2012-04	0.03283	0.0010	0.01452	0.22	-0.01443
2012-05	0.070235	0.05740	0.00818	-0.03	-0.05989
2012-06	-0.01289	-0.02571	0.01217	-0.36	0.039369
2012-07	-0.001441	-0.00782	0.01303	-0.1	0.00084

Table 6: Sample of merged final dataset for RELIANCE Stock

Date	FX_Shock	IIP_Shock	CPI_Shock	Interest_Shock	Excess_HDFC
2024-11	0.0056	-0.01464	-0.00152	0.03	0.02979
2024-12	0.01448	0.0668	-0.00560	-0.04	-0.01843
2025-01	0.01003	0.02278	-0.01024	-0.02	-0.047234
2025-02	0.00785	-0.06497	-0.00465	-0.03	0.014989
2025-03	-0.02048	0.10059	-0.00260	-0.05	0.050468

Table 7: Sample of merged final dataset for HDFCBANK Stock

2. **Regression Results :**

- **For Infosys:**
  - $\alpha = 0.0038$, $R^2 = 2\%$ — very low explanatory power.
  - No significant macro factors; CPI and FX show weak influence.
  - Residuals deviate from normality (JB $p = 0.0432$), but no autocorrelation.

  Overall, the APT model explains very little variation in Infosys' excess returns, and none of the macroeconomic factors were statistically significant. This suggests that either these factors are not primary drivers of Infosys' return or that additional/alternative variables may be required to improve explanatory power.

- **Graphs and Diagnostics**

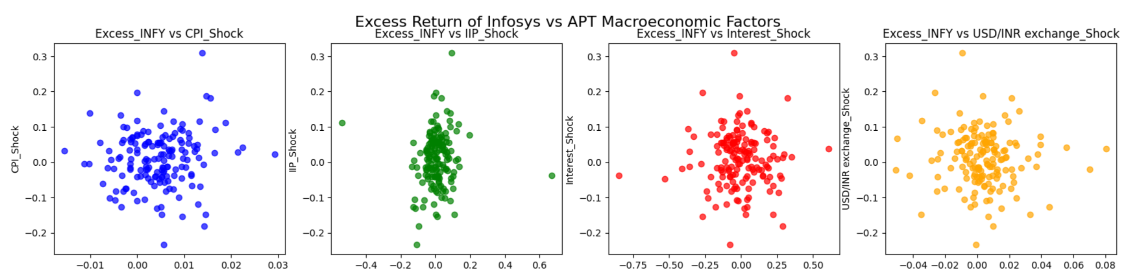

Figure 34: The scatter plots show weak and dispersed relationships between Infosys' excess returns and macroeconomic factors, suggesting limited explanatory power from these individual APT factors.

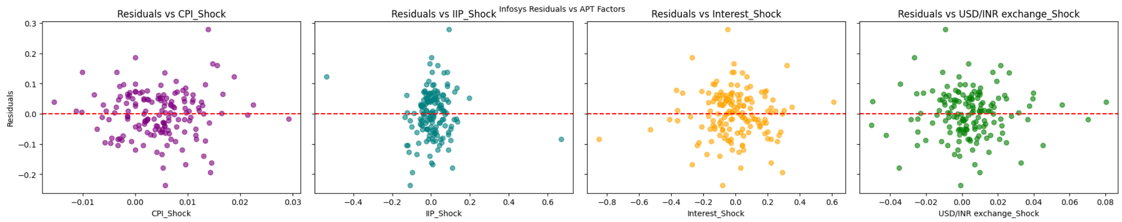

Figure 35: The residuals vs APT factors plots for Infosys show no visible patterns, indicating that the residuals are uncorrelated with the individual macroeconomic shocks—suggesting linearity and weak omitted variable bias from these factors.

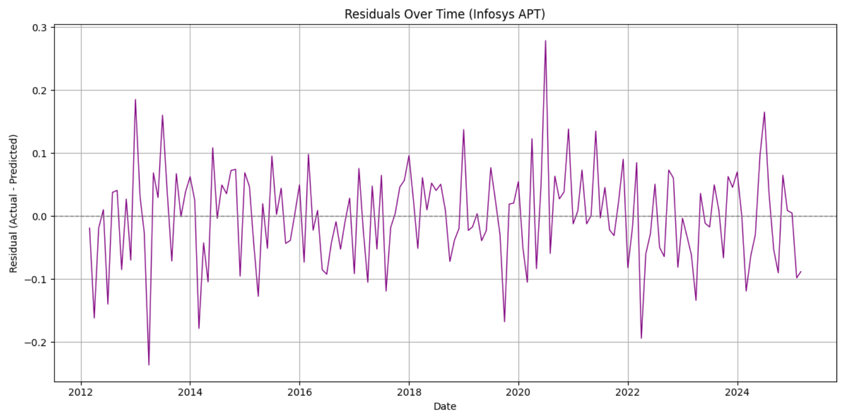

Figure 36: This is a residuals plot over time for Infosys APT, showing the difference between actual and predicted values over the years. The plot exhibits no clear pattern, indicating that the residuals are randomly distributed over time, which is a good sign of the model's stability and that there's no obvious time-related bias in the predictions.

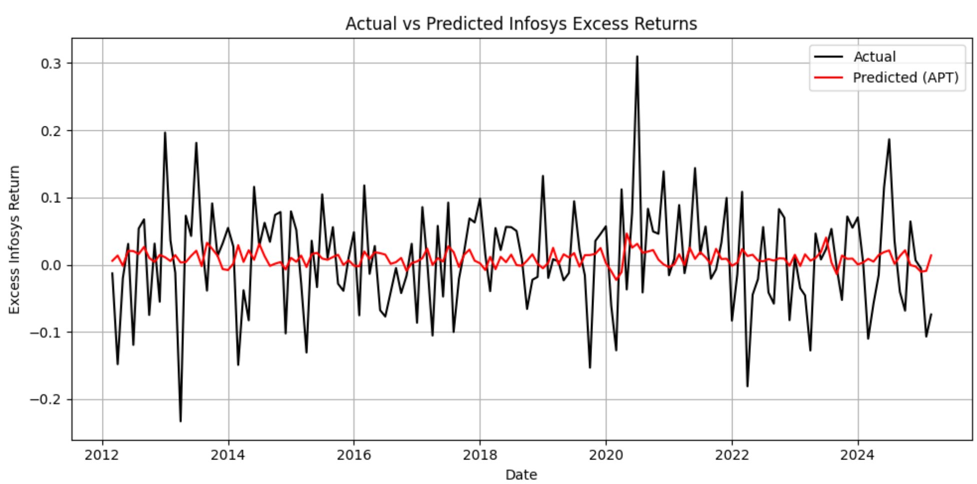

Figure 37: Comparison of actual and APT model-predicted excess returns for Infosys, highlighting the model's ability to capture the general trend but underestimating volatility and extreme return movements.

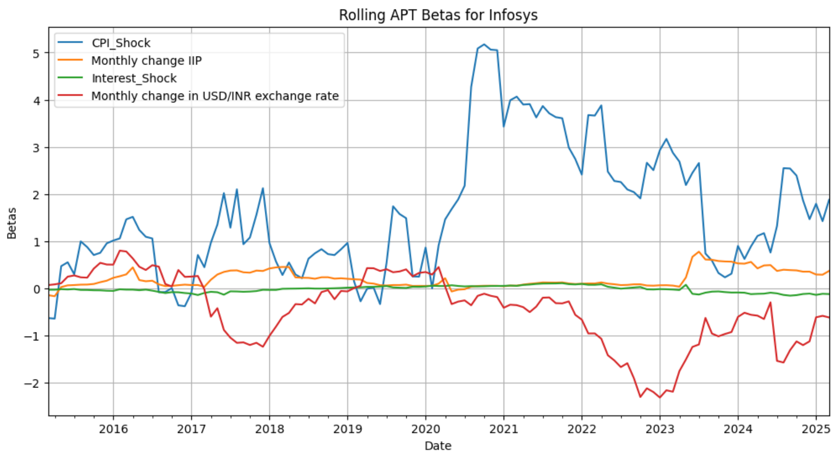

Figure 38: The rolling APT betas for Infosys show how its sensitivity to macroeconomic factors changes over time. CPI shocks have the most impact, especially after 2020, reflecting heightened sensitivity post-COVID. The IIP beta stays mostly flat, with a spike in 2023, suggesting limited influence. Interest rate shocks show near-zero impact throughout because of revenue from abroad, limited domestic demand sensitivity etc.. USD/INR exchange rate betas are strongly negative, especially from 2017–2023, indicating Infosys benefits from a weaker INR, typical for export-driven IT firms.

- **For Reliance:**
  - $\alpha = 0.0059$, $R^2 = 18.7\%$ — moderate explanatory power.
  - CPI ($\beta = 2.33$) and FX ($\beta = -1.55$) are statistically significant.
  - Model captures inflation and currency sensitivity effectively.

  Overall, the APT model provides a moderate fit for Reliance. Both CPI shock and exchange rate changes are significant predictors of its excess return, highlighting its sensitivity to inflation and currency fluctuations. The model's explanatory power is higher than for Infosys, though still leaves room for improvement.

- **Graphs and Diagnostics**

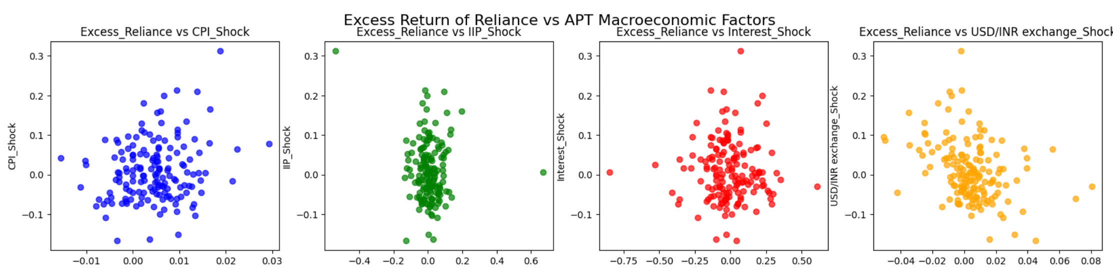

Figure 39: Scatter plots reveal that Reliance's excess returns show a weak positive relationship with CPI shocks, negligible correlation with IIP and interest rate shocks, and a slightly negative relationship with USD/INR exchange rate shocks, indicating varied sensitivities to macroeconomic factors under the APT model.

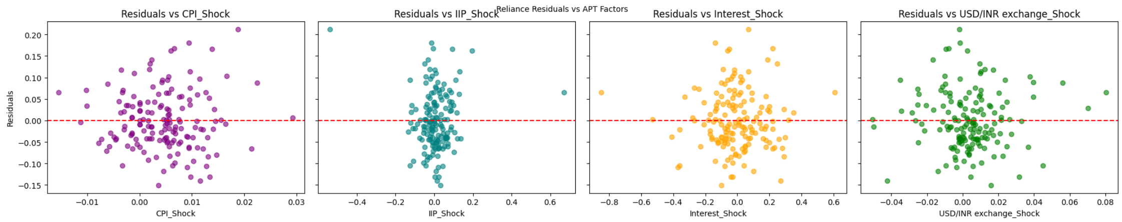

Figure 40: The residual scatter plots show no strong patterns with any APT macroeconomic factors—CPI, IIP, Interest Rate, or USD/INR shocks—indicating that these factors largely explain Reliance's excess returns, with minimal unexplained variance left in the residuals.

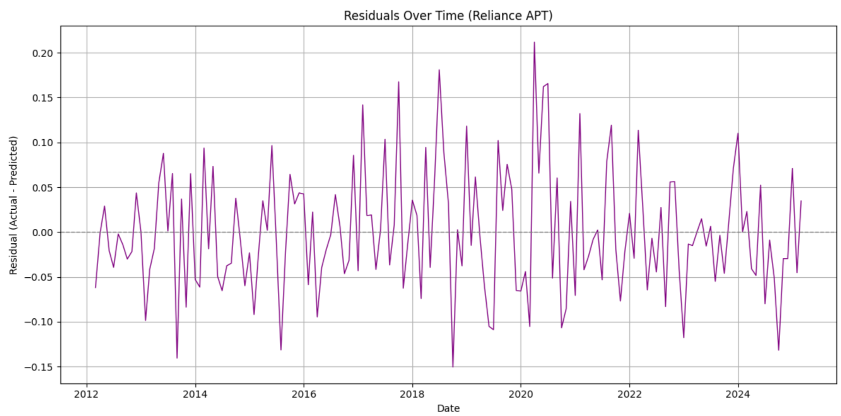

Figure 41: The residuals over time for Reliance under the APT model fluctuate randomly around zero without any persistent pattern or trend, indicating that the model captures the time-varying excess returns well and that there is no clear evidence of autocorrelation or structural misspecification.

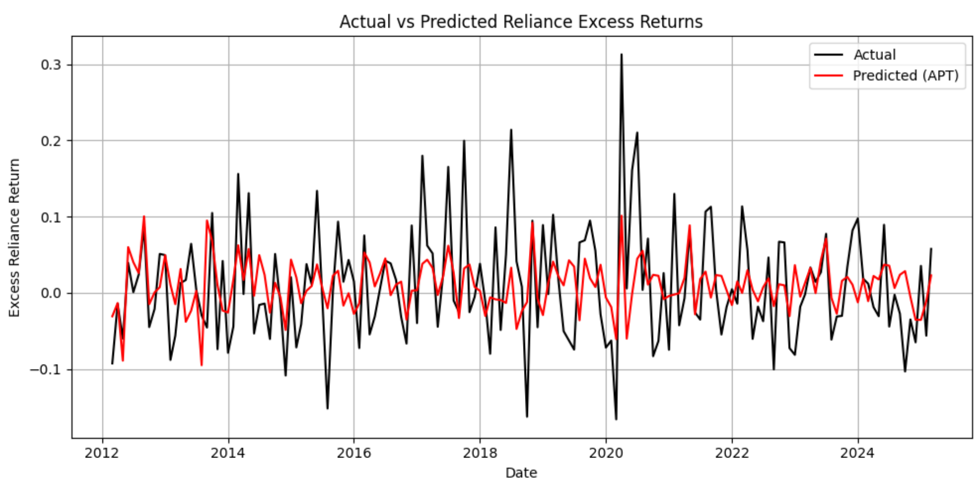

Figure 42: The APT model's predicted excess returns for Reliance closely follow the general trend of the actual returns over time, capturing the broad movement patterns while slightly underestimating extreme fluctuations, indicating reasonable but imperfect explanatory power.

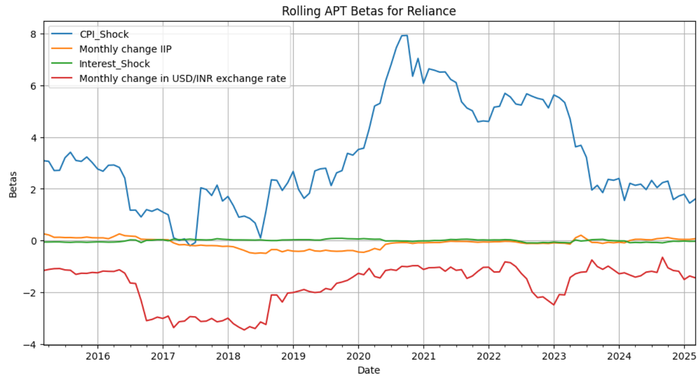

Figure 43: The plot shows rolling APT betas for Reliance, highlighting time-varying sensitivities to macroeconomic factors. CPI_Shock has the highest and most volatile impact, peaking near 8 around 2020–2021, indicating strong inflation sensitivity. The USD/INR exchange rate beta is consistently negative (between -1 and -4), showing adverse effects from rupee depreciation. Monthly change in IIP and Interest_Shock betas remain stable and close to zero, suggesting minimal influence. This reflects that Reliance's returns are most affected by inflation and currency shocks, with limited impact from interest rates and industrial activity.

- **For HDFC BANK:**
  - $\alpha = 0.0095$ ($p = 0.069$), $R^2 = 26.2\%$ — highest APT fit.
  - CPI ($\beta = 1.49$) and FX ($\beta = -1.63$) significant predictors.
  - Residuals stable but fail JB normality test.

  Overall, the APT model for HDFC Bank performs better than for Infosys and Reliance, with the highest explanatory power among the three stocks. Inflation shocks and currency fluctuations appear to be the primary macroeconomic drivers of its excess return.

- **Graphs and Diagnostics**

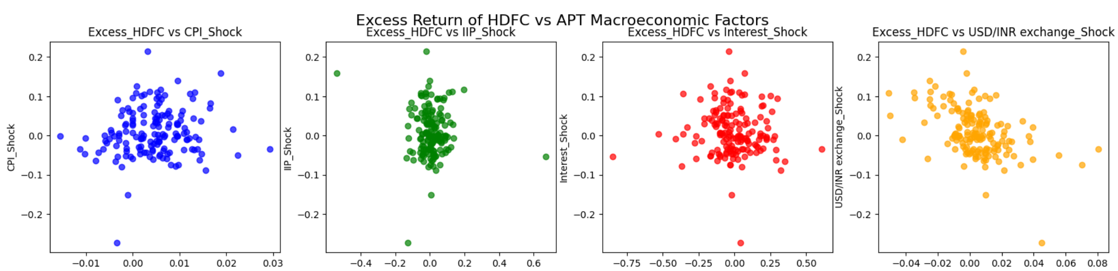

Figure 44: The scatter plots show the relationship between HDFC's excess returns and APT macroeconomic factors. CPI_Shock, IIP_Shock, and Interest_Shock show no strong correlation with HDFC's excess returns, indicating weak or negligible influence. However, the USD/INR exchange rate shock displays a negative relationship, suggesting that rupee depreciation tends to lower HDFC's excess returns.

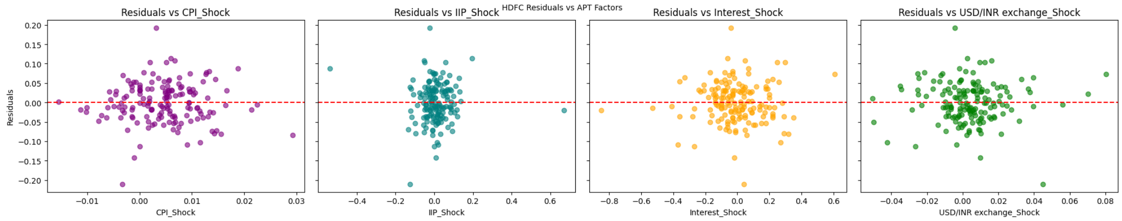

Figure 45: The residual plots for HDFC show that residuals are randomly scattered around the zero line across all APT macroeconomic factors indicating that the APT model adequately captures the systematic variation and no clear patterns remain unexplained by these factors.

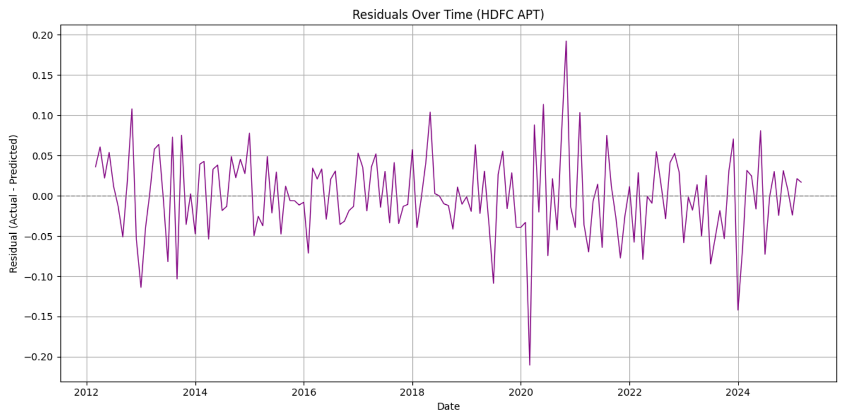

Figure 46: The residuals for HDFC under the APT model show random fluctuations around zero over time, indicating no clear pattern of model misspecification.

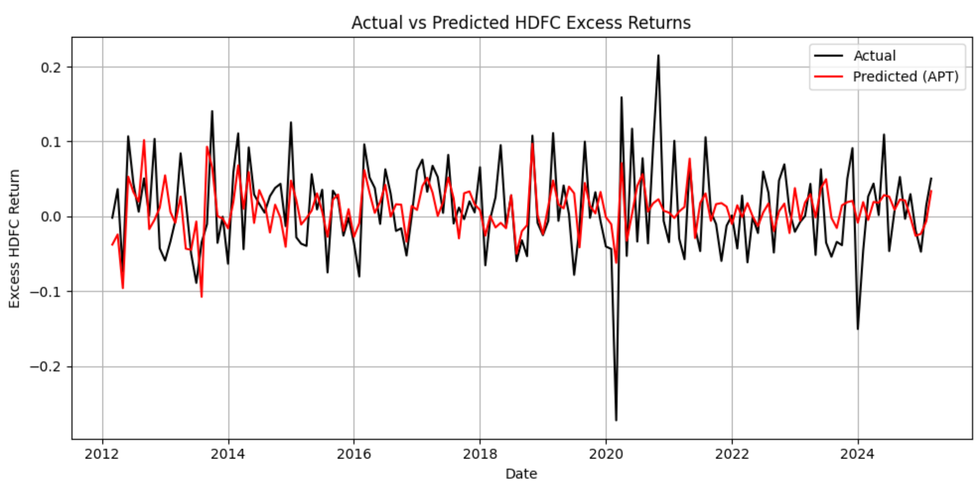

Figure 47: The APT model performs moderately well in predicting HDFC's excess returns, especially in capturing broad movements and trends, but it lags in responsiveness to large return deviations possibly due to unmodeled idiosyncratic factors.

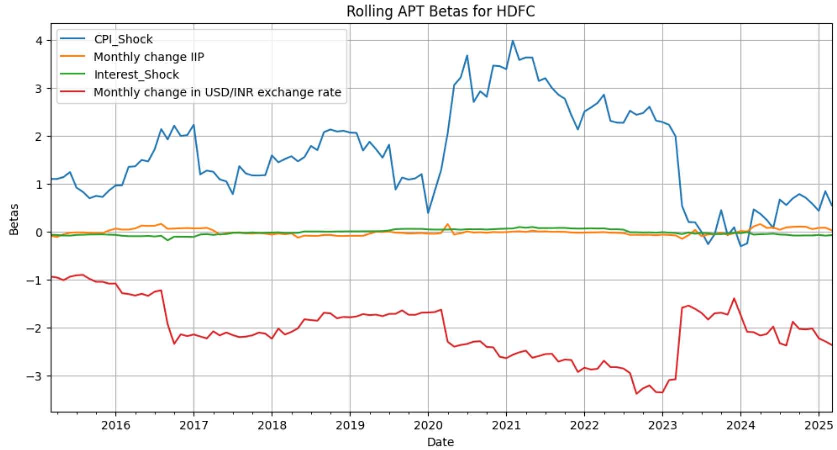

Figure 48: The rolling APT beta plot for HDFC highlights the dynamic sensitivity of the firm's excess returns to key macroeconomic factors over time. Notably, the beta for CPI shock demonstrates substantial variation, reaching a peak of around 4 in 2021, indicating heightened sensitivity to inflationary pressures during that period before declining post-2022. The beta corresponding to the USD/INR exchange rate remains consistently negative, with values dropping below -3 in 2023, suggesting that HDFC's returns are adversely affected by rupee depreciation. In contrast, the beta for industrial production (IIP) changes remains marginally positive and relatively stable, reflecting limited responsiveness to output changes. The interest rate shock beta fluctuates around zero, indicating negligible influence from monetary policy shocks. Collectively, these results imply that HDFC's excess returns under the APT framework are primarily influenced by inflation and exchange rate movements, with these sensitivities evolving over time in response to changing macroeconomic conditions.

Conclusion

This study aimed to assess and compare the effectiveness of three prominent asset pricing models — CAPM, Fama-French 3-Factor, and Arbitrage Pricing Theory — in explaining the excess returns of major Indian stocks: Infosys, Reliance, and HDFC Bank, over the period 2012–2025.

The results indicate that while the **single-factor CAPM** is statistically significant for all three stocks, it explains only a limited portion of return variability, particularly in the case of Infosys (with a low R^2). Reliance and HDFC Bank showed stronger market sensitivity, but the alpha term was statistically insignificant across all stocks, indicating no consistent abnormal returns.

The **Fama-French model** enhanced explanatory power by incorporating size (SMB) and value (HML) factors. Reliance showed the best model fit ($R^2 \approx 46\%$), with a significant negative SMB loading consistent with its large-cap status. Infosys showed a statistically significant negative loading on the HML factor, reflecting its growth-oriented nature. However, alpha remained insignificant across all stocks, supporting the efficient market hypothesis.

The **APT model** provided a macroeconomically grounded explanation of excess returns. It highlighted **CPI shocks** and **USD/INR exchange rate changes** as the most influential drivers, particularly for Reliance and HDFC Bank. Infosys, being an export-driven IT company, displayed strong negative sensitivity to exchange rate movements. While APT had limited explanatory power for Infosys, it performed better for macro-sensitive stocks.

- **Risk Exposures Quantified:** CAPM beta, FFF betas, and APT macro-factor sensitivities were estimated and interpreted for each stock.
- **Alpha Detection:** No statistically significant alpha was observed under any model, implying a lack of persistent abnormal returns.
- **Model Comparison:** The FFF and APT models outperformed CAPM in both explanatory power and economic

insight, with APT offering the best fit for macro-sensitive stocks like HDFC and Reliance.

- **Investor Insights:** Multi-factor models, especially APT, provide a more comprehensive framework for analyzing Indian stock returns, improving risk management and return forecasting for investors.

Future Works

While this study provides comprehensive insights into the applicability of CAPM, Fama-French, and APT models on selected Indian stocks, there are several avenues for future research:

- **Expanding the Stock Universe:** Including a larger and more diverse set of Indian stocks across various sectors and market capitalizations could improve generalizability and robustness of the results.
- **Incorporating Momentum and Liquidity Factors:** Extending the Fama-French model to a five-factor or six-factor version by adding momentum and liquidity effects may offer better explanatory power.
- **Dynamic Factor Modeling:** Applying time-varying parameter models or regime-switching frameworks could capture non-linear or structural changes in factor sensitivities more effectively.
- **High-Frequency and Daily Data Analysis:** Using higher-frequency data may uncover short-term risk dynamics that monthly data cannot capture, particularly useful for traders and risk managers.
- **Machine Learning Approaches:** Leveraging machine learning algorithms (e.g., random forests, XGBoost, or neural networks) to discover non-linear relationships and interactions between returns and risk factors.
- **Behavioral and ESG Factors:** Exploring the impact of behavioral biases or ESG (Environmental, Social, Governance) metrics could enhance traditional models in capturing emerging market investor behavior.

References

[1] Sudipta Das. Empirical evidence of conditional asset pricing in the indian stock market. *Economic Systems*, 39(2):225–239, 2015.

[2] Sudipta Das. Asset pricing test using alternative sets of portfolios: Evidence from india. *Asia-Pacific Financial Markets*, 2019.

[3] Harshita, S. Singh, and Surendra S. Yadav. Indian stock market and the asset pricing models. *Procedia Economics and Finance*, 30:294–304, 2015. IISES 3rd and 4th Economics and Finance Conference.

[4] Botao Huang. Research on the financial model selection between capital asset pricing model, arbitrage pricing model, and fama-french model. In *Proceedings of the 2023 International Conference on Management Research and Economic Development*, Champaign, IL, USA, 2023. College of Liberal Arts & Sciences, University of Illinois Urbana-Champaign, The Authors. Open Access under CC BY 4.0 License.

[5] Shital Jhunjhunwala and Sandra Suresh. Commodity and stock market interlinkages: Opportunities and challenges for investors in indian market. *Global Business Review*, 25(2_suppl):S42–S58, 2024.

[6] Ziyan Tang. Risk-return analysis of equity portfolios: Comparison between capm and fama-french three factor model. In *Proceedings of the 3rd International Conference on Economic Development and Business Culture (ICEDBC 2023)*, pages 227–237. Atlantis Press, 2023.

[7] Ruijun Wu. Model comparison between capm and apt: With focus on application of factor models, 2022. Unpublished manuscript or working paper.

[8] Yuxuan Xiao. Comparison of the applicability of capm and fama-french model in different regions. In *Proceedings of the 2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022)*, pages 2493–2496. Atlantis Press, 2022.